Lead (Pb) contamination in drinking water in low- and middle-income countries: a systematic review and meta-analysis

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Abstract

Lead (Pb) in drinking water causes organ damage, cardiovascular disease, cancers, and lifelong neurological and developmental impairment, disproportionately harming infants and developing fetuses. However, evidence on lead in drinking water in low- and middle-income countries (LMICs) is limited and lacks robust synthesis, impeding action. To address this gap, we conducted a systematic review and meta-analysis of peer-reviewed studies reporting lead in

drinking water in LMICs, according to PRISMA guidelines, to answer the following research questions:

1. What is the estimated prevalence of lead contamination in drinking water in LMICs at concentrations exceeding international guideline values?
2. To what extent does lead contamination in LMICs vary by geography, over time, or by drinking water source type?
3. Are there problematic evidence gaps with respect to the occurrence of lead in drinking water in LMICs, and if so, where is additional evidence most urgently needed?

We searched PubMed, Scopus, and Web of Science for studies published in English since 1969 reporting lead concentrations in drinking water. The decision to include English language studies was made on the basis of >90% of eligible studies being published in English, leading to the expectation that exclusion of non-English studies would not seriously compromise the validity of the systematic review. Study relevance was ranked using supervised clustering and machine learning. Relevant studies were manually screened for inclusion; data were manually extracted from included studies. Within-study risk of bias was scored using quality items defined in this work. Between-study bias was assessed based on continuity and symmetry of the (roughly lognormal) distribution of data included in the review. Of approximately 40,000 search results (for both lead and other TMs), 16,868 scored relevant using a trained machine learning algorithm; of these, 3,367 met inclusion criteria. Fewer than 6% of studies (n= 200) were excluded because they were unavailable in English. Approximately one third (n=1,088) of included studies reported on lead. Central and Southern Asia accounted for 45% of included datasets, while 31% of LMICs were

unrepresented. Many studies (45%) had sites purposively selected for known or suspected contamination; after excluding such "targeted" studies, metaregression indicated that >20% (95% CI: 20-27%) of samples exceeded World Health Organization (WHO) guideline values for lead (n=523).

Potential sources of bias within studies include sample collection and analysis limitations (lower quality studies) and purposive site selection ("targeted" studies); potential sources of bias among studies include language limitations, exclusion of grey literature, geographic heterogeneity of datasets, and potential publication bias. This work suggests that lead contaminates drinking water at levels of health concern in LMICs worldwide, and that increased collective efforts to prevent, manage, and monitor such contamination are merited.

Introduction

Exposure to lead causes adverse health effects [1–9]: these include cardiovascular disease [2], organ damage [4–6], anemia [5] and impaired red blood cell production [7], lifelong neurological and developmental impairment [4,5,10,11], adverse reproductive and birth outcomes [4,7], cancer and/or premature death [6,12,13]. These adverse health effects are most severe for lead exposures during gestation and infancy [4,5,11]. Human exposure occurs through routes such as ingestion and inhalation in outdoor, domestic, and occupational settings [5–7,11,13,14]. As environmental exposure to lead becomes more limited through the phase-out of leaded paint,

gasoline, and other regulatory measures, reducing exposure through drinking water is increasingly important [15].

Understanding the origins of toxic metals (TMs) in drinking water is important because different sources of exposure require different management approaches [16]. Most lead in drinking water arises from corrosion of lead- and lead-containing water system materials and components, such as pipes and fittings [1,2], as occurred in Flint, Michigan [3] and Washington, D.C. [4].

Several studies have reported on lead in drinking water in the USA, Canada, Europe, and other high-income countries (HICs) [5–10]. By contrast, TM contamination in drinking water is far less extensively characterized in low- and middle-income countries (LMICs) [11]. Where LMIC studies report occurrence of TM contamination in water, they may be outdated (e.g., they may predate important regulatory, demographic, economic, and/or analytical methods changes), may be hyper-localized (e.g., study setting may be purposively targeted based on characteristics that reduce generalizability), and/or may be designed and reported in a way that limits internal and/or external validity concerning TM occurrence at concentrations of public health concern in drinking water (e.g., they may not report sampling, analysis, and quality assurance/quality control [QA/QC] methods in sufficient detail to enable meaningful interpretation of results). As a result, the extent of TM occurrence in drinking water in LMIC settings and the extent to which these occurrences go undetected are unclear.

Objectives

This review assembles and summarizes peer-reviewed evidence to address the following research questions:

1. What is the estimated prevalence of lead contamination in drinking water in LMICs at concentrations exceeding international guideline values?

2. To what extent does lead contamination in LMICs vary by geography, over time, or by drinking water source type?
3. Are there problematic evidence gaps with respect to the occurrence of lead in drinking water in LMICs, and if so, where is additional evidence most urgently needed?

Methods

PRISMA Guidelines and Review Registration

The reporting of this review follows PRISMA guidelines [12] (File S1 Checklist). This work is part of a larger systematic review of multiple toxic metals (protocol registered with PROSPERO: CRD42024566116; File S1 Protocol). The current review includes those studies reporting results for lead in drinking water.

Search Strategy

The search string comprised: economic terms, country names, source types, and elements. The economic terms were developed through consultations with the Health Sciences Library at UNC-Chapel Hill. The country terms included in the search string were all countries within the categories of: Low-income economies, middle-income economies as defined by the World Bank (note that the World Bank further subdivides middle-income into Lower-middle-income and Upper-middle-income economies) [13]. Water supply technology types were based on the WHO/UNICEF Joint Monitoring Programme for Water Supply, Sanitation and Hygiene (JMP)

classifications of water supply technology type (e.g., boreholes with handpumps, public tap/standpipes, surface water) [14]. The list of metals and metalloids was selected based on those with which the WHO has established guideline values (Table 1) [2].

Eligibility

Studies were excluded if they were published in or before 1969, unavailable in full-text in English, did not present primary data (e.g., literature reviews, opinion pieces, letters to the editors, commentaries), or did not report concentrations of toxic metals (larger study) or lead (this work) in drinking water samples or water samples from a source likely to be used for drinking water supply (e.g., a surface water or groundwater source elsewhere reported to be a drinking water source for nearby populations, or a water supply technology such as a borehole with handpump that is commonly used for drinking water supply; Table 2). Grey literature was not included.

Search

The search was executed in PubMed (National Library of Medicine), Global Health (EBSCOhost), Scopus (Elsevier), and Web of Science (Clarivate) databases (Table S1 in File S1 Text). The initial search was conducted on November 17, 2018 and was expanded and updated multiple times on December 31, 2021; October 11, 2024;, and (most recently) on March 17, 2025. The initial search yielded 5,864 results that were uploaded to Covidence systematic review screening software. In 2021, the search was updated and expanded, then executed in PubMed, Web of Science, and Scopus, yielding a total of 33,698 results. After deduplication in EndNote, the 26,646 unique results were prioritized for screening as described below. The search was updated on October 11, 2024, and March 17, 2025 with expanded

146 geographic search terms in Scopus, yielding a total of 19,003 new results across databases, of
147 which 13,607 were unique additions, for a total of 46,073 unique results across all searches.
148 The authors added relevant results identified by hand through their previous reading,
149 collaborations, and review of the citations of included studies (Fig. 1).

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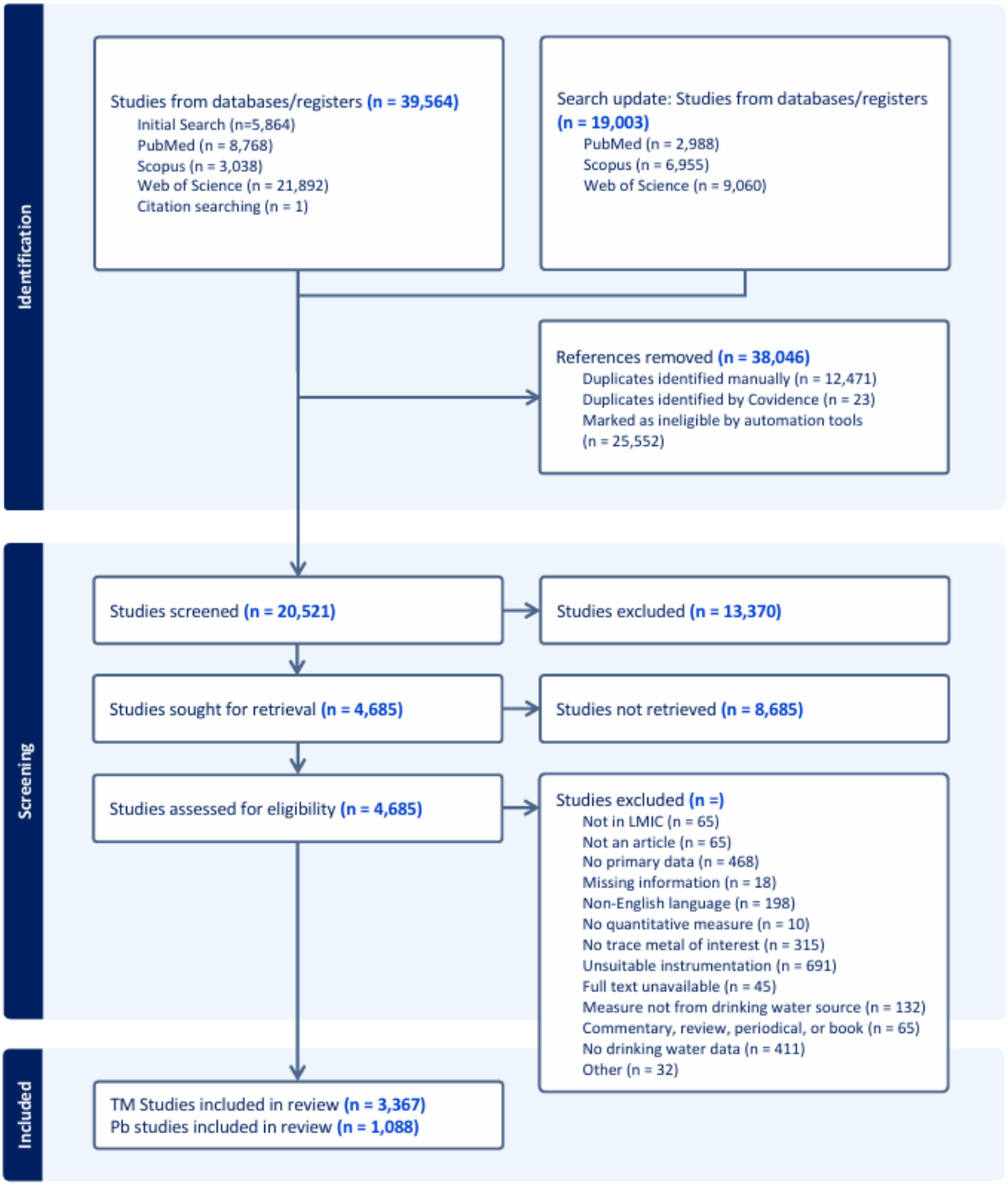

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Fig .1: PRISMA flow diagram for a systematic review identifying publications on lead occurrence in drinking water in LMICs

Refining Search Results: Machine Learning Approach

To prioritize the large number of results, machine learning was used to identify results with the highest likelihood of being relevant. For the original search strategy, we used supervised clustering, a form of semi-supervised machine learning, with ensemble learning and for the search update we used supervised machine learning (Fig. 2) as described in the literature [28-31] and the study protocol (File S1 Protocol). Supervised clustering uses training data in the form of seed studies that are identified at random from search results. Ensemble learning combines results from several individual models to improve predictions. For this project we used six models and each study received an ensemble score (ES) ranging from 0 to 6. Studies with an ES of 0 were not predicted relevant by any of the six models and studies with an ES = 6 were predicted relevant by all six models. Briefly: unique search results from December 2021 (n=26,646) were prioritized for manual screening using supervised clustering (DoCTER [ICF, Virginia, USA]), which prioritizes search results based on title and abstract text using a training dataset. First, 500 randomly selected results were manually screened at the title and abstract level by the first author (Fisher) to identify training data for supervised clustering. Six models were run using training data and all search results and each unique study received an ES ranging from 0 to 6. All studies with ES of 1 or higher were uploaded to Covidence for manual screening (n=9,983). Studies with an ES of 0 (not likely to be relevant) were discarded without manual review (n=16,663). Supervised machine learning was used to prioritize the unique results from the search updates (n=13,607). A random selection of screening results from the original search was used to train the model (DoCTER [ICF, Virginia, USA]) and each study received a probability score. All studies predicted to be relevant were manually screened by the

177 team (n=4,218), as well as the highest ranked 500 studies marked not likely to be relevant as an
178 insurance step. The remaining studies were discarded (n=8,889).

