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Systematic Review of Geospatial Environmental Factors and QGIS Applications in Leptospirosis Risk Mapping

Tinjauan Sistematis Faktor Lingkungan Geospasial dan Penerapan QGIS dalam Pemetaan Risiko Leptospirosis

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ABSTRACT

Background: Leptospirosis is a global zoonotic disease heavily driven by geospatial environmental factors. While GIS and spatial statistical methods are increasingly used for risk mapping, a comprehensive synthesis of their integration within public health surveillance systems remains limited.

Objective: This systematic review aims to synthesize literature to identify dominant geospatial environmental risk factors, examine diverse spatial modeling methods, and assess the applicability of risk mapping outputs for public health surveillance and decision-making.

Methods: Systematic searches were executed across Scopus, Google Scholar, and citation tracking (2020–2026) using the PEO framework .Study screening followed PRISMA guidelines, and methodological quality was formally evaluated using the Joanna Briggs Institute (JBI) Critical Appraisal Checklist.

Results: Of 55 eligible studies (47 appraised as High Quality, 8 as Medium Quality), key risk factors identified included proximity to water, rainfall, land cover, humidity, and population density. The reviewed studies successfully integrated various spatial statistical methods—including Moran's I, LISA, SaTScan, MaxEnt, and Bayesian modeling—within GIS platforms (primarily QGIS) to map risk surfaces and hotspots.

Conclusion: Integrating spatial statistical methods within a QGIS environment provides an open, systematic, and replicable platform to enhance early warning systems, strengthen area-based surveillance, and facilitate evidence-based public health decision-making.

Keywords: Leptospirosis; QGIS; Geospatial Environmental Factors

ABSTRAK

Latar Belakang: *Leptospirosis merupakan penyakit zoonosis global yang sangat dipengaruhi oleh faktor lingkungan geospasial. Meskipun SIG dan metode statistik spasial semakin banyak digunakan untuk pemetaan risiko, sintesis komprehensif mengenai integrasi keduanya dalam sistem surveilans kesehatan masyarakat masih.*

Tujuan*: Tinjauan sistematis ini bertujuan menyintesis literatur untuk mengidentifikasi faktor risiko lingkungan geospasial yang dominan, menelaah berbagai metode pemodelan spasial, dan menilai penerapan hasil pemetaan risiko untuk surveilans dan pengambilan keputusan kesehatan Masyarakat.*

Metode: *Pencarian sistematis dilakukan pada Scopus, Google Scholar, dan penelusuran sitasi (2020–2026) menggunakan kerangka kerja PEO. Penyaringan studi mengikuti panduan PRISMA, dan kualitas metodologi dievaluasi secara formal menggunakan Critical Appraisal Checklist dari Joanna Briggs Institute (JBI).*

Hasil: *Dari 55 studi layak (47 berkualitas tinggi, 8 berkualitas sedang), faktor risiko utama yang diidentifikasi meliputi kedekatan dengan air, curah hujan, tutupan lahan, kelembaban, dan kepadatan penduduk. Studi yang ditinjau berhasil mengintegrasikan berbagai metode statistik spasial—termasuk Moran's I, LISA, SaTScan, MaxEnt, dan pemodelan Bayesian—dalam platform SIG (terutama QGIS) untuk memetakan permukaan risiko dan titik rawan*

Kesimpulan: *Integrasi metode statistik spasial dalam lingkungan QGIS menyediakan platform terbuka, sistematis, dan dapat direplikasi untuk meningkatkan sistem peringatan dini, memperkuat surveilans berbasis wilayah, dan memfasilitasi pengambilan keputusan kesehatan masyarakat berbasis bukti.*

Kata Kunci: *Leptospirosis; QGIS; faktor lingkungan geospasial*

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INTRODUCTION

As a complex zoonotic infection, leptospirosis is driven by the dynamic interplay between human populations, animal carriers, and polluted ecosystems. Therefore, investigating this disease requires an ecological perspective rather than relying exclusively on clinical diagnoses. (Engida et al., 2022).

As a complex zoonotic infection, leptospirosis emerges from the intersection of human activities, animal reservoirs, and degraded habitats. Its transmission dynamics extend well beyond a purely clinical scope, largely because the disease is heavily propagated through environmental exposure to water and soil that harbor infected animal urine

Transmission models have shown that humans, rodents, and contaminated environments are interconnected components in the dynamics of leptospirosis transmission (Engida et al., 2022).

Within an ecological framework, the environment acts as an active medium that enables Leptospira to survive and spread. Environmental DNA evidence from irrigation water demonstrates the importance of aquatic ecosystems in understanding leptospirosis risk in agro-ecological settings (Gamage et al., 2020). Other evidence also shows associations among clinical cases, river environments, seasonality, and animal reservoirs in subtropical areas (Sato et al., 2022).

