Systematic Review of Geographic Information Systems (GIS) Applied to Dengue Detection

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Abstract
Geographic Information Systems (GIS) have become a key tool for the surveillance, detection, and control of dengue, a vector-borne disease with a growing global impact. The objective of this study is to provide a comprehensive overview of the application of GIS in dengue detection through a systematic review based on the PRISMA methodology and a bibliometric analysis. Of a total of 861 documents, 70 studies from the Scopus, Web of Science, PubMed, and Scielo databases were evaluated to identify publication trends, collaborative networks, and the main technologies used. The results reveal a steady increase in publications since 2018, with a notable rise in recent years, indicating a growing interest in this field. The geographic analysis shows a concentration of scientific output in developed countries such as the United States and the United Kingdom, while Thailand stands out as an endemic country with a high incidence and regional leadership in dengue research. The most frequent keywords focus on 'dengue', 'human', and 'epidemic', demonstrating a focus on epidemiological surveillance. However, challenges remain, such as computational limitations and a lack of studies on real-world implementation in contexts with limited infrastructure. Overall, the findings underscore that the applicability of GIS to dengue research is expanding, but still needs strengthening in its applied and contextual dimensions, especially in highly vulnerable countries.

Keywords: Dengue, Detection, Geographic Information Systems, GIS, Review

1. Introduction

Currently, dengue is one of the most prevalent mosquito-borne viruses globally [1], with an estimated 390 million infections annually, of which 96 million presents with clinical symptoms of varying severity [2]. The World Health Organization (WHO) classifies dengue as one of the top ten threats to global health, with a significant impact in tropical and subtropical regions [3]. Despite efforts in prevention and control, early detection and monitoring of outbreaks remain challenges due to the complexity of epidemiological surveillance systems and restrictions on access to rapid diagnostics [4]. In this context, the use of Geographic Information Systems (GIS) in dengue detection represents an encouraging alternative to improve epidemiological surveillance and optimize the distribution of resources in public health [5][6] and [7].

Traditionally, dengue diagnosis has been based on laboratory tests, such as the detection of IgM (immunoglobulin M) and IgG (immunoglobulin G) antibodies, nucleic acid amplification tests, and rapid antigen tests [8] and [9]. However, these methods require specialized infrastructure, which limits their availability in rural or low-resource areas [10][11] and [12]. Furthermore, early symptoms of dengue can be confused with other febrile illnesses, complicating timely diagnosis [13][14] and [15]. To address these limitations, epidemiological monitoring systems based on clinical and environmental data have been established to achieve more accurate dengue detection [12]. In this context, GIS have emerged as innovative tools to improve dengue detection, enabling the integration and spatial visualization of clinical, environmental, and demographic data [16]. These systems allow for the study of geographic patterns of dengue distribution [17], the detection of risk areas, and the assessment of the impact of factors such as temperature, precipitation, and population density [18].

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Through the use of spatial models and statistical techniques, GIS significantly contributes to the prediction of outbreaks and the formulation of more efficient and targeted intervention strategies [19].

Recent studies have shown that the use of GIS can significantly improve dengue detection and prediction capabilities [20] and [21]. Furthermore, various geospatial models based on historical and real-time data have been identified as being able to predict increases in dengue incidence with a high degree of certainty [22]. Likewise, the implementation of spatial analysis and heat maps has allowed early warning systems to be optimized [23], facilitating rapid responses from health authorities and improving resource management [24] and [25].

However, a review of the existing literature reveals that many studies have focused on applying GIS for the spatial description of cases or the detection of transmission hotspots, rather than on a comprehensive analysis of the methodologies used and their limitations. For example, most research centers on mapping incidence and environmental factors, but very few studies combine bibliometric, comparative, or impact assessment approaches. Furthermore, there is little systematization regarding the types of data, spatial scales, and analytical methods used, which hinders the consolidation of a robust methodological framework. This gap justifies the need for a systematic review that synthesizes the available evidence and highlights the remaining shortcomings in the use of GIS for dengue detection.

However, despite advances in the application of GIS in dengue detection, several research gaps remain. One of the main challenges lies in the quality and availability of georeferenced data, as these systems require accurate, timely, and consistent information to function effectively. Furthermore, interoperability between healthcare systems, educational institutions, and technology platforms remains limited, making data consolidation and joint analysis difficult. Another crucial point is the lack of methodological standardization in the use of GIS, which hampers the comparison of results and the validation of proposed models across different research projects.

Based on the above, this study seeks to answer the following research questions: What practical applications of GIS have demonstrated the greatest impact on dengue prevention and control strategies? What are the main challenges and limitations in implementing GIS for dengue detection and monitoring? What opportunities do GIS offer to improve epidemiological surveillance and optimize public health decision-making in the face of dengue outbreaks? The structure of this article is as follows: the theoretical definitions section provides a general overview of the concepts relevant to this study. The methodology section describes the search and selection process for the studies used in the systematic review. The results and discussion section then presents the findings on the application of GIS in dengue detection and compares them with traditional approaches. Finally, the conclusions section summarizes the key findings and suggests future research directions in this area.

2. Background: Definition, Concepts and Related Technologies

2.1 Dengue

Dengue is a viral disease with four antigenically distinct serotypes; infection generates permanent immunity only to the acquired serotype, complicating its epidemiology and immunological control. Dengue, transmitted by Aedes aegypti and Aedes albopictus, is endemic in several regions worldwide. This virus is characterized by high fever, muscle aches, rash, and in severe cases, it can cause bleeding or shock syndrome [26]. Its high spread and recurrence make it a growing threat to global public health, with a particular impact on limited health systems or environmental conditions conducive to the vector.

2.2 Dengue Detection

Traditionally, dengue detection has been performed through clinical, serological and molecular tests such as ELISA for IgM (Immunoglobulin M) and IgG (Immunoglobulin G), and by the detection of NS1 antigens and PCR (Polymerase Chain Reaction) [8] and [9]. These challenges have driven the development of new complementary strategies, including technological approaches and alternative surveillance systems that seek to improve early identification of cases and decrease the spread of the virus, especially in vulnerable areas [10] and [11]. However, its use is restricted by the availability of laboratories, technical resources and response times in some countries [12].