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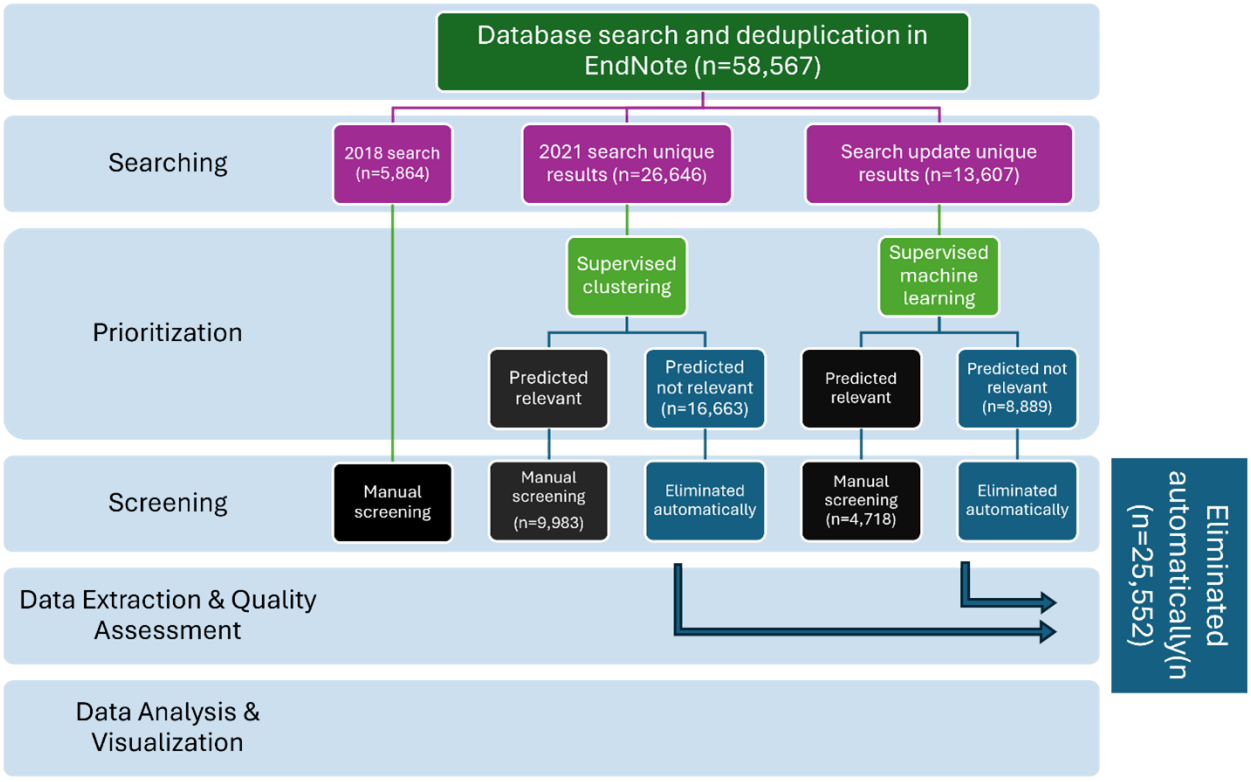

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182 Fig 2. Machine learning in the systematic review screening process.

183 To assess the accuracy of the supervised clustering and supervised machine learning tools, the
184 team calculated the precision (number of true relevant studies out of the pool of studies
185 predicted relevant by the tools) of each subset of citations after title/abstract screening. As
186 expected, the precision decreased as ensemble score decreased for studies from the original
187 search, prioritized using the supervised clustering tool (Table 3, Fig S1 in File S1 Text).

Similarly, for studies from the search update prioritized by supervised machine learning, precision decreased as predicted relevance decreased (Table 4, Fig S2 in File S1 Text).

Manual Screening

Following prioritization, studies were imported into the systematic review software Covidence (Veritas Health Innovation) for screening. The authors developed and documented study screening and data extraction criteria, protocols, and training materials (File S1 Trainings) and developed training tools, which were used to train a pool of screeners and data extractors. This pool included the authors as well as multiple collaborators at The University of North Carolina at Chapel Hill (Chapel Hill, North Carolina, USA), the University of Ghana, Legon (Legon, Greater Accra, Ghana), and the University for Development Studies (Nyankoala, Ghana). Two trained screeners from this pool then independently screened the title and abstract of each included study against the inclusion and exclusion criteria (Table 2); conflicts were resolved by a third screener, generally one of the study authors. At the full text review stage, studies were again independently reviewed by two trained screeners and excluded if they met any exclusion criteria (Table 2).

Data Extraction

Basic study data and metadata (country, region, water source type, sample collection, handling, and analysis methods/instrumentation) were extracted from each study by trained screeners at the full-text screening stage (Table S2 in File S1 Text). Details on the study design and setting, including whether the setting was selected based on a known or suspected source of contamination, were also extracted at this stage.

For studies included at the full-text stage, additional data extraction was conducted by trained data extractors (from the same pool of collaborators described above, and trained using the same set of protocols, documents, and methods described in File S1 Trainings). Extracted data included sample collection, preservation, analysis details, study and setting details, quantitative results, geolocation data, and other key data, as indicated in the data extraction sheet (File S1 Tools). Sample collection details such as the mention of a stagnation period or flushing before sample collection (which affects the concentrations of TMs in water samples); the use of trace-metal clean and/or trace-metal grade acid-washed sampling containers (if specified, which improves method precision); and whether samples were acidified or filtered before analysis (which can dissolve and preserve [acidification] or remove [filtration] particulate or sorbed material from samples, respectively). The details of the analytical method included the type of analytical instrumentation used (e.g., flame AAS vs ICP-MS; File S1 Tools). Where a study reported results for substantively different sample sets (e.g., different water source categories in a single setting, different settings, or different seasons [pre- versus post-monsoon], these were extracted as separate “sample sets” (File S1 Trainings). Each extracted study was reviewed by a different author or trained data extractor, and errors were noted and corrected as a quality control measure.

Data were cleaned and analyzed using STATA 13 (College Station, TX). Bibliometric and methodological summary statistics were compiled; summary statistics of lead occurrence data were calculated, and regression analyses were performed. Bibliometric statistics were disaggregated by country and SDG region [15]. Summary statistics were calculated for the proportion of lead exceedances (the proportion of samples exceeding the WHO guideline value for lead in drinking water [10 µg/L] [2]) across sample sets by meta-regression using the “metareg” command in STATA. This command was used to ensure that studies with larger numbers of samples collected were not overweighted in the analysis. For this purpose, the

proportion of drinking water samples exceeding the WHO guideline value (GV) for lead was determined for studies in which this proportion was directly reported or could be directly derived from provided lead concentration data (e.g., from provided tables, figures, or statistics). Where exceedance rates were not reported and could not be derived, but summary statistics (e.g., range, mean, standard deviation, and number of samples) were reported, the proportion of WHO GV exceedances was estimated as follows: For each sample set, reported lead concentration ranges, means, and standard deviations were used to construct a lognormal distribution and n values were randomly sampled from this distribution (where n = the reported number of samples in the sample set), and the proportion of these sampled values exceeding the WHO GV was recorded (previous studies have reported lognormal distributions of lead and TM concentrations in water) [16]. For studies reporting concentration ranges, sample numbers, and measures of central tendency (e.g., mean or median) but not reporting a measure of variance (e.g., variance or standard deviation), the estimation method described by Hozo et al. for approximating the variance of lognormal distributions was employed [17]. Standard errors for the proportion of exceedances were calculated for each sample set. Where all samples in a sample set exceeded the WHO GV (proportion of exceedances =1) or all samples were below the WHO GV (proportion of exceedances=0), a continuity correction was made to calculate standard errors, in which the proportion of exceedances was set equal to n/(n+1) or 1/(n+1), respectively (in which n = the number of samples in the sample set). This ensured that standard errors would not be undefined. Estimated exceedance proportions were then calculated across all sample sets. For the subset of studies that reported results with sufficient granularity for reported exceedance proportions to be extracted or calculated, these “reported” exceedance proportions were compared to the “estimated” exceedance proportions obtained by the methods described above (Fig S3 in File S1 Text).

Exceedance proportions were also calculated for the subset of studies conducted at sites not selected based on identified contamination (abbreviated as “nontargeted” studies), and the subset of “nontargeted” studies that reported using analytical instrumentation capable of achieving method detection limits below the WHO GV for lead (e.g., ICP-MS- see definition in Table 5). Exceedance proportions were also calculated for the subset of “nontargeted” studies with high method quality scores, as described below.

Data Analysis

Fisher conducted data analyses with support from the UNC Odum Institute and other coauthors, and Purvis validated these analyses.

Study method quality scores were calculated for studies using the criteria shown in Table 5. Method score reflects the suitability of the reported study methods for quantifying lead in drinking water by adding one point for each study quality criterion met. Studies with a method quality score of six or higher out of ten criteria were classified as “high quality.” Estimated exceedance proportions were calculated for all studies, nontargeted studies, and across stratifying variables such as water system type and SDG region using metaregression. Estimated exceedance proportions were compared to reported (measured) exceedance proportions for the subset of studies in which such exceedances were directly reported, and these comparisons were reviewed using diagnostic plots as a further validation measure.

Conventional tests of publication bias (e.g., funnel plots) were adapted for this work, because studies conducted in different geographic locations, at various periods, and/or using other methods could not reasonably be presumed to have similar population distributions of lead concentrations in drinking water; thus a measurement of the symmetry of central tendencies across studies as a function of standard error is not meaningful. However, diagnostic plots

comparing the distribution of central tendencies among studies to an expected distribution (e.g., lognormal distribution) can be inspected for continuity and symmetry over a region of interest- where large unexplained gaps, asymmetrical features, or other deviations from the expected distribution over the region of (0.1*WHO GV) – (10* WHO GV), i.e., 1-100 µg/L for lead in drinking water, can be considered indicative of potential bias among studies in the meta-analysis.

Results

Literature Search and Prioritization

The original 2018 search returned 5864 results, which were screened without prioritization. The expanded 2021 search returned 33,699 studies; 9,983 results were imported into Covidence following prioritization using supervised clustering. One study was added through hand searching. Search updates in 2024 and 2025 yielded an additional 13,607 unique studies. After prioritization with supervised machine learning, 4,685 studies with high expected relevance were imported into Covidence.

A total of 20,521 studies were manually screened by the team. Of these, 1,088 relevant studies reporting on lead in drinking water (out of 2169 included studies reporting on any TM of interest), comprising 1,710 sample sets and approximately 62,000 observations, were included in the final dataset after title/abstract and full-text screening. Fewer than 10% (198 out of 2169) studies were excluded on the basis of language (i.e. being unavailable in English [Fig 1]).

Bibliometric Analysis

The final set of included studies represents 66 countries across six SDG regions. 48% of studies that included datasets for lead in drinking water were from four countries: India, China, Pakistan, and Turkey; the 10 most represented countries account for 73% of datasets (Fig 3, Table 6). Less than half (66 of 137, 47%) of all LMICs were represented in the data. Fewer studies were included from certain SDG regions (such as Latin America and the Caribbean) than others (such as South and Central Asia [Table 7]). Fewer than 1% of returned records were excluded based on English language availability.

