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Integrating species-specific and volunteer-based monitoring to improve population indicators: lessons from the Common Quail

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Data availability statement

Data and code required to reproduce the analyses presented in this study are available via a private Zenodo repository for peer review at:

https://zenodo.org/records/18773685?token=eyJhbGciOiJIUzUxMiJ9.eyJpZCI6IjE2YzMzMjA1LTlkZjEtNDJjZS1iMTNmLWMyODc3NjExNzMxNSIsImRhdGEiOnt9LCJyYW5kb20iOiI3NGQzZDg5ZmFmZjVmZWMwM2M2ZjI1MWEyMDYwOGU2ZCJ9.4mhJdHo-cnr950p70RTAqNgO8GQd5el330_YDf4Uun57Mekaikt9dOlenawysKv0y_QOx1eIp9aPTENgHQ6s0w.

The repository will be made publicly available and archived with a DOI upon acceptance of the manuscript.

Abstract

Breeding Bird Monitoring Schemes (BMS) provide the backbone of large-scale biodiversity assessment and are widely used to inform conservation policy and management. However, for species with low or variable detectability, abundance-based indicators derived from general monitoring schemes may not accurately reflect population dynamics. This issue is particularly relevant for species with highly variable detectability. Using the Common Quail (*Coturnix coturnix*), a widespread farmland game bird, we evaluated how detectability bias influences abundance estimates and long-term population indicators derived from volunteer-based monitoring.

We compared data from a general breeding bird monitoring scheme and a species-specific survey designed to maximize quail detectability. The species-specific survey frequently detected quails in surveys classified as absences by the general monitoring scheme and consistently recorded higher abundances when both methods detected the species. A calibration model incorporating vegetation greenness (NDVI) translated general survey counts into species-specific abundance indicators and showed that differences between monitoring approaches depended on habitat conditions.

Although overall long-term trends were broadly similar between monitoring approaches, substantial differences emerged in high-quality habitats, where detectability bias was strongest and uncorrected indicators suggested population declines that were not supported by calibrated estimates. These results indicate that detectability bias can influence population trend indicators and potentially affect conservation assessments. Integrating species-specific and volunteer-based monitoring provides a practical framework for improving biodiversity indicators without sacrificing the spatial and temporal coverage of large-scale monitoring programs.

1. Introduction

Breeding bird monitoring schemes (BMS) are the cornerstone of large-scale biodiversity assessment worldwide (Gregory et al. 2005, Likens and Lindenmayer 2018). Their standardized protocols, broad spatial coverage and long-term continuity allow robust quantification of population change and ecological responses to environmental pressures through abundance-based indicators and trend indices (e.g.: Devictor et al., 2008; Rigal et al., 2023; Stephens et al., 2016). A defining feature of these schemes is their reliance on trained volunteer observers, whose coordinated effort generates large multispecies datasets that would be unfeasible through professional surveys alone (Moussy et al. 2022). By providing consistent information across extensive temporal and geographic scales, BMS programs play a key role in informing conservation policy, land-use planning and biodiversity indicators at national and international levels (Schmeller et al. 2009, Tulloch et al. 2013). Ensuring the methodological reliability and taxonomic representativeness of these schemes is therefore essential for accurately tracking environmental change (Yoccoz et al. 2001, Kissling et al. 2018).

Despite the success of BMS, their generalist and multispecies design inevitably introduces substantial variation in detection probability across species, habitats and regions (Thompson, W.L. 2002, Diefenbach et al. 2003). Species whose behavior, spatial dynamics or social organization depart from the assumptions of standard count protocols—namely that detectability remains sufficiently consistent across habitats, years and population densities for observed counts to reliably track abundance—may yield biased indicator outputs in general monitoring schemes. Such biases may arise through missed detections, ambiguous records or potential double-counting (Guillera-Arroita et al. 2017). These issues are especially problematic for species that fall outside the core “common bird” set typically covered by BMS programs, including species that exhibit behavioural or ecological characteristics that reduce detectability under standardized survey protocols, such as highly variable vocal activity, weak territoriality, cryptic behaviour, or patchy spatial distributions (Nichols et al. 2007, Sardà-Palomera et al. 2012a).

