Marshall Plan Research Report

Spatial and temporal analysis of iNaturalist contributions in Carinthia

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Abstract

This study investigates the spatial and temporal patterns of citizen science contributions to biodiversity monitoring in Carinthia, Austria, using research grade observation data from the iNaturalist platform. We employed a Negative Binomial regression model with Eigenvector Spatial Filtering to examine the relationships between environmental and other factors and observation counts across 5 x 5 km^2 grid cells. Additionally, we explored both seasonal and hourly contribution patterns for observations gathered between 2015 and 2022, also under consideration of different land cover types. Results showed that built environments, water bodies, proximity to cities and primary roads were associated with increased observation counts, while forest and agricultural areas displayed negative associations and that the proportion of taxa contributed varies by hour of day and season and between land cover categories, with the major species observed in different landmarks across four seasons revealing shifts in user observation interests influenced by time and environment. Hourly contribution patterns further demonstrated varying degrees of user activity at different times. The study's outcomes have important implications for interpreting iNaturalist data in biodiversity research and for developing strategies to enhance participation across diverse habitats and temporal scales in Carinthia.

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1.Introduction and research goals

In recent years, citizen science has emerged as a powerful vehicle for biodiversity monitoring and conservation efforts worldwide. Platforms like iNaturalist have revolutionized the way researchers collect and analyze species occurrence data, allowing for unprecedented spatial and temporal coverage (Seltzer, 2019). The engagement of citizens in scientific research not only contributes to data collection but also fosters environmental awareness and scientific literacy among participants (Bonney et al., 2015). However, the distribution of citizen science contributions is often uneven, influenced by various environmental and socio-economic factors. Understanding these patterns is crucial for optimizing data collection strategies, addressing potential biases in citizen science datasets, and gaining insights into user behavior and environmental engagement.

This study aims to model the spatial distribution of iNaturalist research grade contributions in Carinthia, Austria, using a combination of Negative Binomial regression and Eigenvector spatial filtering regression. By analyzing the relationship between contribution counts and factors such as land cover type, road length, distance to nearest city, and proximity to nature protected parks, we seek to identify key drivers of citizen science participation in the region. This research contributes to the growing body of literature on citizen science engagement and provides valuable insights for conservation planning and biodiversity monitoring in Alpine environments.

By examining the patterns of iNaturalist contributions, we can gain a deeper understanding of how people interact with their environment and what motivates them to engage in scientific activities. This knowledge is essential for several reasons:

1. Enhancing user engagement: Understanding the factors that drive participation in citizen science projects can help platform developers and project managers design more effective strategies to engage and retain volunteers. This could include targeted outreach programs, gamification elements, or educational initiatives tailored to specific user groups or geographic areas (Nov et al., 2014).

2. Improving data quality: Identifying spatial biases in data collection can help researchers develop corrective measures or weighting schemes to ensure more representative sampling. This is crucial for maintaining the scientific integrity of biodiversity studies that rely on citizen science data (Bird et al., 2014).

3. Urban planning and green space management: By analyzing the relationship between land cover types and citizen science activity, this research can provide insights into how urban and suburban environments can be designed to encourage greater interaction with nature and biodiversity (Larson et al., 2020).

4. Bridging the gap between science and society: Citizen science projects like iNaturalist play a crucial role in democratizing science and fostering a sense of environmental stewardship among the public. Understanding participation patterns can help in developing strategies

to broaden engagement and ensure more inclusive citizen science practices (Dickinson et al., 2012).

The choice of Carinthia, Austria as the study area adds another layer of significance to this research. As an Alpine region, Carinthia presents unique challenges and opportunities for citizen science engagement. Alpine environments are known for their rich biodiversity and sensitive ecosystems, making them important areas for conservation efforts (Christian, 2004; Mutton, 1953). However, these regions also face significant threats from climate change and human activities. By focusing on this area, our study can provide valuable insights into how citizen science can contribute to monitoring and conserving Alpine biodiversity.

Moreover, the application of advanced statistical methods, combining Negative Binomial regression with Eigenvector spatial filtering, represents a methodological contribution to the field. This approach allows for a more nuanced analysis of spatially autocorrelated count data, which is common in ecological studies but often challenging to model accurately (Griffith & Peres-Neto, 2006).

In summary, this research aims to:

1. Identify the key environmental and socio-economic factors influencing the spatial distribution of iNaturalist research grade contributions in Carinthia, Austria using a spatial regression model.

2. Provide insights into user behavior and environmental engagement patterns in an Alpine region across different temporal scales and land cover types.

3. Contribute to the broader understanding of citizen science dynamics and their implications for biodiversity monitoring and conservation.

2. Literature review

Citizen science has gained significant traction in ecological research over the past decade, with platforms like iNaturalist playing a pivotal role in this area. Launched in 2008, iNaturalist has become one of the world's largest biodiversity observation networks, amassing records from 2008 March to January 21st 2022 of observations globally (Campbell et al., 2023). The platform's success lies in its user-friendly interface, robust data validation processes, and integration with global biodiversity databases (Nugent, 2018). Research grade observations on iNaturalist are particularly valuable for scientific research, as they provide reliable species occurrence data at a scale previously unattainable through traditional scientific methods (Heberling & Isaac, 2018). These observations meet specific criteria, including having a clear photo, date, and location, and receiving community verification. The growth of iNaturalist and similar platforms has led to a surge in studies exploring the potential of citizen science data for biodiversity monitoring, species distribution modeling, and phenological research (Prudic et al., 2017).

Researchers began to investigate the spatial and temporal contribution patterns in opportunistically collected community science datasets, uncovering variations in observation density based on location and time. Studies show that citizen science data are biased towards areas with higher population density and easier accessibility (Geldmann et al., 2016; Tiago et al., 2017). Specifically, road networks have been linked to higher contribution rates of eBird data (Mair & Ruete, 2016) since the presence of road infrastructure may also influence the likelihood of chance encounters with wildlife, particularly for mobile citizen scientists (e.g., cyclists, motorists) (Troudet et al., 2017). Various studies also looked specifically into temporal, spatial, and taxonomic biases of iNaturalist contributions. For example, a comparison of collections-based bee biodiversity monitoring with photo-based data collections methods showed that a small number of well-trained participants systematically collecting bees more effectively documented biodiversity than thousands of people contributing data through iNaturalist (Turley et al., 2024). The study also revealed strong biases toward large-bodied and non-native species. Analysis of bird observations shared on iNaturalist found evidence that large-bodied birds, common species, as well as species in large flocks are over-represented (Callaghan et al., 2021). iNaturalist users also tend to specialize on a particular group, such as plants or insects, and rarely submit repeat observations of species they had previously recorded (Di Cecco et al., 2021).

To address sampling bias in species distribution models using citizen science data, some researchers have proposed corrective methods, including spatial filtering and the use of background sampling techniques (Phillips et al., 2009).

The presence of protected areas has been associated with increased citizen science activity. National parks and other protected areas often attract more observers, potentially due to their perceived biodiversity value and recreational opportunities (Tulloch et al., 2013). However, the relationship between protected areas and citizen science contributions can vary depending on the region and taxa studied (Tiago et al., 2017). In some cases, remote or less accessible protected areas may receive fewer observations despite their ecological importance. Socio-economic factors also play a role in shaping citizen science participation patterns. Education level, income, and leisure time have been shown to correlate with engagement in citizen science activities (Hecker et al., 2018). Additionally, cultural factors and local environmental attitudes can influence the propensity for nature observation and reporting (Lewandowski & Specht, 2015).

To model the spatial distribution of citizen science data, researchers have employed various statistical techniques. Negative Binomial regression has been widely used to account for overdispersion in count data, which is common in ecological datasets (Ver Hoef & Boveng, 2007). This approach has been successfully applied to model species richness and abundance in citizen science data (Kelling et al., 2015). Eigenvector spatial filtering (ESF) has emerged as a powerful technique to address spatial autocorrelation this issue, allowing for the incorporation of spatial dependencies into regression models (Griffith & Peres-Neto, 2006; Murakami & Griffith, 2015). The ESF method is particularly useful in ecological studies where spatial autocorrelation is common due to underlying geographic processes. The combination of Negative Binomial regression with ESF has shown promise in modeling spatially autocorrelated count data in ecological studies (Bachl et al., 2019). Other approaches to modeling spatial patterns in citizen science data include generalized additive models (GAMs), which can capture non-linear relationships between variables (Fink et al., 2010), and machine learning techniques such as random forests or boosted regression trees, which can handle complex interactions among predictor variables (Elith et al., 2008).

While citizen science has been widely studied in various ecosystems, research on its application in Alpine environments is relatively limited. The use of citizen science data for modeling plant species distributions in the European Alps has been explored, highlighting both the potential and limitations of such data in mountainous regions (Capinha et al., 2013). Alpine ecosystems are characterized by high biodiversity, complex topography, and often limited accessibility. These factors can influence both the distribution of species and the patterns of human observation. Citizen science in Alpine regions may be affected by seasonal variations in accessibility, tourism patterns, and the distribution of charismatic or easily identifiable species (Erschbamer et al., 2009). Furthermore, Alpine environments are particularly vulnerable to climate change, with many species facing potential range shifts or extinctions (Pauli et al., 2012). Citizen science data can play a crucial role in monitoring these changes over time, providing valuable information for conservation planning and climate change adaptation strategies (Theobald et al., 2015).

3.Methodology

Figure 1 shows the overall workflow of this research. Landcover data, road network information, and sociodemographic information, are combined with iNaturalist data for the two main threads of analysis, which are spatial regression and temporal analysis. That is, all these datasets are used to run a negative binomial regression with eigenvector spatial filtering to determine factors associated with increased or decreased iNaturalist observation counts in the study area. Additionally, landcover maps were utilized to examine iNaturalist contributions on hourly and seasonal scales. This analysis yielded various outputs, including histograms and species tables categorized by landcover types. Chi-square tests were subsequently conducted to assess significant changes across different times and landcover types.

