Carinthia II

Part 3

Nature Tech

Published since 1811
215th Year of Carinthia

Volume 2

Issue 2

2025 Verlag des Naturwissenschaftlichen
Vereins für Kärnten

Carinthia Nature Tech (2025) | Volume 2 | Issue 2 | pages 7–26

Assessment of biodiversity patterns based on iNaturalist observation data from Carinthia

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KEYWORDS

- citizen science
- seasonality
- land cover
- contribution bias

ABSTRACT

This study examines the spatial and temporal patterns of citizen science contributions to biodiversity monitoring in Carinthia, Austria, utilizing iNaturalist research-grade observations collected from 2015 to 2022. It investigates potential data collection biases, such as time of day and season, as well as species phenology, including seasonal life cycles, which manifest in temporal patterns of data contributions. Additionally, the study explores how land cover and other variables influence observation counts across 5 × 5 km² grid cells, employing a negative binomial regression model with Eigenvector Spatial Filtering. The temporal analysis also analyzes seasonal shifts in the internationality of iNaturalist contributors in Carinthia. The results reveal significant effects of time of day, season, and land cover on observed species and biodiversity. Most taxonomic families were primarily recorded in forested and semi-natural areas during the summer months. Although artificial surfaces, such as urban fabric, contribute fewer observations in total, they exhibit a bias due to ease of access and longer observation hours during winter, aided by artificial lighting. The study also highlights that iNaturalist contributions in Carinthia during the summer months are predominantly from users who tend to contribute more frequently outside of Austria, suggesting that the summer period attracts more internationally active contributors, such as foreign tourists. This research expands on prior studies of biodiversity monitoring by integrating both local and global scales of contributor behavior.

Bewertung von Biodiversitätsmustern auf Basis von iNaturalist-Beobachtungen in Kärnten

ZUSAMMENFASSUNG

Diese Studie untersucht die räumlichen und zeitlichen Citizen Science Beobachtungen für Biodiversitätsmonitoring in Kärnten, Österreich, basierend auf iNaturalist Daten von 2015 bis 2022. Sie behandelt sowohl systematische Effekte in der Datensammlung, wie z. B. Tageszeit oder Jahreszeit, als auch die Phänologie von Pflanzen und Tieren, wie z. B. saisonale Lebenszyklen, die sich im zeitlichen Ablauf der Beobachtungen widerspiegeln. Darüber hinaus untersucht sie die Beziehungen zwischen Landnutzung und den Beobachtungszahlen in einem 5 × 5 km² Raster, unter Verwendung eines negativen Binomial-Regressionsmodells mit Eigenvector Spatial Filtering. Die zeitliche Analyse umfasst weiters saisonale Veränderungen des globalen Beobachtungsverhaltens von iNaturalist-Nutzern, die in Kärnten Beobachtungen durchgeführt haben. Die Ergebnisse zeigen einen starken Einfluss von Tageszeit, Jahrenzeit und Landnutzung auf die beobachteten Arten und deren Biodiversität. Die größte Biodiversität wurden hauptsächlich in Wald- und Wiesengebieten und während des Sommers beobachtet. Während in absoluten Zahlen versiegelte Flächen, so wie z. B. städtische Umgebungen, eine geringere Anzahl von iNaturalist Beobachtungen als einige andere Landnutzungstypen verzeichnen, weisen sie aufgrund der leichten Erreichbarkeit und der längeren Beobachtungszeiträume während des Winters (aufgrund der künstlichen Beleuchtung) einen systematischen Effekt auf. iNaturalist-Beobachtungen, die in Kärnten während des Sommers erfasst wurden, stammen überwiegend von Nutzer:innen, die eher dazu tendieren, auch außerhalb Österreichs Daten zu sammeln als diejenigen Nutzer, die in Kärnten während des Winters iNaturalist-Beobachtungen erfassen. Das lässt darauf schließen, dass erstere Nutzergruppe international aktiver ist, wie z.B. ausländische Touristen. Diese Forschungsarbeit liefert neue Einblicke im Bereich des Biodiversitätsmonitoring, indem sie sowohl lokale als auch globale Ebenen des Nutzerverhaltens berücksichtigt.

INTRODUCTION

In recent years, citizen science has emerged as a powerful tool for biodiversity monitoring and conservation efforts worldwide. Citizen science platforms have revolutionized the way researchers collect and analyze species occurrence data, allowing for unprecedented spatial and temporal coverage [1]. The engagement of citizens in scientific research not only contributes to data collection, but also fosters environmental awareness and scientific literacy among participants [2]. In addition, long-term citizen science data can be used to observe temporal trends and changes in phenology due to climate change and global warming [3], [4]. iNaturalist stands out as one of the largest unstructured biodiversity citizen science survey projects globally, with over 197 million observations of plants, animals, fungi, and other organisms worldwide as of July 2024 [5]. The platform

https://doi.org/10.71911/cii-p3-nt-2025221

allows users to upload an observation (e.g., photo, identification, sound) of an organism. These observations are being used for biodiversity monitoring, species distribution modeling, and phenological research [6]. Citizen science platforms, such as iNaturalist, add to a range of state-of-the-art tools for biodiversity monitoring including unmanned aerial systems technology and real-time remote sensing applications [7]. The integration of citizen science biodiversity data with advanced spatial modeling techniques has further enhanced our ability to analyze and interpret biodiversity patterns across various landscapes.

Data contributed to citizen science platforms have been used to augment traditional, structured sources of biodiversity data [3], [4]. These efforts increase the number of species records in large geographic areas and lead to a more accurate reflection of species composition compared to traditional scientific references [8]. However, the opportunistic nature of biological recordings via citizen science leads to various biases, including spatial, temporal, and taxonomic [9]. Where people live–or where they visit–could have strong implications for the spatial locations of the data collected, and the interactions between humans and the environment introduce complex spatial and temporal dynamics that shape contribution patterns over time. Understanding contribution patterns to citizen science platforms is crucial for optimizing data collection strategies and addressing potential biases in citizen science datasets. For example, researchers might prefer to use observations from more active users who are more likely to record an exhaustive sample of a particular taxonomic group of interest in a specific area, excluding low-activity users that will not heavily affect sample size [10], [11].

Studies have shown that citizen science data are often biased toward areas with higher population density and greater accessibility [12], [13]. Road networks, in particular, have been linked to increased contribution rates in both eBird [14] and iNaturalist [15] datasets, as the presence of roads can increase the likelihood of chance encounters with wildlife [16]. Proximity to roads has been identified as a strong predictor of iNaturalist contribution abundance, often diminishing the apparent influence of elevation [15]. Collection hotspots are frequently associated with sites that organize public surveys or are regularly visited by recording societies [9]. In addition, protected areas and parks tend to attract more observers, likely due to their perceived biodiversity value and recreational appeal [17]. However, the relationship between protected areas and citizen science contributions varies across regions and taxa [13]. In some cases, remote protected areas or those managed primarily for biodiversity conservation receive relatively few observations despite their ecological importance, as seen in native wetlands and wet and dry forests in Hawaii [18]. Similarly, a comparison of the proportion of pixels with observed versus expected iNaturalist records across the conterminous U.S. revealed a higher-than-expected number of observations in developed areas, with the opposite pattern observed for shrublands and grasslands [10], [11]. There is growing evidence that the type of environment, particularly the distinction between urban and rural settings, influences observers’ behavior and engagement with biodiversity. One study found that urban residents generally have lower species identification skills and weaker emotional connections to nature than rural residents [19] which may (or may not) contribute to reduced participation in citizen science biodiversity mapping. Similarly, residents living greater than 10 km from the nearest forest patch performed worse in bird identification tasks than those living closer [20]. A review of urban biodiversity research over the past 30 years also revealed that most studies remain spatially and temporally limited. Broader use of citizen science and remote sensing could help overcome these limitations and close existing knowledge gaps in urban biodiversity research [21].

