The Evolution of Spatiotemporal Hotspot Prediction in Public Health: Emerging Paradigms from Spatial Epidemiology to GeoAI and Foundation Models

Godwin Tetteh Wayoe[1]; Godson Teye Apaflo[2]; Solomon Doe Adjaottor[3]

[1]School of Computing, Applied Science, & Engineering – Carolina University, USA.
[2]Information Technology and Decision Sciences, University of Energy and Natural Resources, Ghana.
[3]Department of Accounting and Finance – Kwame Nkrumah University of Science and Technology, Ghana.

Publication Date: 2026/08/29

Abstract: Spatiotemporal hotspot prediction has become essential for proactive public health surveillance and intervention. Over several decades, analytical approaches in this field have evolved from classical spatial epidemiology through Bayesian modeling, machine learning, deep learning, GeoAI, and more recently, foundation models. This State-of-the-Art Review systematically traces the evolution of this paradigm, comparing methodological characteristics, strengths, and limitations across successive approaches. This State-of-the-Art Review synthesizes evidence from peer-reviewed studies identified through a structured literature search. It identifies key patterns of advancement, including increasing predictive capability, the re-integration of spatial reasoning, and a growing emphasis on operational scalability and multimodal intelligence. It also highlights persistent challenges related to interpretability, data equity, computational demands, and governance. The synthesis reveals that the current state of the art is defined by the convergence of GeoAI and foundation models, which together offer new possibilities for context-aware and generalizable public health intelligence. The review concludes by outlining evidence-supported future trajectories and emphasizing that continued progress will depend on addressing both technical and institutional challenges.

Keywords: *Spatiotemporal Hotspot Prediction, GeoAI, Public Health Intelligence, Machine Learning, Spatial Epidemiology.*

How to Cite: Godwin Tetteh Wayoe; Godson Teye Apaflo; Solomon Doe Adjaottor (2026) The Evolution of Spatiotemporal Hotspot Prediction in Public Health: Emerging Paradigms from Spatial Epidemiology to GeoAI and Foundation Models. *International Journal of Innovative Science and Research Technology*, 11(8), 1888-1898. https://doi.org/10.38124/ijisrt/26aug740

I. INTRODUCTION

The prediction of spatiotemporal hotspots, defined as geographic areas where disease risk or incidence is disproportionately elevated, has become a cornerstone of modern public health surveillance and intervention planning (Guo & Scott, 2026). As infectious diseases, environmental hazards, and climate-sensitive health threats increasingly exhibit complex spatial and temporal dynamics, the capacity to identify emerging clusters, anticipate outbreak trajectories, and target resources efficiently has grown in both scientific and operational importance. Effective hotspot prediction enables earlier detection, more precise allocation of limited public health resources, and more equitable intervention strategies, particularly in settings where disease burdens are rising or shifting due to environmental and demographic change.

Over the past several decades, analytical approaches to spatiotemporal hotspot prediction have undergone substantial evolution. Early efforts, grounded in spatial epidemiology, focused primarily on detecting spatial clusters and mapping disease distributions using statistical methods such as scan statistics and measures of spatial autocorrelation (Aguilar et al., 2022). These classical approaches, however, struggled with predictive forecasting and the modeling of complex interactions. Bayesian models subsequently addressed limitations related to uncertainty quantification and spatial dependence. The emergence of machine learning improved non-linear predictive capability, while deep learning enabled automated feature learning from complex and high-dimensional data (Ansar et al., 2026; Hu et al., 2025). More recently, the integration of artificial intelligence with geospatial technologies, commonly termed GeoAI, has introduced native spatial reasoning and operational scalability into predictive systems (Guo & Scott, 2026; Nekorchuk et al., 2023). GeoAI refers to the integration of

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26aug740

artificial intelligence methods with geospatial data, spatial analysis, and geographic information science to enable intelligent spatial reasoning and geospatial decision support. Concurrently, the rise of foundation models has begun to offer new possibilities for multimodal reasoning across textual, visual, and location-based data (Resch et al., 2025; Liu et al., 2025). Unlike task-specific deep learning models, foundation models are pretrained on large, diverse datasets and can be adapted across multiple downstream tasks through transfer learning and multimodal reasoning.

Despite these advances, the field lacks a comprehensive synthesis that traces how successive methodological paradigms have transformed the theory and practice of spatiotemporal hotspot prediction. Existing reviews have typically focused on individual techniques, specific disease applications, or narrow technological domains, without systematically examining the intellectual progression from classical spatial methods to contemporary GeoAI and foundation model approaches. This gap limits the ability of researchers and practitioners to understand the cumulative nature of paradigm development, the persistent trade-offs that have accompanied technological progress, and the implications of current frontiers for future public health intelligence.

This review addresses the following questions: How has spatiotemporal hotspot prediction evolved across successive analytical paradigms? What methodological advances characterize each paradigm? What persistent limitations remain? How are GeoAI and foundation models reshaping future public health intelligence? Unlike previous reviews, this study synthesizes the historical evolution of predictive paradigms, compares their methodological characteristics, and proposes an integrated perspective on the convergence of GeoAI and foundation models for future public health intelligence.

➢ *Purpose and Scope of the Review*

This State-of-the-Art Review systematically examines the evolution of spatiotemporal hotspot prediction in public health. It traces the development of analytical paradigms from classical spatial epidemiology through Bayesian modeling, machine learning, deep learning, GeoAI, and foundation models. The review focuses on methodological progression, comparative characteristics, frontier developments, and evidence-supported future trajectories. Its scope is limited to the intellectual and technical evolution of predictive paradigms rather than disease-specific applications or detailed implementation protocols. By synthesizing validated evidence across these paradigms, the review aims to clarify how the field has advanced, identify persistent challenges, and establish a coherent foundation for future research and practice in spatiotemporal public health intelligence.