Biases in detection probability can propagate through population indices, affecting abundance-based indicators, temporal trends and the ability of monitoring schemes to detect true demographic change (Kéry and Schmidt 2008). When detection is variable

or inconsistent, yearly indices may become distorted, trend precision decreases and interannual variability inflates, particularly when uncertain observations are unevenly distributed across space or time (Johnson 2008, Kellner and Swihart 2014). In long-term monitoring schemes, these effects can compromise the reliability and interpretability of population indicators.

As a consequence of these limitations, large-scale biodiversity indicators—such as those produced by the Pan-European Common Bird Monitoring Scheme (PECBMS, Brlík et al. 2021)—typically exclude species with low or highly variable detectability, focusing instead on widespread and consistently monitored taxa (Gregory et al. 2005, 2008, Brlík et al. 2021). This exclusion avoids introducing methodological noise into continental indicators, but it also means that many ecologically relevant or management-sensitive species remain poorly represented in general monitoring outputs. To address this gap, species-specific monitoring programs have been developed using tailored protocols that substantially increase detectability and provide more accurate abundance estimates for species whose behaviour or ecology challenge standardized monitoring (Bibby et al. 2000).

These limitations underscore the need to understand how detectability bias influences biodiversity indicators and conservation assessments, and whether information from species-specific surveys can be used to improve indicators derived from large-scale monitoring schemes (Johnson 2008, Kellner and Swihart 2014).

In this study, we compare indicator outputs from a BMS with those from a species-specific monitoring program for the Common Quail (*Coturnix coturnix*). The Common Quail is a widespread farmland species whose behavioural particularities—most notably its reliance on male vocal activity for detection – mean that strong context- and density-dependent variation in calling behaviour may generate substantial detectability bias under standardized BMS protocols. The species also holds high socioeconomic relevance due to its importance in small-game hunting (Perennou, C. 2009). Consequently, robust population indicators are essential for conservation and management, yet detectability-related uncertainty remains a central point of debate in quail monitoring and harvest regulation (Arroyo et al. 2022). This uncertainty is reflected in the inconsistent treatment of the species across monitoring frameworks, with continental indicators excluding it from trend reporting, while national or regional

programs continue to publish Common Quail population assessments (Brlík et al. 2021, Escandell et al. 2023, ICO 2025).

In this context, we aimed to (1) quantify differences in detection and abundance estimates between a general breeding bird monitoring scheme and a species-specific survey for the Common Quail, (2) evaluate whether environmental conditions could be used to predict and correct these differences, and (3) assess how such corrections influence long-term population trend indicators. More broadly, we asked whether integrating species-specific and volunteer-based monitoring can improve biodiversity indicators for species with variable detectability, and under which conditions detectability-related biases can be reduced.

2. Material and methods

2.1. Study species

The Common Quail (*Coturnix coturnix*) is a small migratory galliform associated with open farmland habitats throughout the Western Palearctic, particularly cereal crops and other herbaceous vegetation (McGowan et al. 2020). Because individuals typically remain concealed within dense vegetation, field detection relies almost entirely on male vocalizations. However, calling activity is highly variable and influenced by both environmental and social factors. The species exhibits a non-territorial mating system characterized by loose and spatially dynamic male aggregations, in which calling behaviour and spatial distribution change in response to social interactions (Rodríguez-Teijeiro et al. 1992, Rodrigo-Rueda et al. 1997, Guyomarc'h et al. 1998, Sardà-Palomera et al. 2011). As a result, detectability can vary substantially among habitats, surveys and population densities.