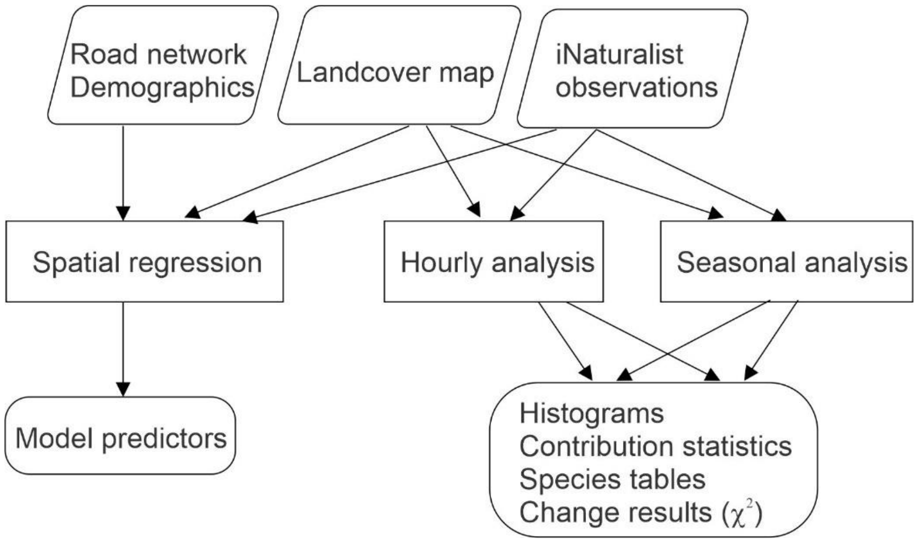

Figure 1. Research workflow

3.1 Data Acquisition and data preparation

a) iNaturalist observations

The research-grade iNaturalist dataset for this study was obtained through the Global Biodiversity Information Facility (GBIF) website (https://www.gbif.org/dataset/50c9509d-22c7-4a22-a47d-8c48425ef4a7) in csv format. GBIF's interface allows for data filtering based on geographical boundary, species, and date ranges. The downloaded dataset includes coordinates of geolocated observation points, timestamps, species identifications (both scientific and common names), anonymized observer IDs, detailed taxonomic information, observation quality grades, URLs to associated photographic evidence, and relevant environmental condition data. Upon download the data were stored in a PostgreSQL database for further analysis. Temporal coverage of the iNaturalist data extends from the platform's inception in the region in 2014 through September 2023, where data between January 1st 2015 and January 1st 2023 were used for this study. iNaturalist enables users to contribute biodiversity observations through multiple platforms: a mobile app for direct field submissions, and a website supporting individual and bulk uploads. Users can submit various types of data, including photographs, audio recordings, and detailed textual information about species, location, date, and other relevant observations. Figure 2 shows the information associated with a research-grade observation on the iNaturalist Website.

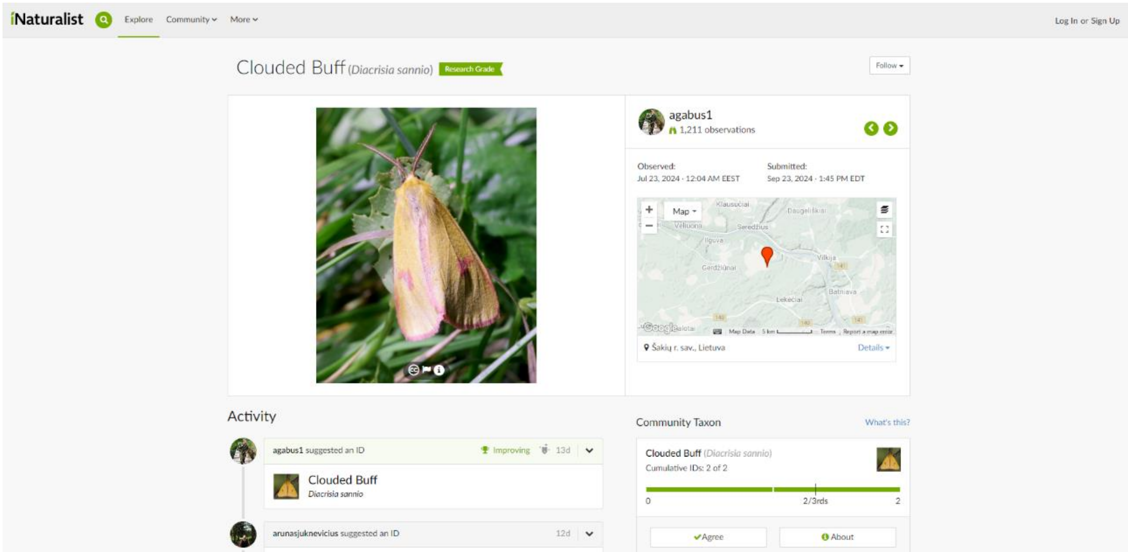

Figure 2. Research grade contribution as shown on the iNaturalist Website

Table 1 lists annual iNaturalist research grade contributions for the study area. It shows substantial growth in iNaturalist usage from 2015 to 2022, both in users contributing per year as well as the contributions per user, which grew about ten-fold since the project beginning.

Table 1. Annual iNaturalist research grade contribution for Carinthia between 2015 and 2022

Year	User Count	Contribution	Mean contributions per user
2015	3	7	2.33
2017	7	62	8.86
2018	16	277	17.31
2019	105	1370	13.05
2020	253	4286	16.94
2021	390	7695	19.73
2022	484	11570	23.90

The distribution of iNaturalist research grade observations in Carinthia for the study period is visualized in Figure 3. Counting observations in a 5 x 5 km^2 grid raster it became apparent that some "super users" had contributed disproportionately large numbers of observations (several thousand points) concentrated within very small areas, potentially skewing the analysis. To ensure a more balanced representation of citizen science contributions across Carinthia, we implemented a threshold approach for the regression as follows. Within each grid cell, we calculated the number of contributions per unique user. The number of records per user were then compiled across all grid cells and sorted. The 95th percentile of user contribution counts from all these users across all cells was determined and set as a threshold. This threshold was then applied to each grid cell, capping the maximum number of observations any single user could contribute to that cell.

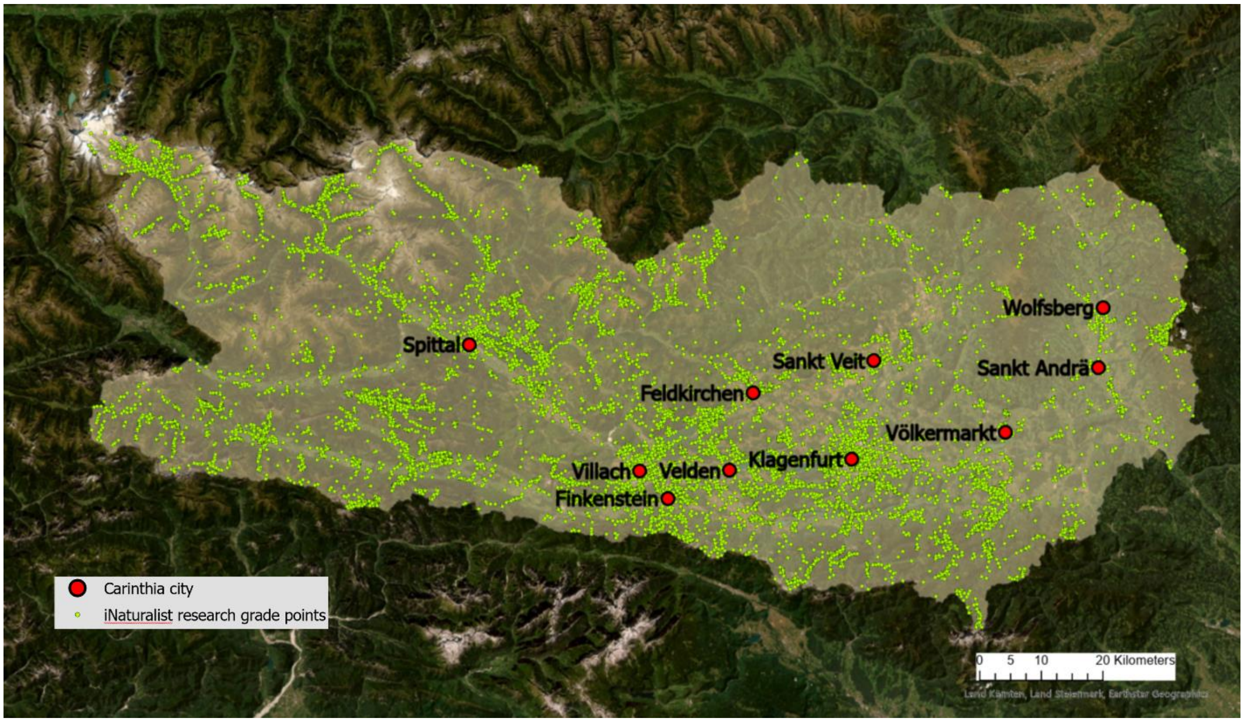

Figure 3. Research grade iNaturalist observations in Carinthia

b) Other geospatial data

This section describes acquisition and preprocessing of other geospatial datasets that were included in spatial regression or temporal analysis.

Administrative boundary of Carinthia: A vector shapefile was obtained from the "Mapog" GIS data repository (https://gisdata.mapog.com/austria/State%20level%201). This dataset, in ESRI shapefile format, provides the official administrative boundaries of Carinthia at a 1:250,000 scale.