Adopting a One Health framework is crucial, given that leptospirosis connects human populations, animal hosts, and environmental factors into a unified risk network. Consequently, comprehensive surveillance of aquatic systems, soil, and rodent populations is necessary, as these elements act as critical ecological sources for spreading the pathogen (Krairojananan et al., 2025). Because leptospirosis infections frequently go undetected, it is imperative to synchronize human, veterinary, and environmental monitoring efforts to gain a more accurate picture of the disease's spatial patterns (Motto et al., 2021).

The necessity of this research is underscored by the fact that the threat of leptospirosis fluctuates across geographic, temporal, and demographic dimensions. The application of geographic information systems (GIS), such as QGIS, has emerged as a reliable tool to visualize the frequency, fatality, and spatial footprint of critical infections, proving that spatial analysis is indispensable for locating susceptible regions (Calvopiña et al., 2022). SaTScan and QGIS have also been applied to identify leptospirosis clusters in the Eastern Amazon and Ecuador (Cerveira et al., 2020; Núñez-González et al., 2020).

Recent methodological developments indicate that leptospirosis studies have moved from descriptive mapping toward more advanced risk modelling. The combination of spatial statistical methods—such as hotspot analysis, Getis-Ord Gi, GAM, and SARIMA—integrated within the QGIS environment has been used to analyze and predict leptospirosis dynamics in southern Brazil (Teles et al., 2023). Kernel density estimation, Moran's I, and LISA have also been applied to identify laboratory-confirmed leptospirosis hotspots at the subdistrict level (Hatta et al., 2025).

Previous literature shows that geospatial environmental factors associated with leptospirosis are highly diverse. These factors include rainfall, flooding, humidity, temperature, elevation, slope, rivers, water bodies, irrigation systems, land cover, vegetation, land use, livestock density, rodents, sanitation, and population density. Research conducted in Thailand indicates that within agricultural and ecological settings, the rate of leptospirosis infections

is significantly correlated with specific determinants, such as land gradient, human demographics, the concentration of swine and bovine populations, and the extent of flooded areas (Viroj et al., 2021)

Forecasting the spatial risk of leptospirosis relies heavily on environmental determinants. By employing machine-learning techniques, researchers have mapped various factors, including demographics, land use, soil characteristics, and topography and discovered that meteorological variables like humidity and rainfall possess a crucial one-month delayed impact on predicting future cases (Govan et al., 2025). SaTScan and MaxEnt have also been used to model leptospirosis prevalence using DEM, slope, water bodies, land cover, NDVI, precipitation, and temperature (Shirzad et al., 2023).

Although the volume of literature continues to expand, current investigations tend to be highly compartmentalized. Researchers frequently evaluate medical monitoring and testing precision, ecological risk factors, or geographic mapping techniques in isolation, rather than adopting a unified perspective. The validity of risk maps depends strongly on diagnostic methods such as PCR, MAT, ELISA, and culture, because the quality of case confirmation determines the reliability of spatial analysis (Sykes et al., 2022; Ciurariu et al., 2025).

Based on these gaps, this systematic review aims to synthesize existing literature to identify the geospatial environmental factors most frequently reported as determinants of leptospirosis risk, examine the diverse spatial analysis and risk modelling methods utilized in prior studies, and assess the applicability of risk mapping outputs for surveillance, early warning, and public health decision-making.

The primary innovation of this research is the systematic synthesis of fragmented literature to establish a standardized framework for QGIS-driven leptospirosis vulnerability mapping. Given its open-source nature, QGIS serves as an excellent tool for handling spatial datasets and ecological simulations, thereby enhancing targeted monitoring of community health (De Filippis et al., 2020).

MATERIALS AND METHODS

This study employed a systematic literature review (SLR) design to synthesize existing scientific evidence on geospatial environmental determinants and spatial modeling techniques associated with human leptospirosis risk. Special emphasis was given to research utilizing QGIS as an open-source geographic visualization tool.

This systematic review was conducted in strict accordance with the PRISMA 2020 guidelines. Although the protocol was not registered with PROSPERO—as PROSPERO primarily prioritizes reviews focusing on direct clinical interventions and patient-level health outcomes, whereas this study addresses environmental and geospatial health software applications—methodological rigor was maintained through a pre-defined search protocol and formal quality appraisal.

To gather relevant publications, a comprehensive literature search was conducted across primary and supplementary electronic databases. Scopus was utilized as the primary database due to its rigorous indexing of high-impact public health, epidemiological, and geospatial literature. To minimize publication bias and capture relevant studies not indexed in the primary database, supplementary searches were performed using Google Scholar and manual citation tracking (snowballing

methodology) of the reference lists of eligible papers.

