Applied Soil Ecology 214 (2025) 106329

Contents lists available at ScienceDirect

Applied Soil Ecology

journal homepage: www.elsevier.com/locate/apsoil

Research paper

Reliability of earthworm data from citizen science: Lessons from 7 years of a French national monitoring protocol

Kevin Hoeffner [a,b,c,1,*], Benjamin Bergerot [a,1], Kevin R. Butt [d], Sylvain Gérard [e], Céline Pelosi [f], Guénola Pérès [c], Maria J.I. Briones [g], Thibaud Decaëns [h], Natacha Delaveau [a], Sarah Guillocheau [a], Mickaël Hedde [e], Hoël Hotte [a,i], Renée-Claire Le Bayon [j], Bart Muys [k], Helen R.P. Phillips [l,m,n], Maxime Poupelin [a], Daniel Cluzeau [a]

[a] University of Rennes, CNRS, ECOBIO [(Ecosystèmes, biodiversité, évolution)] - UMR 6553, Rennes, France
[b] FRB-Cesab, 5 rue de l'école de médecine, 34000 Montpellier, France
[c] UMR, SAS, INRAe, Institut Agro Rennes-Angers, 65 rue de Saint Brieuc, 35042 Rennes Cedex, France
[d] University of Central Lancashire, Ecological Engineering, Preston PR1 2HE, United Kingdom
[e] Eco&Sols, INRAE, IRD, CIRAD, Institut Agro Montpellier, Université Montpellier, Montpellier, France
[f] INRAE, UMR EMMAH 1114 INRAE,Université d'Avignon, Avignon, France
[g] Departamento de Ecología e Biología Animal, Universidad de Vigo, 36310 Vigo, Spain
[h] CEFE, Univ Montpellier, CNRS, EPHE, IRD, Univ Paul Valéry Montpellier 3, Montpellier, France
[i] ANSES, Plant Health Laboratory, Nematology Unit, Domaine de la Motte Au Vicomte, BP 35327, 35653 Le Rheu Cedex, France.
[j] University of Neuchâtel, Institute of Biology, Functional Ecology Laboratory, Emile Argand 11, CH-2000, Neuchâtel, Switzerland
[k] Division of Forest, Nature and Landscape, Department of Earth and Environmental Sciences, KU Leuven, Celestijnenlaan 200E, Box 2411, 3001 Leuven, Belgium
[l] Department of Environmental Sciences, Saint Mary's University, Halifax, Canada
[m] Department of Terrestrial Ecology, Netherlands Institute of Ecology (NIOO-KNAW), Wageningen, Netherlands
[n] Faculty of Biological and Environmental Sciences, University of Helsinki, Helsinki, Finland

ARTICLE INFO

Key-words:
Earthworm morphological group
Data quality
Monitoring
Participants' experience
Participatory science
Training

ABSTRACT

Monitoring biodiversity is seldom comprehensive, as the spatio-temporal resolution needed to accurately reflect dynamic changes of these communities in diverse environments is often lacking. Citizen science offers a promising tool to help fill these gaps, engaging a wider audience in monitoring efforts and thus enhancing our understanding of earthworm ecology. However, a significant challenge arises as earthworms are difficult to identify to the species level in the field by non-experts, necessitating the use of morphotypes as taxonomic proxies. This study evaluates the reliability of earthworm classification into four earthworm morphotypes within the '500 ENI' (Non-intended Effects) Monitoring Network in France. The network relies on annual sampling conducted in agricultural lands by non-specialist participants with subsequent identification verification by earthworm taxonomists. Analyzing >48,000 individual earthworms collected over 950 plots, we calculated two indices: the misclassification rate (MR) and the undetected rate (UR) to assess the reliability of classification into earthworm morphotypes. The results indicated an average MR of 28 % and an average UR of 32 %, which both varied according to morphotypes. Endogeics had lower error rates compared to epigeics, anecics with a red anterior, and anecics with a black anterior. Our findings underscored the significant impact of sampler experience and earthworm community composition on the reliability of classification of individuals into morphotypes by citizens. The results highlight the critical need for enhanced support and guidance for participants with limited experience. Furthermore, we recommend providing additional training or resources to aid in morphotype classification, especially for earthworm communities exhibiting low abundance, low adult proportion, or low morphotype diversity. Encouraging participants to sample during periods favorable for detecting reliable total and adult abundances would also help optimize morphotype detection.

* Corresponding author:
E-mail address: kevin.hoeffner@inrae.fr (K. Hoeffner).
[1] Joint first authorship: These authors contributed equally to this manuscript.

https://doi.org/10.1016/j.apsoil.2025.106329
Received 14 March 2025; Received in revised form 10 July 2025; Accepted 14 July 2025
Available online 22 July 2025

1. Introduction

Among soil biota, earthworms play a pivotal role in the functioning of soils and terrestrial ecosystems. Their engineering activities physically modify their environment, contributing to the maintenance of soil functions and biodiversity, and to the provision of key ecosystem services for human societies (Lavelle et al., 2006; Blouin et al., 2013; Liu et al., 2019). Despite this acknowledged importance, so far, there has been neither consistent nor comprehensive monitoring of earthworm biodiversity over time and space (FAO, 2020; Guerra et al., 2020; Rosa et al., 2020). Previous large-scale studies have provided fundamental insights into global patterns of earthworm communities (Rutgers et al., 2016; Phillips et al., 2019). However, both local and large-scale studies often lack spatiotemporal resolution to reflect the nuanced dynamics of earthworm communities in heterogeneous and changing environments. Notably, these effects are highly context-dependent, underscoring the necessity to delineate the relative effects of varied soil properties, climatic conditions, land uses and management practices on earthworm communities (Forey et al., 2011; Schelfhout et al., 2017; Singh et al., 2021). This limitation is mainly due to project funding, labour, and time constraints, making it difficult to sample earthworm populations, leading to an unreliable representation of their spatial and temporal dynamics. Citizen science offers a promising avenue to overcome this lack of spatiotemporal resolution by bridging knowledge gaps with data acquisition (Dickinson et al., 2010, 2012; Hochachka et al., 2012). By engaging a wider community in the monitoring process, citizen science (also known as participatory science projects) has examined temporal and spatial dynamics, and provided valuable insights into earthworm community dynamics (Baker et al., 1997; Martay and Pearce-Higgins, 2018; Stroud, 2019). This knowledge is essential to support the development of sustainable land management practices that safeguard soil functioning and biodiversity (Brussaard et al., 2007; Bender et al., 2016; Geisen et al., 2019), especially in the context of broader environmental challenges, including climate change, the spread of invasive species, soil pollution, and increasing urbanization (FAO, 2020; Head et al., 2020; Rosa et al., 2020).

Despite the availability of large datasets, under-utilization in mainstream ecological research and decision-making persists, likely due to concerns about the reliability of data from citizen science (Conrad and Hilchey, 2011; Theobald et al., 2015). Critics typically point to lower robustness, replicability, and biases such as non-random sampling and the diverse skill sets and backgrounds of participants (Cohn, 2008; Bonney et al., 2014; Aceves-Bueno et al., 2017; Bayraktarov et al., 2019). To address these concerns, several citizen science projects have implemented different solutions, such as training for participants, specialist validation systems, or adjusting experimental protocols following pilot stages. Aceves-Bueno et al. (2017) conducted a quantitative review from 63 studies across the world that compared citizen science data to data collected by specialists across terrestrial, freshwater, marine and atmospheric domains. They found high reliability of citizen science data in 73 % of reviewed cases. This indicates that, despite the challenges, citizen science can provide trustworthy data, though the quality often varies according to the complexity of the task (Kosmala et al., 2016; Brown and Williams, 2019). Significant research gaps persist in identifying the factors that influence data reliability within citizen science, particularly the role of taxonomic resolution among various species groups. Addressing these gaps has the potential to significantly improve the reliability of the data collected (Steger et al., 2017; Troudet et al., 2017).

There have been several citizen science projects on earthworms, such as Wormsdownunder (Australia), Wormwatch (Canada), Open Air Laboratories (United Kingdom), Observatoire Participatif des Vers de Terre (France) and Bodemdierendagen (Netherlands). These projects asked participants to sample and record the abundance of earthworm individuals, and to classify them into species or morphotypes (groups of individuals that are morphologically distinct from each) based on morphological traits such as colour, body size, and shape of the earthworm (Baker et al., 1997; Martay and Pearce-Higgins, 2018; Stroud, 2019; Burton and Cameron, 2021). Despite these efforts, the systematic evaluation of data reliability from these non-professional researchers has been largely overlooked. Given the crucial role of the data collected by these participants in ecological monitoring and policy-making, an assessment and improvement of trustworthiness remains a priority for the scientific community.

