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RESEARCH ARTICLE

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What you hear may not be what you see: Potential of citizen science methods to use bats as riverine forest quality indicators

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Abstract

Mediterranean habitats will be one of the Eurasian ecosystems more strongly affected by Climate Change, especially their riverine systems. Monitoring these ecosystems, which are endemism hotspots and extremely sensitive to changes in rain regimes and extreme weather events like droughts, is of crucial importance. Decades of citizen science projects have proven their utility in highlighting ecological shifts and conservation action priority areas. The Bat Monitoring Programme (www.batmonitoring.org), for instance, has already been used to develop ecological indicators to evaluate the evolution and conservation status of Mediterranean ecosystems. However, using bats as ecological indicators for aquatic ecosystems has resulted in contradicting results, making its application a little controversial. In the present study, we compared two citizen science protocols (visual counting vs. passive acoustic monitoring) used in the Bat Monitoring Programme to test the utility of trawling bats as indicators of Mediterranean riverine habitat quality at both local and landscape scales. By doing so, we aimed to build a specific ecological indicator to determine habitat quality through visual and acoustic counts. Although both protocols presented similar positive significant responses to riverine forest quality, visual counts are suggested as the best sampling approach due to their simplicity and potential within citizen science projects. Moreover, for the first time, we defined threshold values of trawling bat activity to assign different levels of habitat quality to the sampled rivers. We applied them in NE Iberia to exemplify the benefits of using them in a Mediterranean region and discussed the potential, pros and cons of these two citizen science methodologies to establish a pan-European river biomonitoring programme using trawling bats.

KEYWORDS
bioacoustics, bioindicator, chiroptera, Mediterranean river, trawling bat, waterway survey

1 | INTRODUCTION

The Mediterranean basin has been recently dubbed a 'climate change' hotspot (Newbold et al., 2020). While current rises in temperature will increase precipitation rates in most of the planet, the Mediterranean region will be one of the few that will lose most winter rains, up to 40% in some regions (Newbold et al., 2020; Tuel & Eltahir, 2020). Regarding their biodiversity, Mediterranean biomes will suffer declines in species richness between 10% and 13% for each degree of planetary warming, which could rise to 30% in urbanised areas (Newbold et al., 2020; Zittis et al., 2022). The consequences will be especially visible in forested and freshwater habitats, which will suffer changes at both landscape scale and microclimatic conditions and structure (de Frenne et al., 2021). This is extremely worrying, considering that the Mediterranean basin is one of the major endemism hotspots on the planet, especially for freshwater diversity (Filipe et al., 2013; Tierno de Figueroa et al., 2013). Mediterranean riverine ecosystems are already found in a water-stressed region and present a wide range of taxa dependent on the water and microhabitats they supply (Rocha et al., 2020; Stefanidis et al., 2018) being of particular concern in any climate change scenario.

In this context of anthropogenic-driven changes, having reliable bioindicators is of utmost importance to quantify the extent of these changes' effects on wild animal populations, especially in sensitive ecosystems. Multiple taxa have been shown to reflect fluctuations in climatic conditions, landscape changes and habitat alterations, like butterflies (Dover & Settele, 2009; Lawson et al., 2012; Thomas & Hanski, 2004; Torre et al., 2021), aquatic macroinvertebrates (Hawkes, 1997), fish (Lo et al., 2021), amphibians (Ficetola & Maiorano, 2016) and birds (Dutta, 2017). In order to use them properly as bioindicators, it is crucial to choose the right taxa (Bal et al., 2018) and accurately assess what their population shifts or responses are indicating (Gao et al., 2015), as some of them may reflect differential effects at macro and microscale environmental variables (Götmark et al., 2008; Lawson et al., 2012).

Bats have been considered potential bioindicators for decades (Jones et al., 2009). Various studies have proven that bats are affected by a diverse range of ecosystem alterations like agricultural intensification (Park, 2015), wildfire occurrence (Loeb & Blakey, 2021; López-Baucells et al., 2021), landscape composition (López-Baucells et al., 2017; Morris et al., 2010), light pollution (Hooker et al., 2022) and urbanisation (Russo & Ancillotto, 2015). Being volant, highly vagile animals and potentially found in most habitats, but also with some species having very specific requirements for their diurnal roosts and thus being very selective on the habitats they inhabit, make bats potentially good bioindicators of habitat changes. Yet, it is possible that the bioindicator potential of bats can differ depending on the scale of the environmental characteristics we are assessing. For instance, a study conducted in England and Scotland (Fuentes-Montemayor et al., 2017) showed that the acoustic activity of different bat species was affected differently by the landscape and local habitat characteristics, not only varying according to the scale of the environmental variables assessed and the bat species but also by the survey area (England vs. Scotland).

In riverine ecosystems, using bats as bioindicators have shown fairly contradictory results in the past, as reported by Russo et al. (2021). In Europe, aquatic ecosystem quality assessment using bats has been conducted mainly using trawling bat species (i.e., *Myotis daubentonii*, *Myotis capaccinii* or *Myotis dasycneme*), due to the solid trophic relationship of these species with freshwater habitats (Almenar et al., 2006; Biscardi et al., 2007). In a study conducted in the Northeast Iberian peninsula, López-Baucells et al. (2017) found that visual counting of trawling bats was correlated with riverine forest cover quality (Munné et al., 2003) and forest cover in a 2500 m buffer. However, 1 year later, de Conno et al. (2018) assessed the effectiveness of using acoustic data of multiple bat phonic groups as bioindicators and found negative relationships between trawling bat activity and different riverine habitat quality indices. All these studies have used different methods and indices to assess the utility of trawling bats as indicators, highlighting the need to select the appropriate 'measures' to develop indices of habitat integrity and quality, preferably related to already-established indices like the index of riparian quality (QBR from its Spanish acronyms) (Munné et al., 2003) or macroinvertebrate community indices (Stefanidis et al., 2018).

Trawling bat activity can easily be monitored using citizen science. Waterway surveys using visual counts of trawling bats have already been taking place in some north European territories. These initiatives have provided vast datasets used to monitor trawling bat population trends (Aughney et al., 2009) and even assess habitat selection and use by these species. Nevertheless, as has been reported for other species (Díaz et al., 2013; Dunbar & Brigham, 2010; Michaelsen et al., 2011), the biology and behaviour of trawling bats may differ significantly between the Mediterranean region and its northern counterparts. Therefore, establishing a large-scale citizen science monitoring project for aquatic bats would be necessary to understand these species' relation to changing Mediterranean ecosystems. The Bat Monitoring Programme (www.batmonitoring.org), coordinated by the Natural Sciences Museum of Granollers, adopted the waterway survey protocol already established in the UK and Ireland, hereafter named ChiroRivers, adapted to the Mediterranean bats' phenology. In parallel, the same institution launched the ChiroHabitats protocol, a citizen science acoustic monitoring protocol based on automatic acoustic stations that, when applied in aquatic environments, can also easily detect and record the activity of trawling bats.

