

Geospatial approaches to analysing spatial patterns of stroke incidence and mortality: a systematic review

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Abstract

Stroke is a leading cause of mortality and disability worldwide; however, its burden is unevenly distributed across geographical areas. This systematic review aimed to synthesise studies examining the spatial distribution of stroke incidence, prevalence and mortality, with a review of geospatial analytical approaches used to identify these patterns. A systematic literature search identified 29 studies that applied spatial analysis or spatial modelling techniques to stroke-related outcomes. The included studies demonstrated heterogeneity in geographical scale, spatial units, outcome measures and covariate selection. Methodological quality was assessed using a modified Joanna Briggs Institute (JBI) critical appraisal tool. Overall, stroke incidence and mortality were consistently found to be non-randomly distributed in space, with significant spatial autocorrelation and clustering observed across multiple spatial scales. These spatial patterns were closely associated with area-level factors, including population ageing, socioeconomic conditions and urban–rural characteristics. Environmental exposures and disparities in the spatial distribution of healthcare resources and access to care were also reported to contribute to geographical differences in stroke outcomes. Geospatial methods commonly employed included GIS-based mapping, spatial autocorrelation analyses, spatial regression models and Bayesian disease mapping. Although most studies demonstrated moderate to high methodological quality, variation remained in the justification of spatial unit selection and the control of covariates. In conclusion, the burden of stroke exhibits pronounced spatial heterogeneity shaped by structural, environmental and healthcare accessibility factors. Future geospatial research should adopt evidence-based spatial units and integrated analytical approaches to support place-based stroke prevention strategies and inform health policy development.

Key words: stroke; spatial analysis; geographic information systems; health inequalities; environmental exposure; healthcare accessibility

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Introduction

Stroke is recognised as one of the leading causes of mortality and disability worldwide (Feigin *et al.*, 2017; GBD 2019 Stroke Collaborators, 2021). However, the distribution of stroke incidence and mortality is far from uniform across geographical areas. Even within the same country or region, the burden of stroke varies spatially, with persistently higher incidence or mortality reported in specific locations (Pedigo *et al.*, 2011; van Rheeën *et al.*, 2015; Adzandeh *et al.*, 2016; Dworkis *et al.*, 2020; Freyssenge *et al.*, 2020; Bando *et al.*, 2024; Paulina *et al.*, 2025). These observations suggest that stroke should be understood not merely as an individual-level clinical condition, but also as a public health issue shaped by local context and structural determinants.

Traditionally, stroke epidemiology has focused predominantly on individual-level risk factors and clinical characteristics (Mohammed *et al.*, 2021; Joseph *et al.*, 2024). While this approach has substantially advanced the biological and clinical understanding of stroke, it is limited in its ability to explain geographical disparities and spatial clustering of stroke outcomes. In spatial epidemiology, it has long been recognised that disease occurrence cannot be separated from geographical context (Elliott & Wartenberg, 2004), and that individual-level analyses alone are

insufficient to account for area-level health inequalities. In recent years, an increasing number of studies have examined the spatial distribution of stroke incidence and mortality (Adzandeh *et al.*, 2016; Freyssenge *et al.*, 2020; Tran *et al.*, 2024; Wu *et al.*, 2024). However, substantial variation exists across studies in terms of spatial units, analytical methods and outcome measures, limiting the comparability and synthesis of findings. Some studies have focused primarily on identifying spatial clustering or autocorrelation (Pedigo *et al.*, 2011; van Rheeën *et al.*, 2015; Dworkis *et al.*, 2020; Freyssenge *et al.*, 2020), whereas others have investigated associations with socioeconomic conditions, environmental exposures or healthcare accessibility (Odoi *et al.*, 2014; Luo *et al.*, 2017; Padilla *et al.*, 2021; Leveau *et al.*, 2024; Li *et al.*, 2024). Moreover, it has been repeatedly noted that analytical results may vary depending on spatial unit selection and modelling strategies (Lawson 2018; Kok *et al.*, 2021; Cheung *et al.*, 2024), complicating integrated interpretations of spatial stroke patterns. Stroke outcomes are influenced not only by demographic characteristics but also by environmental exposures and access to healthcare resources (Chen *et al.*, 2015; Luo *et al.*, 2017; Ha *et al.*, 2023; Wu *et al.*, 2024). In particular, healthcare accessibility is strongly determined by the spatial distribution of medical facilities, travel distance and service catchment areas (Guagliardo, 2004), factors that are not adequately captured through individual-level analyses

alone. Recent studies have emphasised the importance of integrating environmental factors — such as air pollution, ambient temperature and heat exposure — with healthcare resource distribution within spatial analytical frameworks (Chen *et al.*, 2015; Ha *et al.*, 2023; Wu *et al.*, 2024) that would assist understanding the structural drivers of stroke burden. A wide range of geospatial methods has been applied in stroke research, including GIS-based mapping, spatial autocorrelation analyses, spatial regression models, Bayesian spatial modelling, and spatiotemporal approaches (Pedigo *et al.*, 2011; Soljak *et al.*, 2011; Odoi *et al.*, 2014; van Rheeën *et al.*, 2015; Freyssenge *et al.*, 2020). Nevertheless, consistency in methodological choices and reporting remains limited. Key elements such as spatial unit definition, confounder control and consideration of boundary effects can substantially influence analytical outcomes, yet their treatment varies widely across studies (Lawson, 2018; Stillwell *et al.*, 2018; Kok *et al.*, 2021). This heterogeneity highlights the need for a systematic assessment of methodological practices and limitations within existing research.

