

1 Title page

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4 **Assessment of Urban Bias in Iberian Butterfly Sampling through Citizen Science Data**

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6 Author information

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17 Declaration of generative AI and AI-assisted technologies in the writing process

18 During the preparation of this work, the author(s) utilized OpenAI's ChatGPT (GPT-4) (2024) to
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21 for the final version of the published article.

22

23 Contribution of authors

24 All authors contributed to the study conception and design. Material preparation, data collection
25 and analysis were performed by Diego Gil-Tapetado. The first draft of the manuscript was

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- 27 Both authors read and approved the final manuscript.

28 **Abstract**

29 Citizen science platforms have revolutionized biodiversity monitoring by enabling large-scale
30 data collection. However, concerns about potential biases, such as urban sampling bias, have
31 raised questions about the quality and representativeness of these datasets. This study assesses
32 the spatial distribution of butterfly observations collected through the citizen science platform
33 *Biodiversidad Virtual* in the Iberian-Balearic region over a 23-year period (2000–2023).
34 Butterfly records were classified into three ecosystem types—urban areas, grasslands, and
35 forests—and three population density zones—urban, peri-urban, and rural areas—using land
36 cover and population density maps. Temporal trends in observation growth and minimum
37 distances of records to urban and rural areas were analyzed. The results show consistent growth
38 in butterfly observations across all ecosystem types, with rural and natural areas contributing
39 significantly more records than urban areas. Observations in grasslands exhibited the highest
40 growth rate, followed by forests and urban areas. The analysis of distances revealed preference
41 for recording biodiversity in natural areas, with records consistently closer to rural areas than
42 urban centers. These findings challenge the perceived dominance of urban bias in citizen
43 science datasets and highlight the capability of citizen science platforms to capture data from
44 diverse ecosystems. This study shows that, for one of the most important georeferenced
45 datasets on butterflies of the Iberian Peninsula, urban biases are minimal, and
46 geographic representation is robust. Further research is recommended to examine
47 cultural and regional factors in other databases, enhancing their application in ecological
48 research and conservation planning.

49 **Keywords**

50 Biodiversity monitoring, Sampling bias, Land cover classification, Lepidoptera, Habitat
51 distribution, Spatial analysis, Conservation data quality

52

53 **1. Introduction**

54 Citizen science platforms have revolutionized biodiversity monitoring and detecting by
55 providing tools that enable the efficient and cost-effective collection of massive amounts of data
56 (Dickinson et al., 2012). These platforms offer numerous benefits for research, allowing
57 investigations to be conducted at various scales and with extensive datasets, making them
58 essential resources for ecological research and conservation (Dickinson et al., 2010). Relevant
59 advancements have been achieved through these platforms, including the early detection of
60 invasive alien species (González-Moreno et al., 2024), the identification of threatened species

61 (Rosa & Freitas, 2024), and the tracking of phenology and migratory patterns (Howard &
62 Davies, 2006; Newson et al., 2016; Sanderson et al., 2021).

63 Despite their advantages, citizen science platforms are subject to various biases that can
64 impact data quality and representativeness (Geldman et al., 2016). The full extent of these
65 biases remains poorly understood, requiring further investigation to mitigate their effects
66 (Dickinson et al., 2010). Among these biases are taxonomic biases (e.g.: misidentification or
67 identification of species that cannot be identified by macroscopic features), which favor
68 charismatic groups like birds while underrepresenting invertebrates and fish (Della Rocca et al.,
69 2024). Large-scale geographic biases are also prominent, with most observations concentrated
70 in developed countries, leaving regions with high biodiversity but low citizen participation
71 poorly covered (Requier et al., 2020). At smaller scales, geographic biases are influenced by
72 accessibility and visitation frequency, both of which play significant roles in the generation of
73 observations (Mair & Ruete, 2016; Hugo & Altwegg, 2017). These limitations can reduce the
74 potential of these platforms to address global ecological questions equitably. However, many
75 “academic” databases also contain errors and biases, and these have to be lived with and
76 methodologies exist to minimize them (Ponder et al., 2001; Wehi et al., 2012; Sánchez-
77 Fernández et al., 2022).