2.3 Geographic Information Systems (GIS)

Geographic Information Systems (GIS) are technological tools that facilitate the collection, analysis, and visual representation of geospatial information [16]. Through maps and digital models, they facilitate decision-making by identifying spatial patterns and relationships between variables [17] and [18]. In the public health sector, GIS are used to monitor diseases, plan health resources, and identify risk areas. Their ability to integrate environmental, demographic, and epidemiological data makes them an essential tool for the monitoring and prevention of dengue.

2.4 GIS Applications in Public Health

In the healthcare field, GIS has been successfully implemented to monitor diseases such as malaria, cholera, and COVID-19 [27]. These tools facilitate the analysis of the geographic distribution of cases, associated environmental factors, and transmission routes [28][29] and [30]. This enables the creation of heat maps, risk analysis, and planning of targeted interventions.

2.5 Technologies for Dengue Detection

Technological evolution has driven the use of various tools for dengue detection. These include Artificial Intelligence (AI) [31], weather sensors [32], vector monitoring drones [33], automated surveillance systems [34], and real-time analysis platforms [35]. These technologies have been implemented in hospitals, laboratories, and national surveillance systems, leading to improved efficiency and coverage of virus detection strategies. Furthermore, their integration with GIS improves the ability to predict and respond to outbreaks, which is essential for decision-making in the public health sector [36].

2.6 Epidemiological Surveillance

Epidemiological surveillance is the continuous process of collecting, analyzing and interpreting data related to diseases, with the aim of guiding prevention and control actions [37]. In the case of dengue, it facilitates monitoring the incidence of cases, detecting patterns of spread, and triggering early warnings [38] and [39]. Some of the tools used include health information systems, georeferenced databases, mobile platforms, and automatic notifications. In this sense, the incorporation of technologies such as GIS and real-time information systems has strengthened this surveillance, making it more accurate, geographically contextual, and useful for more efficient interventions.

2.7 Environmental and Social Factors Associated with Dengue

According to The Lancet Countdown 2024, climatic suitability for dengue has increased significantly, affecting even countries with a high Human Development Index (HDI). The spread of dengue is strongly influenced by environmental factors such as temperature [40], humidity [41][42], rainfall [43] and water accumulation [44], which promote the reproduction of the transmitting mosquito. Social variables such as population density [45], disordered urbanization [43] and human mobility [42] also have an influence. To study these variables, satellite images, meteorological stations and remote sensing [22] have been used. These spatial variables can be examined with GIS to detect areas susceptible to outbreaks, and in turn, their incorporation into predictive models facilitates more effective planning of preventive actions and response to health emergencies.

2.8 Epidemiological Risk Zoning

Epidemiological zoning involves dividing a territory according to its level of vulnerability to diseases such as dengue [46] and [47]. Using tools such as GIS [48], multicriteria analysis [49], and predictive models, combined with spatial, climatic, sociodemographic, and health data [50], maps are generated that identify areas with a higher risk of transmission. This technique facilitates the prioritization of resources, the creation of focused strategies, and the implementation of more effective interventions. In this regard, GIS is highlighted as essential for this process, as it simplifies multivariate analysis and the geographic representation of risks.

3. Materials and Methods

Although the use of GIS in public health has grown significantly in recent years, a gap remains in the literature regarding its specific application to dengue detection and prevention. Most studies focus on mapping case distribution or modeling risks, but few integrate interdisciplinary approaches that combine environmental, social, and technological variables. An exploratory literature review revealed that current studies focus on the spatial description of cases or the detection of transmission hotspots, while only 30% are reviews or integrative analyses of existing literature. This deficiency highlights the need for a systematic review to analyze current knowledge and critically evaluate the most effective GIS applications in this field.

To address this research gap, a systematic review based on the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) method will be conducted. This approach ensures transparency and rigor in the collection, selection, and analysis of scientific literature [51]. It also minimizes risks and facilitates the replicability of results, especially in studies with technological and public health approaches. The use of PRISMA has proven effective in systematizing findings in research that utilizes geospatial and technological tools in the management of communicable diseases.

3.1 Review Approach

Systematic searches were carried out in high-impact scientific databases such as Scopus, Web of Science (WoS), PubMed, and Scielo, to ensure broad, up-to-date, and multidisciplinary coverage of research. These platforms were selected for their academic recognition and their ability to index peer-reviewed literature in the fields of health, technology, geography, and the environment. Additionally, bibliometric tools such as VOSviewer and Bibliometrix will be used to visualize research trends [52], identify scientific collaboration networks, and analyze thematic clusters related to the use of GIS in the study and control of dengue. Scopus provides a comprehensive view of global scientific output [53], while WoS provides a complete overview of scientific output [54]. PubMed provides evidence from an epidemiological and clinical perspective [55], while Scielo helps complement the literature with relevant literature not available elsewhere [56].

The algorithm used in Scopus: (TITLE ("GIS") OR TITLE-ABS-KEY (geospatial) OR TITLE-ABS-KEY (mapping) OR TITLE-ABS-KEY (spatial) AND TITLE-ABS-KEY (dengue) OR TITLE-ABS-KEY (arbovirus) OR TITLE-ABS-KEY (mosquito-borne AND disease) AND TITLE-ABS-KEY (diagnosis) OR TITLE-ABS-KEY (prediction) OR TITLE-ABS-KEY (detection) OR TITLE-ABS-KEY (classification) AND TITLE-ABS-KEY (epidemiology) OR TITLE-ABS-KEY (outbreak) OR TITLE-ABS-KEY (public AND health) AND NOT TITLE-ABS-KEY (chikungunya) AND NOT TITLE-ABS-KEY (zika))

The algorithm used in WoS: (AB=("GIS" OR geospatial OR mapping OR spatial AND dengue OR "mosquito-borne disease" AND prediction OR detection AND epidemiology NOT chikungunya NOT zika))

The algorithm used in PubMed: (((((((GIS[Title/Abstract]) OR (geospatial[Title/Abstract])) OR (mapping[Title/Abstract])) AND (dengue[Title/Abstract])) OR (mosquito-borne disease[Title/Abstract])) AND (detection[Title/Abstract])) NOT (chikungunya[Title/Abstract])) NOT (zika[Title/Abstract])