Against this background, a systematic review synthesising the spatial characteristics of stroke incidence, prevalence and mortality, alongside the factors proposed to explain these patterns, is warranted. This study systematically synthesised existing geospatial studies on stroke by examining spatial patterns, environmental and healthcare resource factors as well as spatial modelling approaches, with the aim of providing an integrated understanding of spatial inequalities in the burden of stroke across regions. In particular, this study investigated the interrelationships among spatial units, covariate selection, and analytical methods, thereby identifying a methodological gap characterised by the lack of standardised geospatial analytical approaches and methodological inconsistencies in the existing literature.

Ultimately, this study proposes a methodological framework to guide the selection of appropriate geospatial approaches in stroke research. Furthermore, by supporting more rigorous spatial analyses, it provides evidence to inform a shift from hospital-centred cerebrovascular management towards mortality reduction and prevention-oriented stroke health policies. In addition, this evidence may contribute to strengthening the roles of nurses and other healthcare professionals in the development and implementation of community-based preventive strategies. Specifically, this review seeks to i) summarise the types and applications of geospatial analytical methods used to identify spatial heterogeneity and clustering of stroke burden; ii) evaluate the consistency and interpretation of findings derived from spatial autocorrelation analyses, spatial regression models, and Bayesian spatial approaches; and iii) critically assess methodological strengths and limitations, including study design, spatial unit selection, data sources, potential biases, and the Modifiable Areal Unit Problem (MAUP).

Materials and Methods

Study design

This study is a systematic review examining spatial analytical and modelling studies of stroke incidence, prevalence, and mortality. The review aimed to identify spatial distribution patterns and associated determinants of stroke burden, with the ultimate goal of informing stroke prevention policies and the allocation of healthcare resources from a geospatial perspective.

Literature selection process

This systematic review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines. Considering the characteristics of observational and spatial epidemiological studies, the PICO framework was adapted rather than strictly applied to formulate the research questions. The Population (P) included studies involving adult stroke patients or population-based analyses at community or national levels. The Intervention (I) referred to the application of spatial analytical methods (e.g. geographical information systems (GIS), spatial autocorrelation, spatial regression), rather than clinical interventions. The Comparison (C) encompassed comparisons across countries, regions or time periods. The Outcomes (O) included spatial distributions of stroke incidence, prevalence or mortality; the presence of spatial clustering; or reported spatial metrics such as Moran's *I* or Local Indicators of Spatial Association (LISA).

Eligible study designs comprised observational studies, including cross-sectional, ecological and time-series studies. Studies applying spatial analytical or modelling techniques — such as spatial autocorrelation analyses (e.g. Moran's *I*, LISA), spatial regression models (e.g., Geographically Weighted Regression (GWR), Bayesian spatial regression), spatial cluster detection or GIS-based disease mapping — were included.

The inclusion criteria were as follows: i) studies analysing stroke incidence, prevalence, or mortality among adult populations or at regional or national population levels; ii) studies employing spatial analytical or spatial statistical methods (e.g. GIS, Moran's *I*, LISA, GWR); iii) studies reporting quantitative spatial indicators such as Relative Risk (RR), Standardised Incidence Ratio (SIR), Age-Standardised Incidence Rate (ASIR), Moran's *I* or comparable spatial clustering measures; iv) observational or spatial modelling studies; v) peer-reviewed journal articles available in full text and published in English or Korean; and vi) studies published from January 2005 onwards. Studies were excluded if they met any of the following criteria: single-centre clinical studies limited to hospitalised patients; studies focusing on stroke pathophysiology or neuroimaging (e.g., functional Magnetic Resonance Imaging (fMRI)); randomised controlled trials, clinical trials or case reports; studies without spatial analytical components; studies not reporting spatial clusters or spatial indicators; grey literature such as theses, conference abstracts or proceedings; studies published before 2005; or articles available only as abstracts.

Data sources and search strategy

The review addressed two questions: i) which health outcomes and covariates have been examined in spatial studies of stroke, and ii) which spatial analytical methods have been applied. A systematic search was conducted using international (PubMed, MEDLINE, ScienceDirect, CINAHL) and Korean (ScienceON, DBpia, KoreaMed, RISS, KISS) databases. The same core search strategy was applied across databases, with minor adaptations according to each database's indexing system and search interface. MeSH and free-text terms were combined and Korean searches were performed in both Korean and English. The full search strategy is provided in *Supplementary Table S1*.

The search terms were designed to capture commonly used spatial analytical approaches; however, more advanced or specialised modelling terms (e.g., Bayesian spatial models or spatiotemporal methods) may not have been fully represented in the search strategy. Records were exported to Microsoft Excel and duplicates were removed. Titles and abstracts were screened

against predefined criteria, followed by full-text review where necessary. The search covered studies published between January 2005 and 20 July 2025.

Data extracted included study characteristics (author, year, region, sample size), spatial units, analytical tools, spatial metrics (e.g. SIR, RR, Moran's *I*, LISA, Getis-Ord *Gi**), covariates, analytical methods, and key findings. Study selection and data extraction were conducted by a single reviewer, which may introduce potential selection bias and affect reliability; this is acknowledged as a limitation. The study selection process was summarised in the PRISMA 2020 flow diagram (Figure 1). Of 1,089 records identified, 1,072 remained after duplicate removal; 416 records were excluded after title and abstract screening, 624 records were excluded for other reasons, and three full-text articles were excluded, leaving 29 studies for the final synthesis (Figure 1).

Quality appraisal

All studies included in this review employed region-based data and adopted cross-sectional ecological designs. Methodological quality was therefore assessed using the Joanna Briggs Institute (JBI) 'critical appraisal checklist for analytical cross-sectional studies', which is widely applied systematic reviews. However, the original JBI checklist does not include items that allow detailed evaluation of the technical appropriateness and validity of spatial statistical methods such as Moran's *I*, LISA, or GWR. To address this limitation, four additional items reflecting key methodological features of spatial analytical studies were incorporated following a review of prior geospatial research, resulting in a modified appraisal tool.

