Are earthworms really in decline? Representative data and rigorous models are needed to assess large-scale, long-term trends in earthworm populations

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Abstract

Declines in aboveground invertebrates have been reported widely but similar assessments belowground are rare. A recent quantitative study aimed to address this gap, presenting findings which suggested alarming long-term declines in earthworm abundance in the UK. Estimating temporal trends in abundance from diverse sources of data presents many challenges and there is a need for rigour toward inference. However, a comprehensive review of the published dataset revealed numerous issues including extensive errors, omissions and various problematic aspects of the data and modelling. For the present study, we have revised the published dataset, with data from 70 of 91 original sources being corrected and/or amended, and augmented with data from additional sources. Reanalysing the revised and augmented datasets and assessing the risk of bias for estimating temporal trends, we demonstrate that the original conclusions are not robust and that the large-scale declines suggested are not supported by the corrected data. The importance of earthworms for soil functional processes and as a food source for animals is well established and therefore significant declines would have critical ecological implications. It is conceivable that earthworm populations in the UK may have declined to some extent in particular environmental contexts, however sound conclusions on temporal trends must be based on correct and representative data and rigorous analyses. We highlight factual errors, omissions and methodological flaws in the original study and appeal to improve data collation, enhance meta-data and encourage long-term monitoring to develop a sound understanding of trends in earthworm populations and typical variability observed under different environmental contexts.

1. Introduction

Declines in populations and diversity have been reported widely for aboveground invertebrates [1-4], but similar assessments for belowground invertebrates are rare. Earthworms dominate the biomass of belowground invertebrates in temperate systems and the importance of earthworms for functional processes in many soils has long been recognised (e.g., 5-6). There have been significant international efforts to gather data on earthworms and associated environmental conditions toward understanding the main drivers of community metrics and predictive mapping of these; in particular, a European-scale earthworm mapping by Rutgers et al. [7] and global assessments by Johnston [8] and Phillips et al. [9]. However, few long-term earthworm datasets with appropriate spatial and temporal resolution exist that allow a robust assessment of long-term trends in species' populations and overall abundance.

Combining different datasets is one approach that attempts to overcome the data limitation. A recent study by Barnes et al. [10] collated selected historic data on earthworm abundance in the UK from various published sources with sampling between 1928 and 2018, derived standardised abundance values, and modelled these using Generalized Linear Mixed Models (GLMMs) to assess temporal changes, in different habitats and accounting for other factors (e.g., sampling method, depth of sampling). These authors reported the notable finding that earthworm abundance in the UK may have undergone long-term decline by 1.6-2.1% per year (equivalent to a 33-41% decline over 25 years) and that these were greatest in broadleaved woodlands (5.7% decline per annum and 77% over 25 years). If they were an accurate reflection of the situation, these are alarming statistics. However, such approaches bringing together diverse datasets are not without their limitations and problems for inference [11-12] and, therefore, rigour in data and model scrutiny is essential.

One key issue is that if the error changes over time then the estimated trend may be wrong. Another significant issue in making descriptive inference from data collated from published studies and other datasets is that they represent a non-probability sample which can lead to biased estimates [12].

This issue may be exacerbated when such data come from a small pool of sources with disparate geographies, without sufficient representation of different driving variables. There is also a risk of bias for temporal trends with potential for confounding space and time [11,13]. Furthermore, there is a range of other risks collating data for meta-study analyses such as errors in data transcription, overlapping or duplicated data, inadequate resolution of geographic location and inconsistency in taxonomic resolution. Gaume and Desquilbet [14] highlighted these issues and others in a comprehensive review of studies included in a database of invertebrate abundance and biomass, used to analyse temporal trends.

The ambition to understand whether there are long-term temporal trends in earthworm populations is welcome, and the effort to collate such data is a significant undertaking. However, evaluating the dataset [15] and approach used to model earthworm abundance [10], we uncovered various problems that undermine their conclusions. In the current study, we have revised the earthworm dataset from [15] and reanalysed using the same modelling approach, then repeated this with an augmented dataset including additional data from recent studies. We compare the outputs of the original and new analyses and assess representativeness and context of data sources in the original dataset. Furthermore, we discuss issues and considerations in collating such data, model requirements to account for other processes and dependencies, and the remaining need for more appropriate analyses with refined data.

2. Methods

2.1 *Evaluation and revision of earthworm dataset*

The original dataset [15] contains data on earthworm and tipulid larvae abundance, standardised to 1 m^2, including 2210 rows with standardised earthworm abundance (59 rows have no value for either earthworm or tipulid abundance). Accompanying data include start year, end year, broad habitat (e.g., Farmland), fine habitat (e.g., Arable), location (typically a 10 km grid reference code), broad method (e.g., Surface), fine method (e.g., Formalin), number of samples, area of a sample, sample size (i.e., a product of the number of samples and area of a sample), sample diameter, sample depth and season of sampling. We checked all these data against the cited, published data sources, and associated literature, and produced a dataset containing original and revised data [16]. To add traceability, columns were also added in this for a row identifier (UniqueID), text description of habitat (Habitat_described), location of data in source used to derive standardised earthworm abundance (Data_location), and whether the data was derived via a biomass conversion equation (Biomass_conversion). The revised dataset contains 1820 rows with standardised earthworm abundance and associated data, including 51 new rows (Unique ID 2775-2825; [16]) with data that had not been included but were found in studies from the original dataset. For various reasons (e.g., duplication of data across sources, inclusion of non-independent data, data only representing one or several species), 547 rows from the original dataset were omitted. In our results section (3.1 and 3.2), we summarise the main issues that were found with the dataset used in Barnes et al. [10]. All revisions, omissions and considerations are also documented by data source in Keith et al. [16].

2.2 *Dataset augmentation, reanalyses and risk of bias assessment*

The literature search described in Barnes et al. [10], while acknowledged as not attempting to be a full systematic review, appears to have evolved over time and the initial choice of journals for manual searching was subjective. Aside from theses, using refined search strings with recognised databases such as Web of Science should identify potential sources in the literature, including soil ecology, agricultural and other ecological journals likely to contain earthworm data (e.g. [17]). Data from several additional sources were added to the revised dataset, including data from known recently published papers and datasets with coverage of farmland, grassland and woodland habitats (see Table S3 in [16]); these resulted in an additional 236 rows (Unique ID 2826-3061; [16]).

