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A Review of Applications of GIS in Pneumoconiosis Research: Implications for Nursing Practice and Occupational Health Nursing

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Abstract

Background: Pneumoconiosis (including silicosis, coal workers' pneumoconiosis, and asbestosis) remains a major occupational health concern, particularly in settings with sustained exposure to respirable mineral dust. Conventional epidemiological approaches often under-represent spatial heterogeneity in exposure contexts, potentially masking localized disease clusters and delaying targeted prevention. Geographic Information Systems (GIS) and spatial statistics provide a means to integrate georeferenced occupational, environmental, and health data, enabling spatially explicit surveillance and risk assessment. This review provides an overview of GIS applications in pneumoconiosis research and discusses implications for nursing practice and occupational health nursing.

Methods: A structured literature search was conducted in Web of Science, Scopus, PubMed, and Google Scholar using combinations of keywords related to pneumoconiosis (e.g., "silicosis", "coal workers' pneumoconiosis", "asbestosis"), GIS (e.g., "geographic information system", "spatial analysis"), and spatial statistical methods (e.g., "Moran's I", "Getis-Ord Gi*", "kernel density", "SaTScan", "spatial regression", "GWR/MGWR"). Eligible publications included peer-reviewed studies applying GIS/spatial analytics to pneumoconiosis outcomes, exposure assessment, clustering/hotspot detection, or spatial risk modeling. Consistent with the template structure, findings are synthesized into three sections: (i) methods to characterize spatial patterns; (ii) hotspot/cluster analysis approaches; and (iii) spatial regression models to identify risk factors.

Results: GIS-enabled mapping and spatial statistics consistently revealed non-random spatial patterns of pneumoconiosis, with clustering frequently aligned with mining, stone processing, construction corridors, and industrial zones. Hotspot methods (e.g., KDE, LISA, Getis-Ord Gi*, scan statistics) were useful in detecting localized high-risk areas for intensified screening and prevention. Spatial regression approaches (e.g., spatial lag/error models, Bayesian CAR, and GWR/MGWR) improved inference by accounting for spatial dependence and local non-stationarity, identifying associations between pneumoconiosis indicators and contextual factors such as industrial density, dust exposure proxies, sociodemographic vulnerability, and access to occupational health services. Nursing-relevant applications include improved surveillance sensitivity, geographically targeted health education, risk communication, and prioritization of screening/referral resources.

Conclusions: GIS and spatial statistics strengthen pneumoconiosis research by uncovering spatial inequities in exposure and disease burden and by improving the explanatory power of risk models. For occupational health nursing, spatially informed evidence supports proactive surveillance, targeted interventions, and resource allocation. Future work should prioritize interoperable data pipelines, privacy-preserving geocoding, and capacity building to integrate GIS into routine occupational health nursing practice.

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Keywords: Geographic Information Systems; Pneumoconiosis; Silicosis; Coal workers' pneumoconiosis; Spatial statistics; Occupational health nursing

1. Introduction

Pneumoconiosis is an irreversible occupational lung disease caused by chronic inhalation of respirable mineral dust, with silicosis, coal workers' pneumoconiosis (CWP), and asbestosis being the most recognized forms (1–3). Despite regulatory controls, pneumoconiosis persists in many regions where extraction, construction, and manufacturing activities remain intensive and where exposure surveillance systems are incomplete (4–6). A defining challenge is that exposure and risk are spatially structured: dust-generating worksites, supply chains, commuting patterns, and worker housing proximity create geographically heterogeneous exposure profiles (7,8). Consequently, research and prevention efforts benefit from analytic approaches that explicitly account for space.

GIS has been widely adopted in public health to map disease distributions, integrate multi-source data, and support spatial decision-making (9–11). In occupational health, GIS enables linkage of worksite location, environmental monitoring, clinical screening outcomes, and contextual determinants (12–14). Spatial statistical tools can detect clustering, identify hotspots, and model risk while accounting for spatial dependence and neighborhood effects (15,16). These capabilities are particularly relevant for pneumoconiosis, where long latency and cumulative exposure often obscure direct exposure-outcome attribution without contextual spatial evidence (17,18).

Occupational health nurses play central roles in surveillance, health education, risk communication, screening coordination, and early referral. However, nursing practice often lacks access to spatially integrated information that can guide targeted actions at scale (19–21). This review summarizes GIS applications in pneumoconiosis research and highlights implications for nursing practice and occupational health nursing. Following the template structure, the review is organized into three sections: (i) spatial pattern identification methods; (ii) hotspot/cluster detection approaches; and (iii) spatial regression methods for risk factor identification.