The final quality appraisal instrument comprised 10 items assessing: clarity of research objectives; appropriateness of data sources and spatial units; clarity of exposure and outcome variables; implementation and reporting of spatial autocorrelation analyses; appropriateness of spatial model selection; control of potential confounding variables; consideration of spatial boundary effects and the MAUP; interpretation of results and external validity; visualisation and reproducibility of analyses; and ethical considerations and data reliability. Each item was rated as "Yes" (1 point), "Unclear" (0.5 points) or "No" (0 points), yielding a total score ranging from 0 to 10. Based on total scores, studies were classified as low quality (<5 points), moderate quality (5–7.5 points) or high quality (8–10 points) (Mohammed *et al.*, 2021). Using this modified 10-item checklist, methodological quality was assessed for all 29 studies included in the final review.

Clarity of research objectives was evaluated based on whether

the study aims and research questions were explicitly and clearly stated. Appropriateness of data sources and spatial units was assessed by examining whether the sources of data — such as national statistics or hospital records — and the selected spatial units (e.g. administrative districts, counties, or municipalities) were adequately defined and justified. Clarity of exposure and outcome variables was determined by whether key indicators, including stroke incidence or mortality and relevant socioeconomic, environmental, or healthcare resource variables, were clearly defined and accompanied by descriptions of measurement methods. Implementation and reporting of spatial autocorrelation analyses were evaluated based on whether spatial tests such as Moran's *I*, LISA, or Getis-Ord *Gi** were conducted and appropriately reported. The appropriateness of spatial model selection was evaluated based on the extent to which the selected model aligned with the underlying data structure and research objectives, rather than solely on reported model fit indices. Specifically, GWR was considered appropriate when spatial non-stationarity was present, indicating that relationships between variables varied across locations, and its adequacy was assessed using criteria such as Akaike's

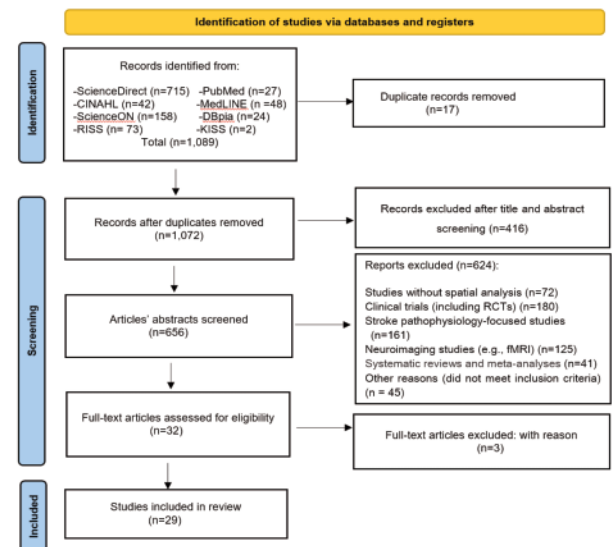


Figure 1. PRISMA 2020 flow diagram of study selection.

Table 1. Distribution of spatial analytical and modelling approaches across the 29 studies included in the systematic review.

Methodological domain	Analytical approach	Specific method	Study (no.)	Percentage
Spatial autocorrelation	Global autocorrelation	Moran's <i>I</i>	9	31.0
Spatial autocorrelation	Local autocorrelation	LISA	2	6.9
Cluster detection	Hotspot analysis	Getis-Ord <i>Gi*</i>	3	10.3
Spatial regression models	Global /Local models	GWR, MGWR, GWGLM	5	17.2
Spatial regression models	Spatial regression	SAR, CAR, spatial regression model	4	13.8
Bayesian spatial models	Disease mapping / smoothing	BYM, BAPC	3	10.3
Spatiotemporal models	Spatiotemporal modelling	Spatiotemporal, DLNM	3	10.3
Descriptive / GIS-based approaches	Mapping / visualization	GIS mapping only	10	34.5

LISA= local indicators of spatial association; GWR=geographically weighted regression; MGWR=multi-scale geographically weighted regression; GWGLM=geographically weighted generalised linear models; SAR= spatial autoregressive models; CAR= conditional autoregressive models; BYM= Besag-York-Mollié model; BAPC= Bayesian age-period-cohort model; DLNM= distributed lag non-linear models; GIS=geographical information systems. Studies may include more than one analytical method; therefore, counts are not mutually exclusive.

Information Criterion (AIC) and the corrected AIC (AICc), The Bayesian Information Criterion (BIC), the adjusted coefficient of determination (R^2), bandwidth optimisation, and reduction of spatial autocorrelation in residuals (Fotheringham *et al.*, 2002, 2015). The Besag–York–Mollié (BYM) model was deemed appropriate for small-area disease mapping where both spatially structured and unstructured random effects needed to be accounted for, particularly in the presence of sparse or unstable data; its suitability was evaluated using Bayesian fit indices such as the Deviance Information Criterion (DIC) and the stability of posterior estimates (Besag *et al.*, 1991; Lawson, 2018). Spatial Autoregressive Models (SAR) were considered appropriate when spatial dependence existed in the outcome or error terms, violating the independence assumption of conventional regression models; their adequacy was assessed through improvements in model fit (e.g., AIC), statistical significance of spatial parameters, and the extent to which residual spatial autocorrelation was reduced (Anselin, 1988; LeSage and Pace, 2009). Distributed Lag Mixed Models (DLMM) or related approaches were considered appropriate for analysing delayed or cumulative effects of time-varying exposures, particularly in spatiotemporal contexts such as environmental health studies; model suitability was evaluated based on information criteria (e.g., AIC/BIC), interpretability of lag-response relationships, and model stability (Gasparrini *et al.*, 2010; Gasparrini, 2014). Overall, model appropriateness was determined by the coherence between model assumptions and the spatial or spatiotemporal characteristics of the data, in combination with diagnostic and fit statistics, rather than by reliance on fit indices alone (Burnham and Anderson, 2002; Spiegelhalter *et al.*, 2002). Control of potential confounders was evaluated based on whether key variables such as age, sex, and socioeconomic factors were adjusted for in the analyses. Consideration of the MAUP was assessed by examining whether limitations related to administrative boundary selection and spatial dependence were discussed. Interpretation and external validity were evaluated based on whether spatial patterns were plausibly interpreted and the generalisability of findings was considered. Visualisation and reproducibility were assessed by examining the adequacy of map presentation and the provision of sufficient methodological detail — such as GIS software or analytical packages — to enable reproducibility. Ethical considerations and data reliability were evaluated based on whether appropriate ethical considerations for the use of public or de-identified data were addressed.