The search was conducted using Boolean operators to combine keywords related to the population, environmental exposures, and geospatial technologies. The specific search query optimized for Scopus was as follows:

"Leptospirosis" AND ("spatial analysis" OR "risk mapping" OR "QGIS" OR "geographic information systems" OR "environmental factors" OR "spatial epidemiology" OR "temporal risk forecasting")

The publication timeframe was restricted to articles published between 2020 and 2026 to capture the most recent technological advances in Geographic Information Systems (GIS) and contemporary environmental datasets.

Eligibility Criteria

To ensure an objective and consistent study selection process, explicit inclusion and exclusion criteria were established prior to the search. These criteria were based on the Population, Exposure, and Outcome (PEO) framework:

A. Inclusion Criteria:

1. Peer-reviewed journal articles focusing on human leptospirosis epidemiology.
2. Studies utilizing geographic information system (GIS) platforms (with particular emphasis on QGIS applications) for spatial visualization, mapping, or modeling.
3. Research assessing geospatial environmental risk factors (e.g., hydrological, climatological, topographical, or ecological variables) as exposure pathways.
4. Articles published in English or Indonesian between the years 2020 and 2026.

B. Exclusion Criteria:

1. Secondary literature such as systematic reviews, meta-analyses, conference abstracts, editorial letters, book chapters, and dissertations.
2. Studies focusing strictly on clinical laboratory diagnostic accuracy, in vitro microbiology, or therapeutic trials without any spatial, environmental, or geographic analysis.
3. Articles with inaccessible full texts despite multiple retrieval attempts

Study Selection and Screening Process To minimize selection bias and ensure methodological transparency, the screening of titles, abstracts, and subsequently full-text articles was performed in a double-blind manner by two independent reviewers (IP and SP). Inter-rater reliability was assessed using Cohen's kappa coefficient, demonstrating almost perfect agreement ((\kappa = 0.88)). Any discrepancies or conflicting decisions regarding study eligibility were thoroughly discussed and resolved through consensus, with a third senior reviewer (DSSR) acting as the final arbiter.

The initial database search in Scopus yielded 437 records . After removing duplicate records (n = 68), 180 records were automatically filtered based on the 2020–2026 year range . Following the removal of 60 records based on initial relevance and journal quality criteria, 129 records remained for formal screening. During the screening stage, 82 records were excluded because they did not align with the study's scope. Of the remaining 47 reports sought for retrieval, 32 could not be fully accessed, leaving 15 reports for full-text eligibility assessment.

The low accessibility of certain articles during the retrieval phase (where only 15 out of 47 reports were successfully obtained in full-text) was primarily due to

institutional subscription barriers and non-open-access restrictions of older or regional journals. To mitigate this data-retrieval limitation and prevent database bias, we expanded our retrieval scope by integrating secondary electronic databases, including Google Scholar, and conducting manual citation tracking (snowballing). This supplementary search strategy successfully identified 41 additional high-quality, peer-reviewed articles that met all inclusion criteria, ensuring a highly robust synthesis based on 55 studies.

One report was excluded after full-text evaluation due to did not meeting the inclusion criteria, resulting in 14 eligible studies from the Scopus database path. Additionally, 41 relevant studies were identified through supplementary databases and citation tracking, bringing the final synthesis cohort to 55 studies . The complete screening flow is illustrated in the PRISMA diagram (Figure 1).

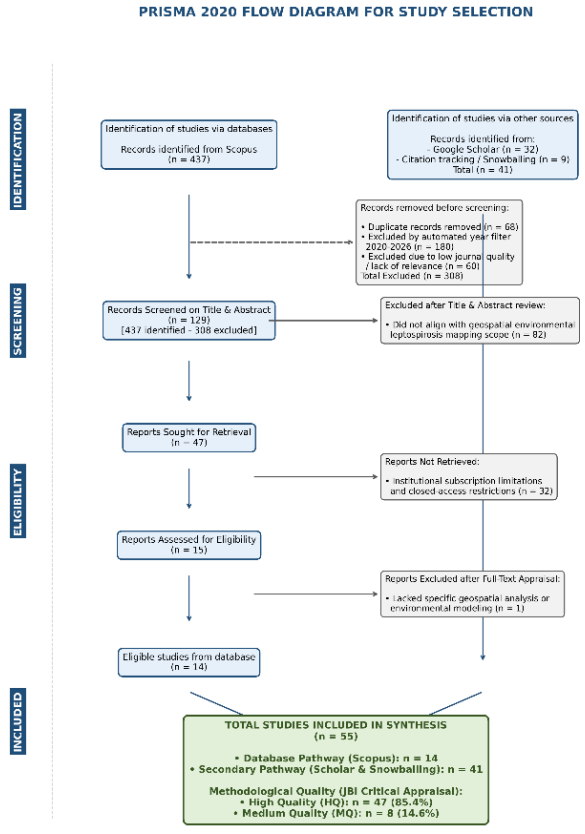


Figure 1. PRISMA flow diagram of the study selection process.