The algorithm used in Scielo: (ti:(GIS)) AND (ab:(dengue)) OR (ab:(detection))

Figure 1 shows a flowchart describing the different stages of the information selection process. The initial search yielded 354 publications from Scopus, 226 from Web of Science, 91 from PubMed, and 190 from Scielo, for a total of 861 documents. After applying thematic filters and including only articles published in scientific journals and systematic reviews based on their scientific quality [57], no specific time range was established for the included articles. After filtering the search according to the predefined inclusion and exclusion criteria, the number of relevant documents was 197 publications from Scopus, 97 from WoS, 59 from PubMed, and 67 from Scielo. Subsequently, the titles and abstracts of each document were screened, resulting in a final distribution of 45 from Scopus, 8 from WoS, 10 from PubMed, and 9 from Scielo. Screening the titles and abstracts of these documents yielded a total of 72 documents. The next filtering stage involved using the Mendeley reference manager to remove duplicate articles. Two duplicate documents were found, and 70 relevant documents were retained for in-depth review.

The search strategies for this systematic review were guided by the importance of collecting relevant multidisciplinary literature on the use of GIS in dengue detection. Databases such as Scopus, WoS, PubMed, and Scielo were consulted, selected for their geographic coverage, editorial quality, and filtering tools. To examine the collected information, tools such as VOSviewer for visualizing co-occurrence networks, co-authorship, and international collaboration [58][59], and Bibliometrix in R, which is effective for identifying thematic trends, publication patterns, and geographic distribution of studies, were used [60] and [61].

The PRISMA methodology was used as a guide to structure the selection process, ensuring a strict, clear, and replicable procedure. This combination of tools and approaches made it possible to accurately map the current state of knowledge and identify the main lines of research in the application of GIS in dengue detection. Furthermore, the systematic approach ensured the quality of the included research and reduced selection bias. Overall, this synthesis seeks to provide a structured and critical perspective on the current landscape, allowing for the identification of knowledge gaps, strengthening evidence-based decision-making, and guiding future research adaptable to epidemiological contexts.

3.1.1 Study Limitations

The central objective of this article was to analyze the use of GIS, specifically in the detection and surveillance of dengue, not arboviruses in general. Although chikungunya and Zika share the same vector, Aedes aegypti and Aedes albopictus, they exhibit significant differences in their epidemiological behavior, diagnosis, clinical manifestations, and spatial dynamics, which would have altered the thematic coherence of the analyzed corpus.

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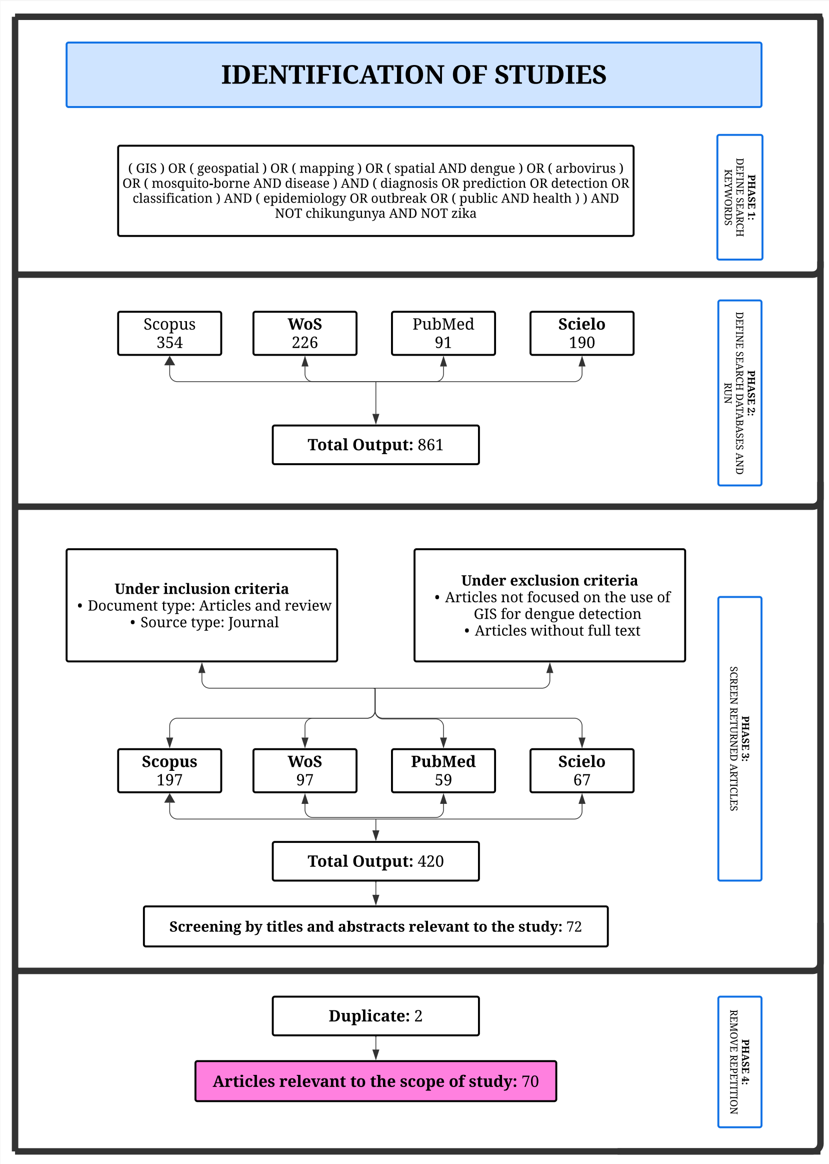

Figure 1: PRISMA flow diagram for dengue detection review

For this reason, including these terms would have broadened the conceptual scope to include a review of Aedes-borne arboviruses, diverting the focus of the objective.

Justification for Excluding Terms

This study was limited to dengue due to its endemic epidemiological behavior, its high global burden, and the methodological maturity achieved in the use of GIS for its detection and surveillance. Although Zika and chikungunya share the same vector, they have different transmission patterns, epidemic duration, and diagnostic strategies, which would have introduced heterogeneity and thematic bias into the analysis. The exclusion of these terms is intended to maintain methodological consistency and internal validity of the study, in accordance with PRISMA guidelines.