II. REVIEW APPROACH AND LITERATURE SELECTION

This State-of-the-Art Review critically examines the evolution of spatiotemporal hotspot prediction in public health from spatial epidemiology to GeoAI and foundation models. Although classical spatial epidemiology and Bayesian disease mapping have longer historical roots, the present review focuses on contemporary literature published between 2020 and 2026 that reflects, synthesizes, and extends these earlier paradigms rather than reconstructing their entire historical development. The review is limited to English-language studies with a primary focus on the United States. Relevant literature was identified through targeted searches of PubMed, Web of Science, Scopus, IEEE Xplore, and Google Scholar using keywords and search strings such as "spatiotemporal hotspot prediction," "spatial epidemiology," "disease clustering," "GeoAI," "foundation models," "geospatial artificial intelligence," and "spatiotemporal forecasting." Studies were screened and included only if they met explicit criteria for relevance to the review's thematic scope and methodological contribution. The final evidence base consists of 17 validated studies. This corpus was intentionally selective and theory-driven, prioritizing landmark and methodologically influential works that illuminate paradigm transitions, comparative strengths and limitations, and persistent challenges, rather than aiming for exhaustive coverage of every available study. The review was conducted in accordance with established principles of methodological transparency, critical and integrative synthesis, conceptual coherence, and evidence-based interpretation appropriate for State-of-the-Art Reviews.

➢ *Conceptual Foundations of Spatiotemporal Hotspot Prediction*

Spatiotemporal hotspot prediction refers to the identification and forecasting of geographic areas where the risk or incidence of disease is significantly elevated relative to surrounding areas or expected baselines. At its core, the field rests on the recognition that disease events are rarely distributed uniformly across space and time. Instead, they frequently exhibit clustering, with elevated risk concentrated in particular locations and periods. Understanding and predicting these concentrations requires analytical frameworks capable of detecting spatial dependence, temporal dependence, and the interactions between them (Guo & Scott, 2026; Aguilar et al., 2022).

To strengthen conceptual clarity, the foundations of the field can be organized into four interrelated dimensions. First, spatial dependence captures the tendency for disease risk at one location to be influenced by risk at nearby locations, commonly assessed through measures such as Moran's I and other indicators of spatial autocorrelation. Second, temporal dependence recognizes that risk at one point in time is shaped by prior conditions, including seasonality, lag effects, incubation periods, and transmission dynamics. Third, diffusion processes describe the mechanisms through which disease spreads across space and time, encompassing contagious, hierarchical, and relocation pathways. Fourth, the prediction objective distinguishes between the retrospective identification of existing clusters and the prospective forecasting of future risk, a distinction that shapes both methodological choices and public health applications.

Spatial dependence arises from multiple mechanisms, including shared environmental exposures, human mobility patterns, vector movement, and social or behavioral interactions that transcend administrative boundaries. Methods that fail to account for spatial dependence risk producing biased estimates and misleading inferences about where and why disease risk is elevated. Temporal dependence is particularly relevant for infectious diseases, which often exhibit autocorrelation through transmission dynamics and cyclical patterns. When spatial and temporal dependence interact, as they frequently do in real-world disease systems, the resulting spatiotemporal processes become substantially more complex to model and predict (Ward et al., 2023; Barket et al., 2025).

It is important to distinguish hotspot detection from hotspot prediction, as these terms are sometimes used interchangeably in the literature despite representing different analytical goals. Hotspot detection is primarily retrospective and descriptive. It seeks to identify existing clusters of elevated risk using methods such as Moran's I, Getis–Ord Gi*, and scan statistics. In contrast, hotspot prediction is prospective and decision-oriented. It aims to forecast where elevated risk is likely to emerge in the future, thereby supporting early intervention and resource allocation. This distinction is fundamental for evaluating the evolution of analytical paradigms, as later approaches increasingly emphasize forecasting capability alongside descriptive cluster identification.

Disease diffusion and clustering remain central concepts. Diffusion describes the processes through which disease spreads across space and over time, while clustering refers to the non-random aggregation of cases in space, time, or both. Hotspot methods seek to identify these concentrations, distinguish true elevations in risk from random variation, and, where possible, anticipate where new concentrations are likely to emerge. These tasks require not only statistical techniques for detecting dependence but also conceptual clarity regarding what constitutes a meaningful hotspot in different epidemiological and public health contexts (Aguilar et al., 2022; Ward et al., 2023).

A further source of conceptual complexity is that the notion of a "hotspot" itself is method-dependent. Different studies operationalize hotspots through incidence thresholds, relative risk estimates, scan statistics, probability surfaces, or anomaly detection procedures (Aguilar et al., 2022; Barket et al., 2025; Nekorchuk et al., 2023).

Because definitions and operational criteria vary, direct comparisons of performance or findings across paradigms can be difficult. Recognizing this variability is essential for rigorous synthesis and for interpreting claims about methodological advancement.

The analytical foundations of spatiotemporal hotspot prediction have historically drawn from multiple disciplines, including epidemiology, geography, statistics, and, more recently, computer science and artificial intelligence. Early approaches emphasized descriptive mapping and statistical tests for spatial clustering. Over time, the field incorporated more sophisticated modeling frameworks capable of handling hierarchical data structures, uncertainty, high-dimensional inputs, and multimodal data sources (Kehkashan et al., 2026; Resch et al., 2025). Across these developments, several persistent analytical challenges have remained central: how to properly account for spatial and temporal autocorrelation, how to balance predictive accuracy with interpretability, how to manage data sparsity and quality issues, and how to translate model outputs into actionable public health intelligence.

These conceptual foundations provide the necessary lens for evaluating how different paradigms have addressed the core problems of spatiotemporal hotspot prediction. Each subsequent paradigm has engaged with these foundational concepts in distinct ways, introducing new methodological tools while also surfacing new limitations and trade-offs. Understanding these conceptual underpinnings is therefore essential for tracing the intellectual evolution of the field and assessing the significance of current frontier developments.

➢ *The Spatial Epidemiology Paradigm*

Spatial epidemiology represents the foundational analytical tradition from which contemporary spatiotemporal hotspot prediction emerged. Emerging from the intersection of classical epidemiology and medical geography, this approach centers on the systematic description and analysis of disease distributions across geographic space. Its origins lie in the recognition that many health events are not randomly distributed but instead exhibit spatial clustering driven by environmental exposures, human behavior, vector ecology, and social determinants (Aguilar et al., 2022; Barket et al., 2025).

Within this paradigm, a hotspot is operationalized as a geographically bounded area in which the observed incidence, prevalence, or risk of a health outcome is statistically elevated relative to surrounding areas or to an expected baseline under spatial randomness. Hotspots are typically identified through formal tests of spatial clustering or relative risk estimation rather than through purely visual inspection. This operational definition distinguishes true elevations in risk from random variation and provides the conceptual basis for the methods described below.