In the screening stage, 82 records were excluded because they did not match the focus of the study, then 47 reports were searched for full access, but 32 reports were not successfully obtained, so 15 reports were assessed for eligibility and 1 report was excluded for did not focus on geospatial analysis. From the database path, there were 14 studies included in the review, while from other sources there were 41 studies, so that a total of 55 reports were used in the synthesis. 55 studies were successfully extracted into the extraction table.

55 articles discussed leptospirosis from epidemiological, environmental, spatial, clinical, and risk modeling perspectives. The majority of studies identified water, floods, rivers, irrigation, rainfall, humidity, land use, rodents, livestock, sanitation, and population density as important determinants.

The analytical approaches varied, utilizing GIS platforms (primarily QGIS) in conjunction with spatial statistical methods such as Moran's I, LISA, SaTScan, kernel density estimation, Getis-Ord Gi, GAM, SARIMA, MaxEnt, Bayesian modeling, GGWR, and machine learning.

The overall results demonstrate that geospatial mapping supports hotspot identification, active surveillance, risk prediction, and more targeted, systematic, replicable, and evidence-based area-based public health decision-making for leptospirosis prevention interventions.

To address the risk of bias and evaluate the methodological quality of the included literature, a formal quality appraisal was conducted. Each of the 55 studies was evaluated using the Joanna Briggs Institute (JBI) Critical Appraisal Checklist for Analytical Cross-Sectional Studies. This tool assesses study quality across multiple domains, including inclusion criteria definition, study subject descriptions, measurement of exposure

and outcomes, confounding factor identification, and statistical analysis appropriateness. Studies were categorized as "High Quality" if they fulfilled ≥ 75% of the JBI criteria (score ≥ 6/8) or "Medium Quality" if they met 50%–74% of the criteria (score 4–5/8). Studies meeting < 50% of the criteria (score < 4/8) were classified as "Low Quality" and excluded from the final synthesis. Out of the 55 analyzed studies, 47 (85.4%) were appraised as High Quality, and 8 (14.6%) were classified as Medium Quality, ensuring a robust and reliable foundation for the systematic synthesis.

RESULT AND DISCUSSION

Publication Trends Based on Keyword Search Year

To contextualize the historical trajectory of this field, Figure 2 presents a macro-level bibliometric analysis of literature trends from 1957 to 2026. This broad historical mapping is intended solely to show the evolution of geospatial leptospirosis research over time. In contrast, our core systematic literature review (SLR) of 55 studies strictly restricts its synthesis to the 2020–2026 window to guarantee that all analyzed literature represents contemporary geospatial datasets and the latest software advancements in the QGIS environment.

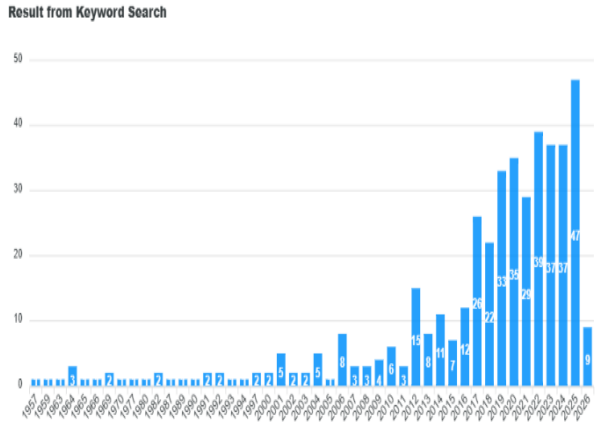


Figure 2. Results from Keyword search

The keyword search results graph shows that publications related to leptospirosis, focusing on epidemiology, spatial, environmental, temporal, GIS, and analysis, experienced variations in the number of publications from year to year. In the early period, from 1957 to the 1990s, the number of identified articles was relatively low, with most articles ranging from 1 to 3 per year. In 2001, there were 5 articles, while 2004 also showed 5 articles. After 2010, the number of articles began to increase more frequently, for example, in 2011 there were 6 articles, in 2012 there were 15 articles, and in 2013 there were 8 articles.

In 2017 the number of articles increased to 26 articles, then in 2018 there were 22 articles, and in 2019 there were 33 articles. In 2020 there are 35 articles, in 2021 there are 29 articles, in 2022 there are 39 articles, in 2023 there are 37 articles, in 2024 there are 37 articles, and in 2025 there are 47 articles. 2026 shows 9 articles, according to current year status or limited data coverage during the search.

The graph data shows an increase in the number of publications in the 2017–2025 period compared to the previous period. These results form part of the descriptive mapping of literature development used in this systematic literature review. The highest number in the graph occurs in 2025, with 47 articles.