Revised and revised+augmented (hereafter called augmented) earthworm datasets were reanalysed using the same GLMM approach as Barnes et al. [10] for Model 1, 3 and 4. Briefly, Model 1 includes Year as a continuous variable, Broad Habitat, Broad method, Season and Depth; Model 3 includes the same as Model 1 with the addition of an interactive term between Year and Broad Habitat; Model 4 includes the same as Model 3 with Fine Habitat replacing Broad Habitat. The original dataset was analysed to ensure reported outputs could be replicated. These analyses were conducted using the R package "glmmTMB" [18]. Point estimates, standard error and confidence intervals were produced with the *emtrends* function in the R package "emmeans" [19]. All statistical analyses were done in R (version 4.4.0; [20]).

We acknowledge that p-values and significance are not useful concepts in the presence of bias, since point estimates are wrong. A qualitative assessment of the data was undertaken to establish risk of bias in the modelled outputs. A key question is whether "the same portion of the focal domain has been sampled over time"; if the answer is "no", then variation in abundance over time could be confounded by variation in space [11]. We mapped earthworm data by Location (i.e., 10 km grid reference where available) across time periods to evaluate the extent to which shifts in time were confounded by shifts in space.

Assessed trends over time are likely to be biased if there are changes in the types of locations that are sampled, with particularly high risk of bias if the locations that are sampled over time vary considerably in the characteristics that will also affect earthworm abundance. Key drivers of earthworm abundance include precipitation, soil chemistry, land cover and management practices (e.g., 9, 21-22). Modelling change over time should account for key drivers to reduce bias; unfortunately, few of the original data sources provide suitable data for this. Instead, we can assess the risk of bias through examining the shifts in the spatial spread of the data over time as a proxy, in addition to the relative changes in broad and fine habitat classifications. We can also consider the potential role of specific studies in determining the overall trends, and whether those studies can be seen as representative of the wider environment.

3. Results

3.1 *Data compilation errors*

General errors and misclassification: There are blank cells for standardised earthworm abundance in 59 rows across 7 sources, and cell calculation errors for 89 rows across 5 sources (with the original dataset including formulas which return '#REF!' for sample size and/or area). The number of replicates was incorrect for over 350 rows, while sample area was incorrect for over 250 rows. There are various instances of habitat, season and method being misclassified when compared to information in the original sources (see documented revisions in Keith et al. [16] for specific examples).

Miscalculation of standardised abundance: Amongst sporadic errors there are several instances where standardised abundance values are markedly different from that in the source, due to miscalculations. These include: the data from study 108 are one-tenth of the correct values, i.e., a calculation error of one magnitude (126 rows, Unique ID 2584-2709; [16]). In study 81, values did not equate to those presented in the source and were also much lower (8 rows, Unique ID 2063-2070; [16]). Data from study 109 are the median values per 20 cm × 20 cm soil pit rather than per 1 m^2, thus represent one twenty-fifth of the correct value (10 rows, Unique ID 2710-2719; [16]). On the other hand, in study 20, the data represents twice the standardised abundance because, as stated in the source, "density estimates from formalin sampling have been multiplied by two" (8 rows, Unique ID 429-436; [16]) and, in study 93, the standardised abundance values were inflated because they were upscaled despite standardisation in the source (14 rows, Unique ID 2296-2309; [16]). In study 51, the data were not standardised given the earthworm density and size of the sampling unit reported (2 rows, Unique ID 1106-1107; [16]).

Duplication of data: There are two types of duplication in the dataset. First, there are several instances where the same data has been derived from different published sources, predominantly from a thesis and subsequent published paper (e.g., study 15 and 67; study 20 and 34) or from different parts of the same source (for example, in thesis chapter and appendix in study 89). Second, the dataset contains duplication through different aggregations of the same data; there are cases where values are included for both individual timepoints/plots and values aggregated across timepoints/plots (e.g., study 70; Unique ID 1455-1643; [16]), and cases where values included are aggregated over space and aggregated over time (e.g., study 15; Unique ID 347-355; [16]).

Exclusion of zero values: Zero values are not included from several studies (e.g., study 13, 38, 42, 54, 75 and 88). In study 75, there are blank cells in 103 rows where earthworms were not recorded in a sample, and abundance should therefore be zero.

Data from selected species: Standardised abundance data from single species or groups of species are included. In study 38, some abundance data represent only *Aporrectodea caliginosa* and only *Lumbricus rubellus* (4 rows, Unique ID 735-738; [16]). In study 49, the biomass data used to estimate standardised abundance represents *Lumbricus* spp. In study 63, some abundance data represent only *A. caliginosa* and only *Lumbricus terrestris* (8 rows, Unique ID 1283-1290; [16]). In study 66, some abundance represents only *Aporrectodea rosea* (12 rows, Unique ID 1326-1337; [16]). In study 70, it appears that some abundance data are for *A. caliginosa* and *Allolobophora chlorotica* only (18 rows, Unique ID 1531-1546; [16]).

3.2 *Uncertainties and suitability of data*

Conversion equations for predicting earthworm abundance: Some earthworm abundance data (217 rows across 10 sources; [16]) are derived using predictive linear models (Equations 1 and 2 in [10], with the graphs of the data and linear models presented in Figures S2 and S3 of the Supplementary file). Equation 2, which predicts total earthworm abundance from wet biomass, is neither statistically nor ecologically sound because it has an intercept at 85 earthworms m^{-2}. Very low (or zero) biomass still results in at least 85 earthworms m^{-2} so standardised abundance will be inflated. The extreme of this is highlighted by several datapoints at or close to zero (e.g., study 42 and 103) but included in the dataset at or close to 85 earthworms m^{-2}, following the biomass predictive equation. While the r-squared value for Equation 2 is reasonable, there is considerable spread around the linear model; this may be partly due to compositional differences in earthworm communities and the fact that taxa differ substantially in their average biomass (e.g., *L. terrestris* will tend to have a much greater biomass than *A. caliginosa*). Equation 1, which predicts total earthworm abundance from abundance of adult earthworms, can suffer from similar inflation, though it is possible for juveniles to be present in the absence of adults, so it may be appropriate in particular instances. Furthermore, the published dataset does not indicate which data are derived via these equations, and therefore the extent of this issue cannot be assessed, as published. Study 49 uses this biomass-to-abundance conversion for a total of 71 datapoints for broadleaved woodlands (Unique ID 1020-1090; [16]). The biomass conversion equation is based on total earthworm abundance but this source reports data from *Lumbricus* only and since this taxon has a much larger average individual biomass, estimates of abundance will be inflated.