Data analysis

For data analysis, this study applied a modified quality appraisal tool based on the JBI approach, incorporating additional items to reflect methodological characteristics specific to spatial analytical research. Based on the quality appraisal results, systematic data extraction and synthesis were conducted for all studies included in the final review. Information extracted from each study included authorship and year of publication; country or region in which the study was conducted; sample size and spatial unit of analysis (e.g. administrative districts, counties, provinces); spatial analytical tools employed (e.g. ArcGIS, GeoDa, GWR); applied spatial statistical methods and key analytical indicators (e.g., SIR, RR, Moran's I , LISA, Getis-Ord G_i^*); presence of spatial clustering; covariates included in the analyses (e.g., age, sex, socioeconomic indices); and principal findings from the spatial analyses. A comprehensive narrative synthesis was ultimately performed based on full-text reviews of 29 spatial analytical studies examining stroke incidence, prevalence, and mortality.

Results

General characteristics of the included studies

The general characteristics of the 29 studies that applied spatial analytical or modelling approaches to investigate stroke incidence and mortality, and in some studies prevalence, are summarised in *Supplementary materials, Table S2*. In terms of publication year, three studies (10.3%) conducted in Korea were published between 2015 and 2017. Among the remaining studies conducted outside Korea, 12 (41.4%) were published between 2011 and 2020, and 14 (48.3%) were published from 2021 onwards, indicating a marked increase in spatial stroke research in recent years. With respect to geographic coverage, nine studies were conducted in the United States, five in Korea, three in China, and two in France. Two studies were conducted at the global level. Single studies were conducted in Nigeria, Canada, Spain, Brazil, Colombia, India, the United Kingdom, and Taiwan. The spatial scope of analysis varied widely, ranging from sub-national units such as states, provinces, counties, districts, and cities to nationwide and global levels.

Study designs, as reported by the original authors, varied across studies. Cross-sectional studies were the most common design ($n = 13$), followed by retrospective longitudinal studies ($n = 7$), ecological studies ($n = 3$) and repeated cross-sectional studies ($n = 2$). In addition, one cohort study, one cohort-based single time-point analysis, one cross-sectional ecological study and one time-stratified case-crossover study were included. All three studies conducted in Korea adopted a cross-sectional design. The spatial units used across studies varied substantially, ranging from fine-scale census-based units such as census blocks and census tracts to intermediate and broader administrative units including counties, districts, municipalities, states and provinces. The Korean studies predominantly employed intermediate-level administrative units. In addition, five studies conducted spatial analyses based on accessibility to stroke centres or hospitals and two studies utilised spatial units defined by the World Health Organization or the Global Burden of Disease framework.

The study populations included hospitalised stroke patients, registry-based cohorts, national mortality records, emergency department visit data and stroke centre-based samples. Sample sizes varied considerably, from several hundred participants in facility-based studies to several million individuals in population-based or nationwide analyses. Most studies focused on adult populations, while some specifically targeted older adults or conducted age-stratified analyses.

A wide range of spatial analytical techniques was used to characterise the spatial distribution and patterns of stroke outcomes. GIS-based mapping was employed in 26 of 29 studies (89.7%) to visualise spatial distributions of stroke incidence or mortality. Spatial clustering and high-risk areas were identified using methods such as Global Moran's I , LISA, Getis-Ord G_i^* and spatial scan statistics in 23 of 29 studies (79.3%). Several studies applied spatial regression approaches, including GWR, multi-scale GWR (MGWR) and geographically weighted generalised linear models. Bayesian spatial models, such as BYM and Conditional Autoregressive (CAR) models, as well as spatiotemporal approaches including Age–Period–Cohort (APC), Bayesian age-period-cohort (BAPC) and Distributed Lag Non-Linear Models (DLNM), were also utilised.

Covariates included in the analytical models most frequently comprised demographic factors such as age and sex, along with major clinical risk factors including hypertension, diabetes mellitus, and atrial fibrillation. Variables related to healthcare resources

— such as the distribution of stroke centres, travel distance or time to medical facilities and healthcare accessibility indices — were commonly incorporated. In addition, several studies included environmental factors (e.g., air pollution, temperature, heat-waves, smoking prevalence) and socioeconomic characteristics such as deprivation indices and urban–rural indicators. Outcome measures used to assess spatial patterns included stroke incidence, mortality, and Standardised Mortality Ratios (SMR), with prevalence reported in a subset of studies. Most studies reported statistically significant spatial clustering, as evidenced by global or local spatial autocorrelation measures, identifying high-risk areas and spatial outliers. Some studies highlighted differences in incidence, mortality risk, or healthcare accessibility between urban and rural areas. Studies incorporating temporal analyses reported changes in stroke counts, age-standardised mortality rates, and shifts in the spatial distribution of high-risk areas over time.