Habitat quality also strongly influences the seasonal distribution and abundance of the species. Quail occurrence shifts in response to crop phenology and harvesting schedules, with individuals rapidly relocating as vegetation structure changes during spring and early summer (Rodríguez-Teijeiro et al. 2009). Previous studies have shown that vegetation greenness (NDVI) provides a reliable proxy for these habitat dynamics,

with higher NDVI values generally associated with greater quail occurrence and abundance (Sardà-Palomera et al. 2012b). The combination of variable vocal activity and strong dependence on dynamic habitat conditions makes the species particularly challenging to monitor using standardized multispecies survey protocols.

2.2. Monitoring schemes and data collection

2.2.1. Common Bird Monitoring Survey (SOCC)

The Catalan Common Bird Monitoring Survey (SOCC, Herrando et al. 2008) is a standardized breeding bird monitoring program based on 3-km linear transects. Each transect is visited twice during the breeding season (15 April–15 May and 16 May–15 June), following a standardized protocol regarding survey timing, duration and weather conditions. All birds detected visually or acoustically during the survey period were recorded.

The SOCC program was established in 2002 and currently includes 638 transects in which Common Quail had been recorded at least once during the study period (N = 205 transects; Figure 1). The starting year was selected because it coincides with the availability of spatially explicit agricultural land-use data, which allowed the identification of suitable habitat for subsequent analyses.

2.2.2. Common Quail Specific Survey (SEC)

The Common Quail Specific Survey (SEC; from its Catalan acronym) is a targeted monitoring protocol originally developed at the University of Barcelona to improve the accuracy of quail counts based on behavioral research and extensive field experience with the species (Rodríguez-Teijeiro et al. 2010, Sardà-Palomera et al. 2012b). The method was designed to maximize the detection of singing males by accounting for their cryptic behavior, socially mediated calling activity and loose male aggregations. SEC surveys were conducted by trained professional personnel along predefined transects, following a structured sequence of listening stops and acoustic stimulation.

Observers moved along a fixed route and stopped at regular intervals to perform short listening sessions outside the vehicle. At each listening point, observers first remained

187 silent for 2 minutes to detect spontaneously calling males. When spontaneous callers
188 were detected, their locations were recorded and these individuals were immediately
189 targeted for capture, as their vocalizations provided reliable positional cues.

190 Following this initial listening period, female calls ("lure") were broadcast to facilitate
191 capture and increase detection probability. Thus, playback was used both when
192 spontaneous callers had already been detected and when no males were initially heard.
193 The playback consisted of two series of 15–20 seconds separated by short listening
194 pauses. Playback was used both to facilitate the capture of spontaneously calling males
195 and to stimulate responses from males that remained silent during the initial listening
196 period. When males responded, their locations were recorded and capture was
197 attempted; otherwise, the playback sequence was repeated three additional times,
198 separated by 30-s listening intervals.

199 Because the same listening and playback-based procedure was applied at all listening
200 points, sampling effort was standardized across sites. While acoustic stimulation was
201 intended to increase detectability and the number of males detected, capture provided
202 individual-level confirmation, allowing observers to discriminate between distinct
203 individuals and to limit potential over-detection arising from moving individuals and
204 repeated or socially mediated vocal responses. Captured males were held temporarily
205 following ethical handling protocols.

206 At the end of the transect, all captured individuals were ringed and subsequently
207 released at the precise point of capture. The final count for each transect consisted of the
208 total number of males detected (captured + uncaptured), mapped at their initial detection
209 position, with the aim of providing a high-detection reference abundance index
210 specifically designed to maximize detectability in accordance with the behavioural
211 characteristics of the species.

212

213 *2.2.3. Paired sampling design for direct comparison between schemes*

214 Between 2021 and 2025, we designed and monitored 28 dedicated SOCC transects
215 across Catalonia, spanning a wide range of suitable quail habitat types and altitudes
216 (38–1158 m a.s.l.) and selected to represent areas where different quail densities were
217 known or expected based on previous monitoring (Figure 1). Transects were
218 progressively incorporated over the study period, resulting in variable annual sampling

effort and partial overlap among years, with the maximum number of active transects reached in 2024 (n = 27). All surveys were carried out during the breeding season, between 1 April and 30 June. To ensure direct comparability between SOCC and SEC data, each transect was surveyed on two consecutive days. The SOCC survey was conducted first, followed the next day by the SEC survey at the same hour of the morning, under very similar weather conditions, by the same observer, and for the same duration. This paired and standardized sampling design minimized short-term variation in quail detectability and provided a robust basis for comparing the two monitoring schemes under equivalent site, habitat, weather and observer conditions.