The present study evaluated the robustness of earthworm data from the '500 ENI' (Non-intended Effects) Monitoring Network, a French National programme assessing the impacts of agricultural practices on farmland biodiversity, involving the annual sampling of around 500 fields by non-academic participants. In this programme, participants record the abundance of earthworms and identify morphotypes before sending the specimens to earthworm specialists for taxonomic analysis and morphotype categorizations. Using 48,946 earthworms collected from 950 plots (from 2012 to 2018), we conducted a comparative analysis between the participants' and the specialists' morphotype classifications. We hypothesized that data reliability is improved by the experience of the participant (i.e., the number of years a citizen scientist has participated in the surveys), the cumulative number of sampled plots, and the ratio of the cumulative number of earthworms to plots sampled per participant. We also assumed that a higher total abundance of earthworms per plot, percentage of adult earthworms, and number of different morphotypes would improve classification reliability.

2. Materials and methods

2.1. 500 ENI (Non-intended Effects) network

The 500 ENI network, established in 2012, is a nationwide biological monitoring initiative managed by the French Ministry of Agriculture (Direction Générale de l'Alimentation - DGAL). Its primary goal is to observe shifts in the frequency or abundance of indicator species in response to agricultural activities, with particular attention on specific taxonomic groups, such as earthworms, plants, coleoptera, and birds (Andrade et al., 2021). The network encompasses 500 fields spread

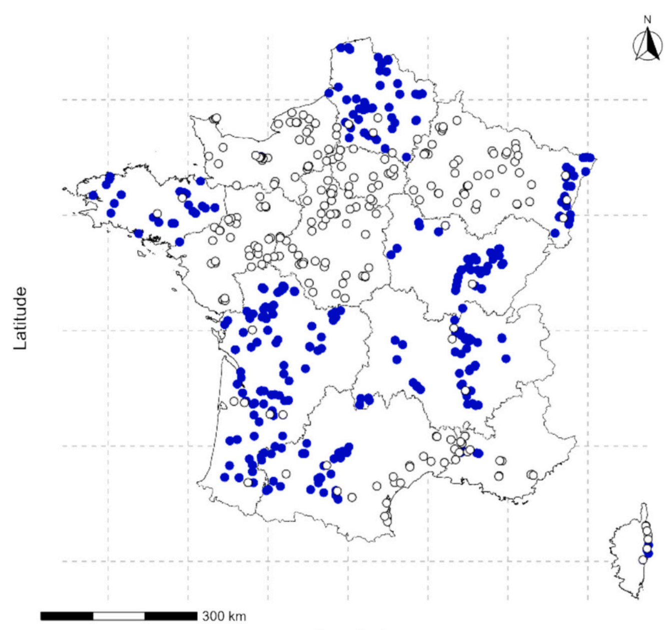

Fig. 1. Location of the 500 ENI network plots across France, including Corsica. Blue circles show plots for which the participants returned samples to the laboratory at least once, while empty circles indicate plots for which no earthworms were returned (from 2012 to 2018).

throughout metropolitan France, including Corsica (Fig. 1). Monitoring efforts are concentrated on three main land uses indicative of France's prevalent agricultural systems: annual crops, vineyards, and market gardens.

The participants were primarily agricultural advisors with no formal scientific background in biodiversity monitoring. Depending on demand, the participants attended a one-day workshop by earthworm specialists before earthworm sampling. This comprised of classroom sessions on earthworm ecology (including morphological characteristics, roles as ecosystem engineers and sensitivity to agricultural management), followed by practical field training to cover sampling techniques and classification into morphotypes. After sampling, a one-day debriefing session was conducted to discuss the results, resolve questions and correct any potential errors in the classification into morphotypes. Continuous access to online educational resources on earthworm ecology and support materials for classification of individuals into morphotypes were also provided to the participants (https://ecobio.univ-rennes.fr/ecobiosoil and navigate to the 'Observatoire Participatif des Vers de Terre' section).

2.2. Earthworm sampling and data collection

Every spring between 2012 and 2018, participants sampled earthworms using a chemical extraction method. Sampling in each plot was conducted within three squared metres, each separated by 6 m. For each plot, two applications of a mustard suspension (300 g of Amora Fine et Forte© in 10 l of water) were used at 15-min intervals. In response to the irritant effect of the isothiocyanate contained in the mustard, earthworms move to the surface. Earthworms were collected for 15 min after the second application of mustard. Following collection, earthworms were counted, categorized into developmental stages (adult or juvenile) and classified into four morphotypes according to Bouché (1977) ecological categories: epigeic (surface-dwelling), anecic (deep-burrowing), and endogeic (shallow-burrowing). The anecic category was further split into two categories based on the cutaneous pigmentation: individuals with a red anterior and those with a black anterior. The decision to use these four morphotypes is based on their relatively distinct characteristics, which facilitate recognition by participants and provide insights into different life strategies within earthworm communities (Bouché, 1977; Hoeffner et al., 2022). However, it is important to note that these categories are not strictly recognized as functional groups (Bottinelli and Capowiez, 2021). Moreover, the classification of species within these categories can also be ambiguous, as there exists a continuum between them that complicates the attribution of certain species to specific categories (Bottinelli et al., 2020). In the field, participants classified live individuals using a simplified identification key (Supplementary Fig. S1) specifically developed for the 500 ENI protocol. From each plot, earthworms of each morphotype were stored separately in alcohol (70 %), photographed, and sent to the university of Rennes for classification validation. However, the process of sending these samples to the university was not systematically enforceable. Indeed, from 2012 to 2018, just 950 samples out of the 3500 plots (500 plots × 7 years) were sent to the laboratory for validation (27 %, Fig. 1). In the laboratory, specialists classified the preserved specimens (fixed in alcohol) using a stereomicroscope to allow detailed morphological examination. Earthworms were counted, and if multiple fragments were found in the same sample that appeared to belong to the same individual (based on size, shape, setae and colour), these fragments were combined to be counted as a single individual. In parallel, individuals were categorized according to their ontogenic stage (adult or juvenile), identified at the most precise taxonomic resolution (Bouché, 1972) and classified into morphotypes (Supplementary Table S1). If classification to a specific taxon was not possible, individuals were assigned a morphotype based on previously defined criteria.

2.3. Reliability indices

To evaluate the reliability of classification of earthworms into morphotypes by participants, for each plot we calculated the misclassification rate (MR) [1] and the undetected rate (UR) [2], both expressed as percentage of individual earthworms incorrectly identified or overlooked within each morphotype (*MTx*) following the approach of (Bergerot and Fontaine, 2024).

$$\text{Misclassification Rate } (\text{MR}_{\text{MTx}}) = (\text{Nv}_{\text{MTx}} - \text{Nm}_{\text{MTx}}) \times 100/\text{Nv}_{\text{MTx}} \tag{1}$$

$$\text{Undetected Rate } (\text{UR}_{\text{MTx}}) = (\text{Ns}_{\text{MTx}} - \text{Nm}_{\text{MTx}}) \times 100/\text{Ns}_{\text{MTx}} \tag{2}$$

Where *Nv* represents the total number of individuals attributed to a morphotype (*MTx*) by a participant; *Nm* the number of individuals correctly attributed to a morphotype (*MTx*) by the participant (according to specialist attribution); and *Ns* represents the total number of individuals assigned to that morphotype (*MTx*) by the specialist, whether or not the participant detected them. Misclassification rate (MR) measures the percentage of incorrectly classified individuals among those detected, with a higher MR indicating a greater misclassification error. The undetected rate (UR) measures the percentage of individuals in a given morphotype that go unnoticed by the participant, despite being present in the sample, with a higher UR indicating a greater incidence of non-detection. These indices are complementary because some morphotypes may be easy to detect but hard to classify correctly (high MR and low UR), while others may be frequently overlooked but correctly classified when detected (low MR and high UR).

2.4. Statistical analysis

Firstly, to analyze the reliability of total earthworm abundance, a one-way ANOVA was used to test whether the number of earthworms counted by participants and by a specialist in each sample varied. Prior to the analysis, assumptions of normality (Shapiro-Wilk test) and homoscedasticity (Bartlett's test) were verified. Secondly, two generalized linear mixed-effects models (GLMMs) were applied to test the response of both the MR and the UR to: (i) the cumulative number of years a participant had been involved in the 500 ENI network until each sampling year (experience), (ii) the cumulative number of plots a participant had sampled until each sampling year (plot sampled), (iii) the ratio of the cumulative number of earthworms sampled to the cumulative number of plots sampled per participant (EW/Plot) and (iv) the morphotypes per se. The 'participant ID' was considered as a random factor in the model. To account for the prevalence of zero counts in our data, we incorporated a zero-inflation component linked to the number of years of participation, the cumulative number of plots sampled and the ratio of the cumulative number of earthworms sampled to the cumulative number of plots sampled. This allowed for a dual modeling approach to distinguish the probability of zero occurrences from the abundance distribution, thus providing a more refined analysis of the data. The model's syntax was glmmTMB(MR or UR ~ morphotype * (experience + plot sampled + EW/plot) + (1| participant ID), ziformula = ~ experience + plot sampled + EW/plot).