78 One specific bias is urban sampling bias, where the higher density of observations in
79 urban areas is driven by easier access and the higher concentration of participants (Ward, 2014).
80 This bias often results in the under-sampling of natural ecosystems such as grasslands and
81 forests, limiting the representation of species inhabiting these habitats. This issue highlights the
82 need to assess the spatial distribution of observations to determine whether these data accurately
83 reflect ecological patterns or are disproportionately influenced by the observer location.

84 This study aims to evaluate the spatial distribution of observations collected through a
85 citizen science platform, focusing on spatial biases in data collection within the Iberian-Balearic
86 region. Butterflies were chosen as the focal taxa due to their visual appeal within citizen
87 science, their relevance in large-scale studies as bioindicators (Parmesan, 2003; Otaki, 2020;
88 Pallottini et al., 2023), and their central role in numerous monitoring programs worldwide—
89 e.g., eButterfly (Prudic et al., 2017), EuropeanBMS (van Swaay et al., 2008), UKBMS (Pollard
90 & Yates, 1994)—. The analysis spans over two decades (2000–2023), with georeferenced
91 observations categorized under two schemes: (1) land use types—urban areas, grasslands, and
92 forests—and (2) population density zones—urban, peri-urban, and rural areas. By analyzing
93 temporal trends, the study seeks to determine whether citizen science data exhibit a significant
94 bias toward urban areas or if they represent a broader range of ecosystems. These findings will

95 provide valuable insights into the quality and representativeness of citizen science data and their
96 applicability in addressing ecological research and conservation challenges.

97

98 **2. Material and Methods**

99 *2.1. Data Collection*

100 Observations of butterfly species from the superfamily Papilionoidea present in the Iberian
101 Peninsula were gathered from the citizen science platform *Biodiversidad Virtual* (currently
102 inside of Observation.org <https://biodiversidadvirtual.observation.org/>). The dataset included
103 georeferenced records from photographs reported between 2000 and 2023 (Supplementary
104 Material S1). These data are uploaded to GBIF until 2018 (GBIF, 2025) and subsequently
105 included in the Observation.org data, being public data from a citizen science platform (Figure
106 1). Data were filtered deleting duplicates and selecting only with Spanish data (where most of
107 records of *Biodiversidad Virtual* are held and has the highest representativeness) excluding
108 Canary Island records.

109 Georeferenced and dated data were categorized using the CORINE Land Cover
110 database (COPERNICUS, 2020) downloaded from Copernicus Global Land Service. The
111 original land cover categories were reclassified into three main ecosystem types: Forests
112 (“Vineyards”, “Fruit trees and berry plantations”, “Olive groves”, “Agro-forestry áreas”,
113 “Broad-leaved forest”, “Coniferous forest”, “Mixed forest”, and “Transitional woodland-
114 shrub”); Grasslands (“Non-irrigated arable land”, “Permanently irrigated land”, “Rice fields”,
115 “Pastures”, “Annual crops associated with permanent crops”, “Complex cultivation patterns”,
116 “Land principally occupied by agriculture, with significant areas of natural vegetation”,
117 “Natural grasslands”, “Moors and heathland”, and “Sclerophyllous vegetation”); and Urban
118 Areas (“Continuous urban fabric”, “Discontinuous urban fabric”, “Industrial or commercial
119 units”, “Road and rail networks and associated land”, “Port areas”, “Airports”, “Mineral
120 extraction sites”, “Dump sites”, “Construction sites”, “Green urban areas”, and “Sport and
121 leisure facilities”). Other types of land cover categories unrelated to butterfly fauna (e.g.:
122 “Glaciers and perpetual snow”, “Salt marshes” or “Bare rocks”) have not been considered in
123 any of the above categories.