Temporal patterns in iNaturalist contributions indicate that user activity peaks globally between May and September, with additional spikes during organized events such as the City Nature Challenge in late April and various bioblitzes [10], [11]. Contributions are also generally higher on weekends compared with weekdays. Similar patterns have been observed in other biodiversity-focused citizen science platforms, such as Artportalen, alongside long-term trends and weather-related effects [22].

Daily and seasonal cycles further shape temporal observation patterns, as they are closely linked both to human activity, such as the preference for data collection on weekends [23], and to phenology, that is, the timing of biological events in plants and animals [24]. Examining the seasonality and hourly distribution of observations in conjunction with environmental factors, such as land cover, can provide valuable insights into these temporal patterns and their associated biases, for example, longer daily observation windows in urban areas due to artificial lighting. Temporal analysis can also reveal unusual phenological events, such as regional flowering peaks, or highlight biases, such as the tendency to record plants during their flowering phase [25]. Furthermore, multi-year analyses of citizen science data aimed at detecting phenological shifts over time must account for systematic effects. For instance, a recurring sampling date, such as the first Saturday in June, shifts one day earlier each year and resets approximately every seven years [23].

In addition to spatial and temporal biases, citizen science datasets are also subject to taxonomic biases, meaning that some species are over- or under-represented. For instance, a comparison between collections-based bee biodiversity monitoring and research-grade iNaturalist observations showed that a small group of well-trained participants systematically collecting bees documented biodiversity more effectively than thousands of individual iNaturalist contributors [26]. On iNaturalist, the basic unit of data is the verifiable observation, which includes a date, georeference, photos or sounds, and excludes captive or cultivated organisms. Observations achieve research-grade status when at least two-thirds of community identifiers agree on a species-level or lower identification. Analyses of bird observations on iNaturalist indicate that large-bodied species, common species, and those occurring in large flocks tend to be over-represented [27]. Users also often specialize in particular taxa, such as plants or insects, rarely submit repeat observations of the same species, and tend to record species common in human-influenced areas, such as monarch butterflies or mallards [10]. Conversely, species that are often hidden, highly mobile, evasive, or difficult to photograph without specialized equipment are typically undersampled [28], [29]. Socio-economic constraints and health limitations, such as those affecting older individuals, have also been identified as barriers to participation in conservation-related citizen science activities [30]. To address such sampling biases in species distribution models, corrective methods including spatial filtering and background sampling techniques have been developed [31].

Participants in biodiversity projects tend to prefer areas with higher species richness and greater taxonomic diversity [32]. Consequently, seasonal variation in observable biodiversity may influence travel patterns, such as the distance traveled to observation sites for participation in citizen science projects. While other georeferenced crowd-sourced data, such as tweets [33], have been used to study global mobility patterns, they lack the biodiversity context that platforms like iNaturalist provide. Analyzing iNaturalist data enables researchers not only to track user movements but also to understand the motivations behind these movements in the context of nature observation. Only a few previous studies have addressed this research gap. For example, an analysis of iNaturalist observations in Hawaii indicated that most contributors were likely visitors [18] while another study found that average travel distances to parks were greater for certain park management types, such as National or State Parks, compared with city or county parks [34].

This study aims to analyze the contribution patterns to iNaturalist, using Carinthia as a case study. As an Alpine region, Carinthia offers diverse opportunities for citizen science engagement due to its rich biodiversity, sensitive ecosystems [35], [36], and distinct winter and summer seasons [37]. Accordingly, the study provides insights into local contribution characteristics for this specific Alpine region, in line with previous local studies that have, for example, identified urban biodiversity hotspots [38]. Using a range of analytical approaches, the study addresses the following objectives: (1) Identify the key environmental factors associated with the spatial distribution of iNaturalist research-grade contributions in Carinthia, and (2) examine hourly and seasonal contribution patterns, including the distribution of contributions across species and taxonomic kingdoms, the influence of land cover on user contributions, and the effect of seasonality on the share of domestic versus international data collection efforts by iNaturalist contributors in Carinthia.

METHODS

Data

iNaturalist observations

Research-grade iNaturalist data were obtained through the Global Biodiversity Information Facility (GBIF) website [39] in CSV format. GBIF provides access to biodiversity data from numerous sources, either by hosting datasets directly or by indexing those maintained by external providers. Among the citizen science contributions for Carinthia available through GBIF during the 2015-2022 study period, iNaturalist ranked fourth, accounting for 15.8% (31,974) of all GBIF records (202,368). Other major contributors include the Biodiversitätsdatenbank Nationalpark Hohe Tauern (17.7%, 35,819 records), the Biodiversitätsdatenbank Salzburg (17.0%, 34,492 records), and Pl@ntNet (16.4%, 33,089 records). Because users may contribute to multiple citizen science platforms–sometimes under different usernames–combining datasets could lead to duplicate observations. Moreover, some platforms focus on specific taxonomic groups. For example, Pl@ntNet primarily targets plants. To ensure taxonomic breadth and maintain consistency while avoiding potential double counting, this study limits its analysis to a single comprehensive source of citizen science data, iNaturalist.

The downloaded iNaturalist research-grade data included georeferenced coordinates, timestamps, species identification, anonymized observer IDs, taxonomic information, observation quality, and URLs to associated photographic evidence. These data were stored in a PostgreSQL database for further analysis, with observations from January 1, 2015, to January 1, 2023, considered. Because observations initially marked as “Needs ID” require time for verification and potential upgrading to research-grade status, we focused on the time period of 2015–2022 to ensure the use of stabilized annual datasets that had sufficient time for community validation. Research-grade observations are particularly valuable for scientific research, as they provide reliable species occurrence data at a scale previously unattainable through traditional methods [40].

Other geospatial data

The following data were used in either spatial regression or temporal analysis. Road polyline data were obtained from the Carinthia Transportation Department through Carinthia University of Applied Sciences. This dataset distinguishes between 12 road classes, which were divided into those with and without car access, followed by the computation of the total length of vehicular and pedestrian-only accessible roads within each 5 × 5 km² grid cell. Next, OpenStreetMap (OSM) road data were downloaded (https://download.geofabrik.de/europe/austria.html), and the direct distance of a grid cell to the nearest OSM primary road was computed. A land cover vector dataset was extracted from the CORINE Land Cover (CLC) 2018 version which was obtained from the Copernicus Land Monitoring Service (https://land.copernicus.eu/en/products/corine-land-cover). It comes with a minimum mapping unit of 25 ha at a scale of 1:100,000. The CLC nomenclature includes 44 land cover types, organized hierarchically in three levels. For this study, the first-level classification with five categories including artificial surfaces, agricultural areas, forest and semi-natural areas, wetlands, and water bodies (Figure 1) was used for regression, whereas the second-level classification with 12 categories was used for charting temporal contribution patterns. Artificial surfaces comprise continuous and discontinuous urban fabric, industrial and transport units, as well as artificial, non-agricultural vegetated areas, such as parks and sport facilities.