Road network: Vector data representing the transportation infrastructure of Carinthia was obtained from Carinthia University of Applied Sciences, based on original road network data was from the Carinthia Transportation Department. This dataset consists of polyline features and distinguishes between 12 road classes. For our analysis, roads were divided into those with and without car access (Figure 4). For further analysis the total length of vehicular and pedestrian-accessible roads within each 5 x 5 km^2 grid cell was calculated. Computation of the distance of a grid cell to the nearest primary road was based on the Open Street Map (OSM) road network, which was downloaded from https://download.geofabrik.de/europe/austria.html.

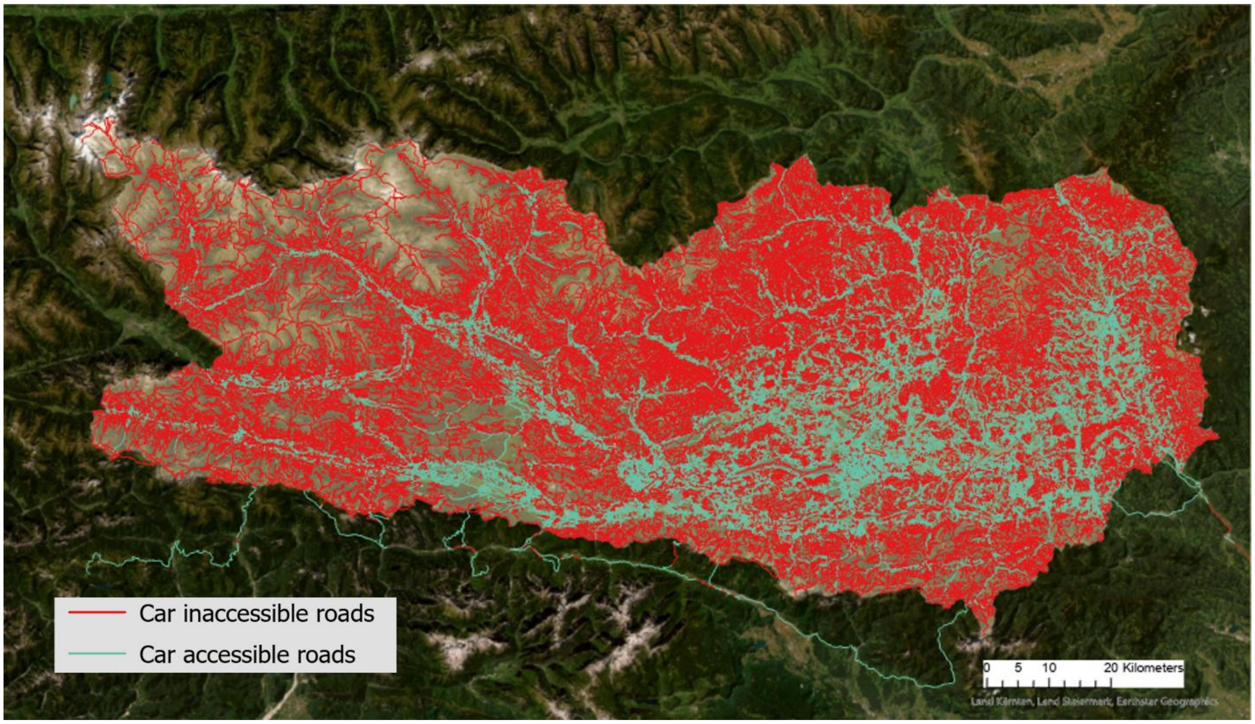

Figure 4. Road network in Carinthia

Land cover: A vector dataset showing land cover data was extracted from the CORINE Land Cover (CLC) 2018 version was obtained from the Copernicus Land Monitoring Service (https://land.copernicus.eu/en/products/corine-land-cover). It provides a standardized classification of land use and land cover types across Europe, with a minimum mapping unit of 25 hectares, minimum width of linear elements of 100 meters, and a scale of 1:100,000. The dataset offers temporal coverage for 2018, with earlier versions available for change analysis. The CLC nomenclature includes 44 land cover classes, organized hierarchically in three levels. For this study, the first-level classification was utilized, which comprised five main categories: Agriculture, artificial surfaces, forest and semi-natural areas, water bodies, and wetlands (Figure 5). For subsequent analysis, we determined the proportion of different land cover classes in each 5 x 5 km^2 grid cell.

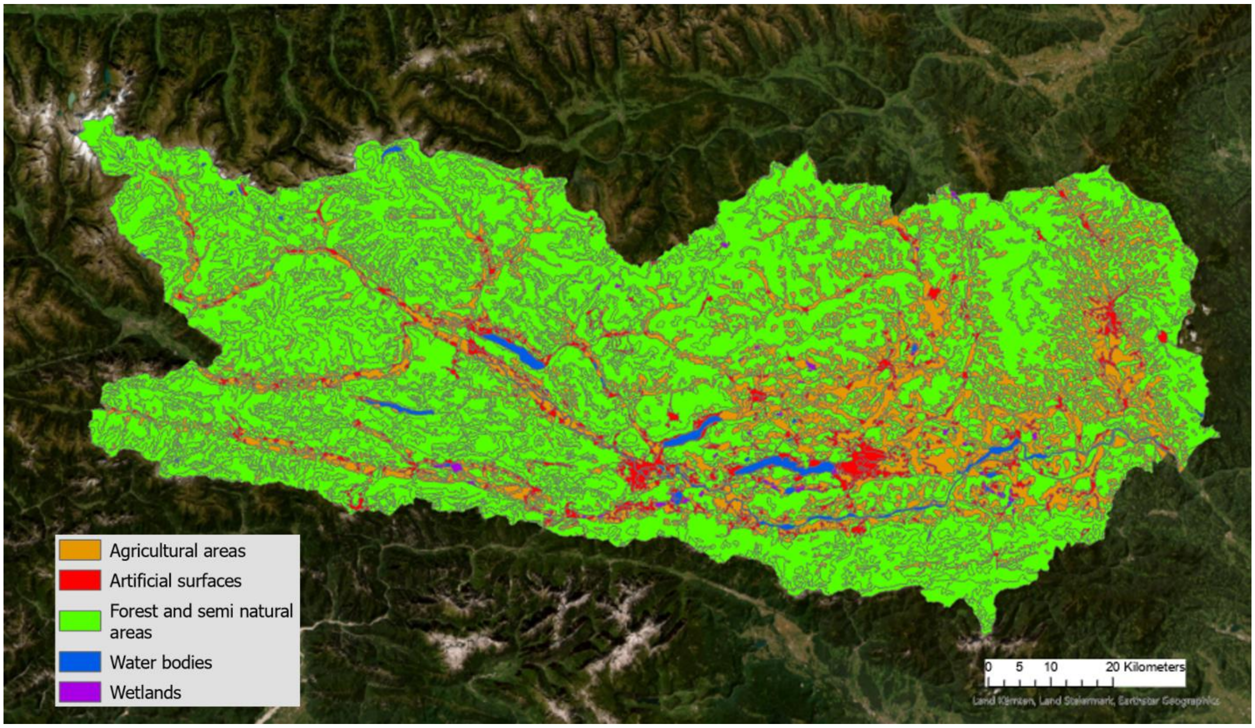

Figure 5. First-level classification of CORINE land cover in Carinthia

Protected areas: Shapefiles delineating protected areas in Carinthia were obtained from multiple sources, primarily the Austrian Federal Ministry for Climate Action, Environment, Energy, Mobility, Innovation and Technology (such as: https://www.noe.gv.at/noe/Naturschutz/Niederoesterreich_ATLAS.html). The dataset encompasses various categories of protected areas across Austria, including national parks, nature reserves, and landscape protection areas. This national-scale dataset served as the foundation for extracting protected areas specific to Carinthia, the study area. To ensure comprehensive coverage, additional data were manually sourced from regional environmental authorities in Carinthia. It is important to note that the term "Protected Area" functions as an umbrella category, subsuming different types of protected areas. In this study, no further distinction was made regarding the number of observations per specific type of protected area [12]. This compilation provides a thorough representation of protected natural areas within the study region. Among 7748 protected areas, 687 intersect with Carinthia, covering around 1,488 km^2.

Urban centers: A point vector layer representing the ten most populous cities in Carinthia (Figure 3) as of 2020 was created based on information from the Austrian Bureau of Statistics (Statistik Austria). This dataset consists of single point geometries for each city center, including Klagenfurt, Villach, Wolfsberg, Spittal an der Drau, Feldkirchen, Sankt Veit an der Glan, Völkermarkt, Sankt

[1] https://www.burgenland.at/natur-umwelt-agrar/natur/naturschutz/kontakt-zu-uns
[2] http://www.noe.gv.at/noe/Naturschutz/Naturschutz.html

Andrä, Finkenstein am Faaker See, and Velden am Wörthersee. For the regression analysis, the distance between each grid cell centroid to the nearest city was computed.

3.2 Negative Binomial Regression

A Negative Binomial regression model was developed to predict the number of observations per nominal 5 x 5 km^2 grid cell. Negative Binomial regression was chosen over Poisson regression due to its ability to handle overdispersion, which is common in ecological count data like species observations. Candidate predictors, computed for each grid cell, included elevation, population total length of pedestrian-only and car-accessible road network, distance to nearest city, distance to nearest protected area, as well as the proportion of land cover for five land cover types, where proportion of wetland was excluded to avoid multicollinearity between these five land cover predictors. The land cover independent variables underwent a logarithmic transformation to address non-normality. A small constant (0.001) was added before applying the natural logarithm to handle zero values. Non-log-transformed variables were then standardized through z-scores. In addition, the model included an offset term (log of cell size in km^2) to account for varying size of grid cells in which iNaturalist observations were taken. To address spatial autocorrelation among regression residuals, ESF was employed, following the approach in (Fang et al., 2019), using the R spdep and sf packages.