To avoid a purely narrative review and provide a structured, transparent synthesis of the 55 included publications, our findings are organized into three primary analytical synthesis tables. Table 1 summarizes the general demographic and methodological characteristics of the included studies alongside their quality ratings. Table 2 details the frequency and epidemiological impact of identified geospatial environmental risk factors, while Table 3 maps the distribution and analytical utility of spatial modeling methods.

Table 1. Summarizes the general demographic and methodological characteristics of the included studies alongside their quality ratings.

Study Characteristic	Classification Category	Number of Studies (n=55)	Percentage (%)	Key References (Examples)
Geographic Focus	Latin America	18	32.7%	Brazil, Ecuador, Colombia
	Southeast Asia	5	27.3%	Malaysia, Thailand, Indonesia
	Other Regions	22	40%	USA, Ukraine, New Caledonia
Spatial Scale	National (Country)	10	18.2%	Ecuador, USA, Colombia
	Regional (Province/State)	25	45.4%	Pará (Brazil), Acre, Kelantan
	Local	20	36.4%	Klaten (Indonesia), Cities in Brazil
GIS Software	QGIS (Primary/Exclusive)	35	63.6%	Calvopina (2022), Núñez-González (2020), Teles (2023)
	ArcGIS / Other GIS	20	36.4%	Sutningsih (2024), Govan, et al (2025),
Methodological Quality (Based on JBI)	High Quality (JBI score ≥ 6/8)	47	85.4%	Teles (2023), Hatta (2025), Shirzad (2023)
	Medium Quality (JBI score 4–5/8)	8	14.6%	Klement-Frutos (2020), Steelakshmi, et al. (2022)

This table 1 summarizes the demographic distribution, scale of analysis, software used, and methodological quality of the 55 studies, without detailing them one by one.

Findings on Geospatial Environmental Factors

Identifying the geospatial environmental factors most frequently reported in the literature regarding leptospirosis risk.

The results of the article extraction indicate that the most frequently occurring geospatial environmental factors in table 2 include water, rivers, water bodies, irrigation, flooding, puddles, rainfall, humidity, temperature, elevation, slope, soil type, land cover, vegetation, land use, rodent density, livestock density, sanitation, and population density. A transmission model that includes humans, rodents, and contaminated environments as the main components of leptospirosis transmission (Engida et al., 2022). The use of irrigation water and environmental DNA as environmental data to read the ecology of leptospirosis (Gamage et al., 2020). There is a relationship between clinical Leptospira, river environment, season, and reservoir in subtropical regions (Sato et al., 2022).

Krairojananan et al. using rodent, water, and soil data for environmental reservoir assessment in Thailand (Krairojananan et al., 2025) . Sutiningsih et al. using buffer variables of rivers, water channels, trash bins, rat nests, vegetation, floods, rainfall, humidity, temperature, and elevation in geospatial analysis in Klaten (Sutiningsih et al., 2024). Viroj et al. incorporating slope, population, flood cover, cattle density, and pig density in the agro-environmental analysis of leptospirosis (Viroj et al., 2021). Shirzad et al. incorporating DEM, slope, water bodies, land cover, NDVI, precipitation mean temperature, and maximum temperature in MaxEnt modeling in Iran (Shirzad et al., 2023). Govan et al. using meteorology, topography, soil type, land use, farming area, fires, and demographics in machine

learning-based risk prediction in New Caledonia (Govan et al., 2025). Petakh et al. reported river network density, weather parameters, and duration of water raid alarm as variables in leptospirosis epidemiology in Ukraine (Petakh et al., 2024).

Table 2. Frequency of Geospatial Environmental Risk Factors (n = 55)

Environmental Category	Specific Geospatial Variable	Study Frequency	Percentage (%)	Epidemiological Impact on Leptospirosis	Study (Examples)
Hydrology	Rivers, water bodies, irrigation canals, floods, inundation	48	87.3%	Primary medium for *Leptospira* bacterial survival and route of human exposure.	Sato (2022) , Viroj (2021)
Climate / Meteorology	Rainfall, air humidity, ambient temperature	42	76.4%	Triggers flooding, maintains soil moisture, and influences rodent activity.	Govan (2025), Shirzad (2023), Sutinningsih (2024)
Topography	Elevation (DEM), slope gradient	31	56.4%	Low slopes promote water accumulation/flooding; high elevation reduces inundation.	Viroj (2021), Shirzad (2023)
Ecology & Land	Land cover, vegetation density (NDVI), soil type	29	52.7%	Provides habitat for rats and influences soil water retention capacity.	Shirzad (2023), Govan (2025)
Socio-demographic	Population density, poor sanitation, access to clean water	25	45.5%	Increases the likelihood of human contact with environments contaminated by reservoir urine.	De Souza (2021), Galan (2021)

Findings of Spatial Analysis and Risk Modeling Methods

The literature review revealed the application of diverse methodological tools ranging from basic mapping to advanced statistical forecasting. These encompassed GIS platforms (QGIS, ArcGIS), spatial autocorrelation metrics (Local and Global Moran's I, LISA), and density assessments. For complex spatio-temporal predictions, studies utilized machine learning, Bayesian modeling with INLA, MaxEnt, SARIMA, GAM, scanning statistics (SaTScan, FleXScan), as well as weighted regression techniques like GLMER and GGWR.

