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iNaturalist and Early Detection & Distribution Mapping System provide complementary data for monitoring non-native herpetofauna in Florida

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Florida hosts one of the world's highest concentrations of non-native herpetofaunal species, making it a critical setting for understanding invasion dynamics. As citizen science becomes increasingly integrated into invasive species monitoring, there has been a growing focus on the research potential of individual platforms. This study compares two biodiversity reporting platforms, iNaturalist and Early Detection & Distribution Mapping System (EDDMapS), providing novel insights into detection biases and data complementarity. Data availability was compared between EDDMapS and iNaturalist as a function of species traits using generalized linear models, human population density level using a generalized linear model with a binomial distribution and spatial coverage of species using minimum convex polygons. EDDMapS reported proportionally more species of higher maximum body mass than iNaturalist. iNaturalist yielded more introduced herpetofauna observations across more Florida counties, in urban areas, whereas EDDMapS reported greater species richness, reflecting the database's inclusion of professional rapid response reports and broader coverage of non-urban habitats. While total observations were strongly associated with species range size, EDDMapS exhibited significantly larger grid-based ranges than iNaturalist, indicating broader spatial coverage when controlling for observations. Our results suggest that

using both platforms in one easy-access system—EDDMapS's professional reports for early detection and iNaturalist's high-volume observations for long-term monitoring—could be effective for comprehensive management.

1. Introduction

With an increasingly connected world and growing human population, biological invasions have become an important focus of conservation and management ecology [1,2]. Within the last 50 years, research has examined the extent of anthropogenic alterations to ecosystems that have facilitated the intentional or accidental spread and possible establishment of non-native plant and animal species [2–4]. While not all introduced species are classified as invasive and potentially harmful to an ecosystem, there remains management interest to monitor all introduced species [5,6]. While it is uncommon for introduced species to establish non-native populations, those that become invasive can cause severe negative ecological impacts [7,8]. Once established, invasive species may outcompete natives for space and resources [9] and alter trophic dynamics [10,11]. Once a species becomes established, it becomes increasingly challenging to eradicate [12,13]. The stages of invasioncontrol are prevention, eradication, containment and asset-based protection, where the cost to control efforts increases significantly as the stages progress [14]. This emphasizes the importance of early detection and rapid response of introduced species [15,16]. By identifying and tracking emerging populations before they reach the point of ecological dominance, natural resource managers can mitigate damage more effectively. This is especially true for taxa such as reptiles and amphibians, which are often cryptic and are able to persist for a long period of time without detection [17,18].

Herpetofauna represent the classes of Reptilia and Amphibia, which are frequently studied together because of their similar ecology and physiology [19]. Herpetofauna have historically been understudied in wildlife research, as funding has often favoured more charismatic vertebrates [20,21]. However, owing to their large-scale declines in the last half century, interest and research have increased, with more studies focusing on herpetofauna conservation, management and distribution [21,22]. Herpetofauna are common non-native species in subtropical climates owing to pet trade introductions, lack of natural predators and their ectothermic physiology [23,24]. Urban areas in particular can facilitate the establishment of non-native herpetofauna, providing warmer microclimates, artificial refuges and abundant anthropogenic food resources that support survival and reproduction [25–27]. These habitats also serve as primary introduction points, as many herpetofauna enter the environment through the pet trade and escape or are released near human settlements [28,29]. Thus, urbanization plays a dual role—enhancing both the ecological success and detectability of non-native herpetofauna, while also introducing observation bias owing to the concentration of citizen scientists in developed areas [30].

Florida currently has one of the highest numbers of non-native herpetofaunal species globally, which has led to dramatic changes in ecosystem functionality, biodiversity and species distribution [24]. The state is particularly susceptible to introductions because of its subtropical climate, numerous shipping ports, active pet trade and weather events such as hurricanes that can facilitate escapes from captivity [26]. There are around 137 taxa introductions documented from 1863 to 2015 [25,27]. Species such as the Argentine black and white tegu (*Salvator merianae*), green iguana (*Iguana iguana*) and Burmese python (*Python bivittatus*) are among some of the most problematic non-native reptile species introduced to Florida, as they outcompete native species for food while displacing them from their habitat [24,28,29]. Many non-native herpetofauna in Florida are cryptic, frequently exhibiting camouflage that reduces detectability. Consequently, their populations and distributions may be underestimated [17,31], impeding timely conservation responses to their ecological impacts. Ecologically, Florida contains three ecoregions—Southeastern Plains, Southern Coastal Plain and Southern Florida Coastal Plain [32]. It also contains extensive wetland habitats, including the Greater Everglades, which are difficult to access, allowing herpetofauna to expand with limited management pressure. Florida also has a large human population with 21.5 million occupants and is the third most populous state in the United States (US;[33]). This large population size means that more people are available to participate in citizen science initiatives. Finally, because the Early Detection & Distribution Mapping System (EDDMapS) originated with a focus on the southeastern US, this region has had the most time to integrate agencies onto the platform [34].

Monitoring herpetofauna populations has traditionally relied on in-field methods, which require intensive field effort and expert identification skills [35]. In recent decades, a new platform for

aggregating such data emerged through the use of EDDMapS (https://www.eddmaps.org/). This system's primary purpose is to provide a real-time picture of invasive and pest species distribution across North America, helping to identify newly established species and their spread [36,37]. Since its launch in 2005, the observations have expanded to account for 8.43 million observations of non-native organisms across North America as of 10 November 2025. This platform was created as a centralized database for agencies, programmes, partners and individuals working on non-native and invasive species, while also welcoming contributions from the general public [38,39]. Submitted observations are reviewed and verified by a network of trained local and state experts before being published on the site [34]. Data are made available to provide producers and stakeholders with up-to-date information on the spread and distribution of invasive species [40]. In Florida, EDDMapS has partnered with the Florida Fish and Wildlife Conservation Commission, Florida Natural Areas Inventory, Florida Invasive Species Partnership, Florida Exotic Pest-Plant Council, National Park Service, U.S. Fish and Wildlife Service, The Nature Conservancy and the University of Florida to create a centralized database of their non-native species records [39]. Other agencies and members of the public may also submit records to the platform, which has been promoted through the IveGot1 (https://www.eddmaps.org/project/florida/) website, application and hotline for reporting non-native animals and plants in Florida.

While EDDMapS can be a useful tool in detecting the early establishment of introduced species, it has a much smaller public audience compared to broad-scale participatory citizen science platforms. For example, the citizen science platform, iNaturalist (https://www.inaturalist.org/), has had significant increases in user activity over recent years, with over 9.4 million users as of 18 October 2025 [32,41,42] compared to the 233 435 registered users on EDDMapS [43]. iNaturalist was created in 2008 as a multi-taxa citizen science platform hosted by the California Society of Sciences and National Geographic Society [44]. Gradually, this platform expanded until it became an independent non-profit in 2023. On the platform, users submit photos and/or audio recordings of organisms and are asked to provide the location, date and time and an initial identification of the species with the help of computer vision, a family of machine learning algorithms that analyses imagery to provide a list of identification suggestions. Afterwards, members of the iNaturalist community provide their identification of the organism. Observations with more than two-thirds agreement on the species identification and that pass the iNaturalist data quality assessment [45]—which requires complete and accurate metadata, appropriate licensing and recent evidence of an organism—acquire a 'research grade' status. This status indicates that the observation has been validated and can be used for ecological research [46]. Research grade data are shared with the Global Biodiversity Information Facility (GBIF; https://www.gbif.org/), where researchers can download the data and obtain a DOI reference. With iNaturalist's extensive user base and consistent user contributions, it has become one of the most influential and reliable tools in determining ecological biodiversity within systems globally [47,48]. Consequently, the iNaturalist platform has been used in documenting introduced species, as users do not need prior knowledge of species status when uploading observations [18,40,49,50].