The Negative Binomial regression model, incorporating environmental and other predictor variables as well as spatial eigenvectors, can be expressed as equation (1):

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

where λ is the expected count of observations, $X_1 ... X_n$ are the predictor variables, $EV_1 ... EV_m$ are eigenvectors, 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. This process allows for the identification of the most parsimonious model that accounts for both environmental factors and spatial autocorrelation.

Several diagnostic procedures were performed to assess model quality and validity. 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.

3.3 Seasonal and daily variations in observation patterns

The study analyzed iNaturalist research-grade contributions in Carinthia, Austria, from 2015 to 2022 (Figure 6). These observations can be considered a representative sample of all iNaturalist observations, given that the data quality of taxonomic information of research grade and NeedsID observations is comparable (Hochmair et al., 2020). The temporal analysis focused generally on change in contribution patterns (e.g. abundance, number of taxa or users, proportion of taxonomic groups, most frequently observed species) (1) across four seasons and (2) throughout a day. Some of these analyses are conducted separately for different land cover types. For both seasonal and hourly analyses, abundance and taxonomic composition was aggregated from multi-year data covering the study period.

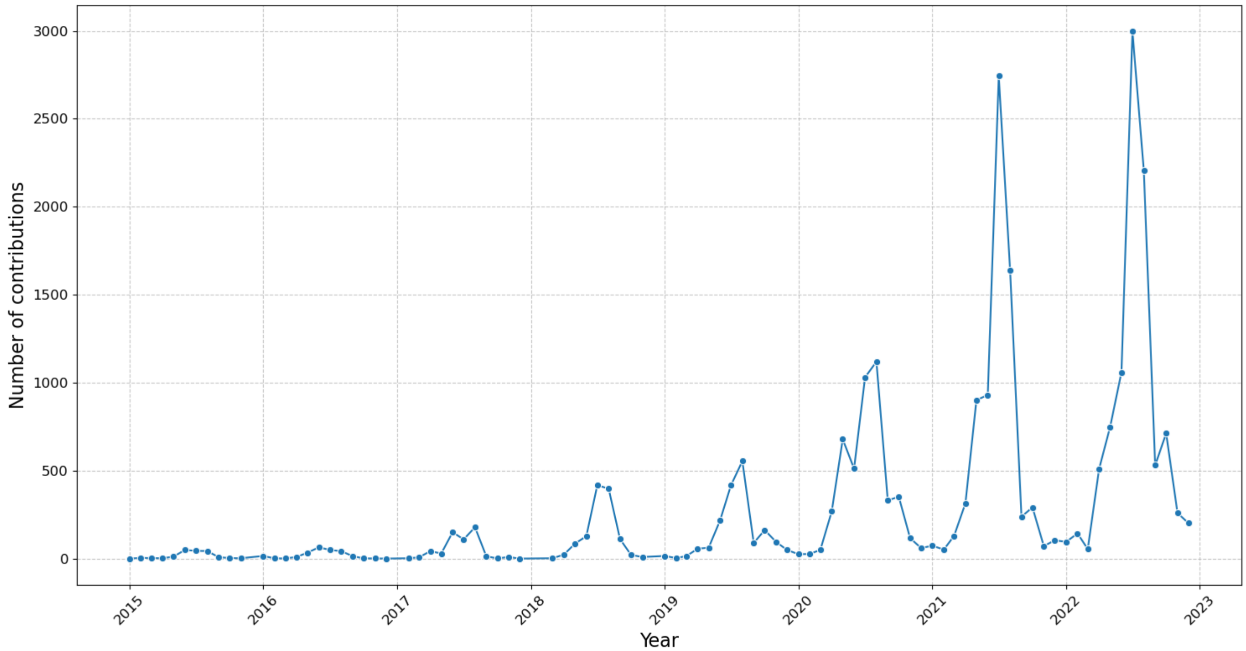

Figure 6. Monthly contributions of iNaturalist research grade data in Carinthia from 2015 to 2022

More specifically, the distribution of hourly contributions to different kingdoms was compared between four seasons. These were spring (time stamp of contribution between March and May), summer (June-August), fall (September-November), and winter (December-February). Standard deviations of hourly observations distributions were then computed to provide insight into differences in daily observation windows across different seasons. Chi-square tests were performed on hourly contribution data to different kingdoms for the four seasons to identify the statistical significance of hourly changes in the share of different kingdoms across the day. In addition, a chi-square test was used to assess the statistical significance in the share of contributions to different kingdoms between the four seasons.

The role of land cover type in contribution patterns was analyzed in multiple ways. That is, we used a chi-squared test to analyze the statistical significance in the change of proportion of observations to different land cover areas throughout a day (conducted for four seasons), as well as that of the change in the proportion of contributions to different land cover types across four seasons. We also compared the observed and expected (based on land cover area) number of observations for different land cover types for the four seasons, followed by chi-square tests. Additional descriptive statistics, such as the number of hours a day that comprise 90% of observations for each land cover type and season, as well as the number of unique family and genus taxa for different land cover types in different seasons provide more details about temporal changes in activity patterns for different land cover types. Finally, comparison of the three most frequently observed species for each land cover type and season demonstrates the seasonal change in primary mapped species across a year for different land over types.

4. Results

4.1. Regression analysis

The final model (Table 2) only includes significant predictors, where some of the coefficients associated with spatial eigenvectors (EVs) are not displayed for conciseness. Most EVs included in the model displayed VIF values close to 1, suggesting their effectiveness in capturing spatial autocorrelation without introducing significant multicollinearity. The distance to the nearest protected area had to be removed due to multicollinearity.

The residuals from the model without integration of spatial eigenvectors showed significant spatial autocorrelation (Moran's $I = 0.198$, $p < .0001$) which disappeared after incorporating the spatial eigenvectors (Moran's $I = 0.005$, $p = 0.377$).

Table 2. Significant predictors of iNaturalist observations in Carinthia

Variable	Estimate	p-value
(Intercept)	1.52	< 0.001
LC proportion: Artificial surfaces	0.22	< 0.001
LC proportion: Forest and semi-natural areas	-0.79	< 0.001
LC proportion: Water bodies	0.14	< 0.001
LC proportion: Agriculture	-0.21	< 0.001
Nearest distance to city	-0.18	< 0.001
Nearest distance to primary road	-0.13	< 0.05
EV2	-3	< 0.001
EV4	5.48	< 0.001
EV208	3.37	< 0.001
EV163	-2.78	<0.001
EV9	-4.20	< 0.001
EV11	-6.64	< 0.001
EV131	-3.33	< 0.001
EV16	4.46	< 0.001
EV154	-3.52	< 0.001
EV10	-2.9	<0.05
EV30	-4.19	<0.001
Other 53 selected Eigenvectors		
Number of observations	456	
Moran' I of residuals	0.005	0.377
McFadden's R-squared	0.12	
McFadden's adjusted R-squared	0.10	

The model results indicate that proportion of artificial surfaces and water bodies are positively associated with iNaturalist observations, while proportion of forested areas and agricultural lands show negative associations. Proximity to cities and primary roads is linked to increased observation counts.

4.2. Temporal contribution pattern

Figure 7 presents the hourly distribution of numbers of contributions and unique users across the four seasons. Summer exhibits the highest overall activity, peaking at around 12 p.m. with a maximum of about 250 unique users contributing about 2000 observations per hour. Winter displays the lowest activity with a maximum of about 40 unique users contributing about 120 observations per hour.