Unsuitable methods to quantify earthworm abundance: Several methods included are not appropriate for estimating earthworm abundance. First, the use of counting earthworm cast density ('Casts' as Fine Method; 44 rows in total) is not reliable, and this is not mentioned in Barnes et al. [10]. Second, the use of Tullgren extraction is not an appropriate method for earthworm sampling, as it is biased towards extraction of smaller organisms. For example, study 96 (Unique ID 2316-2351; [16]) reports associated biomass values at less than 0.02 g dry weight per core which are likely ascribed to only very small juvenile earthworms and enchytraeid worms (family Enchytraeidae).

Uncertainty of higher-level taxonomic resolution: Some studies that merely reported "Oligochaeta" or "Haplotaxida" where standardised abundance was very high probably reported enchytraeid worms. Again, study 96 (Unique ID 2316-2351; [16]), which used Tullgren extraction, reports associated biomass values at less than 0.02 g dry weight per core which are likely ascribed to only very small juvenile earthworms and enchytraeids. Study 87 (Unique ID 2222-2227; [16]) reported some exceptionally high abundances of Oligochaetes in winter samples but it is not stated whether these include both earthworms and enchytraeids – given the organic soil and high moisture in the wetland reedbed habitats of this study, it seems very likely that these values include enchytraeids.

*Sampling in unrepresentative or extreme conditions***:** Data are included from sampling under extreme or experimental conditions or from specific microhabitats that may not be representative of habitat conditions. Examples include: sampling timepoint after prolonged drought (Study 64); soils which have been sterilised and placed back in plots (Study 85); heavily trampled (Study 50) or experimental compaction treatment (Study 81); flooding by seawater following sea wall breaches (Study 55); sampling in and under cow pats (Study 31 and 75; [16]).

Issues with habitat classifications: The suitability of habitat classifications is not straightforward or clearly linked to sample-level habitat attributes for some data. In study 1 (Unique ID 1-21; [16]) the habitat is classified as Woodland-Scrub but the text description of the habitat in the source notes it as an "*area of scrub-grassland...dense vegetative cover dominated by grasses...bramble…and willow-herbs…interspersed with young oak trees…and thickets of hawthorn…blackthorn…and dogwood..*" and we note the composition of the earthworm community is typical of grassland. This raises serious doubts for definitively including these data as woodland and such nuance has critical implications when few studies represent a time period for a habitat class. In study 90, the habitat is classified as woodland (Unique ID 2272-2277; [16]) but the text describes these as an 'Arable Orchard' and a 'Grass Orchard'. The spacing and management of orchards suggests a woodland classification is not clear and the UKHab classification [23] places 'intensive orchards' under Arable and horticulture. Indeed, we note that the earthworm abundances of the arable orchard and grass orchard in this study are typical of arable and pasture systems, respectively. There are also instances where the historical context of a site and other factors are not considered. For example, in study 68 earthworms were sampled in a young Eucalyptus plantation on a reclaimed mining site with a sandy loam texture, as well as the reference (former) land use being incorrectly classified as broadleaved woodland (Unique ID 1386-1387; [16]); such conditions, atypical of woodland, may be better classified as industrial. Furthermore, uplands/moorland have areas of limestone and rough grassland, and historically farmed land, which support larger earthworm populations and more species than the matrix of truly organic soils [24] suggesting a need for more granular classification.

3.3 ***Reanalyses of revised and augmented dataset***

For the model of change over time across all habitat types (Model 1), compared to using the original dataset [15] where the effect of Year indicated a significant 1.6% decline per year (-0.016, p = 0.006), the effect of Year reduced toward zero and was non-significant using both the revised (-0.003, p = 0.582) and augmented datasets (-0.001, p = 0.843) (Figure 1; Table S1). This was the same for unweighted and weighted models (Table S1).

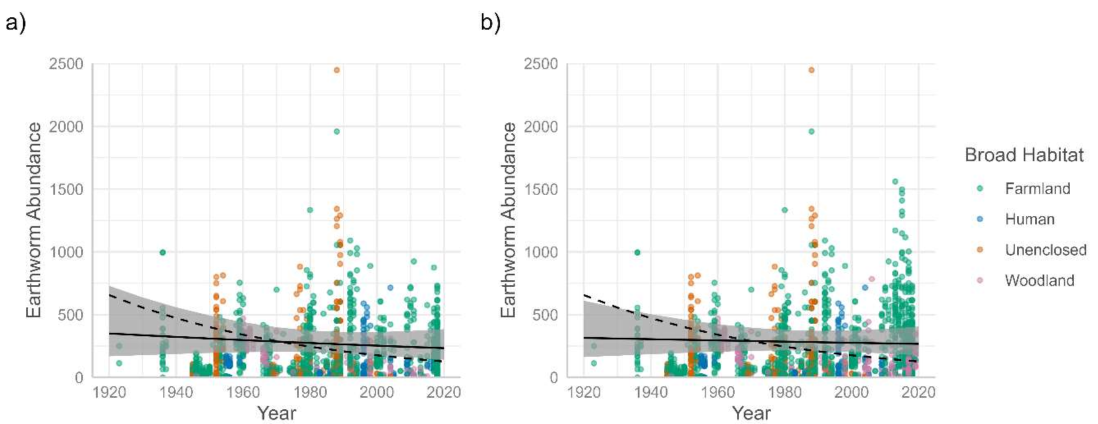

Fig 1. **The overall predicted change in standardised earthworm abundance per m^2 based on the revised dataset (a) and the revised plus augmented dataset (b).** Unweighted models only, mean estimate (black line) and 95% confidence interval (grey shading), with mean estimate from original dataset for comparison (dashed line).

For the unweighted model evaluating trends for specific Broad Habitats (Model 3), revising and augmenting the datasets reduced the estimated annual change (Figure 2). The Year × Farmland effect reduced toward zero and was non-significant using both the revised (-0.002, p = 0.581) and augmented datasets (-0.001, p = 0.911) (Figure 2; Table S2). The Year × Human effect remained insignificant for revised (-0.013, p = 0.209) and augmented datasets (-0.012, p = 0.269) (Figure 2; Table S2). The Year × Unenclosed effect, significantly positive with the original dataset, became slightly negative but non-significant using the revised (-0.002, p = 0.824) and augmented datasets (-0.004, p = 0.661) (Figure 2; Table S2). The Year × Woodland effect remained significant though was less negative using the revised (-0.036, p = 0.011) and augmented datasets (-0.029, p = 0.001) than the original dataset (Figure 2; Table S2). Data from study 49 (Lakhani & Satchell, 1970) represents 47% of broadleaved woodland data and issues with the data (see 3.2) and its representativeness (see 3.4) have been identified. Therefore, we tested the sensitivity of this model by removing this highly influential data set (study 49). Repeating Model 3 using the augmented dataset with study 49 removed, reduces the Year × Woodland effect (-0.019, p = 0.06) with the 95% confidence interval including zero, i.e., no change over time (Figure 2). Weighted models gave no significant Year × Broad Habitat effects using either revised or augmented datasets (Table S2).