Thirdly, two generalized linear mixed-effects models (GLMMs) were applied to test the response of both the MR and the UR to (i) the total earthworm abundance at plot level (earthworm abundance), (ii) the proportion of adults (percentage), (iii) the number of morphotypes (number of morphotypes) within the plot, and (iv) the morphotypes per se. The 'participant ID' effect was considered as a random factor in the model with individual identifiers for each year of sampling to account for inter-annual variability. As before, we incorporated a zero-inflation component linked to morphotypes, total abundance and percentage of adults. For the number of morphotypes, categorized into classes, pairwise comparisons were conducted to examine differences between levels. The model's syntax was: glmmTMB (MR or UR ~ morphotype * (earthworm abundance + number of morphotype + percentage of adult) + (1| participant ID), ziformula = ~ earthworm abundance + number of morphotype + percentage of adult).

The decision to run two separate sets of models, one focusing on participant-level factors and the other on plot-level factors, was necessary due to the differing levels of aggregation, independent of the potential interactions between variables. The response variables, MR and UR, used in the GLMMs were modeled using both Poisson and negative binomial distributions, respectively, using the glmmTMB package (Brooks et al., 2023), with their suitability verified by testing for overdispersion and outliers using the package DHARMa (Hartig and Lohse, 2022). All predictive variables were derived from validated data by the specialists. Additionally, correlation matrices were used to ensure that the correlation coefficients among explanatory variables remained below 0.7 (Dormann et al., 2013) to reduce the risk of multicollinearity affecting our models. To ensure analysis robustness and mitigate the influence of outliers, we calculated the 2.5 % to 97.5 % quantiles for each numerical predictor and restricted the dataset to values within these quantile ranges, thereby focusing on the most representative data.

All statistical analyses were performed using R software version 4.3.2 (R Core Team, 2023).

3. Results

3.1. Reliability of total abundance and morphotype classification

A strong relationship was found between the total number of earthworms counted by the participants and those by the specialists, as evidenced by regression analysis (F-value = 17,337, $P < 0.001$, Adjusted R-squared = 0.95, Fig. 2). Cumulative total abundance across all plots by the participants amounted to 49,751 earthworms, while the number counted by the specialists was lower (48,946 individuals). On average, specialists calculated lower earthworm abundance than participants (0.88 ± 15 SD individuals per plot).

The total number of earthworms counted in each morphotype by both participants and specialists showed a significant relationship across all morphotypes (Supplementary Fig. S2). Notably, the strongest correlation was observed for endogeics ($R^2 = 0.88$) and was weaker for epigeics, anecics with a black anterior, and anecics with a red anterior ($R^2 = 0.48$, 0.54, and 0.67, respectively, Supplementary Fig. S2). The mean misclassification rate (MR) was 28 % ± 1 % but did vary between morphotypes: epigeics MR (7143 individuals) was 38 % ± 2 %; anecics with a red anterior MR (14,780 individuals) was 29 % ± 2 %; anecics with a black anterior MR (10,004 individuals) was 40 % ± 2 %; and endogeics MR (24,279 individuals) was 13 % ± 1 %. Similarly, the mean undetected rate (UR) was 32 % ± 1 % and also varied across morphotypes: epigeics UR was 40 % ± 2 %; anecics with a red anterior UR was 29 % ± 2 %; anecics with a black anterior UR was 46 % ± 2 %; and endogeics UR was 21 % ± 1 %.

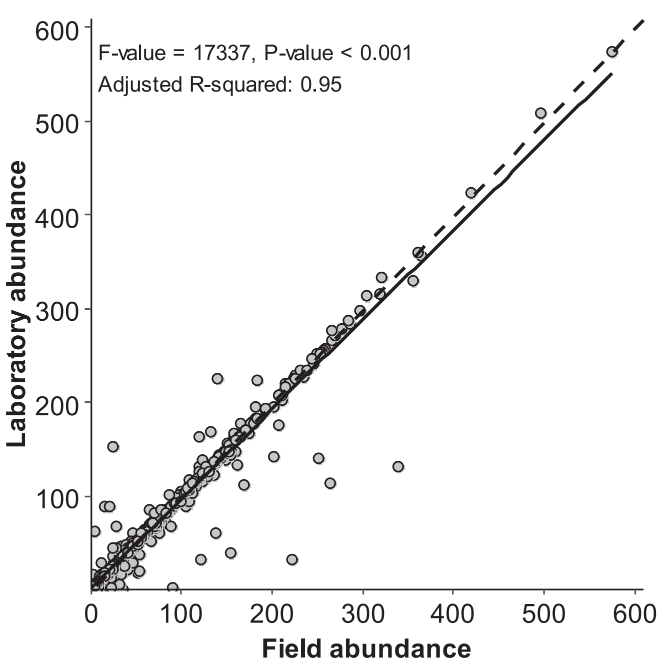

Fig. 2. Relationship between the total abundance of earthworms recorded by the participants (field) and specialists (laboratory). Each point represents a sampling plot. The dashed line depicts a line with a slope of 1, indicating perfect correlation between earthworm abundance values recorded by participants and those derived from specialists. The solid line represents the regression line fitted to the data. Statistical analysis above the scatterplot displays the F-value and *P*-value from the ANOVA, plus the Adjusted R-squared value.

3.2. Human factors explaining data discrepancies

The MR significantly decreased with the increasing cumulative number of plots sampled, regardless of the morphotype (Fig. 3a, Table 1). Additionally, the MR was found to be related to the cumulative number of earthworms sampled per plot, with effects varying depending on the morphotype (Table 1). A higher cumulative number of earthworms sampled per plot resulted in a decrease in MR for epigeics, anecics with a black anterior, and endogeics, but led to a slight increase for anecics with a red anterior (Fig. 3b, Table 1). The number of years of participation in the network (experience) did not significantly affect the MR (Table 1).

The undetected rate (UR) significantly decreased with the increasing cumulative number of plots sampled and the cumulative number of earthworms sampled per plot, without variation in effects across different morphotypes (Fig. 4a and b, Table 1). The number of years of participation in the network did not significantly affect the UR (Table 1).

3.3. Earthworm community parameters explaining data reliability

The misclassification rate (MR) was significantly related to the number of earthworm morphotypes per plot, the percentage of adult earthworms per plot, and the total earthworm abundance per plot, with effects varying across the different morphotypes (Table 2). An increase in earthworm abundance within a plot led to a decrease in the MR for anecics with a black anterior and endogeics, and to an increase for epigeics, but had no significant effect on anecics with a red anterior (Fig. 5a, Table 2). An increase in the proportion of adult earthworms was

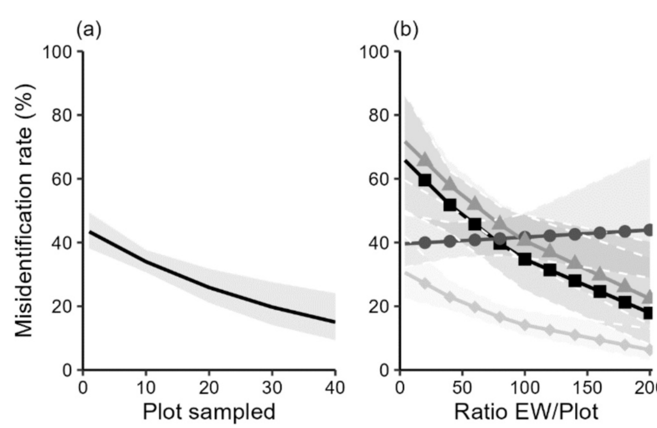

Fig. 3. Predicted Misclassification Rate (MR) ± standard deviation across (a) the cumulative number of plots sampled, and (b) the cumulative number of earthworms identified per plot by each participant. Earthworm morphotypes are represented using different symbols: EPI (epigeics, squares), ANE_RA (anecics with a red anterior, circles), ANE_BA (anecics with a black anterior, triangles), and END (endogeics, diamonds).

Table 1
ANOVA Type II Wald Chi-Square Tests for the model predicting misclassification and undetected rate. The table presents the degrees of freedom (df), Chi-squared values (Chisq), and the associated *P*-values for each predictor and interaction in the model. Significant predictors, shown in bold, include the morphotype (MT), the number of years a person has participated in the 500 ENI network (Experience), the cumulative number of earthworms they have identified (Earthworm identified), the cumulative number of plots they have sampled (Plot sampled) and a ratio of the cumulative number of earthworms identified to the cumulative number of plots sampled (EW/Plot) on the MR and UR indices and the interaction terms of morphotype with Experience, morphotype with Earthworm identified, morphotype with Plots sampled and morphotype with the ratio EW/Plot. For the misclassification rate model, the conditional R^2 was 0.94 and the marginal R^2 was 0.74; for the undetected rate model, the conditional R^2 was 0.93 and the marginal R^2 was 0.54.