124 The data were also classified into urban, peri-urban and rural areas, by reclassifying the
125 Gridded Population of the World version 4 (GPWv4) human population raster (CIESIN-
126 Columbia University, 2018) using the following criteria : ≥ 1000 people km^2 , periurban >250
127 people km^2 within a 15-km distance from urban extent edge, and rural <250 people km^2 and/or

128 >15 km from the urban extents edge, and is commonly used as a representative of the
129 urbanization level in ecological studies (Cano et al. 2014; Polidori et al. 2021)

130 2.2. Data Analysis

131 Accumulation butterfly data by year were calculated for each ecosystem type. Temporal trends
132 in citizen science contributions across the ecosystems were visualized using line graphs. The
133 curve or linear adjustment for each ecosystem type were calculated by obtaining the estimated
134 increase in data for each ecosystem type. A descriptive analysis was conducted to assess
135 whether the data exhibits a spatial bias toward urban areas or if the observations are more
136 evenly distributed among the three ecosystem types.

137 We also calculate the minimum distance of each record to the closest urban and rural
138 area. With this information we performed an ANOVA test to show whether the means of the
139 distances between the two areas are different or which are smaller.

140 Reclassification of CORINE LandCover and human population was performed in
141 ArcGIS for Desktop v 10.8 (ESRI, 2019) using the function *Reclass*. Data analysis (ANOVA
142 and minimum distances) and visualization were performed using the R software (version 4.3).
143 The *ggplot2* package was used for creating graphs and *sf* and *dplyr* to the distance calculation.

144 3. Results

145 The analysis showed temporal trends in the annual frequency of butterfly observations across
146 the three ecosystem types: forests, grasslands, and urban areas. The total number of
147 observations increased steadily for all ecosystem categories from 2000 to 2023 (Figure 2A).
148 Observations in forest areas showed a consistent increase throughout the study period,
149 contributing significantly to the overall dataset (linear adjustment $y = 1561.7x - 7654.8$, $R^2 =$
150 0.9431). Observations in grassland ecosystems exhibited the highest growth rate over the study
151 period, surpassing urban areas and approaching the number of observations recorded in forests
152 toward the end of the analyzed period (linear adjustment $y = 1379.2x - 6764.4$, $R^2 = 0.9453$).
153 Finally, observations in urban areas also increased over time but at a slower pace compared to
154 forests and grasslands (linear adjustment $y = 362.17x - 1884.4$, $R^2 = 0.9266$). Following this, the
155 increase of urban records is the smallest among all the studied ecosystem categories ($\Delta_{urban} =$
156 $362.17 < \Delta_{forest} = 1561.7$ and $\Delta_{grasslands} = 1379.2$).

157 The same pattern is observed with the area types and the butterfly records by year
158 (Figure 2B). In this case, the number of peri-urban and urban registers is much lower than the
159 number of rural registers, which shows that the annual increases are also smaller (linear

160 adjustment_{rural}: $y = 2874.2x - 14205$, $R^2 = 0.9429$; linear adjustment_{periurban}: $y = 292.02x - 1463.3$,
161 $R^2 = 0.9266$; linear adjustment_{urban}: $y = 286.8x - 1367.7$; $R^2 = 0.9266$).

162 The mean of the distances of each record to rural and urban areas are different
163 (ANOVA: $F = 3019.8$; $p < 2e-16$) being higher to the urban areas and smaller to rural areas
164 (Figure 3). This and previous analyses demonstrate that citizen science records pertain to
165 photographs of volunteers and appear to be unbiased by proximity to cities.

166

167 **4. Discussion**

168 The study reveals the consistent growth in butterfly records across all ecosystem types over a
169 23-year period (an average of ~ 3500 butterfly photographs and records per year). Rural and
170 natural areas contributed considerably more observations than urban regions. These findings
171 challenge the commonly perceived urban bias in citizen science data, demonstrating instead a
172 more balanced spatial distribution of observations.