Methodologically, the paradigm relies on techniques designed to identify spatial clusters and quantify spatial dependence. Scan statistics, such as those implemented in SaTScan, have been widely used to detect statistically significant geographic clusters of disease cases. Measures of spatial autocorrelation, including Moran's I and Geary's C, provide tools for assessing whether disease risk exhibits spatial dependence, while point pattern analysis and kernel density estimation enable visualization and characterization of disease distributions. Disease mapping techniques, often based on standardized incidence or mortality ratios, have further supported the identification of areas with elevated risk (Ward et al., 2023; Aguilar et al., 2022). These methods collectively emphasize the description and statistical confirmation of spatial patterns rather than the explicit modeling of underlying processes or the generation of forward-looking predictions.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26aug740

The strengths of the spatial epidemiology paradigm lie in its interpretability and direct policy relevance. By producing maps and statistical tests that clearly identify high-risk areas, this approach has proven valuable for outbreak investigation, resource targeting, and hypothesis generation regarding environmental or social risk factors. Its relatively accessible methodological requirements and long history of application in public health surveillance have contributed to its enduring use, particularly in settings where rapid descriptive analysis is prioritized over complex predictive modeling (Barket et al., 2025).

Table 1 Comparative Overview of Core Methods in the Spatial Epidemiology Paradigm

Method	Primary Purpose	Principal Strength	Principal Limitation
Moran's I	Detect global spatial autocorrelation	Highly interpretable	Not predictive
Geary's C	Measure local spatial dependence	Computationally simple	Limited forecasting capacity
SaTScan (scan statistics)	Detect statistically significant clusters	Strong policy relevance	Primarily retrospective
Kernel Density Estimation (KDE)	Visualize spatial density of events	Easy to implement and interpret	Exploratory rather than inferential

Despite these contributions, the paradigm exhibits important limitations that have driven subsequent methodological development. Spatial epidemiology approaches have traditionally offered limited capacity for prediction, particularly over longer time horizons, as they focus more on describing existing patterns than on modeling the dynamic processes that generate them. Many early methods also assume spatial stationarity, meaning that relationships between risk factors and disease outcomes are assumed to remain constant across space, an assumption that often fails in heterogeneous real-world environments. Furthermore, while spatial dependence is central to the paradigm, temporal dynamics and spatiotemporal interactions have historically received less systematic attention. These constraints become particularly evident when attempting to forecast emerging hotspots or to account for complex, non-linear interactions among multiple risk factors (Ward et al., 2023; Kehkashan et al., 2026).

These limitations, combined with growing demands for probabilistic inference and the ability to borrow statistical strength across areas, created the conditions for the emergence of Bayesian modeling approaches. The transition reflected a broader recognition that while spatial epidemiology provided essential descriptive and exploratory tools, more advanced frameworks were needed to support inference under uncertainty and to improve estimation in data-sparse settings. This shift marked the beginning of a broader evolution toward paradigms that could integrate spatial analysis with more sophisticated statistical and computational methods.

➢ *The Bayesian Modeling Paradigm*

Bayesian modeling emerged as a significant advancement in spatiotemporal hotspot prediction by addressing several key limitations of classical spatial epidemiological approaches. While spatial epidemiology excelled at descriptive cluster detection and pattern visualization, it offered limited capacity for probabilistic inference, uncertainty quantification, and estimation in data-sparse settings. Bayesian methods introduced a coherent statistical framework capable of explicitly modeling spatial and temporal dependence while providing full posterior distributions for risk estimates (Ward et al., 2023; Paulson et al., 2026). Bayesian methods expanded hotspot prediction beyond retrospective cluster identification by enabling probabilistic forecasts of future disease risk and estimation of the likelihood that specific regions would exceed predefined epidemiological thresholds. This shift enabled researchers to move beyond purely descriptive analyses toward more rigorous inference under uncertainty.

Central to the Bayesian paradigm is the use of hierarchical modeling structures that allow for the incorporation of spatial and temporal random effects. Conditional autoregressive (CAR) and intrinsic CAR (ICAR) models have been widely adopted to account for spatial dependence by assuming that risk in one area is influenced by risk in neighboring areas. These models are often embedded within larger hierarchical frameworks that can simultaneously account for covariate effects, temporal trends, and unstructured heterogeneity. The development of computationally efficient methods, particularly Integrated Nested Laplace Approximation (INLA), has further expanded the practical applicability of Bayesian approaches by reducing the computational burden associated with Markov Chain Monte Carlo methods (Ward et al., 2023).

One of the most important contributions of Bayesian modeling lies in its principled treatment of uncertainty. By producing full posterior distributions rather than point estimates, Bayesian methods allow for coherent probabilistic statements about disease risk and the probability that risk exceeds defined thresholds. This capability has proven especially valuable for small-area estimation, where data are often sparse and traditional estimates can be unstable (Ward et al., 2023; Paulson et al., 2026). Through the mechanism of borrowing statistical strength across space and time, Bayesian hierarchical models can generate more reliable risk estimates in areas with limited data while properly reflecting the uncertainty associated with those estimates.

Despite these strengths, the Bayesian modeling paradigm also introduced new challenges. The computational demands of complex hierarchical models can be substantial, particularly when using traditional Markov Chain Monte

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26aug740

Carlo techniques, although INLA has mitigated this issue to some extent. Additionally, Bayesian analyses require careful specification of prior distributions, and results can be sensitive to prior choice, raising concerns about subjectivity. The technical expertise required to implement and validate Bayesian models has also limited their accessibility compared to some earlier spatial epidemiological methods. Furthermore, while Bayesian approaches improved inference and uncertainty quantification, they did not always deliver substantial gains in predictive performance on complex, high-dimensional datasets (Ward et al., 2023; Kehkashan et al., 2026).

These limitations, combined with growing demands for higher predictive accuracy and greater scalability, contributed to the subsequent shift toward machine learning approaches. As datasets became larger and more complex, and as the need for automated pattern recognition increased, the field began to explore methods capable of capturing non-linear relationships with less reliance on strong parametric assumptions (Kehkashan et al., 2026). Bayesian modeling thus served as a critical bridge between classical spatial statistics and data-driven predictive paradigms, advancing the field's capacity for rigorous inference while also revealing the need for more flexible and scalable approaches to hotspot prediction.