These last two protocols have great potential under the umbrella of bioindication and citizen science, as seen in López-Baucells et al. (2017) and Tuneu-Corral et al. (2020). However, to be able to use them for conservation on the ground, it is crucial to understand what shifts in these species' activity mean concerning both local and landscape habitat variables. Also, providing reference activity values and thresholds to be used in later environmental quality assessments would be of utmost importance to develop robust, consistent and easy-to-use indicators. In the present study, we compared the two surveying protocols to elucidate how the monitoring of these species could be integrated as riverine ecosystem bioindicators. This study's specific aims were as follows: (1) Comparing the similarity of the survey results obtained through two different citizen science protocols (visual vs. acoustics counts) for assessing trawling bat activity; (2) Assessing the effects of environmental conditions at local or micro-habitat and landscape levels on trawling bat activity; (3) Summarising the pros and cons of each citizen science protocol for the establishment of a potential pan-European trawling bat biomonitoring project (4) Developing an ecological indicator based on trawling bat activity to infer habitat quality quickly and effectively in the field, based on previously known and well-spread biological indicators.

2 | MATERIALS AND METHODS

2.1 | Study area

The study was conducted in the north-eastern Iberian Peninsula, in a region with a 'dry-summer' or 'Mediterranean' climate according to the Köppen classification (Peel et al., 2007). The sampling sites were selected across two main river basins: the Segre basin (inland) and the Fluvià basin (coastal). While the Segre area is characterised by dry summers and cold winters and a landscape that combines extensive agricultural lands and steep mountainous chains, the Fluvià basin presents a mild climate and overall high humidity, with a mosaic landscape combining agricultural lands and more extensive forests. Both areas have known breeding colonies of both *Myotis daubentonii* and *Myotis capaccinii*. A total of 60 sites were surveyed using the two sampling protocols (see next section for more information) between May and August 2021 (37 in the Segre basin and 23 in the Fluvià basin, Figure 1a,b respectively). In the landscape analysis, 58 other locations sampled visually by volunteers during the last year were also added to the dataset, covering more or less evenly the rest of the regions within the state, with sampling sites ranging approximately from 0 m to 1000 m.a.s.l., and covering a wide variety of habitats (from urban rivers to high mountain streams in the Pyrenees) (Figure 1c).

2.2 | Visual sampling or 'ChiroRivers'

The visual surveys were conducted by adapting the ChiroRivers protocol from the Bat Monitoring Programme (see www.batmonitoring.org/rivers). While in the ChiroRivers protocol, the surveyor selects four sampling points to count trawling bat passes for 10 min each using a torch or a headlamp pointing across the river (totalling 40 min), we sampled one point per survey, but for 1 h. Also, instead of counting them using the light of manual torches, trawling bat activity was recorded using infrared cameras at the river level, an equivalent method to that proposed in the Bat Monitoring Programme. By using video cameras, we could gather all the recordings for future reference.

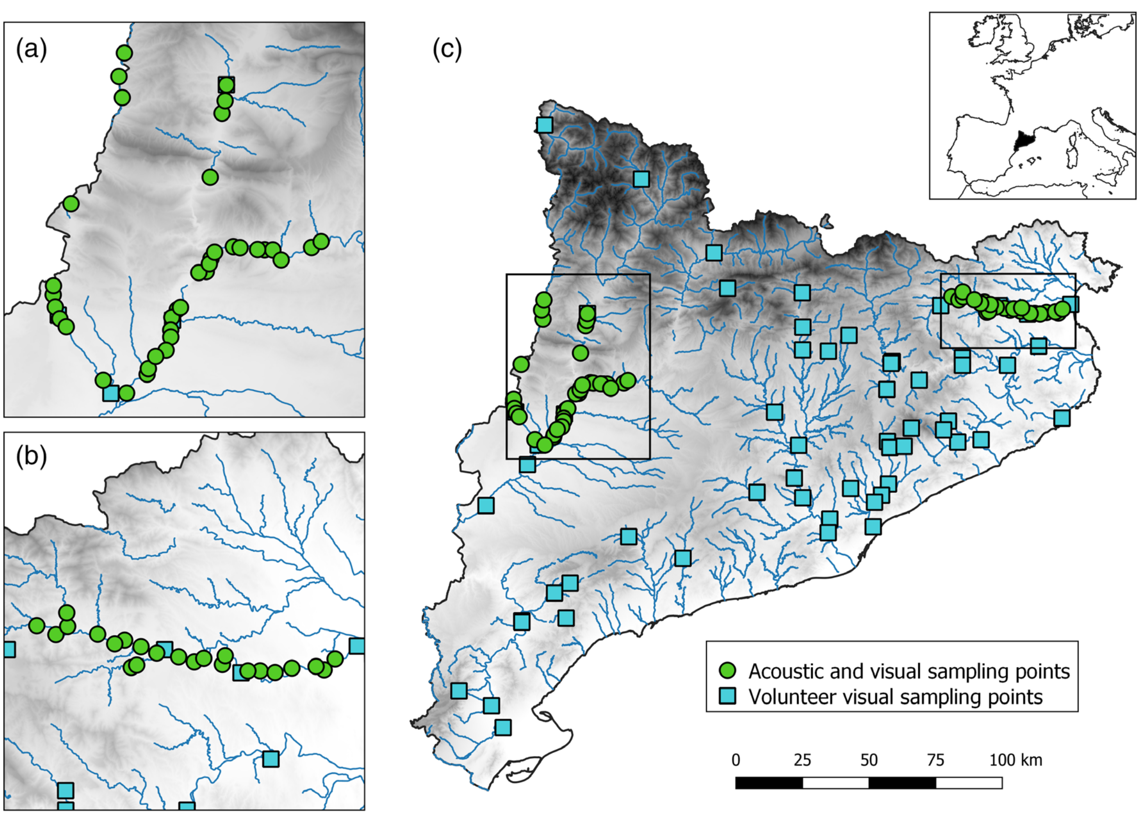

FIGURE 1 Study area: (a) Segre and (b) Fluvià basins (Catalonia, Spain), surveyed from May to August 2021 using both visual counts and passive acoustic surveys (green circles) and (c) northeastern Iberia network of ChiroRiver transects, including all the locations surveyed by volunteers using visual counts (blue squares). [Color figure can be viewed at wileyonlinelibrary.com]

The camera was placed using a small tripod facing the river stream perpendicularly with one external near-infrared (IR) focus. The camera started recording 1 h after sunset and recorded for one consecutive hour, coinciding with the peak activity period for trawling bats during the breeding period. The bat activity count was done manually by counting a 'visual pass' each time a trawling bat crossed the middle of the light beam of the IR focus.