2.3. Habitat availability and vegetation greenness

To quantify the amount and quality of suitable breeding habitat available for Common Quails along each transect and season, we combined agricultural land-use information with remotely sensed vegetation indices. First, we identified the agricultural land-use categories considered suitable for the species based on previous studies (Rodríguez-Teijeiro et al. 2009, Sardà-Palomera et al. 2012). These included cereal crops, fallows, legume crops, and herbaceous dryland mosaics, which represent the primary breeding habitats for the species in Mediterranean farmland systems. All polygons corresponding to these land-use categories were extracted from two official agricultural mapping systems: SIGPAC (the national land-parcel identification system) and DUN (the Catalan annual agricultural declaration system), both of which provide georeferenced information on crop types and field boundaries for each year between 2005 and 2025. A detailed description of the selected land-use categories is provided in Supporting Information.

For each 3-km transect and year, we quantified the amount of suitable habitat within a 300-m buffer centered on the survey route. This buffer width was selected based on previous calibration analyses comparing alternative spatial extents around transects. Differences between SEC and SOCC counts were most pronounced within the first 300 m, whereas discrepancies became substantially smaller at greater distances. In addition, uncertainty associated with estimating detection distances and assigning detections to habitat conditions increases with distance from the transect. Consequently, habitat

metrics derived from a 300-m buffer were considered the most appropriate representation of the habitat conditions influencing detections by both monitoring protocols and were retained for calibration analyses.

To characterize vegetation greenness and structure, we extracted the Normalized Difference Vegetation Index (NDVI) for each transect buffer using Landsat surface reflectance imagery (Landsat 5, 7, 8 and 9; 30-m resolution). NDVI was calculated from 15-day Landsat composites (30-m resolution) between 1 April and 30 June of each year following standard cloud and shadow masking procedures. Transect-level NDVI was obtained by averaging all pixels contained within each buffered transect area. Processing was conducted in Google Earth Engine (Gorelick et al. 2017).

To classify SOCC transects into broad habitat-quality categories, we performed a k-means clustering analysis based on three NDVI descriptors calculated for each transect: the mean NDVI during the breeding season, the within-season standard deviation, and the interannual standard deviation (see Supporting Information). These metrics respectively captured overall vegetation greenness, short-term seasonal variability, and longer-term temporal stability. All variables were standardized prior to clustering. A two-cluster solution was selected based on minimization of the within-cluster sum of squares, yielding two distinct habitat-quality groups: transects characterized by high and consistently stable vegetation greenness across both short- and long-term NDVI dynamics (high-quality habitat), and transects with lower and/or more variable NDVI values (low-quality habitat).

2.4. Model building and projection

We developed a calibration model to relate SOCC counts to the higher-detection SEC counts, with the aim of accounting for detectability-related differences between the two monitoring schemes. For each paired SOCC–SEC survey, the SEC count was used as a higher-detection reference indicator of local abundance, and its relationship with the corresponding SOCC count was modelled using a generalized linear modelling framework. SOCC counts were included as the main predictor, and both linear and quadratic forms of the SOCC term were evaluated. Habitat covariates such as suitable-habitat area and NDVI were incorporated to account for local environmental variation,

and interaction terms between SOCC and NDVI were also included among the candidate formulations.