2. Data used and Methods

2.1. Data used

To investigate applications of GIS and spatial statistics in pneumoconiosis research, peer-reviewed scientific publications were collected primarily from Web of Science, Scopus, PubMed, and Google Scholar. The targeted period emphasized the era of expanded GIS adoption in health research (approximately 2000 onward), while foundational methodological papers were included when necessary for method explanation (9,16).

2.2. Methods

Searches were conducted using combinations of pneumoconiosis terms with GIS/spatial method terms. Section 3.1 (Spatial pattern identification): keyword combinations included "pneumoconiosis" OR "silicosis" OR "coal workers' pneumoconiosis" OR "asbestosis" with "spatial pattern", "spatial autocorrelation", "Moran's I", "Geary's C", "Ripley's K", "nearest neighbor", and "semivariogram". Section 3.2 (Hotspot/cluster analysis): combinations included pneumoconiosis terms with "hotspot", "kernel density estimation", "LISA", "Getis-Ord Gi*", "DBSCAN", "SaTScan", "spatial scan statistic", "Poisson model", and "Bernoulli model". Section 3.3 (Spatial regression for risk factors): combinations included pneumoconiosis terms with "spatial regression", "OLS", "spatial lag model", "spatial error model", "CAR", "Bayesian spatial model", "GWR", and "MGWR". Eligible studies included: (i) GIS mapping/analysis linked to pneumoconiosis outcomes; (ii) exposure assessment using spatial data; (iii) cluster/hotspot detection; or (iv) spatial regression/risk modeling with pneumoconiosis indicators. Study selection and synthesis followed a narrative scoping approach consistent with the journal template's review style.

3. Results and discussion

3.1. Spatial patterns of pneumoconiosis

Spatial epidemiology provides tools to quantify whether pneumoconiosis distributions exhibit non-random clustering and to describe geographic heterogeneity in burden (9,11). Figure 1 illustrates a generic spatial cluster map concept for pneumoconiosis rates and a spatiotemporal cluster depiction to highlight how risk evolves across time windows. In many occupational contexts, cases are not evenly distributed but instead concentrate around dust-intensive industries and specific geographic corridors (12,14). Methods used to assess spatial patterns include global clustering/dispersion tests (e.g., nearest neighbor ratio, Ripley's K for point data where individual case coordinates are available), and spatial autocorrelation statistics (e.g., Moran's I, Geary's C) for areal data aggregated by administrative units (15,16). Global Moran's I has been commonly applied to assess whether pneumoconiosis rates across districts/provinces are spatially correlated, reflecting shared exposure contexts or shared determinants such as industrial zoning and workforce mobility (15,18). Beyond global indices, exploratory spatial data analysis tools (e.g., Moran scatterplots, semivariograms, and correlograms) provide insight into the scale of spatial dependence and support appropriate model specification in subsequent analyses (15,17).

Data from Table 1 summarizes representative spatial pattern methods and their primary uses in pneumoconiosis research. Importantly, interpretation should consider the modifiable areal unit problem (MAUP) and data availability constraints: individual-level geocoded cases enable point pattern analyses but may be limited by privacy and incomplete georeferencing; administrative aggregation may obscure within-unit heterogeneity yet remains common in occupational surveillance (11,19). Nearest neighbor ratio and Ripley's K have been applied in occupational and environmental epidemiology to examine clustering of geocoded disease cases around industrial sources, providing initial evidence of non-random spatial aggregation where individual location data are available (8,13). Global Moran's I and Geary's C are the most frequently used methods in pneumoconiosis research, particularly in studies of coal workers' pneumoconiosis and silicosis aggregated at administrative levels, where significant positive spatial autocorrelation has been reported, indicating regional clustering of disease burden (15,16,22). Using local Moran's I, the spatial clustering analysis for rates of health care utilization for Medicare beneficiaries with Other Related Pneumoconiosis as the discharge diagnosis showed two distinctive cluster patterns in 2011-2013 in states of Kentucky, West Virginia, Virginia and Pennsylvania in USA (Figure 1) (22). Semivariogram and correlogram analyses have been employed to characterize the spatial dependence scale of exposure or disease indicators, supporting spatial interpolation and subsequent risk modeling in occupational and environmental health studies (8,16). Moran scatterplots and other exploratory spatial data analysis (ESDA) maps are widely used to visualize local patterns (high–high and low–low areas), assisting in the identification of priority regions for occupational health surveillance and preventive interventions (15,23).