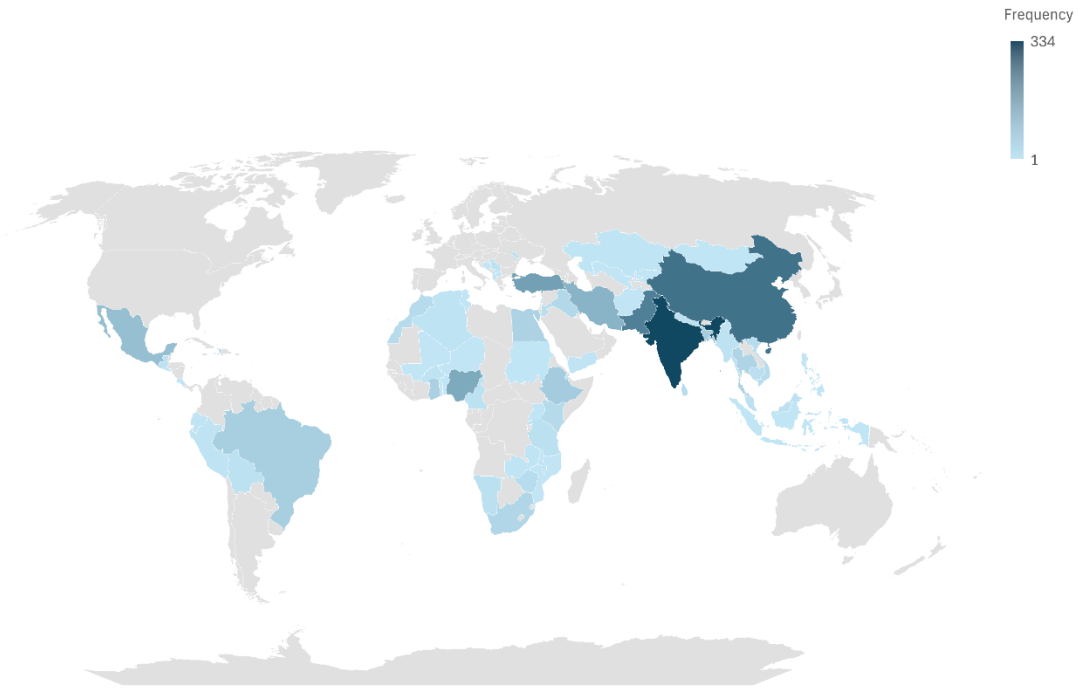


Fig 3: Number of studies from low- and middle-income countries reporting on concentrations of toxic metals and metalloids in drinking water, by country

Many studies (37%) reported on samples or locations selected because of a known or suspected potential source of lead contamination ("targeted" studies). Mining, agriculture, industrial sources, wastewater, and landfills were the most frequently listed potential sources (Table 8).

Inductively coupled plasma mass spectrometry, atomic absorption spectroscopy, and inductively coupled plasma atomic emission spectroscopy were the most reported analytical methods (Table 9). However, the analytical methods were not adequately specified in 7% of publications reporting on lead.

Study quality varied widely regarding the suitability of methods used for quantifying lead in drinking water. The overall proportion of high-quality studies was 5% (Table 10). In most cases (64%), studies failed to document adequate quality assurance/quality control (QA/QC) procedures.

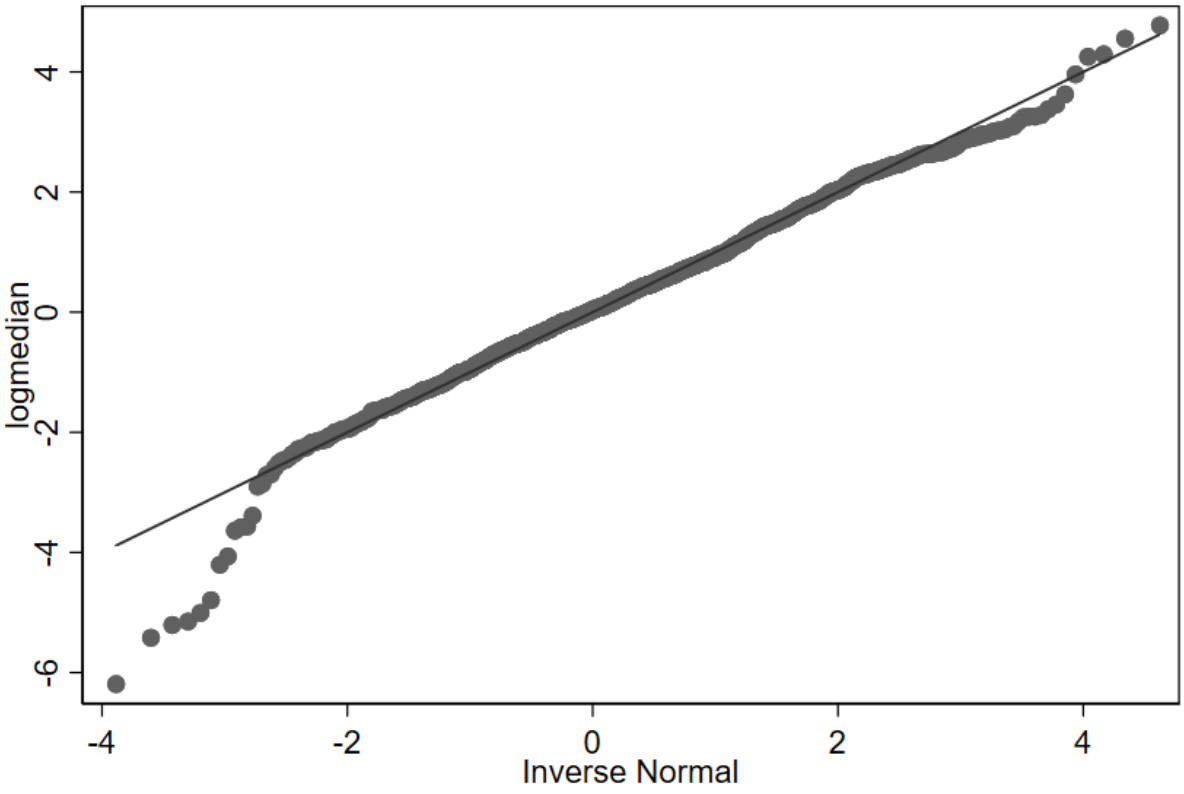
Metaregression of estimated exceedance proportions indicated that more than 25% of samples exceeded the WHO guideline value for lead in drinking water across all sample sets (95% CI = 24-28%). For the subset of studies that reported results with sufficient granularity for exceedance proportions to be extracted or calculated, these "reported" exceedance proportions were compared to the "estimated" exceedance proportions obtained by the methods described above; reasonable agreement was obtained by the two methods (Fig S3 in File S1 Text).

Metaregression of exceedance estimates for all "nontargeted" studies indicated that 24% of these studies (95% CI = 20-27%) exceeded the WHO GV (Table 11), and this figure decreased to 23% (95% CI = 18-27%) when only studies using more sensitive instrumentation (ICP-MS) from LMIC settings other than China were considered (datasets from China [PRC] had systematically lower levels of lead than those from other settings ex-PRC and were therefore

removed for some sub-analyses Fig S4 in File S1 Text). Similarly, median lead concentrations across datasets were high for all studies as well as nontargeted studies (Table 12).

An inspection of the concentration distribution showed broad, roughly lognormal distributions for lead in drinking water for both estimated and reported sample set median and mean values (Fig 4, Fig S1 in File S1 Text). Overall, median lead concentration in drinking water was higher than the WHO GV of 10 µg/L across studies, with the estimated median across nontargeted studies being 27 µg/L (95% CI 14-40 µg/L) across 317 datasets for which suitable values and standard errors could be estimated (Table 12).

Lead occurred across source types with roughly comparable frequency except springs; however, the small number of datasets reporting on lead in water from springs should be noted (Fig 5, Table 13). Lead occurrence was less prevalent in East and Southeast Asia (ESEA) and Latin America and the Caribbean (LAC) than in other SDG regions; however, differences between ESEA and other settings were less pronounced when data from PRC were omitted (Fig 6, Table 13; Table S3 in File S1 Text). Lead occurrence did not vary significantly by decade of publication (Figure 7, Table S4 in File S1 Text).



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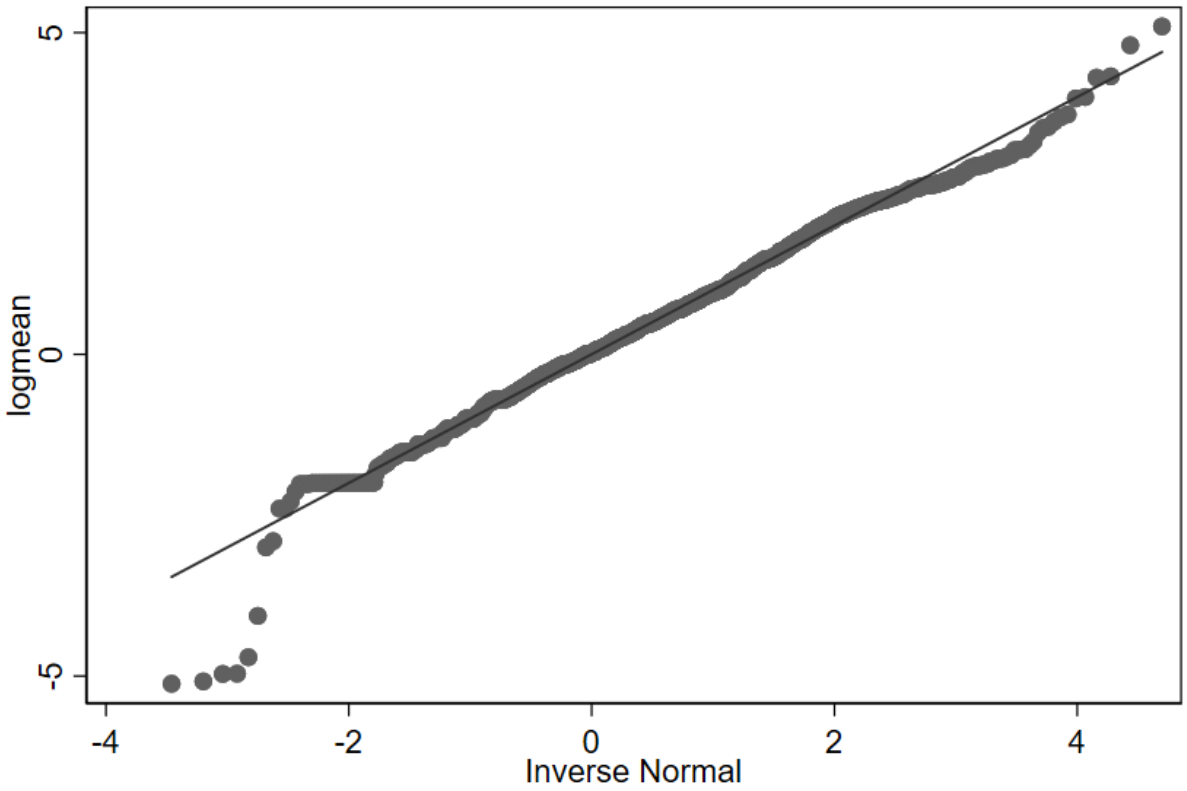

Fig 4: Diagnostic plots of the distribution of log-transformed median and mean lead concentrations (µg/L) for drinking water sample sets from low- and middle-income countries vs normal distribution

