Evaluations of Climate-Informed Early Warning Systems for Foodborne, Waterborne, and Vector-Borne Diseases: A Scoping Review

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Abstract

Climate change is altering infectious disease risk over time and across geographies. These changing risks can negatively impact human health and pose challenges to health systems. Anticipating outbreaks before they happen and implementing adaptive measures can help reduce the burden of climate-sensitive infectious diseases. Climate-informed early warning systems (CIEWS) are integrated systems of climate and infectious disease risk monitoring, forecasting, and prediction that inform communication and preparedness efforts for timely action to reduce disease risk in advance of hazardous events. CIEWS can provide critical information for public health systems to adapt to the changing risk of infectious diseases. While extensive research has advanced predictive models for potential use in CIEWS, evidence of the effectiveness of these tools once operationalized has not been well described. In this scoping review, we examine the evidence base evaluating operational CIEWS targeting foodborne, waterborne, and vector-borne diseases. We conducted a search in Global Index Medicus, Scopus, and PubMed. Of the 9,917 unique articles screened, 21 met eligibility criteria. Included articles described 17 unique CIEWS and spanned five WHO regions (the Americas, Western Pacific, Africa, South-East Asia, and Eastern Mediterranean). All but one article presented a CIEWS for a vector-borne disease, with dengue most prominently represented. Most evaluations of CIEWS focused on statistical performance of the model, with only two evaluations of CIEWS effectiveness, and four evaluations of the system's operational features. There are significant evidence gaps and a need for more research to demonstrate the effectiveness and cost-effectiveness of operational CIEWS, particularly for foodborne and waterborne

diseases. Evaluations of CIEWS are critical for ensuring systems are useful, usable, and effectively informing anticipatory action for climate-sensitive infectious diseases.

1. Introduction

Rising land and ocean temperatures, changes in precipitation, and other climatic factors are altering patterns of infectious disease transmission, often increasing the risk of outbreaks and threatening human health [1]. Foodborne (FBD), waterborne (WBD), and vector-borne diseases (VBD) are among the infectious diseases most aggravated by climate hazards [1,2]. For example, evidence suggests that global mean temperatures are expanding the suitable geographic range for mosquito-borne disease (MBD) transmission [3]. Additionally, higher temperatures, flooding, heavy rainfall, and drought are linked to an increase in diarrheal diseases, particularly in areas with limited access to improved water and sanitation [4,5]. Despite these concerning trends, public health adaptation measures inadequately address the needs of the most at-risk populations [6].

Anticipating outbreaks before they happen and implementing adaptive measures can help reduce the burden of climate-sensitive infectious diseases (CSIDs) in high-risk areas. Integrating climate variables into early warning systems (EWS) improves predictions and provides critical information for public health systems to adapt to the changing risk of infectious diseases [7]. These climate-informed early warning systems (CIEWS) can inform public health adaptation measures, such as prepositioning of testing and treatment supplies in health facilities; outbreak prevention and early response; vector management; and community health promotion[8].

While extensive research has advanced predictive models for use in CIEWS, evidence of the effectiveness of these tools once operationalized as CIEWS has not been well

described. A recent scoping review on infectious diseases and climate change reported that most studies focused on surveillance or modeling, while evaluations of real-world EWS or adaptation programs were rare [9]. Similarly, a 2022 review of CSID modelling tools identified 37 fully developed tools, of which only 21 were made into accessible software products or used to inform stakeholders [10]. A scoping review of EWS for VBDs—not limited to climate-informed, operational systems—further reported that none of the 37 included studies assessed EWS integration into routine surveillance systems or examined the feasibility of translating model outputs into public health actions [7].

In 2021, the World Health Organization (WHO) established guidance for assessing both technical and operational aspects of CIEWS, covering five steps: 1) defining the outbreak, 2) evaluating structural and statistical features, 3) evaluating performance (retrospective), 4) evaluating effectiveness and cost-effectiveness (prospective), and 5) evaluating operational features [11]. While many studies have described the development and evaluation of the statistical features of predictive models for CIEWS, the extent to which operationalized CIEWS have been evaluated, is unknown. Evidence of the utility, accessibility, and effectiveness of CIEWS in informing public health planning and anticipatory actions is critical to scaling these tools across regions facing the highest risk of CSIDs [12,13].

The aim of this scoping review is to describe the extent to which operational CIEWS have been evaluated. By examining the evidence of operational CIEWS that have been evaluated over the last 25 years, we identify strengths, weaknesses, and other key characteristics of implemented systems. We then summarize knowledge gaps to inform

91 further research on the operationalization and effectiveness of these critical climate
92 adaptation interventions.

93 2. Methods

94 2.1 Protocol and search strategy

95 This scoping review protocol followed the Preferred Reporting Items for Systematic
96 reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) guidelines
97 and was developed following the guidance from the JBI Scoping Review Methodology
98 Group [14,15]. The protocol was pre-registered in Open Science Frameworks (DOI:
99 10.17605/OSF.IO/5W2FN). For the purposes of this review, we adapted the United
100 Nations Office for Disaster Risk Reduction's general definition of an EWS to define a
101 CIEWS as an integrated system of climate and infectious disease risk monitoring,
102 forecasting, and prediction that informs communication and preparedness efforts
103 for timely action to reduce disease risk in advance of hazardous events [16]. We
104 considered a CIEWS to be operational if actively used to predict disease risk in real time
105 and inform an anticipatory action. We applied WHO's quality criteria for the evaluation of
106 CIEWS to determine whether studies have evaluated the performance, effectiveness, or
107 operational features of their system (steps 3–5 referenced above) [11]. Given that most
108 CIEWS modelling work has focused on FBD, WBD, and VBD [17], this review is limited
109 to CIEWS studies of diseases transmitted through these three pathways.