173 There was greater growth in records and a higher number of observations in non-urban
174 in our results, contrasting with those of Hugo and Hazell (2017). These authors found a greater
175 sampling effort near urban areas and main roads in South Africa, a pattern that could be
176 influenced by the own region or country characteristics and associated accessibility challenges.
177 Also, in contrast with our results, Geldmann et al. (2016) observed that in Denmark, higher
178 population density correlated with increased sampling intensity across species datasets,
179 suggesting that cultural and demographic factors, play a significant role in shaping sampling
180 patterns. These differences highlight the importance of regional characteristics and participant
181 motivations in influencing data collection efforts. The Iberian Peninsula has a much higher
182 proportion of rural and natural areas compared to other European countries (EUROSTAT, 2024)
183 and has few dangerous organisms to humans (i.e.: poisonous and toxic fauna, parasites and
184 vectors of diseases and endemic diseases) compared to other countries in the world (Li et al.,
185 2024). This, together with relatively favorable climatic conditions, could explain the differences
186 observed in the contributions of other authors. Moreover, the cultural factor may also play an
187 important role in the non-existence of this bias in this territory. For example, in certain areas of
188 the Iberian Peninsula (Catalonia) a usual and recurrent hobby of people is to go into the natural
189 areas to contribute to photographs and data of wildlife.

190 The distances of records to natural areas were consistently shorter than those to urban
191 areas, suggesting a deliberate cultural preference for documenting biodiversity in natural
192 environments. It is plausible that the recreational and aesthetic appeal of these areas motivates

193 participants to engage in citizen science projects, although further research is needed to confirm
194 how these factors influence participation. Cultural perceptions of natural areas as biodiversity-
195 rich spaces may also play a significant role, with participants prioritizing these areas based on
196 their intrinsic ecological and educational value (Hugo & Altwegg, 2017). While accessibility
197 influences spatial biases to some extent (Millar et al., 2019), the intentional focus on natural
198 habitats reflects broader sociocultural and motivational drivers. These findings emphasize the
199 need to account for both logistical and cultural factors when interpreting spatial patterns in
200 citizen science data, underscoring the importance of proper study design and statistical
201 adjustments to maximize the utility and representativeness of these datasets (Brown et al., 2019;
202 Robinson et al., 2018).

203 The Iberian-Balearic region demonstrates a relatively well-represented sampling effort
204 for butterflies (García-Barros et al., 2023), however some rural areas still need to be more
205 sampled (e.g.: grasslands areas of the central Iberian Peninsula used for agricultural activities).
206 As a geographically critical biodiversity hotspot, the Iberian Peninsula faces challenges such as
207 rural abandonment and urban concentration, which could introduce geographic biases in data
208 collection (Pascual et al., 2011; Quintas-Soriano et al., 2023). However, the results of this study
209 align with those from well-sampled regions such as Great Britain, where most of the territory is
210 well-represented, and spatial biases have not negatively impacted distribution models for birds
211 (Johnston et al., 2020).