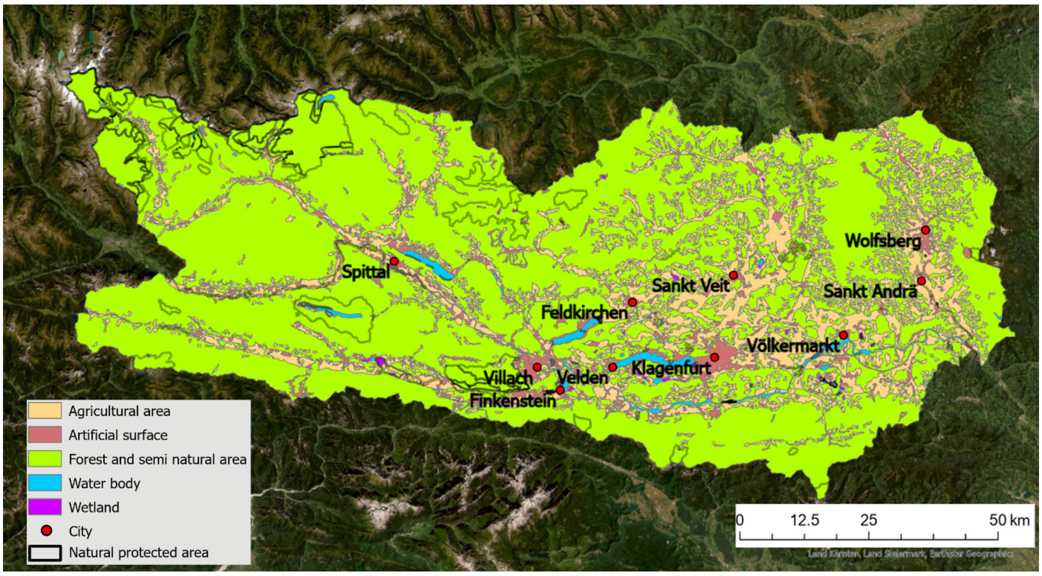

Fig. 1

Figure 1: First-level classification of CORINE land cover, protected areas and cities/towns in Carinthia

Abbildung 1: *Oberste Ebene der CORINE-Landnutzungsklassen, Naturschutzgebiete und Städte/Gemeinden in Kärnten*

Shapefiles delineating protected areas in Carinthia (see Figure 1) were obtained from multiple sources, including the Austrian Federal Ministry for Climate Action, Environment, Energy, Mobility, Innovation and Technology. This national-scale dataset served as the foundation for extracting protected areas specific to Carinthia. Additional data were manually sourced from regional environmental authorities in Carinthia, leading to 687 protected areas intersecting with Carinthia and covering 837 km².

A 10 × 10 km² elevation raster was obtained from the Austrian Open Government Data portal, and its mean elevation and slope were resampled to the 5 × 5 km² analysis grid.

The locations of the ten largest cities and towns in Carinthia as of 2020 (see Figure 1) were obtained from the Federal Statistical Office of Austria ("Statistics Austria"), with population sizes ranging from approximately 9000 to 102,000 residents. For the regression analysis, the distances between each grid cell and the nearest city (town) and protected area, respectively, were computed.

Modeling spatial contribution patterns

A negative binomial regression model was developed to predict the number of observations per nominal 5 × 5 km² grid cell where the size of grid cells is smaller along the boundary of the study area. Published literature provides several suggestions for the grid size to be used for quadrant count analysis. One method, for example, considers study area size and number of events, which gives a recommended grid size of 2 × 2 km^2 for our dataset [41]. However, this grid size results in numerous empty cells, poor model fit of the negative binomial regression, and only a few significant coefficients. It also leads to excessive computation time when incorporating Eigenvector Spatial Filtering (ESF). Therefore, the 5 × 5 km^2 grid struck an optimal balance between preservation of spatial details in contribution patterns and computational efficiency.

Besides grid size, contribution counts per cell were also considered in data preparation. Counting observations in the 5 × 5 km^2 grid raster revealed that some “super users” had contributed disproportionately large numbers of observations (several thousands) concentrated within local areas, which could not be explained by environmental variables. These isolated contribution hotspots could not be predicted through regression analysis and were therefore mitigated as follows to avoid biased model results. Within each grid cell, the number of contributions per unique user were computed. These values were then sorted across all grids. The 95th percentile was set as a threshold that was then applied to each grid cell, capping the maximum number of observations any single user could contribute to any cell. Capping contributions from super users is a common practice when modeling activity rates from crowd-sourced data. For example, this can be done by retaining only one record when multiple images are taken within the same minute or by excluding photos with identical coordinates and owner IDs, as applied in Flickr datasets [42], [43].

Candidate predictors, computed for each grid cell, included mean elevation, slope, supply of pedestrian-only and car-accessible roads, distance to nearest city and nearest protected area, and proportion of the first four land cover types shown in Figure 1, with wetland as the default land cover category. The land cover-related variables underwent a logarithmic transformation to remove non-normality. In addition, the model included an offset term (log of cell size in km^2) to account for the varying size of grid cells in which iNaturalist observations were taken. To address spatial autocorrelation among regression residuals, ESF was employed [44], using the R packages spdep and sf.

The negative binomial regression model, incorporating land cover and other predictor variables as well as spatial eigenvectors (EVs), can be expressed as:

$$\log(\lambda) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n + \text{offset}(\log(\text{area})) + \gamma_1 EV_1 + \ldots + \gamma_m EV_m + \varepsilon \quad (1)$$

where λ is the expected count of observations, $X_1 \ldots X_n$ are the predictor variables, $EV_1 \ldots EV_m$ are EVs, indexed β and γ symbols represent coefficients for predictor variables and eigenvectors, respectively, which are to be estimated, and ε is the error term.

To construct the final negative binomial regression with selected eigenvectors, a forward stepwise selection procedure was implemented based on the Akaike Information Criterion (AIC), which balances model fit and complexity. Variables with a Variance Inflation Factor (VIF) > 5 were flagged for potential removal due to multicollinearity among predictors. Spatial autocorrelation in model residuals was evaluated using Moran’s I, and McFadden’s R-squared was calculated to assess overall model fit.

Seasonal and daily variations in observation patterns

The temporal analysis examined changes in contribution patterns, including data abundance, number of taxa and users, proportion of taxonomic groups, and most frequently observed species, (1) across the four seasons; and (2) throughout the day. Some analyses were performed separately for different land cover types. For both seasonal and hourly analyses, abundance and taxonomic composition were aggregated from multi-year data (2015-2022) into four seasonal periods and 24-hour intervals, respectively. Additional descriptive statistics, such as the number of hours per day accounting for 90% of observations for each land cover type and season, were calculated to provide further insight into temporal variation in data abundance across different land cover types. Seasons were defined as spring (March through May), summer (June through August), fall (September through November), and winter (December through February). Chi-square tests were performed on different types of hourly and seasonal contribution data to identify the statistical significance of hourly or seasonal changes in the proportion of contribution to different kingdoms, taxonomic categories, and land cover types, respectively. A small number of observations, i.e., 50 in spring, 557 in summer, 56 in fall, and 15 in winter, with a timestamp of exactly "00:00:00" were excluded from all hourly-related analyses, because they lacked actual timestamp information.

Taxonomic variety in observation patterns

Related analyses report the number of unique families and genera across different land cover types and seasons. Finally, comparisons of the three most frequently observed species for each land cover type and season illustrate the phenological patterns of recorded species throughout the year.

RESULTS

Spatial contribution patterns

Tab. 1

Table 1:
Significant predictors for iNaturalist observations in Carinthia

Tabelle 1:
Signifikante Prädikatoren von iNaturalistbeobachtungen in Kärnten

Variable	Estimate	IRR	p-value
(Intercept)	1.472	4.358	< 0.001
LC proportion: Artificial surface (log)	0.226	1.253	< 0.001
LC proportion: Forest and semi-natural area (log)	-0.737	0.479	< 0.001
LC proportion: Water body (log)	0.130	1.138	< 0.001
LC proportion: Agriculture (log)	-0.218	0.804	< 0.001
Nearest distance to city [km]	-0.212	0.809	< 0.001
Nearest distance to primary road [km]	-0.136	0.873	< 0.05
EV2	-3.032	0.048	< 0.001
EV4	5.490	242.138	< 0.001
EV5	-2.816	0.060	< 0.001
EV6	-2.553	0.078	< 0.001
EV7	4.047	57.226	< 0.001
EV9	-4.339	0.013	< 0.001
EV10	-4.382	0.013	< 0.001
EV14	-3.745	0.024	< 0.001
EV15	-3.763	0.023	< 0.001
EV16	3.970	53.000	< 0.05
EV17	2.105	8.207	< 0.001
Other 53 selected Eigenvectors			
Number of observations	456		
Moran's I of residuals	0.005		0.377
McFadden's R-squared	0.12		
McFadden's adjusted R-squared	0.10		

Regression analysis

The final model (Table 1) shows significant predictors after removal of predictors due to multicollinearity and only a subset of significant coefficients associated with EVs for conciseness. Most EVs included in the model exhibit VIF values close to 1, underlining their effectiveness in capturing spatial autocorrelation without introducing multicollinearity. The residuals from the model without EVs demonstrated significant spatial autocorrelation (Moran's $I = 0.198$, $p < 0.0001$) which was mitigated after incorporating EVs (Moran's $I = 0.005$, $p = 0.377$). Elevation and the distance to protected areas were non-significant. The contribution densities in forested areas, artificial surfaces, and protected areas are 1.85 points/km^2, 11.34 points/km^2, and 4.25 points/km^2, respectively. This suggests that protected areas may function as transitional zones between artificial surfaces and forested land cover types, exhibiting neither particularly high nor low contribution densities, which likely renders this variable non-significant.