110 The search string included keywords for climate variables, disease-related
111 terms, EWS terms, and evaluation terms, some of which were adapted from a

landscape analysis of software tools for CSIDs (S1 Search string) [18]. We limited the search to English language publications from 2000 to 2025, given the language abilities of the team and assuming the most relevant technological innovations in CIEWS have occurred in the last 25 years. A health sciences librarian with expertise in scoping reviews provided guidance during the development and validation of the search strategy. We ran the search on September 9, 2025, across three databases: Scopus, PubMed, and Global Index Medicus. We identified two additional articles not captured in the database search through hand-searching on August 5, 2026.

2.2 Relevance and screening process

The reviewers included studies meeting the following criteria:

1. Primary quantitative or qualitative research published in a peer-reviewed journal or in the grey literature (e.g., program evaluation report, government report)
2. Studies of CIEWS for FBD, WBD, or VBD of human health significance
3. Evaluations of CIEWS against any of the quality criteria in assessment steps 3, 4 or 5 of the WHO guidance on evaluating CIEWS for infectious diseases—performance (retrospective phase), cost-effectiveness (prospective phase) or operational features—either for stand-alone CIEWS or integrated into national surveillance systems [11]
4. Studies of EWS with a climate variable in the prediction model

Studies were excluded if they met any of the following criteria:

1. Studies describing or assessing a model that has not been operationalized as a CIEWS
2. Studies limited to the spatial prediction of vectors without incorporating any human health data
3. Studies limited to describing the development or implementation of a CIEWS but not assessing the system against any of the WHO CIEWS evaluation criteria in steps 3, 4 or 5
4. Articles with repetitive results previously reported in another study
5. Comments, editorials, protocols, or secondary research
6. Studies whose full text was not available

We uploaded the search results into Covidence for deduplication, screening, and review [19]. Prior to starting the review, two reviewers (KO, AI) tested the protocol through a pilot review of 25 records [20]. The team achieved 80% agreement in the pilot phase, surpassing the 75% benchmark for high heterogeneity as defined by JBI's Manual for Evidence Synthesis [20].

Three reviewers (MR, KO, AI) assessed records for eligibility in two stages using proportional screening. Reviewers initially screened titles and abstracts and excluded records not meeting eligibility criteria. One reviewer screened each record, and a second independent reviewer validated a 10% random sample of all records for consistency (proportional agreement = 94%). At the full text review stage, two reviewers assessed each record for eligibility (proportional agreement = 73% to 92%). For any disagreements between reviewers during the first or second stage, the three reviewers met to discuss and arrived at a consensus.

2.3 Critical appraisal

After completing full text review, the reviewers (MR, KO, AI) applied the Mixed Methods Appraisal Tool (MMAT) to assess the quality of the selected studies [21]. Two reviewers per article conducted the appraisal, and a third reviewer resolved discrepancies. We first applied two screening questions to identify general concerns with the clarity of the research questions and data collected to address the questions. If a study had major quality issues at screening that made further appraisal infeasible, it did not advance further. We then assessed studies passing the screening questions against a set of five additional questions specific to the study design. If reviewers identified issues with three or more questions, the study was ultimately considered high risk of bias for its specific study design type, while issues with one to two questions were considered medium risk and no issues considered low risk.

2.4 Data charting and synthesis

We charted data from included studies related to study identification information, study characteristics, the WHO quality criteria for evaluating CIEWS, and funding sources (S3 Data charting template). If two articles discussed the same CIEWS, we did not make any assumptions or carry over information from one article to another. Two reviewers independently charted data from each article (MR, KO, AI), and a third reviewer (MR, KO) resolved any discrepancies between the two entries. After the data charting phase, we derived several new variables from the original variables to further categorize and synthesize extracted data. For example, we grouped the types of predictive models into three broad categories: regression, time-series analysis, machine learning, or a

combination thereof. We then organized the results into tables and narratively described key themes and notable findings.

3. Results

3.1 Selection of sources of evidence

The database searches returned 9,917 unique records that were screened. Of the 157 records proceeding to full text review, 136 were excluded for not meeting eligibility criteria (Fig 1). Reviewers charted data from 21 included articles.

Fig 1. PRISMA diagram. An overview of the selection of sources of evidence.

3.2 Characteristics of sources of evidence

The 21 articles described 17 unique CIEWS, with one CIEWS for dengue in Mexico reported in three articles, one for cholera in Bangladesh covered in two articles, and one for dengue in Brazil described in two articles (Table 1). One article presented the same CIEWS for dengue in Mexico but also described a CIEWS in Colombia, which we considered as a unique tool. CIEWS for VBDs were the most common (n = 18), revealing evidence gaps for WBDs (n = 3) and FBDs (n = 0). Two articles described CIEWS for multiple VBDs, while the remaining covered one disease. The VBD with greatest coverage was dengue (n = 10), followed by malaria (n = 5). The articles spanned over 20 countries, including three multi-country studies and one study covering two regions. The region of the Americas was most widely represented (n = 9) (Fig 2). Most articles (n = 16) were authored by at least one individual based in a low- or middle-

198 income country (LMIC). Among the included articles, public institutions were the most
199 common funders (n = 13), while one study reported private funding, and two had a mix
200 of both public and private funding. Five articles did not mention any funding source.