In order to better cope with geographical variability, data from 58 other locations sampled visually by volunteers were also added to the dataset (only in the landscape analysis and in the models for visual counts), totalling 118 locations (Table S1). Of these 58 points, 51 were sampled during July 2022, while the other seven came from other years. The volunteers followed the ChiroRivers protocol, selecting four sampling points and counting the visual bat activity for 10 min at each point. For the landscape analysis, our dataset (60 min) and the volunteer dataset (40 min) were standardised to the average activity per 10 min.

2.3 | Acoustic sampling or 'ChiroHabitats'

Acoustic sampling of bat activity was conducted following the citizen science protocol called 'ChiroHabitats' from the Bat Monitoring Programme (www.batmonitoring.org). Audiomoth ultrasound detectors were used to passively record acoustic bat activity from 30 min before sunset to 30 min after sunrise. The detectors were programmed according to the ChiroHabitats protocol (sample rate of 250 kHz and medium gain), generating 5-minute-long wav files. AudioMoths were deployed using custom-made waterproof boxes at around 1 m height directly facing the river to maximise the recording of trawling *Myotis* bats (see here the boxes' specificities: https://www.batmonitoring.org/habitats/en/protocol/).

The 5-minute-long files were later processed using the Kaleidoscope software (Wildlife Acoustics, Illinois, USA), dividing each file into 5-second-long files, using the following signal parameters in the settings: minimum and maximum frequency range of 8–120 kHz, minimum and maximum length of detected pulses of 2–500 ms, maximum inter-syllable gap of 500 ms and a minimum number of pulses of two. These files were also automatically classified using the automatic classifier provided by Kaleidoscope Pro, which classified them at the species level. Finally, each resulting file was manually validated and, if needed, reclassified to either a bat species or a phonic group (groups of species that can not be acoustically distinguished).

The measure for acoustic bat activity was a 'bat pass', defined as a 5-second-long file containing at least two pulses of a bat species or phonic group (see, e.g., Azam et al., 2015; Millon et al., 2015; Torrent et al., 2018). The results of all the ChiroHabitats surveys are currently uploaded and publicly available on the online platform www.batmonitoring.org. For the present study, only bat passes of the phonic group 'Myotis 50' (i.e., *Myotis* species with frequencies of maximum energy between 40 and 70 kHz) were used in the models. From previous and current bat trapping sessions conducted in the studied rivers (Blanch et al. 2023), in which 429 out of 434 trapped *Myotis* bats were trawling species, we can confirm that most of the *Myotis* recorded acoustically corresponded to the trawling species *M. daubentonii* or *M. capaccinii*.

2.4 | Local variables

The habitat characteristics of each sampling site were assessed by adapting the 'Projecte Rius' citizen science protocol of the Associació Habitats (www.projecterius.cat) to quantify the health status of a 100-m-long river stretch. It includes different well-spread and used measures and ecological indicators to assess the hydromorphological and biological quality.

For the hydromorphological quality, we assessed several categorical physical characteristics of the rivers, such as river width, depth, water speed and temperature. Hydromorphological quality also included the QBR index (Munné et al., 2003), spanning from 0 to 100, which is calculated using scores from four numerical variables measured from a 100-m-long river stretch (each spanning from 0 to a maximum score of 25) and a categorical variable affecting the resulting scores of the others. These measures are as follows:

- Total riparian cover: percentage of vegetation cover in the river margin excluding annual herbaceous plants, and degree of connectivity to the closest woodland, assessed visually and from satellite images respectively.
- Cover quality: composition of native plant species (i.e., total number of native tree species and shrub species), degree of continuity of the tree community in the river edge, and the structure of the tree community (i.e., gallery forest). Man-made buildings, the presence of garbage and different levels of non-native tree species lower the results of this value.
- Cover structure: riverine forest structural complexity, with highest values representing more structured forests with various vegetation levels and covering larger areas of the river edge, calculated from the percentages of tree cover within the total riparian cover. Shrub and helophyte covers increase the final score. Yet, the score was lowered if trees and shrubs were found in separated patches or if trees were planted in a linear fashion.
- Channel alterations: different scores according to artificial structures in the river, with unmodified river channels having the highest score, fully channelised rivers having the lowest. Other structures like wells or bridges further lowered the score.
- Geomorphological type: physical and geological characteristics of the substrate and the river margins. Geomorphological type has no score, and it only affects how the final score of cover quality is measured.

The biological quality was calculated with an adaptation of the Biological Monitoring Working Party (Hawkes, 1997), in which each macroinvertebrate taxon is given a score from 1 to 10 according to the water quality where they are usually found. Macroinvertebrates were sampled using the kick sampling technique and hand nets. All caught macroinvertebrates were classified to family level. For each sampling point, two Biological Monitoring Working Party (BMWP) indices were calculated: the absolute BMWP summing the scores of all the families found there (aBMWP), and the relative BMWP, summing the scores of all the families divided by the number of families found in the sampling point (rBMWP). The detailed variables of each sampling point are presented in Table S2, and the field sheet used to collect the data can be downloaded from Appendix 1.

2.5 | Landscape variables

At the landscape level, different variables were extracted for each sampling point using QGIS v.3.16.14-Hannover (QGIS Development Team, 2020) from a vectorised version of the S2GLC 2017 Land Cover Map of Europe (Rybicki et al., 2020). We used buffers of 50, 100, 500, 1000 and 2000 m from which we extracted the percentage of 12 different land covers categories (i.e., artificial surfaces, natural material surfaces, broadleaf tree cover, coniferous tree cover, herbaceous vegetation, moors and heathland, sclerophyllous vegetation, cultivated areas, vineyards, marshes, peatbogs and water bodies). Except for the forest habitats (broadleaf tree cover and coniferous tree cover), the rest were grouped into three categories: urban (artificial surfaces), open (natural material surfaces, herbaceous vegetation, moors and heathland, sclerophyllous vegetation, cultivated areas and vineyards) and aquatic (marshes, peatbogs and water bodies). Both forest types were kept separate because, in the Mediterranean region, riverine forests mostly correspond to broadleaf forests, while coniferous forests are usually more abundant. Thus, we obtained a total of five habitat categories. Also, for each buffer size, the Shannon diversity index was calculated from the original 12 land cover categories to measure the diversity of habitats.

2.6 | Statistical analyses

First, we used simple linear models with acoustic and visual counts to see if both protocols were correlated and provided comparable data.