Methodological quality assessment of included studies

The methodological quality of the included studies was assessed using a modified version of the JBI Appraisal Checklist (*Supplementary materials, Table S3*). Each item was scored as Yes (1 point), No (0 points), or Unclear (0.5 points), yielding a total score ranging from 0 to 10. Overall study quality was categorised as high (8–10 points), moderate (5–7.5 points), or low (<5 points). Across the 29 included studies, total quality scores ranged from 6.0 to 10.0. Seventeen studies were classified as high quality, and 12 studies were rated as moderate quality; no study was assessed as low quality. The detailed score distribution included four studies with a score of 10, one with 9.5, ten with 9, two with 8, four with 7, two with 6.5 and six with 6. At the item level, spatial autocorrelation analyses and their reporting (Q4) were adequately addressed in 19 studies, while the appropriateness of spatial analytical methods (Q5) was judged satisfactory in 18 studies. Control of potential confounding factors (Q6), such as age, sex and socioeconomic variables, was adequately implemented in 16 studies. In contrast, explicit consideration of boundary effects and the MAUP (Q7) was observed in only six studies. Clarity of research objectives (Q1) was satisfied in 29 of 29 studies (100%), validity of data sources and spatial units (Q2) in 27 studies (93.1%) and clear definition and measurement of key variables (Q3) in 28 studies (96.6%). In addition, visualisation quality, interpretation of findings, and reporting of analytical procedures (Q8–Q9) were generally well documented across studies, indicating overall satisfactory reporting standards for spatial epidemiological research.

Characteristics of spatial analytical and modelling approaches in stroke research

The overall distribution of spatial analytical methods across the included studies is summarised in Table 1, providing an overview of the methodological approaches employed across studies. Spatial autocorrelation methods were applied in 23 of 29 studies (79.3%), representing the most frequently used analytical approaches, while descriptive GIS-based mapping was used in 26 studies (89.7%). In contrast, advanced spatial and spatiotemporal modelling approaches were less commonly employed. In relation to the appraisal framework, the appropriateness of model selection varied across studies. Several studies demonstrated alignment between model choice and underlying spatial data characteristics, whereas others relied primarily on descriptive or exploratory approaches without fully addressing model assumptions or spatial dependencies.

Key determinants of spatial patterns in stroke incidence and mortality

Across the included studies, stroke incidence and mortality were unevenly distributed across space. Statistically significant spatial autocorrelation and clustering patterns were reported in 24 of the 29 studies (82.8%). These spatial distributions were commonly analysed in relation to area-level demographic and socioeconomic characteristics, with covariates such as population ageing, educational attainment, income level and urban–rural classification either incorporated as covariates or identified as factors associated with spatial variability. Several studies identified high-risk clusters concentrated in metropolitan areas, while others reported relatively high incidence or mortality clusters in specific rural regions. Studies conducted at national or large regional scales similarly demonstrated pronounced geographic disparities in stroke burden across regions.

Environmental influences on spatial patterns of stroke incidence and mortality

Spatial analyses incorporating environmental factors commonly examined exposures such as air pollutants (e.g. particulate matter $\leq 2.5 \mu\text{m PM}_{2.5}$ and particulate matter $\leq 10 \mu\text{m PM}_{10}$), ambient temperature and heat-waves as key determinants of the geographic distribution of stroke outcomes. Some studies reported higher stroke mortality or age-standardised mortality rates in areas with elevated levels of air pollution, while increased stroke-related deaths or emergency department visits were observed in regions experiencing frequent heat-waves or extreme temperature exposure. The effects of environmental factors were not spatially uniform; not even when identical exposure indicators were applied, the magnitude and direction of associations with stroke outcomes varied by region. In addition, several studies incorporated temporal dimensions, presenting spatiotemporal changes in the relationship between environmental exposures and stroke incidence or mortality.

Healthcare resource and accessibility factors shaping spatial stroke patterns

Studies that considered healthcare resources and accessibility included variables such as the spatial distribution of healthcare facilities and stroke centres, travel distance or time to medical services and hospital service areas as key determinants of spatial patterns in stroke incidence and mortality. Some studies reported relatively limited access to specialised stroke care facilities in rural areas or small cities, with these regions often reporting higher stroke mortality or more limited treatment access. Furthermore, multiple studies analysed regional disparities in healthcare resource allocation in relation to stroke treatment utilisation, access to thrombolysis, and short-term or one-year mortality. Spatial analyses incorporating healthcare accessibility indicators frequently visualised or identified regional inequalities through mapping or cluster detection approaches.

Types of spatial analytical modelling approaches

The overall distribution of spatial analytical methods across the included studies is summarised in Table 1. Spatial analytical approaches varied across studies and can be broadly categorised into four main methodological groups: cluster detection methods, spatial regression models, Bayesian spatial models and spatiotemporal modelling approaches.

First, cluster detection methods, including Global Moran's I , LISA and Getis–Ord G_i^* , were applied in 23 of the 29 studies (79.3%), representing the most frequently used analytical

approaches. These methods were primarily used to identify spatial clustering, hotspots and high-risk areas. While they provide valuable insights into spatial structure, they are limited in their ability to incorporate multiple covariates or support inferential modelling.

Second, spatial regression models, such as GWR, MGWR, SAR models and GWGLM, were applied in 14 of the 29 studies (48.3%). These approaches enable the estimation of spatially varying relationships between risk factors and stroke outcomes by accounting for spatial heterogeneity. However, they may be sensitive to spatial scale and multicollinearity.

Third, Bayesian spatial models, including CAR and BYM models, were applied in 9 of the 29 studies (31.0%). These models allow for the incorporation of spatial dependence through structured random effects and enable stabilisation of estimates in small-area analyses. Fourth, spatiotemporal modelling approaches, such as DLNM, APC or BAPC models, were applied in 8 of the 29 studies (27.6%). These approaches facilitate the joint analysis of spatial and temporal dynamics, particularly in studies examining environmental exposures and temporal trends. Overall, the most frequently used approaches were cluster detection methods, whereas more advanced modelling techniques, including Bayesian and spatiotemporal models, were less commonly applied. This distribution indicates variability in methodological complexity and suggests that many studies relied on exploratory approaches rather than advanced inferential modelling.