201 **Table 1. Study characteristics of articles included in the scoping review of CIEWS**
202 **evaluations (n = 21).**

Study	Country or Region	WHO Evaluation Criteria (Step Number)	Disease (Type of Disease)	Climate Variables	Epidemiologic Variables	Modeling Approach
Anyamba et al. (2010)	East and Southern Africa	Retrospective (step 3), operational (step 5)	Rift Valley Fever (VBD)	Temperature, NDVI, precipitation, outgoing longwave radiation	Lab-confirmed cases, suspected cases, reported cases	Not specified
Benitez-Valladares et al. (2021)	Mexico	Prospective (step 4)	Dengue (VBD)	Unspecified meteorological data	Reported cases	Regression
Cardenas et al. (2022)	Mexico, Colombia	Retrospective (step 3)	Dengue, Zika, Chikungunya (VBD)	Temperature, humidity, precipitation	Hospitalizations, lab-confirmed cases, clinically confirmed cases, probable cases, suspected cases	Not specified
Fletcher et al. (2025)	Barbados	Retrospective (step 3)	Dengue (VBD)	Temperature, precipitation	Lab-confirmed cases	Regression
Gbaguidi et al. (2025)	Benin	Retrospective (step 3)	Malaria (VBD)	Temperature, humidity, precipitation, wind speed	Lab-confirmed cases	Machine learning
Hussain-Alkhateeb et al. (2018)	Brazil, Malaysia, Mexico	Retrospective (step 3), operational (step 5)	Dengue (VBD)	Temperature, humidity, precipitation	Hospitalizations (primary variable), lab-confirmed cases, suspected cases, serotypes	Regression/tim series
Javaid et al. (2023)	Pakistan	Retrospective (step 3)	Dengue, malaria, leishmaniasis (VBD)	Temperature, humidity, precipitation	Reported cases	Machine learning

Kahn et al. (2019)	Mozambique	Retrospective (step 3)	Vibrio cholerae (WBD)	Flooding from cyclones	Reported cases, cholera incidence	Machine learning
Koolhof et al. (2017)	Australia	Retrospective (step 3)	Ross River Virus (VBD)	Temperature, precipitation, daily tidal data	Reported cases	Regression
Koolholf et al. (2020)	Australia	Retrospective (step 3)	Ross River Virus (VBD)	Temperature, humidity, precipitation, southern oscillation index, vapor pressure, sea level pressure, evapotranspiration, sea surface temperature, sea level, river flow	Lab-confirmed cases	Regression
Lowe et al. (2014)	Brazil	Retrospective (step 3)	Dengue (VBD)	Temperature, precipitation	Reported cases	Regression
Lowe et al. (2016)	Brazil	Retrospective (step 3)	Dengue (VBD)	Temperature, precipitation	Lab-confirmed cases (confirmed by laboratory exams or clinical and epidemiological evidence)	Not specified
Merkord et al. (2017)	Ethiopia	Operational (step 5)	Malaria (VBD)	Temperature, precipitation, NDVI, EVI, SAVI, NDWI	Reported cases	Time-series
Nusrat et al. (2024)	Bangladesh	Retrospective (step 3)	Vibrio cholerae (WBD)	Temperature, precipitation	Hospitalizations	Regression
Pakhtigian et al. (2024)	Bangladesh	Prospective (step 4)	Vibrio cholerae (WBD)	Temperature, precipitation	Not specified	Not specified
SanchezTejeda et al. (2023)	Mexico	Operational (step 5)	Dengue (VBD)	Temperature, humidity, precipitation	Hospitalizations, suspected cases	Time-series
Schlesinger et al. (2024)	Colombia	Retrospective (step 3)	Dengue (VBD)	Temperature, precipitation	Hospitalizations	Time-series
Shi et al. (2016)	Singapore	Retrospective (step 3)	Dengue (VBD)	Temperature, humidity	Reported cases	Regression/tim series
Smith et al. (2017)	Solomon Islands	Retrospective (step 3)	Malaria (VBD)	Precipitation, mean sea level,	Reported cases	Regression

				southern oscillation index		
Wimberly et al. (2022)	United States	Retrospective (step 3)	West Nile Virus (VBD)	Temperature, humidity, precipitation, vapor pressure deficit	Lab-confirmed cases, reported cases	Regression/tim series
Zhang et al. (2024)	Namibia	Retrospective (step 3)	Malaria (VBD)	Temperature, aridity index, distance to water, EVI, day and night land surface temperature, potential evapotranspiration, temperature suitability index, tasselled-cap brightness, tasselled-cap wetness	Lab-confirmed cases	Regression/ machine learning

Acronyms: VBD = vector-borne disease; WBD = waterborne disease; NDVI = normalized difference vegetation index; EVI = enhanced vegetation index; SAVI = soil-adjusted vegetation index; NDWI = normalized difference water index

Fig 2. Map of study locations of articles included in the scoping review. Countries where included studies were conducted are shaded in blue. Note there were three multi-country studies.