Together, EDDMapS and iNaturalist represent the largest publicly available spatial datasets containing non-native herpetofauna in Florida and have substantial potential to inform management. For this reason, we focused on these two platforms in this study. While both EDDMapS and iNaturalist may offer valuable data on introduced species, they have not been directly compared to investigate their effectiveness and potential advantages and disadvantages. Because these platforms serve different audiences, with EDDMapS primarily used by land managers and professionals, whereas iNaturalist receives a broad base of public users, a comparative analysis could provide a more comprehensive understanding of how non-native species distributions can be studied and monitored in the future.

Because iNaturalist users are concentrated in urbanized regions, data from the platform may over-represent human-dense areas, while EDDMapS records may reflect professional detections in more natural or management-focused landscapes [30]. While there are other known factors that bias the spatial distribution of iNaturalist data, such as distance to roads, protected land status, elevation and land cover type [30,51], we focus on population density because it is related to regions with a higher density of roads, less protected land and greater accessibility. Additionally, this investigation is meant to be a starting point towards evaluating how spatial biases influence data availability to interpret apparent distribution patterns of non-native herpetofauna.

Our aim was to compare how EDDMapS and iNaturalist represent non-native herpetofauna across Florida in terms of species reporting, spatial coverage and distribution across the population-density gradient. We anticipated that differences in contributors, observer expertise and platform goals would influence which species are reported and where those observations occur. For example,

species representation on iNaturalist may be higher for species that are large-bodied, commonly encountered in urban environments or active during the day [52]. Observations are also expected to be concentrated in accessible, human-dense areas because iNaturalist relies on volunteer reporting rather than structured surveys [53]. By contrast, EDDMapS incorporates professional rapid-response programmes, targeted management surveys and reports from natural resource agencies, which may generate broader habitat coverage despite lower overall reporting volume. Given these differences, we had three objectives: (i) to comprehensively compare the data available from iNaturalist and EDDMapS and to determine how species traits may explain differences in species representation between platforms across all recorded non-native herpetofauna in Florida; (ii) to understand the differences in data availability as a function of population density; and (iii) to understand the overall distribution (i.e. range size) of non-native species across Florida. Corresponding to these objectives, based on known platform user bases and sampling differences, we expected: (i) species frequently reported on one platform would also be frequently reported on the other (cross-platform concordance), but cross-platform differences in species representation would vary with body size, activity period and habitat preference; (ii) iNaturalist observations would occur disproportionately in more urbanized areas compared to EDDMapS; and (iii) for an equal level of sampling effort, EDDMapS would exhibit broader spatial coverage owing to targeted professional reporting. This comparison will provide insights into how different data streams contribute to our understanding of species invasions and their spatial patterns.

2. Methods

2.1. iNaturalist

To obtain iNaturalist observations, we used GBIF to obtain all Florida records of class Amphibia and Reptilia on 29 August 2024, which is the standard recommended practice for accessing research grade data from iNaturalist [54,55]. We then filtered data to include observations taken between January 2014 and August 2024. The start date was selected as it coincides with a significant increase in iNaturalist user adoption and data quality improvements [56]. Moreover, focusing on the most recent decade provides data that are most relevant for current non-native species management. To determine which species were non-native, we referenced multiple resources (see the electronic supplementary material, table S1,S2 for a source list for each species' status assignment). To identify non-native species, we primarily referenced a research paper that contained a list of non-native reptiles and amphibians in [27]. For species not present in that list, we located them in The Reptile Database using the R package reptiledbr [57] and inspected the described distributions to confirm that Florida is not included in the species' native range [58], and for amphibians, we used the U.S. Geological Survey Nonindigenous Aquatic Species Database to locate species and determine their status in Florida [59]. For native species, we referenced The Reptile Database and denoted native species where the distribution included Florida [57], the Florida Museum's checklist of Florida herpetofauna, where species are indicated as native [60], the University Florida (UF) Wildlife Extension's description of native habitat for frogs and toads in Florida [61], AmphibiaWeb where the description denoted Florida as the native range [62], and the U.S. Geological Survey Nonindigenous Aquatic Species Database to locate species and determine their status in Florida [59].

Any observations marked as 'captive/cultivated' are not considered 'research grade'. However, we acknowledge that some captive organisms may not be correctly marked as such by the community. Therefore, for all species with five or less observations on the platform, we manually screened observations for any signs of captivity, such as animals appearing in cages, being located at facilities that house captive animals (e.g. zoos or nature centres), being inside buildings or being held by a person. To do this, on 27 October 2024, we conducted two searches on iNaturalist, one for reptiles and one for amphibians in Florida with 'research grade' observations (which excludes captive observations) between January 2014 and August 2024. For any observations that were questionable, we examined the observation for any further description by the original observer to confirm that the animal was found in the wild. In most cases, we observed strong interest from the iNaturalist community around newly documented species in the state, with members often asking observers whether the organism was found in the wild, and receiving confirmation that it was by the observer. Of the observations manually screened, we found no evidence of these observations being of captive individuals, so no

manual overrides were made. While it is possible that a few observations may not have been correctly marked as 'captive/cultivated', we expect this to be rare.

2.2. Early Detection & Distribution Mapping System

We requested and obtained all EDDMapS observations of introduced reptile and amphibian species across Florida from January 2014 to August 2024. This time frame was selected to ensure direct comparability with the iNaturalist dataset. Individual species observations extracted from EDDMapS were confirmed to be non-native, with those classified as native to Florida, using the methodology described above, removed from the data. EDDMapS requires that observations are not of captive or intentionally placed organisms, and we expect that observations of these species are removed during the verification process [14,37]. EDDMapS can retrieve introduced species data to some degree from iNaturalist [63]. Since our goal was a cross-platform comparison, we removed iNaturalist-derived records from the EDDMapS dataset prior to analysis to ensure independence between platforms and prevent inflated agreement in observation counts and spatial coverage. Overlapping records were identified using EDDMapS metadata fields indicating iNaturalist origin and excluded from the cleaned EDDMapS dataset used in analysis. A total of 9258 iNaturalist observations were removed from the EDDMapS dataset. EDDMapS reports include a coordinate accuracy field (CoordAcc), which we treated as coordinate uncertainty (metres) where available and used this measure to screen observations where positional precision could affect inference (e.g. the population density model, see §2.3).

2.3. Data aggregation

All data collected from both iNaturalist and EDDMapS were downloaded and cleaned using R v. 4.4.3 [64], relying on the *Tidyverse* package for data manipulation [65]. Both EDDMapS and iNaturalist incorporate privacy measures to obscure the locations of sensitive or newly detected species, which may influence the spatial patterns of publicly available observations. Data from both iNaturalist and EDDMapS were assessed to ensure that all species included were introduced to Florida. All species names were converted to traditional binomial nomenclature to ensure continuity between iNaturalist and EDDMapS data (electronic supplementary material, table S1). To ensure taxonomic consistency across platforms, all species names from iNaturalist and EDDMapS were standardized using the GBIF taxonomic backbone. This approach harmonizes nomenclature by aligning species records to a single, global taxonomy, reducing discrepancies caused by synonyms [66]. For this study, we only examined species-level categories to maintain consistency across datasets. For the analyses, we included all non-native species observations, regardless of establishment status, because management interest extends to newly released species and establishment has not been defined for many of the species considered in this study. For the population density analysis and range distribution analysis, we applied the same positional filter to both the iNaturalist and EDDMapS datasets, retaining only records with reported coordinate uncertainty ≤1000 m [67,68]. iNaturalist records include coordinate uncertainty (metres), and EDDMapS records include a CoordAcc (converted to metres). This methodology removed 13 422 observations from the iNaturalist dataset (13.9% of data) and 19 species (21.8% of species); this includes all geoprivacy-obscured observations which have coordinate uncertainties that exceed the threshold. From the EDDMapS dataset, 1187 observations (1.9% of data) and three species (1.6% of species) were filtered out.

