Geolocating Social Media for Crisis Management: A Systematic Literature Review

Anshuman Rangaraj
University of Cincinnati
rangarar@mail.uc.edu

Charishma Nadipalli
University of Cincinnati
nadipaca@mail.uc.edu

Rob Grace
University of Cincinnati
rob.grace@uc.edu

Muhammad Imran
Qatar Computing Research Institute
Hamad Bin Khalifa University
mimran@hbku.edu.qa

ABSTRACT

To assess the state of social media geolocation research and inform its application to crisis management, we conducted a systematic literature review of 46 peer-reviewed studies published between 2020–2024. These studies establish a pre-generative AI baseline for understanding how emerging large language model (LLM) approaches may extend geolocation capabilities. Our review reveals inconsistently defined geolocation inference goals and spatial resolution targets, a predominant—though not universal—focus on Twitter/X, and goal-contingent uses of methods and data sources that constrain operational applicability in crisis contexts. Synthesizing these findings, we introduce a standardized conceptual framework for classifying geolocation inference goals and spatial resolutions, enabling consistent comparison across existing and LLM-based approaches. We conclude by highlighting the need and opportunities to align social media geolocation research with operational needs and requirements in crisis management contexts.

Keywords

Geolocation, social media, geographic information systems, emergency management.

INTRODUCTION

Social media is a critical information source for crisis management professionals, providing real-time information about unfolding events, emerging risks, and affected populations and their information needs (Purohit et al., 2025; Reuter & Kaufhold, 2018). Using platforms such as Facebook, Instagram, Weibo, and X/Twitter, citizens post and organize information about crisis impacts and needs (Chauhan & Hughes, 2018; Herrera, 2021), producing rich, multimodal data that can be gathered and analyzed at scale to support situational awareness and decision-making (Li et al., 2018). However, for crisis management professionals, including local emergency services, emergency management agencies, and humanitarian organizations, the value of social media hinges on accurately inferring *where* crisis impacts and impacted people are located (Zade et al., 2018).

In practice, most social media posts lack explicit geographic metadata, sharply limiting their direct use for spatial analysis in crisis contexts (Carley et al., 2016; Morstatter et al., 2013; Wang et al., 2016). Reliance on geotagged content alone introduces systematic bias, as geotagging behavior varies across regions, demographics, and crisis-related posting (Hecht & Stephens, 2014; Huang & Carley, 2019). Even when geotags are present, their validity depends on the inference goal: users frequently post about remote events—especially during crises—leading to eyewitness biases when geotags are treated as ground truth (Crampton et al., 2013; Grace, 2021; Robertson & Feick, 2018). Together, these limitations make geolocation inference using multimodal spatial cues essential for the actionable use of social media, both with and without native geographic coordinates.

In response, researchers have developed rule-based, machine and deep learning, graph-based and hybrid approaches methods to geolocate social media using heterogeneous inputs such as text, metadata, images, and social networks (Ajao et al., 2015; Jurgens et al., 2015; Hu et al., 2023; Luo et al., 2020; Singh et al., 2019; Xu et al., 2020; Zheng et al., 2018). This pre–large language model (pre-LLM) literature shows that large-scale geolocation can support a range of crisis management objectives (Imran et al., 2020). However, despite methodological progress, this body of work remains fragmented and inconsistently aligned with crisis-management requirements. Specifically, existing approaches:

- **Focus primarily on Twitter/X**, reflecting historical data access rather than the diverse platforms people use during crises (Ajao et al., 2015; Jurgens et al., 2015; Zheng et al., 2018);
- **Frame geolocation tasks in method-centric terms** (e.g., city-level classification) without explicitly defining the underlying inference goal and target spatial resolution (e.g., locating a place mentioned in a social media post versus the geographic origin of the post), making it difficult to determine whether different techniques are addressing the same problem and hindering alignment with application-specific requirements (Imran et al., 2020; Singh et al., 2019; Zade et al., 2018);
- **Lack a conceptual framework** for systematically defining and distinguishing inference goals and associated spatial resolutions, making it difficult to compare studies, aggregate findings, or establish benchmarks across heterogeneous approaches (Johnson et al., 2016; Zheng et al., 2018).