Table 1 Methods used for studies of spatial patterns of pneumoconiosis

Methods	Purposes of study	Spatial unit	Study
Nearest neighbor ratio/ Ripley's K	Identify clustering/dispersion of geocoded cases	Point data	(8,13)
Global and local Moran's I/ Geary's C	Quantify overall and local spatial autocorrelation of rates	Areal units	(15,16,22)
Semivariogram/ correlogram	Characterize spatial dependence scale	Continuous/areal	(8,16)
Moran scatterplot / ESDA maps	Visualize spatial association patterns	Areal units	(15,23)

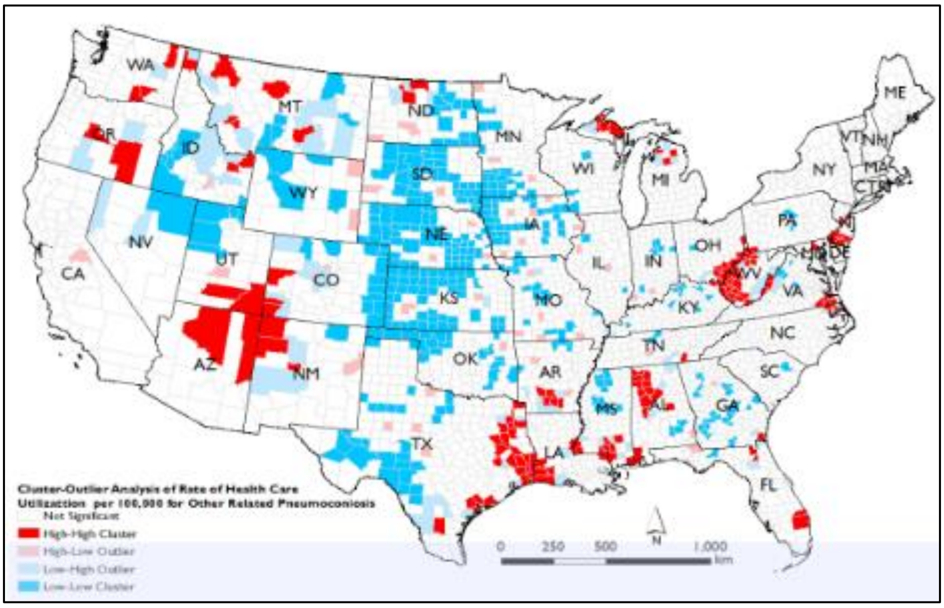

Figure 1 Spatial clustering analysis of four-year rate of health care utilization for medicare beneficiaries with other related pneumoconiosis as the discharge diagnosis, 2011-2014 (22)

3.2. Hotspots of pneumoconiosis and high-risk exposure zones

Beyond identifying overall clustering, occupational health practice often requires pinpointing actionable "hotspots"-localized areas where intensified screening, dust control audits, and worker education can be prioritized (21,24). Hotspot detection methods can be broadly categorized into density-based approaches (e.g., kernel density estimation, KDE), local autocorrelation measures (e.g., LISA/local Moran's I), and scan statistics that evaluate statistically significant clusters under explicit probability models (15,16). KDE is useful when case locations are available and aims to identify localized concentrations of events, producing continuous "heat maps" that support rapid situational awareness (25). Local indicators of spatial association (LISA) identify statistically significant high-high clusters (hotspots) and low-low clusters (coldspots), enabling interpretation of local spatial dependence and potential underlying drivers (15,23). Getis-Ord Gi* focuses on intensity of high values in local neighborhoods and is widely applied in hotspot mapping in public health and can be adapted for occupational disease surveillance (26). Scan statistics (e.g., SaTScan) provide formal cluster detection under Poisson or Bernoulli models, allowing for detection of purely spatial and space-time clusters while adjusting for population at risk (27–29). In pneumoconiosis, these methods can be used with denominators such as number of workers in dusty industries, mine employment counts, or screened worker populations to distinguish true risk clusters from variations in population size or screening intensity (30,31). However, surveillance artifacts must be considered: differential screening coverage, reporting policies, or diagnostic capacity can create apparent hotspots unrelated to true exposure differences (19,21). Methods used for studies of hotspots of pneumoconiosis were summarised in Table 2.