To determine the most appropriate calibration structure, we fitted a full set of candidate models combining: (1) different NDVI metrics, (2) alternative error distributions (Poisson and two negative-binomial parameterizations, NB1 and NB2, representing linear and quadratic mean–variance relationships, respectively), (3) the presence or absence of zero-inflation components, (4) linear versus quadratic SOCC effects and (5) models with or without a random intercept for transect identity. Candidate models were compared using Akaike's Information Criterion (AIC), and the most parsimonious model was selected. All models were inspected for residual patterns, dispersion and potential outliers following standard diagnostic procedures. Final model performance was evaluated by assessing the agreement between predicted and observed SEC counts. The relative contribution of individual predictors was subsequently examined using ΔAIC values derived from reduced models.

After selecting the final calibration model, SOCC counts from all transects where Common Quail had been detected at least once between 2005 and 2025 were converted into SEC-equivalent abundance indicators. For each transect and year, the observed SOCC count together with the corresponding habitat covariates was entered into the calibration model. Because subsequent trend analyses were performed using TRIM, which requires integer count data, model predictions were rounded down to the nearest integer before being used as calibrated abundance indicators. This conservative approach avoided inflating abundance estimates while maintaining compatibility with the indicator modelling framework.

2.5. Trend analysis

We assessed long-term population trends for both the original SOCC counts and the calibrated SEC-equivalent indicators. Annual SOCC and SEC-equivalent counts were obtained by selecting, for each transect and year, the maximum value from the two SOCC visits, following the standard procedure used by the Catalan Institute of Ornithology (ICO) for deriving official SOCC trends.

For each dataset, we fitted TRIM log-linear models with site and time effects to estimate annual population indices and impute missing values (Van Strien et al. 2004). To obtain a single overall indicator trend, we regressed the logarithm of the TRIM-imputed annual index against time using ordinary least-squares regression; the slope of this regression provided an estimate of the average annual rate of change.

To evaluate whether trends differed across habitat quality, each transect was assigned to one of the NDVI-based habitat clusters (see Supporting Information), and the TRIM and log-linear trend analyses were repeated separately for each habitat group. Differences between SOCC and calibrated SEC-equivalent trends were tested using linear models fitted to the logarithm of the TRIM-derived annual indices, including time, data series and their interaction as explanatory variables. All analyses were conducted in R (version 4.4.2) using the rtrim package (Bogaart et al. 2020).

3. RESULTS

3.1. Observed detection and count differences across schemes

The paired SOCC–SEC surveys revealed clear differences in detectability between the two monitoring schemes. In 32% of surveys where SOCC recorded no Common Quails, the SEC protocol detected at least one calling male (mean ± SD = 4.0 ± 3.4). The opposite pattern occurred only once, when SOCC detected a single calling male and SEC recorded no individuals. Overall, presence–absence detections differed significantly between methods, with a clear asymmetry favouring SEC detections when SOCC failed (McNemar's test, $p = 0.033$).

Across all surveys, the SEC generally recorded higher numbers of calling males than the SOCC. In 71% of paired surveys, SEC detected more individuals than SOCC, whereas counts were identical in 26% of surveys and higher under SOCC in only one case (3%).

Consistently, SEC detected significantly more Common Quail males per survey than SOCC (paired Wilcoxon signed-rank test: $p < 0.001$), with a mean difference of 3.5 individuals per survey. On average, SOCC detected approximately 2.9 calling males per

345 survey, whereas SEC detected approximately 6.4, corresponding to a 2.2-fold increase
346 in detected males under the SEC protocol (Figure 2).

347

348 *3.2. Calibration model performance*

349

350 Model comparison showed that the best-performing calibration model was a negative-
351 binomial formulation (NB1) including mean NDVI, together with linear and quadratic
352 SOCC terms and SOCC × NDVI interactions. Models including random intercepts or
353 zero-inflation components showed consistently higher AIC values.

354 The final calibration model (Table 1) captured a substantial proportion of the variability
355 in SEC counts, providing a robust basis for converting SOCC-derived counts into SEC-
356 equivalent abundance indicators (Supplementary material S3). Standard residual
357 diagnostics indicated no relevant overdispersion, no zero inflation and no influential
358 outliers, confirming robust model behaviour.