The model results indicate that the proportion of artificial surfaces and water bodies are positively associated with iNaturalist observations, while the proportion of forested areas and agricultural lands in a 5 × 5 km^2 cell shows negative associations. Proximity to cities and primary roads is linked to increased observation counts. Since the link function of a negative binomial model is the natural log, the interpretation of regression coefficients (e.g., β_1), is that each one-unit increase in the mean of a predictor (e.g., $\bar{x}1$) increases the mean number of observations contributed to a 5 × 5 km^2 cell by a multiplication factor $\exp(\beta_1)$, which gives the incidence rate ratio (IRR). For example, using the mean of 18.585 km for the "nearest distance to city" predictor across all cells, an increase of the distance by 1 km results in an IRR of $e^{-0.212} = 0.809$ and will lead, on average to a decline of $(1-0.809) = 19.1\%$ of observations in a cell. The effect sizes of the model variables with their 95% confidence intervals are expressed as IRR in Figure 2 (intercept and eigenvectors excluded), revealing the largest effect of log-transformed forest and semi-natural areas among significant predictors.

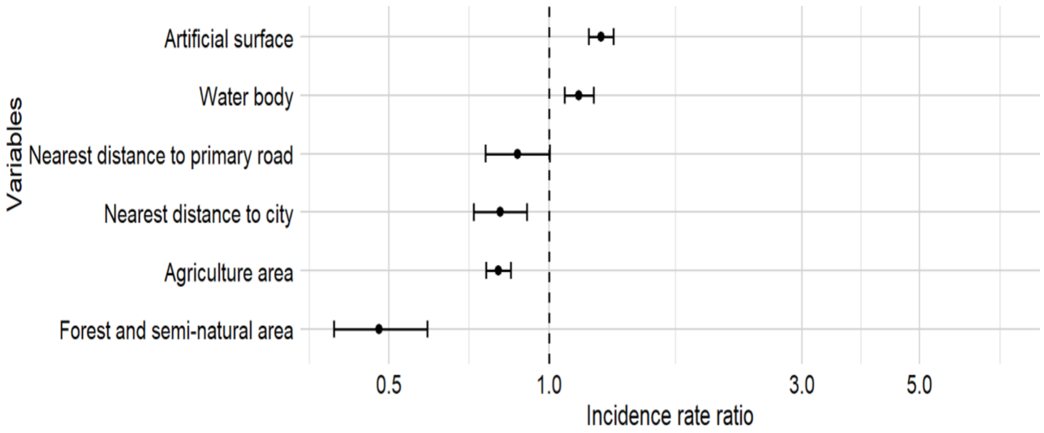

Fig. 2

Figure 2: Effect size of predictor variables

Abbildung 2: *Effektgrößen der Regressionsvariablen*

Contributions to land cover types

Users who contributed at least one iNaturalist observation in Carinthia during summer between 2015 and 2022 added observations to 2.78 CORINE land cover types (level 2, 12 types) on average (median: 2, maximum: 11). The right-tailed distribution (Figure 3a) and the log-log plot (Figure 3b) indicate that most users concentrated their observations on a few land cover types and that the number of contributors exhibited a power law relationship with the number of land cover types contributed to ($R^2 = 0.919$).

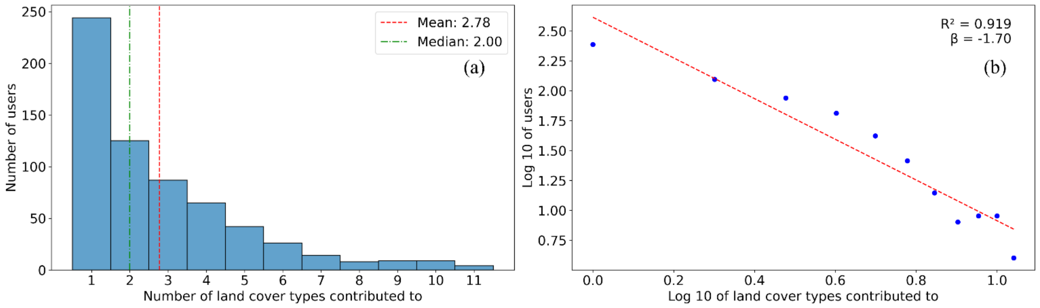

Fig. 3

Figure 3: Distribution of land cover types contributed to expressed as histogram (a) and log-log plot (b)

Abbildung 3: *Statistische Verteilung der Anzahl von Landnutzungsklassen mit Beobachtungen pro Nutzer, visualisiert als Histogram und Punktdiagramm mit logarithmischer Achsenskalierung*

Temporal contribution patterns

Seasonality of contributing individuals

Of the 825 iNaturalist users who contributed iNaturalist observations in Carinthia between 2015 and 2022, 68.3% contributed data in only a single season, 18.1% in two seasons, 6.9% in three seasons, and 6.7% in all four seasons (in any year). The first group represents typical seasonal visitors and one-time contributors, where the last group represents committed and probably local contributors taking observations throughout the year.

Contributions to biodiversity across days and seasons

The proportion of contributions to different kingdoms varies by hour and season (Figure 4). At the 12 pm peak in summer, Animalia comprises 45.4% of contributions, Plantae 51.8%, and Fungi 2.7%, whereas in fall the proportion of Animalia (63.1%) and Fungi (16.3%) increases but drops for Plantae (20.6%). Kingdom Animalia generally dominates the daily tails of early morning and late evening hours across seasons, often reaching 90-100% of observations, possibly due to nocturnal animal activity. Protozoa and Bacteria appear only sporadically in small numbers, e.g., with 1 observation for Protozoa between 8:00-9:00 in summer and 1 observation between 11:00-12:00 in fall, and 1 observation for Bacteria between 10:00-11:00 in both summer and fall. Summer exhibits the highest overall activity with a maximum of about 250 unique users contributing around 2000 observations per hour around noon, whereas winter is the opposite with a maximum of about 40 unique users contributing around 120 observations per hour around noon.