Table 2 Methods used for studies of hotspots of pneumoconiosis

Methods	Purposes of study	Strengths	Key cautions	Study
KDE	Identify localized concentration of cases	Intuitive visualization; flexible	Sensitive to bandwidth choice; needs point data	(24,25)
LISA/local Moran's I	Detect statistically significant local clusters	Identifies high-high/low-low areas	Sensitive to neighborhood definition	(15,18)
Getis-Ord Gi*	Detect intensity of hotspots	Straightforward hotspot mapping	Choice of distance band affects results	(26,32,33)
Scan statistics (Poisson/Bernoulli)	Detect significant clusters (space / space-time)	Formal testing; adjusts for population	Requires careful denominator; circular window limits	(27–30)

Kernel density estimation (KDE) has been widely applied in public and occupational health to visualize localized concentrations of disease cases and exposure-related outcomes, supporting rapid identification of high-risk areas in settings with geocoded case data (24,25). Local indicators of spatial association (LISA/local Moran's I) have been frequently used to detect statistically significant local clusters of occupational diseases, including pneumoconiosis, by identifying high–high and low–low areas that reflect spatially structured exposure contexts (15,18). Getis–Ord Gi* statistics are commonly employed for hotspot intensity mapping in epidemiological studies, enabling straightforward identification of areas with significantly elevated disease burden and supporting targeted surveillance and intervention planning (26,32,33). Data from Figure 2 illustrates an example of the identification of the hot spots of of coal workers' pneumoconiosis cases using medicare claims data 2011-2014 and Getis–Ord Gi* statistics in seven contiguous states: Illinois, Indiana, Kentucky, Ohio, Pennsylvania, Virginia, and West Virginia USA (33). Scan statistics implemented in SaTScan, under Poisson or Bernoulli models, have been extensively used to detect significant spatial and space–time clusters of respiratory and occupational diseases while adjusting for population at risk, and have proven particularly valuable in pneumoconiosis surveillance to distinguish true risk clusters from variations in workforce size or screening coverage (27–30).