2.4. Platform data availability comparison

To assess the data availability between iNaturalist and EDDMapS for all non-native herpetofauna in Florida, aggregated data were joined by species name and identified based on the application. Although detections of introduced species may increase over time as populations become established, most non-native herpetofauna in Florida lack reliable establishment dates and opportunistic reporting data are not well-suited for estimating abundance trajectories. Therefore, rather than attempt to model uncertain establishment timelines, we restricted analyses to a shared 2014–2024 window (see §§2.1 and 2.2) to ensure temporal comparability between platforms. Total observations of each introduced herpetofauna species across each platform were reported as numeric values across all years. The R package *ggplot2* was used to generate maps and visual relationships between herpetofauna species

across iNaturalist and EDDMapS [69]. Maps were generated for both iNaturalist and EDDMapS data to indicate the total number of introduced herpetofauna species per Florida county. To assess whether species counts were correlated across platforms, we used a Spearman's rank correlation, comparing the number of iNaturalist observations to EDDMapS observations for each species. This method was chosen to accommodate the strongly positively skewed species observation count data in both datasets ([70]; electronic supplementary material, figure S1) and to assess monotonic associations using ranks, thereby reducing sensitivity to extreme values and differences in absolute reporting volume between platforms. Correlations were calculated in R using the cor.test() function [64].

Additionally, to assess species traits that may explain differences in species representation between platforms, we gathered species trait data from the ReptTraits and AmphiBIO databases [71,72]. These databases provided trait data on 88.7% of species that were found in both the iNaturalist and EDDMapS datasets. Both datasets provided information on activity time, maximum body mass (g) and species habitat association. We evaluated these traits as candidate correlates of cross-platform species representation, since they may be associated with how species are being reported across the two platforms. This analysis was designed to compare relative species representation between platforms and does not estimate detection probability or correct for search effort, as standardized effort data were not available for either dataset. Activity time was a categorical variable and included cathemeral, crepuscular, diurnal and nocturnal from the ReptTraits database and diurnal, nocturnal and crepuscular from the AmphiBIO database. In the ReptTraits database, only one activity time was defined, but for AmphiBIO, multiple may be defined. If this was the case, we categorized the species as cathemeral. Only one species was considered crepuscular in our dataset, so we removed it from the analysis. We chose to use maximum body mass as the size measurement because this field had the most complete data and is a more uniform measure across different groups of animals compared to body length measurements. Habitat association was defined differently for the ReptTraits and AmphiBIO databases. In the ReptTraits database, species habitat associations are based on The International Union for Conservation of Nature categorizations and include savannah, forest, shrubland, grassland, wetlands, caves, rocky, subterranean and desert. For analysis, we removed habitats that had less than five species classified as associated with the habitat type. We additionally removed the desert habitat because there are no deserts in Florida. Therefore, the habitat associations used in analysis were savannah, forest, shrubland, grassland, wetlands and rocky. In the AmphiBIO database, they classify habitat association as foraging stratum classification, which includes fossorial, terrestrial, aquatic and arboreal. However, because only seven species in our dataset had habitat classifications from AmphiBIO, we excluded amphibians from the habitat analysis. Using this data, we expected species representation on iNaturalist relative to EDDMapS to differ by body size, activity period and habitat association. In particular, we expected iNaturalist to contribute a higher proportional share of records for species associated with human-accessible environments and for species whose records are more common in opportunistic public reporting.

To model the data, we used generalized linear models (GLMs) with the log-transformed proportional ratio of iNaturalist to EDDMapS as the response for all species that were found in both datasets. To calculate this variable, we individually calculated the proportion of each species in the iNaturalist and EDDMapS datasets to account for differences in total observation numbers between platforms. Then we divided the proportion of iNaturalist observations by the proportion of EDDMapS observations for each species and log-transformed this ratio to make it normally distributed. We decided to log-transform the response instead of using a log-link family in the model so that we could directly assess the log-ratio of representation, rather than simply accounting for it within the model structure. This variable was approximately normally distributed (electronic supplementary material, figure S2). The variables activity time, maximum body size and habitat associations were modelled separately because we did not expect interactions among these variables. For all models, performance was evaluated using simulation-based residual diagnostics implemented in the simulateResiduals function of the *DHARMa* package in R [73]. All models were fitted using a Gaussian family. Activity time was modelled using three separate models, one for each activity group, to assess whether reporting differed significantly across platforms within each group. Model diagnostics indicated no major violations of distributional assumptions, as assessed using simulated residuals (electronic supplementary material, figure S3). Maximum body size was log-transformed because it was highly positively skewed (electronic supplementary material, figure S2), and this resulted in the best residual behaviour for this model (electronic supplementary material, figure S4). For habitat associations, since an individual species could be associated with multiple habitat types, we defined the six habitats as binary variables. We checked for correlation among habitat variables and found no concerning

correlations. Therefore, we modelled the habitat variables together in one model to account for possible interactions among habitat types. Model diagnostics indicated no major violations of distributional assumptions, as assessed using simulated residuals (electronic supplementary material, figure S3). We visualized the data using coefficient plots for activity time and habitat associations, and scatter plots with linear trend lines and s.e. for maximum body mass. Figures were combined using the *patchwork* package [74].

2.5. Data availability as a function of population density

To understand the data availability in both iNaturalist and EDDMapS across a population-density gradient, Florida population data were obtained from the Gridded Population of the World v. 4.11 dataset, accessed via Google Earth Engine as a tagged image file (.tif) containing the estimated number of persons per square kilometre for the state of Florida [75]. This dataset has a spatial resolution of 30 arc-seconds and is provided in the WGS84 coordinate reference system. The R package *raster* was used to extract population density values from the raster at the coordinates of each iNaturalist and EDDMapS record [76]. Since raster extraction reflects both raster cell size (approx. 1 km) and record positional precision, we harmonized positional accuracy across platforms prior to analysis using coordinate uncertainty metadata. Population density (persons per km^2) was retained as a continuous predictor across both platforms. We used a GLM with a binomial distribution to model dataset source (iNaturalist versus EDDMapS) as a function of population density, with platform as the response variable and population density as the predictor. The response was encoded as 1 for iNaturalist and 0 for EDDMapS, so the model estimates the probability of a record being from iNaturalist based on a 1-unit increase in the predictor variable. Population density exhibited a strong positive skew (electronic supplementary material, figure S5). To improve interpretability and better capture the functional relationship between population density and the probability of a record being from a given platform, we compared a binomial GLM including population density in its raw form with a model using log-transformed population density as the predictor. Model performance was evaluated using simulation-based residual diagnostics implemented in the simulateResiduals function of the *DHARMa* package in R [73]. Log-transforming population density resulted in improved residual behaviour and overall model performance, and this transformation was retained in the final model (electronic supplementary material, figure S5).