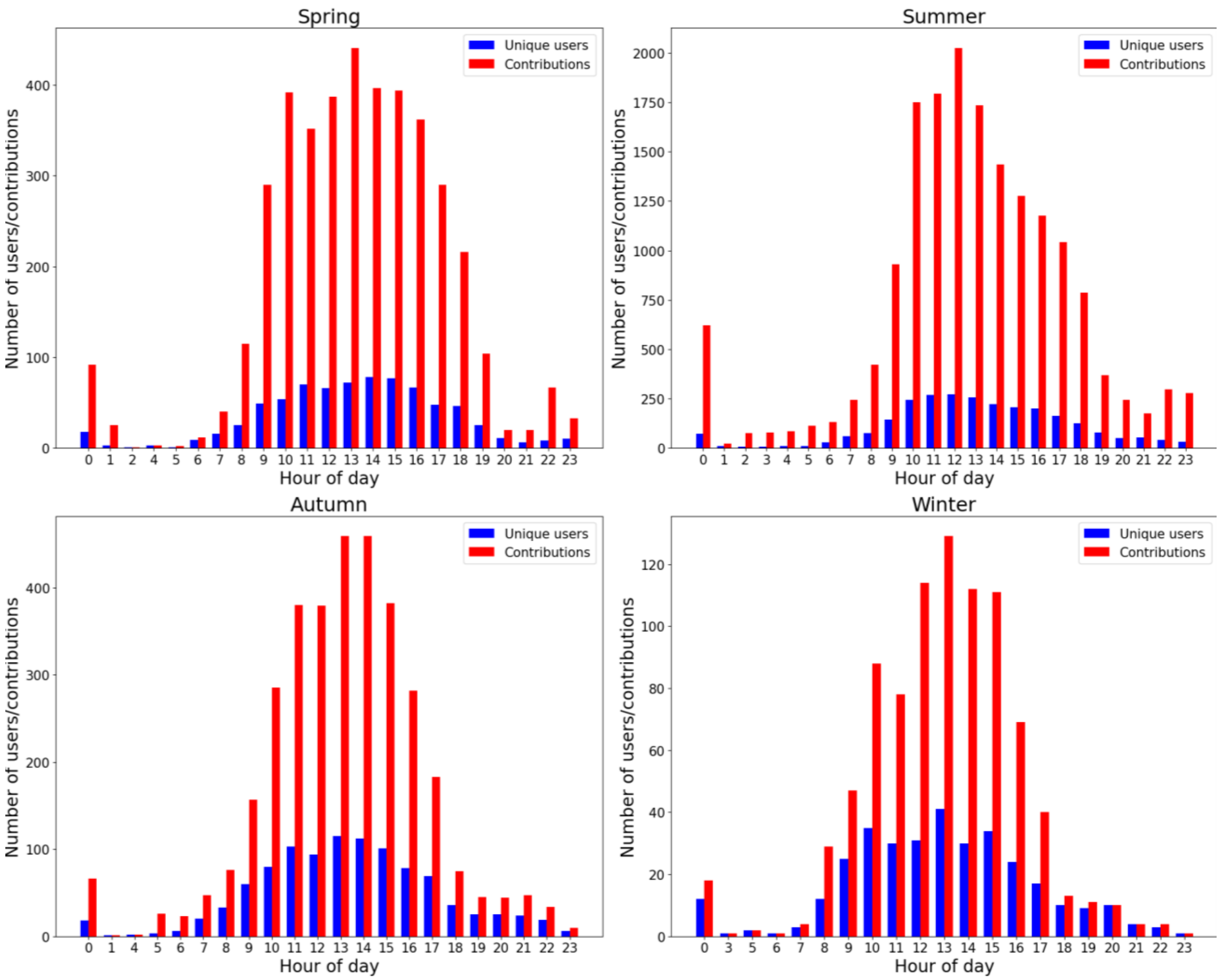

Figure 7. Hourly distribution contributions and unique users by season

The proportion of contributions to different kingdoms varies by hour and season (Figure 8). For instance, at the 12 pm peak in summer, Animalia comprises 45.4%, Plantae 51.8%, and Fungi 2.7%, whereas fall observations at 12 pm reveal Animalia at 63.1%, Plantae at 20.6%, and Fungi at 16.3%. Regarding variation across the day, it can be noted that Animalia dominates early morning and late evening hours across seasons, often reaching 90-100% of observations, likely due to nocturnal animal activity and reduced plant visibility. Fungi observations are more prominent in fall, reaching up to 16.4% at 12 pm. Protozoa and Bacteria appear sporadically, with minimal percentages, indicating occasional observations of these less visible kingdoms.

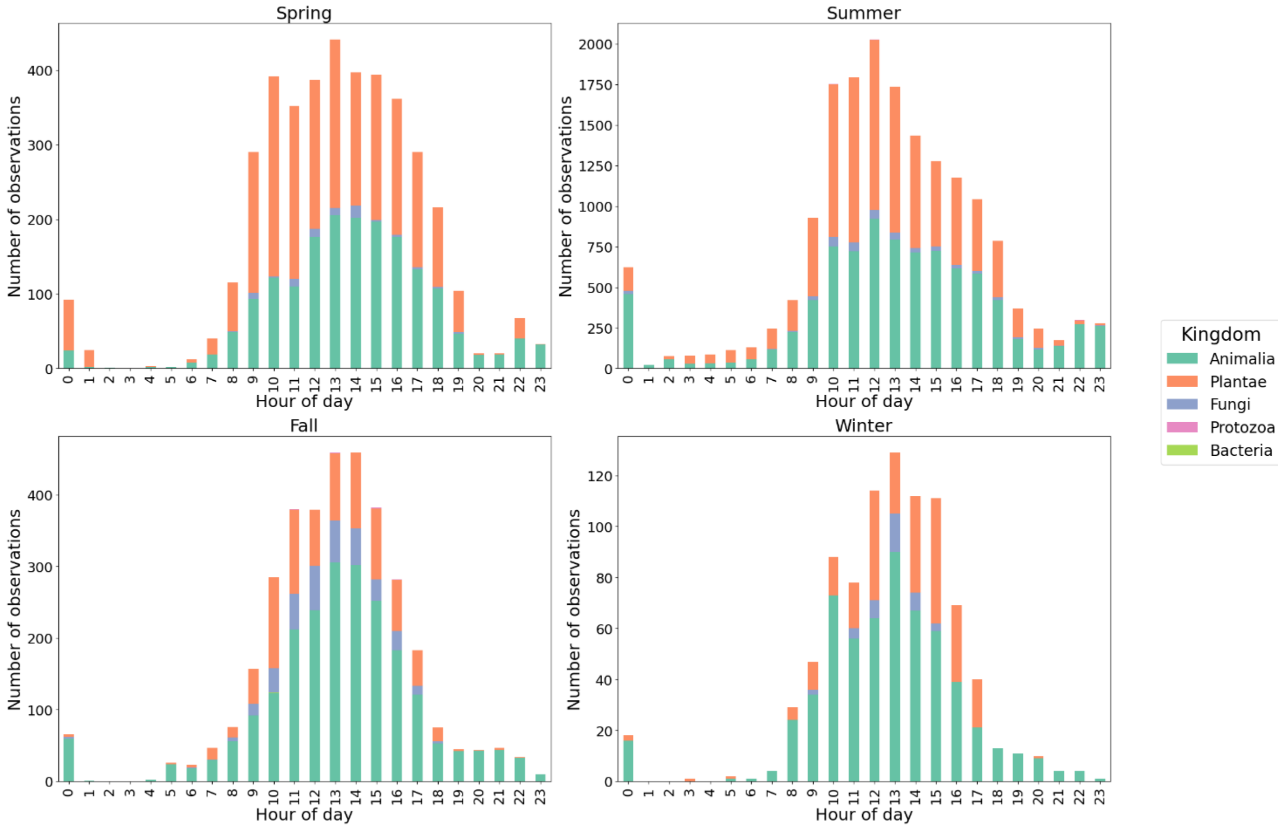

Figure 8. Hourly distribution of kingdoms by season in Carinthia

Results of chi-square tests based on number of observations in Figure 8 show that the change in proportion of observations across kingdoms across a day are statistically significant for spring ($X^2 = 2081.04$, df = 23, $p < 0.001$), summer ($X^2 = 6896.16$, df = 23, $p < 0.001$), fall ($X^2 = 1942.68$, df = 23, $p < 0.001$), and winter ($X^2 = 584.04$, df = 23, $p < 0.001$), and this change is also significant between seasons ($X^2 = 1415.67$, df = 12, $p < 0.001$).

The mean peak hour and standard deviation (in hours) of the distribution of observation counts in Figure 8 are shown for different seasons in Table 3, revealing longest observation hours for summer and shortest observation hours for winter. At a more detailed level, the hour ranges covering 90% of observations (Table 4), varied across land cover types and seasons. Agricultural areas show the widest range (17 hours) in summer, while wetlands had the narrowest range (5 hours) in winter. Overall, these numbers confirm earlier standard deviation results in that summer offers the longest observation windows for iNaturalist data collection. During winter the observation window is longest for artificial surfaces (due to artificial lights allowing data collection at evening and night) whereas they are longest in agricultural areas during summer (possibly due to little canopy and thus long natural daylight in summer).

Table 3. Mean hour and standard deviation of hourly contributions by season

Season	Total Observations	Mean Contribution Hour	Standard Deviation (hours)
Spring	4,005	13.29	3.73
Summer	16,553	13.18	3.91
Fall	3,406	13.21	3.21
Winter	871	13.02	2.90

Table 4. 90% observation hour ranges across seasons and land cover types

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 species most often observed in Carinthia at a given hour, together with their number of observations in parentheses, are listed in

Table *5*. Different seasons are dominated by different species, as explained in more detail in the discussion section.

Table 5. Most frequently observed species per hour of day in four seasons

Hour	Spring	Summer	Fall	Winter
0	🌼Goat's Beard (2)	🐞Red-black Longhorn Beetle (8)	🐌Roman Snail (3)	🐦 Common Buzzard (2)
1	🐞Larder Beetle (1)	🐞Marbled Minor Moth (2)	▯Northern White-breasted Hedgehog (1)	—
2	▯Stone Marten (1)	🐞Dotted Clay Moth (3)	—	—
3	—	🐞Ingrailed Clay Moth (3)	—	🌼Common Reed (1)
4	🐦Great Cormorant (1)	🌼Fragrant Orchid (3)	🐦European Goldfinch (1)	—
5	🐦Song Thrush (1)	🌳Mountain Pine (3)	🐞 Issus Bug (2)	🕷Daddy Long-legs Spider (1)
6	🐦Song Thrush (2)	🌼Alpine Thrift (3)	🐞Bow-winged Grasshopper (2)	🐦Spotted Flycatcher (1)
7	🐦Barn Swallow (3)	🌼Yellow Oxeye (7)	🐞Drone Fly (2)	🐦Common Blackbird (1)
8	🌼Greater Celandine (4)	🌳European Elder (4)	🐞 Migrant Hawker (2)	▯ Red Squirrel (3)
9	🐌Great Grey Slug (5)	🌼Common Spotted Orchid (8)	🐞Western Conifer Seed Bug (3)	🐦 Common Blackbird (3)
10	🌼Western Marsh Orchid (5)	🌼Common Spotted Orchid (14)	🐞Western Conifer Seed Bug (6)	🐦Common Blackbird (5)
11	🌼 Fly Honeysuckle (5)	🦋Silver-washed Fritillary (30)	🐞Western Conifer Seed Bug (10)	🐦Eurasian Siskin (5)
12	🌼Bird's-eye Speedwell (5)	🐟Wels Catfish (32)	🐞Western Conifer Seed Bug (8)	🌳Common Hazel (6)
13	🦋Map Butterfly (7)	🐟Wels Catfish (39)	🐞Western Conifer Seed Bug (10)	🐦Eurasian Coot (5)
14	🌼Bugle (7)	🐟Wels Catfish (31)	🐞Western Conifer Seed Bug (14)	🐦Common Blackbird (6)
15	🦎Common Wall Lizard (14)	🦋Silver-washed Fritillary (24)	🐞Harlequin Ladybird (8)	🐦Mute Swan (5)
16	🌼Coltsfoot (6)	🦋Silver-washed Fritillary (14)	🐞Western Conifer Seed Bug (9)	🐦 Eurasian Coot (6)
17	🐸Fire Salamander (5)	🐟Wels Catfish (99)	🐞Western Conifer Seed Bug (10)	🌳Common Hazel (4)
18	🐦Common Blackbird (8)	🐟Wels Catfish (21)	🐞Western Conifer Seed Bug (5)	🐞Western Conifer Seed Bug (2)
19	🐞Blue Featherleg (3)	🌼Small Balsam (6)	🐞European Hornet (3)	🕷Daddy Long-legs Spider (2)
20	🐞Blue Featherleg (3)	🐞Lesser Stag Beetle (9)	🐞Western Conifer Seed Bug (2)	🕷Buzzing Spider (2)
21	🐞Hebrew Character Moth (2)	🐞Field Cricket (4)	🕷Walnut Orb-weaver Spider (5)	🕷Buzzing Spider (1)
22	🐞Latticed Heath Moth (3)	🐞Green Arches Moth (5)	🐞Old World Bollworm (2)	🕷Daddy Long-legs Spider (1)
23	🐞Brimstone Moth (2)	🐸Common Toad (4)	🐞House Fly (1)	🐞Harlequin Ladybird (1)