Then, four models were made with acoustic and visual bat activity (as the response variables) and local and landscape variables (as explanatory variables) separately. GLMs were performed with a Negative Binomial distribution to account for the overdispersion of the data using the *glm.nb* function from the MASS R package (Venables & Ripley, 2002). Explanatory variables included: QBR score, the four numerical components of the QBR (i.e., total riparian cover, cover structure, cover quality and channel alteration), river width, maximum depth, water speed, temperature and transparency, aBMWP and rBMWP indices, water pH and sampling point altitude. All explanatory variables were scaled from 0 to 100 using the *scale* function. Other measured categorical variables (e.g., geomorphological type, different river substrate categories, shadow over the river and presence of different structures in the channel, see Table S2) were excluded from the final models for local environmental traits as they showed no relevant differences in bat activity between the different levels. The river basin was further divided into the Fluvià basin and three branches of the Segre basin (i.e., Segre, Noguera Ribagorçana and Noguera Pallaresa) to account for the largest size of the Segre and the different water regimes of the different branches. The correlation between all the numerical explanatory variables was assessed using the *corrplot* function from the corrplot package (Wei & Simko, 2021), and one variable within each pair with a correlation value above 0.7 was excluded. Multicollinearity of the resulting saturated model was assessed using variance inflation factors with the *vif* function from car R package (Fox & Weisberg, 2019), excluding those variables with a VIF value above five. For the final model selection, we used a multi-model approach, using a saturated model including all the selected numerical and categorical variables with the *dredge* function of the MuMIn R package (Barton, 2022) to test all possible models with the selected variables. In the dredge approach, the final model was selected as the model containing the highest number of variables and the lowest AICc value from the models with a delta-AICc value lower than two. Non-converging models were excluded. To compare the usefulness of the different pairs of models (acoustics vs. visual), R^2 values were compared to see how well each model adjusted to data variability using the formula $1-\left(\frac{deviance}{nulldeviance}\right)$.

Regarding the models with the local environmental variables, the overall QBR results and the four numerical QBR components (i.e., total riparian cover, cover quality, cover structure and channel alteration scores) were highly correlated. With the aim of assessing small-scale forest characteristics, we performed two groups of models, one containing the four separated QBR components and another with the total QBR score (each type of model with both acoustics and visual counts as the response variables). No multicollinearity was found for any variable. As the models with the separated QBR components presented lower AICs and higher R^2, these are the ones discussed in the present study (the results of the models with the final QBR score are included in Table S3). The final models for acoustics included cover quality, cover structure, channel alteration, relative BMWP, water temperature and river basin. For the visual activity, the final model included cover quality, cover structure, water temperature and transparency, river basin and altitude above sea level.

Regarding the models with landscape variables, due to the low number of sampling points in the acoustics models, only the simplified habitat variables (open, urban, aquatic, broadleaf forest and pine forests) were kept. In contrast, the original cover variables were used for the visual models. In order to choose the proper buffer size, a saturated model was run for every buffer size and the ones with the lowest AIC were chosen. None of the variables showed autocorrelation, but broadleaf forest cover was excluded due to some issues with multicollinearity. The final model for acoustic data included open habitats, urban covers in a 50 m buffer and basin, while for visual data, it included herbaceous, natural material surfaces, peatbog, urban covers, Shannon index in a 100 m buffer and basin.

2.7 | Development of a habitat quality ecological indicator using bat activity

To develop a user-friendly and practical ecological indicator using trawling bat activity, we needed to define a gradient of key threshold values that could be easily understood and used to assign sampling localities to either good or bad habitat quality. The success of ecological indicators depends on their simplicity and practicality in the field to assess characteristics and habitat quality that cannot easily be calculated with georeferenced image systems and require other more complex methodologies.

Amongst all our models, the environmental variables at the local scale surrounding the habitat (e.g., cover quality, cover structure, total riparian cover) were those that resulted in more highly significant results. Therefore, we selected this model to define the gradient of key threshold values to assign a quality value to a specific site. In order to design the ecological indicator, we modelled the effect of the environmental variable on bat activity, and extracted the regression lines of said effects using the *predictorEffect* function from the *effects* package (Fox & Weisberg, 2019). We established the categorical limits of different qualities using the different possible scores of the three selected variables, scaling them from 0 to 100 using the *scale* function and establishing four different categories: bad quality (0–25 scores), deficient quality (25–50), good quality (50–75) and optimal quality (75–100). Then, in order to determine the thresholds of bat activity, we calculated the predicted bat activity at the limits of each habitat quality using the extracted regression line of the effect.

Finally, we applied the resulting categories to all the ChiroRivers censuses registered in the Bat Monitoring Programme platform (www.batmonitoring.org) to exemplify the usefulness of such ecological indicators. The resulting classifications can be found online and are all communicated to the citizen science project volunteers.

3 | RESULTS

We recorded a total of 529,577 acoustic bat passes, from which 103,612 corresponded to the Myotis 50 phonic group. We also counted a total of 5,815 visual bat passes of trawling bats in the video recordings. *Myotis* nightly bat activity ranged from 0 to 6387 bat passes per night (average of 1,726.87 ± 1,709.05) and ranged from 0 to 519 visual bat passes in 10 min (average of 96.91 ± 133.29). We only had one night without acoustic bat passes and six nights when we did not record any flying *Myotis* over the water. Although trawling Myotis' acoustic and visual activity were significantly correlated, with a p-value of $3.28e^{-8}$, their correlation value was not as high as expected, being $R^2 = 0.41$ (Figure 2).

3.1 | Local-scale environmental effect models

At the local scale, for the models with the acoustic datasets and the four separated QBR scores, cover quality was the variable that showed the strongest significant response ($p < 0.005$), positively related to bat activity (see Figure 3 and Table 1). Cover structure, however, seemed to decrease it ($p < 0.05$), with rBMWP and water temperature showing a similar negative effect ($p < 0.05$). For the models using visual data, very similarly, cover quality and cover structure had significant positive and negative effects respectively

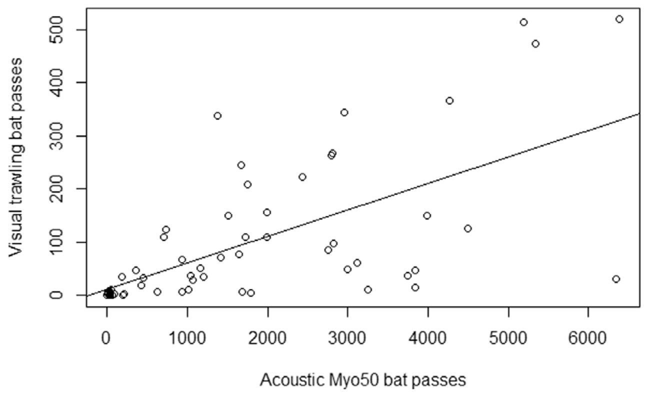

FIGURE 2 Correlation between acoustic bat passes (*Myotis* 50 phonic group) per night and trawling bat counts using near Infrared video recordings per 10 minutes in the same sampling localities in the northeastern Iberian Peninsula.

($p < 0.05$). Water temperature and altitude above sea level also had significant negative effects ($p < 0.005$ and 0.05 respectively). Between both models, the first one (with acoustics) presented a R^2 score of 0.41, while the second (with visual counts) had a score of 0.26.