2.6. Range distribution

To understand the distribution of non-native individuals from both EDDMapS and iNaturalist across Florida, minimum convex polygons (MCPs) were generated for species with more than five observations on both iNaturalist and EDDMapS. MCPs were fitted using the *adehabitatHR* package in R [77]. MCPs were generated to assess the range of introduced herpetofauna species observed both in iNaturalist and EDDMapS. For the range analysis, MCPs were selected instead of kernel density estimations (KDEs) owing to their ability to generate straightforward, standardized polygons that are more practical for management purposes, in contrast to KDE methods, where bandwidth and smoothing parameters can affect range outcomes [78,79]. All MCPs were set to 95% to estimate the primary occurrence of all recorded species, with 5% representing possible outliers and global positioning system errors in observations [80,81]. GLMs were fitted to examine the differences in MCP areas between iNaturalist and EDDMapS, while controlling for the number of observations. The MCP area exhibited a slight right skew, while the number of observations was strongly right-skewed (electronic supplementary material, figure S6). We tested multiple models using both the Gaussian family and Gamma family with log link, with and without log-transformations of MCP area and number of observations (see explanation of tested models in the electronic supplementary material, figure S7). Model performance was evaluated using simulation-based residual diagnostics implemented in the simulateResiduals function of the *DHARMa* package in R [73]. The model with MCP area as the response variable, with platform and log-transformed number of observations as predictors, and a Gaussian family, showed the best residual behaviour and overall model performance (although DHARMa residuals did show deviation for the 0.25 quantile, all other formal diagnostic tests passed), and was retained as the final model (electronic supplementary material, figure S7). The R package *lme4* was then used to conduct mixed-effect models with species as a random effect variable [82] because we were interested in the overall difference between both platforms (i.e. average effect size), averaged

across different species. Species was included as a random intercept to account for interspecific differences in detectability and distribution unrelated to platform or sampling effort. This model was also fitted using a Gaussian distribution. Model performance was evaluated using simulation-based residual diagnostics implemented in the simulateResiduals function of the *DHARMa* package in R [73] and was considered acceptable for inference, although some residual structure remained (electronic supplementary material, figure S8). We additionally used the isSingular function in the *lmer* package to test the model for singularity [82] and found that the model is not singular, indicating that the inclusion of species as a random effect was supported by the data.

To validate and complement the MCP-derived range estimates, we implemented an approach where we compare the number of grid cells covered by each platform (hereafter referred to as the grid-range area) to evaluate how reporting intensity in iNaturalist and EDDMapS influenced perceived range size. A uniform grid, with 10 km cell widths, was created over the state of Florida using the *sf* and *tigris* packages in R [83]. Observation points were projected to an equal-area coordinate system, assigned grid cells and range size for each species and platform was quantified as the total area of occupied cells [83,84]. Prior to grid assignment, we removed exact duplicate raw-coordinate records within species and platform to avoid counting repeated identical locations. Range area was computed from unique species × platform × grid-cell occupancy, so each grid cell contributed at most once per species, regardless of the total observations within the cell. This reduces the influence of localized sampling intensity (spatial clustering) at the grid resolution, while preserving differences in spatial extent between platforms. Similar to the MCP range comparisons, we modelled grid-range areas as a function of platform and observation count. The grid-range area and number of observations were right-skewed (electronic supplementary material, figure S9). We tested multiple models using both the Gaussian family and Gamma family with log link, with and without log-transformations of grid-range area and number of observations (see explanation of tested models in the electronic supplementary material, figure S10). Model performance was evaluated using simulation-based residual diagnostics implemented in the simulateResiduals function of the *DHARMa* package in R [73]. The model with log-transformed grid-range area as the response variable, with platform and log-transformed number of observations as predictors, and a Gaussian family, showed the best residual behaviour among the candidate models and was retained as the final model (electronic supplementary material, figure S10). Although some residual structure remained, formal DHARMa tests for dispersion, outliers and zero-inflation passed. These deviations likely reflect inherent variability in grid-range area measurements and are unlikely to meaningfully affect the interpretation of predictor effects. We additionally conducted a mixed-effects model with species as a random effect. Model performance was evaluated using simulation-based residual diagnostics implemented in the simulateResiduals function of the *DHARMa* package in R [73] and was found to have acceptable residual behaviour and overall model performance, although residuals showed deviation across 0.5 and 0.75 quantiles (electronic supplementary material, figure S11). We additionally used the isSingular function in the *lmer* package to test the model for singularity [82] and found that the model is not singular, indicating that the inclusion of species as a random effect was supported by the data.

3. Results

3.1. Platform data availability comparison

A total of 141 940 observations were collected from both EDDMapS (n = 44 361, after removal of iNaturalist duplicates) and iNaturalist (n = 97 579) from 2014 to 2024. Across both platforms, we documented 130 unique introduced herpetofaunal species, including 29 species recorded exclusively by iNaturalist and 47 species recorded exclusively by EDDMapS, while 54 species were shared between both datasets (electronic supplementary material, table S1). Taxonomically, iNaturalist contained 83 species consisting of 75 reptiles and eight amphibians, while EDDMapS contained 101 species consisting of 94 reptiles and seven amphibians. Of the 130 species observed from both platforms, 121 were classified as reptiles and nine as amphibians. The top five most commonly observed introduced herpetofauna species in iNaturalist were brown anole (*Anolis sagrei*; n = 42 129), Cuban tree frog (*Osteopilus septentrionalis*; n = 10112), green iguana (*I. iguana*; n = 8575), northern curly-tailed lizard (*Leiocephalus carinatus*; n = 6209) and Peter's rock agama (*Agama picticauda*; n = 6693). A total of 19 species were reported only once on iNaturalist, while 27 species were reported once on EDDMapS. The top five most commonly observed introduced herpetofauna species in EDDMapS

included Burmese python (*P. bivittatus*; $n = 9184$), Argentine black and white tegu (*S. merianae*; $n = 8154$), green iguana (*I. iguana*; $n = 6533$), Peter's rock agama (*Ag. picticauda*; $n = 4050$) and brown anole (*An. sagrei*; $n = 3299$). Spatially across Florida, the county comparison showed that Miami-Dade County had the most observations for iNaturalist ($n = 27233$) and EDDMapS ($n = 18304$; figure 1A). All counties contained at least 1 iNaturalist observation of introduced herpetofauna, with Madison County having the lowest number of observations ($n = 2$; figure 1A). Liberty, Hamilton and Holmes counties contained no introduced herpetofauna data from EDDMapS ($n = 0$; figure 1B).

There was a significant positive association between iNaturalist and EDDMapS species counts ($\rho = 0.65$, $n = 53$, $p < 0.001$; figure 1B), meaning that species with more observations in one dataset tended to also have more observations in the other dataset. There was no significant difference in species representation across the platforms for nocturnal, cathemeral and diurnal species ($\beta = -0.405$, s.e. = 0.320, $n = 13$, $p = 0.230$; cathemeral: $\beta = -0.262$, s.e. = 0.212, $n = 10$, $p = 0.248$; diurnal: $\beta = -0.089$, s.e. = 0.251, $n = 25$, $p = 0.727$; figure 2A). We found very strong evidence of a negative relationship between maximum body mass and species representation between platforms, where iNaturalist reported a significantly higher proportion of species with lower maximum body mass compared to EDDMapS ($\beta = -0.621$, s.e. = 0.080, $n = 53$, $p < 0.001$; figure 2B). We found little to no evidence that habitat associations influenced platform data availability ($n = 53$, $p > 0.05$; figure 2C).

3.2. Data availability as a function of population density

iNaturalist observations occurred in areas with higher population density than EDDMapS observations (figure 3). Observations differed significantly across the population-density gradient with higher population density associated with greater odds that records originated from iNaturalist rather than EDDMapS ($\beta = 0.267$, s.e. = 0.002, $z = 115.49$, $p < 0.001$; figure 3). For every one-unit increase in log-transformed population density, the odds that a record originated from iNaturalist increased by 31% relative to EDDMapS.