PRISMA Rationale and Rigor

The PRISMA design required inclusion and exclusion criteria. During the planning phase, the inclusion of “arbovirus”, “Zika”, and “chikungunya” was considered, but initial tests showed that the results duplicated and dispersed the literature, generating noise and reducing the specificity of the dengue analysis. Therefore, the Boolean filter AND NOT TITLE-ABS-KEY (chikungunya) AND NOT TITLE-ABS-KEY (zika) was applied to maintain the internal validity and comparability of the included studies.

Applicability Considerations
Dengue was prioritized in this study due to its sustained global epidemiological relevance, being recognized by the WHO as one of the greatest threats to global health [3]. The scientific justification constitutes the starting point for vector-borne diseases where GIS has demonstrated greater methodological maturity and empirical validation, unlike Zika or Chikungunya, where geospatial models are still in exploratory stages. For this reason, limiting the analysis to dengue allows for more precise, reproducible, and useful conclusions for the design of geographic surveillance systems applied to this disease.

3.2 Analysis
The initial stage of the analysis focuses on a bibliometric analysis of the articles selected from the selected databases. The frequency of publication by year, the country of origin of the research, the journals in which the research was published, and the research methods used are analyzed. Initial findings show a steady increase in scientific production related to the use of GIS for dengue identification. The publications focus primarily on specialized publications in technology, public health, geoinformation, and epidemiology. Geographically, studies from tropical and subtropical countries with a high incidence of dengue, such as Thailand, Brazil, and Indonesia, stand out.

To ensure the quality and relevance of the studies presented, a comparison was made between the predominant methodological approaches in the literature and the objectives of this review. Studies focused on outbreak mapping, spatial risk modeling, and convolutional neural networks for outbreak detection were identified as predictors of dengue incidence. Furthermore, there is evidence of an increase in the number of studies that combine GIS with machine learning to improve the accuracy of predictive models, highlighting the technical evolution in this field.

4. Results and Discussion
Bibliometric analysis of records obtained from Scopus, Web of Science, PubMed, and Scielo identified significant patterns in research related to the use of GIS in dengue detection and monitoring. The temporal evolution of publications, their geographic distribution, the most frequently used keywords, and collaborative networks among authors and institutions were examined. The data indicate a steady increase in academic output on the topic. Countries such as the United States, the United Kingdom, and Thailand appear as leaders in knowledge generation, while nations with significant technological potential, such as Japan and China, also exhibit significant output. The most prominent keywords include terms like "dengue", "human", and "epidemic", demonstrating a multidisciplinary approach that integrates public health and digital mapping.

However, this geographic leadership in scientific production contrasts sharply with the global distribution of the disease. This is because the global burden of dengue is concentrated primarily in Latin America and Southeast Asia, countries where the social and health impact is more severe, but where research output is particularly limited. This discrepancy highlights an implementation gap, where knowledge generation is concentrated in countries with advanced infrastructure, while endemic areas continue to face basic difficulties in collecting and managing geospatial data. This can be interpreted as geospatial solutionism, where a trend is toward developing sophisticated tools that, while scientifically relevant, are not adaptable to the needs of local health systems. This gap poses a significant challenge for the academic community: ensuring that innovations developed in highly technological environments are transferable, sustainable, and contextually applicable in countries with limited resources.

4.1 Analysis Bibliometric
Bibliometric analysis is a quantitative technique that allowed an organized exploration of scientific production on GIS applied to dengue, evaluating key indicators such as the number of publications, citations and relationships between authors. To achieve this objective, specialized tools such as VOSviewer, which allows visualizing co-authorship networks and relationships between keywords [58], were used, while Bibliometrix, developed in R, facilitated the identification of thematic trends and the analysis of citation patterns [60]. These tools provide a visual and analytical perspective of the field, allowing to detect how academic interest in the use of geospatial technologies in public health has evolved, as well as the main areas of research concentration. This type of study is especially useful for mapping the development of a developing area and for guiding future research towards thematic gaps.

4.1.1 Keyword co-occurrence map
The keyword co-occurrence map developed with VOSviewer allowed for the graphical representation of the most frequently used terms in the titles, abstracts, and metadata of the analyzed articles [62].

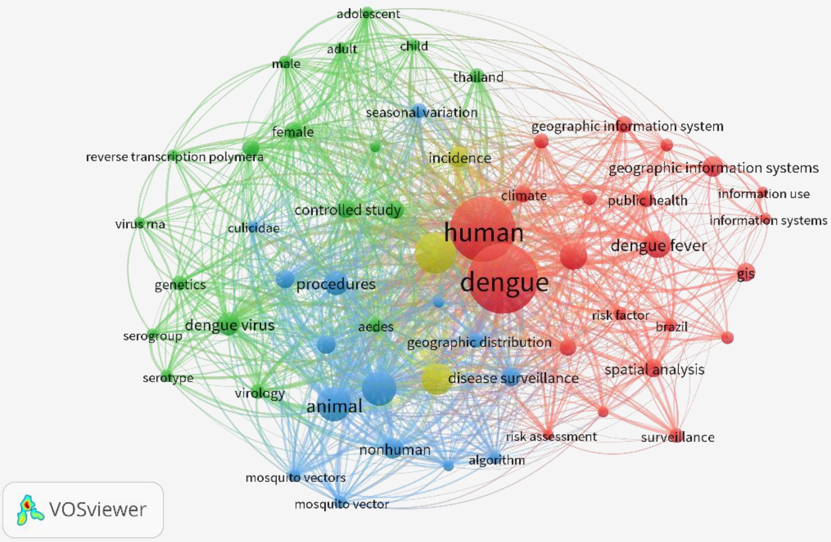

Figure 2: Keyword co-occurrence map in VOSviewer

This illustration revealed the strong association between concepts such as "GIS", "dengue outbreaks", "remote sensing", and "vector surveillance", indicating a predominant orientation toward the use of environmental and geospatial data to anticipate and control epidemic outbreaks. The automatic grouping of these terms facilitated the identification of key subtopics, such as risk prediction, satellite data integration, and heat map creation [22] and [23]. This approach not only facilitates the prediction of the topic's conceptual structure but also allows for tracking the evolution of methodological approaches over time, highlighting the recent incorporation of predictive models with machine learning and geospatial big data techniques.