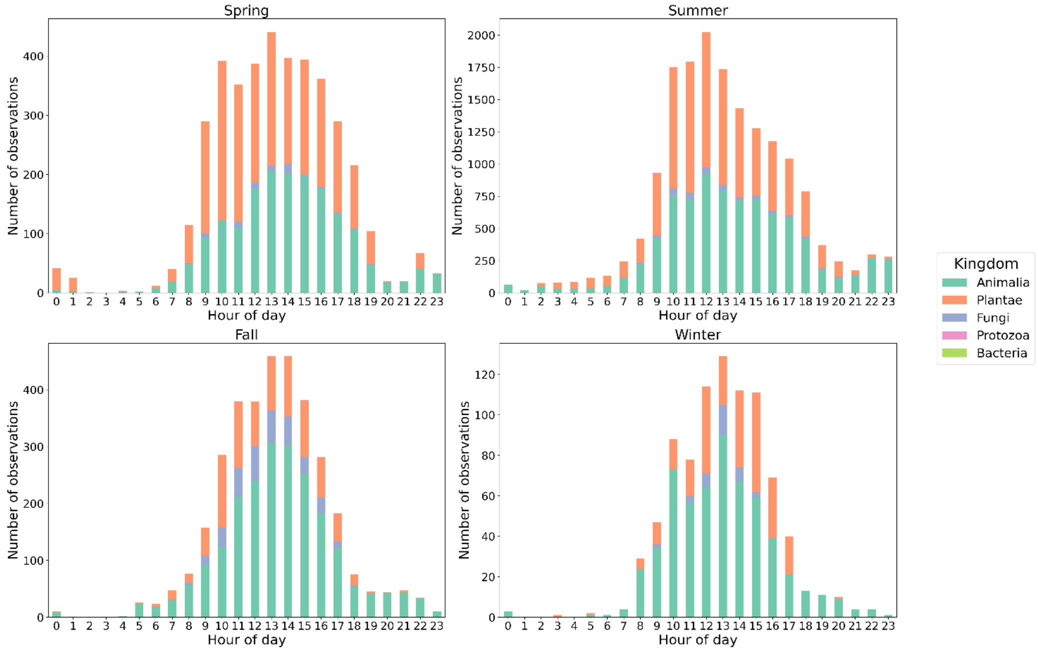

Fig. 4

Figure 4: Hourly distribution of kingdoms by season in Carinthia

Abbildung 4: *Anzahl der stündlichen Beobachtungen in Kärnten, unterteilt nach Reich*

Results of chi-square tests based on number of observations in Figure 4 show that the change in the hourly proportion of observations falling into different kingdoms is statistically significant for spring ($X^2 = 2127.01$, df = 23, $p < 0.001$), summer ($X^2 = 7336.29$, df = 23, $p < 0.001$), fall ($X^2 = 2019.01$, df = 23, $p < 0.001$), and winter ($X^2 = 603.08$, df = 23, $p < 0.001$). The proportions of kingdoms also vary significantly between seasons. For instance, Plantae dominates in spring (51.7%) and summer (51.8%), while Animalia is more prevalent in fall (63.1%) and winter (56.1%).

Seasonality of contribution patterns across land cover types

Table 2 lists the three most frequently observed species in four land cover types across four seasons. Some apparent patterns emerge, such as the predominance of butterfly and other insect observations during summer and fall for agricultural areas, followed by a shift toward more observations of birds during winter. This pattern aligns with natural phenological changes and shifts in species visibility [25], [45]. Artificial surfaces show a mix of urban-adapted species, with birds and insects dominating. Forest and semi-natural areas display high biodiversity, featuring a variety of plants, insects, and amphibians, with notable seasonal shifts from spring flowers to summer butterflies and fungi (fly agaric) in fall. Water bodies demonstrate a clear focus on aquatic species observed in summer, and birds during the remaining seasons. Each land cover type reflects its unique ecological characteristics, with seasonal variations in the most frequently observed species, highlighting the diverse habitats and seasonal dynamics of the region. The wetland habitat land cover type was excluded due to its limited number of recorded species.

Tab. 2

Table 2:
Top three observed species in four land cover types across four seasons

Tabelle 2:
Die am häufigsten drei beobachteten Arten in vier Landnutzungsklassen während der vier Jahreszeiten

Season	Artificial surfaces	Forest and semi natural areas	Agricultural areas	Water bodies
Spring	common blackbird *Turdus merula* (15)	white butterbur *Petasites albus* (24)	common bugle *Ajuga reptans* (12)	Eurasian coot *Fulica atra* (4)
	common bugle *Ajuga reptans* (14)	common wall lizard *Podarcis muralis* (21)	meadow clary *Salvia pratensis* (12)	great crested grebe *Podiceps cristatus* (4)
	greater celandine *Chelidonium majus* (14)	coltsfoot *Tussilago farfara* (20)	fumewort *Corydalis solida* (11)	sedge warbler *Acrocephalus schoenobaenus* (3)
Summer	Japanese oak silk moth *Antheraea yamamai* (22)	silver-washed fritillary *Argynnis paphia* (102)	silver-washed fritillary *Argynnis paphia* (35)	Wels catfish *Silurus glanis* (245)
	Himalayan balsam *Impatiens glandulifera* (18)	heath spotted orchid *Dactylorhiza maculata* (86)	meadow brown *Maniola jurtina* (33)	European perch *Perca fluviatilis* (35)
	silver-washed fritillary *Argynnis paphia* (16)	common frog *Rana temporaria* (55)	European peacock *Aglais io* (29)	pumpkinseed *Lepomis gibbosus* (25)
Fall	western conifer seed bug *Leptoglossus occidentalis* (48)	fly agaric *Amanita muscaria* (23)	western conifer seed bug *Leptoglossus occidentalis* (31)	mute swan *Cygnus olor* (13)
	Asian lady beetle *Harmonia axyridis* (31)	fire salamander *Salamandra salamandra* (22)	European peacock *Aglais io* (16)	mallard *Anas platyrhynchos* (8)
	common blackbird *Turdus merula* (16)	Alpine chough *Pyrrhocorax graculus* (16)	Asian lady beetle *Harmonia axyridis* (16)	common darter *Sympetrum striolatum* (7)
Winter	common blackbird *Turdus merula* (15)	European beech *Fagus sylvatica* (12)	Eurasian blue tit *Cyanistes caeruleus* (10)	mallard *Anas platyrhynchos* (9)
	great tit *Parus major* (11)	Norway spruce *Picea abies* (8)	common blackbird *Turdus merula* (10)	Eurasian coot *Fulica atra* (9)
	daddy long-legs spider *Pholcus phalangioides* (10)	common hazel *Corylus avellana* (7)	common chaffinch *Fringilla coelebs* (8)	Eurasian beaver *Castor fiber* (6)

Legend: bird butterfly other insect flowering plant tree fish amphibian reptile fungus arachnid mammal
Silhouettes sourced from PhyloPic (https://www.phylopic.org), all public domain (CC0).

Table 3 presents the typical daily observation window lengths, showing the number of hours per day that account for 90% of observations across different land cover types and seasons. The data indicate that summer generally provides the longest observation windows for iNaturalist data collection, with the exception of water bodies, which exhibit slight deviations. In winter, the longest observation window (11 hours) occurs on artificial surfaces, likely due to the influence of artificial lighting. In contrast, during summer, the longest observation window is observed in agricultural areas (17 hours), possibly attributed to minimal canopy cover and fewer obstructions to sunlight, resulting in extended natural daylight.

Tab. 3

Table 3:
90% observation hour ranges across seasons and land cover types

Tabelle 3:
90% Beobachtungsfenster während der vier Jahreszeiten in fünf Landnutzungsklassen

Season	Artificial surfaces	Forest and semi natural areas	Agricultural areas	Water bodies	Wetlands
Spring	11.00	10.00	13.55	12.05	11.00
Summer	15.00	16.00	17.00	11.00	12.00
Fall	14.00	8.00	11.00	11.80	8.00
Winter	11.00	8.00	8.35	9.00	5.00

The number of observations across the five land cover types by hour of the day and season are plotted in Figure 5 and summarized in Table 4. The relative abundance of contributions is highest in forest and semi-natural areas during spring (44.3%), summer (57.5%), and fall (36.7%), which also correspond to the highest biodiversity levels among all land cover types in these seasons (Figure 6). In winter, agricultural surfaces show the highest relative abundance of contributions (35.4%) and the greatest biodiversity for that season (see Figure 6). The proportion of contributions from artificial surfaces is lowest in summer (13.5%), suggesting that observers spend more time exploring natural areas outside of urban environments during this period. A chi-square test of independence indicates that the distribution of observations across different land cover types varies between seasons ($X^2 = 1349.86$, df = 12, $p < 0.0001$). Furthermore, the proportion of contributions to different land cover types varies significantly by hour of day for spring ($X^2 = 898.46$, df = 4, $p < 0.001$), summer ($X^2 = 1886.91$, df = 4, $p < 0.001$), fall ($X^2 = 1263.45$, df = 4, $p < 0.001$), and winter ($X^2 = 494.37$, df = 4, $p < 0.001$).