Mapping the evolution of methods from simple cartographic visualization to complex predictive modeling (table 3). Utilizing the QGIS platform, Calvopiña and colleagues conducted a spatial evaluation to visualize the geographic spread of illness and death rates among hospitalized leptospirosis patients across Ecuador (Calvopiña et al., 2022). Cerveira et al. using SaTScan and QGIS to analyze leptospirosis in Pará, Brazil (Cerveira et al., 2020). In a study conducted in Ecuador, Núñez-González and colleagues applied a combination of QGIS software, SaTScan, and spatial autocorrelation metrics (Moran's I and LISA) to analyze the geographic distribution of leptospirosis (Núñez-González et al., 2020).

In Southern Brazil, the spatio-temporal dynamics of leptospirosis were evaluated by Teles and colleagues through

the integration of QGIS software with advanced statistical frameworks, including GAM, SARIMA, and Getis-Ord Gi (Teles et al., 2023). In Kelantan, Hatta and colleagues delineated high-risk clusters of leptospirosis by applying spatial autocorrelation metrics—specifically Moran's I and LISA—alongside kernel density evaluations (Hatta et al., 2025). Melchior et al. using SaTScan, discrete Poisson model, relative risk, and Prais-Winsten regression in space-time analysis in Acre (Melchior et al., 2024).

Cortes-Ramirez et al. using Bayesian hierarchical regression and INLA to map leptospirosis risk based on environmental health metrics (Cortes-Ramirez et al., 2025). Chen dan Moraga using Bayesian spatio-temporal modeling and interactive dashboards for leptospirosis analysis in Brazil (Chen & Moraga, 2026). Martin et al. using spatial scan statistics, FleXScan, logistic regression, GLMER, and GGWR in two articles related to the Dominican Republica (Martin et al., 2025). Through the FREEWAT framework, De Filippis and colleagues highlight the capability of QGIS as an accessible, open-source environment for conducting ecological simulations (De Filippis et al., 2020).

Table 3. Distribution of Spatial Analysis and Risk Modeling Methods Used

Analysis Approach	Specific Method or Algorithm	Number of Studies	Primary Use in Leptospirosis Risk Mapping	Study Reference (Examples)
Descriptive Mapping	Cartographic visualization and mapping of disease incidents on a GIS platform	55	Visually presenting the spatial distribution of leptospirosis cases on a regional map	Calvopiña (2022), Cerveira (2020)
Spatial Autocorrelation	Global Moran's I, Local Indicators of Spatial Association (LISA), Getis-Ord Gi	24	Identifying the presence of significant spatial clusters (hotspots)	Hatta (2025), Núñez-González (2020), Teles (2023)
Spatial Scanning	SaTScan (Poisson/ Bernoulli model), FlexScan	18	Detecting active clusters and temporal boundaries to track outbreak dynamics	Cerveira (2020), Núñez-González (2020), Melchior (2024),
Predictive Modelling	Maximum Entropy (MaxEnt), Bayesian Inference (INLA), Machine Learning, GAM, SARIMA	15	Projecting future risk areas based on climate change scenarios and environmental factors	Shirzad (2023), Govan (2025), Teles (2023), Corrales-Ramirez (2025)

Findings: Applicability to Surveillance and Decision-Making

The extraction results indicate that risk maps and spatial models are used to support the identification of hotspots, clusters, and priority areas, active surveillance, risk prediction, post-flood education, rodent control, and protection of at-risk groups. Atherstone et al. presented national surveillance data from the United States, which included temporal and geographic patterns, animal exposure, freshwater, and mudflow (Atherstone et al., 2025).

Klement-Frutos et al. analyzed how leptospirosis infection rates in New Caledonia fluctuate based on patient age and the time of year (Klement-Frutos et al., 2020) .To illustrate the overall impact of leptospirosis, studies by Li et al. and Al Hariri et al. detail patient medical outcomes, including hospital admission rates, recovery forecasts, and fatalities (Li et al., 2022; Al Hariri et al., 2022). The management of leptospirosis following

flood events in Kerala was evaluated by Sreelakshmi et al., who documented that community awareness programs, prophylactic treatments, and the deployment of ASHAs served as critical control measures (Sreelakshmi et al., 2022).