		Misidentification rate		Undetection rate	
	df	Chisq	P-value	Chisq	P-value
Morphotype	3	**117.7**	**< 0.001**	**79.6**	**< 0.001**
Experience	4	3.4	0.497	1.7	0.800
Plot sampled	1	**15.2**	**< 0.001**	**13.9**	**< 0.001**
EW/Plot	1	**11.6**	**< 0.001**	**18.2**	**< 0.001**
MT x Experience	12	9.6	0.653	13.2	0.354
MT x Plot	3	0.2	0.983	4.7	0.197
MT x EW/Plot	3	**17.4**	**< 0.001**	7.5	0.057

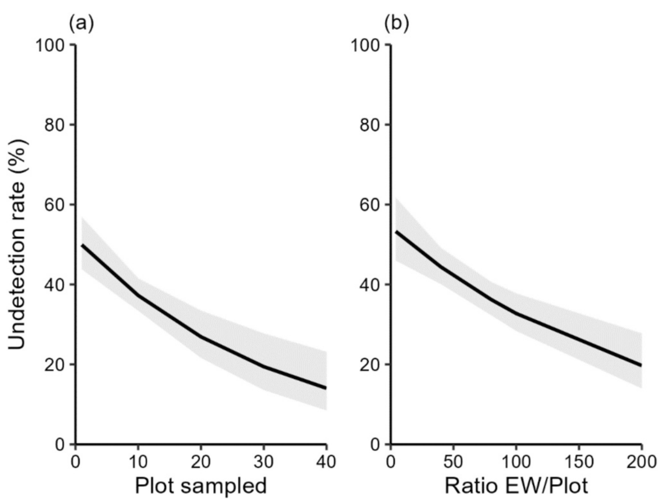

Fig. 4. Predicted Undetected Rate (UR) ± standard deviation across (a) cumulative number of plots sampled, and (b) cumulative earthworms identified per plot by each participant.

related to a decrease in MR for epigeics, anecics with a black anterior, and endogeics, while it was related to an increase in MR for anecics with a red anterior (Fig. 5b, Table 2). An increase in morphotype range was associated with a significant decrease in MR for all morphotypes (Fig. 5c, Table 2). For epigeics and anecics with a black anterior, the MR decreased, becoming more pronounced when moving from three to four morphotypes. Specifically, for epigeics, the MR dropped from 66 % to 37 %, and for anecics with a black anterior, it reduced from 60 % to 45 % (Fig. 5c, Table 2). In the case of anecics with a red anterior, a decrease was observed when the number of morphotypes increased from two to three, with no significant change observed at a diversity level of four (66 %, 39 %, and 37 % respectively, Fig. 5c, Table 2). For endogeics, an increase in the number of morphotypes from one to two led to an important decrease in MR (from 55 % to 28 %), followed by a minimal change between the levels of three and four (25 % to 22 %, Fig. 5c, Table 2).

The undetected rate (UR) was significantly related to the number of morphotypes, the percentage of adult earthworms, and the total

Table 2
ANOVA Type II Wald Chi-Square Tests for the model predicting misclassification and undetected rate. The table presents the degrees of freedom (df), Chi-squared values (Chisq), and the associated P-values for each predictor and interaction in the model. Significant predictors, shown in **bold,** include the morphotype (MT), earthworm abundance, the number of morphotypes (Number of morphotypes) and the percentage of adults and the interaction terms of morphotype with Earthworm abundance, morphotype with Number of morphotypes and morphotype with Percentage of adults. For the misclassification rate model, the conditional R^2 was 0.16 and the marginal R^2 was 0.08; for the undetected rate model, the conditional R^2 was 0.12 and the marginal R^2 was 0.03.

		Misidentification rate		Undetection rate	
	df	Chisq	P-value	Chisq	P-value
MT	3	3116.6	< 0.001	2039.7	< 0.001
Earthworm abundance	1	112.3	< 0.001	540.1	< 0.001
Number of MT	3	1113.9	< 0.001	26.1	< 0.001
Percentage of adults	1	29.0	< 0.001	288.5	< 0.001
MT x Earthworm abundance	3	592.5	< 0.001	192.0	< 0.001
MT x Number of MT	9	601.7	< 0.001	231.5	< 0.001
MT x Percentage of adults	3	333.6	< 0.001	33.5	< 0.001

earthworm abundance per plot, with the effects varying across the different morphotypes (Table 2). An increase in earthworm abundance per plot significantly lowered the UR for all morphotypes, with a more marked decrease for both anecics with either a red or a black anterior and endogeics than for epigeics (Fig. 6a, Table 2). Additionally, an increase in the proportion of adult earthworms led to a decrease in the UR across all morphotypes, with a more pronounced reduction observed for epigeics and both anecics with a red or a black anterior than for endogeics (Fig. 6b, Table 2). Furthermore, the impact of an increase in the number of morphotypes varied between the morphotypes (Fig. 6c, Table 2). For epigeics, the UR was higher when 1 morphotype was detected (67 %) followed by 2 morphotypes (64 %), 3 morphotypes (56 %), and lowest with 4 morphotypes (59 %). Greater uncertainty was observed when only 1 morphotype was present (Fig. 6c, Table 2). For anecics with a red anterior, the UR was significantly lower in the presence of 1 and 2 morphotypes than in the presence of 3 and 4 morphotypes (39 %, 42 %, 47 %, and 49 %, respectively). In the case of anecics with a black anterior, the UR was significantly higher in the presence of 1 (63 %), 3 (58 %), and 4 (58 %) morphotypes compared to 2 being present (53 %, Fig. 6c, Table 2). For endogeics, the UR was notably higher in the presence of 1, followed by 2, 4, and then 3 morphotypes (48 %, 41 %, 36 %, and 32 % respectively, Fig. 6c Table 2).

4. Discussion

4.1. *Assessment of the data reliability from a country-wide monitoring network*

The present study revealed that citizen science can provide reliable data on earthworm abundance, which is comforting for future and past published studies using total earthworm abundance data derived from citizen science (Baker et al., 1997; Stroud, 2019; Billaud et al., 2021). The strong correlation between results provided by participants and specialists' data aligns with similar findings from several citizen science projects (Aceves-Bueno et al., 2017). The slightly lower abundance recorded by the specialists, compared to participant records, can be attributed to earthworms being fragmented during extraction and sorting, and these fragments often being counted separately by participants but grouped by specialists in the laboratory. It should be noted that the use of a chemical extraction method, which encourages earthworms to surface for easy collection, rarely results in fragmented earthworms. Consequently, the reliability of abundance data might become compromised when employing other physical extraction methods, such as hand sorting, which have a higher likelihood of fragmenting earthworms during collection. Additionally, occasional miscounts may have

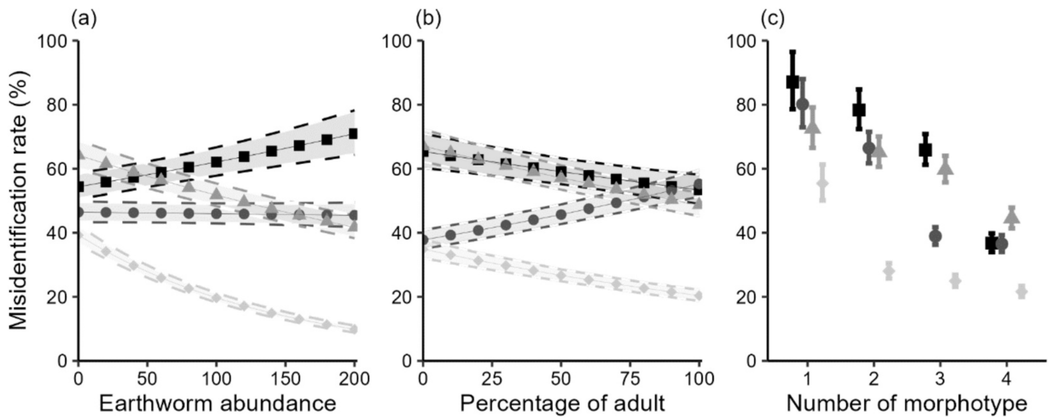

Fig. 5. Predicted Misclassification Rate (MR) ± standard deviation across (a) the total abundance of earthworms, (b) the percentage of adult individuals, and (c) the number of earthworm morphotypes per plot. Earthworm morphotypes are represented using different symbols: EPI (epigeics, squares), ANE_RA (anecics with a red anterior, circles), ANE_BA (anecics with a black anterior, triangles), and END (endogeics, diamonds).