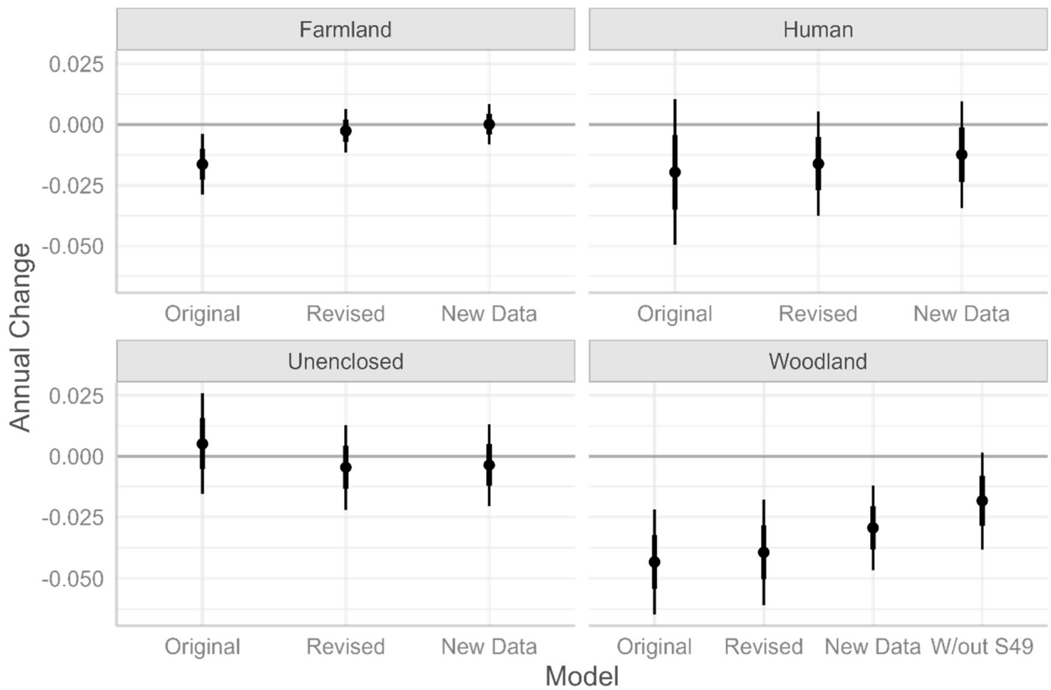

Fig 2. **The predicted annual change for each broad habitat category for the original, revised and augmented (‘New Data’) datasets, for unweighted models.** Model estimates are shown as the predicted mean (dot), the standard error (thick line) and the 95% confidence interval (thin line). The woodland broad habitat category also shows the effect of removing the influential study 49 (Lakhani and Satchell 1970, see Section 3.3 and 3.4).

For Model 4, unweighted models using both revised and augmented datasets altered the annual change trends for specific Fine Habitats (Figure 3). The Year × Arable effect remained insignificant using both the revised (0.007, $p = 0.253$) and augmented datasets (0.007, $p = 0.226$), though with marginal increases compared to marginal declines using the original model (Figure 3, Table S3). Similar was found for the annual change in pasture, with the Year x Pasture effect insignificant and closer to zero for revised (-0.001, $p = 0.872$) and augmented datasets (0.001, $p = 0.892$)(Figure 3, Table S3). Annual change in Grass and Mixed fine habitats remained slightly negative and slightly positive, respectively, with both revised and augmented datasets (Figure 3). Both Human fine habitats, with evidence of significant declines using the original dataset, had insignificant interactions with Year and tended toward zero using both revised and augmented datasets (Figure 3, Table S3). The Year × Moorland effect, compared to no change using the original dataset, showed a significant increase with revised (0.028, $p = 0.038$) and augmented datasets (0.029, $p = 0.027$), and with the overall annual change being greater (Figure 3, Table S3). For Mixed/Conifer Woodland, trends were similar using original, revised or augmented datasets (Figure 3, Table S3). The Year × Broadleaved Woodland effect remained significant though was less negative using the revised (-0.049, $p < 0.001$) and augmented datasets (-0.036, $p < 0.001$) than the original dataset (Figure 2; Table S3). Again, as for the Broad Habitat analyses, repeating Model 3 using the augmented dataset with study 49 removed, reduces the Year × Woodland effect (-0.025, $p = 0.022$) with the 95% confidence interval of annual change including zero (Figure 3). Weighted models presented mostly similar differences between fine habitat trends using original, revised and augmented datasets, with the exception of the Year x Wetland effects which indicated large significant declines using revised and augmented datasets (Table S3).