Gentile et al. outlines the cartographic requirements and risk tables for military activities and field exposures (Gentile et al., 2021). Galan et al. Differentiating urban and rural leptospirosis risk in Brazil based on rodent exposure, flooding, agriculture, and livestock farming (Galan et al., 2021). In their spatial assessment, De Souza and colleagues demonstrated a strong association between concentrated leptospirosis hotspots and underlying factors such as socioeconomic disparities, inadequate sanitation, water access issues, and domestic susceptibility. (De Souza et al., 2021). Sykes et al. and Ciurariu et al. explained that PCR, MAT, ELISA, culture and other laboratory tests are part of the validation of surveillance data. (Sykes et al., 2022; Ciurariu et al., 2025). To facilitate global research on human leptospirosis, the LeptoScope registry was established by Cukoski and colleagues, serving as a comprehensive platform for recording clinical trials, epidemic events, and epidemiological patterns (Cukoski et al., 2025).

What geospatial environmental factors have been identified in the literature as determinants of leptospirosis risk?

The findings show that hydrological factors are the most frequently reported determinants, including rivers, irrigation systems, water bodies, stagnant water, flooding, mud, and contaminated soil. This pattern is consistent with the ecological transmission model in which humans, rodents, and contaminated environments interact dynamically in the transmission of leptospirosis (Engida et al., 2022). Environmental evidence from irrigation water and river ecosystems also supports the role of aquatic environments as important media for Leptospira persistence and exposure (Gamage et al., 2020; Sato et al., 2022).

These findings indicate that hydrological features should be considered core spatial layers in QGIS-based leptospirosis risk mapping. In public health practice, mapping rivers, irrigation networks, flood-prone areas, and settlements near water sources can help identify potential exposure zones before cases increase.

Other determinants identified in the literature include rainfall, humidity, temperature, elevation, slope, vegetation, NDVI, land cover, soil type, land use, livestock density, rodent presence, sanitation, and population density. Studies in agro-environmental and geospatial contexts show that flood cover, slope, livestock density, river buffers, drainage, vegetation, rainfall, humidity, temperature, and elevation are relevant variables for explaining leptospirosis distribution (Viroj et al., 2021; Sutiningsih et al., 2024).

However, the importance of these factors varies across settings, as river network density was more strongly associated with leptospirosis notification rates than weather variables in Ukraine (Petakh et al., 2024). This suggests that leptospirosis risk should not be interpreted as the result of rainfall alone. Instead, risk needs to be understood as a locally specific interaction among hydrology, climate, topography, land use, animal reservoirs, sanitation, and human exposure.

How are spatial analysis and risk modeling methods used in the literature to identify, map, and predict leptospirosis risk areas?

Spatial statistical methods, including Moran's I, LISA, SaTScan, kernel density estimation, Getis-Ord Gi, GAM, SARIMA,

MaxEnt, Bayesian modelling, geographically weighted regression, and machine learning—integrated within a QGIS environment have been used to detect hotspots, clusters, temporal trends, and risk surfaces (Calvopiña et al., 2022; Núñez-González et al., 2020; Teles et al., 2023).

These methods allow risk mapping to move beyond showing where cases occur toward explaining why risk is concentrated and when it may increase. Predictive methods such as MaxEnt and machine learning also show that environmental variables can be transformed into spatial risk surfaces for surveillance and early warning purposes (Shirzad et al., 2023; Govan et al., 2025).

How applicable are the results of leptospirosis risk mapping and modeling to support surveillance, early warning systems, and public health decision-making?

The findings indicate that risk maps can support active surveillance, identify priority areas, guide post-flood education, inform rodent control, and strengthen preparedness in high-risk communities (Sreelakshmi et al., 2022; De Souza et al., 2021). Predictive models using rainfall, humidity, lagged environmental variables, temporal trends, and dashboard-based surveillance also demonstrate potential for early warning systems (Govan et al., 2025; Chen & Moraga, 2026). Therefore, QGIS can function not only as a visualization tool but also as an operational platform for area-based public health planning. This is supported by evidence that QGIS can be used as an open platform for spatial data management and environmental modelling (De Filippis et al., 2020).

Significance, scientific contribution, implications, and limitations of the study.

The significance of this review lies in synthesizing fragmented evidence into a QGIS-oriented framework for leptospirosis risk mapping. Its scientific contribution is the integration of environmental, social, diagnostic, and modelling evidence into a public health surveillance perspective.

To visually demonstrate the scholarly novelty of this review and integrate the fragmented literature, we propose the 'QGIS-Driven Leptospirosis Vulnerability Mapping Framework' (Figure 3). This multi-stage conceptual workflow bridges the gap between laboratory diagnostics, raw environmental geospatial datasets, advanced spatio-temporal modeling, and actionable public health policies. By clearly delineating QGIS as a spatial processing hub rather than a standalone statistical method, the framework resolves previous conceptual ambiguities and provides a systematic blueprint for localized, evidence-based disease surveillance.