The articles described a range of methodologies for developing CIEWS predictive models (Table 1). Regression was the most common modelling approach (n = 7). Time-series (n = 3), machine learning (n = 3), and a combination of regression and time-series (n = 3) were equally represented. One study used an approach combining regression and machine learning. Four studies did not specify a modeling approach. Examples of regression methods included linear regression, logistic regression, negative binomial regression, Poisson regression, stepwise regression, hierarchical models, and weighted sum geospatial models. Examples of time-series methods were ARIMA, moving averages, and distributed lag models. Finally, examples of machine

learning methods included support vector machine algorithms, random forest, decision tree, light gradient boosting machine, and diffusion models.

Most articles listed more than one climate variable in their predictive models (n = 18), with six articles reporting four or more climate variables (Table 1). The most frequent climate variable was temperature (n = 18), followed by precipitation (n = 17), and humidity (n = 8). Seven articles presented CIEWS models that incorporated more than one epidemiologic variable. The most common variables used were reported cases (n = 10), lab-confirmed cases (n = 9), suspected cases (n = 4), and hospitalizations (n = 5). Articles using the term “reported cases” did not specify how or if such cases were confirmed.

Most CIEWS model outputs were predictions of disease incidence (n = 6), outbreak probability (n = 8), or risk indices or maps (n = 8). Model outputs were primarily at subnational scales (n = 18), while one produced outputs at a national scale [22], and another internationally spanned Southern and Eastern Africa [23]. One study did not provide information on the geographic scale of risk predictions [24].

3.3 Critical appraisal of evidence

Using the MMAT, we determined that most studies were of high methodological quality. Only one study did not pass the first two screening questions, because it did not have clearly defined research questions [25]. When proceeding to the five study-design-specific questions, 16 studies were classified as low risk of bias, three as medium risk of bias, and one as high risk of bias. Reasons for medium risk of bias included inadequately defined variables [26], unspecified or inadequate assessment of model

accuracy [26,27], and insufficiently representative sample for the research objective [28]. The study with a high risk of bias did not clearly describe the data collection methods, data sources, or the analysis approach [25].

3.4 Results of individual sources of evidence

We referenced the WHO Quality Criteria for the Evaluation of CIEWS for Infectious Diseases to categorize the approaches to evaluating CIEWS, with a focus on performance, effectiveness, and operational features (Steps 3–5 of the evaluation guidance) [11]. Most of the studies (n = 17) described statistical performance of CIEWS models under Step 3, the retrospective phase of evaluation (Table 2). Only two studies evaluated the effectiveness of a CIEWS in the prospective phase under Step 4 [29,30]. Four studies assessed operational features of CIEWS under Step 5 through qualitative methods such as interviews with end users [23,25,31,32].

3.4.1 Evaluations of CIEWS performance

Among the 17 studies that included evaluations of CIEWS models in the retrospective phase (Step 3), the most common measures of model performance were sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and area under the curve (AUC) (Table 2). Two studies did not provide details on how model accuracy was assessed [23,26], and one study described a qualitative model validation through field observations due to lack of health surveillance datasets [27]. Studies that covered multiple regions or countries reported variable performance across different locations. Several studies employed multiple modelling approaches and compared

261 performance across models. Overall, findings demonstrated adequate model

262 performance based on the measures (Table 2).

263 **Table 2. Model performance assessment results in retrospective studies included**
264 **in the scoping review (n = 17).**

Study	Performance metric	Key metric results
Anyamba et al. (2010)	Accuracy – Unspecified metric	Temporal and spatial prediction accuracy were assesse Africa, 65% of human case locations mapped to areas ic This metric was lower in Sudan (50% of cases), followe Southern Africa (20%).
Cardenas et al. (2022)	Sensitivity, PPV	Sensitivity and PPV were calculated for each alarm indic rainfall) for each country (Colombia, Mexico) and for eac Zika). For dengue, sensitivity ranged from 74 to 100% a chikungunya, sensitivity ranged from 77 to 93% and PP sensitivity ranged from 50 to 100% and PPV ranged fro assess chikungunya in Mexico, so the Chikungunya valu
Fletcher et al. (2025)	AUC, TPR, FPR	AUC, TPR, and FPR were calculated for each model. AU ranged from 0.55 to 0.81. FPR ranged from 0.29 to 0.48 0.80, a TPR of 0.81, and an FPR of 0.29.
Gbaguidi et al. (2025)	RMSE, MSE, MAE, R^2	MAE, RMSE, MSE, and R^2 were calculated for the basic calibrated model. The basic model had an MAE of 2.30, 7.270335, and an R^2 of 0.68. The validated model had a an MSE of 7.42, and an R^2 of 0.80. The calibrated mode 1.82, an MSE of 3.33, and an R^2 of 0.80.
Hussain-Alkhateeb et al. (2018)	Sensitivity, PPV	Sensitivity and PPV were calculated for each outbreak in rainfall) for each country (Brazil, Malaysia, Mexico). The indicators was not used for each country. In Brazil, sens PPV ranged from 40% to 88%. In Malaysia, sensitivity ra ranged from 71% to 80%. In Mexico, sensitivity ranged f from 50% to 83%.
Javaid et al. (2023)	Precision, recall, F1-score, accuracy results	Precision, recall, and F1-score were calculated for each leishmaniasis) across each model across each feature s temperature) and then all together, across all data samp Accuracy was calculated for each model across all featu 2700: precision ranged from 70% to 94%, recall ranged from 74% to 94%, and accuracy ranged from 79.14% to precision ranged from 69% to 93%, recall ranged from 7 71% to 95%, and accuracy ranged from 78.28% to 91.6 ranged from 58% to 96%, recall ranged from 36% to 98 97%, and accuracy ranged from 69.92% to 93.97%. Dat from 63% to 96%, recall ranged from 33% to 98%, F1-sc accuracy ranged from 71.06% to 92.96%.
Kahn et al. (2019)	Accuracy – Unspecified metric	The study states that the accuracy of the model was eva predicted places with high risk.
Koolhof et al. (2017)	Sensitivity, specificity, NPV, PPV, K-fold cross-validation	Sensitivity, specificity, NPV, PPV, and K-fold cross-valid location (n = 5). Sensitivity ranged from 0 to 1, specificity