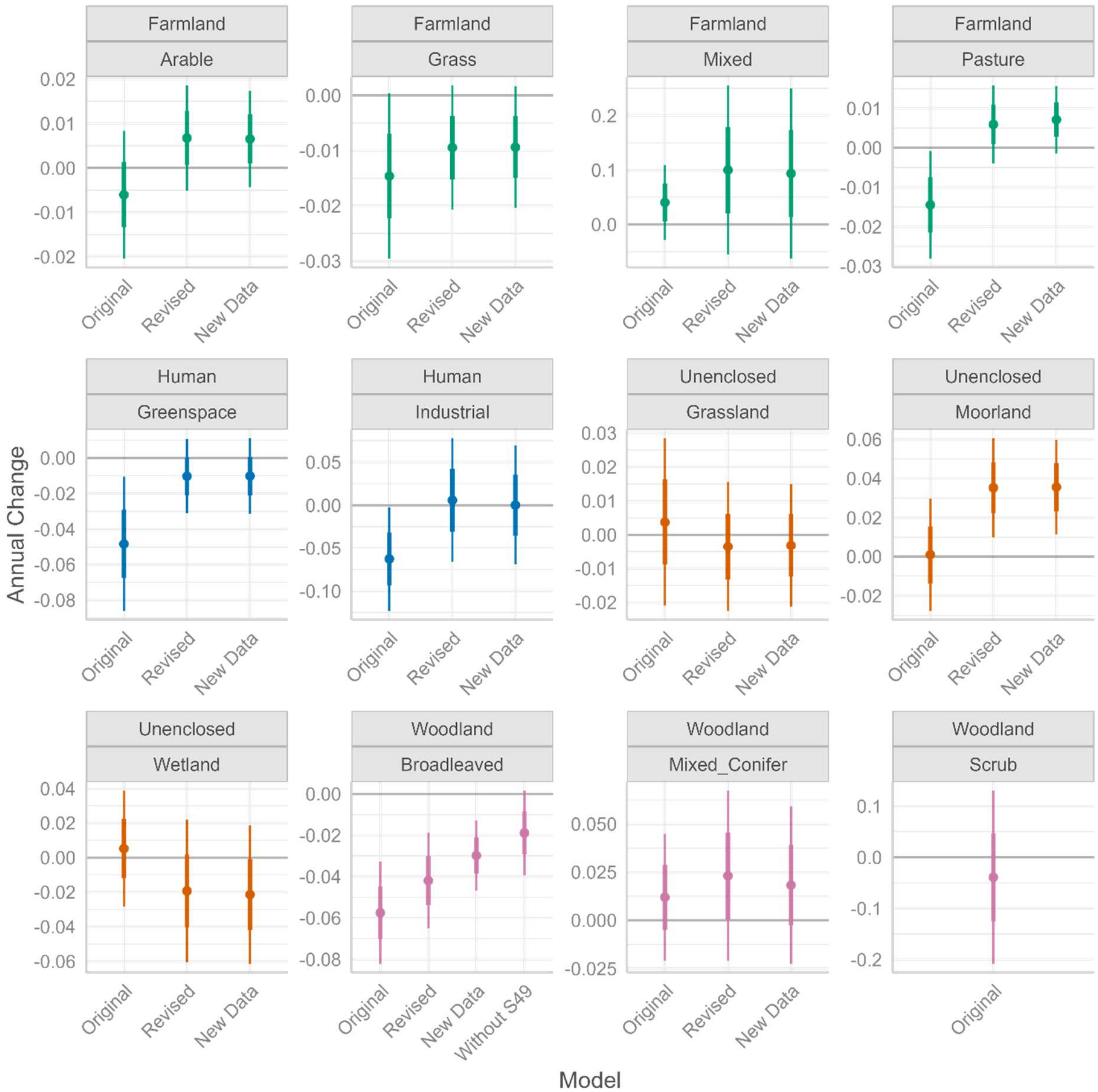

Fig 3. **The predicted annual change for each fine habitat category for the original, revised and augmented datasets, for unweighted models.** Model estimates are shown as the predicted mean (dot), the standard error (thick line) and the 95% confidence interval (thin line). The broadleaved woodland habitat category also shows the effect of removing the influential study 49 [25]. Following reclassification of habitat types there were insufficient scrub woodland observations to run the new models, so no results are shown.

As with the original dataset, there was consistently lower earthworm abundance under summer sampling and chemical extractant sampling methods across all models using the revised and augmented datasets, for both unweighted and weighted models (Table S1-3).

3.4 ***Risk of bias and representativeness***

Shifts in the types of locations that are included within the models can be seen both across and within habitats (Figure 4). There were no unenclosed habitats from the 21st century included within the original Barnes et al. model. Within the farmland categories, the most numerous and therefore the most influential on the overall model fit, there is a shift from being largely dominated by sampling within Scotland pre-1960 to being dominated by sampling within the Midlands and Eastern England later in the time series. The extreme in the original dataset is represented by the Scrub fine habitat data coming from two studies separated by 14 years (1976-78, 1992), with one in South-East England (Cambridgeshire, Unique ID 1-21 [16]) and one in North-East Scotland (Aberdeenshire, Unique ID 678 & 683 [16]). Consequently, the importance of different driving factors that influence earthworm abundance may change based on these confounded spatial and temporal differences

The sparsity within the early time series means that the modelled trends are vulnerable to being strongly influenced by earlier studies. Similarly, where there are few data sources, the influence of individual studies (and their environmental context) may be disproportional (Figure 5). This is particularly evident within the broadleaved woodland habitats, which had 152 datapoints from 13 sources in the original analyses (126 datapoints across 13 sources in revised analyses). Almost half of these datapoints (71 out of 152) came from one source - Lakhani and Satchell [25] who surveyed three broadleaved woodlands in the early 1960s and, from weekly sampling, recorded biomass, with Barnes et al. [10] deriving many estimates of relatively high earthworm abundances. However, this study specifically focused upon limestone woodlands, a relatively rare broadleaved woodland type within the UK. Limestone woodlands are expected to have higher earthworm abundances due to their optimal soil pH and high-quality litter inputs. In contrast, study 68 (Unique ID 1383-1394 [16]) sampled woodland sites with low pH soils (3.9 at Gisburn, 4.1 at Rogate) in which lower earthworm abundances would be expected. Therefore, the estimates of change within broadleaved woodland are confounded by the presence of changes in habitat suitability (i.e., soil pH) across the time series. As noted in section 3.2, there are also concerns about the appropriateness of the estimation of earthworm abundance from the data in Lakhani and Satchell [25]. Removing Lakhani and Satchell's study (Study 49) from the model presents 95% confidence intervals including zero for earthworm abundance trends in the woodland broad habitat or broadleaved woodland fine habitat types (section 3.3; Figures 2 and 3, respectively).

Similarly, diverse conditions may be found in other habitat classes with limited data. The Farmland-Grass habitat classification (162 datapoints from 19 sources in the original analyses; 123 datapoints across 19 sources in revised analyses) includes leys, margins, meadows, and set-aside; earthworm abundance in leys and set-aside will depend on time since disturbance, with recently ploughed leys having fewer earthworms.

Including habitat type as a predictor in the model may account for some of the changes in relative frequency of habitat types; however, it will not be capable of accounting for changes in the site characteristics that influence earthworm abundance on top of the habitat type changes. The clear shifts in spatial locations that occur over this time series indicate that any analysis of this data is at a high risk of bias.