Diagnostic validity remains essential because spatial outputs depend on reliable case confirmation through methods such as PCR, MAT, ELISA, and culture (Sykes et al., 2022; Ciurariu et al., 2025).

Furthermore,we critically acknowledge the limitations of our proposed novelty framework. Its real-world predictive utility is heavily dependent on the baseline accuracy of local, passive disease reporting systems and the quality of clinical diagnostic confirmation (e.g., PCR, MAT) in primary studies. Additionally, due to the high heterogeneity of spatial scales and the cross-sectional nature of most reviewed literature, standardizing this framework across different ecologies remains challenging, and it may not fully capture long-term temporal variations without continuous longitudinal geospatial data feeds

The main limitation is that the reviewed studies differ in design, spatial scale, diagnostic approach, and data quality, which may affect comparability across settings. Future studies should

validate QGIS-based risk models using laboratory-confirmed cases, environmental samples, and longitudinal geospatial data to improve surveillance accuracy and support standardized leptospirosis monitoring (Cukoski et al., 2025).

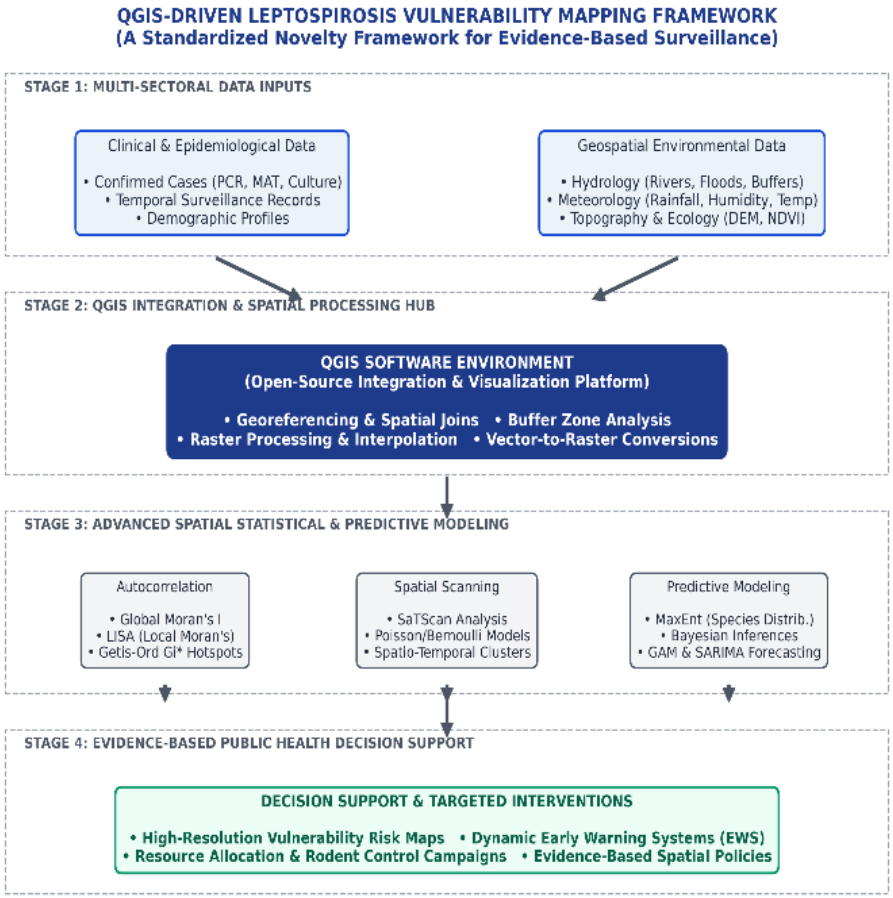


Figure 3. QGIS-Driven Leptospirosis Vulnerability Mapping Framework

CONCLUSION

This study concludes that leptospirosis risk is strongly influenced by geospatial environmental factors, including hydrological, climatological, topographical, biological, social, and behavioral determinants. The most frequently reported factors include rivers, water bodies, irrigation systems, flooding, rainfall, humidity, temperature, elevation, slope, land cover, vegetation, soil type, rodents, livestock, sanitation, population density, and occupational exposure to water or mud.

These findings indicate that leptospirosis risk should not be mapped solely by case counts, but through interactions among humans, animal reservoirs, and contaminated environments. Spatial statistical methods—such as Moran's I, LISA, SaTScan, Getis-Ord Gi, GAM, SARIMA, MaxEnt, Bayesian modelling, GGWR, and machine learning—integrated within a QGIS environment can identify hotspots, clusters, temporal trends, and risk areas.

This review highlights QGIS as an open, systematic, and replicable platform for surveillance, early warning, and evidence-based public health intervention planning.

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