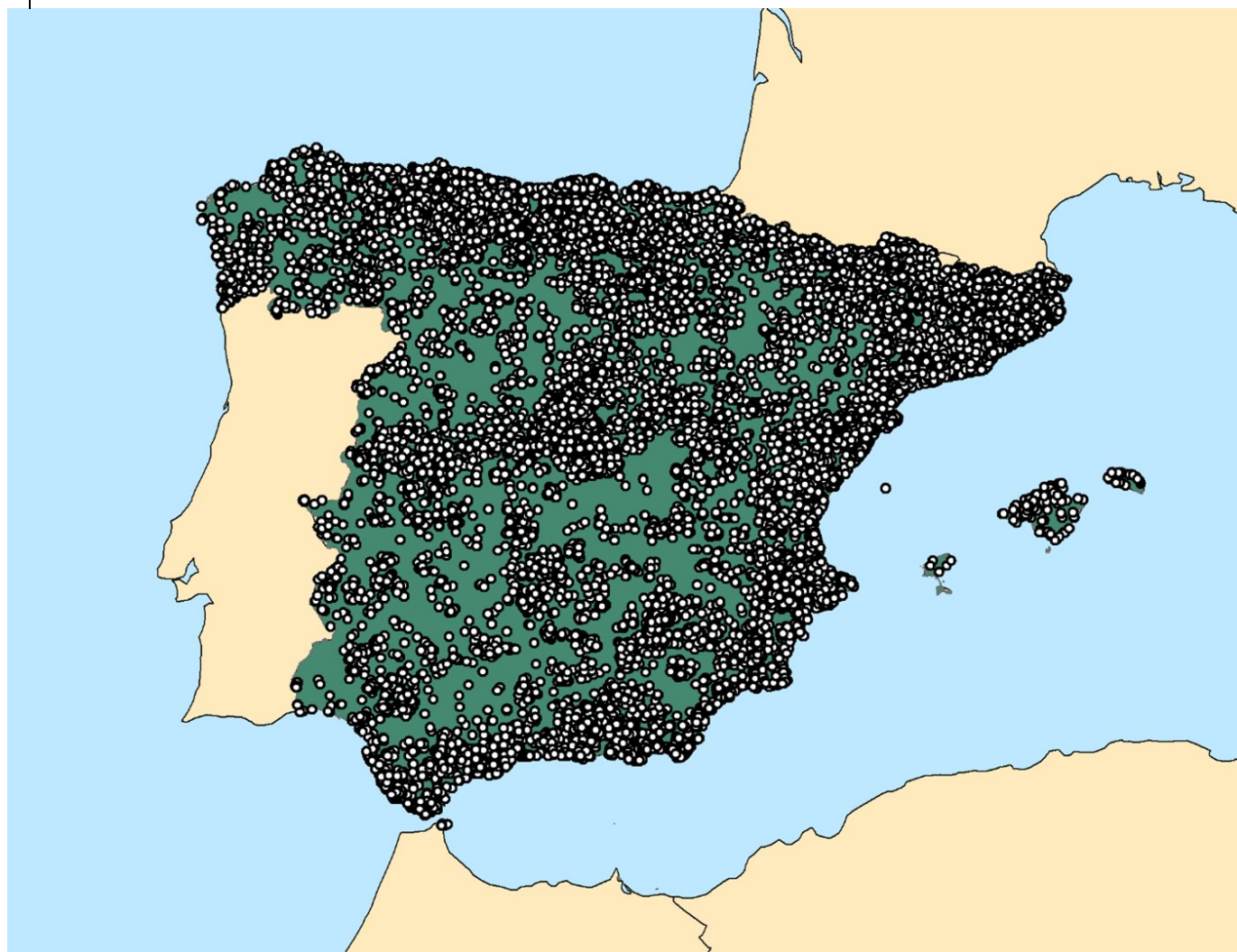
212 The Iberian Peninsula, as a well-sampled region, provides an excellent case for
213 employing citizen science data, particularly using platforms like *Biodiversidad Virtual*. This
214 study demonstrates that, at least for this platform, urban biases are minimal, and geographic
215 representation is robust. This may allow us to affirm with more confidence, for example, that
216 the observation of a species in an urban area rather than a rural area is not due to a bias in the
217 information from a citizen science source, but rather to a real pattern. Citizen science data
218 represent a valuable resource, significantly reducing economic costs and accelerating
219 knowledge generation by eliminating traditional data collection processes. However, it is crucial
220 to analyze each database and region individually, as cultural factors may influence data
221 collection patterns. Identifying and minimizing biases and errors within these datasets will
222 enhance their transformation into robust scientific data, maximizing their utility and ensuring
223 their effective application in ecological research and conservation planning.

224

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226 We would like to thank all the generators of georeferenced biogeographic data and information

227 who contribute data altruistically to the *Biodiversidad Virtual* repository. Thanks to their work
228 and passion for nature we can make these scientific contributions and make progress in closing
229 many knowledge gaps.



231

232 **Figure 1. Geographic distribution of butterfly observations in the Iberian-Balearic region**

233 Map showing butterfly records from the *Biodiversidad Virtual* database. Only records from the

234 Iberian-Balearic region are represented and included in the analysis due to the high

235 representativeness of this territory.