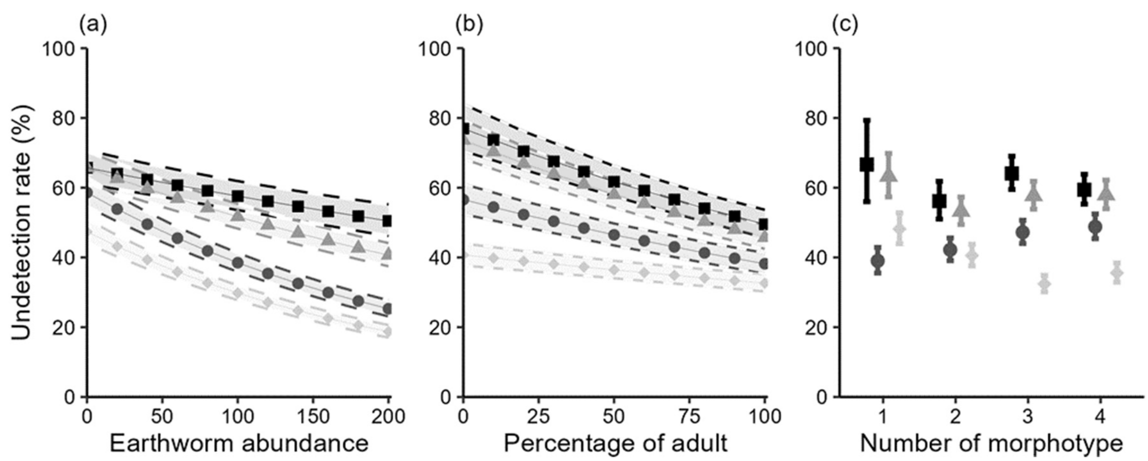

Fig. 6. Predicted Undetected Rate (UR) ± standard deviation across (a) the total abundance of earthworms, (b) the percentage of adult individuals, and (c) the diversity of earthworm morphotypes per plot. Earthworm morphotypes are represented using different symbols: EPI (epigeics, squares), ANE_RA (anecics with a red anterior, circles), ANE_BA (anecics with a black anterior, triangles), and END (endogeics, diamonds).

occurred when participants inadvertently included non-earthworm entities, such as insect larvae. However, total earthworm abundance is not always a good indicator of management systems (Pelosi et al., 2009; Cluzeau et al., 2012), and details of morphotypes are often more helpful in assessing the effects of environmental pressures.

Based on nearly 50,000 individuals, we observed a strong relationship between the total earthworm counts recorded by participants and specialists, with an overall morphotype misclassification rate (MR) of 28 %. While these results are encouraging, the reliability of classifications remains context-dependent and should be evaluated with regard to the intended application of the data. The 20.9 % misidentification rate in butterfly identification by non-specialists, as reported by Bergerot and Fontaine (2024), shows that such error rates are standard even in well-studied taxa. Potential biases in participant engagement may have influenced these results; for instance, the 27 % of participants who sent samples to the laboratory may have been more committed or attentive to the data collection process, potentially leading to more accurate results. Nevertheless, this level of reliability highlights the potential value of citizen science data using the morphotype approach (Stroud, 2019) for monitoring earthworm community dynamics and soil health. Morphotypes can act as proxies for various life strategies, with each type responding differently to distinct environmental pressures and contributing differently to soil functioning (Briones and Schmidt, 2017; Huang et al., 2020). This difference in life strategies enhances their usefulness for detecting changes in soil health. Thus, when included, citizen scientists are able to make meaningful contributions to assessments of ecosystem state and degradation in relation to land management. The 28 % MR necessitates caution in result interpretation, particularly when faced with factors that may heighten unreliability. In this context, endogeics, the most collected morphotype with ca 25,000 individuals, exhibited the lowest MR at 13 %. This suggests that participants were relatively proficient at identifying this morphotype. This high level of accuracy is likely attributable to the distinctive lack of pigmentation in endogeics, which sets them apart from the other morphotypes. Conversely, epigeics, anecics with a red anterior, and anecics with a black anterior had higher MR and UR rates (29–40 %). The overlapping morphological traits of these morphotypes likely contributed to these higher error rates. This highlights the necessity for specific training or improved differentiation characteristics. However, it could also indicate the need to include additional morphotypes in the classification system or refine the existing system in order to reduce MR in future studies. Additionally, we propose that the development of correction methods could be employed to adjust the participant-identified morphotype abundances (Isaac et al., 2014; Freitag et al., 2016), based on the MR for each morphotype and general patterns of confusion between morphotypes. The correction methods would help to recalibrate the reported data to more accurately reflect the abundance of each morphotype, thereby enhancing the robustness of data analysis and increasing the reliability of conclusions drawn. However, reducing the observed UR of 32 %, ranging across morphotypes from 21 % to 46 %, is a crucial challenge to increase the robustness of citizen science research. These high values underscore a critical need for strategies to understand and address the factors contributing to the higher UR, as overlooking this aspect may introduce significant biases and affect the integrity of research findings. While the 'law of large numbers' suggests that these errors could be smoothed out with a vast number of observations (Kosmala et al., 2016; Szabo et al., 2023), it is crucial to acknowledge that this statistical principle may obscure the persistent biases that can distort ecological understanding and interpretations of earthworm community dynamics.

4.2. Greater participant practice is valuable

In the present study, the cumulative number of sampled plots and the cumulative number of earthworms sampled per plot influenced the MR and UR, unlike the cumulative number of years that a participant had been involved in the 500 ENI network. These findings suggest that practical experience, rather than the number of years of participation in the network, plays a crucial role in the reliability of earthworm classification skills (Jiguet, 2009; Crall et al., 2011; Kelling et al., 2015). Overall, an increase in the cumulative number of plots sampled and the cumulative number of earthworms sampled per plot generally reduced MR and UR, indicating an essential role of evidence-based practice and/or growing familiarity with morphotype classification. However, an exception was observed for anecic earthworms with a red anterior, where an increase in the cumulative number of earthworms sampled per plot slightly increased MR. This trend may be due to their morphological similarity to epigeic and anecic earthworms with a black anterior, particularly during juvenile stages, since these three groups often share size and dark pigmentation of an anterior-posterior colour gradient (at least for those species occurring in agricultural land in the study region). Such resemblances could lead participants to misidentify these morphotypes persistently, irrespective of the cumulative number of earthworms identified.

The critical role of evidence-based practice and/or growing familiarity with morphotype classification can be extrapolated to specialists in the field of earthworm taxonomy, where varying degrees of experience also play a significant role in the accuracy of species classification. As with participants, earthworm specialists continuously practice their skills in the classification of a wide array of earthworm species, highlighting the universal importance of practice-based experience in accurately identifying earthworms. While it is crucial to focus on new members of the network, who typically have less practical experience, we must also consider participants who engage infrequently in classification activities, as they may also be prone to errors. This approach optimizes resource allocation by focusing on those who require the most guidance. However, considering the high annual turnover commonly observed in such networks (Andrade et al., 2021), it becomes imperative to implement continuous and reinforced training programmes to accommodate new participants each year. This could include specialist-led training sessions in addition to mentorship approaches, where seasoned participants offer guidance to newcomers. Such interactions not only enhance participants' skills but could also provide opportunities to learn about science and engage in scientific practices, and may significantly impact citizens' awareness and attitudes toward environmental issues (Bonney et al., 2014; Locritani et al., 2019; Abhijith et al., 2024). These aspects may also support long-term engagement by reinforcing the feeling of contributing meaningfully to scientific and environmental goals. Additionally, mobile applications with machine learning or cross-validation (Serret et al., 2019; Jäckel et al., 2023) could improve classification reliability, making participation more accessible and impactful.

Citizen science initiatives on earthworm communities have primarily focused on agricultural lands, where participants are directly engaged in soil management and seek to understand biodiversity function, mainly through metrics such as abundance or biomass of earthworms and their functional groups (Baker et al., 1997; Stroud, 2019; Billaud et al., 2021; Burton and Cameron, 2021). In contrast, citizen science in natural environments often involves naturalists and conservationists interested in specific species within valuable habitats, necessitating identification to the species level, while quantification of abundance or biomass is less critical. Despite challenges such as the scarcity of soil fauna specialists, citizen networks in natural environments could provide valuable baseline data to contextualize agricultural findings and assess restoration impacts. A key challenge remains identifying effective incentives for land managers to engage in long-term monitoring, which could also inform strategies to encourage broader citizen participation.