➢ *The Machine Learning Paradigm*

Machine learning marked a notable shift in spatiotemporal hotspot prediction by emphasizing predictive accuracy and the capacity to capture complex, non-linear relationships within large datasets. Unlike classical spatial statistics, machine-learning approaches enabled the integration of heterogeneous data sources, including meteorological, mobility, socioeconomic, and remote-sensing data, thereby expanding hotspot prediction from retrospective mapping to dynamic forecasting. Rather than relying primarily on explicit statistical modeling of spatial and temporal dependence, this paradigm favored data-driven approaches that could automatically detect patterns across high-dimensional inputs. The transition was fueled by growing data availability and the practical need for reliable short- and medium-term forecasting in public health settings (Ansar et al., 2026; Hu et al., 2025).

A range of classical machine learning techniques found application in this domain, including ensemble methods such as Random Forests and Gradient Boosting, alongside regularized regression and support vector machines. Because conventional machine-learning algorithms lack explicit spatial reasoning, researchers often incorporated engineered features representing geographic proximity, temporal lags, seasonality, or neighborhood characteristics. These approaches proved effective at identifying non-linear interactions among multiple risk factors without requiring strong assumptions about underlying data distributions. Their ability to manage high-dimensional inputs made them especially suitable for analyses involving numerous environmental, demographic, and behavioral variables (Hu et al., 2025; Sánchez-Díaz et al., 2024).

One of the main advantages of machine learning approaches lies in their strong predictive performance and relative ease of implementation. In many comparative evaluations, these models have outperformed traditional statistical methods in forecasting tasks, particularly when the primary goal is accuracy rather than causal explanation. At the same time, techniques for assessing variable importance have offered useful insights into influential risk factors, even when internal model logic remains difficult to interpret (Ansar et al., 2026; Hu et al., 2025).

Nevertheless, machine learning approaches also brought notable limitations. Reduced interpretability has been a persistent concern, as many models function in ways that are not easily explained to stakeholders or regulators. Additionally, standard implementations often lack built-in mechanisms for handling spatial and temporal dependence, sometimes requiring supplementary techniques or feature engineering. Risks of overfitting and limited generalizability to new populations or time periods have also been noted as practical constraints (Kehkashan et al., 2026; Hu et al., 2025).

These shortcomings, particularly around interpretability and the limited native treatment of spatiotemporal structure, helped motivate interest in deep learning approaches. While machine learning advanced predictive capability considerably, the need for models that could learn hierarchical representations directly from complex and unstructured data sources encouraged exploration of neural network architectures. This shift represented both a continuation of machine learning's predictive focus and a response to its constraints in handling increasingly rich data environments in public health.

➢ *The Deep Learning Paradigm*

Deep learning extended earlier machine learning approaches by enabling models to automatically learn hierarchical representations from complex, high-dimensional inputs. Unlike many traditional machine learning methods that often depend on manual feature engineering, deep neural networks can identify intricate patterns directly from sources such as medical imagery, sensor streams, satellite observations, and sequential health records. This capacity has proven especially relevant in spatiotemporal hotspot prediction, where meaningful signals frequently exist within unstructured or multimodal data (Kehkashan et al., 2026; Sayeed et al., 2025).

Unlike earlier machine learning approaches that often required manually engineered spatial and temporal features, deep learning architectures such as convolutional neural networks (CNNs) for spatial feature extraction from raster and geographic data, long short-term memory (LSTM) and gated recurrent unit (GRU) models for temporal disease dynamics, convolutional LSTM (ConvLSTM) networks for joint spatiotemporal forecasting, and graph neural networks (GNNs) for modeling spatial relationships among locations enabled more direct representation learning of dynamic geographic processes. These architectures allowed models to capture evolving disease patterns across both space and time. Spatiotemporal transformers have further extended these

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26aug740

capabilities and serve as a conceptual bridge toward foundation models. Architectures such as CNNs, recurrent and LSTM networks, and graph neural networks have been applied across various tasks. These models have shown strong results in areas including environmental exposure assessment, disease forecasting from physiological signals, and satellite-based environmental analysis. By learning layered representations, deep learning approaches have reduced the need for extensive domain-driven feature specification, allowing more flexible modeling of complex spatiotemporal processes (Sayeed et al., 2025; Liu et al., 2025).

A notable strength of deep learning lies in its performance on complex and unstructured data when sufficient training data are available. The ability to process multimodal inputs and apply transfer learning has further expanded its utility in public health contexts (Kehkashan et al., 2026; Liu et al., 2025).

At the same time, deep learning introduces substantial practical challenges. These models typically require large volumes of high-quality labeled data and significant computational resources. More importantly, limited interpretability remains a major concern. Although explanation methods such as SHapley Additive exPlanations (SHAP), Local Interpretable Model-agnostic Explanations (LIME), attention mechanisms, and saliency approaches have improved model transparency, important questions remain regarding whether these explanations provide sufficient causal understanding or operational trust for public health decision-making. Deep learning approaches are also vulnerable to learning spurious correlations and may generalize poorly when applied to new distributions (Kehkashan et al., 2026; Sayeed et al., 2025).

These limitations, combined with the increasing availability of geospatial big data and advances in geographic artificial intelligence (GeoAI), encouraged the development of approaches that integrate deep learning capabilities with explicit spatial representation and geographic reasoning. While deep learning advanced the field's capacity to model complex patterns, the need for systems that could more effectively incorporate geographic context and support real-time decision-making encouraged the development of paradigms that combine deep learning's representational power with explicit spatial reasoning (Guo & Scott, 2026; Liu et al., 2025).

III. THE GEOAI PARADIGM

GeoAI emerged as a response to the limitations of earlier paradigms in explicitly incorporating spatial structure and supporting operational public health workflows.

Many conventional deep learning implementations did not explicitly encode geographic relationships or spatial hierarchies, instead relying on engineered representations of location. GeoAI extends these approaches by incorporating geographic structures and spatial relationships as intrinsic components of model design. GeoAI differs from earlier AI applications in geospatial domains by treating geographic context as a fundamental component of representation and reasoning rather than as an additional predictor variable. This shift enables models to incorporate spatial relationships, geographic hierarchy, and contextual interactions directly into prediction processes (Guo & Scott, 2026; Nekorchuk et al., 2023). At the core of the GeoAI paradigm is the fusion of AI methods with explicit spatial reasoning.