359 An AIC-based assessment of predictor contributions revealed that SOCC counts were
360 the dominant component of the calibration model. Removing the linear SOCC term
361 together with its interaction produced the largest increase in AIC (ΔAIC = 53.5),
362 followed by the quadratic SOCC term (ΔAIC = 20.0), indicating a strong non-linear
363 relationship between SOCC and SEC counts. NDVI-related terms also contributed
364 substantially to model performance (ΔAIC = 11.9), and NDVI interactions further
365 improved model fit (ΔAIC = 8.9), showing that the strength of the SOCC–SEC
366 relationship varied along the NDVI gradient. In contrast, available habitat surface had
367 no detectable effect (ΔAIC = -1.9). Overall, calibration performance was primarily
368 driven by SOCC activity, while habitat greenness played an important role in
369 modulating the relationship between SOCC and SEC counts.

370 Examination of model predictions revealed that the magnitude of the calibration
371 correction varied across the SOCC–NDVI space. The largest discrepancies between
372 SOCC and predicted SEC-equivalent indicators occurred when SOCC counts were low
373 and NDVI values were high, indicating that under-detection in SOCC was greatest in
374 greener habitats and at low observed densities. In contrast, predicted SEC-equivalent
375 counts and SOCC converged under conditions of low NDVI or when SOCC counts

were relatively high (≥4). These patterns reflect the structure of the fitted SOCC × NDVI interactions (Figure 3).

3.3. Population trends

Applying the calibration model to the full SOCC dataset yielded SEC-equivalent abundance indicators for all transect–year combinations with available predictor information (N = 205 transects, 2005–2025).

TRIM analyses revealed modest differences in temporal patterns between the original SOCC counts and the calibrated SEC-equivalent indicator series. Across 2005–2025, the SOCC-based population index showed a slight decline (–2.1% per year), whereas the calibrated series remained approximately stable (+0.1% per year). A joint analysis of both series indicated limited statistical evidence for differences in long-term trends (time × series: $\beta = -0.028$, $p = 0.066$), suggesting that, when all transects were pooled, both indices described broadly comparable overall trajectories (Figure 4A).

However, analyses stratified by NDVI-based habitat clusters revealed marked habitat-dependent differences. In transects characterized by high and stable NDVI values, the interaction between time and data series provided strong statistical evidence of divergence ($\beta = -0.047$, $p = 0.0079$). In these greener habitats, SOCC-based indices showed a clear decline (–4.51% per year), whereas the calibrated SEC-equivalent indicator series remained stable (+0.15% per year), indicating diverging temporal trajectories between the two approaches (Figure 4B). Thus, the influence of detectability bias on long-term indicators was concentrated in the habitats most strongly associated with quail occurrence.

In contrast, in transects with low or highly variable NDVI, the interaction provided little statistical evidence of divergence ($\beta = -0.016$, $p = 0.306$), and both SOCC and calibrated series produced similar long-term indicator trends (SOCC: –1.36% per year; SEC-equivalent: +0.29% per year). In these habitats, the two monitoring approaches yielded broadly comparable temporal patterns, with limited divergence across the study period (Figure 4C).

4. DISCUSSION

Breeding bird monitoring schemes face important challenges when applied to species whose behavioural or ecological characteristics generate large variation in detectability across space and time (Thompson, W.L. 2002, Diefenbach et al. 2003, Guillera-Arroita et al. 2017). The Common Quail is a clear example of this broader class of species, as its irregular calling activity, spatially dynamic male aggregations and complex mating system generate patterns of occurrence and abundance estimates that standard multispecies protocols may struggle to capture consistently. By combining a species-specific monitoring protocol with parallel surveys, we quantified the extent to which these biological traits influence detectability and the consistency of population indicators, and evaluated whether integrating targeted and broad-scale monitoring can improve biodiversity indicators for species with variable detectability.