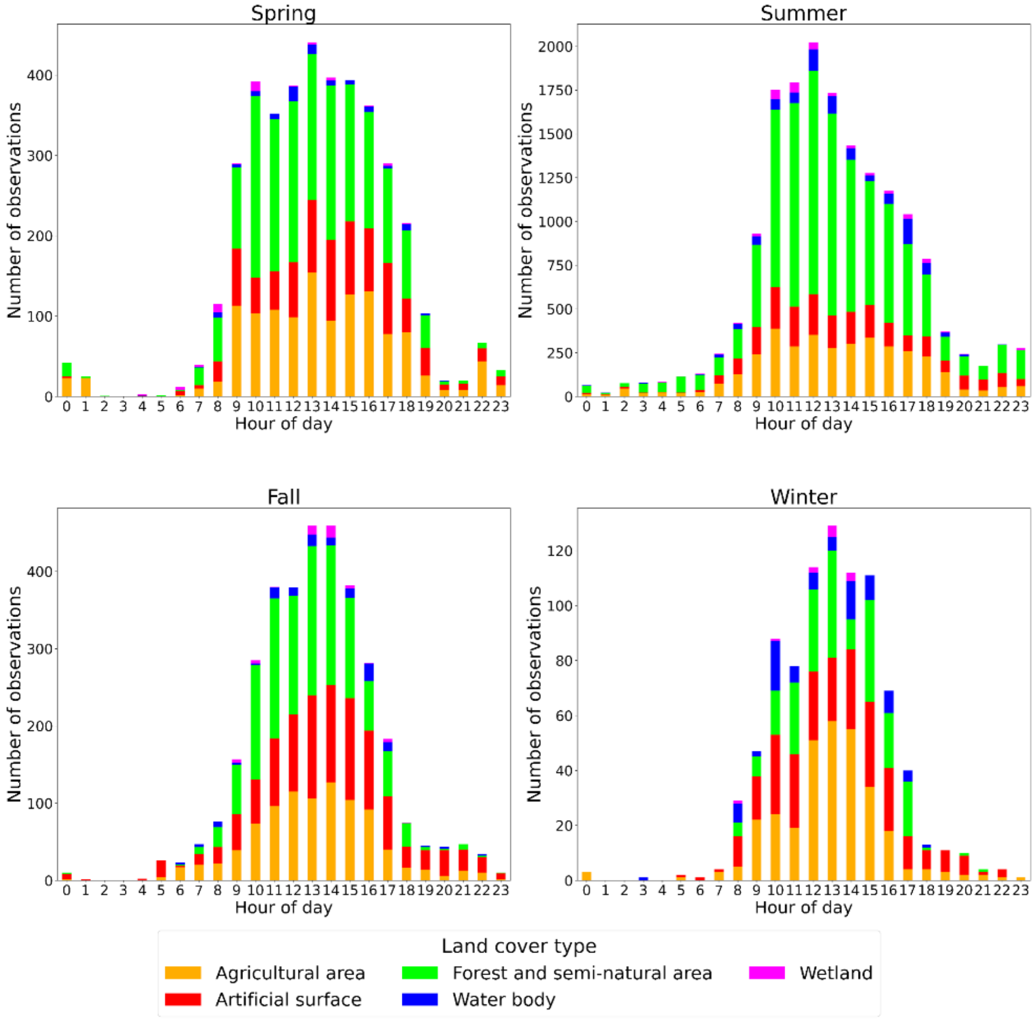

Fig. 5

Figure 5:
Hourly contribution numbers for different land cover types across four seasons

Abbildung 5:
Stündliche Beobachtungszahlen in fünf Landnutzungsklassen während der vier Jahreszeiten

Tab. 4

Land cover type	Spring	Summer	Fall	Winter
Agricultural surface	1270 (31.3%)	3772 (22.0%)	939 (27.1%)	**314 (35.4%)**
Forest and semi natural area	**1798 (44.3%)**	**9830 (57.5%)**	**1272 (36.7%)**	216 (24.4%)
Artificial surface	848 (20.9%)	2308 (13.5%)	1081 (31.2%)	264 (29.8%)
Water body	94 (2.3%)	874 (5.1%)	123 (3.6%)	81 (9.1%)
Wetland	45 (1.1%)	325 (1.9%)	47 (1.4%)	11 (1.2%)

Table 4: Number and percentage of observations falling into five different land cover types for four seasons (numbers in bold indicate land cover with highest proportion of contributions)

Tabelle 4: *Anzahl und Prozentanteil der Beobachtungen, unterteilt in fünf Landnutzungsklassen und vier Jahreszeiten (fettgedruckte Zahlen beziehen sich auf die Landnutzungsklasse mit dem höchsten Beobachtungsanteil)*

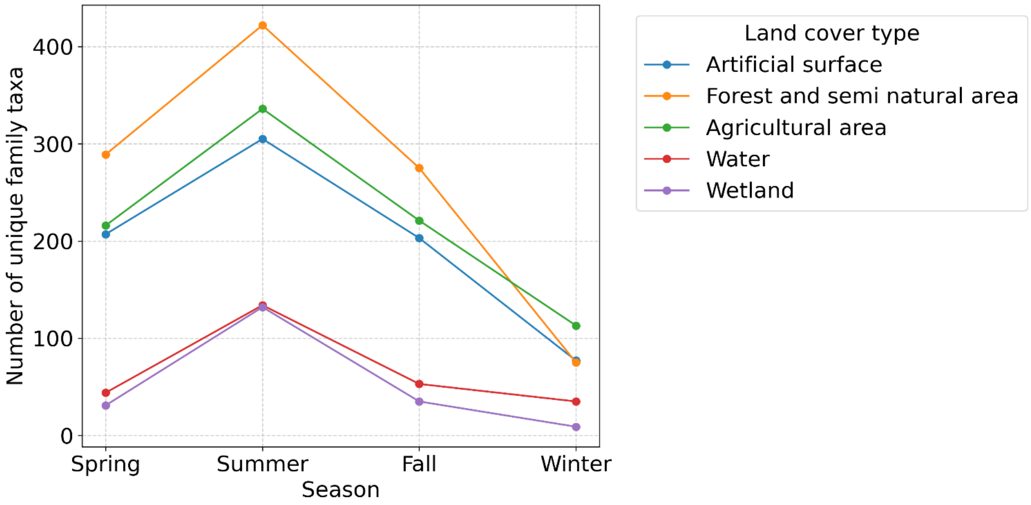

Fig. 6

Figure 6: Number of different family taxa observed across four seasons and five land cover types

Abbildung 6: *Anzahl der verschiedenen Familien in Beobachtungen während der vier Jahreszeiten in fünf Landnutzungsklassen*

Taxonomic variety of contributions

The number of contributed family-level taxa across land cover types for all four seasons is illustrated in Figure 6. Forest and semi-natural areas exhibited the highest taxonomic diversity in spring, summer, and fall, while agricultural areas showed the greatest diversity in winter. Across all land cover types, taxonomic diversity peaked in summer and reached its lowest levels in winter.

Global visitation patterns of iNaturalist contributors

For this analysis, we identified iNaturalist users who contributed at least once during winter or summer in Carinthia between 2015 and 2022, and retrieved the total number of countries they contributed to during this period (Figure 7). Users contributing in summer (mean = 4.29, median = 3) were active in a greater number of countries than those contributing in winter (mean = 3.57, median = 1). This indicates that winter contributors were more likely to be local, whereas summer contributors tended to be visitors who also submitted observations from other countries. During summer, which showed the highest level of international participation, the top three countries of contribution following Austria were Germany (230 users), Italy (194 users), and Croatia (121 users). In contrast, winter observations reflected lower international involvement, with most non-Austrian users originating from Germany (113 users), Italy (42 users), and the United States (39 users).