		ranged from 0.034 to 0.263, NPV ranged from 0.973 to 1 ranged from 0.0224 to 0.1814.
Koolhof et al. (2020)	Pearson's correlation coefficient	Pearson's correlation coefficient was used to determine and observed RRV notifications in each local governmer correlation ranged from 0.19 to 0.88.
Lowe et al. (2014)	AUC, RPSS	RPSS was calculated for each microregion included in th 0.01 to 1. AUC and ROC were calculated for disease ev threshold and a high-risk threshold. AUC was 0.86 and (thresholds, respectively.
Lowe et al. (2016)	Hit rate, false alarm rate, sensitivity, FPR	The forecast model had a hit rate of 57%, a false alarm The null model had a hit rate of 33%, a false alarm rate
Nusrat et al. (2024)	Visual analysis of information	Due to a lack of data for validation, the model was valida hospital cases in the region, outbreak timing, and preser (elevation and population density). Observations corrobo model appeared to capture the high-risk areas more suc
Schlesinger et al. (2024)	Sensitivity, Specificity, PPV, NPV, and Sensitivity + PPV	Sensitivity, specificity, PPV, and NPV were calculated fo Sensitivity ranged from 0.83 to 1.00, specificity ranged fr 0.60 to 1.00, and NPV ranged from 0.88 to 1.00. Sensitiv this total value ranging from 1.52 to 2.00 across the mur
Shi et al. (2016)	MAPE	MAPE was calculated for each model across the forecas MAPE degraded slowly over time (17% error when forec forecasting 3 months). In the step-down and SARIMA m forecasting 3 months.
Smith et al. (2017)	Pearson's correlation coefficient, Spearman rank correlation, R^2, Adjusted R^2, and LOOCV R^2	Pearson's correlation coefficient, Spearman rank correla calculated for each region (n = 3). Pearson's correlation 0.90, Spearman rank correlation ranged from –0.09 to – $_{adj}$ ranged from 0 to 0.80, and R^2 $_{LOOCV}$ ranged from 0.0 t Whitney U-test showed that rainfall terciles were signific malaria transmission categories.
Wimberly et al. (2022)	AUC, TE, MAE, SE	AUC, TE, MAE, and SE were computed for each model had the highest AUC (>0.85 across the forecast weeks) generally below 2.0). SE values across the forecast wee ensemble and combined models.
Zhang et al. (2024)	Pearson's correlation coefficient, RMSE	The model predicting at the health facility level was valid observed and predicted weekly case counts was 0.907. model fit.

Acronyms: AUC = area under curve; PPV = positive predictive value; TPR = true positive rate; FPR = false positive rate; RMSE = root mean squared error; MSE = mean squared error; MAE = mean absolute error; NPV = negative predictive value; RPSS = ranked probability skill score; MAPE = mean absolute percentage error; LOOCV = leave one out cross validation; TE = temporal error; SE = spatial error

3.4.2 Evaluations of CIEWS effectiveness

Two studies examined CIEWS effectiveness in the prospective phase (Step 4) of the WHO Quality Criteria for evaluating CIEWS. Both studies used comparison groups to

measure CIEWS effectiveness in mitigating outbreaks or reducing disease incidence. We found no studies evaluating the cost-effectiveness of an operational CIEWS.

Benitez-Valladares et al. compared the effects of alarm-informed dengue response activities across districts that experienced an outbreak and those that did not [29]. Across the 11 districts with outbreak alarms, vector control activities were significantly lower in the outbreak districts versus the non-outbreak districts [29]. Differences between the two groups were explained by the type and timeliness of response to alarms, with outbreak-affected districts exhibiting late responses and non-outbreak districts maintaining routine vector control activities and additional measures in response to alarms [29].

Pakhtigian et al. used a quasi-experimental design to evaluate the effectiveness of CIEWS risk information from the CholeraMap tool disseminated through a mobile application (CholeraApp) in changing behaviors, risk perceptions, and cholera incidence [30]. The evaluation employed a differences-in-differences analysis to determine if receiving risk information was associated with improved outcomes in the intervention group versus the comparison groups [30]. While evaluation showed no statistically significant differences between groups for behavioral outcomes or health outcomes, intervention groups receiving risk information and educational messages reported feeling better equipped to manage cholera risks [30].