Differences between the two monitoring approaches were evident not only in abundance estimates but also in basic presence–absence detection, highlighting detectability itself as a major source of divergence. Poor agreement in low-count situations suggests that many individuals remain undetected when spontaneous calling activity is low, a pattern common to species whose vocal behaviour varies over short temporal scales (Bibby et al. 2000, Sutherland 2006). Under these conditions, passive multispecies surveys may fail to detect a substantial fraction of individuals, whereas targeted protocols using acoustic stimulation can reveal a larger proportion of the population (De Rosa et al. 2022). These results indicate that detectability differences can affect not only local abundance estimates but also the composition of occurrence datasets and, ultimately, the population indicators derived from them.

NDVI emerged as a key environmental predictor in the calibration model, indicating that habitat greenness and phenological state modulate the relationship between SOCC and SEC counts. Importantly, the magnitude of the correction was not constant across sites: discrepancies were greatest in high-NDVI habitats when the BMS protocol recorded low counts, suggesting that under-detection is most pronounced under the habitat conditions most strongly associated with quail occurrence. Because NDVI varies considerably among regions and years (Pettorelli et al. 2005), the degree of underestimation in BMS data is inherently context dependent. Accordingly, the

calibration does not act as a uniform multiplier but as a habitat-mediated adjustment shaped by local vegetation dynamics.

In contrast, suitable habitat area had no detectable effect, probably because all paired transects were located in landscapes where quails are regularly present and habitat extent was not limiting. Within this range of conditions, habitat quality—as captured by NDVI—appeared to outweigh habitat quantity in determining both local abundance and detectability. Importantly, this implies that detectability bias is not randomly distributed across the landscape, but is concentrated in habitats that contribute disproportionately to the breeding population and are therefore of relevance for conservation assessment.

From a temporal perspective, integrating information from the species-specific survey refined the ability of general BMS data to describe long-term indicator trends. Although the uncorrected BMS series broadly captured the overall regional trajectory of the species, substantial differences emerged in habitats characterized by high and stable NDVI values, where uncorrected indicators suggested declines that were not supported by the calibrated series. These results indicate that detectability bias can influence not only local abundance estimates but also the interpretation of long-term population trends, particularly in the habitats most strongly associated with quail occurrence.

Because calling activity varies across seasons, years and habitat conditions, detectability-related variability may propagate into abundance-based indicators and reduce their ability to reflect underlying demographic change (Kéry and Schmidt 2008, Kellner and Swihart 2014). By accounting for habitat-dependent differences between monitoring schemes, the calibrated indicators may more closely reflect underlying temporal dynamics and improve the reliability of trend assessment.

Although the calibration improves the consistency of local abundance indicators, it should not be interpreted as a direct estimator of absolute population size at regional or larger spatial scales. Common Quail populations are highly dynamic during the breeding season, with individuals frequently relocating in response to vegetation phenology, harvesting schedules and social interactions (Puigcerver et al. 1989, Rodríguez-Teijeiro et al. 2009, Sardà-Palomera et al. 2012b). Recent GPS-based tracking data further indicate movements among neighbouring transects and, occasionally, across much larger distances within the same breeding period (Sardà-Palomera et al. 2025, unpublished data). Such mobility implies open populations with

substantial turnover, increasing the risk of double counting when observations are aggregated across space and time. Consequently, the relationship between SOCC and SEC counts should be interpreted primarily as a calibration of detectability rather than as a direct estimator of regional population size.

This limitation does not preclude the use of calibrated counts for trend assessment and population indicators, provided that population openness and movement are considered within appropriate analytical frameworks. Additional information on movement rates, seasonal redistribution and connectivity among breeding areas could help refine future calibration approaches and facilitate the integration of movement information into hierarchical or state-space models. Until then, monitoring outputs are likely to be most informative when interpreted within relatively narrow temporal windows and at biologically meaningful spatial scales.

Despite these limitations, BMS remain an indispensable component of large-scale biodiversity monitoring, providing unparalleled temporal and geographic coverage that no species-specific program could realistically achieve. The challenge, therefore, is not to replace general monitoring schemes, but to complement them in ways that explicitly address detectability-related bias.