It thus remains unclear which techniques address specific inference goals, spatial resolutions, platforms, and data sources. Meanwhile, LLMs now offer capabilities well suited to crisis geolocation (Hu et al., 2023; Yin et al., 2025), but applying them without synthesizing prior methods risks perpetuating conceptual inconsistencies and neglecting pre-LLM advances. Clarifying inference goals and evaluation criteria to organize both pre-LLM and LLM-based approaches is therefore essential for advancing research that deploys social media geolocation to meet defined operational crisis-management needs.

To address these gaps, we conduct a systematic review of 46 peer-reviewed studies (2020–2024) that introduce and evaluate social media geolocation methods. We classify studies by geolocation goal, input sources, spatial resolution, and model family, and propose a conceptual framework to compare approaches and identify opportunities for applying both pre-LLM and LLM-based methods in crisis management.

METHODS

We conducted a systematic literature review of social media geolocation methods, identifying studies that infer the locations of events, users, and posts. Throughout the review process, the authors worked collaboratively, iteratively resolving disagreements that arose during the study identification, selection, and classification steps. Following PRISMA guidelines (Sarkis-Onofre et al., 2021), we describe this process, beginning with our research questions, selection process, data extraction, and classification procedures.

Research Questions

1. What geolocation inference goals are addressed in social media geolocation research?
2. What methods are used to infer locations from social media?
3. Which social media platforms and data sources are used for geolocation?
4. What spatial resolutions do studies achieve?

Study Selection Process

We identified 46 studies for inclusion in the study based on the following three-phase study selection process:

Identification*:* Using the query (geolocat* AND "social media"), we identified records from Scopus (n=354) and Web of Science (n=233). Excluding records which were not English-language conference and journal articles published between 2020-2024 (n=597), and removing duplicates (n=204), we identified 383 records for screening (Figure 1).

Initial screening (abstract only): We screened 383 abstracts and excluded records that (E1) did not mention a social media geolocation method (n=64) or (E2) did not introduce a geolocation inference method (n=229), such as studies analyzing pre-geolocated data or relying solely on native geotags. This yielded 90 records for full review. Although motivated by crisis management, we did not limit the corpus to crisis contexts. Instead, we focus on methodological inference goals (e.g., locating a described event) and spatial resolutions, including general-purpose studies with transferable approaches. Organizing methods by goal and resolution enables alignment with operational crisis management requirements.