3.2 | Landscape-scale environmental effect models

At the landscape level, the models with the lowest AIC corresponded to the buffer at 50 m around the sampling point for acoustic activity models and at 100 m for visual counts (the results of all the models at different buffer sizes are included in Table S4). The final models built with the acoustic data showed a negative effect of urban cover ($p < 0.005$) on trawling bats' activity in a 50 m buffer (see Figure 3 and Table 1). However, the final model built with the visual counts showed a significant negative effect of peatbog ($p < 0.05$) and herbaceous ($p < 0.01$) habitat covers in a 100 m buffer, as well as a marginally negative effect of urban cover and Shannon's index score (both with $p < 0.1$). In both landscape models, basin was a significant variable for trawling bat activity accounting for regional differences. The R^2 scores for landscape models were 0.29 and 0.36 for acoustics and visual counts, respectively.

3.3 | Development of a habitat quality ecological indicator using trawling bat activity

Of all the significant variables from our local models, we chose cover quality to develop an ecological indicator based on trawling bat activity that would provide easy-to-use threshold values to assign a specific habitat quality assessment to each sampled locality. We chose cover quality as this variable is strongly related to the presence of native and pristine riparian vegetation, and one of the main ecological problems currently found in Mediterranean rivers is the increase in allochthonous and invasive species, which are of major conservation concern (Badalamenti et al., 2018; Bruno et al., 2019; Munné

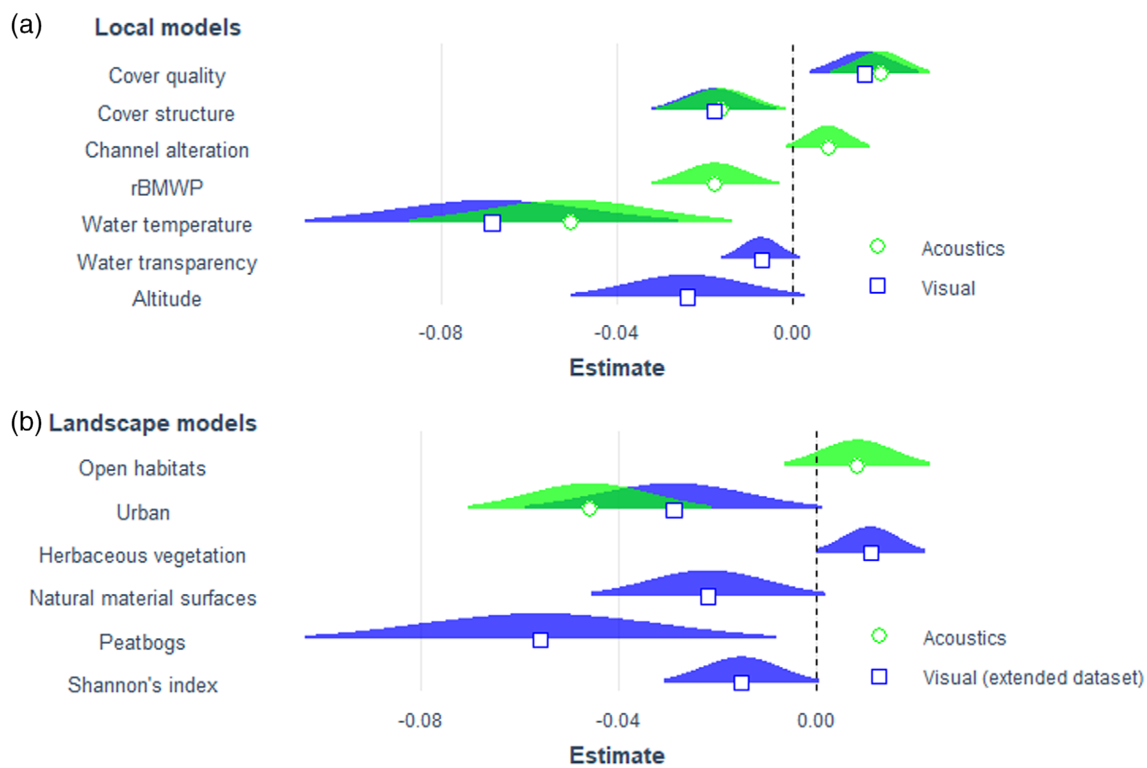

FIGURE 3 Estimates and modelled effects of the selected environmental variables on trawling bat activity, including the models at local (a) and landscape (b) scales, using acoustics (green circle) and visual data (blue square). The results at the landscape scale using visual bat activity include the full dataset with the extra sampling points from the volunteers. The different basin categories have been excluded from the figure for better visualisation of the effects of the environmental variables. [Color figure can be viewed at wileyonlinelibrary.com]

et al., 2003; Salinas et al., 2000). Also, following the QBR index protocol as a baseline, the cover quality score is the one that covers the most diverse characteristics of the habitat surrounding the sampling point, as it takes into account the composition of the floral community in the sampling point, the coverage of the community and some aspects of the structure (i.e., riparian forest in gallery) and anthropogenic alterations of the river (see Materials and Methods for more details).

We summarised the pros and cons of both citizen science protocols in Table 2 following the expert criteria of the authors. Due to the easiness and high potential of the ChiroRiver (visual counts) within citizen science projects and its overperformance compared to the ChiroHabitats in terms of workload, we selected this method to develop the ecological indicator. The effect of cover quality on visual bat activity followed an exponential regression line and thus an exponential model was used to develop the threshold values for our index. The final threshold values in visual counts (bat passes/10 min) defining the different cover quality categories were as follows: 0–5 for bad scores, 6–7 for deficient, 8–11 for good and more than 12 for optimal quality (Figure 4).

Finally, we applied this indicator to classify the 58 points sampled by the volunteers (Supplementary material 1). Of the 51 points, 13 had no presence of trawling bat activity, 21 had a bad quality (both summing 68% as bad quality), four had a deficient quality (8%), two had good quality scores (4%) and 10 had optimal quality scores (20%).

4 | DISCUSSION

This study is the first to test the performance of two citizen-science protocols to use trawling bat activity as bioindicators and to develop an ecological indicator of riverine forest quality based on categorised bat activity levels. Our results show that both acoustic and visual bat activity have the potential to reflect specific characteristics of the riparian forests affecting their activity, especially forest quality and vegetation structure, but visual counts overperformed the acoustics in terms of ease of use in the field and data analysis workload. The local variables of the microhabitats were shown to relate better with trawling bat activity than larger landscape-scale characteristics, suggesting that the relative abundance of trawling *Myotis* should preferably be used to test or indicate habitat quality at the local scale or microhabitat. Below we further discuss considerations for establishing a Mediterranean riverine biomonitoring protocol using trawling bats and the pros and cons of the different citizen science methods used in the present work.

4.1 | Acoustic versus visual counts sampling protocols

In our study, both sampling methodologies (visual counts and acoustics) presented similar results regarding the effect of habitat

TABLE 1 Results of the Negative Binomial GLM models at local and landscape levels and with acoustic and visual bat activity as response variable, with the variables included in the final models and the significance of each variable according to the *p*-value.