4.3. Challenges in classifying earthworms from particular communities

Our results highlighted that an increase in the proportion of adult earthworms generally reduced the MR and UR (except for the MR of anecics with a red anterior). This trend is largely explained by the fact that adults, with their distinct morphological traits (body size, tubercula, clitellum), are more easily recognizable than juveniles, which helps to differentiate morphotypes. Moreover, the number of morphotypes in a community reduced MR for all morphotypes. Thus, the presence of contrasting patterns seems to help classify earthworms more accurately. Furthermore, an overall increase in earthworm abundance lowered the MR and UR (except for the MR of epigeics). This trend may partly stem from the increased probability of encountering adults and a larger number of morphotypes in the community, with the consequences explained above. Additionally, a community with many individuals potentially hosts a wider range of phenotypes within each morphotype. This would provide a more distinct set of characteristics, accentuating the differences between the morphotypes and aiding in more accurate classification by participants. For epigeics, the inverse trend might be attributed to the lower abundance of epigeic individuals in agricultural soils (Cluzeau et al., 2012), suggesting that the higher cumulative number of earthworms sampled increases the likelihood of overclassification (thereby increasing MR). Overall, our study highlights the necessity for participants to sample a diverse range of habitats, when feasible, as this approach is crucial for enhancing the overall abundance of earthworms, the proportion of adults, and the chances of encountering a wide array of morphotypes. In addition, it would be advantageous to encourage participants to sample during the most favorable periods for detecting reliable total and adult abundances, and then optimize morphotype detection. If resources are limited, emphasizing the need to conduct earthworm sampling when conditions, particularly climatic conditions, are most favorable (Whalen, 2004; Eggleton et al., 2009), may involve adapting sampling periods each year, to account for local or regional climatic specificities, rather than simply relying on "autumn" or "spring" as the optimal period. Furthermore, proposing sampling protocols that inherently collect more earthworms, for instance, by increasing the sampling surface area without significantly adding to time constraints, can also be effective (Schmidt, 2001; Bartlett et al., 2010; Pelosi et al., 2014). Such strategic adjustments in sampling periods, protocols, and habitat diversity could greatly reduce MR and UR in participatory science projects, contributing to a more comprehensive understanding of earthworm distribution.

However, the number of morphotypes within the communities did not show a clear effect on the UR. There was no distinct trend for epigeics and anecics with a black anterior. Whereas for anecics with a red anterior, an increase in the number of morphotypes tended to increase UR, and for endogeics, the opposite was observed. These findings suggest that the community composition of earthworms in each sample plays a significant role in the reliability of how citizen scientists classify earthworms. This raises interesting issues about the cognitive process of classification in participatory science: the presence of a high number of different morphotypes may act as a reference framework, aiding in more accurate categorization. This underscores the need for more comprehensive training and reference materials for citizen scientists, particularly in areas where morphotype diversity is low. Improved training and clearer identification resources may not only increase data reliability, but also boost participants' engagement by making the task more accessible and rewarding.

5. Conclusions

Our study has demonstrated significant correlations between data obtained by citizens and specialists on earthworm abundance, either as total numbers or individual morphotypes, confirming that non-specialist data can be encouragingly reliable. However, our findings also reveal different misclassification and undetected rates between morphotypes, related to the challenges posed by the morphotype assignment by non-specialist identifiers. Our analysis indicates that these errors are influenced by practical field experience, such as the number of plots a participant has sampled, rather than by the number of years they have been involved in the program, which did not show a significant effect. While a greater cumulative number of earthworms collected per plot can increase reliability for most morphotypes, this relationship is not applicable to anecic earthworms with a red anterior. We also found that less diverse and juvenile-dominated communities present greater challenges for accurate classification. Additional learning support and guidance to participants with less experience will further improve the classification process. By fostering improved participant training and adapting sampling strategies to diverse environmental conditions, citizen science can become an even more effective tool in the understanding and conservation of soil ecosystems.

CRediT authorship contribution statement

Kevin Hoeffner: Writing – original draft, Visualization, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Benjamin Bergerot:** Writing – original draft, Supervision, Formal analysis, Conceptualization. **Kevin R. Butt:** Writing – original draft, Conceptualization. **Sylvain Gérard:** Writing – original draft, Conceptualization. **Céline Pelosi:** Writing – original draft, Supervision, Project administration, Conceptualization. **Guénola Pérès:** Writing – original draft, Supervision, Project administration, Conceptualization. **Maria J.I. Briones:** Writing – original draft, Conceptualization. **Thibaud Decaëns:** Writing – original draft, Conceptualization. **Natacha Delaveau:** Writing – original draft, Conceptualization. **Sarah Guillocheau:** Writing – original draft, Conceptualization. **Mickaël Hedde:** Writing – original draft, Conceptualization. **Hoël Hotte:** Writing – original draft, Conceptualization. **Renée-Claire Le Bayon:** Writing – original draft, Conceptualization. **Bart Muys:** Writing – original draft, Conceptualization. **Helen R.P. Phillips:** Writing – original draft, Conceptualization. **Maxime Poupelin:** Writing – original draft, Conceptualization. **Daniel Cluzeau:** Writing – original draft, Supervision, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The French Ministry of Agriculture developed the 500 ENI network under the Ecophyto framework with funding from the French Office for Biodiversity (Office Français de la Biodiversité). We extend our gratitude to all individuals who have contributed to data collection in the field and to those who have played a role in coordinating this extensive data network. Special thanks to Camilla Andrade for her pivotal role in coordinating the 500 ENI network from 2012 to 2018. This research is a product of the "LandWorm" group funded by the synthesis center CESAB of the French Foundation for Research on Biodiversity (FRB; www.fondationbiodiversite.fr). Helen R. P. Phillips was supported by the European Union's Horizon 2020 research and innovation program under the Marie Skłodowska-Curie grant agreement No. 101033214 (GloSoilBio).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apsoil.2025.106329.

Data availability

The data that has been used is confidential.

References

Abhijith, K., Kumar, P., Omidvarborna, H., Emygdio, A.P.M., McCallan, B., Carpenter-Lomax, D., 2024. Improving air pollution awareness of the general public through citizen science approach. Sustain. Horiz. 10, 100086. https://doi.org/10.1016/j.horiz.2023.100086.

Aceves-Bueno, E., Adeleye, A.S., Feraud, M., Huang, Y., Tao, M., Yang, Y., Anderson, S. E., 2017. The accuracy of citizen science data: a quantitative review. Bull. Ecol. Soc. Am. 98, 278–290.

Andrade, C., Villers, A., Balent, G., Bar-Hen, A., Chadoeuf, J., Cylly, D., Cluzeau, D., Fried, G., Guillocheau, S., Pillon, O., Porcher, E., Tressou, J., Yamada, O., Lenne, N., Jullien, J., Monestiez, P., 2021. A real-world implementation of a nationwide, long-term monitoring program to assess the impact of agrochemicals and agricultural practices on biodiversity. Ecol. Evol. 11, 3771–3793. https://doi.org/10.1002/ece3.6459.

Baker, G.H., Thumlert, T.A., Meisel, L.S., Carter, P.J., Kilpin, G.P., 1997. "Earthworms Downunder": a survey of the earthworm fauna of urban and agricultural soils in Australia. Soil biol. Biochem., 5th international symposium on earthworm. Ecology 29, 589–597. https://doi.org/10.1016/S0038-0717(96)00184-8.

Bartlett, M.D., Briones, M.J.I., Neilson, R., Schmidt, O., Spurgeon, D., Creamer, R.E., 2010. A critical review of current methods in earthworm ecology: from individuals to populations. Eur. J. Soil Biol. 46, 67–73.

Bayraktarov, E., Ehmke, G., O'Connor, J., Burns, E.L., Nguyen, H.A., McRae, L., Possingham, H.P., Lindenmayer, D.B., 2019. Do big unstructured biodiversity data mean more knowledge? Front. Ecol. Evol. 6, 426167.

Bender, S.F., Wagg, C., van der Heijden, M.G.A., 2016. An underground revolution: biodiversity and soil ecological engineering for agricultural sustainability. Trends Ecol. Evol. 31, 440–452. https://doi.org/10.1016/j.tree.2016.02.016.

Bergerot, B., Fontaine, B., 2024. Data quality of National Monitoring Schemes: filling the gap between specialists and the general public. Land 13 (8), 1252. https://doi.org/10.3390/land13081252.

Billaud, O., Vermeersch, R.-L., Porcher, E., 2021. Citizen science involving farmers as a means to document temporal trends in farmland biodiversity and relate them to agricultural practices. J. Appl. Ecol. 58, 261–273. https://doi.org/10.1111/1365-2664.13746.

Blouin, M., Hodson, M.E., Delgado, E.A., Baker, G., Brussaard, L., Butt, K.R., Dai, J., Dendooven, L., Peres, G., Tondoh, J.E., Cluzeau, D., Brun, J.-J., 2013. A review of earthworm impact on soil function and ecosystem services: earthworm impact on ecosystem services. Eur. J. Soil Sci. 64, 161–182.

Bonney, R., Shirk, J.L., Phillips, T.B., Wiggins, A., Ballard, H.L., Miller-Rushing, A.J., Parrish, J.K., 2014. Citizen science. Next steps for citizen science. Science 343, 1436–1437. https://doi.org/10.1126/science.1251554.

Bottinelli, N., Capowiez, Y., 2021. Earthworm ecological categories are not functional groups. Biol. Fertil. Soils 57, 329–331.

Bottinelli, N., Hedde, M., Jouquet, P., Capowiez, Y., 2020. An explicit definition of earthworm ecological categories – Marcel Bouché's triangle revisited. Geoderma 372, 114361.