Discussion

This systematic review included studies that examined the spatial characteristics of stroke incidence and mortality, and in some studies prevalence, across diverse countries and regions. The included studies employed a wide range of study designs, including cross-sectional, longitudinal, and repeated cross-sectional approaches, and used heterogeneous spatial units of analysis, such as administrative areas, healthcare service regions, census units, and grid-based systems. Outcome measures and covariate structures also varied according to study objectives and data sources, reflecting the methodological diversity of spatial analyses in stroke research. Across most studies, stroke incidence and mortality did not exhibit random spatial distributions. Instead, significant spatial autocorrelation and clustering patterns were consistently reported, with stroke burden remaining concentrated in specific geographic areas over time. These spatial inequalities were observed at international, national, regional, and sub-regional levels, indicating that stroke risk is linked not only to individual-level factors but also to area-level structural characteristics. Studies incorporating environmental factors reported spatial associations between stroke outcomes and exposures such as air pollution, rising temperatures, and heat-waves. Higher stroke-related indicators were frequently observed in regions with elevated environmental exposures; however, the magnitude and direction of these associations varied by geographic context. This variability suggests that environmental determinants interact with local socioeconomic and climatic conditions in shaping the spatial distribution of stroke risk.

Key determinants of spatial patterns in stroke

The included studies repeatedly identified demographic structure, socioeconomic conditions, and urban–rural context as correlates of spatial variation in stroke outcomes. In particular, population ageing, educational attainment, and regional socioeconomic disparities were closely related to the formation of spatial clusters.

This body of evidence suggests that area-level structural characteristics—such as ageing, education, and income—are likely to contribute to geographic differences in stroke burden, beyond what can be explained by individual-level risk factors alone. A study examining stroke mortality trends in Colombia (1999–2017) reported that deaths occurred predominantly among older adults and individuals with primary-level education. Despite potential underreporting in less developed regions, higher mortality rates were observed in economically more developed areas (Paulina *et al.*, 2025), indicating that socioeconomic development does not necessarily coincide with lower stroke mortality. Similarly, a spatial analysis using the Besag–York–Mollié (BYM) model in central Tennessee (1999–2007) reported elevated stroke mortality risks in rural census tracts and in areas with a high proportion of residents aged 65 years or older (Odoi & Busingye, 2014). These examples illustrate how demographic ageing and regional vulnerability may coincide with concentrated stroke mortality in specific areas.

Evidence on organised stroke systems highlights the potential value of structured emergency medical service triage and timely transfer to appropriate stroke centres (CDC, 2025). Using CDC-related data, one analysis reported that approximately 20% of US adults lived in census tracts located more than 60 minutes by road from specialised stroke treatment facilities, and about 65% of these tracts were rural (Schieb *et al.*, 2025). These areas also reported higher prevalence of stroke and coronary heart disease, consistent with the possibility that healthcare accessibility may mediate links between socioeconomic disadvantage and stroke outcomes. Notably, evidence regarding urban–rural differences was not uniform. In Osun State, Nigeria, an analysis of hospitalised stroke patients (1990–2012) reported higher incidence in urban areas than rural areas, a pattern interpreted as being related to the spatial distribution of facilities involved in stroke diagnosis and care (Adzandeh *et al.*, 2016). This contrast illustrates that a simple urban–rural dichotomy is insufficient; spatial variation appears to depend on how healthcare resources are distributed and accessed within specific contexts.

The importance of education as an area-level determinant was also supported by a study in eastern Appalachian Tennessee, where census tracts with a higher proportion of residents with low educational attainment had higher stroke mortality risks (Pedigo *et al.*, 2011). At the global level, an analysis stratifying 183 countries by income group (2000–2021) reported that ASMRs were highest in Asia and southern Africa and lowest in Europe and North America (Xing *et al.*, 2025). Hotspots and cold spots were more prominent in low- and middle-income countries and persisted over time. Another global analysis reported increases in absolute stroke cases and Disability-Adjusted Life Years (DALYs) since 1990, alongside overall declines in Age-Standardised Incidence and Mortality Rates (ASIR and ASMR) (Qian *et al.*, 2025). However, improvements varied by region and socio-demographic level, with middle-Socio-Demographic index (SDI) countries reporting marked increases in stroke burden associated with population ageing and growth. As the SDI integrates income, education, and fertility, these patterns are consistent with the proposition that widening absolute and relative inequalities are shaping the geographic distribution of stroke burden. The magnitude and direction of spatial disparities nevertheless varied across studies, in part reflecting differences in spatial units and analytical approaches. This underscores the importance of carefully considering spatial scale and methodological heterogeneity in future research.

Spatial impacts of environmental factors

Studies incorporating environmental exposures frequently reported associations between stroke outcomes and air pollution, ambient temperature, and heat-waves. These associations were not spatially uniform; similar exposure levels were linked to different outcomes across regions, highlighting the relevance of spatial heterogeneity when evaluating environmental impacts. In China, one study reported significant spatial autocorrelation in PM_{2.5}-attributable stroke mortality from 1990 to 2015, with high-risk areas shifting from northeastern to central and south-western regions over time (Luo *et al.*, 2017). Climate-related analyses reported comparable heterogeneity. In Taiwan, projections suggested that daily maximum temperatures exceeding 34 °C were associated with increased risks of stroke-related emergency department visits, particularly for ischaemic stroke, and that temperature-related ischaemic stroke incidence could rise substantially under global warming scenarios of 2 °C to 4 °C. Regional effects were most pronounced in Taichung, Hsinchu, Yilan, and Taitung (Wu *et al.*, 2024). In Nanjing, China, an analysis of the 2010 heatwave reported increased stroke mortality during extreme heat periods with marked geographic variation; rural areas and locations with high heat exposure and vulnerability reported the highest risks (Chen *et al.*, 2015). In South Korea, a spatiotemporal analysis reported that as concentrations of major air pollutants declined, mortality from ischaemic stroke and intracerebral haemorrhage also decreased, while earlier-period associations between specific pollutants and ischaemic stroke mortality weakened over time (Ha *et al.*, 2023). Together, the evidence indicates that environmental influences on stroke outcomes may vary across both space and time.