		Estimate	Std. error	*t* value	*p*-value
Local models					
Acoustic activity					
$R^2 = 0.41$	(Intercept) ***	11.932	1.587	7.516	0.001
	Cover quality ***	0.020	0.006	3.484	0.001
	Cover structure *	−0.016	0.007	−2.243	0.029
	Channel alteration ·	0.008	0.005	1.660	0.103
	rBMWP *	−0.017	0.007	−2.357	0.022
	Water temperature **	−0.051	0.018	−2.819	0.007
	Basin Noguera Pallaresa	−1.160	0.669	−1.733	0.089
	Basin Noguera Ribagorçana ***	−6.090	0.765	−7.960	0.001
	Basin Segre ·	−0.657	0.385	−1.707	0.094
Visual counts					
$R^2 = 0.26$	(Intercept) ***	9.491	2.294	4.138	0.001
	Cover quality *	0.016	0.008	2.135	0.038
	Cover structure *	−0.018	0.009	−2.089	0.042
	Water temperature **	−0.068	0.026	−2.661	0.010
	Water transparency	−0.007	0.005	−1.321	0.192
	Altitude ·	−0.024	0.016	−1.491	0.142
	Basin Noguera Pallaresa	0.565	1.128	0.501	0.619
	Basin Noguera Ribagorçana ***	−3.332	1.179	−2.825	0.007
	Basin Segre	0.172	0.630	0.272	0.787
Landscape models					
Acoustic activity (50 m buffer)					
$R^2 = 0.29$	(Intercept) ***	7.501	0.292	25.703	0.000
	Open	0.008	0.008	1.011	0.317
	Urban ***	−0.046	0.014	−3.373	0.001
	Basin Noguera Pallaresa	−0.309	0.688	−0.449	0.655
	Basin Noguera Ribagorçana ***	−2.741	0.513	−5.339	0.000
	Basin Segre	0.168	0.377	0.447	0.657
Visual counts (100 m buffer)					
$R^2 = 0.36$	(Intercept)	1.369	0.969	1.413	0.161
	Herbaceous *	0.011	0.006	1.850	0.067
	Natural material surfaces ·	−0.022	0.013	−1.669	0.098
	Peatbogs *	−0.056	0.026	−2.128	0.036
	Shannon's index ·	−0.015	0.009	−1.732	0.086
	Urban ·	−0.029	0.016	−1.740	0.085
	Basin Besòs	−0.465	0.978	−0.476	0.635
	Basin Ebre	0.301	0.939	0.321	0.749
	Basin Fluvià **	2.365	0.806	2.936	0.004
	Basin Gaià	−0.749	1.801	−0.416	0.678
	Basin Llobregat ·	1.516	0.848	1.788	0.077
	Basin Noguera Pallaresa **	2.719	0.915	2.970	0.004
	Basin Noguera Ribagorçana *	2.200	1.007	2.185	0.031
	Basin Segre ***	2.500	0.811	3.082	0.003
	Basin Ter **	2.280	0.882	2.586	0.011
	Basin Tordera	1.322	0.958	1.379	0.171

Note: The significance of each variable corresponds to ***$p < 0.005$, **$p < 0.01$, *$p < 0.05$ and $p < 0.1$.

TABLE 2 Comparison of acoustic and visual citizen science protocols pros (+) and cons (–) for trawling bat monitoring in a citizen science project. The first row includes the links to the respective protocols.

ChiroHabitats (acoustics)	ChiroRivers (visual counts)
www.batmonitoring.org/habitats	www.batmonitoring.org/rivers
- Two days of fieldwork required	+ One day of fieldwork required
- Need of purchasing specialised equipment	+ No specialised equipment needed
- Longer and more specialised training required	+ Almost no training required
- Large datasets, but less specific for trawling bats	+ Only focusing on trawling bats
- Much longer posterior data processing	+ Immediate results
+ Higher statistical explanatory power	- Lower statistical explanatory power

characteristics on their activity levels, which is further confirmed by the significant correlation between them (Figure 2). However, previous studies have shown that these detection methods do not always present the same performance when assessing bat activity. In a study on Hawaiian hoary bats (Gorresen et al., 2017), the authors found that most flying bats recorded with video cameras were not detected using acoustics, which is particularly surprising regarding the relatively low-frequency long-range calls of the species. Trawling *Myotis* bats present frequency-modulated calls that are usually above 40 kHz of peak frequency (van de Sijpe, 2011), which makes the detection distance of their calls relatively low (Adams et al., 2012; Monadjem et al., 2017). Another study, aiming to find the correlation between acoustics and visual counts of emerging bats in caves (Revilla-Martín et al., 2020), found that, while you could correlate both variables, the correlation was very site-specific and also influenced by the distance the ultrasound recorder was placed from the cave entrance. This could potentially happen with trawling bats as different environmental characteristics like river width, vegetation clutter, or terrain around the water could make bats more difficult to see and record (Wang et al., 2014), affecting their detectability. This challenge was also supported by the acoustics model that included the total QBR score as an explanatory variable, in which the geomorphological type of the river bank seemed to affect the resulting bat activity (Table S3). Surprisingly, none of our final models included river width nor water speed, while other studies have shown that both variables are extremely important in selecting the most appropriate hunting grounds (Almenar et al., 2009; López-Baucells et al., 2017; Todd & Williamson, 2019). Because sampling sites were explicitly selected to detect trawling bats, it is possible that the hydromorphological characteristics of the rivers we sampled did not present enough variability to significantly influence their foraging activity.

In terms of methodological limitations, neither of the protocols allows the identification of trawling bats at the species level (Table 2). This constraint is a determining factor in all types of acoustic surveys. Most *Myotis* bat species present frequency-modulated calls that make it difficult to distinguish between different species acoustically (van de Sijpe, 2011). Thus, while we have confidence that most of the acoustic bat passes in our models correspond to trawling bats (mist-netting was carried out in the same areas to confirm *Myotis* spp), we cannot assure that no other *Myotis* species were included in our acoustic dataset. Similarly, while visual counts can certainly be assigned to trawling bats, our study area presented two different trawling bat species, *Myotis daubentonii* and *Myotis capaccinii*, (as seen in Blanch et al., 2023), that cannot be distinguished through visual detections. While these two species differ in roost selection, studies on foraging habitat use have previously found that both species usually select forested riparian habitats (Almenar et al., 2006; de Conno et al., 2018; Todd & Williamson, 2019; Warren et al., 2000), rather than non-vegetated river transects, so their potential as riverine forest bioindicator could be similar. However, more thorough research would still be needed to discern specific differences between them.