Graph neural networks represent an important development within GeoAI because they model geographic entities as interconnected networks, allowing prediction systems to capture relationships among locations based on proximity, mobility, connectivity, or functional similarity. Other important developments within GeoAI include the integration of hierarchical spatial indexing systems such as H3 grids, and the incorporation of satellite and remote sensing data into predictive models. These approaches allow for more accurate modeling of spatially structured phenomena and facilitate the fusion of diverse data sources, including mobility traces, environmental sensors, disease surveillance records, and unstructured textual reports (Liu et al., 2025; Guo & Scott, 2026). The result is a class of systems capable of generating spatially contextualized intelligence that aligns more closely with the operational needs of public health agencies.

A defining feature of GeoAI has been its strong emphasis on operational deployment. Compared with earlier research-oriented approaches, GeoAI has placed greater emphasis on operational integration, although evidence of sustained deployment within routine public health systems remains limited. Operational platforms that combine real-time data ingestion, automated event extraction, environmental monitoring, and predictive analytics have demonstrated the potential of this paradigm to move beyond proof-of-concept applications. These systems support continuous monitoring, near-real-time forecasting, and the generation of actionable alerts, representing a significant advancement in the translation of analytical methods into public health practice (Guo & Scott, 2026; Nekorchuk et al., 2023).

The strengths of the GeoAI paradigm include its capacity for native spatial reasoning, effective multi-source data fusion, and relatively high operational readiness compared to purely research-oriented deep learning models. By embedding geographic context directly into analytical workflows, GeoAI systems can produce outputs that are more directly usable for targeted interventions and resource allocation. The paradigm has also benefited from advances in cloud computing and earth observation technologies, which have made large-scale geospatial data processing more accessible (Onyeabor & Onyeabor, 2025; Liu et al., 2025).

Nevertheless, GeoAI also presents notable challenges. The integration of AI with geospatial technologies introduces substantial system complexity, requiring expertise across multiple domains, including artificial intelligence, geographic information science, remote sensing, and public health. Data harmonization across heterogeneous sources

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26aug740

remains difficult, and the performance of GeoAI systems is highly dependent on the quality and timeliness of input data streams. Furthermore, while operational platforms have been successfully deployed in several contexts, questions regarding long-term sustainability, scalability across different health systems, and governance frameworks for AI-supported decision-making remain active areas of development (Guo & Scott, 2026; Onyeabor & Onyeabor, 2025).

These characteristics position GeoAI as both a culmination of prior evolutionary trends and a foundation for subsequent developments. By combining the predictive strengths of deep learning with explicit spatial intelligence and operational focus, the paradigm has advanced the field's capacity to generate timely and contextually relevant public health intelligence. Although GeoAI improved spatial reasoning and multimodal integration, many systems remained task-specific, requiring separate models for different diseases, locations, and prediction objectives. Foundation models emerged partly in response to this limitation by enabling reusable representations that can be adapted across multiple geospatial and public health tasks (Resch et al., 2025; Liu et al., 2025).

➤ *Foundation Models and Emerging Public Health Intelligence*

Foundation models represent the most recent major development in the evolution of spatiotemporal hotspot prediction, introducing capabilities that extend beyond those of previous paradigms. Unlike previous paradigms, foundation models aim not only to predict hotspots but also to synthesize heterogeneous evidence, transfer knowledge across contexts, and support higher-level reasoning about emerging public health risks. These large-scale, pre-trained models, including large language models and multimodal architectures, offer unprecedented generalizability and the ability to reason across diverse data types such as text, imagery, and location-based information. Their emergence has been driven by advances in large-scale pre-training, retrieval-augmented generation techniques, and the increasing availability of multimodal geospatial and health datasets (Resch et al., 2025; Kolokoussis et al., 2025).

A defining characteristic of foundation models is their capacity for multimodal intelligence. Unlike earlier paradigms that typically specialized in structured data, imagery, or text, foundation models can integrate and reason across multiple modalities simultaneously. This enables new forms of analysis, such as extracting complex geographic and contextual information from unstructured reports, enriching mobility data with semantic understanding, or combining satellite imagery with textual descriptions for more nuanced environmental health assessments. Early applications have demonstrated the potential of these models to perform tasks that previously required separate specialized systems, suggesting a move toward more unified and flexible analytical frameworks (Wang et al., 2025; Liu et al., 2025).

The strengths of foundation models lie in their generalizability and adaptability. Once pre-trained, these models can be rapidly applied to new tasks with relatively little additional training, reducing the time and resources needed to develop specialized solutions. Techniques such as retrieval-augmented generation further enhance their utility by allowing models to access external knowledge bases, improving factual accuracy and enabling more complex reasoning. These characteristics position foundation models as potentially transformative for public health intelligence, particularly in scenarios requiring the synthesis of heterogeneous information sources (Resch et al., 2025; Wang et al., 2025).

However, the adoption of foundation models also introduces significant challenges. The computational and financial costs associated with training and deploying large models remain substantial, raising questions about accessibility and equity. A more fundamental concern is the risk of hallucinations, where models generate plausible but factually incorrect outputs, which can be particularly problematic in high-stakes public health contexts. Additionally, while these models show strong performance on many tasks, rigorous prospective validation in operational public health settings remains limited. Governance issues, including data privacy, bias amplification, accountability for model outputs, and the ethical use of generative capabilities, are still under active development (Kolokoussis et al., 2025; Resch et al., 2025).

Foundation models are increasingly being explored as a potential component of the next generation of public health intelligence systems, although evidence of sustained operational deployment remains limited. Their integration with GeoAI approaches, particularly in operational platforms that combine multimodal reasoning with spatial intelligence, represents a significant convergence of capabilities. This integration suggests that the field is moving toward hybrid systems that leverage the generalizability of foundation models alongside the spatial reasoning and operational focus developed within the GeoAI paradigm. As these systems mature, they are likely to play an increasingly important role in shaping how spatiotemporal health intelligence is generated, interpreted, and applied in public health practice (Guo & Scott, 2026; Wang et al., 2025).