Spatial implications of healthcare resource distribution and accessibility

Studies that incorporated healthcare resources and accessibility consistently highlighted the spatial distribution of facilities, travel distance, and service coverage as correlates of regional differences in stroke outcomes. Areas with limited access to specialised stroke care were more likely to report higher mortality or lower treatment utilisation, emphasising the importance of spatial allocation of healthcare resources across the continuum of care.

In Spain, healthcare accessibility and economic development were associated with geographic disparities in ischaemic stroke mortality and case fatality, with higher mortality among adults aged 60 years or older reported in south-western areas with lower accessibility and economic indicators (Leveau *et al.*, 2024). In South Korea, an analysis of hospital service areas in Gyeonggi Province reported substantial geographic variation in quality indicators and one-year mortality; rates of acute reperfusion therapies (intravenous thrombolysis and endovascular thrombectomy) and within-area treatment utilisation differed by more than threefold across service areas (Jung *et al.*, 2024). In the United States, GIS-based studies described pronounced access gradients: in North Carolina, South Carolina and Georgia, fewer than half of residents could reach a Joint Commission-certified primary stroke centre within 30 minutes, and poor access overlapped with higher mortality in several rural counties (Khan *et al.*, 2011). In Wisconsin, rural and small-town areas reported the longest travel times to advanced stroke centres and higher standardised mortality ratios, consistent with the concept of “stroke care deserts” (Halada *et al.*, 2024). National analyses similarly reported that around one-fifth of US adults lived more than 60 minutes by road from certified stroke treatment facilities, with access-vulnerable areas concentrated in

rural settings; these areas also tended to report higher prevalence of stroke and major cardiovascular risk factors and lower socioeconomic status (Schieb *et al.*, 2025).

Accessibility challenges extended beyond acute care. In Tennessee, outpatient stroke rehabilitation services were reported to be concentrated in urban areas, with rural and high-prevalence regions reporting longer travel distances and times to rehabilitation facilities (Tran *et al.*, 2024). Telemedicine was identified as a potential mitigating strategy in some contexts. In Ontario, geospatial modelling suggested that incorporating telestroke programmes increased the proportion of the population able to access thrombolysis within 30 minutes from approximately 72% to 91%, expanding eligibility to over 2.5 million additional individuals (Jewett *et al.*, 2017). This suggests that telemedicine may partially offset the spatial constraints of fixed healthcare infrastructure, particularly in geographically underserved areas.

Methodological implications of spatial modelling approaches

This systematic review examined the methodological approaches used in spatial analyses of stroke incidence and mortality, with a particular focus on the selection and application of spatial analytical and modelling techniques. Overall, the distribution of spatial analytical methods across the included studies suggests a predominant reliance on exploratory approaches, particularly spatial autocorrelation measures such as Moran’s I and descriptive GIS-based mapping. While these methods are useful for identifying spatial patterns, they are limited in their ability to account for spatial dependence and underlying data structure. In contrast, more advanced spatial and spatiotemporal modelling approaches, including GWR, SAR models, and Bayesian models, were applied in 11 of 29 studies (37.9%), indicating relatively limited use compared with exploratory approaches. This indicates that the appropriateness of model selection varied across studies, with some demonstrating alignment between model choice and spatial data characteristics, whereas others relied on conventional approaches without fully addressing model assumptions or spatial dependencies. Spatial analytical approaches can be broadly distinguished according to their methodological functions, including exploratory spatial data analysis, spatial regression modelling, Bayesian spatial modelling, and spatiotemporal modelling, each addressing different aspects of spatial processes. Exploratory spatial data analysis methods, such as Global Moran’s I, LISA and Getis–Ord G_i^* , are primarily used to detect spatial dependence and identify clustering patterns or hotspots. These approaches provide an initial understanding of spatial structure; however, they are limited in their ability to incorporate multiple covariates or support inferential modelling (Anselin, 1995). Spatial regression models — including GWR, MGWR, spatial autoregressive SAR models and GWGLM — extend beyond exploratory analysis by enabling the estimation of relationships between risk factors and outcomes while accounting for spatial heterogeneity and dependence. These models are particularly useful when associations vary across space and when localised inference is required (Fotheringham *et al.*, 2002).

Bayesian spatial models, such as BYM and conditional autoregressive CAR models, further enhance analytical capacity by incorporating spatially structured random effects. These approaches allow for information sharing across neighbouring areas and stabilisation of estimates, making them especially suitable for small-area analyses with sparse or unstable data (Besag *et al.*, 1991). Spatiotemporal modelling approaches, including DLNM and APC/BAPC models, enable the joint analysis of spatial and temporal dynamics, capturing lagged effects and evolving patterns over

time. These models are particularly relevant for investigating environmental exposures and long-term epidemiological trends, although they require more complex data structures and interpretation (Gasparrini *et al.*, 2010; Riebler & Held, 2017a and 2017b).