Using VOSviewer and a minimum of 5 keyword co-occurrences; 819 keywords co-occurred, and four significant clusters were identified. Figure 2 shows a network visualization map of the four key co-occurring clusters with 58 elements, 1188 links, and a total link strength of 3220. The keywords with the highest number of links are the most impactful and prominent within the topic under consideration. The keywords with significantly larger nodes than the rest are "dengue", "human", and "epidemic". The size of a keyword's node indicates how frequently it is mentioned in studies, while the size of nearby keywords reflects its co-occurrence in research. The clusters are represented by colors and indicators. The identified colors allowed for the identification of the main research sub-areas within the field: the red cluster groups terms such as "human", "dengue", and "prediction", reflecting a focus on epidemiological analysis and the identification of risk factors associated with the incidence and spread of the disease. The green cluster contains words such as "dengue virus", "controlled study", and "virology", suggesting a line of research focused on the clinical, virological, and experimental aspects of the virus and its biological behavior. The blue cluster includes terms such as "procedures", "virus transmission", and "mosquito vector", highlighting studies focused on transmission mechanisms and vector control. Finally, the yellow cluster is made up of words such as "epidemic", "incidence", and "disease outbreaks", which are related to research on outbreak dynamics and the monitoring of spatial incidence patterns at the population level.

In this study, this information on choosing keywords appropriately can serve as a guide for future researchers, as it allows for more effective indexing and retrieval of related studies. This bibliometric analysis demonstrates that the study focuses on the development and use of geographic information systems applied to dengue detection, and in turn, explores the relationship between emerging technologies and their implementation in identifying factors. The connection and size of the nodes in the analysis suggest a significant interconnection between the relationship of geographic information systems and detection technologies, underscoring the relevance of a relational approach in this respect.

4.1.2 International co-authorship map

Co-authorship analysis facilitates the identification of research collaboration networks among researchers, revealing the structure of scientific production in a given field [63]. This approach allows us to understand the formation of research communities and identify the influence of the most prominent authors in the field. The minimum number of documents identified in VOSviewer per author was set to 1 to filter the widest possible range of co-authorship, and in turn, a minimum of 50 citations per author allowed for the analysis of additional aspects regarding improvements in that aspect. This generated 52 authors, including the lead author and their co-authors. The largest set of connected articles was 16 documents. These connected elements generated 12 clusters and 228 links. Figure 3 shows researchers Louis VR, Tozan Y., and Wilder-Smith A. as the most frequent collaborators. This co-authorship network represents an improvement in the collaborative capabilities of an international network of researchers, signifying a considerable advance in the areas of technology applied to dengue detection.

4.1.3 Collaboration map by country

The analysis of collaboration between countries facilitates the identification of scientific production worldwide, showing the ranking of the leading countries in research in that sector, and in turn, shows their underrepresentation. Using the VOSviewer tool, the number of documents per country was set to 3 documents in order to maximize the data and obtain data for the analysis. The number of countries detected by the VOSviewer software was 47, of which 17 countries met the established criteria. Figure 4 shows the countries active in research in GIS applied to dengue detection. These connected elements resulted in 4 clusters, 50 links and a total link strength of 88. Likewise, the United States, the United Kingdom and Thailand are presented as the strongest nodes. This indicates that researchers from these countries are the ones with the most contributions in studies on geographic information systems applied to dengue detection [64]. These results are consistent with previous studies, which show a concentration of scientific production in countries with greater investment in technology and health aspects, such as the United States, the United Kingdom and Brazil [7], which lead the production and implementation of technologies developed for dengue surveillance.

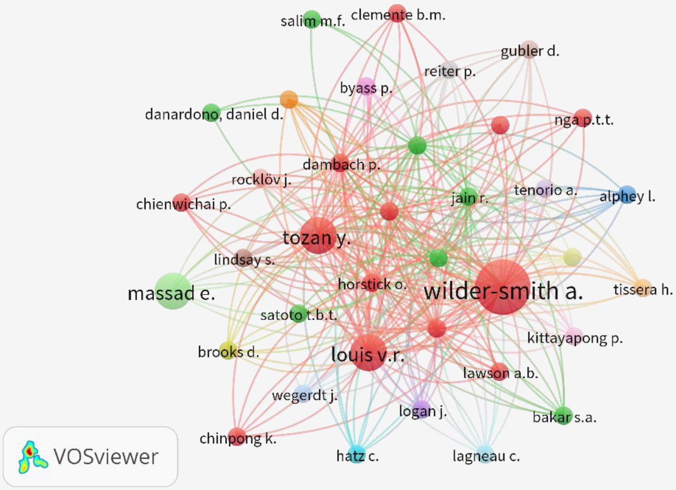

Figure 3: Co-authorship map in VOSviewer

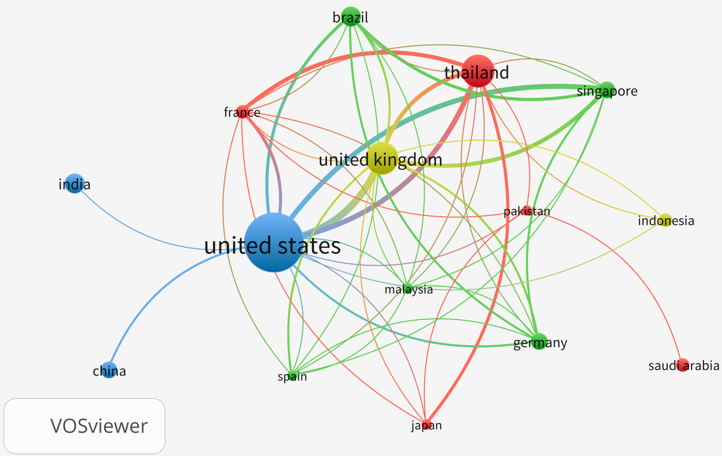

Figure 4: Country co-occurrence map in VOSviewer

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However, the concentration of research in these countries raises significant implications. While the United States and the United Kingdom lead the development of advanced geospatial models, most of the countries most affected by dengue, such as those in Latin America, Africa, and Southeast Asia, lack the same technological or financial capacity to implement such systems. This disparity represents a structural problem in the distribution of knowledge, where the disconnect between technological innovation and real epidemiological needs [65]. In summary, the limited concentration of research in tropical and subtropical countries [3], as well as in some countries with high levels of technology [12], demonstrates a minimal interest in social and health regulations, even given the great importance of the health sector worldwide. This gap not only limits the applicability of GIS technologies in endemic contexts but also reflects the need to strengthen international cooperation in order to identify these inequalities and guide future funding and collaborative strategies that promote more balanced research.