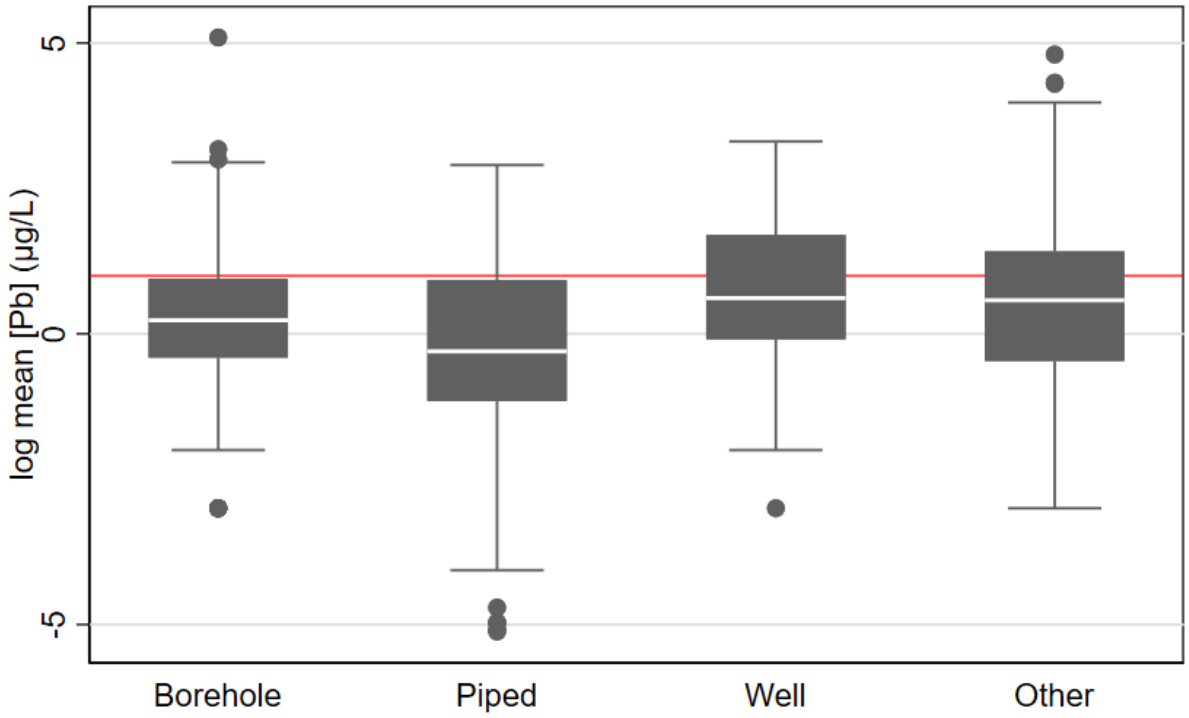

Fig 5: Distribution of mean lead concentrations for drinking water sample sets from low- and middle-income countries, by water source type. Red line denotes WHO Guideline Value.

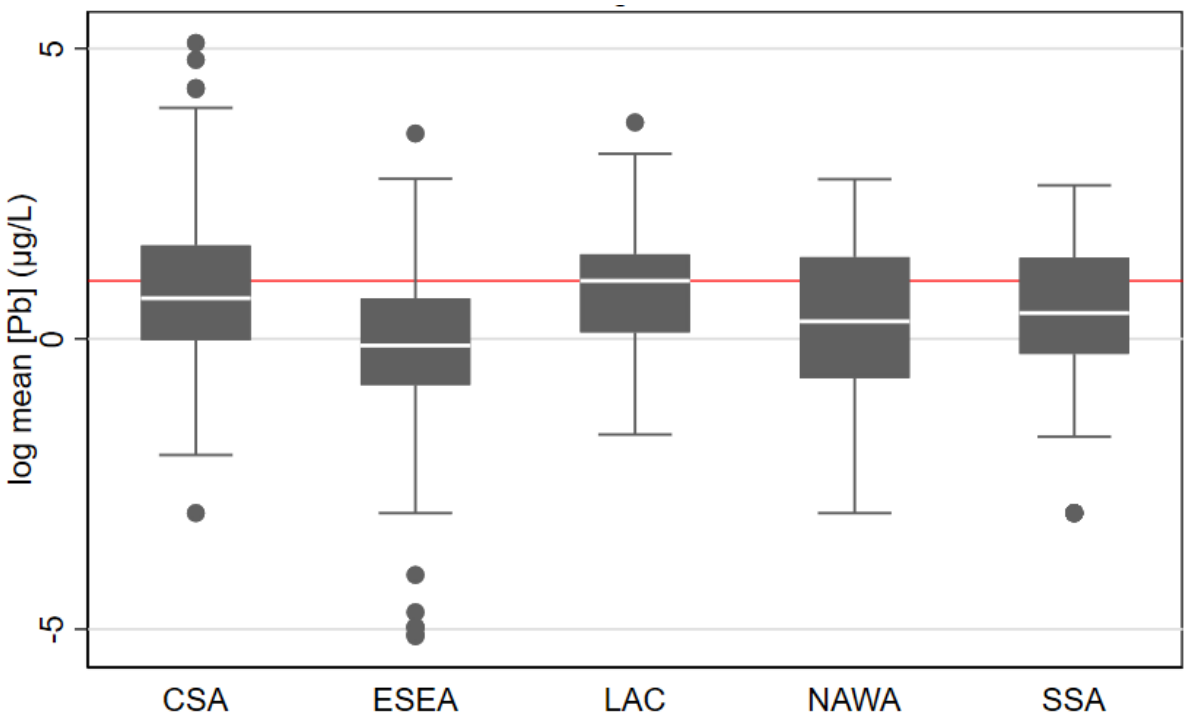

Fig 6: Distribution of mean lead concentrations for drinking water sample sets from low- and middle-income countries, by SDG region (CSA: Central and Southern Asia; ENA: Europe and North America; ESEA: East and Southeast Asia; LAC: Latin America and the Caribbean; NAWA: North Africa and Western Asia; SSA: Sub-saharan Africa). Red line denotes WHO Guideline Value.

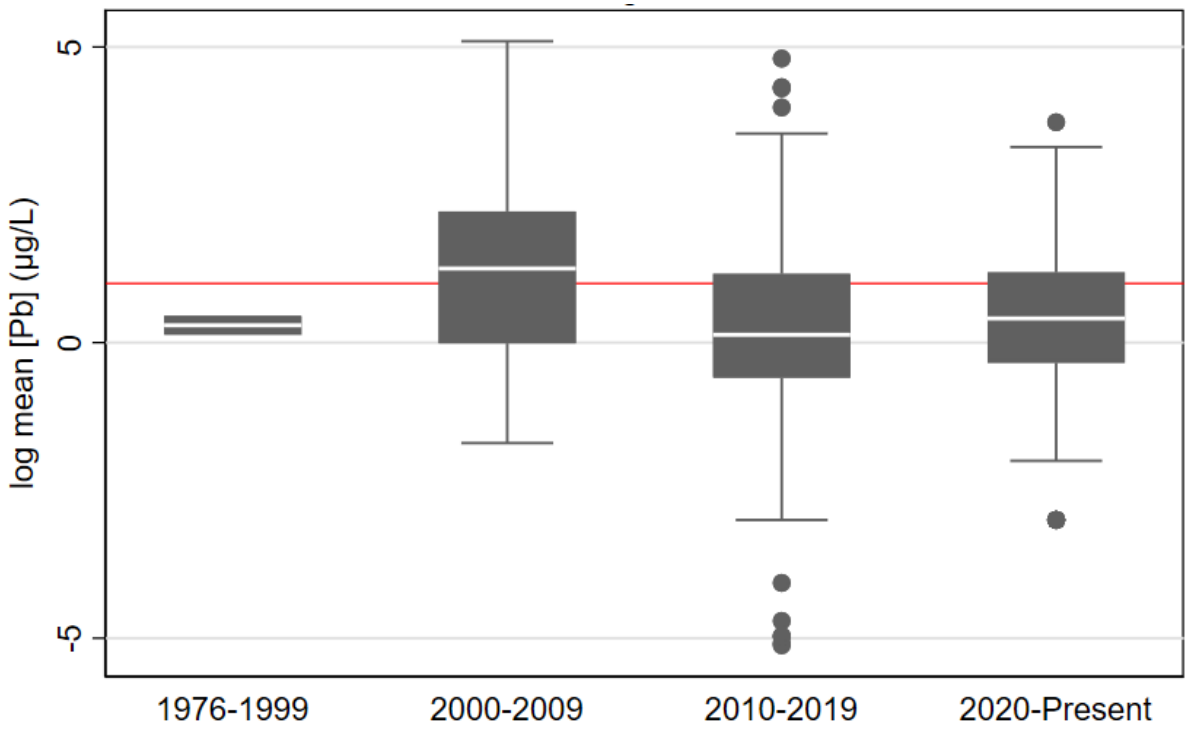

Fig 7: Distribution of mean lead concentrations for drinking water sample sets from low- and middle-income countries, by decade of study publication. Red line denotes WHO Guideline Value.

Discussion

The results suggest the widespread occurrence of lead in concentrations that raise public health concerns about drinking water in low- and middle-income countries worldwide. Lead concentrations in drinking water exceeded WHO GVs in a substantive minority of samples

394 across all studies and “nontargeted” studies, irrespective of source type, SDG region, or decade
395 of observation/publication.

396 The distribution of lead concentrations was roughly lognormal; where samples exceeded WHO
397 GVs, the extent of this exceedance was also roughly lognormally distributed (Fig 4, Table 13).

398 We conclude that the contamination of drinking water by lead is a widespread public health
399 concern. While there is no known safe level of lead exposure and the WHO GV for lead in
400 drinking water is set based on analytical achievability [2], it is nevertheless a relevant
401 benchmark to consider as countries work to progressively decrease the proportion of water
402 samples exceeding this threshold and generally decrease lead concentrations and occurrence.
403 Thus, reporting the proportion of samples exceeding GVs, as well as the central tendency of
404 concentrations across pooled samples, as we have done here, can be a valuable approach to
405 synthesizing and communicating large numbers of observations across diverse systems and
406 settings for analysis at a high level. Such synthesis should indicate the extent of lead
407 occurrence across systems and settings, rather than a precise or localized estimate.

408 These results go beyond previous work but are consistent with prior studies emphasizing the
409 widespread occurrence of lead contamination in drinking water and the need for additional
410 monitoring and surveillance in LMIC settings [18–20].

411

412 Limitations

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414 Data availability and data quality are both limited in this study. Many countries are not
415 represented in any published English language studies, while others have little included
416 evidence. Although fewer than 1% of returned records were excluded based on English

language availability, excluding evidence unavailable in English language peer-reviewed articles indexed in major databases was a limitation of the current review. Specifically, while more than 90% of recent peer-reviewed articles in science, engineering, and health fields that are indexed in major databases searched in this review are available in English [21], a substantive minority of such indexed studies (most notably many from China) are not, and this represents a limitation of the current work. Furthermore, a substantive proportion of non-English language articles are not indexed in the databases searched in this study or most systematic reviews conducted in English; this proportion increases when expanded to include grey literature and other non-peer-reviewed evidence sources (ibid). Thus, this limitation is a feature of the inclusion criteria and the search parameters. Future updates to this work will seek to include additional evidence published in select additional languages and additional evidence from the grey literature, as feasible.Most included studies received low method quality scores for quantifying lead in drinking water (method quality score is distinct from overall study quality because many included studies are adequately designed for other purposes, but do not sufficiently quantify lead in drinking water at µg/L concentrations). These low scores reflect numerous limitations, including failure to report sampling and/or analysis methods and failure to include and document quality assurance/quality control (QA/QC) measures. While the collective evidence showed modest risk of bias (Fig 4), it is helpful to note that measurement bias, selection bias (concerning sampling sites), publication bias, and other biases cannot be ruled out in this work.

The inaccessibility of raw data or suitable (i.e., nonparametric) summary statistics for some studies complicated data analysis, and parameters were estimated in some cases, reducing the precision of results. Most included studies provide parametric summary statistics, whereas lead concentrations in drinking water tend to be lognormally distributed [16]; nonparametric statistics were therefore estimated as described in Methods. The use of meta-regression methods helps provide more generalizable pooled estimates of lead occurrence in drinking water across all

LMICs and within SDG regions despite such limitations among individual studies; however, meta-analysis of additional nationally representative sample sets would improve estimates if and when such data become available.