➤ *Comparative Evolution of Predictive Paradigms*

The evolution of spatiotemporal hotspot prediction across six major paradigms of Spatial Epidemiology, Bayesian Modeling, Machine Learning, Deep Learning, GeoAI, and Foundation Models reveals a coherent yet non-linear trajectory of methodological advancement. Beginning with spatial epidemiology's focus on descriptive pattern detection and spatial clustering, the field progressively incorporated more sophisticated frameworks for modeling dependence, quantifying uncertainty, capturing complex patterns, and integrating diverse data sources. Each paradigm built upon the capabilities of its predecessors while addressing specific limitations, resulting in a cumulative expansion of analytical power. However, this progression has also been characterized by recurring trade-offs, particularly between predictive performance and interpretability, and between technical sophistication and operational accessibility (Hu et al., 2025; Kehkashan et al., 2026).

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26aug740

Early paradigms, centered on spatial epidemiology and Bayesian modeling, prioritized interpretability, statistical rigor, and the explicit modeling of spatial and temporal dependence. These approaches provided strong foundations for inference and small-area estimation but offered limited capacity for handling high-dimensional or unstructured data and for generating accurate long-range predictions. The subsequent adoption of machine learning and deep learning paradigms marked a significant shift toward data-driven predictive performance. These approaches demonstrated superior ability to capture non-linear relationships and to learn directly from complex inputs, yet they often did so at the cost of reduced model transparency and weaker native mechanisms for incorporating spatial structure (Ansar et al., 2026; Hu et al., 2025).

The emergence of GeoAI represented a deliberate effort to re-integrate spatial reasoning and operational utility into predictive systems. By combining advances from deep learning with explicit geospatial architectures and real-time data integration, GeoAI systems have achieved higher levels of practical applicability than many earlier research-oriented models. More recently, foundation models have introduced a new dimension of generalizability and multimodal reasoning, enabling the synthesis of textual, visual, and location-based information within unified frameworks (Guo & Scott, 2026; Resch et al., 2025; Wang et al., 2025). This development has further expanded the field's analytical repertoire while raising new questions about reliability, governance, and equitable access.

Across these paradigms, several consistent patterns emerge. Predictive capability has generally increased over time, driven by advances in representation learning, multimodal data fusion, and computational infrastructure. At the same time, the interpretability of models has often declined as complexity increased, prompting ongoing efforts to develop explainable approaches. Spatial reasoning, a core concern in the earliest paradigms, was partially de-emphasized during the machine learning and deep learning phases before being actively reintroduced and enhanced in GeoAI and certain foundation model applications. Operational readiness has also varied considerably, with GeoAI currently representing the most mature paradigm in terms of deployed systems, while foundation model applications remain largely in earlier stages of operational integration (Liu et al., 2025; Onyeabor & Onyeabor, 2025).

These patterns suggest that the field has not followed a simple path of replacement, in which one paradigm supplants another. Instead, the evolution reflects a process of accumulation and strategic integration, in which valuable elements from earlier approaches are retained and combined with new capabilities. The current convergence of GeoAI and foundation models exemplifies this dynamic, as systems increasingly seek to combine the spatial intelligence and operational focus of GeoAI with the generalizability and multimodal reasoning of foundation models (Resch et al., 2025; Guo & Scott, 2026). This integrative trend points toward a future in which hybrid approaches, rather than single dominant paradigms, are likely to define the state of the art in spatiotemporal hotspot prediction.

Table 2 Evolution of Spatiotemporal Hotspot Prediction Paradigms

Paradigm	Core Objective	Representative Methods	Principal Strengths	Principal Limitations
Spatial Epidemiology	Detect and describe spatial patterns and clusters	Scan statistics, spatial autocorrelation, point pattern analysis, disease mapping	High interpretability, policy-relevant mapping, strong descriptive power	Limited predictive capability, assumes spatial stationarity, weak temporal integration
Bayesian Modeling	Provide probabilistic inference with uncertainty quantification	Hierarchical models, CAR/ICAR, INLA, spatiotemporal random effects	Principled uncertainty quantification, borrowing of strength, robust small-area estimation	Computationally intensive, prior sensitivity, requires specialized expertise
Machine Learning	Maximize predictive accuracy through data-driven modeling	Random Forests, Gradient Boosting, SVM, ensemble methods	Strong predictive performance, handles non-linear relationships, scalable	Limited interpretability, weak native spatial modeling, risk of overfitting
Deep Learning	Automatically learn hierarchical representations from complex data	CNNs, RNNs/LSTMs, Graph Neural Networks, transfer learning	Superior performance on unstructured/high-dimensional data, automatic feature learning	High data and computational requirements, low interpretability, risk of spurious correlations
GeoAI	Integrate AI with explicit spatial reasoning and operational systems	GNNs, satellite-AI fusion, H3 grids, multimodal analytics, operational platforms	Native spatial reasoning, strong operational deployment, effective multi-source data fusion	High system complexity, significant data harmonization needs, requires cross-domain expertise
Foundation Models	Enable generalizable, multimodal reasoning across tasks	LLMs, multimodal models (vision-	High generalizability, rapid task adaptation, strong multimodal reasoning	High computational cost, risk of hallucinations,

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26aug740

		language), RAG, generative AI		limited rigorous validation in public health

Table 3 Comparative Characteristics of Successive Predictive Paradigms

Paradigm	Interpretability	Prediction Capability	Data Requirements	Computational Complexity	Scalability	Real-Time Applicability	Operational Readiness
Spatial Epidemiology	High	Moderate	Moderate	Low	High	Moderate	Very High
Bayesian Modeling	High	High	Moderate to High	Moderate to High	Moderate	Moderate	High
Machine Learning	Moderate	High	High	Moderate	High	High	High
Deep Learning	Low to Moderate	Very High	Very High	High	High	High	Moderate to High
GeoAI	Moderate to High	High	High	Moderate to High	High	Very High	High
Foundation Models	Low to Moderate	High to Very High	Very High	Very High	High	Emerging	Low to Moderate

➢ *Persistent Challenges and Unresolved Questions*

While the preceding analysis highlights clear progress across paradigms, it also reveals that certain fundamental tensions have proven remarkably durable. These enduring challenges cut across methodological traditions and warrant closer examination. Rather than viewing them as isolated shortcomings of individual paradigms, it is more productive to understand them as structural features of the field that have persisted despite technological advancement.