4.1.4 Distribution of publications by year

Analyzing the distribution of publications by year allows us to identify research trends at specific times based on the evolution of the topic. Figure 5 shows the number of articles published on the subject of GIS over time. During the early years of the period analyzed (2007–2010), production was relatively scarce, with only one article published in 2007 and a lack of scientific production between 2008 and 2010. This suggests that in those years, the application of GIS in this area was in its initial phase, with a low level of development and interest on the part of researchers and the scientific community.

Since 2011, growing interest has been observed, with publications appearing in all subsequent years. In 2012 and 2015, two articles were published each year, while in 2016, the number of articles reached four, suggesting a progressive consolidation of the geospatial approach to dengue studies. However, this evolution is not linear, as there are clear changes in the number of documents, reflecting a possible shift in scientific interests. The highest point is 2021, with 10 published documents, suggesting a notable interest in this topic in the post-pandemic period. Likewise, the year 2024 is shown with 12 documents, suggesting a boom in GIS research for dengue detection.

Overall, a gradual trend with ups and downs stands out, which suggests a growing recognition of the potential of GIS as a strategic tool for surveillance and early detection of dengue [66] and [5]. This behavior suggests how the scientific community has been progressively exploring new applications of GIS, particularly in the face of the challenges posed by dengue [67]. As accessibility to geospatial technologies increases, it is a matter of time before the number of investigations continues to grow in recent years, favored by the need and interest of the community in the health sector.

4.1.5 Distribution of publications by journals

Analyzing of the distribution of publications by scientific journals allows us to identify the disciplines that contribute most to the development of knowledge on the application of GIS in dengue detection. Figure 6 shows the distribution of the selected articles according to the journal in which they were published.

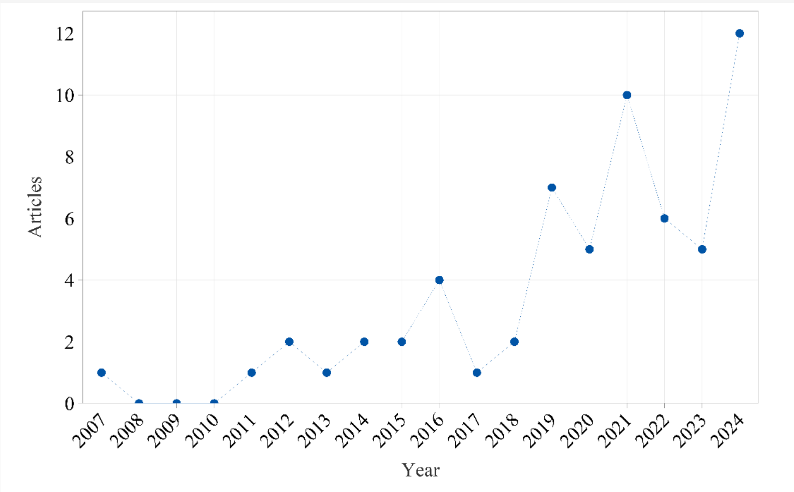

Figure 5: Distribution of publications by year

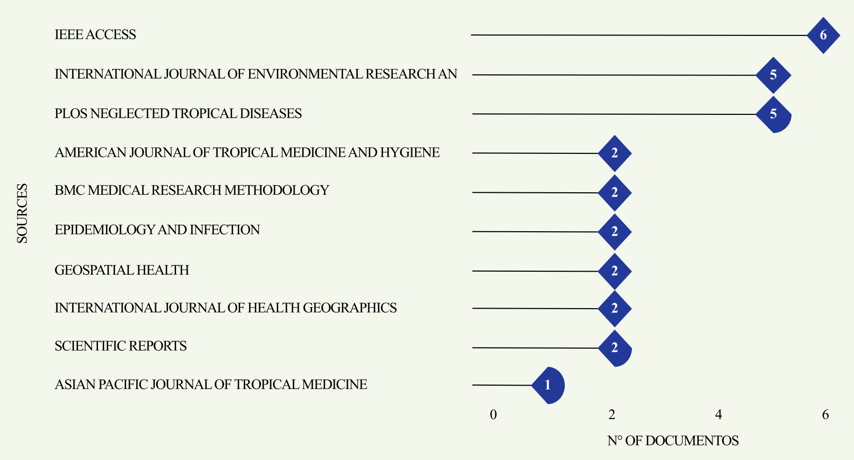

Figure 6: Distribution of published articles by journal titles

IEEE Access leads in the number of publications, with six articles in total. This journal is characterized by its open, multidisciplinary approach and its focus on engineering, artificial intelligence, and applied computer science. Its prominence in this field reflects a growing trend toward a technological approach to dengue, suggesting a shift toward perspectives driven by engineering and computer science. Following with five publications each are the International Journal of Environmental Research and Public Health and PLOS Neglected Tropical Diseases. These journals, focused on environmental health, medical geography, and applied science, reflect the importance of the topic, as well as the growing interest in addressing dengue from different disciplines.

Overall, this distribution suggests that interest in the use of GIS in dengue monitoring is being driven by publications focused on technology [68], environmental health [69], tropical medicine, and spatial analysis [70]. However, the predominance of publications in engineering journals indicates the need to more actively integrate clinical and social perspectives, ensuring that technological innovations maintain their practical relevance in environments where disease has the greatest impact.

4.2 Content Review

The final analysis included 70 documents selected using the PRISMA methodology, focusing on studies related to GIS in dengue detection and prevention. The selection considered research focusing on the technologies used, their applications in geospatial contexts, and the challenges and opportunities involved in their implementation. The thematic distribution revealed a structuring of the review around three main questions, each developed in a substantive manner.