Figure 8 offers a complementary perspective on the international activity of iNaturalist users who contributed at least once to Carinthian observations. It displays the proportion of observations made in Austria relative to total user contributions, separated by season

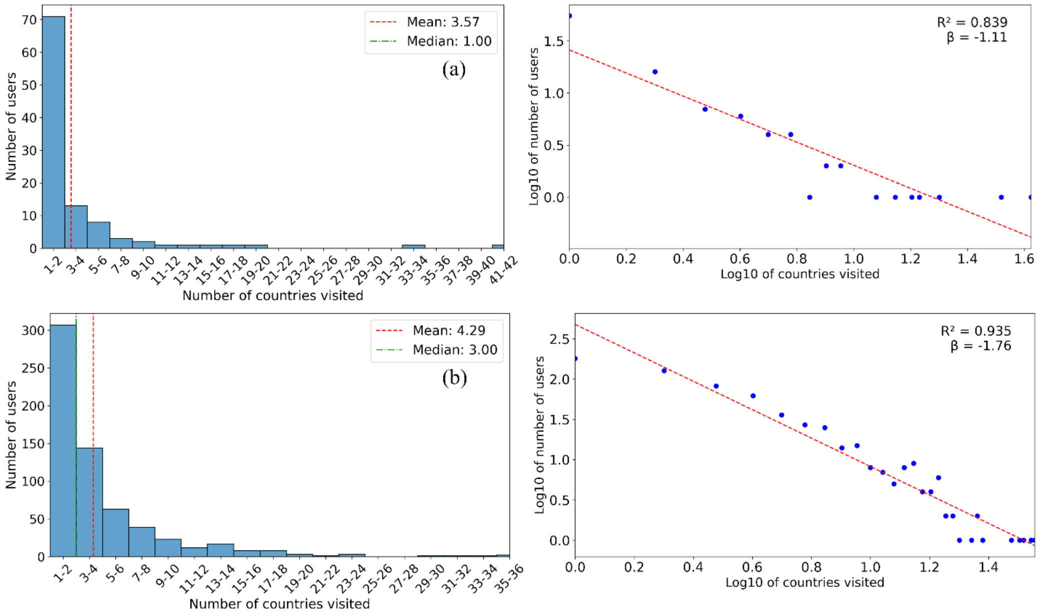

Fig. 7

Figure 7: Distribution of visited countries and corresponding log-log plots in winter (a) and summer (b)

Abbildung 7: *Statistische Verteilung von besuchten Ländern und entsprechende Punktdiagramme mit logarithmischer Achsenskalierung während des Winters (a) und des Sommers (b)*

and summarized over the study period. During summer, a substantial share of users (54.1%) recorded 90% or fewer of their observations in Austria, followed by spring (40.1%), indicating higher international mobility among contributors, likely reflecting visiting or traveling users. In contrast, the distributions for fall and winter suggest predominantly local (Austrian) contributors, with few users submitting observations from outside of Austria.

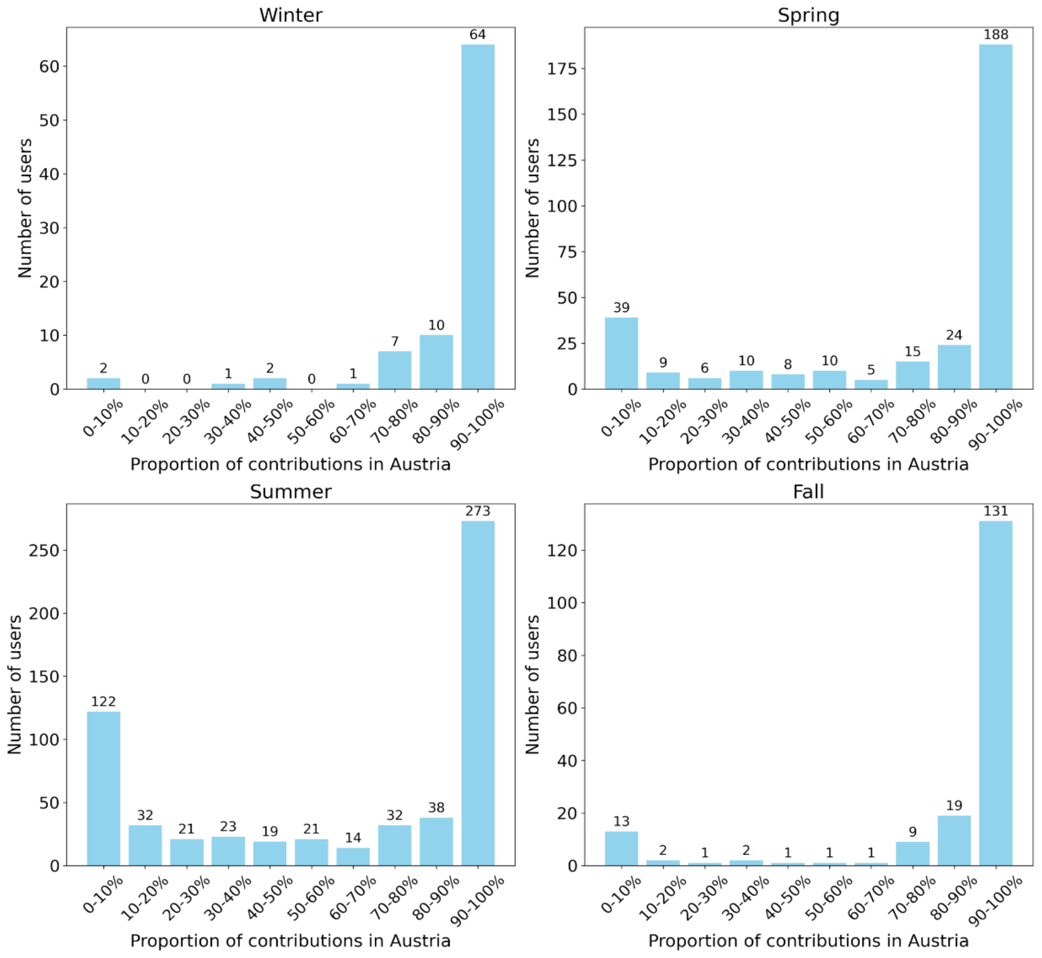

Fig. 8

Figure 8: Distribution of users contributing different proportions of observations to Austria by season

Abbildung 8: *Statistische Verteilung von Nutzern mit verschiedenen Anteilen von Beobachtungen in Österreich während der vier Jahreszeiten*

DISCUSSION

Land use cover and observation patterns

Although urban environments generally support fewer native plant and animal species [46], our results show a positive association between artificial surface land cover and observation density. This pattern reflects user contribution bias and supports previous findings that cities act as hotspots for biodiversity monitoring [47]. Some insect species frequently enter buildings during colder months, increasing their visibility to observers and leading to an overrepresentation of records from artificial surfaces [48]. Consequently, such observations may misrepresent the true outdoor distribution of these species. For example, in our dataset, 67.6% of annual observations of the Western conifer seed bug and the Asian lady beetle on artificial surfaces occurred in October and November alone, making them the most frequently recorded species in fall (compare Table 2). iNaturalist records lack an explicit indicator denoting whether an observation was made indoors, which constrains the ability to evaluate potential overrepresentation arising from insects that have entered buildings. Nonetheless, the iNaturalist *Never Home Alone: The Wild Life of Homes* project (https://www.inaturalist.org/projects/never-home-alone-the-wild-life-of-homes) provides relevant contextual information regarding data collection within indoor environments. As of September 2025, it had accumulated over 67,000 observations of more than 8,200 species worldwide, a negligible fraction compared to the hundreds of millions of total iNaturalist records. This pattern suggests that indoor observations are unlikely to introduce substantial bias.