3.3. Range distribution

After filtering records with coordinate uncertainty greater than 1000 m, the spatial extent of species reporting, measured by MCP area, was strongly associated with the total number of observations ($\beta = 18\,723$, s.e. = 4896, $n = 60$, $t = 3.92$, $p < 0.001$; electronic supplementary material, figure S12), with each 10% increase in observations corresponding to a 1784 ± 914 km^2 larger MCP area. When controlling for observation count, MCP size did not significantly differ between platforms ($\beta = 4385$, s.e. = 10 358, $n = 60$, $t = 0.42$, $p = 0.674$; figure 4). A mixed-effects model including species as a random intercept showed similar platform effects (estimate = 4460, s.e. = 9674, $t = 0.461$). The random effect of species accounted for approximately 13% of the total variation in MCP area (intra-class correlation = 0.13), indicating that differences among species contribute meaningfully to range size. This indicates that while reporting effort affects raw spatial extent, inherent differences among species drive true variation in range size independent of platform or observation count.

Grid-range area increased strongly with observation count ($\beta = 1.65$, s.e. = 0.04, $n = 177$, $t = 41.26$, $p < 0.001$; electronic supplementary material, figure S13), indicating that reporting effort remained a dominant predictor of spatial extent. After accounting for observation count, iNaturalist records occupied a significantly smaller grid-range area than EDDMapS (estimate = −0.620, s.e. = 0.10, $n = 177$, $t = -6.501$, $p < 0.001$; electronic supplementary material, figure S14). A generalized linear mixed-effects model including species as a random intercept showed similar platform effects (estimate = −0.267, s.e. = 0.04, $t = -6.653$) and showed modest among-species variation ($\sigma^2 = 0.007$).

4. Discussion

Our findings demonstrate that both iNaturalist and EDDMapS provide extensive data on introduced herpetofauna in Florida, but they differ in reporting tendencies based on species traits, the population-density gradient they sample and spatial coverage of Florida. Both platforms contributed extensive data with 130 total introduced herpetofauna species reported. Although non-native species lists for reptiles and amphibians in Florida have been published, they can quickly become outdated, and, in recent years, they may rely on information generated by professionals and citizen scientists, such as

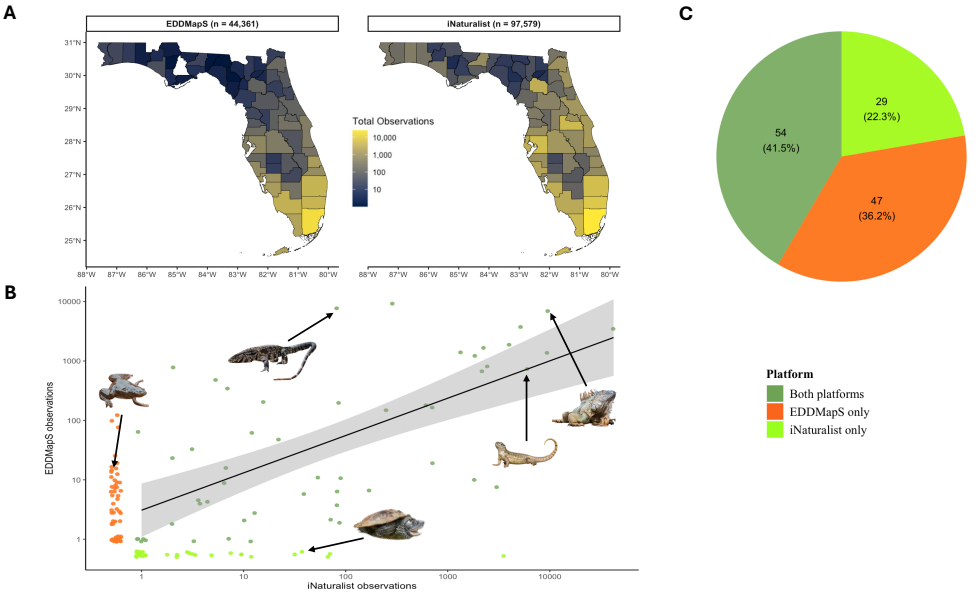

Figure 1. Comparison of introduced reptile and amphibian species across Florida from EDDMapS and iNaturalist observations. (A) The spatial distribution of total observations per county from EDDMapS (left; $n = 44, 361$) and iNaturalist (right; $n = 97, 579$). Warmer colours indicate counties with more observations. (B) Log–log scale comparison of total species-level observations between EDDMapS and iNaturalist for 54 common introduced species. The black line represents a linear regression fit (±95% shaded confidence interval) between the number of observations from EDDMapS and iNaturalist. Photographs were taken by authors (*Iguana iguana*, *Leiocephalus carinatus*, *Salvator merianae*) or by iNaturalist users: otsile makokomale (*Xenopus laevis*), and gotcritters (*Graptemys pseudogeographica*), and are CC-BY-NC (Creative Commons Attribution-NonCommercial). Images were modified to remove the background. (C) Comparison of non-native herpetofauna species presence between iNaturalist only (bright green), EDDMapS (orange), and both platforms (dark green) in Florida.

the platforms examined here. For instance, in 2015, researchers compiled a list of introduced species in Florida from vouchered specimens and photographs dating back as far as 1863 [27]. Although that study covered a different time frame, approximately half of the species it documented were also found in our study. We identified 62 species not recorded in the 2015 list, which may reflect introductions that occurred after its publication. This illustrates the value of EDDMapS and iNaturalist for providing valuable and up-to-date data for compiling non-native species lists. Additionally, we found that only 53 species were shared between applications, highlighting important differences in species coverage. iNaturalist recorded more total observations than EDDMapS, yet the spatial overlap and the significant positive association between species observations across platforms suggest some degree of complementarity. For instance, using both platforms can contribute to more equally distributed observations across species of different sizes. Spatial-coverage differences depended on the range metric. In the MCP analysis, platform differences were not statistically significant once observation count (and species-level variation) was accounted for, indicating that MCP extent was strongly driven by sampling intensity. By contrast, the grid-range area metric showed consistently broader spatial coverage in EDDMapS after controlling for observation count, suggesting that EDDMapS records are distributed across a larger portion of Florida for a given level of reporting. These results suggest that EDDMapS records are more geographically dispersed across Florida (consistent with broader grid-range area), while iNaturalist contributes higher observation volume that is more concentrated in urbanized areas. Together, our findings support the notion that integrating data from both platforms provides a more comprehensive understanding of introduced herpetofauna distributions.