Legend: 🐦 Bird 🦋 Butterfly 🐞 Other insect 🌼 Flowering Plant 🌳 Tree 🐟 Fish 🐸 Amphibian 🦎 Reptile 🍄 Fungus 🕷 Arachnid ▯ Mammal 🐌 Mollusk

The number of observations falling into the five land cover classes at different hours of the day are plotted in Figure 9 and summarized by season in Table 6. Contributions to forest and semi-natural areas dominate spring (44.3%), summer (57.5%), and fall (36.7%), whereas the proportion of observations during winter is highest for agricultural surfaces (29.8%). The share of artificial surfaces among all seasons is smallest during summer, suggesting that observers can find time to move into nature away from built structures to add observations during that season. A chi-square test of independence ($X^2 = 1349.86$, df = 12, $p < 0.0001$) reveals a statistically significant association between season and land cover type, indicating that the distribution of observations across different land cover types varies between seasons. Also, the proportion of contributions to different land cover classes varies significantly by hour of day for all seasons, i.e. 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, $p < 0.001$).

Table 6. Number of observations falling into different land cover types across four seasons

Land cover types	Spring	Summer	Fall	Winter
Agricultural surfaces	1270	3772	939	314
Artificial surfaces	848	2308	1081	264
Forest and semi natural areas	1798	9830	1272	216
Water bodies	94	874	123	81
Wetlands	45	325	47	11

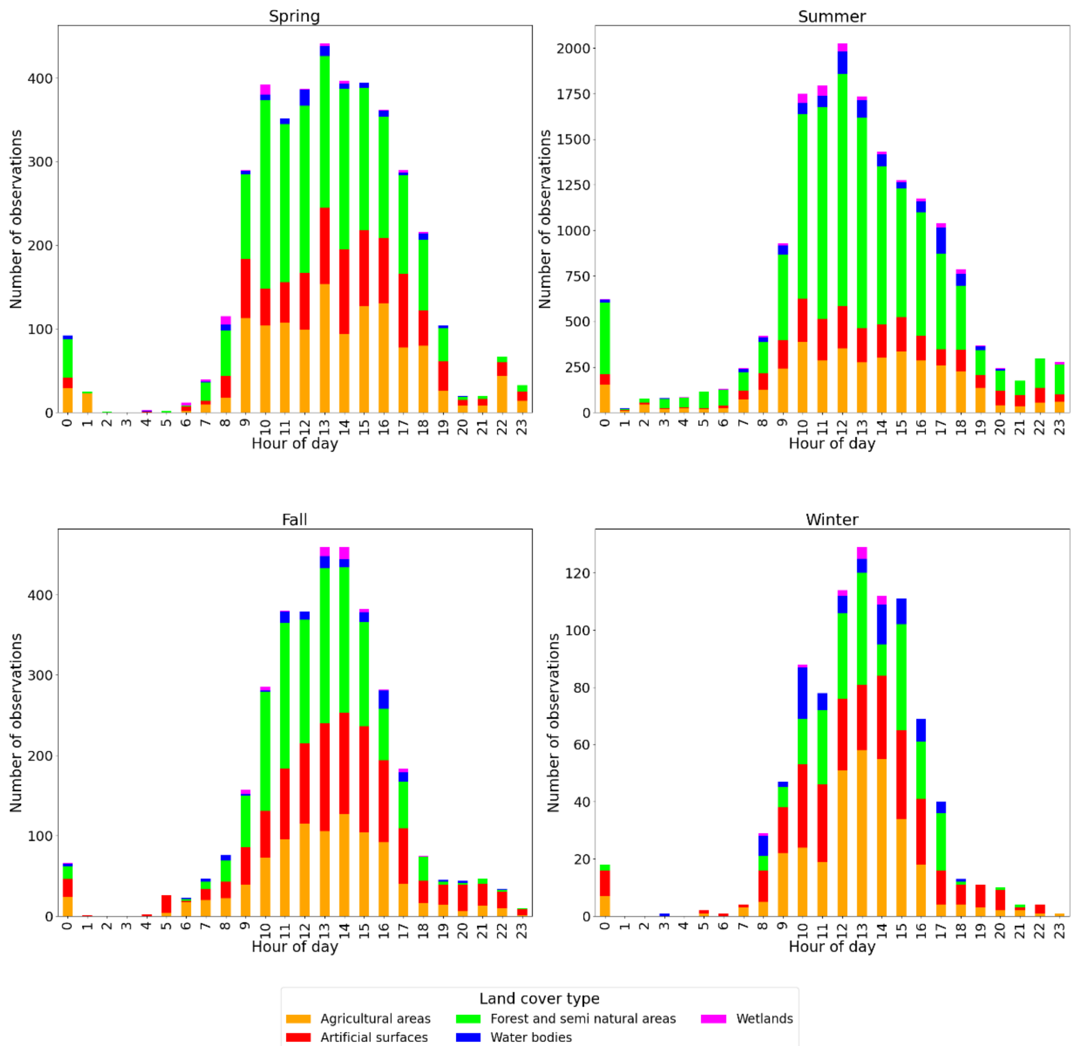

Figure 9. Hourly contribution numbers for different land cover types across four seasons

Figure 10 provides a more detailed insight into biodiversity mapping across seasons and land cover types by plotting the corresponding number of unique family (a) and genus (b) taxa. Forest and semi-natural areas showed the highest taxonomic diversity across for spring, summer, and fall, which matches findings of highest observation counts in forest and semi-natural areas for these three seasons (Table 6). In winter, agricultural areas revealed highest biodiversity, also matching highest contribution numbers in Table 6 for that land cover type. All land cover types exhibited peak diversity in summer and lowest diversity mapping in winter.

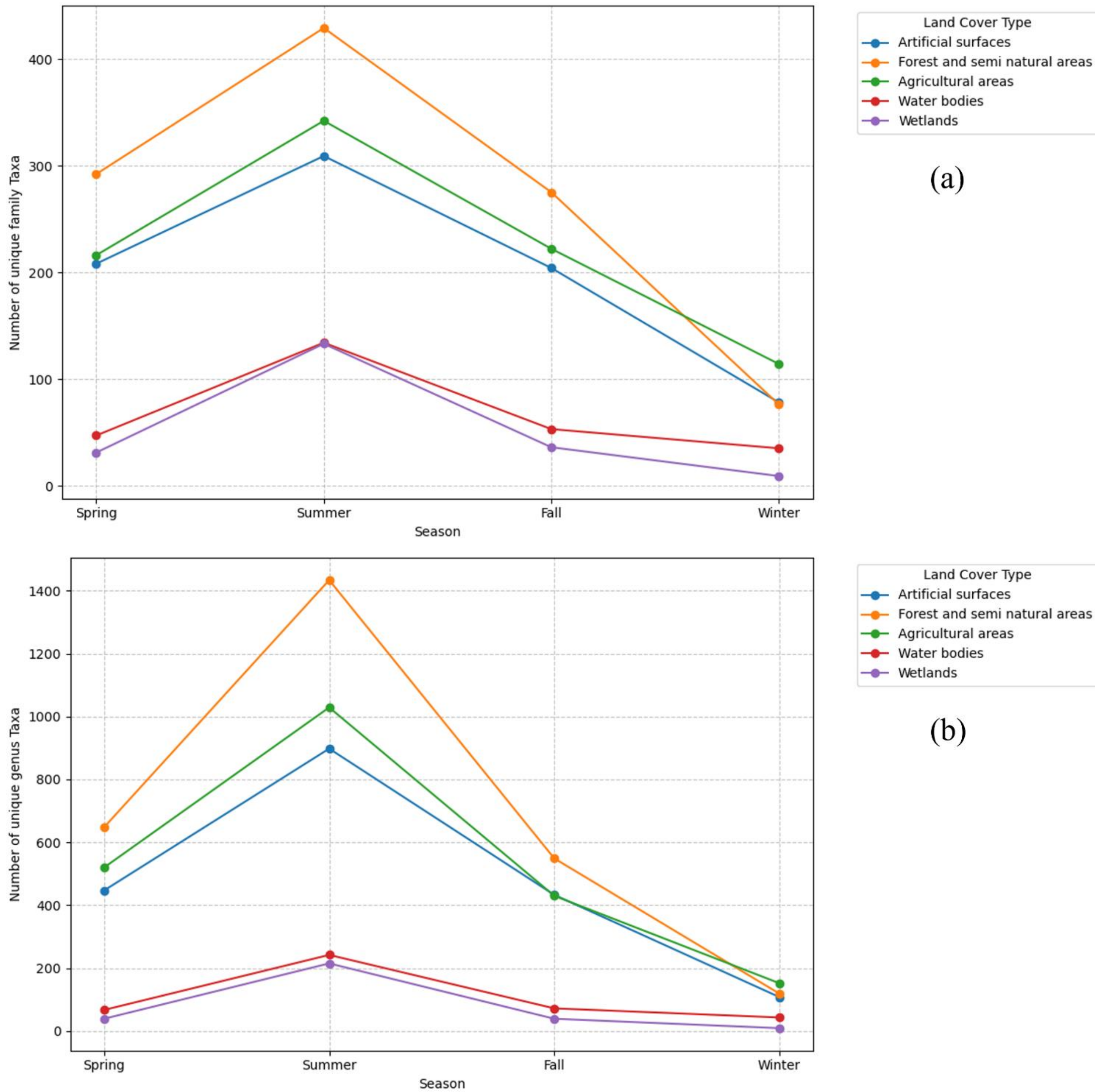

Figure 10. Number of different family (a) and genus (b) taxa observed across for seasons and five land cover types