Pooled estimates of exceedance proportions help inform decisions to undertake or enhance management and monitoring of lead in drinking water at the national, regional, and global scales in LMICs, but have low generalizability to specific populations or subnational locations. Many included studies (45%) are ”targeted,” i.e., they concern settings selected because of previously identified or suspected localized sources of contamination. Such studies have low generalizability to locations free from such issues. Those studies that are not located in settings selected based on previously identified sources of lead contamination are likely to be more representative of typical exposures, and incorporation of additional high-quality “non-targeted” data as they are published, particularly in understudied LMIC settings, will reduce uncertainty and increase the generalizability of estimates.

Locating and including additional sample sets within unpublished grey literature, government records, and non-English language studies may also improve generalizability. Evidence may be especially challenging to obtain in contexts where governments constrain the publication of research and grey literature and where publication of water quality results may be perceived as politically problematic. Further work may seek to delineate such evidence gaps and explore alternative means of assessing potential occurrence through parallel evidence, modeling estimates, or other means.

Thus, the present estimates help inform countries’ decisions on *whether* to undertake or enhance actions in response to lead in drinking water and are likely adequate to justify broad primary prevention and monitoring. In other words, it is doubtful that including more and better data will change our assessment that lead in drinking water in LMIC settings is a global issue requiring timely action. However, additional high-quality local data are needed to decide *how*

best to act and *where* to target actions most intensively to prevent optimally and progressively remediate lead occurrence in drinking water in LMICs. In some cases, such data may be slow or challenging to obtain, and governments may seek to apply the precautionary principle in acting on available data while continuing to address evidence gaps as feasible. In other cases, nationally representative monitoring and surveillance of lead in drinking water may be possible soon, if not already underway.

Sources of Bias

Potential sources of bias in individual studies in this work include the study quality factors noted above: 1) limitations in sample collection and analysis methods, 2) “targeted” studies, and 3) incomplete reporting of methods and raw data. Potential sources of bias across studies include 1) language barriers (exclusion of non-English language studies); 2) exclusion of grey literature; 3) differential water quality monitoring and research support and capacity across settings (both between and within countries and regions [e.g., rural/urban biases]); 4) potential publication bias (which may include both a greater tendency to publish results with noteworthy conclusions in settings in which research publication is unrestricted, and a potentially lower likelihood of publishing results that may be perceived as politically problematic in contexts in which governments may exert some control over publication and research support concerning political priorities). It should be noted that publication bias cannot be easily assessed using statistical and graphical methods that assume a common central tendency of outcomes across settings (e.g., odds ratio for a given association), since the central tendency of TM occurrence data cannot be assumed to be constant across study types and settings.

Implications for Policy, Practice, Research, and Monitoring

These results may prompt LMICs to consider reviewing, strengthening, and/or adopting additional national policies, strategies, and regulations on lead in drinking water, including widespread policies and actions to prevent and monitor the occurrence of lead in drinking water and the use of lead-containing parts, materials, and alloys in the construction of new water systems. Such actions may include developing or updating regulations and policies to ensure that supply chains for drinking water system components are free from unsuitable parts and materials (e.g., brass fittings with high lead content), that new and existing water systems are designed and operated with lead exposure prevention in mind (including the use of optimized corrosion control treatment, where appropriate), and away from known sources of lead exposure likely to contribute to such contamination (e.g., smelting activities), and are managed to minimize the risk of subsequent lead contamination (e.g., monitoring and/or managing land-use and industrial activities likely to produce severe lead contamination impacting water sources and watersheds). Implementers may likewise strengthen measures to verify that source water for new water supplies does not exceed national standards for lead before new water systems are commissioned. They may further wish to undertake representative water quality monitoring to track progress on lead in drinking water across subnational regions and over time, if they intend to demonstrate progress on national and international targets related to safely managed drinking water.

Progressive remediation of existing water systems containing unsuitable components or heavily impacted by nearby land use or activities may also be appropriate for achieving national water quality targets in many settings. Since remediation may be more costly and slower than primary

prevention, risk-based prioritization of systems according to the estimated likelihood and intensity of lead contamination, population served, and remaining design life could be helpful. Integrating remediation with scheduled maintenance activities and other rehabilitation activities to achieve economies of scale, where possible, could also be beneficial.

As part of a set of evidence-informed actions to enhance progress on access to safely managed drinking water, LMICs that do not currently monitor lead in community water supplies should consider initiating such monitoring and surveillance efforts at an intensity commensurate with their resources and the types of water supply systems in use. Those that do conduct such monitoring should periodically review their monitoring strategies to ensure that lead concentrations in drinking water are quantified before and after water system installation using suitable sample collection, analysis, and QA/QC methods, and that monitoring strategies are consistent with available evidence and analytical methods. The resulting monitoring data inform management of lead in drinking water at the national and local levels and help ensure policies, implementation strategies, and targets on drinking water quality are aligned. Results should also be reported to affected populations and captured in national and local management information systems to enhance transparency and sector coordination (e.g., between water, environment, health, and finance agencies). Sampling, monitoring, analysis, reporting, and/or knowledge management capacities may benefit from additional strengthening and coordination in many countries.

Finally, research targeting high-priority evidence gaps can further inform policies and actions to prevent exposure to lead in drinking water. Better characterizing and understanding the root causes of lead occurrence in water across geographies, system types, and land

use/demographic variables enables more effective preventive and corrective actions. Further innovation, optimization, piloting, and adoption of low-cost preventive and corrective solutions, monitoring tools, and approaches could facilitate better detection and management. Implementation science research could also enhance the efficiency of monitoring data to inform implementation. Characterizing the extent of human exposure to lead from drinking water and other sources and determining the associated disease burdens could highlight the importance of managing and monitoring these hazards, build institutional support for further action, and enable water, environment, health, and finance decision-makers to contextualize better the hazards associated with exposure to lead in drinking water among other competing priorities and opportunities.

Where called for, additional research and monitoring can likely be undertaken in parallel with timely preventive action, rather than delaying or replacing prevention activities. In our estimation, the available evidence is now sufficient to justify several “no-regrets” primary prevention activities in many LMIC settings. While further evidence is likely to yield more accurate, more precise, and higher-resolution (e.g., more geographically disaggregated) estimates of the extent of lead occurrence in drinking water of different types across LMIC settings, it is unlikely to change the big-picture finding that lead occurrence in drinking water at levels of public health concern is widespread among the LMIC settings included in this review, and that primary prevention activities can enhance progress on safely managed water access and protect vulnerable sub-populations in these settings. Timely and effective prevention, monitoring, progressive remediation, and evidence-generating actions such as those described above would be highly likely to reduce lead exposure, protect the health of large populations across LMICs, and support progress on safely managed drinking water access under SDG 6.1.

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589

590 Author Contributions

591 All authors approve of the submitted manuscript, accept accountability for their contributions
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602

603 Table 1. Toxic metals and metalloids included in the larger systematic review of TM
604 contamination in drinking water in low- and middle-income countries; this study reports only on
605 lead

Element	Rationale (Guidelines for Drinking Water Quality, 4th Ed.)	WHO GV (ug/L, where applicable)	Source Category (Guidelines for Drinking Water Quality, 4th Ed.)
Antimony	Health	20	Contaminants from pipes and fittings
Arsenic	Health	10	Naturally occurring
Cadmium	Health	3	Industrial sources and human dwellings
Chromium	Health	50	Naturally occurring
Copper	Health	2000	Contaminants from pipes and fittings
Iron	Aesthetic acceptability, disinfection (c.f. Browning et al.)	300*	Naturally occurring
Lead	**Health**	**10**	**Contaminants from pipes and fittings**
Manganese	Acceptability, Disinfection, Health effects (c.f. Browning et al.)	100*	Naturally occurring
Mercury	Health	6	Industrial sources and human dwellings
Nickel	Health	70	Contaminants from pipes and fittings
Selenium	Health	40	Naturally occurring
Uranium	Health	30	Naturally occurring

606 *Not health-based

607

608

609 Table 2: Inclusion and exclusion criteria for study selection

Inclusion Criteria	1. Based in a low- or middle-income country (LMIC, according to the World Bank's Country and Lending Groups) 2. Provides a quantitative measure of toxic metals and/or metalloids in water sample (larger systematic review); of lead in water sample (this work) 3. Discusses a toxic metal of interest: Antimony, Arsenic, Cadmium, Chromium, Copper, Iron, Lead, Manganese, Mercury, Nickel, Selenium, Uranium (larger systematic review); lead only (this work) 4. Contaminant appears in a drinking water source (or a source likely to be used for drinking such as groundwater in a setting reported to rely on groundwater for drinking water supply) 5. Peer-reviewed publication, article, or book chapter written in English since 1969
Exclusion Criteria	1. Duplicate 2. Non-English Language 3. Study is not based in LMIC, or the setting cannot be determined 4. Does not provide a quantitative measure of any TM of interest (larger systematic review); of lead (this work) 5. TM/lead is not measured in drinking water sources (or sources likely to be used for drinking, such as groundwater or surface water from a water body documented as being a source of drinking water for human settlements) 1. Example: only measured in sources or food or diet 2. Only measured in nonpotable surface or recreational water source 3. Only measured in animals, i.e., animal studies 4. Only measured in human blood, bone, or tissue, i.e., it is a human health assessment 5. Only measured in prepared samples or laboratory solutions to which TMs have been added (e.g., in studies focused on the testing of remediation techniques) 6. The study is a commentary or review that does not present primary data

Table 3. Precision of studies prioritized by supervised clustering (as a function of ensemble score)

Ensemble Score	Precision
6	55%
5	48%
4	51%
3	42%
2	34%

1	19%

615
616

617 Table 4. Precision of studies from supervised machine learning (for results returned in all search
618 updates) by predicted relevance group. Group 1 studies were predicted most likely to be
619 relevant by supervised machine learning; Group 5 studies were predicted least likely to be
620 relevant.

621

Precision Trend (Combined Search Updates)				
Relevance Probability from ML	**Group**	**Total Studies Screened**	**Total Studies Relevant (ti/ab)**	**Precision**
Highest	1	1000	856	86%
	2	1000	632	63%
	3	1000	406	41%
	4	1000	237	24%
Lowest	5	717	70	10%

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624

625 Table 5: Criteria for calculating method quality scores for included studies

Criterion	Rationale	Definition/Detail
Analytical methods used were described	If methods are not described, their suitability cannot be confirmed	Methods are described in sufficient detail to be reproduced
Analytical methods included the use of standards, blanks, and appropriate QC procedures	Use of these measures enables differentiation between true positive samples and contamination or imprecision	Use of field or laboratory blanks is mentioned in methods; instrument calibration is mentioned in methods
Laboratory instrumentation used was described	If instrumentation is not described, its suitability cannot be confirmed	Instrumentation is described in sufficient detail to confirm its suitability for TM analysis
Laboratory instrumentation was sufficiently sensitive to	If instrumentation offers precision insufficient to	Instrumentation offers a method detection level for TM

detect TMs of interest in drinking water at µg/L concentrations	distinguish TM concentrations that are above vs below WHO GV in samples, study cannot quantify GV exceedances	of interest that is < WHO GV. ICP-MS, ICP-OES, and GF-AAS generally provide adequate sensitivity for most TMs of interest.
The type of container used to collect water samples was described	If sample collection containers are not described, their suitability for TM sampling cannot be determined	Sample container materials are described in sufficient detail to assess their suitability for TM sampling.
The type of container used was adequate	Containers that are not manufactured, cleaned, or washed in such a way that they are likely to be trace-metal free may introduce contamination, preventing quantitation of TMs in water samples.	Containers made from virgin or acid-washed PP, HDPE, PTFE, glass, or other inert material are unlikely to introduce substantive TM contamination. Reused local beverage containers or unspecified containers may introduce such contamination
The sample handling procedure was described	If sample collection procedures are not described, their suitability for TM sampling cannot be determined	Sample handling procedures are described in sufficient detail to be reproduced.
The sample handling procedure was adequate (included sample preservation with appropriate acid)	Without proper sample preservation, TMs of interest may volatilize, precipitate, or sorb to container surfaces, leading to underestimation of their concentration in water samples.	Samples are collected at the water source and preserved with trace-metal free acid prior to transport and analysis. Typically, final pH should be <=2.0
Samples were not filtered prior to analysis	Filtration can remove particulate TM contamination	Methods do not mention filtration of samples prior to analysis
Stagnation period observed	Stagnation provides an exposure profile representative of first-draw water samples, which are typically of greatest concern when characterizing water-system derived TM exposure in drinking water.	For TMs classified by the Guidelines for Drinking-Water Quality as being commonly derived from plumbing and water system components (e.g., Sb, Cu, Pb), an additional point was added for studies that reported applying

		a stagnation period of any kind before sample collection

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627

628 Table 6: Numbers of included sample sets in low- and middle-income countries reporting
629 quantitative data on the occurrence of lead in drinking water, by country