Bouché, M.B., 1972. Lombriciens de France: écologie et systématique, INRA-Annales de Zoologie Ecologie, Animale. ed. INRA, France.

Bouché, M.B., 1977. Strategies lombriciennes. Ecol. Bull. Soil organisms as components of ecosystems 25, 122–132.

Briones, M.J.I., Schmidt, O., 2017. Conventional tillage decreases the abundance and biomass of earthworms and alters their community structure in a global meta-analysis. Glob. Chang. Biol. 23, 4396–4419.

Brooks, M., Bolker, B., Kristensen, K., Maechler, M., Magnusson, A., McGillycuddy, M., Skaug, H., Nielsen, A., Berg, C., van, Bentham K., Sadat, N., Lüdecke, D., Lenth, R., O'Brien, J., Geyer, C.J., Jagan, M., Wiernik, B., Stouffer, D.B., 2023. glmmTMB: generalized linear mixed models using template model builder.

Brown, E.D., Williams, B.K., 2019. The potential for citizen science to produce reliable and useful information in ecology. Conserv. Biol. 33, 561–569. https://doi.org/10.1111/cobi.13223.

Brussaard, L., de Ruiter, P.C., Brown, G.G., 2007. Soil biodiversity for agricultural sustainability. Agric. Ecosyst. Environ. 121, 233–244. https://doi.org/10.1016/j.agee.2006.12.013. Biodiversity in Agricultural Landscapes: Investing without Losing