Figure 11 provides a complementary view of contributions to different taxa and land cover types across seasons. For this chart, species were divided into five categories according to their class level. The five categories were Birds (consisting only of the class Aves), Animals (including classes such as Mammalia, Amphibia, Squamata, and various invertebrate classes), Plants (encompassing classes like Magnoliopsida, Liliopsida, and various plant divisions), Insects (specifically the class Insecta), and Fungi (including various fungal classes such as

Agaricomycetes and Lecanoromycetes). Any class not explicitly listed in these categories was classified as "Others". The bar chart reveals a high proportion of insects during summer and fall for all land cover types except for water related ones, whereas plants show a higher proportion during spring. A chi-square test was conducted for each land cover type to examine the change in proportion of observations to different taxonomic categories across seasons. The results revealed significant differences in the seasonal distribution for all land cover types, i.e., forest and semi-natural areas ($X^2 = 1161.65$, df = 15, $p < 0.001$), agricultural areas ($X^2 = 1233.99$, df = 15, $p < 0.001$), artificial surfaces ($X^2 = 1283.98$, df = 15, $p < 0.001$), water bodies ($X^2 = 274.82$, df = 15, $p < 0.001$), and wetlands ($X^2 = 141.02$, df = 15, $p < 0.001$).

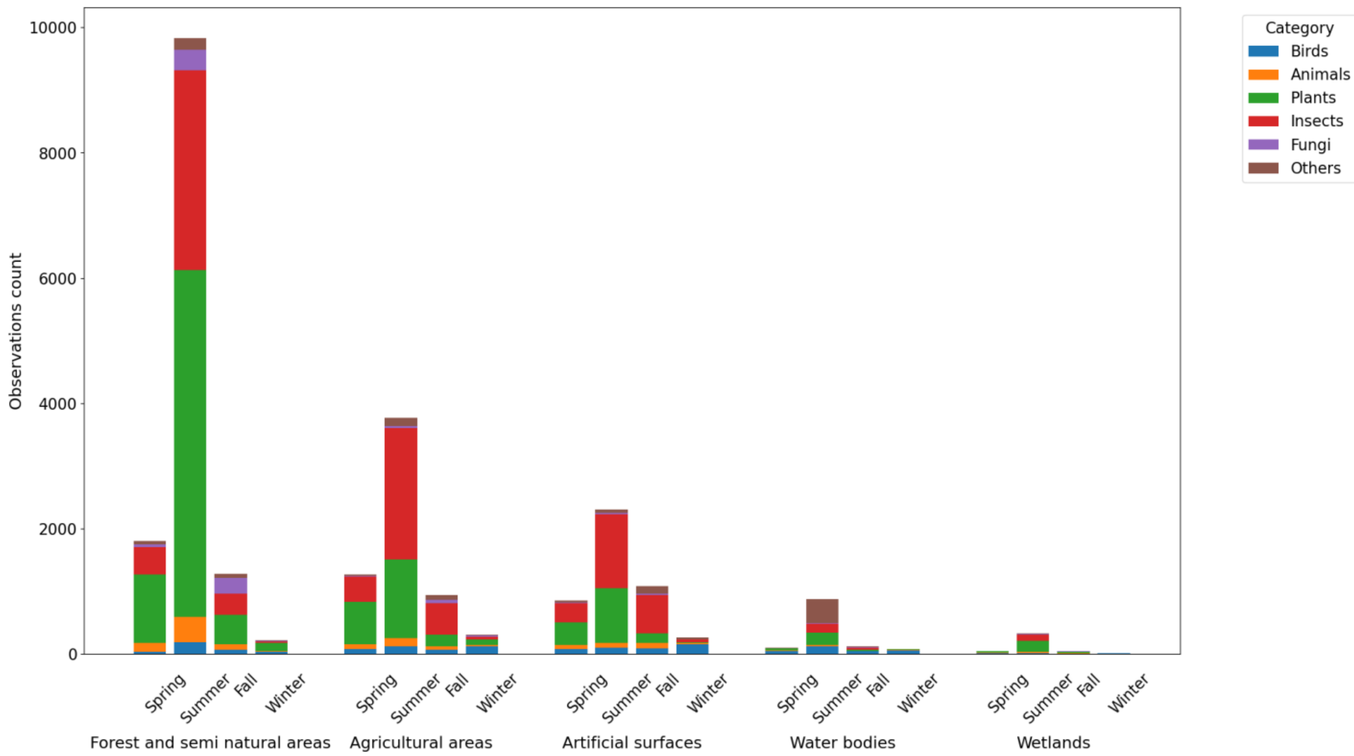

Figure 11. Seasonal species category observation number of land cover types

Using the proportion of area for each land cover type within the study area and the total number of observations per seasons allow for a comparison of expected and observed number of observations for each land cover category (Table 7). Results chi-square tests conducted for each season show significant differences between observed and expected counts for examined land cover types ($p < .0001$) for each season. Notably, forest and semi-natural areas were consistently underrepresented across all seasons, while artificial surfaces were most overrepresented, as indicated by standardized residuals. This suggests a bias in observation efforts towards more accessible or human-populated areas.

Table 7. Seasonal patterns in land cover type observations relative to area

Season	Land Cover Type	Observed Count	Expected Count	Standardized Residual	Representation
Spring	Agricultural areas	1270	818.05	15.8	Over
	Artificial surfaces	848	168.6	52.32	Over
	Forest and semi natural areas	1798	3013.64	-22.14	Under
	Water bodies	94	44.31	7.47	Over
	Wetlands	45	10.4	10.73	Over
Summer	Agricultural areas	3772	3451.76	5.45	Over
	Artificial surfaces	2308	711.39	59.86	Over
	Forest and semi natural areas	9830	12715.99	-25.59	Under
	Water bodies	874	186.96	50.25	Over
	Wetlands	325	43.9	42.43	Over
Fall	Agricultural areas	939	698.42	9.1	Over
	Artificial surfaces	1081	143.94	78.1	Over
	Forest and semi natural areas	1272	2572.93	-25.65	Under
	Water bodies	123	37.83	13.85	Over
	Wetlands	47	8.88	12.79	Over
Winter	Agricultural areas	314	178.74	10.12	Over
	Artificial surfaces	264	36.84	37.43	Over
	Forest and semi natural areas	216	658.47	-17.24	Under
	Water bodies	81	9.68	22.92	Over
	Wetlands	11	2.27	5.79	Over

The most frequently observed three species in four land cover types across four seasons are shown in Table 8. Numbers in parentheses indicate the number of observations counted across the study period. Species for wetlands are not reported due to the small number of observations. The legend symbols categorize observations into birds, butterflies (separated from insects for better visualization), other insects, flowering plants, trees, fish, amphibians, reptiles, fungi, arachnids, and mammals. Some apparent patterns emerge, such as the predominance of butterfly and insect observations during summer and fall for agricultural areas, followed by a shift towards more observations of birds during winter.

Table 8. Top 3 observed species in four land cover types across four seasons

Season	Agricultural areas	Forest and semi natural areas	Artificial surfaces	Water bodies
Spring	🌼 Common bugle (12)	🌼 White butterbur (24)	🐦 Common blackbird (15)	🐦 Eurasian coot (4)
	🌼 Meadow clary (12)	🦎 Common wall lizard (21)	🌼 Common bugle (14)	🐦 Great crested grebe (4)
	🌼 Fumewort (11)	🌼 Coltsfoot (20)	🌼 Greater celandine (14)	🐦 Sedge warbler (3)
Summer	🦋 Silver-washed fritillary (35)	🦋 Silver-washed fritillary (102)	🦋 Japanese oak silk moth (22)	🐟 Wels catfish (245)
	🦋 Meadow brown (33)	🌼 Heath spotted orchid (86)	🌼 Himalayan balsam (18)	🐟 European perch (35)
	🦋 European peacock (29)	🐸 Common frog (55)	🦋 Silver-washed fritillary (16)	🐟 Pumpkinseed (25)
Fall	🐞 Western conifer seed bug (31)	🍄 Fly agaric (23)	🐞 Western conifer seed bug (48)	🐦 Mute swan (13)
	🦋 European peacock (16)	🦎 Fire salamander (22)	🐞 Asian lady beetle (31)	🐦 Mallard (8)
	🐞 Asian lady beetle (16)	🐦 Alpine chough (16)	🐦 Common blackbird (16)	🐞 Common darter (7)
Winter	🐦 Eurasian blue tit (10)	🌳 European beech (12)	🐦 Common blackbird (15)	🐦 Mallard (9)
	🐦 Common blackbird (10)	🌳 Norway spruce (8)	🐦 Great tit (11)	🐦 Eurasian coot (9)
	🐦 Common chaffinch (8)	🌳 Common hazel (7)	🕷 Daddy long-legs spider (10)	▯ Eurasian beaver (6)

Legend: 🐦 Bird 🦋 Butterfly 🐞 Other insect 🌼 Flowering Plant 🌳 Tree 🐟 Fish 🐸 Amphibian 🦎 Reptile 🍄 Fungus 🕷 Arachnid ▯ Mammal

5. Discussion

The analysis of iNaturalist contributions in Carinthia reveals complex patterns of citizen science participation across spatial and temporal dimensions. These patterns provide valuable insights into the dynamics of biodiversity observation and the factors influencing citizen science engagement. The following discussion examines the implications of our findings, addressing the spatial distribution of observations, seasonal and hourly contribution patterns, and their relevance to biodiversity monitoring and citizen science initiatives. By exploring these aspects, we aim to contribute to a better understanding of the strengths and limitations of citizen science data in biodiversity research and conservation efforts.