- What practical applications of GIS have demonstrated the greatest impact on dengue prevention and control strategies?
- What are the main challenges and limitations in implementing GIS for dengue detection and monitoring?
- What opportunities do GIS offer to improve epidemiological surveillance and optimize public health decision-making in the face of dengue outbreaks?

The previous points focus on the content review structure illustrated in Figure 7, which provides a guide for conducting a detailed and deductive analysis of each document. This approach is divided into subsections, which provide a description of the status of prevention strategies, challenges and limitations, and GIS opportunities for this study.

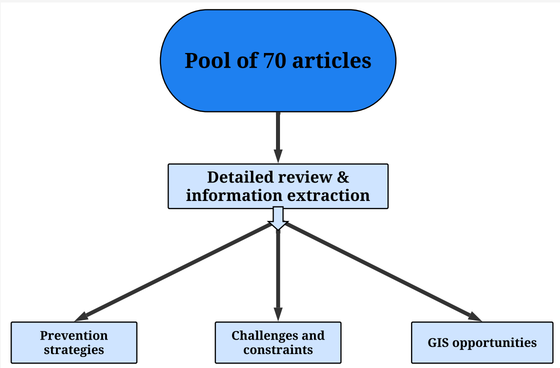

Figure 7: Structure of the systematic content review

4.2.1 Dengue prevention and control strategies

Figure 8 shows the distribution of 25 articles on dengue prevention and control strategies. This filtered analysis highlights a growing interest in the human-vector framework, which enables interaction

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with corporate systems, networks, and data [71], thus enabling a focus on the dengue-human population relationship, thereby interrupting disease transmission. Another notable point is the use of machine learning for dengue prediction, which involves the application of machine learning algorithms and models to analyze large volumes of data [72][73] and predict the severity of dengue outbreaks before they occur. To a lesser extent, the use of convolutional neural networks (CNNs) to predict dengue incidence based on epidemiological and climatic data for visual detection and vector control stands out [74][75] and [76]. Together, these results indicate that the human-vector framework for surveillance and the use of machine learning for dengue prediction are important aspects in the integration of technologies for dengue detection.

4.2.2 Challenges and limitations in the implementation of GIS

Figure 9 shows the distribution of 20 articles on the challenges and limitations of GIS implementation. The analysis found that the underlying challenges in implementing these technologies relate largely to the accuracy and quality of GIS [77]. Despite the advances and capabilities of these tools, successful implementation does not depend solely on the software. If the underlying geographic data is incorrect, incomplete, or of low quality, all analysis, visualization, and decision-making tools built on them will also be flawed. On the other hand, restrictive linear models represent a challenge due to the use of simplistic analysis tools within a sophisticated framework [78], which prevents it from reaching its potential to accurately model and predict complex real-world phenomena.

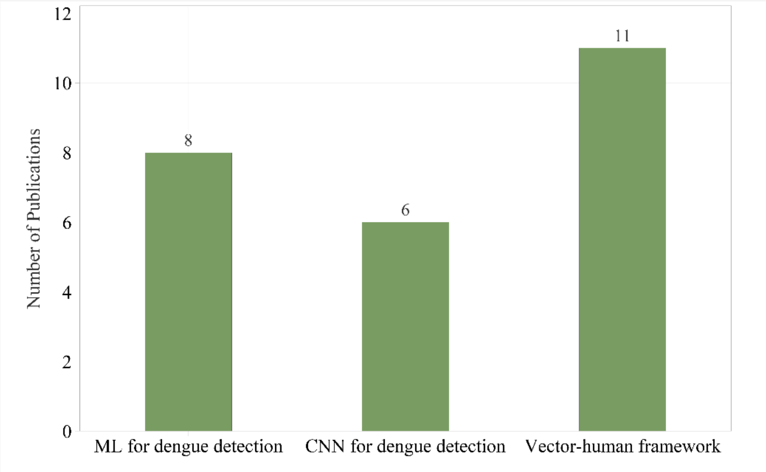

Figure 8: Distribution of articles by prevention strategies

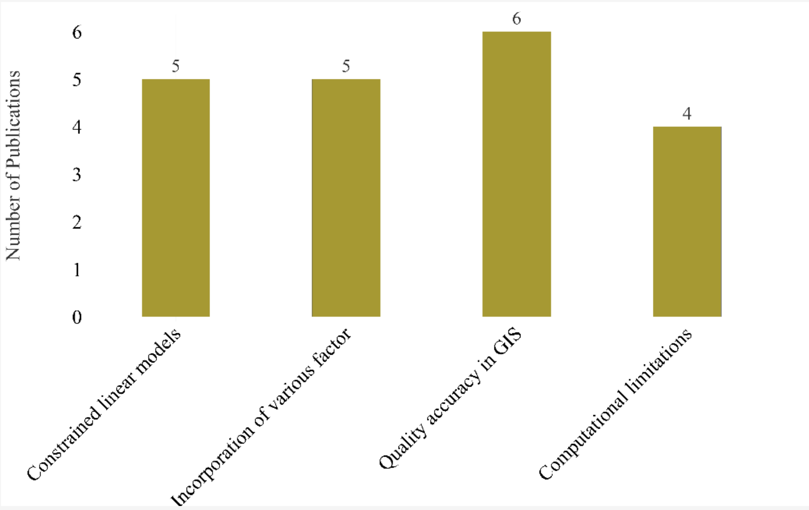

Figure 9: Distribution of articles on challenges and limitations

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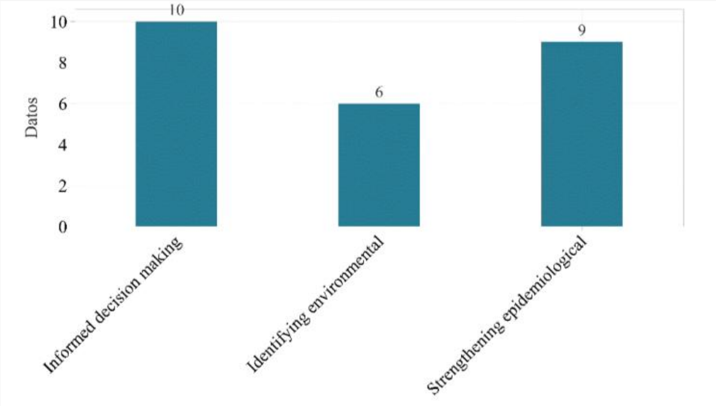

Figure 10: Distribution of articles on GIS opportunities

Likewise, the incorporation of multiple factors is shown as a limitation, which indicates that, although the strength of GIS lies in its ability to integrate multiple layers of data, the process itself represents technical, logistical, and quality challenges that can limit its effective implementation [79]. In this sense, data quality, technical complexity, and lack of coordination prevent GIS from reaching its full potential and becoming a truly comprehensive prevention and control tool. On the other hand, among the challenges are computational limitations, which refer to the obstacles that arise from the lack of hardware and software resources to efficiently process the large amount of data and the complex analyses that GIS require [80] and [81]. With this in mind, it is noted that there are various challenges and limitations in the implementation of GIS, which require an effective and rapid solution to avoid future problems.