3.4.3 Evaluations of operational features of CIEWS

Four studies qualitatively assessed operational features of CIEWS through methods, such as comparative analyses and interviews with end users [23,25,31,32]. The studies

described operational features, including timeliness of alerts to inform responses, usability, interpretability, and integration and acceptability within national surveillance programs. Several of these studies also included recommendations or actions taken to improve CIEWS based on user feedback. While several studies indicated that CIEWS were relevant and useful for informing timely actions to mitigate outbreaks, evaluation findings also revealed issues with compatibility and accessible formats for interpreting and sharing data with key stakeholders.

Anyamba et al. compared current response time informed by the CIEWS with response time in prior Rift Valley Fever outbreaks to examine the timeliness of alerts [23]. Overall for East Africa, the early warning information provided in 2006 facilitated implementation of national preparedness and early detection and response activities approximately two months earlier compared with the previous 1997–1998 outbreak [23].

Merkord et al. collected feedback from CIEWS stakeholders and end users through post-implementation workshops [31]. Suggestions to improve operational aspects of the CIEWS for malaria focused on improving the reports and outputs generated by the model to enhance usability, such as dashboards, maps, and web-based, interactive reports.

Hussain-Alkhateeb et al. collected data on operational features through questionnaires and semi-structured interviews with health officers and other CIEWS users [32]. The operational evaluation examined plausibility of applying the tool in routine surveillance, user-friendliness, satisfaction, and lessons learned [32]. Evaluation findings demonstrated a general consensus around the CIEWS usability for mitigating dengue outbreaks and positive views of data collection modalities and interpretations [32].

Recommendations to improve usability and usefulness included adopting a more accessible programming languages and interface and obtaining more timely meteorological data [32].

Sanchez Tejeda et al. conducted a qualitative review of the CIEWS integration process [25]. The evaluation results revealed that acceptability among ministry of health and municipality staff was variable [25] Users encountered issues with data integration and other data challenges [25]. Interviewed climatologists recommended adopting weather prediction models from national climate services and using data formats and programming languages compatible with open-source and commonly used software [25].

4. Discussion

4.1 Summary of the Evidence

4.1.1 Evaluations of CIEWS

In this scoping review, we aimed to determine to what extent operational CIEWS have been evaluated on their performance, effectiveness, and operational features. Of the 21 articles included in this review, most CIEWS evaluations focused on model performance, while four described operational aspects and only two evaluated effectiveness. This finding is consistent with a review of EWS for VBDs, which found that most studies reported on model performance but did not examine EWS integration and minimally described users' perspectives of EWS [7].

While we found two effectiveness studies, none of the studies assessed the cost-effectiveness of an operational CIEWS. During the full text review, we encountered one study that included a cost-loss analysis of a CIEWS for malaria in Uganda and demonstrated a positive economic benefit across a range of decision points and transmission events [33]. However, the study was not included in our review, as the CIEWS was not operational. Broader economic analyses of climate information services and EWS are promising and warrant further investigation to demonstrate the specific economic benefits of CIEWS. For instance, an exploratory analysis of climate services for health estimated that investments in such services could generate economic benefits ranging from 3.6 to nearly 70 times the investment cost [34]. The Global Commission on Adaptation has also demonstrated that a US$1 investment in EWS returns more than US$9 on average over 10 years [35].

Evaluations of effectiveness and operational aspects of CIEWS are particularly critical, as evidence indicates that partially active alert systems rarely go beyond the sending of alerts to systematically inform public health actions [36]. More research is needed to understand and address implementation gaps, so that early warnings reach communities and decision makers who would most benefit from the information. In areas highly impacted by CSIDs, public interest in receiving early warnings has been demonstrated [37].

4.1.2 Other Evidence Gaps

The included articles spanned diverse geographies; however, we found few articles in Southeast Asia (n = 2) and the Eastern Mediterranean (n = 1), revealing evidence gaps in these regions. Most articles described CIEWS for VBD—and MBD specifically—with

only three articles covering CIEWS for WBD and none for FBD. This finding is consistent with other papers that similarly reported most CIEWS tools were developed for VBD [17,38]. Over half of the included articles described a CIEWS for dengue, with malaria as the second-most frequently studied disease, similar to findings from other reviews of EWS [7,17]. The emphasis on dengue and malaria is expected, given the high burden of these CSIDs in Latin America and sub-Saharan Africa [7,17,36,39]. However, the scientific community should also prioritize other diseases affecting marginalized groups and diseases that are among the most sensitive to climate change (e.g., cholera, campylobacter, salmonella, leishmaniasis, Zika) [36,40].

Temperature and precipitation were the most widely reported climate variables used in CIEWS models. Humidity was cited as a variable in less than half the articles (n = 8), although this climate factor is important to consider, given its possible modulatory effects on rainfall and temperature [36]. Most articles included three or fewer climate variables in their models (n = 14). However, evidence suggests that including additional climate variables may enhance model performance by better capturing the complexity of climate factors influencing infectious disease transmission [39].

4.1.3 Operationalization

During full text review of 157 articles, the most frequent reason for exclusion was that the CIEWS model was not operationalized (n = 103). We found several studies that went beyond model development to produce user-friendly outputs and decision-support tools for public health planning (e.g., dashboards, risk maps, health facility stock prepositioning); however, these studies were proof-of-concept rather than fully operational tools and thus were not included [41–43].