A central and recurring tension across the evolution of spatiotemporal hotspot prediction is the trade-off between predictive performance and interpretability. While machine learning and deep learning paradigms significantly improved the modeling of complex patterns, they frequently did so at the cost of model transparency. Post-hoc explanation techniques such as SHAP and LIME have provided partial mitigation, yet they have not fully resolved concerns about trust, accountability, and regulatory acceptance. These concerns have become even more pronounced with the rise of generative foundation models and their associated risk of hallucinations (Kehkashan et al., 2026; Wang et al., 2025).

Data-related challenges have proven equally persistent. Advanced methods, particularly deep learning and foundation model approaches, typically require large volumes of high-quality labeled data. In practice, public health surveillance data are often incomplete, delayed, or subject to reporting biases, especially in low-resource settings. This has contributed to persistent performance disparities between well-resourced and data-sparse regions, raising important questions about equity in the benefits of technological advancement. The integration of multimodal data sources, while analytically promising, has also introduced significant difficulties in data harmonization and quality assurance (Liu et al., 2026; Onyeabor & Onyeabor, 2025).

Computational and infrastructural demands represent another enduring constraint. Later paradigms have required substantial computational resources for both training and inference, limiting accessibility for many public health agencies. Although cloud computing and more efficient architectures have helped narrow this gap, the divide between what is technically feasible in research settings and what is practically sustainable in operational environments remains substantial (Sayeed et al., 2025; Resch et al., 2025).

Ethical and governance challenges have grown in salience as models have become more complex and autonomous. Questions surrounding data privacy, algorithmic bias, accountability for model-driven decisions, and the appropriate division of responsibility between human experts and AI systems remain actively debated. The rapid development of foundation models has intensified these concerns, particularly regarding responsible use, transparency, and the potential for unintended consequences. Governance frameworks capable of keeping pace with technological change while ensuring ethical and equitable application are still underdeveloped (Kolokoussis et al., 2025; Wang et al., 2025).

Finally, the translation of research innovations into sustainable operational systems continues to present significant difficulties. While several GeoAI platforms have demonstrated successful deployment, questions regarding long-term maintenance, institutional integration, workforce capacity, and financial sustainability persist (Guo & Scott, 2026; Nekorchuk et al., 2023). This implementation gap underscores the need for greater attention to organizational and socio-technical factors alongside methodological development.

Collectively, these challenges indicate that the evolution of spatiotemporal hotspot prediction cannot be understood solely in terms of technical progress. Many of the most significant barriers are structural and institutional in nature. Addressing them will require coordinated efforts across methodological innovation, data infrastructure, ethical governance, and operational implementation science.

IV. LIMITATIONS

This State-of-the-Art Review has several limitations that should be acknowledged. The literature search was restricted to English-language publications, which may have excluded relevant studies published in other languages. The review also placed primary emphasis on studies with a United States focus, potentially limiting the generalizability of findings to other geographic and health-system contexts. In addition, the final evidence base comprised 17 validated studies. While these were selected for their direct relevance to the review themes, the relatively modest number constrains the breadth of empirical coverage. Research on foundation models in geospatial health is evolving rapidly, and newer developments may have emerged after the literature search was completed. As a State-of-the-Art Review, the analysis further relies on qualitative synthesis and interpretive judgment rather than formal quantitative meta-analysis. These limitations should be considered when interpreting the findings and the evolutionary narrative presented.

➢ *Future Directions*

Building on current frontier developments, the field is likely to advance along several interconnected trajectories. Continued maturation of geospatial foundation models is expected to form one major line of progress, with particular emphasis on spatially grounded large language models, vision-language geospatial models, and systems capable of multimodal reasoning across textual, visual, environmental, and mobility data. More efficient architectures suitable for operational deployment and improved domain adaptation will further support this trajectory, enabling more sophisticated integration of heterogeneous data sources for hotspot prediction.

A second major trajectory centers on the development of trustworthy public health AI. Efforts to enhance explainability, fairness, and responsible AI governance are expected to intensify, as trust and accountability become increasingly critical for widespread adoption. Research in this area will need to advance privacy-preserving and fairness-aware learning approaches that perform reliably in data-sparse settings, alongside the creation of standardized benchmarks and validation frameworks for geospatial health applications.

A third trajectory focuses on operational public health intelligence. Operational scaling of integrated GeoAI platforms will remain a priority, with greater attention to standardization, interoperability, and long-term institutional sustainability. Progress in this direction will depend on stronger engagement with implementation science, real-time decision support, institutional adoption, and sustainable deployment of predictive systems within routine public health practice. Greater attention to human-AI collaboration mechanisms and frameworks that bridge the gap between promising research models and enduring operational systems will also be essential.

Integration of climate and environmental drivers into predictive models will grow in importance across these trajectories. Collectively, these directions point toward a future in which spatiotemporal hotspot prediction becomes more generalizable, multimodal, operationally embedded, and responsive to both technical capabilities and societal needs.

➢ *Implications for Practice*

Beyond its academic contribution, this review has several implications for public health practice and system design. First, the persistent trade-off between predictive performance and interpretability suggests that operational systems should incorporate explainability mechanisms from the outset rather than as an afterthought. Second, the recurring challenges related to data equity indicate that agencies operating in low-resource settings may benefit from hybrid approaches that combine simpler, more interpretable models with selective use of advanced techniques where data quality permits. Third, the growing convergence of GeoAI and foundation models highlights the importance of investing in data infrastructure, interoperability standards, and workforce capacity alongside algorithmic development. Finally, the implementation gap identified across multiple paradigms underscores the value of treating operational deployment and long-term sustainability as core design considerations rather than secondary concerns.

V. CONCLUSION

The evolution of spatiotemporal hotspot prediction in public health reflects a broader intellectual and methodological transformation, moving from descriptive spatial analysis toward increasingly sophisticated, data-driven, and operationally integrated systems of public health intelligence. Across six major paradigms, the field has achieved substantial advances in predictive capability, multimodal reasoning, and decision support, while simultaneously exposing persistent tensions between predictive performance and interpretability, technological sophistication and equitable accessibility, and methodological innovation and practical implementation.

This State-of-the-Art Review has traced the progression of these paradigms, compared their methodological characteristics, examined emerging frontiers, and identified evidence-supported directions for future development. A central insight arising from this synthesis is that progress has depended not merely on the replacement of earlier approaches by newer ones, but on the cumulative integration of complementary capabilities across paradigms. In particular, the convergence of GeoAI and foundation models signals a transition from isolated predictive tools toward more comprehensive and context-aware systems for public health intelligence.