4.1. Platform data availability comparison

The comparison in data availability between both platforms highlights key differences in how each platform captures herpetofauna observations in Florida, reflecting their distinct user bases and data collection goals. The greater number of total observations in iNaturalist probably stems from its accessibility and popularity among casual users and citizen scientists [41,46]. iNaturalist's mobile-friendly interface, real-time feedback and social features encourage more frequent reporting,

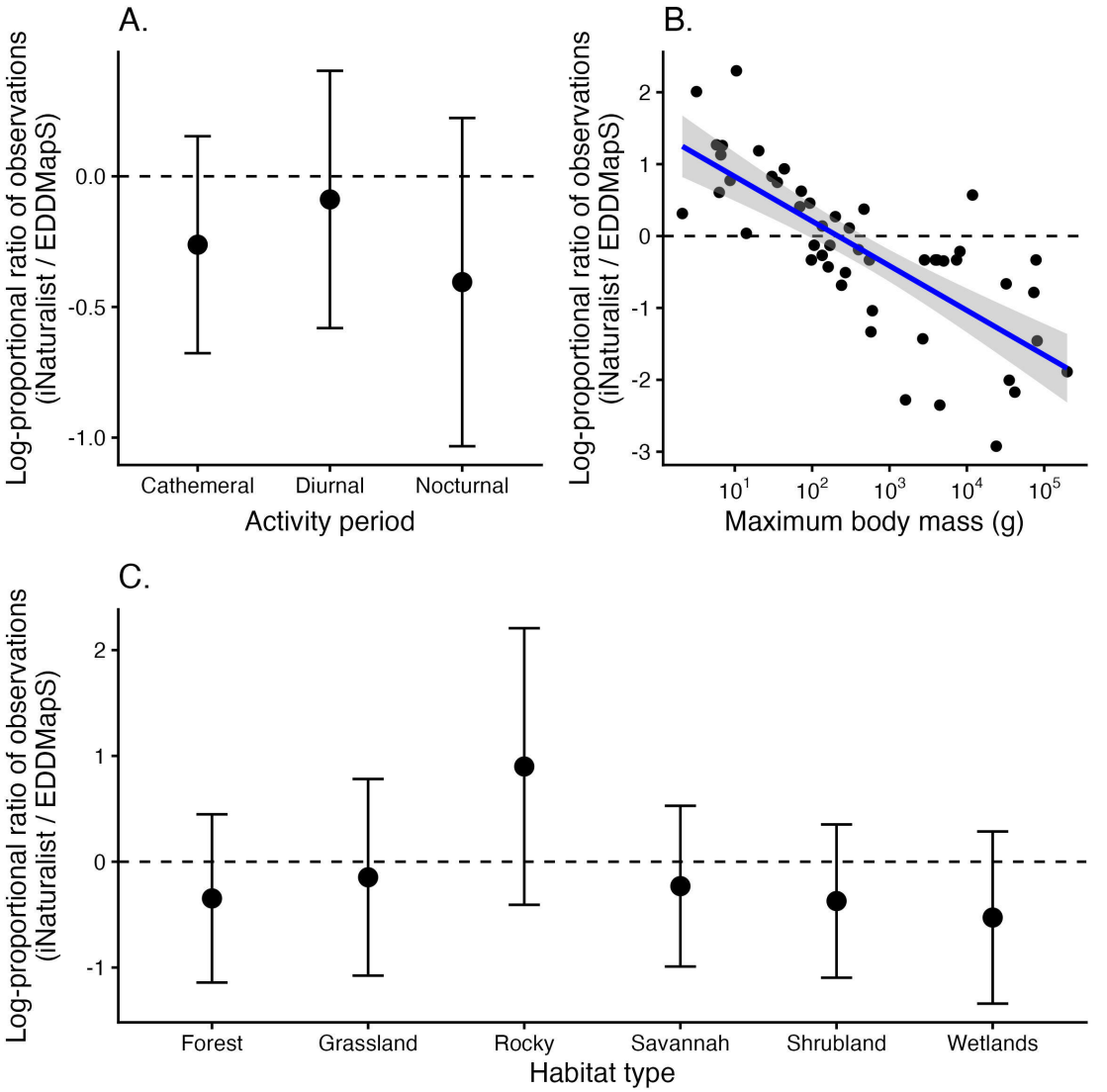

Figure 2. Comparison of the log-transformed proportional ratio of observation counts ($\log_{10}$[(iNaturalist observations/total iNaturalist observations) ÷ (EDDMapS observations/total EDDMapS observations)]) from the iNaturalist and EDDMapS platform for all species present in both datasets compared to (A) active time, (B) maximum body mass (g) and (C) habitat association [85,86]. (A) and (C) are coefficient plots of model outputs, while (B) displays the raw data, linear trend line and s.e. (A) and (B) include data from amphibians and reptiles, while (C) only includes data from reptiles. Values above 0 indicate that iNaturalist had a higher proportional observation count, while negative values indicate EDDMapS had a higher proportional observation count. Maximum body mass is displayed on a log-transformed scale. Maximum body mass was the only variable that significantly explained the log-proportional ratio of observations.

primarily in densely populated urban areas where more people encounter and report wildlife [48]. This user-friendly system makes reporting introduced herpetofauna easier for non-specialized observers [46,48]. By contrast, EDDMapS is oriented more towards the early detection and rapid response by professionals or volunteers who are aware of non-native species to report through IveGot1 and has less of a bias towards urban areas, which may explain its higher species richness despite having fewer observations [37]. Users contributing to EDDMapS are typically more taxonomically informed or may be targeting specific hotspots of invasions, leading to more comprehensive species documentation despite the lower volume [35]. With only 53 species overlapping between iNaturalist and EDDMapS, this suggests that there are meaningful differences in data selectivity and observer expertise between both platforms. For example, species such as the Argentine black and white tegu, while common in EDDMapS observations, were relatively under-represented in iNaturalist, possibly owing to trapping programmes for this species [87], which increases the rate of professional reporting compared to iNaturalist users who are subjected to their less conspicuous behaviour or low detectability in areas where observers commonly frequent [85]. The dominance of brown anoles and green

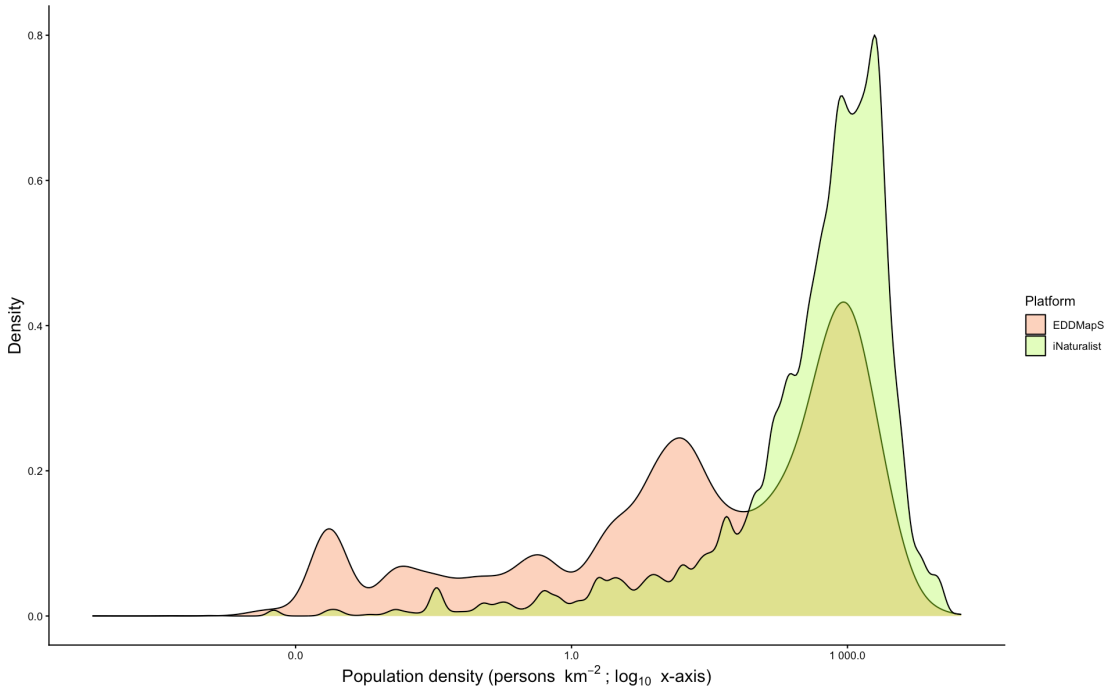

Figure 3. Distribution of introduced reptile and amphibian observations across population-density gradients in Florida. Density plot comparing the frequency of observations from EDDMapS (orange) and iNaturalist (green) along a log-transformed population-density gradient, represented by human population density. iNaturalist observations are more strongly associated with higher density areas (urbanized areas), while EDDMapS observations are more broadly distributed across low- to mid-density areas, reflecting the differences in observer behaviour and data collection strategies between platforms.

iguanas reflects the bias towards urban areas by both platforms and the population density of these species across their range [23,86,88]. While we did not examine temporal trends between platforms, EDDMapS does provide valuable historical records. Between 2000 and 2013, there were 8113 observations of 157 non-native reptiles and amphibians in Florida.