InterestSymposium on Agrobiodiversity at the First Open Science Conference of DIVERSITAS.
Burton, V.J., Cameron, E.K., 2021. Learning more about earthworms with citizen science. Front. Young Minds 8, 548525. https://doi.org/10.3389/frym.2020.548525.
Cluzeau, D., Guernion, M., Chaussod, R., Martin-Laurent, F., Villenave, C., Cortet, J., Ruiz-Camacho, N., Pernin, C., Mateille, T., Philippot, L., Bellido, A., Rougé, L., Arrouays, D., Bispo, A., Pérès, G., 2012. Integration of biodiversity in soil quality monitoring: baselines for microbial and soil fauna parameters for different land-use types. Eur. J. Soil biol. Bioindication in Soil Ecosystems 49, 63–72.
Cohn, J.P., 2008. Citizen science: can volunteers do real research? BioScience 58, 192–197. https://doi.org/10.1641/B580303.
Conrad, C.C., Hilchey, K.G., 2011. A review of citizen science and community-based environmental monitoring: issues and opportunities. Environ. Monit. Assess. 176, 273–291. https://doi.org/10.1007/s10661-010-1582-5.
Crall, A.W., Newman, G.J., Stohlgren, T.J., Holfelder, K.A., Graham, J., Waller, D.M., 2011. Assessing citizen science data quality: an invasive species case study. Conserv. Lett. 4, 433–442. https://doi.org/10.1111/j.1755-263X.2011.00196.x.
Dickinson, J.L., Zuckerberg, B., Bonter, D.N., 2010. Citizen science as an ecological research tool: challenges and benefits. Annu. Rev. Ecol. Evol. Syst. 41, 149–172. https://doi.org/10.1146/annurev-ecolsys-102209-144636.
Dickinson, J.L., Shirk, J., Bonter, D., Bonney, R., Crain, R.L., Martin, J., Phillips, T., Purcell, K., 2012. The current state of citizen science as a tool for ecological research and public engagement. Front. Ecol. Environ. 10, 291–297. https://doi.org/10.1890/110236.
Dormann, C.F., Elith, J., Bacher, S., Buchmann, C., Carl, G., Carré, G., Marquéz, J.R.G., Gruber, B., Lafourcade, B., Leitão, P.J., Münkemüller, T., McClean, C., Osborne, P.E., Reineking, B., Schröder, B., Skidmore, A.K., Zurell, D., Lautenbach, S., 2013. Collinearity: a review of methods to deal with it and a simulation study evaluating their performance. Ecography 36, 27–46. https://doi.org/10.1111/j.1600-0587.2012.07348.x.
Eggleton, P., Inward, K., Smith, J., Jones, D.T., Sherlock, E., 2009. A six year study of earthworm (Lumbricidae) populations in pasture woodland in southern England shows their responses to soil temperature and soil moisture. Soil Biol. Biochem. 41, 1857–1865.
FAO, I.. State of knowledge of soil biodiversity - status, challenges and potentialities: report 2020. FAO, Rome, Italy. 2020. https://doi.org/10.4060/cb1928en.
Forey, E., Barot, S., Decaëns, T., Langlois, E., Laossi, K.-R., Margerie, P., Scheu, S., Eisenhauer, N., 2011. Importance of earthworm-seed interactions for the composition and structure of plant communities: a review. Acta Oecol. 37, 594–603.
Freitag, A., Meyer, R., Whiteman, L., 2016. Strategies employed by citizen science programs to increase the credibility of their data. Citiz. Sci. Theory Pract. 1. https://doi.org/10.5334/cstp.6.
Geisen, S., Wall, D.H., van der Putten, W.H., 2019. Challenges and opportunities for soil biodiversity in the Anthropocene. Curr. Biol. 29, R1036–R1044. https://doi.org/10.1016/j.cub.2019.08.007.
Guerra, C.A., Heintz-Buschart, A., Sikorski, J., Chatzinotas, A., Guerrero-Ramírez, N., Cesarz, S., Beaumelle, L., Rillig, M.C., Maestre, F.T., Delgado-Baquerizo, M., Buscot, F., Overmann, J., Patoine, G., Phillips, H.R.P., Winter, M., Wubet, T., Küsel, K., Bardgett, R.D., Cameron, E.K., Cowan, D., Grebenc, T., Marín, C., Orgiazzi, A., Singh, B.K., Wall, D.H., Eisenhauer, N., 2020. Blind spots in global soil biodiversity and ecosystem function research. Nat. Commun. 11, 3870. https://doi.org/10.1038/s41467-020-17688-2.
Hartig, F., Lohse, L., 2022. DHARMa: Residual Diagnostics for Hierarchical (Multi-Level / Mixed) Regression Models.
Head, J.S., Crockatt, M.E., Didarali, Z., Woodward, M.-J., Emmett, B.A., 2020. The role of citizen science in meeting SDG targets around soil health. Sustainability 12, 10254. https://doi.org/10.3390/su122410254.
Hochachka, W.M., Fink, D., Hutchinson, R.A., Sheldon, D., Wong, W.-K., Kelling, S., 2012. Data-intensive science applied to broad-scale citizen science. Trends Ecol. Evol. 27, 130–137. https://doi.org/10.1016/j.tree.2011.11.006.
Hoeffner, K., Butt, K.R., Monard, C., Frazão, J., Pérès, G., Cluzeau, D., 2022. Two distinct ecological behaviours within anecic earthworm species in temperate climates. Eur. J. Soil Biol. 113, 103446. https://doi.org/10.1016/j.ejsobi.2022.103446.
Huang, W., González, G., Zou, X., 2020. Earthworm abundance and functional group diversity regulate plant litter decay and soil organic carbon level: a global meta-analysis. Appl. Soil Ecol. 150, 103473.
Isaac, N.J.B., van Strien, A.J., August, T.A., de Zeeuw, M.P., Roy, D.B., 2014. Statistics for citizen science: extracting signals of change from noisy ecological data. Methods Ecol. Evol. 5, 1052–1060. https://doi.org/10.1111/2041-210X.12254.
Jäckel, D., Mortega, K.G., Darwin, S., Brockmeyer, U., Sturm, U., Lasseck, M., Moczek, N., Lehmann, G.U.C., Voigt-Heucke, S.L., 2023. Community engagement and data quality: best practices and lessons learned from a citizen science project on birdsong. J. Ornithol. 164, 233–244. https://doi.org/10.1007/s10336-022-02018-8.
Jiguet, F., 2009. Method learning caused a first-time observer effect in a newly started breeding bird survey. Bird Study 56, 253–258. https://doi.org/10.1080/00063650902791991.
Kelling, S., Johnston, A., Hochachka, W.M., Iliff, M., Fink, D., Gerbracht, J., Lagoze, C., Sorte, F.A.L., Moore, T., Wiggins, A., Wong, W.-K., Wood, C., Yu, J., 2015. Can observation skills of citizen scientists be estimated using species accumulation curves? PLoS One 10, e0139600. https://doi.org/10.1371/journal.pone.0139600.
Kosmala, M., Wiggins, A., Swanson, A., Simmons, B., 2016. Assessing data quality in citizen science. Front. Ecol. Environ. 14, 551–560. https://doi.org/10.1002/fee.1436.
Lavelle, P., Decaëns, T., Aubert, M., Barot, S., Blouin, M., Bureau, F., Margerie, P., Mora, P., Rossi, J.-P., 2006. Soil invertebrates and ecosystem services. Eur. J. Soil biol., ICSZSoil animals and ecosystems ServicesProceedings of the XIVth international colloquium on soil biology 42. Supplement 1, S3–S15. https://doi.org/10.1016/j.ejsobi.2006.10.002.
Liu, T., Chen, X., Gong, X., Lubbers, I.M., Jiang, Y., Feng, W., Li, X., Whalen, J.K., Bonkowski, M., Griffiths, B.S., Hu, F., Liu, M., 2019. Earthworms coordinate soil biota to improve multiple ecosystem functions. Curr. Biol. 29, 3420–3429.e5. https://doi.org/10.1016/j.cub.2019.08.045.
Locritani, M., Merlino, S., Abbate, M., 2019. Assessing the citizen science approach as tool to increase awareness on the marine litter problem. Mar. Pollut. Bull. 140, 320–329. https://doi.org/10.1016/j.marpolbul.2019.01.023.
Martay, B., Pearce-Higgins, J.W., 2018. Using data from schools to model variation in soil invertebrates across the UK: the importance of weather, climate, season and habitat. Pedobiologia 67, 1–9. https://doi.org/10.1016/j.pedobi.2018.01.002.
Pelosi, C., Bertrand, M., Roger-Estrade, J., 2009. Earthworm community in conventional, organic and direct seeding with living mulch cropping systems. Agron. Sustain. Dev. 29, 287–295. https://doi.org/10.1051/agro/2008069.
Pelosi, C., Chiron, F., Dubs, F., Hedde, M., Ponge, J.-F., Salmon, S., Cluzeau, D., Nélieu, S., 2014. A new method to measure allyl isothiocyanate (AITC) concentrations in mustard—comparison of AITC and commercial mustard solutions as earthworm extractants. Appl. Soil Ecol. 80, 1–5. https://doi.org/10.1016/j.apsoil.2014.03.005.
Phillips, H.R.P., Guerra, C.A., Bartz, M.L.C., Briones, M.J.I., Brown, G., Crowther, T.W., Ferlian, O., Gongalsky, K.B., van den Hoogen, J., Krebs, J., Orgiazzi, A., Routh, D., Schwarz, B., Bach, E.M., Bennett, J.M., Brose, U., Decaëns, T., König-Ries, B., Loreau, M., Mathieu, J., Mulder, C., van der Putten, W.H., Ramirez, K.S., Rillig, M.C., Russell, D., Rutgers, M., Thakur, M.P., de Vries, F.T., Wall, D.H., Wardle, D.A., Arai, M., Ayuke, F.O., Baker, G.H., Beauséjour, R., Bedano, J.C., Birkhofer, K., Blanchart, E., Blossey, B., Bolger, T., Bradley, R.L., Callaham, M.A., Capowiez, Y., Caulfield, M.E., Choi, A., Crotty, F.V., Crumsey, J.M., Dávalos, A., Diaz Cosin, D.J., Dominguez, A., Duhour, A.E., van Eekeren, N., Emmerling, C., Falco, L.B., Fernández, R., Fonte, S.J., Fragoso, C., Franco, A.L.C., Fugère, M., Fusilero, A.T., Gholami, S., Gundale, M.J., López, M.G., Hackenberger, D.K., Hernández, L.M., Hishi, T., Holdsworth, A.R., Holmstrup, M., Hopfensperger, K.N., Lwanga, E.H., Huhta, V., Hurisso, T.T., Iannone, B.V., Iordache, M., Joschko, M., Kaneko, N., Kanianska, R., Keith, A.M., Kelly, C.A., Kernecker, M.L., Klaminder, J., Koné, A.W., Kooch, Y., Kukkonen, S.T., Lalthanzara, H., Lammel, D.R., Lebedev, I.M., Li, Y., Jesus Lidon, J.B., Lincoln, N.K., Loss, S.R., Marichal, R., Matula, R., Moos, J.H., Moreno, G., Morón-Ríos, A., Muys, B., Neirynck, J., Norgrove, L., Novo, M., Nuutinen, V., Nuzzo, V., Mujeeb Rahman, P., Pansu, J., Paudel, S., Pérès, G., Pérez-Camacho, L., Piñeiro, R., Ponge, J.-F., Rashid, M.I., Rebollo, S., Rodeiro-Iglesias, J., Rodríguez, M.Á., Roth, A.M., Rousseau, G.X., Rozen, A., Sayad, E., van Schaik, L., Scharenbroch, B.C., Schirrmann, M., Schmidt, O., Schröder, B., Seeber, J., Shashkov, M.P., Singh, J., Smith, S.M., Steinwandter, M., Talavera, J.A., Trigo, D., Tsukamoto, J., de Valença, A.W., Vanek, S.J., Virto, I., Wackett, A.A., Warren, M.W., Wehr, N.H., Whalen, J.K., Wironen, M.B., Wolters, V., Zenkova, I.V., Zhang, W., Cameron, E.K., Eisenhauer, N., 2019. Global distribution of earthworm diversity. Science 366, 480–485. https://doi.org/10.1126/science.aax4851.
R Core Team, 2023. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna.
Rosa, I.M.D., Purvis, A., Alkemade, R., Chaplin-Kramer, R., Ferrier, S., Guerra, C.A., Hurtt, G., Kim, H., Leadley, P., Martins, I.S., Popp, A., Schipper, A.M., van Vuuren, D., Pereira, H.M., 2020. Challenges in producing policy-relevant global scenarios of biodiversity and ecosystem services. Glob. Ecol. Conserv. 22, e00886. https://doi.org/10.1016/j.gecco.2019.e00886.
Rutgers, M., Orgiazzi, A., Gardi, C., Römbke, J., Jänsch, S., Keith, A.M., Neilson, R., Boag, B., Schmidt, O., Murchie, A.K., Blackshaw, R.P., Pérès, G., Cluzeau, D., Guernion, M., Briones, M.J.I., Rodeiro, J., Piñeiro, R., Cosín, D.J.D., Sousa, J.P., Suhadolc, M., Kos, I., Krogh, P.-H., Faber, J.H., Mulder, C., Bogte, J.J., Wijnen, H.J. van, Schouten, A.J., Zwart, D. de, 2016. Mapping earthworm communities in Europe. Appl. Soil Ecol. 97, 98–111.
Schelfhout, S., Mertens, J., Verheyen, K., Vesterdal, L., Baeten, L., Muys, B., De Schrijver, A., 2017. Tree species identity shapes earthworm communities. Forests 8, 85. https://doi.org/10.3390/f8030085.
Schmidt, O., 2001. Time-limited soil sorting for long-term monitoring of earthworm populations. Pedobiologia 45, 69–83. https://doi.org/10.1078/0031-4056-00069.
Serret, H., Deguines, N., Jang, Y., Lois, G., Julliard, R., 2019. Data quality and participant engagement in citizen science: comparing two approaches for monitoring pollinators in France and South Korea. Citiz. Sci. Theory Pract. 4, 22.
Singh, J., Cameron, E., Reitz, T., Schädler, M., Eisenhauer, N., 2021. Grassland management effects on earthworm communities under ambient and future climatic conditions. Eur. J. Soil Sci. 72, 343–355. https://doi.org/10.1111/ejss.12942.
Steger, C., Butt, B., Hooten, M.B., 2017. Safari science: assessing the reliability of citizen science data for wildlife surveys. J. Appl. Ecol. 54, 2053–2062. https://doi.org/10.1111/1365-2664.12921.
Stroud, J.L., 2019. Soil health pilot study in England: outcomes from an on-farm earthworm survey. PLoS One 14, e0203909. https://doi.org/10.1371/journal.pone.0203909.
Szabo, J.K., Forti, L.R., Callaghan, C.T., 2023. Large biodiversity datasets conform to Benford's law: implications for assessing sampling heterogeneity. Biol. Conserv. 280, 109982. https://doi.org/10.1016/j.biocon.2023.109982.
Theobald, E.J., Ettinger, A.K., Burgess, H.K., DeBey, L.B., Schmidt, N.R., Froehlich, H.E., Wagner, C., HilleRisLambers, J., Tewksbury, J., Harsch, M.A., Parrish, J.K., 2015. Global change and local solutions: tapping the unrealized potential of citizen science

for biodiversity research. Biol. Conserv. 181, 236–244. https://doi.org/10.1016/j.biocon.2014.10.021.

Troudet, J., Grandcolas, P., Blin, A., Vignes-Lebbe, R., Legendre, F., 2017. Taxonomic bias in biodiversity data and societal preferences. Sci. Rep. 7, 9132. https://doi.org/10.1038/s41598-017-09084-6.

Whalen, J.K., 2004. Spatial and temporal distribution of earthworm patches in corn field, hayfield and forest systems of southwestern Quebec, Canada. Appl. Soil Ecol. 27, 143–151. https://doi.org/10.1016/j.apsoil.2004.04.004.