The future of spatiotemporal hotspot prediction will depend not only on continued advances in artificial intelligence and geospatial analytics, but also on progress in addressing enduring challenges related to data equity, model transparency, governance, and long-term operational sustainability. Ultimately, realizing the full potential of emerging paradigms will require the development of systems that effectively combine predictive intelligence, spatial reasoning, multimodal integration, and human expertise to support more responsive, equitable, and evidence-informed public health action.

REFERENCES

[1]. Aguilar, J., Bassolas, A., Ghoshal, G., Hazarie, S., Kirkley, A., Mazzoli, M. & Sadilek, A. (2022). Impact of urban structure on infectious disease spreading. *Scientific Reports, 12*, 3816. https://doi.org/10.1038/s41598-022-06720-8.

[2]. Ansar, F., Waheed, M. A., Zafar, U., Kolapo, A., Sarfaraz, W., & Rashid, K. (2026). Revolutionizing heart failure management with artificial intelligence: A narrative review of diagnostic, prognostic, and therapeutic innovations. *Health Science Reports, 9*(4), e71855. https://doi.org/10.1002/hsr2.71855.

[3]. Barket, S.-E., Karim, M. R., & Salan, M. S. A. (2025). Bayesian spatio-temporal disease mapping of COVID-19 cases in Bangladesh. *PLOS ONE, 20*(2), e0316621. https://doi.org/10.1371/journal.pone.0316621.

[4]. Guo, C., & Scott, P. (2026). EpiGIS pro: An AI-powered geospatial intelligence platform for integrated disease surveillance and predictive analytics. International Journal of Health Geographics. Advance online publication. https://doi.org/10.1186/s12942-026-00479-1.

[5]. Hu, Y., Zhang, X., Slavin, V., Belsti, Y., Tiruneh, S. A., Callander, E., & Enticott, J. (2025). Beyond comparing machine learning and logistic regression in clinical prediction modelling: Shifting from model debate to data quality. *Journal of Medical Internet Research, 27*, Article e77721. https://doi.org/10.2196/77721.

[6]. Kehkashan, T., Abdelhaq, M., Al-Shamayleh, A. S., Riaz, R. A., Abdullah, M., Ahmed, A. I. A., & Akhunzada, A. (2026). Sustainable and interpretable heart disease prediction: A clinical decision support approach for biomedical healthcare applications. *Scientific Reports*. Advance online publication. https://doi.org/10.1038/s41598-026-37840-0.

[7]. Kolokoussis, P., Mu, L., & Kamel Boulos, M. N. (2025). The generative revolution: A brief introduction. *International Journal of Health Geographics*, *24*(1), Article 7. https://doi.org/10.1186/s12942-025-00392-z.

[8]. Liu, L., Franklin, R., Cheong, J., Cong, T., Byun, J. S., Oh, A. Y., & Torous, J. (2025). H3-MOSAIC: Multimodal generative AI for semantic place detection from high-frequency GPS on H3 grids in mental health geomatics. *International Journal of Health Geographics*, *24*, Article 35. https://doi.org/10.1186/s12942-025-00423-9.

[9]. Liu, L., Huo, C., Beccia, A. L., Richmond, T. K., & Austin, S. B. (2026). Spatial and telehealth accessibility to eating disorder treatment in the United States: Evidence from registry and LLM-augmented data. *International Journal of Health Geographics*. Advance online publication. https://doi.org/10.1186/s12942-026-00474-6.

[10]. Nekorchuk, D. M., Bharadwaja, A., Simonson, S., Ortega, E., França, C. M. B., Dinh, E., Reik, R., Burkholder, R., & Wimberly, M. C. (2023). The Arbovirus Mapping and Prediction (ArboMAP) system for West Nile virus forecasting. *JAMIA Open, 6*(4), ooad110. https://doi.org/10.1093/jamiaopen/ooad110.

[11]. Onyeabor, C. F., & Onyeabor, U. S. (2025). Integrating geospatial technologies and machine learning for monitoring and assessing environmental impacts of mining activities in the South East of Nigeria: A structured review. *FUDMA Journal of Sciences*, *9*(1), 406–422. https://doi.org/10.33003/fjs-2025-0901-3197.

[12]. Paulson, K. R., Fuglstad, G.-A., Li, Z. R., & Wakefield, J. (2026). Temporal models for estimation and short-term forecasting of neonatal mortality rates in sub-Saharan Africa. *The Annals of Applied Statistics*, *20*(1), 322–345. https://doi.org/10.1214/25-AOAS2100.

[13]. Resch, B., Kolokoussis, P., Hanny, D., Brovelli, M. A., & Kamel Boulos, M. N. (2025). The generative revolution: AI foundation models in geospatial health—applications, challenges and future research. *International Journal of Health Geographics*, *24*, Article 6. https://doi.org/10.1186/s12942-025-00391-0.

[14]. Sánchez-Díaz, C. T., Babel, R. A., Iyer, H. S., Goldman, N., Zeinomar, N., Rundle, A. G., Omene, C. O., Pawlish, K. S., Ambrosone, C. B., Demissie, K., Hong, C.-C., Lovasi, G. S., Bandera, E. V., & Qin, B. (2024). Neighborhood archetypes and cardiovascular health in Black breast cancer survivors. *JACC: CardioOncology*, *6*, 405–418. https://doi.org/10.1016/j.jaccao.2024.04.007.

[15]. Sayeed, A., Gupta, P., Henderson, B., Kondragunta, S., Zhang, H., & Liu, Y. (2025). GOES-R $PM_{2.5}$ evaluation and bias correction: A deep learning approach. *Earth and Space Science, 12*(2), e2024EA004012. https://doi.org/10.1029/2024EA004012.

[16]. Wang, Z., Li, M.-H., Baxter, P., Zhorayev, O., Wei, J., Kovacs, V., Zhao, Q., Yang, C., & Koizumi, N. (2025). Implementing large language model and retrieval augmented generation to extract geographic locations of illicit transnational kidney trade. *International Journal of Health Geographics*, *24*, Article 10. https://doi.org/10.1186/s12942-025-00397-8.

[17]. Ward, C., Brown, G. D., & Oleson, J. J. (2023). Incorporating infectious duration-dependent transmission into Bayesian epidemic models. *Biometrical Journal, 65*(3), e2100401. https://doi.org/10.1002/bimj.202100401.