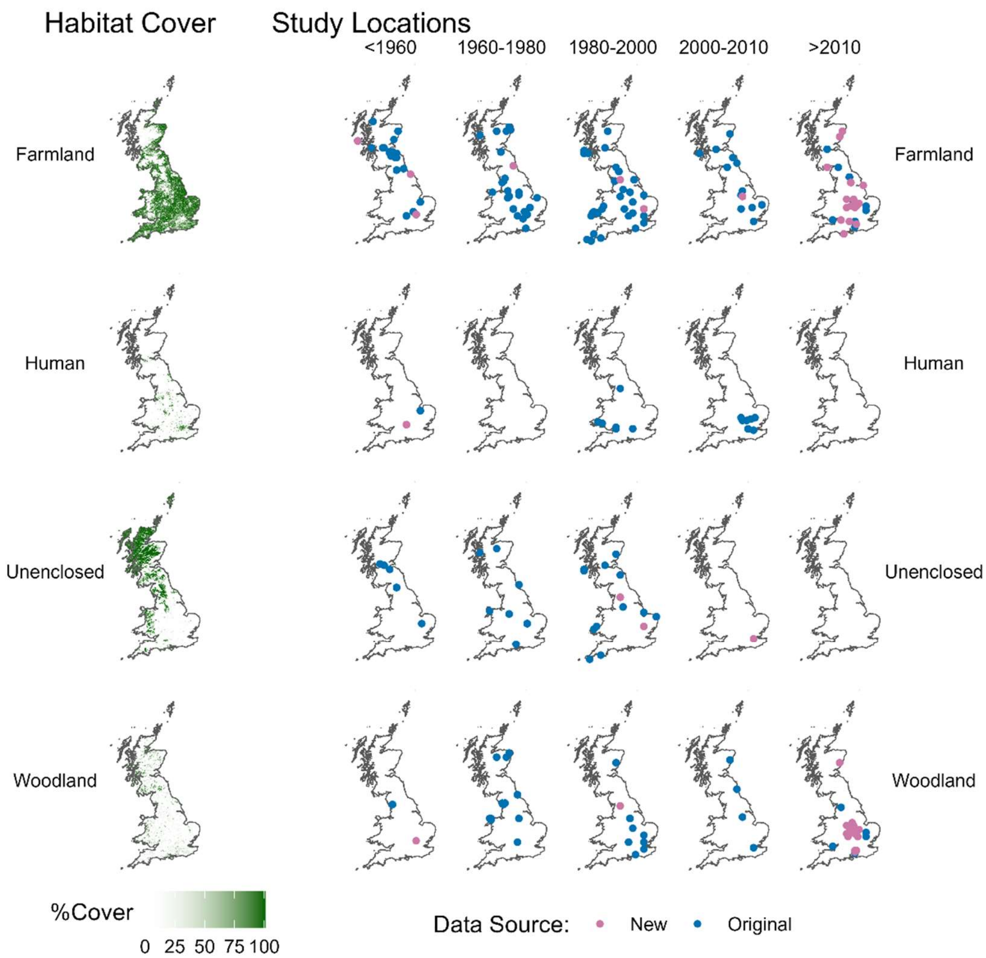

Fig 4. **The change in study locations over time within the four broad habitats (right), and the spread of those habitats across Great Britain (left).** Broad habitat cover data for Great Britain is sourced from the Land Cover Map 1990 [26]. Study locations are shown as the central point of the 10 km square, or in the cases where only the 100 km square is known the central point of the 100 km square. Studies whose locations are coarser than 100 km (i.e., estimates across England or Wales) are not included. Studies that were included in Barnes et al. [10] are shown in blue, additional studies are shown in pink. Broad habitat for each study is the reclassified version, which differs from the Barnes et al. [10] classification for ten points.

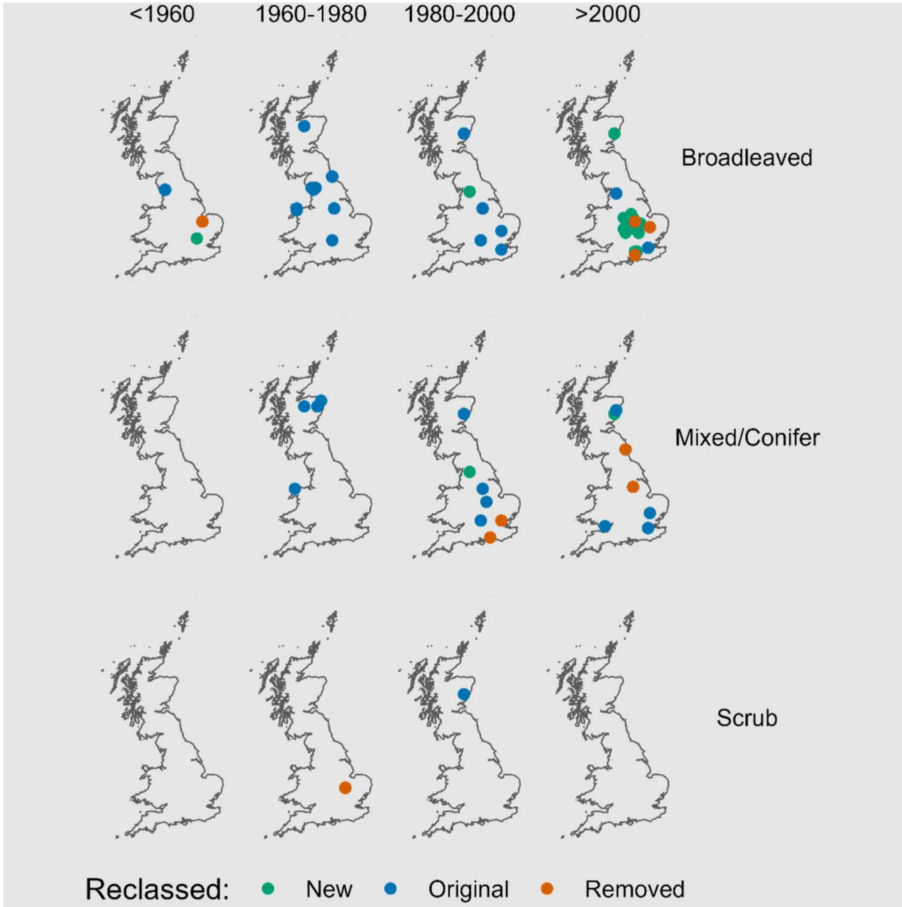

Fig 5. **The locations of the sites across the woodland fine habitats over time.** Studies are included if they were originally in Barnes et al. [10] as woodland sites or if they represent sites added from additional literature (green). Sites that were originally included in Barnes et al. [10] are coloured by whether they remained the fine habitat designated by Barnes et al (blue) or whether we have reclassified them as different habitats (orange).