5.1. Regression

The positive association of iNaturalist contribution counts with proportion of artificial surfaces suggests that urban and developed areas attract citizen science activity, possibly due to higher population density and easier access to communication technology, such as Wi-Fi and cell phone towers. The positive association with water bodies could be attributed to the attractiveness of these ecosystems to both wildlife and nature enthusiasts. Conversely, the negative relationship with forest and semi-natural areas indicates challenges in accessing remote locations, due to lack of roads that allow motorized traffic, and time needed to travel from urban areas to remote locations. The negative association with agricultural areas might reflect lower biodiversity in intensive farming landscapes, limited public access to these private lands and remote location relative to urban areas. As can be expected, proximity to cities and proximity to primary roads is associated with increased contributions. This suggests that citizen scientists are active near urban centers where they likely reside. Primary roads provide easy and fast access to areas surrounding them, which explains higher observation in these areas.

While our model explains some of the variation in iNaturalist observations, there may be other influential factors not captured in this analysis. These could include temporal variations (e.g., seasonal effects), specific habitat characteristics, or socio-economic variables.

These findings have several implications for enhancing citizen science initiatives and biodiversity conservation in Carinthia. For education and outreach, targeted efforts to promote iNaturalist usage in agricultural and forested areas could help balance the spatial distribution of observations and provide a more comprehensive picture of Carinthian biodiversity. Regarding data interpretation and biodiversity monitoring, analysists should be aware of the spatial biases in iNaturalist data when interpreting biodiversity patterns and species distributions.

5.2. Seasonal and hourly contribution patterns

The temporal patterns observed in iNaturalist contributions reveal significant variations across seasons and hours. Reduced observation activity during winter and nighttime activity can be expected due to shorter daylight hours in winter and challenges in spotting and photographing plants and wildlife during darker conditions. The underrepresentation of Protozoa and Bacteria points to limitations in citizen science data capture for microscopic life forms, which is consistent with earlier studies (Chandler et al., 2017). The autumn peak in Fungi observations partially aligns with typical mushroom fruiting seasons of edible mushrooms in Austria which is late summer and fall because of more rain and warm daytime temperatures (Maguire, 2022). This demonstrates how natural phenological patterns can influence data collection.

These results are consistent with studies on other citizen science platforms. For instance, significant seasonal and diurnal patterns in bird observations from eBird have identified peak activity during spring and early morning hours (Boakes et al., 2016). Similarly, strong seasonal trends in marine citizen science data have been reported, comparable to our findings of increased summer activity (Welvaert & Caley, 2016).

The hourly distribution of user activity across seasons in Figure 7 reveals a pattern of daytime-focused observations, with peak hours around 12 pm in summer, gradually shifting to 2 pm in winter. This pattern is similar to that found in the analysis of eBird data (Wiggins & He, 2016), which showed that observation times closely followed daylight hours across seasons.

The consistently low activity during early morning hours across all seasons, coupled with a small peak at midnight (Figure 7), raises questions about the accuracy of nighttime observations. This pattern may indicate a data artifact similar to that identified in an analysis of eBird data, where default timestamps led to overrepresentation of midnight observations (Courter et al., 2013). A similar type of bias, however in the spatial domain, is commonly found the location of spatial data points where latitude and longitude entries are missing, leading to Null Island, a fictional place located at 0° latitude and 0° longitude in the WGS 84 geographic coordinate system (Juhász & Mooney, 2022).

*Summer months reveal the highest activity and diversity (*Figure 10*,*

Table 5). For several hours per day, species observations of Silver-washed Fritillary (up to 30 counts at 11 am) and Wels Catfish (up to 99 counts at 5 pm), dominate hourly observation counts, indicating favorable conditions for both terrestrial and aquatic species. Spring displays a more even distribution of observation numbers across different species with the Common Wall Lizard having most hourly observations (14 counts at 3 pm), suggesting a period of balanced biodiversity as nature awakens. Fall is dominated by the Western Conifer Seed Bug for 10 hour-periods, possibly due to its seasonal migration or increased visibility. Winter shows the lowest overall activity, with observations primarily of common bird species like the Common Blackbird, reflecting the challenges of the cold season for many organisms. Nocturnal observations (8 pm through 5 am) are present across all seasons, albeit in lower numbers, highlighting the importance of round-the-clock biodiversity monitoring. The data also reveals temporal niche partitioning, with different species being most active at different times of the day across seasons, underscoring the complex dynamics of ecosystem activity patterns. This information is valuable for understanding local biodiversity, seasonal phenology, and could inform conservation efforts and wildlife management strategies in the region.

Figure 9 shows notable changes in contribution patterns across seasons and land cover types. Forest and semi-natural areas dominate observations, particularly in spring and summer, often exceeding 50% of hourly data points collected. The proportion of hourly contributions to agricultural areas typically ranges from 20-40% across seasons. Artificial surfaces exhibit lowest proportions during summer, possibly due to favorable weather and daylight conditions that encourage exploration of natural areas, such as forests, lakes and rivers during that season. Water bodies and wetlands generally constitute small proportions of contribution throughout the year. Diurnal patterns are evident, with most activity concentrated between 8 am and 6 pm. Agricultural areas show the largest 90% observation range (17 hours) in summer, whereas shortest observation hours are generally observed during winter. Winter also displays the lowest overall activity and highest variability in proportions, likely due to reduced biodiversity and observer activity. These fluctuations highlight the complex interplay between land cover, seasonal changes, and observation patterns in citizen science data collection.

The list of primary mapped species for different land cover types across four seasons (Table 8) shows some noticeable trends in seasonal transitions. For example, spring observations in agricultural areas focus on flowering plants, transitioning to butterflies in summer, then to butterflies and other insects in fall, and finally to birds in winter. This pattern aligns with natural phenological changes and shifts in species visibility. Artificial surfaces display flowering plants and insects primarily during spring and summer, whereas fall is dominated by insects and winter by birds. Forest and semi-natural areas are the only land cover with fungi being the most mapped taxon (Fly agaric in fall), whereas winter is dominated by trees. For water bodies, birds dominate fall through spring, whereas an increase in fish observations can be observed in summer (possibly due to increased fishing activity or better water visibility). Wetlands are the only land cover with mammals (beavers) being among the top three mapped species, which was observed during in winter.

These temporal patterns have important implications for biodiversity monitoring. The seasonal and diurnal variations in data collection suggest potential biases in species representation, particularly for nocturnal or winter-active species. This aligns with concerns about the need to account for temporal biases in citizen science data when used for biodiversity assessments (Dickinson et al., 2010).

6. Conclusions and Future Work

The presented analysis of iNaturalist data in Carinthia reveals numerous spatial and temporal data contribution patterns. Some of these variations across space and time may be based on actual differences in presence of organism and seasonal phenology, such as fungi being the most observed species during summer in forest areas or insects and butterflies dominating observations in agricultural areas during summer and fall. However, others, especially abundance related measures, may be artefacts caused by imbalanced collection efforts. For example, the positive association with urban areas suggest potential spatial biases in data collection which can be caused by a larger population in urban areas and thus an over proportional number of potential iNaturalist contributors in these areas compared to more remote areas, such as forests. Future initiatives should focus on addressing spatial and temporal gaps in data collection to ensure a more comprehensive representation of Carinthian biodiversity. To further explore the complex influences between different environments and observation patterns, future research should employ more advanced analytical methods. These could include intersection and interaction analyses to better understand how various environmental factors combine to affect observation patterns. Additionally, machine learning techniques such as random forests or gradient boosting could be applied to capture non-linear relationships and interactions between variables. Time series analysis methods could also be implemented to more deeply investigate temporal trends and seasonality effects. Moreover, integrating data from multiple citizen science platforms and comparing results with professional biodiversity surveys could provide a more holistic view of Carinthia's biodiversity and help identify areas where citizen science efforts could be better aligned with scientific needs.

As citizen science continues to grow and evolve, several challenges and opportunities emerge for future research. The importance of integrating citizen science data with professional scientific datasets to create more comprehensive and robust biodiversity monitoring systems has been emphasized (Chandler et al., 2017). This integration will require the development of advanced statistical methods to address biases and uncertainties in citizen science data, particularly for use in policy-making and conservation (Isaac et al., 2014). Our future studies will also explore motivational factors and barriers to participation in citizen science. Additionally, investigating the long-term impacts of citizen science participation on environmental attitudes, behaviors, and scientific literacy will be crucial for understanding the broader societal benefits of these initiatives

(Bonney et al., 2015). Ethical considerations surrounding data privacy, intellectual property rights, and the use of citizen-generated data in scientific research and decision-making processes also warrant further attention (Resnik et al., 2015). Addressing these challenges and exploring these new directions will be essential for maximizing the potential of citizen science in biodiversity research and conservation.

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