Barriers to operationalizing these systems may include lack of funding and dedicated personnel, insufficient granularity of data, absence of formalized partnerships for data sharing, and limited technical capacity within local government institutions, among other challenges [39]. End users and stakeholders across climate and health sectors should be involved in CIEWS design from the beginning to ensure accessibility and usefulness of the system and increased likelihood of operationalization [13,44,45]. Findings from a qualitative study of CIEWS implementation in Ecuador revealed the importance of engaging Ministry of Health leadership and other institutional authorities to address compatibility issues between current outbreak management procedures and CIEWS tools [46]. While the field of CIEWS model development has integrated innovative, approaches, such as artificial intelligence-driven processes, it is important to strike a balance between predictive accuracy of advanced models and feasible solutions for end users in resource-constrained environments [47].

4.2 Limitations

While 103 records were excluded because the CIEWS model was not operationalized, it is possible that operationalization occurred but was not described in the paper. However, operationalization is a widely recognized challenge in EWS research, due to resource constraints and limited institutional capacity for transitioning from pilot tools to fully operational systems used to inform public health decisions [36].

Our selection of databases limited the amount of grey literature retrieved, as Scopus, PubMed and Global Index Medicus primarily index scientific, peer-reviewed literature. We may have missed evaluations that were informally published as reports on websites

or shared internally rather than in being published in scientific journals. For example, we excluded four articles that met the criteria for operational CIEWS but did not evaluate system performance, effectiveness, or operational aspects. It is possible that these systems were evaluated, but results were internally shared with stakeholders or documented elsewhere. While Global Index Medicus indexes public health literature generated in LMICs, we may have also missed articles published in local journals not indexed in the three targeted databases or in languages other than English.

Another limitation is that our search string may have missed relevant articles. While we tested our search string and sought guidance during development and validation process with a health sciences librarian specializing in systematic reviews, our search terms were not fully exhaustive of all climate, evaluation, disease, and early warning terms. For example, we later identified two relevant articles through hand searching that were not captured in the initial search [27,30].

5. Conclusion

Extensive work has been done on CIEWS model development and testing, particularly for VBDs; however, there is limited published research demonstrating the effectiveness of operational CIEWS. Most evaluations of CIEWS focus on statistical performance while very few examine effectiveness in preventing or mitigating outbreaks, cost-effectiveness, or operational features of these systems. CIEWS should be co-designed and evaluated with end users to ensure effective implementation of solutions adapted to local needs and contexts. Evaluation results should be publicly available, so CIEWS

designers and implementers can apply lessons learned to enhance anticipatory action for CSIDs more broadly.

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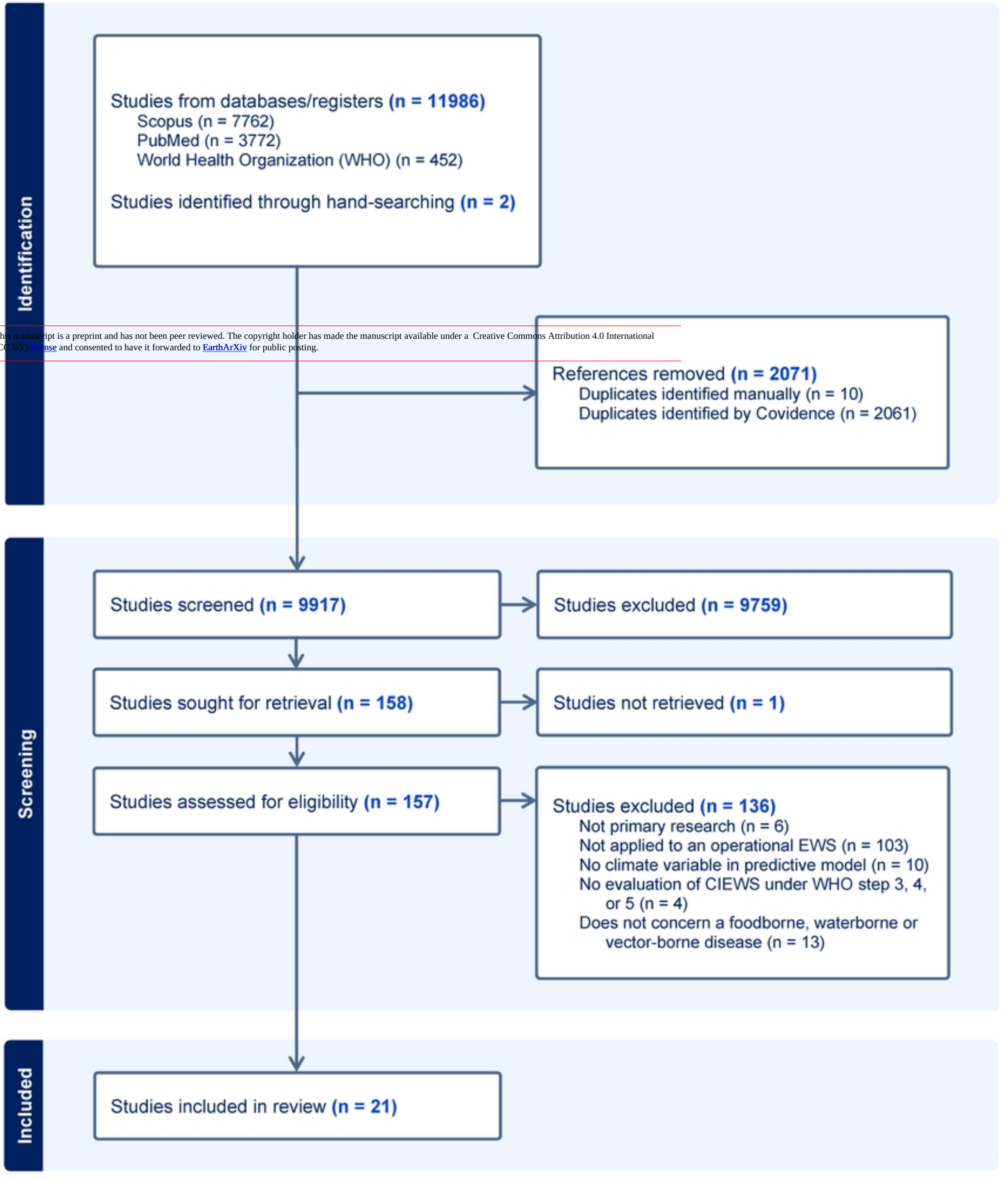
Supporting information captions