236

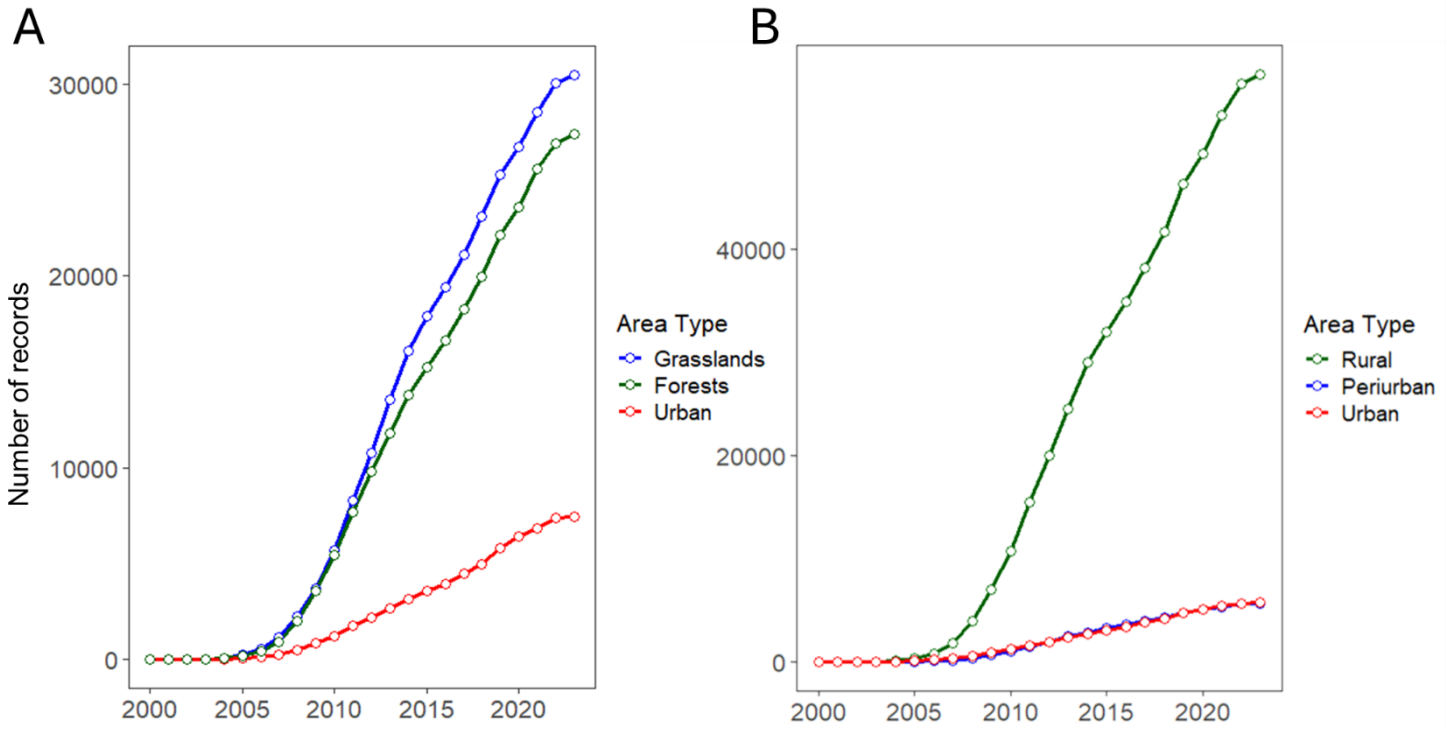
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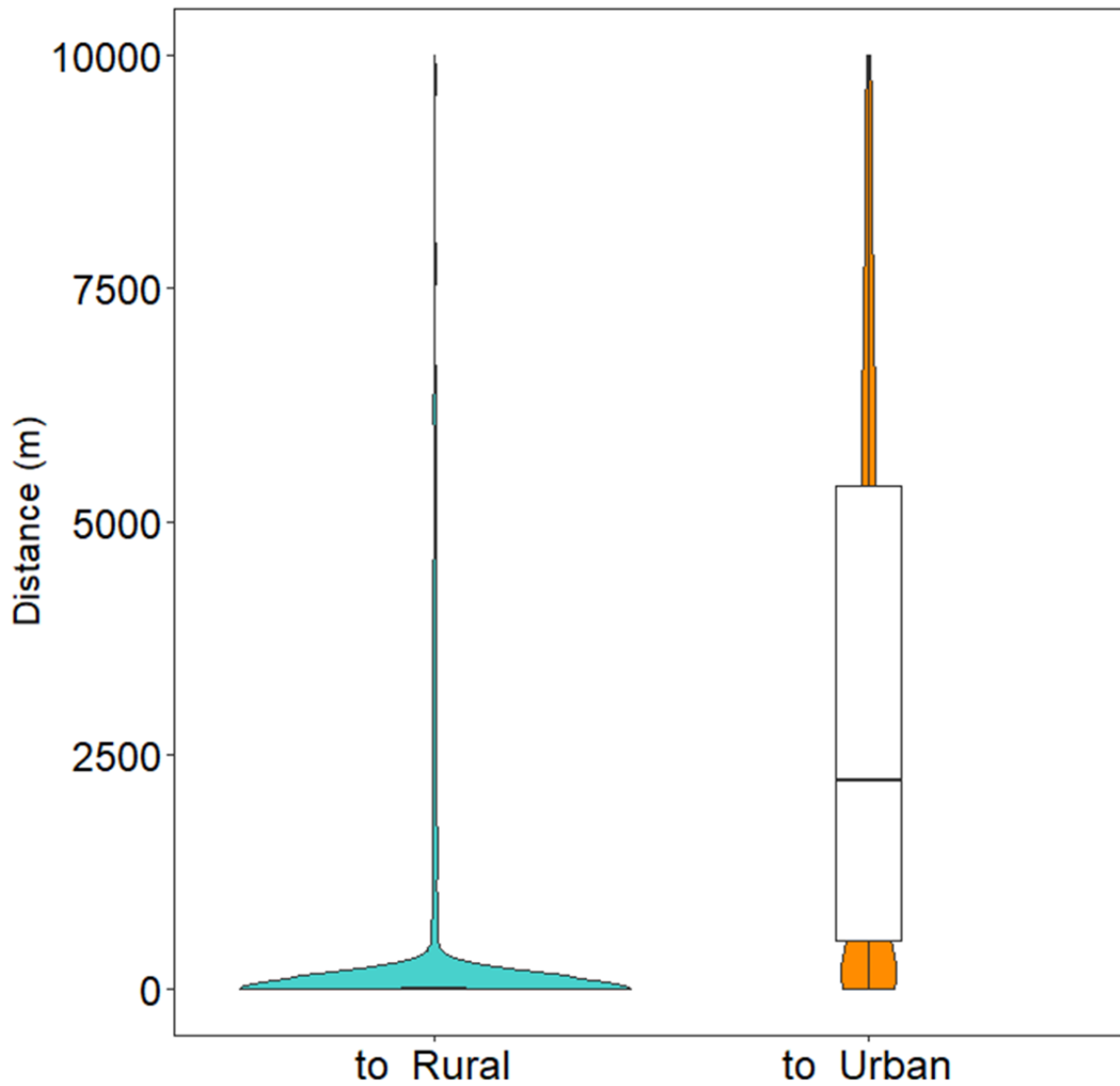


242 **Figure 2. Temporal trends in butterfly observations by ecosystem type** A) Temporal trends
 243 in cumulative butterfly observations across three ecosystem types: forests, grasslands, and urban
 244 areas, based on data collected through the citizen science platform *Biodiversidad Virtual*
 245 between 2000 and 2023. B) Temporal trends in cumulative butterfly observations across three
 246 area types: rural, periurban, and urban areas.

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249



250 **Figure 3. Distance analysis of butterfly observations to rural and urban areas** Violin and
 251 boxplot plot with the minimum distances in meters of each record of butterflies from
 252 *Biodiversidad Virtual* database to the closest rural and urban area.

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