4.2 | Scale- and protocol-dependent responses of trawling bats to environmental conditions

The sampling methodologies in our study performed differently according to the scales at which environmental variables were assessed. Overall, local models presented better performance (lower AICs) than models at the landscape level. However, different protocols provided divergent results: the acoustics model presented higher R^2 at the local level, whereas the visual count model was better at the landscape level, probably due to those including the volunteer-based censuses and, therefore, landscape variability. At the landscape level, smaller buffer sizes resulted in better-adjusting models, presenting lower AICs and higher R^2 scores (Table S4). Buffers of 50 and 100 m were chosen to explain our datasets. Landscape variables have been proven to be good predictors of bat presence–absence (Arthur et al., 2014; Ducci et al., 2015) but performed very poorly when using relative abundance effects. López-Baucells et al., 2017 also found that landscape variables only showed some effect on trawling bat presence–absence data, while they found no significant results for overall bat activity. Being volant mammals, bats present a relatively high capacity to choose specific habitats or areas to forage, causing a lot of variation in plots that are very close together. Moreover, visual models probably performed better at the landscape level than the acoustics model because our dataset for visual landscape models was larger and more geographically widespread (we included volunteer-collected data), presenting a higher diversity of landscape and land-cover features.

4.3 | Trawling bats as bioindicators

While both activity measures (visual counts and acoustics) were good indicators of different parameters of the quality of riverine

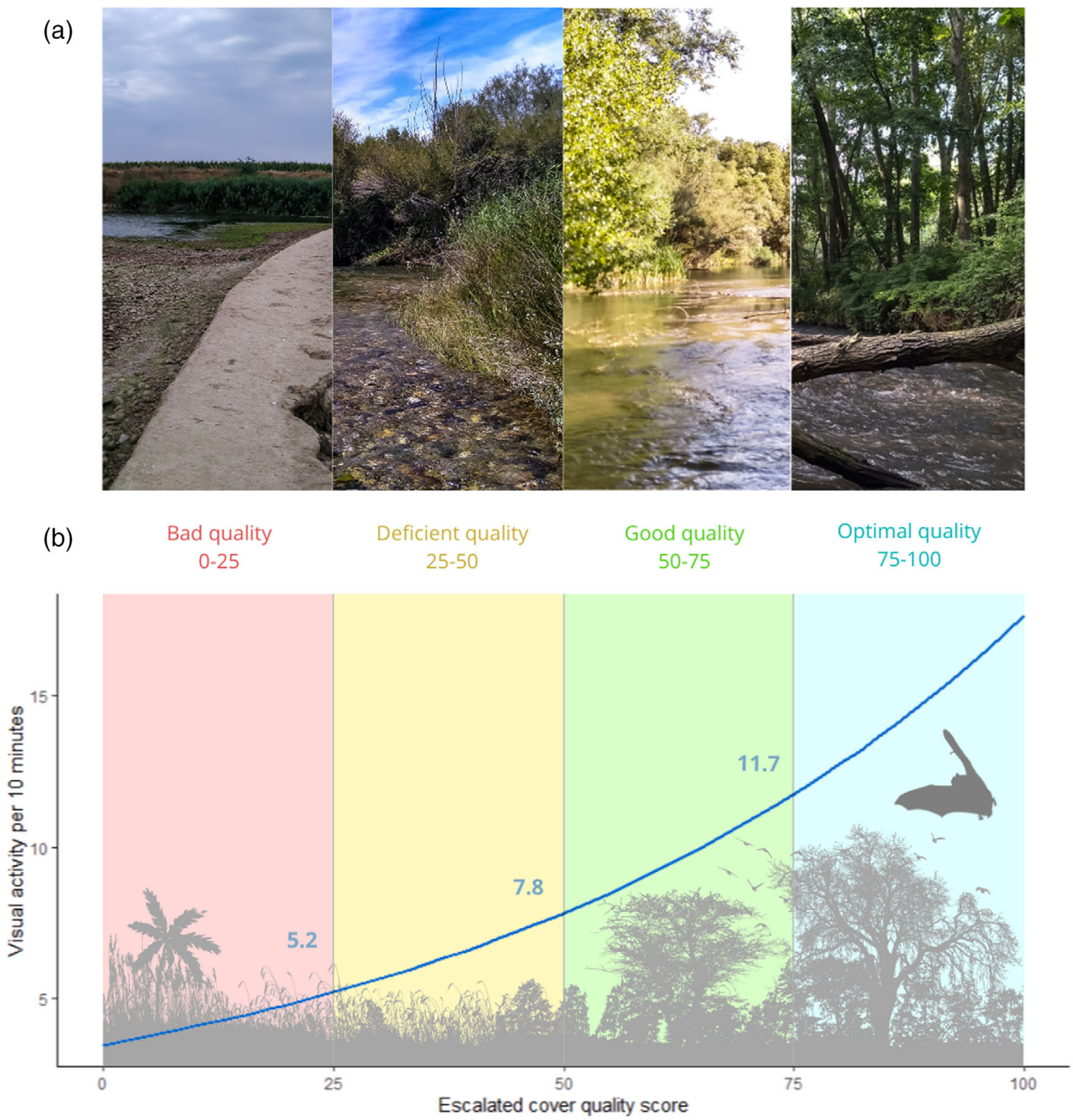

FIGURE 4 Cover quality categories (bad, deficient, good and optimal) included in the newly developed ecological indicator based on trawling bat activity. Examples of sampling points with the different indicator scores (a). Expected trawling bat activity (blue line) sampled using visual counts is shown using an exponential model (b). The values of visual bat activity thresholds are indicated to improve their utility and usefulness. [Color figure can be viewed at wileyonlinelibrary.com]

ecosystems, the whole QBR score was finally excluded from the selected variables on the models. This contradicts, to some extent, the previous work by López-Baucells et al. (2017), which found that high visual trawling bat activity was indicative of high QBR scores. Our fieldwork was concentrated in areas with relatively high bat activity, with almost no sampling points where trawling bats were absent, and relatively high QBR scores. Therefore, it is likely that our dataset did not include enough variation to account for the total QBR index score variability. Nevertheless, as shown by our results (with both acoustic and visual data), when the four components of the QBR index were included separately, cover quality and cover structure showed significant effects. Our results indicate that even in areas with relatively high trawling bat activity, these can be used to understand fine-scale variations in the structure of the vegetation around the fluvial area, ultimately related to a certain degree of quality and maturity of the riparian forest.

On one hand, cover quality accounts for the total number of native tree and shrub species, continuity and cover of the tree community along the river margin, riverine forest community structure (e.g., in gallery), presence or not of non-native trees and its prevalence (e.g., presence of communities of non-native trees) and presence of human structures or garbage. Our models showed a significant positive relationship between trawling bat activity and river transects with more naturalised and native vegetation and in which the forest is more structured in a gallery. We found no studies regarding cover quality and relating trawling bat activity specifically with the degree of naturalisation of the riverine forest cover. The presence of trees and shrubs near the river margin has already been proven to promote the activity of endangered trawling bat species like *Myotis capaccinii* in Almenar et al. (2009), which was present and abundant in our study area. The authors reported a strong preference for this species to forage in rivers with forested margins than in rivers with reeds or no vegetation. Yet, this study only showed preference using presence–absence data of forested vegetation but did not assess this effect at a fine-scale habitat. Thus, considering the two species of trawling bats converging in our study area, this specific bat guild's activity seems to be effective in monitoring river forest quality in the Mediterranean region.