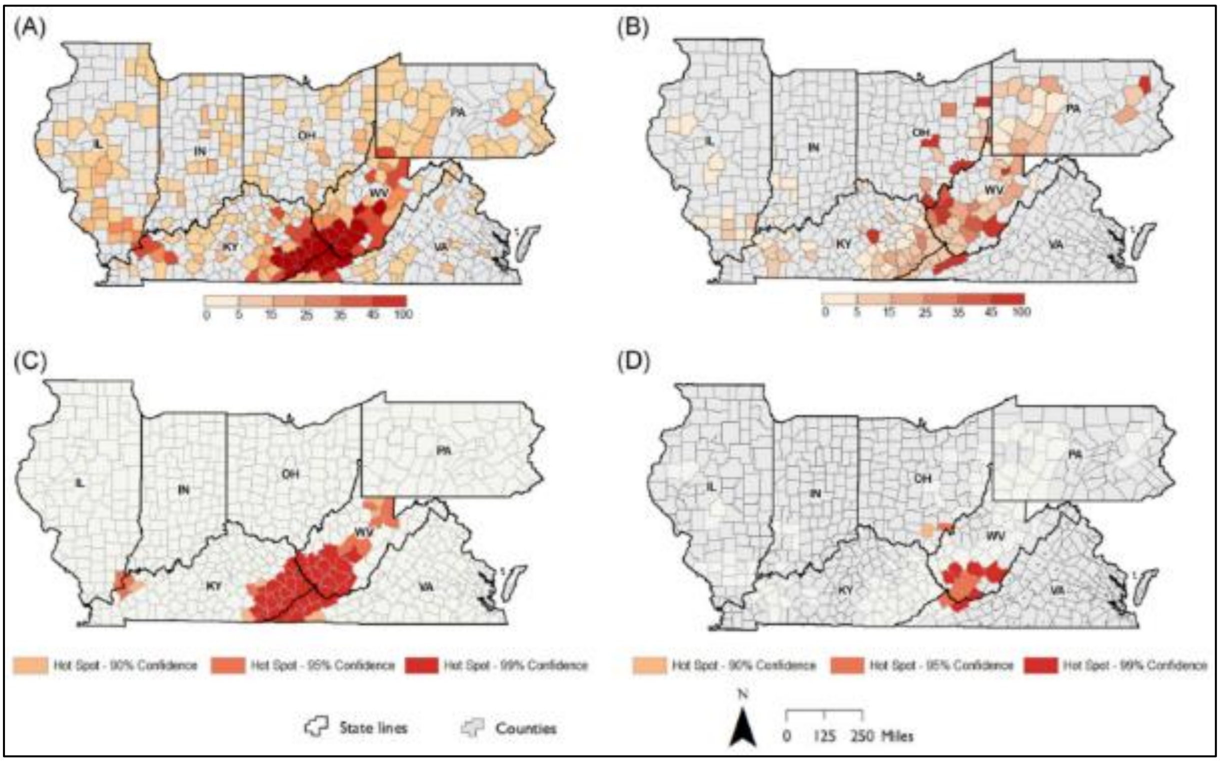

Figure 2 Hot spots of of coal workers' pneumoconiosis cases using medicare claims data 2011-2014 in seven contiguous states: Illinois, Indiana, Kentucky, Ohio, Pennsylvania, Virginia, and West Virginia USA (33)

3.3. Spatial regressions for identifying pneumoconiosis risk factors

Hotspot and clustering analyses are descriptive and inferential regarding location-based aggregation but do not by themselves identify risk factors. To evaluate associations between pneumoconiosis outcomes and contextual drivers (e.g., industrial density, dust exposure proxies, socioeconomic vulnerability, regulatory enforcement, and health service accessibility), spatial regression approaches are essential (34–36). Classic OLS regression assumes independent residuals; spatial dependence violates this assumption and can bias inference (34). Spatial lag and spatial error models address dependence by incorporating a spatially lagged dependent variable (lag model) or spatially autocorrelated errors (error model) (35). In occupational health contexts, these models can capture spillover effects such as shared labor markets, commuting patterns, and cross-boundary industrial emissions (36,37). Bayesian spatial models, such as conditional autoregressive (CAR) models, provide flexible frameworks for disease mapping and risk factor analysis, especially when dealing with small-area counts and uncertainty quantification (38–40). For pneumoconiosis, CAR models can be used to smooth risk estimates across neighboring areas and to jointly model risk and covariates while managing sparse counts and heterogeneous denominators (39,40). Spatial non-stationarity is another critical issue: relationships between risk predictors and pneumoconiosis outcomes may vary across space (41,42). Geographically weighted regression (GWR) and multiscale GWR (MGWR) estimate location-specific coefficients, identifying regions where certain factors exert stronger influence (R38–R40). This is operationally relevant because intervention strategies may differ across industrial regions: for example, high-risk mining basins may require intensive dust control engineering, whereas construction corridors may benefit from enforcement of respirator programs and mobile screening units.

Table 3 Studies on spatial regressions for identifying pneumoconiosis risk factors

Methods	Purposes of study	Suitable data	Typical outputs	Study
Scatter plots, OLS (baseline)	Identify associations (no spatial dependence)	Areal data	Global coefficients; residual diagnostics	(34,35,43)
Spatial lag / spatial error models	Account for spatial dependence	Areal data	Dependence parameters; improved inference	(34–36)
Bayesian CAR models	Small-area risk smoothing + covariates	Counts + denominators	Posterior risk; credible intervals	(38–40)
GWR / MGWR	Identify spatially varying associations	Areal/continuous	Local coefficients; maps of effects	(41,42,44)

Data from Table 3 summarizes spatial regression approaches and their use cases. Ordinary least squares (OLS) regression has commonly been used as a baseline approach in occupational and environmental health studies to examine associations between pneumoconiosis indicators and contextual factors, although residual spatial autocorrelation often limits inference when spatial dependence is present (34,35). In addition, scatter plots have been commonly used for measure the correlation of pneumoconiosis-asthma with exposure time and IgE in patients (43). Spatial lag and spatial error models have been applied to account for spatial dependence in areal pneumoconiosis data, improving model fit and yielding more reliable estimates of relationships between disease burden and regional exposure proxies or industrial characteristics (34–36). Bayesian conditional autoregressive (CAR) models have been widely used in disease mapping to smooth small-area pneumoconiosis risk while incorporating covariates, providing posterior risk estimates and credible intervals that are particularly useful for surveillance and decision-making in occupational health (38–40). Geographically weighted regression (GWR) and multiscale GWR (MGWR) have been employed to explore spatially varying associations between pneumoconiosis outcomes and risk factors, revealing regional heterogeneity in effect sizes and supporting geographically targeted prevention strategies (41,42,44).