Given that species are introduced into Florida via shipping ports and the pet trade, it is critical to have as many people monitoring introductions as possible [89]. Early detection enables rapid response, allowing managers to remove species from the environment before they become established and when the cost of management is lowest [90]. Given that iNaturalist primarily contains citizen scientists, this platform may be powerful for identifying novel species on private property or in urban settings such as near shipping ports or reptile facilities. On the other hand, the IveGot1 programme allows the general public to call in non-native species observations, and while most of the EDDMapS data did come from state agencies, it is possible that people are more willing to call in species when they are out of the ordinary. In this study, we found that both iNaturalist and EDDMapS contained unique species not present on the other platform, indicating that it would be most valuable to use both datasets to track new introductions.

When we compared the proportional observation frequency of species between platforms, we found that activity patterns and habitat associations did not explain cross-platform differences in species representation, whereas body mass did. Specifically, EDDMapS contained a relatively greater proportional representation of larger-bodied species than iNaturalist. This pattern may reflect differences in platform user communities, reporting pathways or management priorities rather than direct differences in detectability. EDDMapS observations are often collected by professionals who target species during periods of activity, whereas iNaturalist observations are generally opportunistic and not focused on specific taxa. While it is unlikely that many iNaturalist users intentionally visit parks at night to make observations, nocturnal species may still be encountered in urban areas, where users can record them with relatively little effort. For example, introduced geckos such as the Indo-Pacific gecko (*Hemidactylus garnotti*) and the tropical gecko (*Hemidactylus mabouia*) can be found on buildings at night [91]. Additionally, non-native frogs may be recorded on iNaturalist via audio recordings. Additionally, EDDMapS probably contributes proportionally more large-bodied species because these species are of higher management priority because of their potential for higher ecological impact. For instance, large-bodied species such as Burmese pythons, Nile monitors (*Varanus niloticus*),

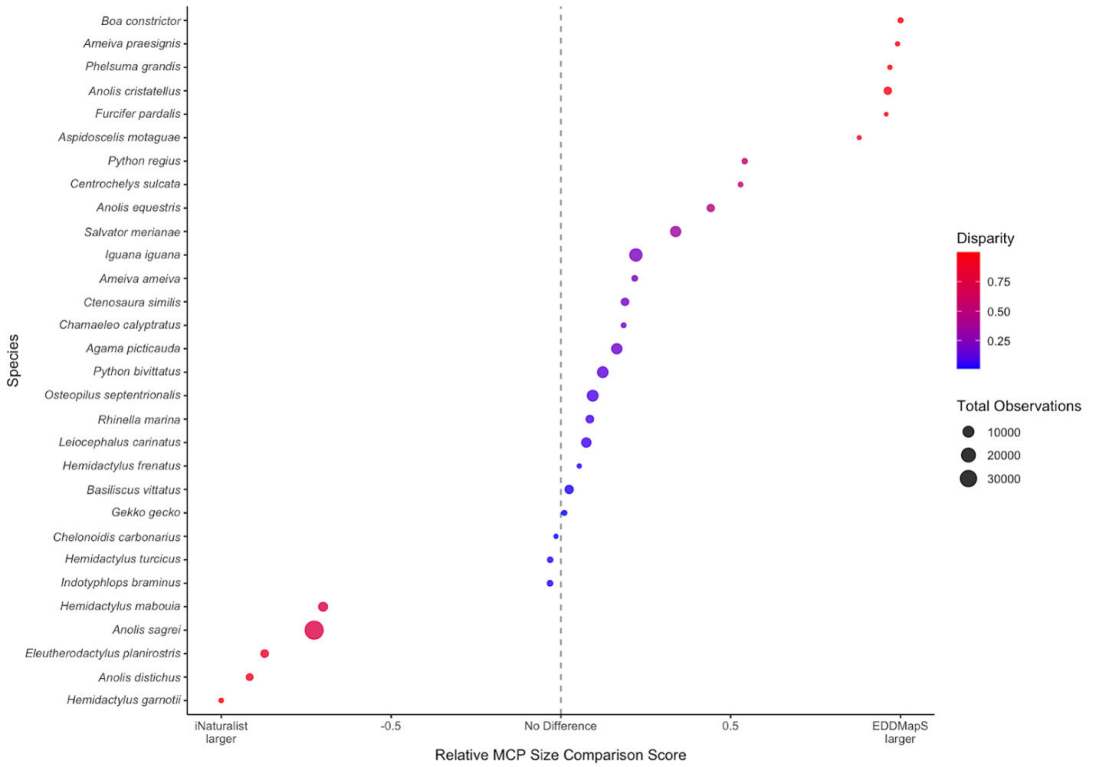

Figure 4. Comparison of species' 95% MCP range sizes derived from iNaturalist and EDDMapS data. Each point represents an introduced reptile or amphibian species in Florida, with the *x*-axis showing the relative difference in relative MCP sizes between datasets. Negative values indicate larger iNaturalist ranges, while positive values indicate larger EDDMapS ranges. Point size is proportional to the total number of observations across both datasets, while the point colour indicates the magnitude of disparity in MCP estimates between EDDMapS and iNaturalist. Most species display moderate to no differences; however, some exhibit substantial disparity, highlighting data-specific variation in spatial coverage.

green iguanas and Argentine black and white tegus are some of the highest-priority invasive species in Florida and therefore may be more strongly represented in EDDMapS records generated through agency programmes and reporting networks [92,93]. For reptiles, we did not find any differences in proportional observation frequency between platforms in terms of the habitat species' occupy. This could not be assessed for amphibians because of the sparse data coverage in AmphiBIO. Future studies could fill in the sparse data coverage through literature review to ascertain if amphibian habitat association affects observation frequency between platforms. While the trait analysis presented in this paper may explain some differences in species representation between platforms, it does not estimate detection probability. Additionally, sampling effort is not reported by either platform, so search effort could not be incorporated into models. To investigate this topic further, future studies could calculate detection probability for each species and then compare these estimates across platforms.

Geographically, the near-universal county coverage in iNaturalist compared to notable gaps in EDDMapS underscores the use of crowdsourced platforms to broaden the spatial distribution of sampling of introduced species. These differences are probably linked to broader spatial distribution of iNaturalist users, particularly in areas where professional monitoring may be somewhat limited, such as on private properties [41,46]. The modest correlation between platforms' species observation counts reflects both shared patterns (common species remaining common) and distinct differences stemming from user behaviour, observer effort and platform intent. Ultimately, our findings suggest that iNaturalist excels at providing large volumes of data on established herpetofauna, while EDDMapS can capture a wider range of species. However, the high proportion of species reported less than five times on EDDMapS suggests that this platform is better able to capture rarer species or early detection events that may be missed by citizen science platforms.