Although not examined in this study, previous research found that the spatial bias of species occurrence records across multiple biodiversity databases has changed over time, varying among land use categories. Specifically, site visitation probability derived from crowd-sourced datasets increased more strongly in urban areas than in other land use types [49]. Therefore, when estimating long-term trends in species distributions from crowd-sourced data, analyses should account for temporal changes in spatial sampling bias.

The overall positive association of iNaturalist observations with water bodies observed in our study likely reflects both the ecological appeal of these habitats to wildlife and the attraction they hold for nature enthusiasts and the general public for recreational activities [50], which can lead to oversampling of freshwater organisms [51]. Individual user behavior can further amplify this observation bias. A striking example in our dataset is a single user who recorded 245 observations of Wels catfish in 2022, primarily using an underwater camera while diving at Millstätter See, making this species the most frequently observed in water bodies during summer (see Table 2). This user alone accounted for 82.5% of all fish records, demonstrating how specialized activities, such as diving or boating, can disproportionately influence species representation in certain environments. The behavior of “super users,” who contribute exceptionally large numbers of observations, deviates from typical patterns linked to land cover or time of day, representing an outlier-driven user contribution bias that is distinct from other forms of sampling bias.

The negative relationship between iNaturalist contribution numbers and forested, semi-natural, and agricultural areas reflects the challenges of accessing remote locations, the additional time required to travel from urban centers, and the comparatively lower biodiversity of intensively farmed landscapes in Austria [52]. This insight highlights opportunities for education and outreach, suggesting that targeted initiatives could promote iNaturalist usage in agricultural and forested areas, thereby improving the spatial coverage of observations and providing a more comprehensive picture of

Carinthian biodiversity. Previous studies have shown that iNaturalist observations tend to cluster around tourist hotspots, particularly ecotourism sites rather than cultural sites [53], indicating that visits to cultural locations are generally less motivated by species observation than visits to natural sites. While the current study focused on the role of land cover types for biodiversity mapping, future work could analyze the role of different types of tourist and recreational sites for iNaturalist contribution behavior in Carinthia and explore its relationship with either official visitation counts or review counts from different online platforms, such as TripAdvisor, Yelp, or Google [54]. This could help to further disentangle the joint effect of phenology and user contribution bias in observed contribution patterns. Our dataset did not reveal a significant association between protected areas and iNaturalist mapping activities, representing a middle ground between previously reported patterns of either oversampling or undersampling in protected areas, which often vary depending on their location [55].

Temporal observation patterns

The temporal patterns in iNaturalist contributions show substantial seasonal and daily variation, influenced both by plant and animal phenology, as well as by observer schedules and daylight availability. Reduced activity in winter is expected due to shorter daylight hours, difficulties in spotting and photographing organisms under low-light conditions, and the decreased activity of many species, such as insects, small mammals, amphibians, and reptiles, which may hibernate [56], [57]. Previous studies reported strong seasonal trends in freshwater fish observations, with higher counts in summer as fish retreat to deeper waters during winter [58], consistent with the summer peak in fish observations seen in our dataset. Similarly, the autumn peak in fungal observations aligns partially with the fruiting season of edible mushrooms in Austria, which occurs in late summer and fall [59]. The low number of observations for Protozoa and Bacteria highlights the limitations of citizen science in capturing microscopic life forms [60], with records appearing only sporadically in summer and fall.

Our analysis reveals seasonal shifts in contribution bias, as measured by the distance between observation sites and the nearest city, with the magnitude of these changes varying by land cover type. For instance, the median distance for observations in forest and semi-natural areas increases from 14.3 km in winter to 18.9 km in summer, a rise of about 32%, whereas for artificial surfaces the increase is more pronounced, from 4.7 km to 8.9 km, or roughly 89%. This pattern indicates that the typical urban-centric overrepresentation is partially alleviated in summer, when human activities extend further into areas away from large urban settlements. Consequently, summer provides a more balanced and less biased dataset compared to winter.

The hourly distribution of user activity across seasons reveals a clear pattern of daytime-focused observations, with peak activity around 12:00 pm in summer, shifting to 1:00 pm in winter (see Figure 4). Similarly, analysis of eBird data [61] demonstrated that observation times closely track daylight hours across seasons. Previous research has also examined additional factors influencing observation bias, such as weekday, temperature, and precipitation. For example, one study assessed these effects using several tree species in the Iberian Peninsula, which retain a consistent appearance throughout the year [62]. While a similar approach could be applied in Carinthia, stronger seasonal variation in this region makes identifying species with year-round consistent appearance more challenging.

Limitations

Observations recorded exactly at midnight were excluded from the temporal analysis, as they likely represent data artifacts. Similar patterns have been noted in analyses of eBird data, where default timestamps (12:00 a.m.) led to an overrepresentation of midnight observations [23]. A comparable data artifact, though occurring in the spatial domain, arises when latitude and longitude values are missing from point records, resulting in the appearance of a fictional “Null Island” located at 0° latitude and 0° longitude in the WGS 84 geographic coordinate system [63].

The identification of highly active contributors (“super users”) led us to exclude some of their observation data from the spatial regression analysis, as their excessive numbers of contributions were unlikely to be explained by environmental factors and were more plausibly driven by personal motivations. Some super users may seek recognition by uploading numerous photos of the same individual organism each day, without an apparent intent to add genuine scientific value to the iNaturalist dataset. Others are (semi)professionals, such as members of local societies or participants in organized events like the City Nature Challenge or bioblitzes, who use the platform to document and manage their field data over multiple years. Their contributions often hold substantial scientific value, which can also result in repeated observations of the same species across time [10]. An examination of the top ten users in our dataset indeed reveals distinct contribution patterns. Some focus on a few taxa (for example, monitoring Lepidoptera or fungi at a single site throughout the year), whereas others document a broad range of species across many taxa and locations. Although both groups generate large volumes of data, the scientific value of their contributions cannot easily be inferred from their activity patterns alone. Regardless of motivation, including all data from these super users in the spatial regression analysis would give disproportionate influence to a small subset of individuals, potentially biasing the results. Their contributions, however, remain included in descriptive analyses to reflect the full spectrum of citizen science participation. Finally, examining anomalous activity patterns among individuals may still yield valuable insights into atypical participation behaviors among iNaturalist super users [64].

Land cover analyses relied on first- and second-level CORINE classifications derived from satellite imagery. While widely used, this approach can mask local conditions and functional differences within classes. For example, monoculture spruce plantations are typically classified as “forest and semi-natural areas,” although their ecological and functional characteristics more closely resemble agricultural land. Similarly, the second-level “pasture” class may encompass both species-rich meadows and intensively managed grasslands for cattle, the latter being more akin to “heterogeneous agricultural areas.” These limitations are inherent to the CORINE dataset but could be partially addressed by incorporating local land use data where available.

CONCLUSIONS AND FUTURE WORK

The analysis of iNaturalist data in Carinthia reveals several notable spatial and temporal patterns in data contributions. Some of these patterns likely reflect genuine ecological and phenological variation, such as fungi being most frequently observed in forest areas during the fall. Other patterns, however, may result from imbalanced sampling effort, including the overrepresentation of observations in densely populated areas. This study highlights user contribution biases that have received little attention in previous research, such as the influence of “super users” and the interaction of seasonality with proximity to cities and land use type. Future initiatives should aim to address spatial and temporal gaps in data collection to provide a more comprehensive and representative picture of Carinthian biodiversity [65]. To further investigate the complex relationships between environment and observation patterns, future research should apply additional analytical approaches. Machine learning methods, such as random forests or gradient boosting, could help capture non-linear relationships and interactions among variables. Time series analyses would allow deeper exploration of temporal trends and seasonal effects. Furthermore, integrating data from multiple citizen science platforms or online review sources, and comparing these with professional biodiversity surveys, could provide a more comprehensive understanding of Carinthia's biodiversity and help identify priority areas for targeted citizen science efforts [60].

ACKNOWLEDGEMENTS

This research was supported by the Austrian Marshall Plan Foundation through a scholarship awarded to the first author.

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