630

Country	Frequency
Afghanistan	1
Albania	1
Algeria	6
Argentina	0
Armenia	0
Bangladesh	50
Benin	1
Bolivia	10
Bosnia and Herzegovina	1
Brazil	48
Burkina Faso	5
Cambodia	13
Cameroon	10
China	244
Colombia	0
Costa Rica	3
Cuba	0
Djibouti	3
Ecuador	3
Egypt	41
El Salvador	1
Ethiopia	54
Ghana	45
Guatemala	9
Haiti	12
India	334
Indonesia	2
Iran	107
Iraq	29
Jordan	16
Kazakhstan	4

Kenya	23
Kosovo	8
Kyrgyzstan	2
Lebanon	12
Macedonia	1
Malawi	4
Malaysia	9
Mali	1
Mexico	82
Moldova	8
Mongolia	2
Morocco	22
Mozambique	1
Myanmar	7
Namibia	12
Nepal	10
Niger	1
Nigeria	127
North Cyprus	18
Pakistan	215
Palestine	6
Peru	5
Philippines	1
Rwanda	1
Serbia	8
South Africa	33
Sri Lanka	19
Sudan	2
Tanzania	12
Thailand	37
Togo	1
Tunisia	2
Turkey	148
Uganda	2
Uzbekistan	1
Vietnam	20
Yemen	3
Zambia	4
Zimbabwe	20
Total	1943

631

632

633 Table 7: Numbers of included datasets by SDG Region

SDG Region	Number of Datasets	Percent
Central and Southern Asia	640	38.9
Eastern and South-Eastern Asia	339	20.6
Sub-Saharan Africa	302	18.4
North Africa and Western Asia	213	13.0
Latin America and the Caribbean	124	7.5
Europe and Northern America	26	1.6
Oceania	N/A	N/A
Total	2050	100

634

635 Table 8. Proportion of included studies that selected study sites based on presence of
636 previously identified contamination (by source)

Potential Source	n	Proportion
Wastewater	206	12.0%
Mining	198	11.6%
Industrial	197	11.5%
Agriculture	186	10.9%
Landfill	169	9.9%
Geogenic	116	6.8%
Corrosion	41	2.4%
Smelting	23	1.3%
Other	40	2.3%

637

638

639 Table 9. Analytical method used across all included datasets.

Analytical Method	n	Proportion
ICP-AES	321	26.8%
ICP-MS	817	68.2%
UV-Vis	40	3.3%
Electrochemical	16	1.3%
Other	4	0.3%

640

641

642 Table 10. Study Method Quality Score ("high quality" study = a score of 7 out of 10 possible
643 method quality items.

644

Method Quality Score	n	Proportion
0	189	11.0
1	464	27.1
2	604	35.3
3	73	4.3
4	69	4.0
5	80	4.7
6	112	6.5
7	76	4.4
8	34	2.0
9	9	0.5
10	3	0.2

645

646

647 Table 11. Proportion of samples exceeding WHO Guideline Value for lead across all included
648 sample sets, for a) all included studies in which lead was quantified; b) the subset of those
649 ("nontargeted") studies in which the setting was not reported as having been purposively
650 selected due to a known or suspected specific source of contamination; c) the subset of those
651 "representative" studies that were "high-quality" ("high quality" study = a score of >=7 out 9
652 possible method study quality items); and d) the subset of those "nontargeted" studies in which
653 water samples were analyzed by ICP-MS (generally capable of differentiating between samples
654 exceeding vs conforming with GVs when used properly with suitable sample collection,
655 handling, analysis, and quality control).
656

Exceedances	Proportion	95% CI (Lower)	95% CI (Upper)	n
a) All studies	25.6%	23.5%	28.1%	1220
b) Nontargeted	23.7%	20.3%	27.1%	523
c) Nontargeted: high-quality	23.4%	20.1%	26.8%	521
d) Nontargeted: ICP-MS	18.9%	15.2%	22.6%	368
e) Nontargeted: ICP-MS, ex-PRC	22.7%	18.0%	27.4%	264

657

658

659 Table 12. Median concentration of lead across all sample sets for which values could be
660 estimated

Dataset type	Conc (µg/L)			n
a) All studies	50	36	65	854
b) Nontargeted	27	14	40	317
c) Nontargeted: high-quality	--*	--*	--*	--*

d) Nontargeted: ICP-MS	24	11	37	251
e) Nontargeted: ICP-MS, ex-PRC	32	14	51	175

*Insufficient usable observations to estimate

Table 13. Proportion of samples from nontargeted studies exceeding WHO Guideline Value for lead* across included sample sets by A) source type and B) SDG region**, by metaregression

Source Type	Proportion	95% CI (Lower)	95% CI (Upper)	n
Borehole	0.339	0.266	0.412	148
Piped	0.318	0.187	0.448	50
Surface	0.320	0.222	0.418	85
Spring	0.556	0.358	0.753	27
Wells	0.228	0.160	0.296	130
Other	0.272	0.176	0.369	68

Region	Proportion	95% CI (Lower)	95% CI (Upper)	n
SSA	0.358	0.246	0.469	73
NAWA	0.383	0.287	0.479	93
CSA	0.389	0.324	0.454	193
SEA	0.131	0.080	0.181	143
LAC	0.127	0.0	0.256	25
EUR	N/A	N/A	N/A	N/A

* As calculated by meta-regression using the “metareg” STATA command

**SSA: sub-Saharan Africa; NAWA: North Africa and Western Asia; CSA: Central and Southern Asia; SEA: Eastern and South-east Asia; LAC; Latin America and the Caribbean; EUR: Europe

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704

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709 middle-income countries, by water source type

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711 middle-income countries, by SDG region

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713 middle-income countries, by decade of study publication

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715 middle-income countries, by SDG region (CSA: Central and Southern Asia; ENA: Europe and
716 North America; ESEA: East and Southeast Asia; LAC: Latin America and the Caribbean;
717 NAWA: North Africa and Western Asia; SSA: Sub-saharan Africa). Red line denotes WHO
718 Guideline Value.

719 Fig 7: Distribution of mean lead concentrations for drinking water sample sets from low- and
720 middle-income countries, by decade of study publication. Red line denotes WHO Guideline
721 Value.

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Supporting Information Files

File S1 Checklist. PRISMA Checklist.

File S1 Code. Code used for all calculations in this study (to be uploaded upon acceptance).

File S1 Data. Cleaned data used for all calculations in this study (to be uploaded upon acceptance).

File S1 Protocol. PROSPERO protocol for this systematic review.

File S1 Studies. Table of all studies included in this systematic review.

File S1 Text. Tables and figures presenting supporting information referenced in this study.

- Table S1. Search Strategy
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- Fig S4. Reported vs estimated proportion of exceedences for the subset of studies for which the proportion of exceedances of the WHO GV for lead was reported or could be extracted from available data.
- Fig S5. Diagnostic plots of the distribution of log-transformed median and mean lead concentrations for drinking water sample sets from low- and middle-income countries vs normal distribution for studies from a) median for all LMICs; b) mean for all LMICs; c) median for all LMICs ex-PRC; d) mean for all LMICs ex-PRC ; e) median for studies from China (PRC); and f) mean for studies from China (PRC).

File S1 Tools. Training tools and materials used to train screening and extraction teams in this study.

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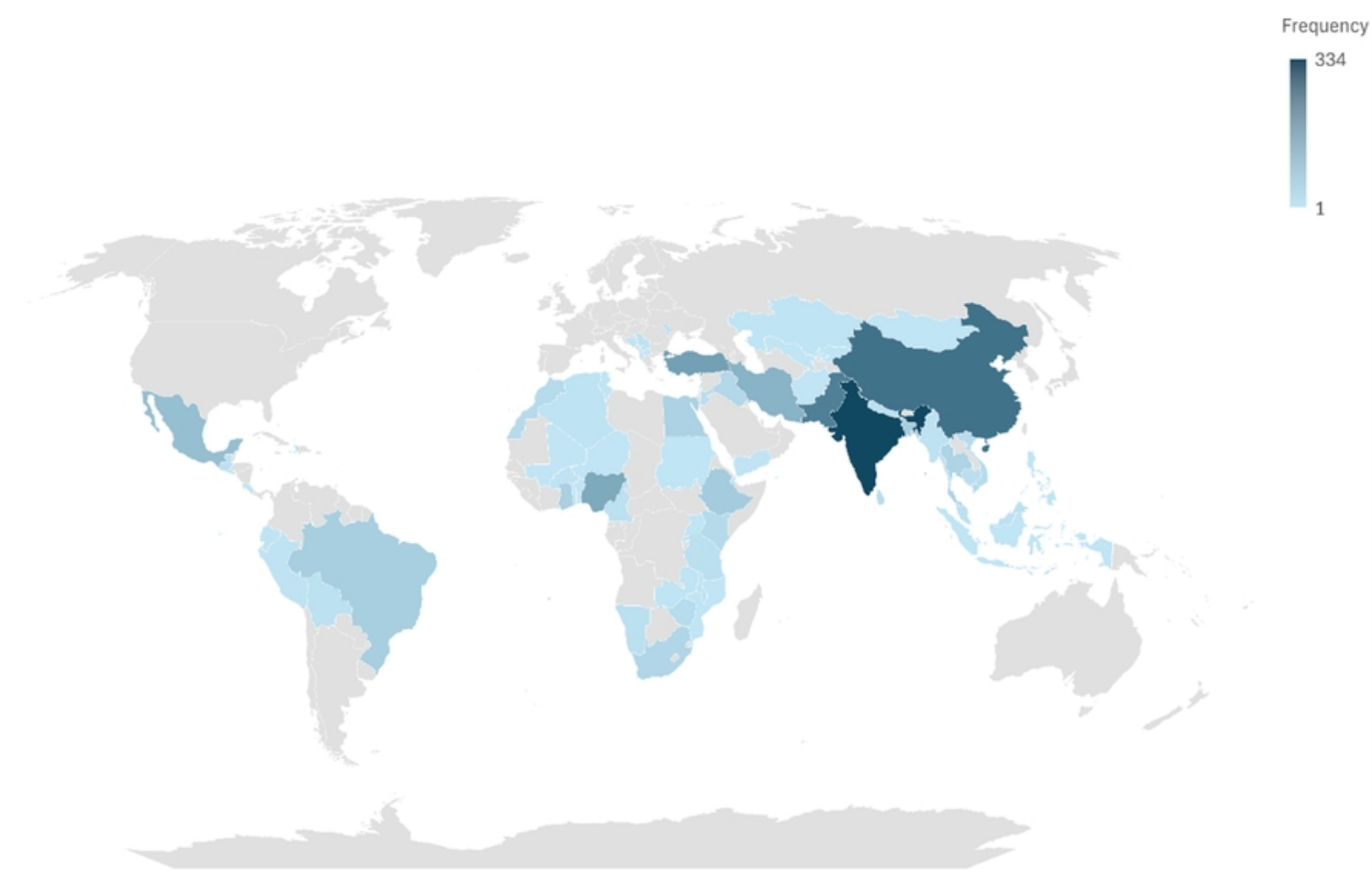