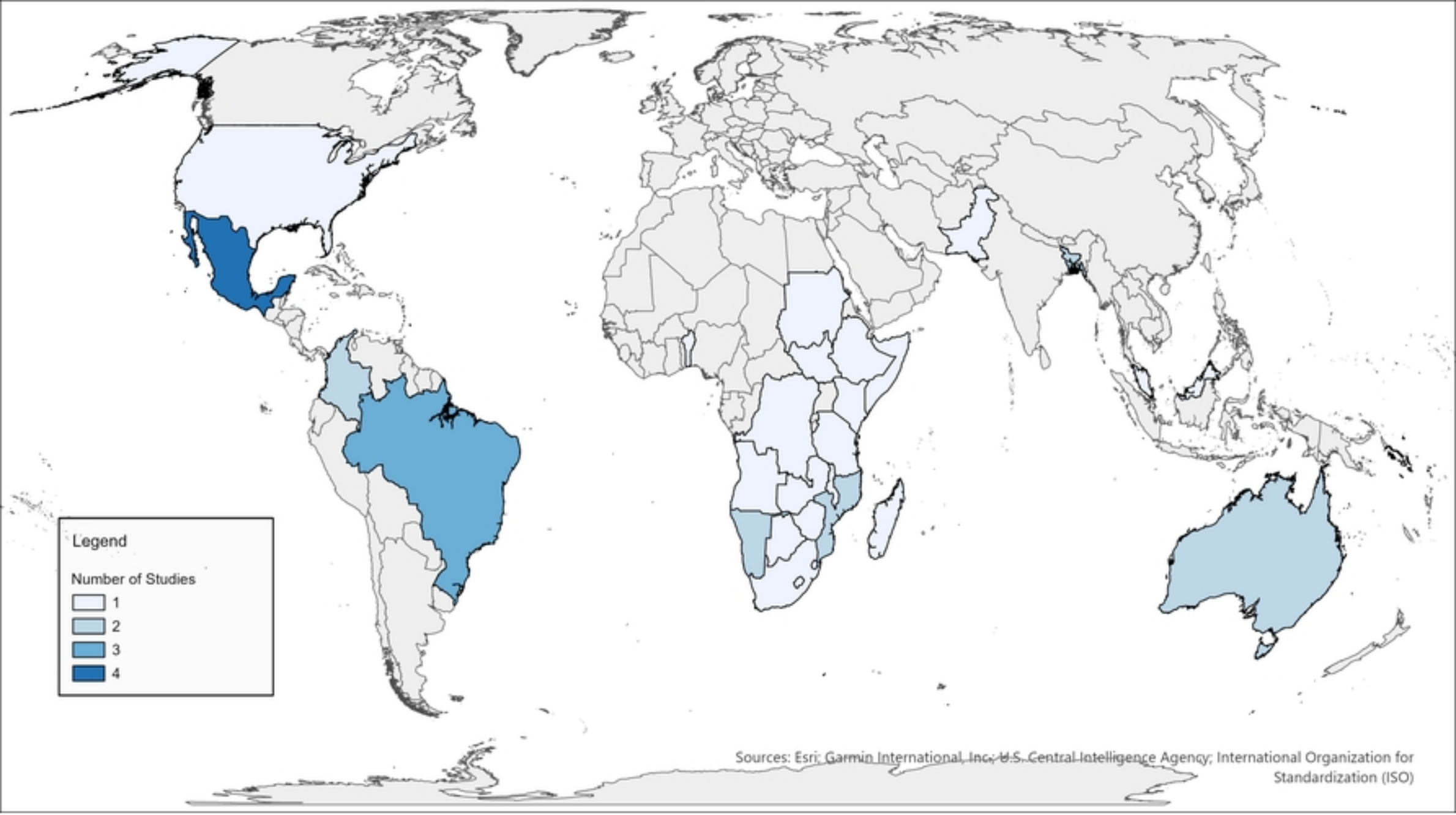
S1 Search string.

S2 PRISMA-ScR checklist.

S3 Data charting template.



Figure


Legend
Number of Studies
1
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Sources: Esri, Garmin International, Inc., U.S. Central Intelligence Agency, International Organization for Standardization (ISO)

Figure