More generally, the present study illustrates how species-specific and broad-scale monitoring schemes can be combined to improve biodiversity indicators for species with variable detectability. By integrating information from targeted surveys into a general monitoring framework, it is possible to retain the extensive spatial and temporal coverage provided by BMS programs while reducing some of the biases associated with imperfect detection.

Similar approaches could be explored for other species that are difficult to monitor using standard survey protocols. Dedicated monitoring programs increasingly rely on passive acoustic recorders, thermal-imaging devices and camera traps to maximize detection (Sugai, et al. 2018, Lahoz-Monfortand and Magrath, 2021, Wearn and Glover-Kapfer 2019), providing high-quality reference data that could be used to calibrate or validate broad-scale monitoring outputs in a manner analogous to the approach presented here.

Overall, our study shows that information from general breeding bird monitoring schemes can be combined with species-specific surveys to improve the interpretation of abundance indicators and long-term trends for species with highly variable detectability. Our results demonstrate that detectability bias is influenced by habitat conditions and therefore cannot be assumed to be constant across space or time. The relationship between general and species-specific surveys is therefore likely to vary among regions, years and management contexts and may require local calibration to identify the most appropriate model structure.

More broadly, our results highlight the value of combining broad-scale volunteer-based monitoring with targeted high-detection surveys to generate more robust and interpretable population indicators. Such complementary approaches offer a practical pathway for improving biodiversity assessments while preserving the extensive spatial and temporal coverage provided by long-term monitoring programs.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

AI Statement

During the preparation of this work, the authors used ChatGPT (OpenAI) to assist with language editing and improvement of manuscript structure. All scientific content,

interpretation and conclusions were reviewed and validated by the authors, who take full responsibility for the final manuscript.

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669 **TABLES**

670

671 Table 1 Summary of the negative-binomial calibration model (NB1) relating SEC
672 counts to SOCC counts and habitat variables.

Predictor	Estimate	SE	z	p-value
Intercept	1.739	0.104	16.690	<0.001
SOCC	1.218	0.166	7.343	<0.001
$SOCC^2$	–0.370	0.090	–4.125	<0.001
NDVI (15-day mean)	0.266	0.112	2.387	0.017
Habitat area (ha)	–0.034	0.087	–0.388	0.698
SOCC × NDVI	–0.499	0.146	–3.412	<0.001
$SOCC^2$ × NDVI	0.184	0.063	2.919	0.003

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FIGURE CAPTIONS

Figure 1. Geographic distribution of transects used in this study across Catalonia. Blue lines show the 28 specifically designed SOCC transects monitored with both SOCC and SEC protocols between 2021 and 2025, which were used to calibrate the SOCC–SEC relationship. Green lines represent all SOCC transects where at least one Common Quail was detected between 2005 and 2025 (N = 205), for which the calibration model was applied to generate SEC-equivalent abundance-based indicators.

Figure 2. Mean number of Common Quail males detected per transect (± SD) by the SOCC and SEC protocols. Only transects with confirmed quail detection were included. Bars show mean values and error bars indicate standard deviation.

Figure 3. Predicted SEC-equivalent counts across the SOCC–NDVI space, based on the final NB1 calibration model. The response surface illustrates the combined non-linear effects of SOCC counts and vegetation greenness (15-day mean NDVI), together with their interaction.

Figure 4. Temporal dynamics of the population index derived from original SOCC counts (red) and from SEC-equivalent calibrated indicators (blue). Solid lines show annual TRIM indices and shaded areas represent standard errors. Dashed lines indicate the fitted log-linear trends, with annual percentage changes shown at the right of each panel. (A) All transects combined. (B) Transects within high and stable NDVI habitats. (C) Transects within low or highly variable NDVI habitats. * denotes support for divergent SOCC and SEC-equivalent trends (time × series interaction; $p < 0.05$).