4.2. Data availability as a function of population density

Our results showed that iNaturalist observations were significantly more concentrated in higher population density areas than EDDMapS. Consistent with this pattern, increasing population density was associated with higher odds that an observation originated from iNaturalist rather than EDDMapS. This disparity probably reflects iNaturalist's reliance on opportunistic participation that is more concentrated in urban and suburban settings, aligning with known sampling biases in participatory science platforms [94–96]. By contrast, EDDMapS observations tended to occur in less densely populated areas, consistent with a greater contribution from targeted monitoring and management-oriented reporting in rural or natural landscapes [34]. To reduce the potential bias from spatial support mismatch, we applied the same coordinate-uncertainty screening (≤1000 m) and extracted population densities from an approximately 1 km raster, which aligns with the effective precision of the filtered records. These results reinforce the notion that each platform captures a distinct subset of introduced herpetofauna: iNaturalist through opportunistic, urban-driven engagement, and EDDMapS through structured, and often management-oriented surveying. Recognizing this complementary dynamic is essential in maximizing the use of both platforms in statewide biodiversity monitoring and invasive species management [97].

4.3. Range distribution

We found that spatial extent of species reporting was strongly associated with the number of observations, as species with more observations had significantly larger reported ranges. This highlights a common challenge in biodiversity data collection, where spatial coverage often reflects where people are looking, rather than where species are truly present [98,99]. However, the broader spatial reach and volume of citizen science observations help overcome these biases, especially when aggregated over time and across users, making platforms like iNaturalist valuable tools for detecting introduced species [86,100–102]. In the MCP analysis, range size increased strongly with observation count, and platform differences were not statistically distinguishable once observation count (and species-level variation) was accounted for. This indicates that reporting effort is a dominant driver of MCP extent, and that apparent platform differences in MCP size largely reflect differences in sampling intensity and species-specific spatial structure [103–105]. To complement the MCP analysis and provide a robustness check using an alternative range metric, we applied a grid-range area estimation that quantified species' occupied area as the sum of all 10 km cells containing at least one record [70,71]. This analysis confirmed the strong positive relationship between observation number and estimated range size, while showing that EDDMapS consistently encompassed greater grid-range areas than iNaturalist across comparable sampling intensities. This grid-range area analysis confirmed the strong effort–range relationship and, unlike MCP, showed that EDDMapS occupied a significantly larger grid-range area than iNaturalist after accounting for observation count, indicating broader spatial dispersion of EDDMapS records. The contrast between the MCP and grid-range results highlights how different metrics respond differently to clustered reporting. MCPs are defined by the outermost observations and therefore primarily capture the extent of peripheral records, but are less informative for how observations are distributed within that extent. As a result, two platforms can produce similar MCP estimates even when one is dominated by repeated observations [78,79]. By contrast, the grid-range metric quantifies occupied space rather than repeated observations within the same space, making it more robust to localized observer clustering and better able to detect broader geographical dispersion [83,84]. In this study, that distinction helps explain why platform differences emerged more clearly for the grid-range area than for the MCP and aligns with literature showing that opportunistic citizen science observations are often clustered near population centres and other accessible areas [95–97].

Beyond observation effort and platform, species identity explained additional variation in range size, probably reflecting urban area bias, differences in reporting context and species-specific representation across both platforms. Since EDDMapS records are more geographically dispersed (as reflected in the grid-range area analysis), while iNaturalist concentrates more heavily in urban areas, species traits such as urban affinity and conspicuousness make some species more likely to be observed by iNaturalist compared with EDDMapS. For introduced herpetofauna, these reporting patterns may favour species that are well-adapted to urban environments and human-modified landscapes [106,107]. For example, species such as the brown anole and green iguana are not only tolerant of urban environments but are also visible and active during daylight hours, making them more likely to be observed on both iNaturalist and EDDMapS [108]. By contrast, species with cryptic behaviours,

nocturnal activity patterns or limited occurrence in human-dominated areas may be under-represented in opportunistic reporting [108,109]. We suggest that understanding these species-specific differences is an avenue of further research that can be helpful to interpret current observation patterns when assessing the potential spread of introduced herpetofauna in Florida's changing landscapes.

4.4. Implications

Given that early detection and rapid response are the most cost-effective strategies for managing non-native species [110], our results should be interpreted as describing differences in reporting records and representation patterns produced by each platform's user base and data pipeline, not effort-corrected monitoring performance or detection probability. Within this scope, both platforms can contribute valuable data to guide rapid response efforts. Since we did not correct for sampling effort, spatial clustering or unequal geographical coverage, platform differences in the population-density gradient and spatial extent metrics may partly reflect where observers and monitoring programmes operate, rather than underlying species distributions. For instance, iNaturalist contained records of species such as the Central American boa (*Boa imperator*) and the red-bellied short-necked slider (*Emydura subglobosa*), which were not reported on EDDMapS. Conversely, EDDMapS contained records of the red tegu (*Salvator rufescens*) and several monitor (*Varanus*) species absent from iNaturalist. While this study is, to our knowledge, the first to directly compare species records across iNaturalist and EDDMapS, we did not evaluate the spatiotemporal dynamics of new records—such as which platform was first to document new county-level occurrences of non-native species—nor did we comprehensively compare spatial biases between platforms, such as those related to distance to road, protected land status and land cover [30,51]. Additionally, while we applied a coordinate-uncertainty filter to both platforms, EDDMapS does not provide comparable uncertainty information for all records; thus, low-precision or generalized locations may contribute errors in raster-derived population density values and inflate spatial extent estimates. Finally, any residual duplication or cross-posting between platforms could inflate concordance in species counts and spatial overlap. We reduced this risk by identifying and excluding EDDMapS records flagged as iNaturalist-derived prior to cross-platform comparison. We additionally did not explore species by establishment status because this information is not readily available for most of the species examined in this study. Future research should explore these questions to further clarify the potential of both platforms in supporting early detection and rapid response initiatives.

While having multiple platforms can provide complementary insight in monitoring and detecting introduced species, the redundancy and fragmentation in data can create challenges for large-scale synthesis and response coordination [111]. iNaturalist's high observation volume and public accessibility make it a powerful tool for monitoring established introduced species, especially in areas not routinely assessed by professionals [40,46,112]. Furthermore, iNaturalist is increasingly used in biodiversity research [113], highlighting the future potential as its contributors and identifiers continue to increase [114]. Complementing iNaturalist, EDDMapS provides structured data and high taxonomic reliability and may be particularly well-suited for early detection reporting of rarer species. Together, these platforms can provide large volumes of data to more effectively inform population assessments and monitoring efforts [115–117]. This can contribute to a growing body of literature that is using citizen science and open-source data to study herpetofauna [118–121] and inform comprehensive management strategies.

Ethics. This work did not require ethical approval from a human subject or animal welfare committee.

Data accessibility. All data and code used in this study are available on Zenodo: [122]. Supplementary material is available online [123].

Declaration of AI use. We have not used AI-assisted technologies in creating this article.

Authors' contributions. L.G.: conceptualization, data curation, formal analysis, investigation, methodology, visualization, writing—original draft, writing—review and editing; M.Z.: conceptualization, data curation, formal analysis, investigation, methodology, validation, visualization, writing—original draft, writing—review and editing; B.M.M.: conceptualization, data curation, formal analysis, investigation, methodology, validation, visualization, writing—original draft, writing—review and editing; C.T.C.: conceptualization, data curation, formal analysis, funding acquisition, investigation, methodology, project administration, supervision, validation, visualization, writing—original draft, writing—review and editing.

All authors gave final approval for publication and agreed to be held accountable for the work performed therein.

Conflict of interest declaration. We declare we have no competing interests.

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