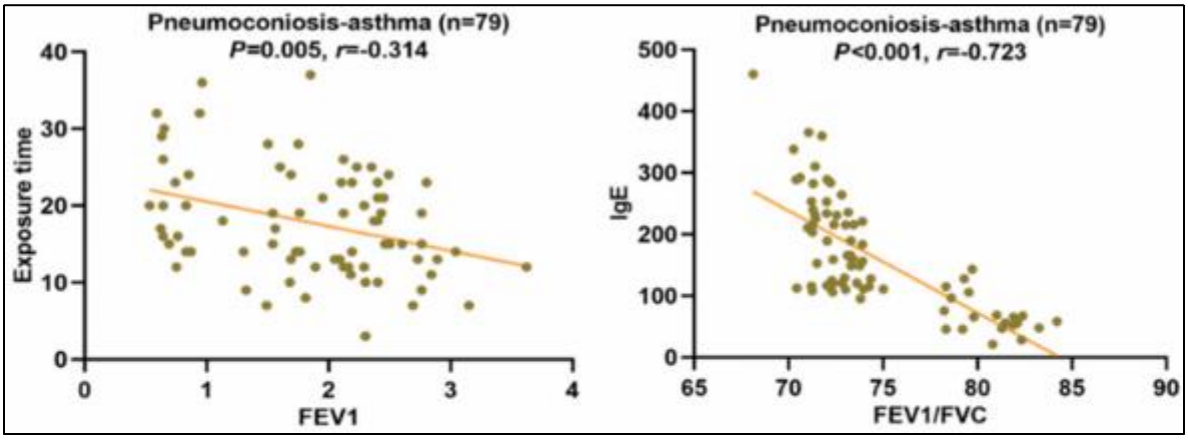

Figure 3 Scatter plots of the correlation of pneumoconiosis-asthma with exposure time and IgE in patients (43)

3.4. Implications for nursing practice and occupational health nursing

The integration of GIS and spatial analytics into pneumoconiosis prevention aligns with contemporary nursing roles emphasizing surveillance, prevention, and health promotion (19,21,24). First, GIS supports spatially informed occupational health surveillance by enabling nurses and occupational health teams to visualize screened populations, follow-up status, and spatial concentrations of abnormal findings. Such tools can improve the sensitivity of surveillance systems by detecting early geographic signals of elevated risk that warrant targeted audits or screening outreach (21). Second, hotspot mapping and cluster detection enable targeted health education and risk communication. Occupational health nurses can deploy location-tailored interventions such as respirator fit-testing campaigns, dust exposure education, smoking cessation support (given synergistic respiratory risk), and referral pathways in high-risk zones (24,45). Third, spatial regression outputs can inform evidence-based prioritization, directing limited resources (e.g., mobile X-ray/CT units, spirometry, clinical referrals) toward areas where modeled risk is highest and where structural barriers limit access to occupational health services.

Implementation requires careful governance: geocoding worker residences or worksites raises privacy issues, necessitating aggregation, anonymization, and secure data handling. Interoperability between clinical, occupational, and environmental monitoring systems is often limited, and nurses may require training to interpret spatial outputs for practice translation. Capacity building-basic GIS literacy, interpreting hotspots, understanding spatial bias-should be incorporated into occupational health nursing education and continuing professional development (19,21,24).

4. Conclusion

This review demonstrates that GIS and spatial statistical methods provide critical added value for pneumoconiosis research by revealing non-random spatial patterns, identifying localized high-risk hotspots, and improving risk factor inference under spatial dependence and heterogeneity. Evidence from spatial pattern analysis, hotspot detection, and spatial regression highlights persistent geographic inequities in exposure and disease burden that are often obscured by conventional epidemiological approaches. For occupational health nursing, spatially informed findings support proactive surveillance, geographically targeted screening, tailored health education, and more efficient allocation of prevention and referral resources. Integrating GIS into routine occupational health nursing practice can strengthen early detection and prevention, particularly in dust-intensive industrial regions. Future research should prioritize interoperable spatial data systems, privacy-preserving analytics, and capacity building to enable sustainable translation of GIS evidence into occupational health nursing and policy practice.

Compliance with ethical standards

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Disclosure of conflict of interest

The authors declare no conflict of interest.

Statement of ethical approval

Ethical approval approved by authorized committee.

Statement of informed consent

Informed consent was obtained from all individual participants included in the study.

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