Taken together, these methodological distinctions indicate that the suitability of spatial analytical approaches depends on their alignment with the underlying data structure and research objectives. Despite the widespread application of spatial analytical methods, important methodological limitations remain insufficiently addressed. In particular, relatively few studies explicitly considered issues related to spatial boundary definition and MAUP that encompasses both scale effects, whereby the magnitude or direction of associations may vary depending on the size of spatial units, and zoning effects, whereby results may differ according to the configuration of administrative boundaries even at the same scale (Stillwell *et al.*, 2018). Importantly, failure to adequately address MAUP may not only introduce statistical bias but also lead to misinterpretation of spatial health inequalities, particularly in policy and resource allocation contexts. To mitigate these challenges, advanced methodological approaches such as MGWR and hierarchical Bayesian spatial models — including CAR and BYM models — have been increasingly proposed (Fotheringham *et al.*, 2017; Besag *et al.*, 1991). MGWR enables regression coefficients to vary across multiple spatial bandwidths, allowing different covariates to operate at distinct spatial scales and reducing reliance on a single fixed spatial unit. In contrast, CAR and BYM models explicitly incorporate spatial dependence through structured random effects, facilitating information sharing across neighbouring areas and stabilising estimates in small-area analyses. Although these approaches do not eliminate sensitivity to spatial unit selection, they provide more robust frameworks for accounting for spatial structure and multi-scale processes, thereby reducing potential interpretative distortions associated with MAUP. Analytical strategies that fail to account for spatial dependence, heterogeneity, or temporal dynamics may lead to incomplete or potentially biased interpretations.

The findings of this review also highlight important considerations regarding the evaluation of methodological quality. Assessing the appropriateness of spatial model selection requires more than reporting model rationale or fit indices such as AIC or DIC. Instead, it should consider whether the selected model aligns with the underlying data structure, satisfies key assumptions (e.g. spatial dependence, non-stationarity), and is supported by appropriate diagnostic evaluation, including residual spatial autocorrelation and model stability. This perspective reinforces the need to move beyond reporting-based assessment towards a more comprehensive evaluation of methodological rigor in spatial epidemiological research. Spatial analytical approaches and spatial machine learning represent two distinct but potentially complementary paradigms in geospatial epidemiology. Classical spatial analysis refers to a set of statistically grounded methods designed to explicitly model spatial dependence, spatial autocorrelation, and spatial heterogeneity (Anselin, 1995; Fotheringham *et al.*, 2002; Besag *et al.*, 1991). In contrast, spatial machine learning refers to the application of data-driven algorithms capable of modelling complex, non-linear and high-dimensional relationships (Biau & Scornet, 2016; Chen & Guestrin, 2016). However, conventional machine learning models do not explicitly account for spatial dependence or spatial scale unless specifically adapted, which may lead to biased inference or overoptimistic predictive performance when applied to spatial data (Roberts *et al.*, 2017). In addition, classical spatial analytical models are inherently constrained in accommodating large numbers of covariates due to spatial multicollinearity, limited

sample sizes, and model structure, thereby prioritising parsimony and interpretability (Dormann *et al.*, 2013). Recent developments in spatial machine learning, including spatially aware algorithms, spatial cross-validation, and graph-based models, have attempted to address these limitations (Janowicz *et al.*, 2020; Reichstein *et al.*, 2019). These hybrid approaches offer promising opportunities to integrate spatial dependence with predictive modelling. Overall, advancing spatial epidemiological research will require approaches that combine the interpretability and theoretical rigor of classical spatial models with the flexibility and predictive power of machine learning methods. The search strategy primarily focused on stroke-specific terminology, which may have limited the identification of relevant studies embedded within broader cardiovascular or cerebrovascular disease frameworks. As a result, geospatial and methodological studies that did not explicitly use ‘stroke’ in titles, abstracts, or keywords may have been missed. Recent studies applying geospatial and machine learning approaches to broader cardiovascular outcomes further highlight the potential methodological diversity that may not be fully captured by stroke-specific search strategies (Kianfar *et al.*, 2026). Future reviews may benefit from broader search strategies that incorporate related cardiovascular outcomes and methodological frameworks, including studies applying geospatial and machine learning approaches.

Finally, examining healthcare resources and accessibility consistently showed that the spatial distribution of medical facilities, healthcare service areas, and travel distance or time to care was associated with geographic variation in stroke incidence and mortality. In particular, rural and small-area populations with limited access to specialised stroke care more frequently experienced higher mortality rates or poorer treatment outcomes, highlighting the public health relevance of spatial inequities in healthcare resource allocation. A wide range of spatial analytical approaches was applied across the included studies, including GIS-based mapping, spatial autocorrelation measures, spatial regression models, Bayesian spatial models, and spatiotemporal analyses. While spatial autocorrelation analyses were commonly used for cluster detection, spatial regression and Bayesian models contributed to quantifying regional heterogeneity in stroke risk. Nevertheless, heterogeneity in spatial unit selection, model choice, and covariate specification limited comparability across studies.

Conclusions

Although the included studies demonstrated moderate to high methodological quality, notable heterogeneity was observed in approaches to confounder adjustment, justification of spatial unit selection, and rationale for model choice. Future spatial epidemiological research on stroke should adopt clearer criteria for selecting spatial units and analytical models aligned with study objectives, and should integrate environmental exposures and healthcare accessibility within multidimensional frameworks to more systematically characterise spatial inequalities in stroke burden. Importantly, this review demonstrates that spatial inequalities in stroke burden are not merely reflections of geographic variation, but are also shaped by methodological decisions regarding spatial units and analytical frameworks. Even when comparable regional data are analysed, the identification of high-risk areas and the interpretation of key determinants may vary according to whether spatial autocorrelation analyses, spatial regression models, or Bayesian spatial approaches are applied. Given the strong dependence of stroke outcomes on timely acute care and healthcare

accessibility, stroke represents a condition for which spatial analytical frameworks have particularly direct implications for prevention strategies and health resource allocation. Accordingly, future research and policy development should prioritise transparent justification and standardisation of spatial analytical approaches when addressing spatial inequalities in stroke burden.

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Online supplementary materials

Table S1. Full search strategy.

Table S2. Reviewed studies on spatial associations of stroke incidence, prevalence and mortality.

Table S3. Methodological quality assessment of included spatial epidemiological studies.

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