4. Discussion

4.1 Clear challenges in derivation of meta-datasets

The findings of the recent study by Barnes et al. [10] suggest alarming long-term declines in earthworm abundance in the UK. Subsequently, evidence of declines in earthworm populations was selected as an emerging issue in the horizon scan of conservation issues [27]. The study's findings have also attracted wide attention from public media outlets (e.g., 28-30). Given the importance of earthworms for the dynamics of soil structure, hydrology and nutrient cycling, and as a major food source for other animals, significant declines would have critical ecological implications. It is therefore imperative that we have a sound understanding of trends in earthworm populations and typical variability observed under different environmental contexts.

Review of the dataset used by Barnes et al. [10] led to data from 70 of 91 sources being corrected and/or amended before reanalysis. Data compilation errors were extensive including basic and general errors and misclassification, miscalculation of standardised earthworm abundance, duplication of data, exclusion of zero values for earthworm abundance, and inclusion of data from selected earthworm species (rather than total earthworm abundance). There were also additional sources of uncertainty and problematic aspects of data suitability, including implausible conversion equations for predicting standardised earthworm abundance from biomass, unsuitable methods to quantify earthworm abundance, use of data at higher levels of taxonomic resolution (i.e., Haplotaxida, Oligochaeta), data from sampling in unrepresentative or extreme conditions, and issues with habitat classifications. Furthermore, the ability to inspect and validate collated data is helped by meta-data, but in the original dataset [15] there is no information associated with data to determine where exactly in a source the values were extracted (e.g., table or figure numbers) or how values are derived (calculations). This is a clear hurdle to re-use and re-analyses, and partly the reason for the time taken to review and revise the original dataset.

Gaume and Desquilbet [14] undertook a similar review of the InsectChange database [31] which had supported a meta-analysis reporting declines in the abundance of terrestrial insects. They found a total of 553 issues, affecting 161 out of 165 datasets, with various types of problem including errors, inconsistencies, methodological issues and information gaps. The review of Gaume and Desquilbet [14] and the revised dataset in the present study demonstrate the practical challenges of initiatives bringing together multiple datasets in a consistent framework. Collating diverse data from a relatively small pool of sources that differ in space and time also comes with significant inferential challenges, as noted in Barnes et al. [10]. Echoing the response of Thomas et al. [32] to the insect decline findings of Sanchez-Bayo & Wyckhuys [2], there is a need for robust data and rigorous analyses. The study by Barnes et al. [10] has highlighted a lack of systematic monitoring of earthworm communities, at least in the UK, but without such data it is questionable to attempt to decipher long-term trends in earthworm populations that may be taking place against the backdrop of land management changes and fluctuating climate.

4.2 No robust evidence of decline

Leaving some of the debated modelling issues aside, our reanalysis of the revised and augmented datasets using the same models generally highlights a lack of consistency with the original model outputs. In particular, the estimates of annual change in earthworm abundance are close to zero and non-significant with the revised or augmented datasets for the model of change over time across all habitat types (Model 1). For the models evaluating trends for specific Broad Habitats (Model 3) and Fine Habitats (Model 4), most remain around or tend toward zero with the revised or augmented datasets. We acknowledge that the modelled outputs using revised and additional data here do not provide a definitive conclusion, but they point toward a dynamic stability over time and they suggest that the magnitude of the declines reported by Barnes et al. [10] appear to be grossly overestimated. In an unrelated paper, Müller et al. [33] reanalysed 27 years of insect biomass data from Germany, adding more recent insect biomass data and including sample-level climate data. Insect biomass in the recent samples returned to that reported in the 1980s and they concluded that “temporal variation in weather conditions explained most of the temporal changes in insect biomass”. Accounting for the effects of recent and current climatic conditions may provide a more realistic assessment of long-term trends in earthworm abundance, too.

Earthworm activity, apparent abundance, and population dynamics are also known to be influenced by the prevalent weather conditions through their effect on soil conditions, particularly moisture. Earthworms are dependent on soil moisture with seasonal behaviours that avoid (moving to depth) or resist (diapause) drier soil conditions in summer [34]. Several long-term studies of earthworm populations have been published from single sites in the UK that highlight the dynamic impact of climate on earthworm populations. For instance, through monthly sampling of earthworms over 6 years (March 2002 to February 2008) at a woodland site in southern England, Eggleton et al. [35] demonstrated both seasonal fluctuations in measured abundances and longer-term trends reflecting the prevalent climate. Butt et al. [36] monitored earthworms over two decades (1998 to 2019) in a grassland in north-west England, presenting evidence of major earthworm declines in dry years such as 2003, but an ability to recover. Recent European-scale modelling indicates that earthworm species distributions may be impacted by changing climate over the next fifty years [37]. Expanded distribution of some earthworm species under climatic changes have also been predicted in the UK [38].

There is ample evidence that land use and management impact earthworm abundance, composition and activity (e.g., 21, 39-41). Organic and upland soils, typically with acidic pH, have low earthworm densities and tend to be dominated by fewer species (42-43). In agricultural soils, earthworm communities are greatly influenced by land management practices; disturbance through tillage is a key factor and cultivated systems tend to contain a relatively low abundance of earthworms (50–200 individuals m^{-2}), depending on time since cultivation and crop type. Grassland or pasture systems generally contain much greater abundances (300–600 individuals m^{-2})[44-46]. The expectation of widespread declines in intensive agricultural soils in the UK (akin to findings on other invertebrates e.g., [47]) does not appear to play out.

4.3 Woodlands revisited

Where declines were reported in Barnes et al [10] for particular habitats using existing data and models, it appears unlikely that they are driven by any specific temporal factors but rather by the particularities of the small set of sources from which data are derived. Indeed, Barnes et al. [10] raise the caveat that ‘the accuracy of any habitat-specific trend produced is dependent on the assumption that studies are equally representative of that habitat-type through time’. Focusing on the headline decline in broadleaved woodland earthworms (77% over 25 years), it is clear this assumption is not met. The study of Lakhani & Satchell [25] dominates the Woodland data with ~47% of broadleaved woodland values in the original dataset. However, it is spatially restricted, temporally restricted, temporally autocorrelated, and the estimation of earthworm abundance from the biomass of the *Lumbricus* genus is dubious and problematic. It is also evident, visualising these data (Figure 5), that shifts in space are confounded with shifts in time across the broadleaved woodland data.