4.2.3 GIS opportunities to improve epidemiological surveillance

The opportunities offered by the use of GIS to improve epidemiological surveillance are diverse in their general application. Figure 10 shows the distribution of 25 articles on these opportunities. First, informed decision-making is presented as an opportunity, as it transforms the way health officials approach problems [82], moving from making decisions based on intuition, experience, or isolated data to making strategic and effective decisions supported by in-depth spatial analysis, maximizing the impact on dengue prevention and control [83] and [84].

Likewise, strengthening epidemiological surveillance is found to be a key tool that improves and optimizes all phases of the respective process [85]. Due to the comprehensive improvement in surveillance, results become more accurate, rapid, and comprehensive, as it allows public health authorities not only to count cases but also to understand the complex geography of the disease and respond more boldly and efficiently to prevent and control dengue outbreaks [86]. In turn, the identification of environmental changes highlights the potential for GIS to analyze and monitor changes in the physical environment, which contribute to the spread of diseases. This, in turn, strengthens the anticipatory response capacity of public health systems [87]. This highlights the fact that monitoring the environment makes it possible to anticipate risk, develop more accurate predictive models, and plan public health interventions that not only respond to outbreaks but also aid in their prevention. Accordingly, research in this field continues to advance, making it essential to ensure an inclusive approach that maximizes the potential opportunities offered by the use of GIS technologies for dengue detection and prediction.

5. Conclusions

This study conducted a comprehensive analysis of the application of GIS in dengue detection. The research integrated bibliometric analysis and a review of 70 studies, identifying technologies related to the detection and prevention of this disease. The results show a steady growth in publications since 2018, with a notable increase starting in 2020. This increase demonstrates a growing interest in this area, driven by advances in technological solutions for dengue detection.

The studies analyzed identify the United States, the United Kingdom, and Thailand as pioneers in this literature, demonstrating a strong geographic concentration in developed countries. On the other hand, countries such as Spain, Malaysia, and Singapore barely appear in the co-occurrence networks, indicating the need to promote initiatives and provide financial support for these and other nearby locations. The review also notes that the most frequent keywords were 'epidemic', 'human', 'dengue', and 'prediction', which define the central themes of current research. Furthermore, the co-authorship analysis reveals very active collaborative networks, highlighting researchers such as Louis VR, Tozan Y., and Wilder-Smith A. These collaborations are fundamental to the advancement of knowledge and to addressing the challenges of dengue detection and prevention. The use of tools such as VOSviewer and Bibliometrix has been crucial in understanding the connections between topics and authors, allowing us to identify areas that have not yet been thoroughly investigated. The results demonstrate that, despite significant progress, there is still much room for exploration and improvement. Therefore, this study not only offers a clear view of the evolution of knowledge about GIS applied to dengue detection, but also serves as a guide for future research.

Finally, it is essential to continue analyzing the strategies, challenges, and opportunities in this field to ensure inclusive and equitable development. As technology advances, it is crucial to foster collaboration across disciplines to ensure that these innovations and combinations effectively improve our well-being.

6. Gaps in the Literature

Despite the notable increase in research on GIS applied to dengue detection and prevention, the bibliometric analysis of the literature reveals several limitations that point to a clear path for future research. First, a clear geographical bias was identified, detailed in Figure 4, with most studies concentrated in developed countries, while countries with the highest epidemiological burden, such as Latin America and Southeast Asia, are poorly represented. This gap limits the global applicability of the models and hinders technology transfer to resource-constrained contexts.

Second, the results of the analysis showed that most studies focus on the development of models and methodologies [88][89] and [90], with a notable absence of longitudinal studies evaluating the real-world and sustainable implementation of these tools in long-term public health programs. This suggests that despite the importance and evolution of dengue fever in global terms [91], the determining factors for detection are still under investigation [92]. Likewise, the indices indicate that climate susceptibility has increased considerably [93], which has resulted in greater conditions to be considered in future studies. Finally, a limited integration of advanced, nonlinear predictive models capable of reflecting the complex interactions between climatic, social, and environmental factors was detected. This suggests that the research is still in a methodological rather than an applied stage, where advances in accuracy and scalability are needed to transform GIS into a key operational tool within national epidemiological surveillance systems.

In this regard, for research on GIS and dengue to advance significantly, it is crucial that future research focus on overcoming these limitations. It is necessary to promote studies in the most vulnerable and least developed countries and to develop models that capture the complexity of their environments. Addressing these gaps will allow GIS-based solutions to be not only technologically viable but also inclusive, equitable, and truly effective for dengue control and prevention.

7. Considerations for Future Research

Based on the identified gaps, it is proposed that future research focus on more specific and contextualized lines of work:

- Prioritize applied research in high-incidence countries, particularly in Latin America and Southeast Asia, to evaluate the scalability and cost-effectiveness of GIS models in resource-limited contexts.
- Design longitudinal and impact evaluation studies that directly quantify the effectiveness of GIS in reducing dengue incidence, as well as its influence on resource optimization and public health decision-making.
- Integrate low-cost, open-source geospatial technologies with participatory citizen science data collection strategies to overcome data scarcity and computational limitations.
- Develop hybrid and adaptive predictive models, combining environmental, climatic, and social data with machine learning techniques, to improve the capacity for early detection and outbreak prediction.
- Explore interoperability between GIS systems and national health platforms, ensuring that research results can be integrated into institutional practice for surveillance and epidemiological response.

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