Fig 3

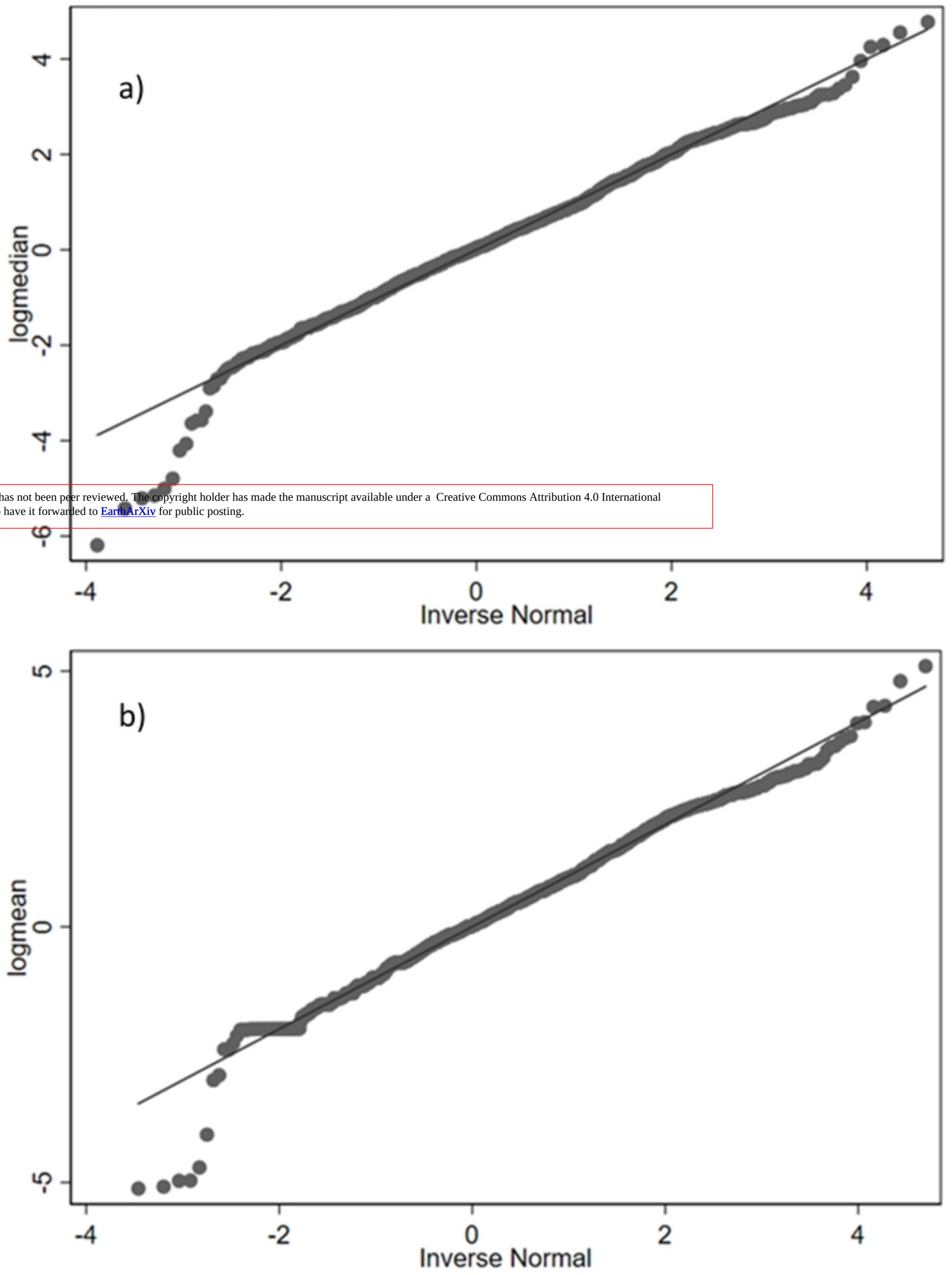

Fig 4

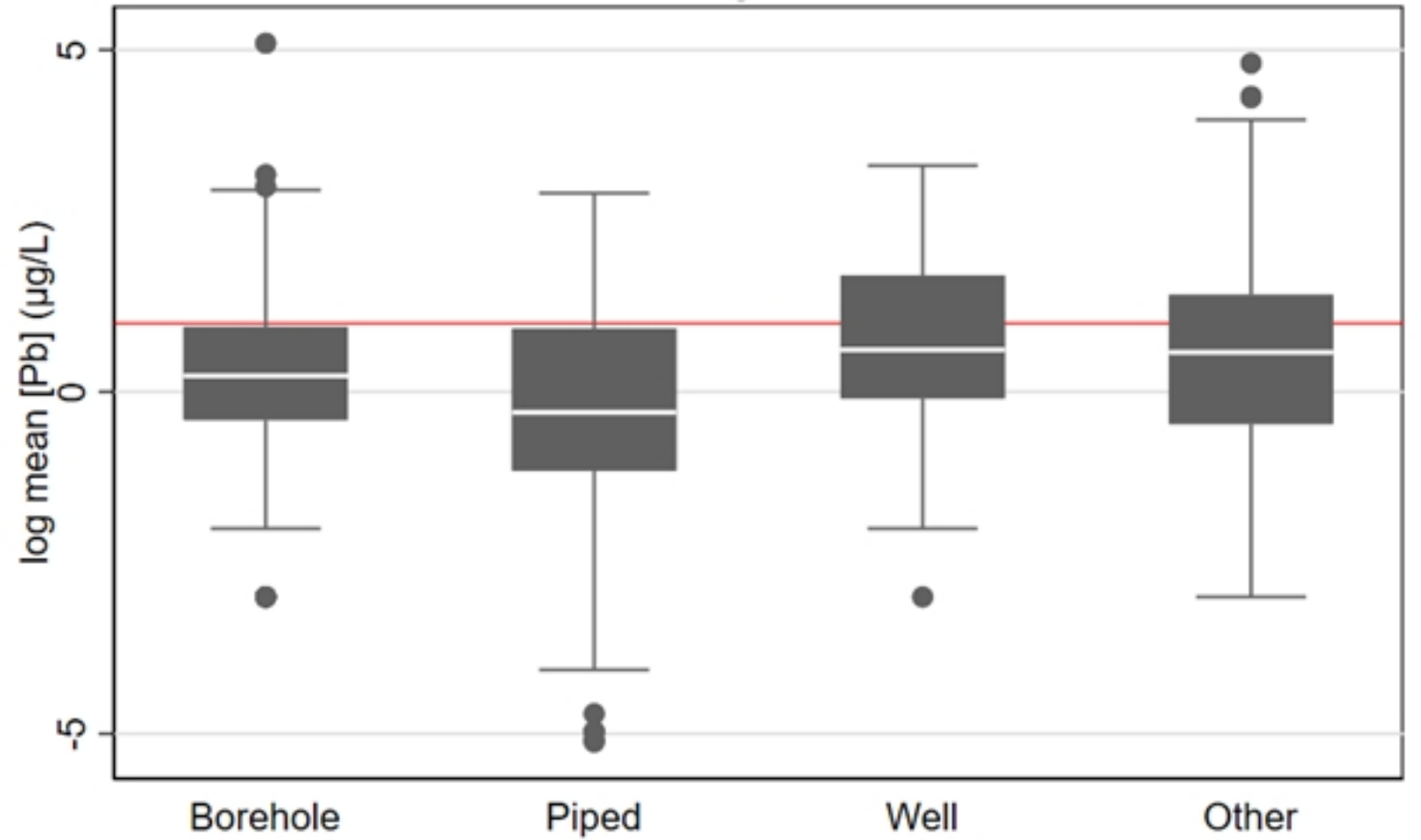

Fig 5

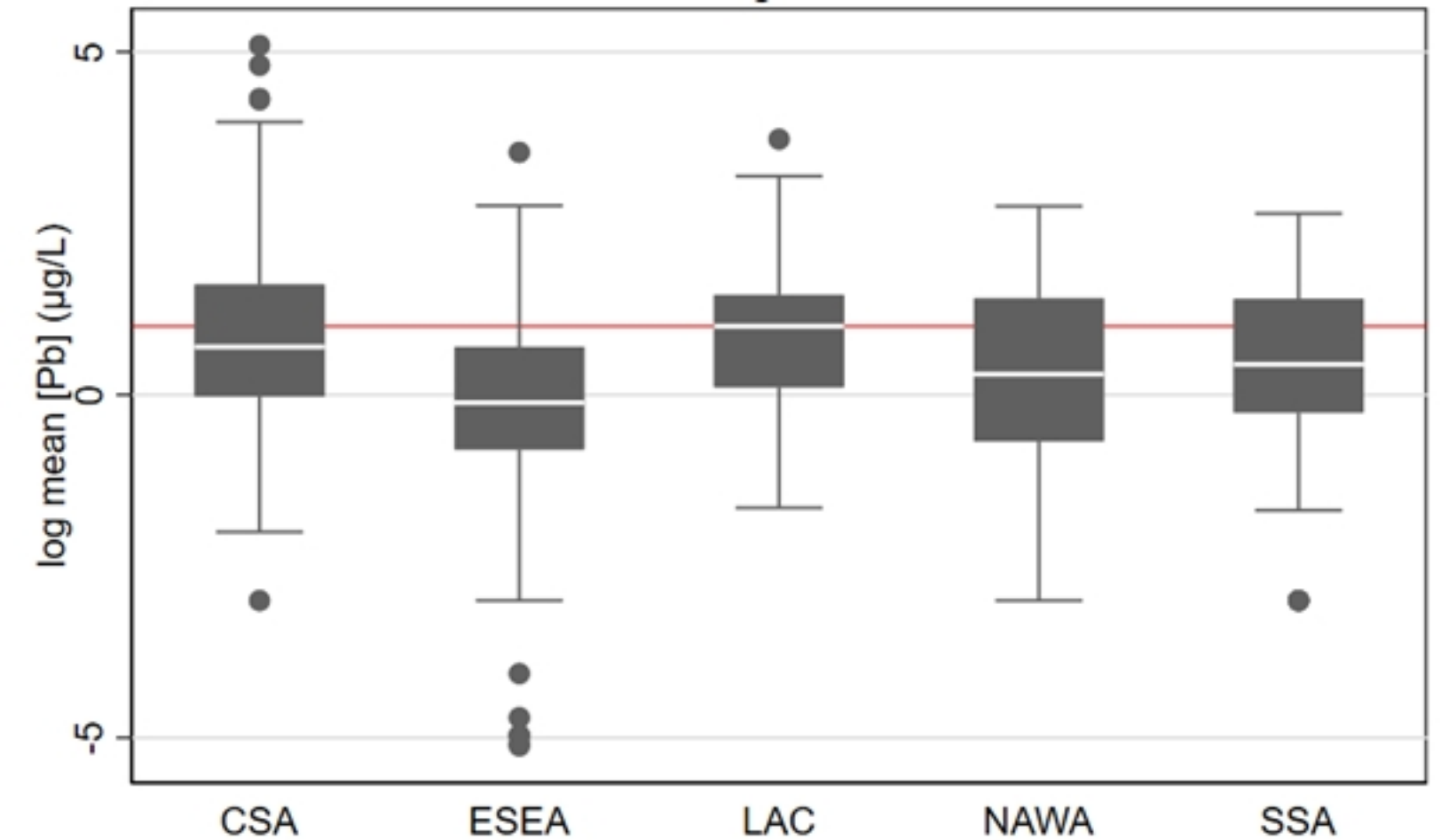

Fig 6

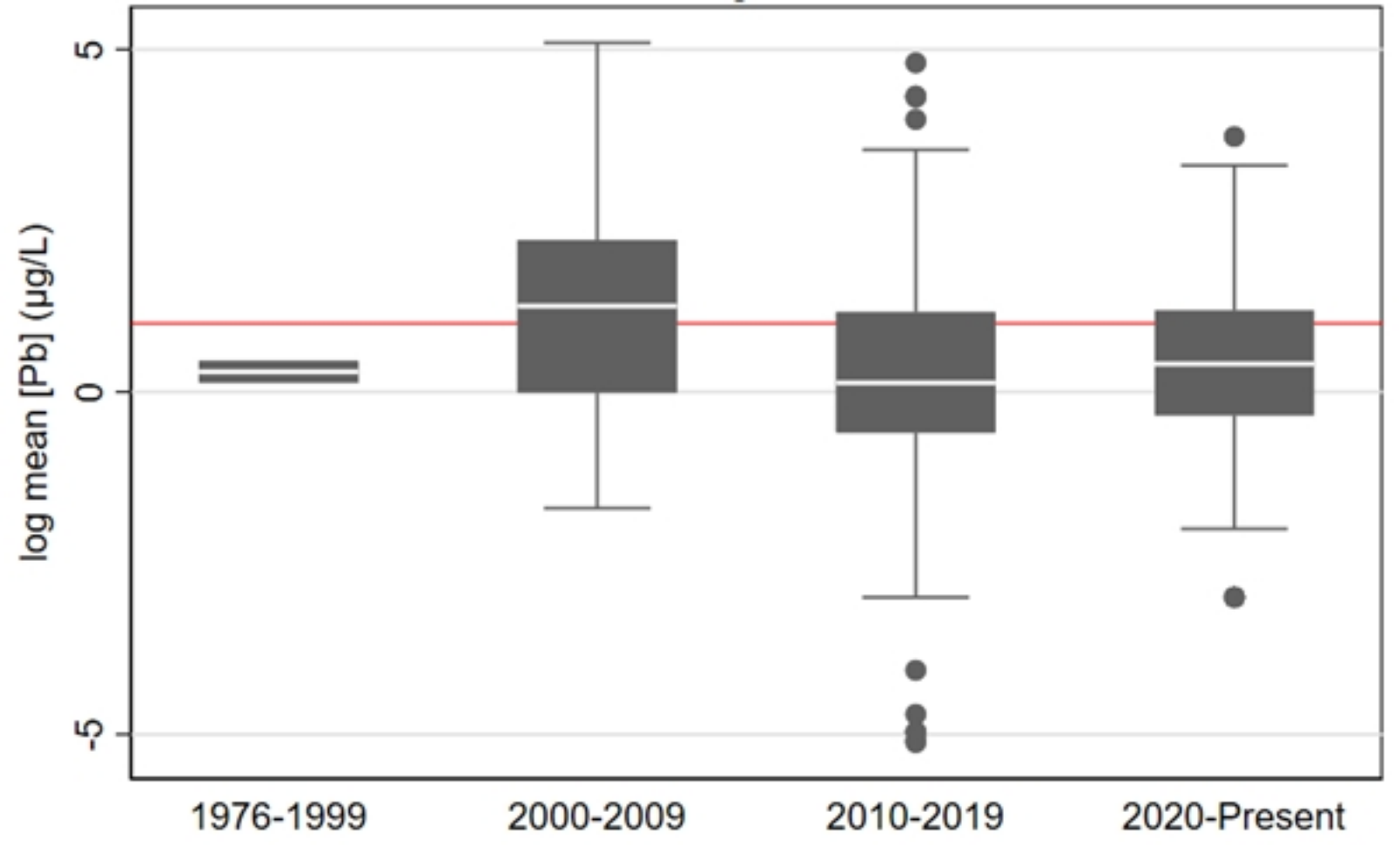
log mean [Pb] (µg/L)
5
0
-5
1976-1999
2000-2009
2010-2019
2020-Present

Fig 7

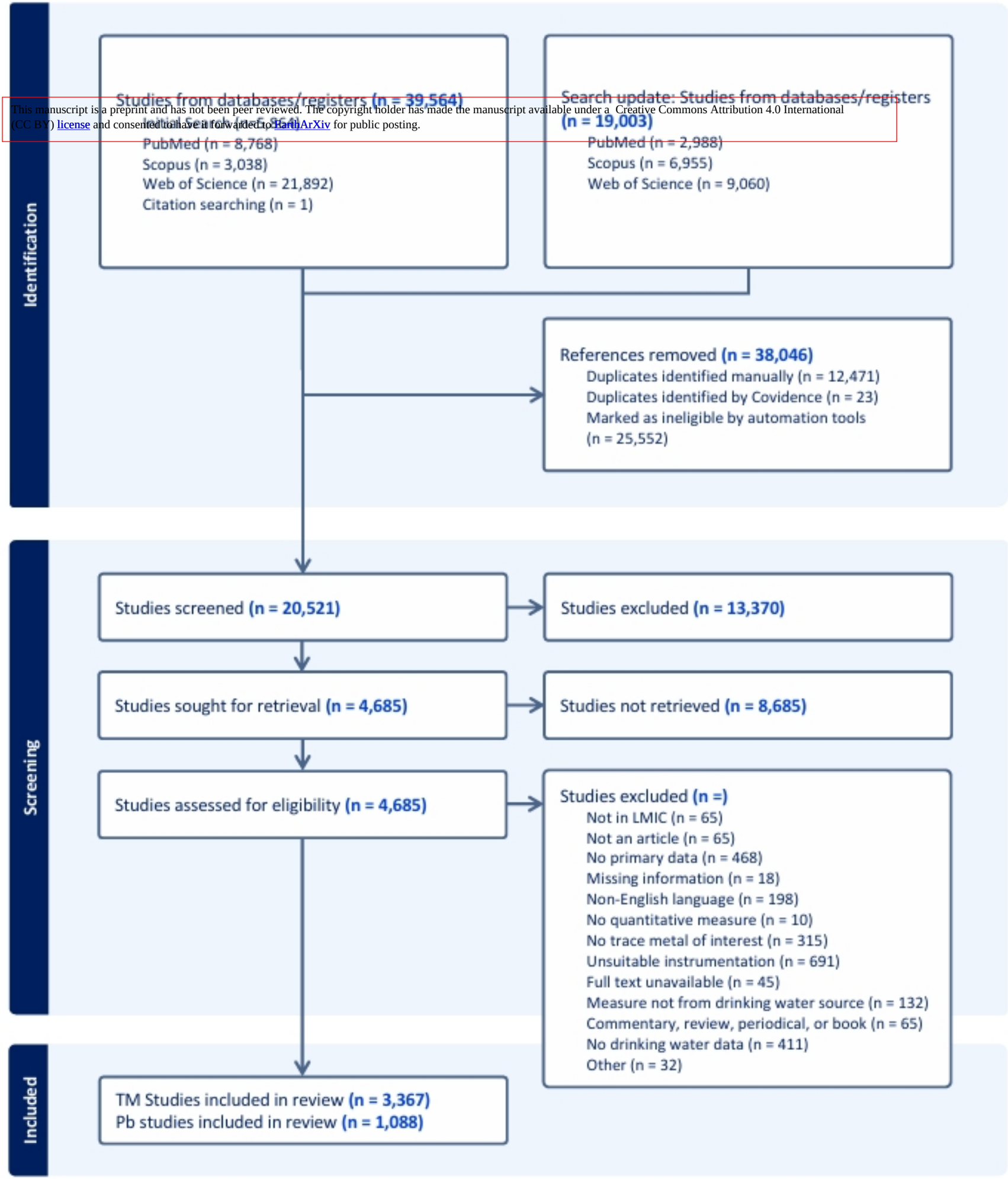

Fig. 1

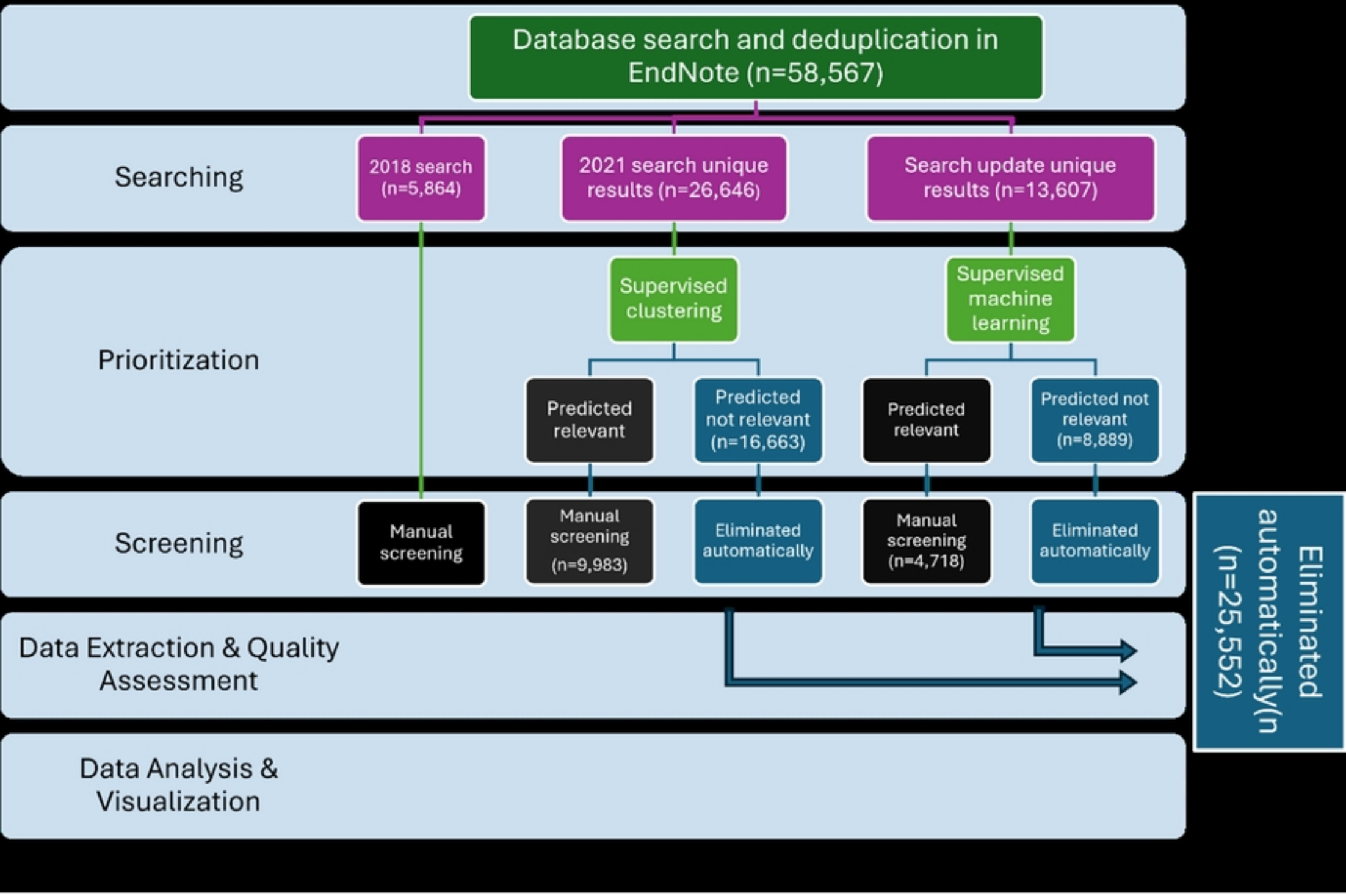
Database search and deduplication in EndNote (n=58,567)
Searching
2018 search (n=5,864)
2021 search unique results (n=26,646)
Search update unique results (n=13,607)
Prioritization
Supervised clustering
Supervised machine learning
Predicted relevant
Predicted not relevant (n=16,663)
Predicted relevant
Predicted not relevant (n=8,889)
Screening
Manual screening
Manual screening (n=9,983)
Eliminated automatically
Manual screening (n=4,718)
Eliminated automatically
Eliminated automatically(n (n=25,552)
Data Extraction & Quality Assessment
Data Analysis & Visualization

Fig. 2