Forest soils can have widely varying earthworm populations dependent on soil characteristics and litter inputs (48-49), with clear effects of tree type and tree species (e.g., 48- 51), driven by differences in litter quality and subsequent effects on soil characteristics. Additionally, there is further nuance in the context of these studies that determine earthworm abundance, that are not accounted for in coarse habitat classifications. In addition to the modelled variables (year, season, sampling method, depth), differences between woodlands in soil pH, hydrology, previous land use, and stand age all influence the status of earthworm communities.

Barnes et al. [10] note that “declines in woodland biodiversity [moths, birds] appear greatest in south-East England and contrast with more positive trends in the north”. However, there are exceptionally few earthworm data from woodlands in SE England so there is no way to support this suggested climate-related mechanism, even though it is expected that geographical patterns of changing climate should impact earthworm populations. Ascribing causal mechanisms to these data is therefore highly speculative, and particularly given that estimation of causal effects requires much stronger assumptions than correlations or descriptive parameters.

4.4 Further considerations on data and modelling

While data compilation errors and uncertainties have been largely addressed through revising the dataset, there are further aspects of the data and modelling that may have a bearing on findings. First, there is huge variation in the spatial extent of derived abundance values. Standardised earthworm abundance values in the Barnes et al. [15] dataset are based on spatial scales ranging from individual sampling plots to fields/parcels to multiple locations across a region to country-wide (i.e., England). Combining data representing completely different spatial scales, and already aggregations across those spatial scales, presents significant challenges. Values for standardised earthworm abundance (i.e., means for habitat × method × season) represent vastly different sample numbers, with contributing data being influenced by multiple varying environmental factors. Weighting by sample area is not sufficient to address such differences in spatial extent because it assumes that variability is equivalent across scales.

Another spatial issue is that the model uses a 10 km grid square reference code as a random term to account for spatial dependence of data within the same 10 km grid square (152 datapoints from 5 sources use 'England' as the value for the random term). However, the model doesn't know their relative positions in space, so it doesn't account for proximity of grid squares or wider geographical separation of sampling locations. One example is provided by Study 49 [25], where two sites are approximately 1 km apart but represented by different 10 km grid square reference codes. This raises clear issues around spatial autocorrelation not being accounted for in the analyses. Other fine-scale spatial and temporal data dependencies should also be accounted for. For instance, different depths from the same sampling location should not be treated as independent datapoints, and frequent within-study repeat site measurements (e.g., weekly sampling) should be addressed as temporal autocorrelation.

There may also be an issue in assuming a depth of zero for chemical extractant methods. Chemical extraction methods expel earthworms from the soil to the surface and in the dataset these have been assigned a depth of zero. Hand-sorting samples earthworms from a known volume of soil whereas chemical extraction methods sample earthworms from an unknown volume of soil, with effective depth likely dependent on soil type/texture and moisture conditions. These methods also have bias in the recovery of different ecological groups (e.g., 53).

Finally, Barnes et al. [10] used the year coefficient from GLMM for earthworm density to estimate how it has changed over time. The model included habitat as a covariate, which raises some questions. It appears that the authors included habitat to guard against the possibility that apparent trends in abundance could in fact be explained by changes in which habitats were sampled over time. This logic is sound, but it also applies to the many other variables that were presumably sampled inconsistently over time (e.g. climate). If these other variables also affect earthworm abundance, then failing to include them in the model will also bias the estimated year effect. Another question concerns what is actually being estimated by the year effect. Including habitat in the model means that the year effect represents the part of the trend not explained by changes in habitat. This is not the total effect of year that the headline result of a 33-41% decline in abundance implies.

4.5 Data future

Ristok et al. [54] flag one of the key messages from the first comprehensive soil biodiversity assessment in Germany that “For evaluating the implications of environmental change, an understanding of (long-term) temporal variation in soil biodiversity and ecosystem functions is urgently required”. It is conceivable that earthworm populations in the UK may have declined to some extent in particular environmental contexts arising through time (e.g., soils under intensive agriculture with increasing droughts). However, evidence of large-scale and long-term declines (and particularly conclusions of alarming earthworm declines) must be based on unbiased and consistent data, and analyses that account for differences in driving variables.

There are benefits of striving to collate data at consistent and fine spatial scales (e.g., field) and temporal scales (e.g., week or month). This can be lacking for historical studies and datasets where this information may not be recorded and is not retrievable from linked sources. Inclusion of data averaged over seasons or years, and over regions or countries, does not allow relevant temporal and spatial context to be accounted for. Collating data from diverse studies and locations through time presents multiple challenges for determining temporal ecological trends, some of which may be insurmountable. As concluded by Dornelas et al. [55], the “Availability of long-term, large-scale, high-resolution data is the single most important factor limiting progress in understanding temporal patterns in biodiversity”. We would advocate the addition of ‘representative’ to this list.

We need systematic data from long-term and relatively frequent earthworm community assessments across a representative network of sites to evidence widespread declines in habitats or geographical specificity in trends for regions under different climates. Hohberg et al. [56] note that “population trends for species remain largely unknown due to the lack of long-term, large-scale monitoring programs”. In the UK, this type of approach was recently initiated in England in 2023 as part of the England Ecosystem Survey and National Forest Inventory Plus projects [57]. In Germany, though already relatively well studied, the National Soil Monitoring Centre is preparing establishment of a long-term monitoring program [56]. There has also been a recent call for international collaboration to enrich and extend earthworm time-series data [58]. We appeal to improve data collation, enhance meta-data and encourage systematic long-term monitoring. Only through robust data collection and rigorous modelling is it likely that we can provide a definitive answer as to whether earthworm populations are in decline.

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Supporting information captions

S1 Table. Comparison of GLMM outputs for different datasets with Model 1. Estimated effects and significance for model terms using Original, Revised and Revised+Augmented (=Augmented) datasets; *p<0.05, **p<0.01, ***p<0.001.

S2 Table. Comparison of GLMM outputs for different datasets with Model 3. Estimated effects and significance for model terms using Original, Revised and Revised+Augmented (=Augmented) datasets; BH trend = Broad Habitat × Year, *p<0.05, **p<0.01, ***p<0.001.

S3 Table. Comparison of GLMM outputs for different datasets with Model 4. Estimated effects and significance for model terms using Original, Revised and Revised+Augmented (=Augmented) datasets; FH trend = Fine Habitat × Year, *p<0.05, **p<0.01, ***p<0.001.