On the other hand, cover structure is obtained from the percentage of tree, shrub and helophyte cover and their spatial distribution (i.e., a proxy of forest structure complexity) as well as the presence of tree plantations. Our results showed that trawling bat activity was reduced in transects with a higher riverine forest structural complexity (i.e., more continuous forest mixing various vegetation types within the same forest clutches). Contrary to the cover quality score, this seems to contradict most studies showing that a more structured cover translates into higher *Myotis* bat activity scores (Almenar et al., 2009; López-Baucells et al., 2017; Tuneu-Corral et al., 2020). Yet, as we can observe comparing López-Baucells et al. (2017) and de Conno et al. (2018), depending on the riverine habitat index used, the effects of forest clutter on trawling bat activity vary drastically. Also, bat responses to forest clutter are very species-specific. Yates and Muzika (2006), and Novella-Fernandez et al. (2022) found that the effect of various forest structural characteristics on bat occupancy models varied between different *Myotis* species.

Our results also showed that acoustic trawling bat activity was significantly lower with higher levels of urbanisation around the sampling plots. Other studies have shown the detrimental effects of urban and artificial constructions on bat species like *Eptesicus serotinus* (Arthur et al., 2014), yet these results are often very species- and trait-specific (Jung & Threlfall, 2018). Urbanisation may be related to lower water quality and prey availability (Li & Kalcounis-Rueppell, 2018) which probably makes trawling bats avoid these areas as foraging grounds. Also, urban areas usually show higher light pollution, negatively altering bat activity patterns for light-sensitive bat species like trawling bats (Haddock et al., 2019; Hooker et al., 2022; Laforge et al., 2019; Russo et al., 2019). However, our results only show a significant effect with acoustic methods, with visual activity only presenting a marginally significant response.

It is also relevant that acoustic bat activity appears to be negatively affected by higher rBMWP scores. This goes in accordance with the results found by De Conno et al. (2018) with lower acoustic trawling bat activity with higher scores of macroinvertebrate indices. In this study, other bats appeared to lower their acoustic activity with higher macroinvertebrate scores. Previous work by López-Baucells et al. (2017) found no significant effects of macroinvertebrates indices on visual trawling bat activity. Visual counts were positively affected by herbaceous cover, which probably represented most of the habitat in more naturalised landscapes, and negatively affected by the amount of peatbogs. This may be due to the almost absence of peatbogs in the sampled points, only circumstantially appearing in areas with no visual trawling bat activity.

4.4 | Ecological indicator of riparian habitat quality

In this study, we developed for the first time an ecological indicator of riparian cover quality based on the trawling bat activity levels (specifically for visual count data). We provided specific thresholds to classify surveyed rivers into four categories (bad, deficient, good and optimal). Additionally, we applied this indicator in NE Iberian rivers to test its usefulness at the local scale (Figure S1). While we found it useful to locate idoneous areas for trawling bat habitat conservation, we also detected that it could be somehow misleading when applied in non-suitable sampling points for trawling bats. For instance, when we applied the indicator in a ChiroRivers transect carried out at high altitudes with some turbulent waters (northwesternmost location Figure S1), we got very inconsistent and conflicting results. We encourage other research teams, naturalists and conservationists to adopt and adapt the method and apply it in their countries in order to start a pan-European monitoring programme, as it has already been done for other taxonomical groups like butterflies (van Swaay et al., 2019) or macroinvertebrates (Stefanidis et al., 2018). We acknowledge that some regional variations might hamper the broad application of the method, but slight adjustments would be enough to adapt it to any other European region.

4.5 | Selection of a citizen science protocol for biomonitoring

One of the main drawbacks of using bats as bioindicators is that, in many cases, the true extent of the relationship between the variables and the bioindication index has not been fully assessed (Russo et al., 2021). The development of the proposed categories of bat activity will help to relate trawling bat activity levels to specific habitat quality. Establishing protocols and bat activity indicators has become a crucial need to be able to highlight conservation priority targets in a continental context (Ewers & Didham, 2006; Jones et al., 2009; Tuneu-Corral et al., 2020). Protocols to monitor trawling bat activity using visual waterway surveys have been conducted for several decades in countries like the United Kingdom and Ireland, resulting in excellent long-term population trends for the species (Aughney et al., 2009). The results of our models and reference values are probably more representative of the Mediterranean area, but our methods can easily be replicated and compared in any European territory.

Our results prove that, while the two citizen science protocols can be used as relevant indicators of habitat quality in Mediterranean rivers, the ChiroRivers is the most appropriate due to the ease of use, low data analyses workload and potential within a citizen science project. As explained above, acoustics models adjusted better for the variability of our dataset, at least at the local scale. However, when aiming to establish a potential network of citizen scientists to monitor riverine habitat quality, there are other aspects to consider to choose the most suitable protocol for volunteers (e.g., certain aspects to increase participation and motivation).

While at prior, our results would suggest that ChiroHabitats would be the most adequate method to be used as a bioindicator of river quality, other factors would suggest ChiroRivers as the most appropriate (Table 2). When comparing the ChiroHabitats and ChiroRivers protocols, while the former requires at least 2 days of relatively short fieldwork (one to deploy the detector and another to take it back), the second can be conducted in a single night of visual sampling in the river stretch (i.e., less than 2 h). Frensley et al. (2017) already found that one of the main factors regarding long-term volunteer involvement in citizen science is the time needed to conduct the sampling, the differing abilities in using different tools for data gathering, and the time needed to analyse the raw data to obtain tangible results. While the ChiroRiver offers immediate results, the ChiroHabitat requires much more time and effort. The volunteer must learn acoustic detector programming, bat call identification and have the time to manually check thousands of recordings (Mas et al., 2022; Nelson & Gillam, 2020). Also, while the ChiroRivers requires higher fieldwork time, this is usually seen as positive by most naturalist volunteers, who are often more willing to spend time on the field than analysing data on a computer. That is why fieldwork time was left as neither positive nor negative in Table 2, as this matter can be highly subjective depending on individual experiences. Finally, another critical issue is the costs associated with participation in a citizen science project. While the ChiroHabitats requires the volunteer to purchase an acoustic ultrasound recorder, the ChiroRivers only requires a hand torch. Thus, we propose that the ChiroRivers waterway survey may be more adequate for establishing citizen-science river monitoring due to its simple methodology, affordability and immediate observable results.

Our work sets the base to use a citizen science project to establish a network of trawling bat monitoring transects as indicators of riverine quality in the Mediterranean region. The following decades will be of utmost importance as breaking points for climate change-induced habitat alterations (Pörtner et al., 2022). Networking between different regions and monitoring at large scales will be crucial for data collection, assessing the effects of these changes, and developing proper mitigation measures in riparian areas, a conservation priority in the Mediterranean basin and many other dry areas on the planet.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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