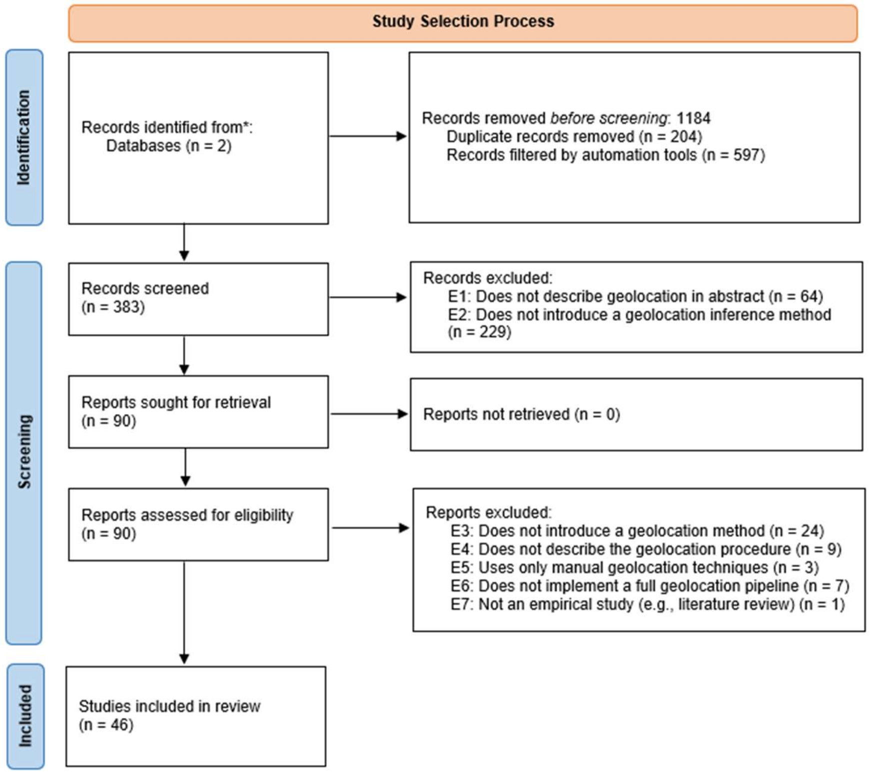

Figure 1. Study selection process

Eligibility screening (full text): In the second screening round, we reviewed 90 full-text articles and excluded studies that: (E3) did not introduce a geolocation method (n=24); (E4) did not describe the procedure or data sources (n=9); (E5) relied solely on manual geolocation (n=3); (E6) did not implement a full pipeline linking social media data to geographic coordinates (n=7); or (E7) were non-empirical (n=1). This process yielded 46 studies for inclusion.

Data Extraction and Classification

We analyzed the 46 included studies by extracting and classifying key attributes of their geolocation methods to answer our four research questions.

Goals: We coded each study's geolocation goal as the stated objective guiding its design (e.g., predicting a user's home location, reconstructing post locations), based on problem formulation rather than application domain. Because prior work lacks a consistent typology, we developed an iterative classification scheme that synthesizes goal framing across studies. We define geolocation as the task of inferring a geographic location, regardless of whether it refers to a place, event, user, or other entity. We identify five goal categories: mentioned, implicit, user, post, and eyewitness geolocation.

Platform: We identified the social media platform from which data was obtained, including X/Twitter, BrightKite, Facebook, Flickr, Foursquare, Instagram, Reddit, Sina Weibo, and YouTube.

Data Source: The type of social media data used for inferring the geolocation target. We classified the following data sources:

- *Text*: Includes the content of user posts, including timelines or message histories.
- *Profile*: Information explicitly stated in a user's profile. May include self-reported location, bio keywords, or language preferences.
- *Metadata*: Non-geotag information attached to posts, such as timestamps, user UTC offset, user time zone, user account creation time, etc.
- *Images*: Images shared in posts. Location may be inferred from visual recognition (e.g., landmarks) and text extracted from images such as street sign information (Gu et al., 2022).

- *Network*: Social connections or interactions, such as friends, followers, mentions, and/or retweets.

Resolution: To standardize how spatial precision is reported across studies, we classified geolocation resolution into five distance-based bins derived from how locations were represented or evaluated in each paper:

- *Point*: Coordinate-level or address-level geolocation with precision finer than 100 m.
- *Neighborhood*: Local-area geolocation between 100 m and 1 km (e.g., neighborhoods, districts).
- *Municipal*: City- or municipality-level geolocation between 1 km and 25 km.
- *Regional*: Coarse geolocation exceeding 25 km (e.g., counties, provinces, multi-city regions).
- *Unclear*: The spatial resolution cannot be confidently classified into a single distance bin based on reported evidence, or the study reports multiple resolutions without specifying how they are used or evaluated.

When resolution was implied rather than explicitly stated, classification relied on descriptions of ground truth labels, evaluation metrics, or application context.

Method: We classified each paper by model family, defined as the general methodological paradigm for producing the location output, excluding minor preprocessing or post-processing steps. Model families were operationalized as follows:

- *Rule-Based:* Deterministic inference using handcrafted rules, gazetteer matching, regular expressions, or heuristic scoring without model training.
- *Machine Learning:* Supervised or unsupervised classical machine learning (ML) over manually engineered features (e.g., TF-IDF, n-grams) using algorithms such as SVM, logistic regression, Random Forest, KNN, or K-means.
- *Deep Learning*: Neural networks trained via gradient-based optimization that learn representations automatically, including CNNs, RNNs, LSTMs, transformer encoders (e.g., BERT when fine-tuned), and graph neural networks.
- *Graph-Based:* Inference driven primarily by non-neural relational network structure (e.g., label propagation, random walk, community detection, homophily-based inference).
- *LLM:* Inference relying primarily on pretrained generative transformer models via prompting (e.g., GPT-style zero-shot or few-shot reasoning) rather than task-specific training.
- *Hybrid:* Integration of two or more of the above model families that are both required for geolocation inference.

We use these high-level model family categories to support systematic comparison across heterogeneous technical approaches while keeping our primary focus on geolocation goals rather than architectural detail. We do not develop a fine-grained taxonomy, as comprehensive method surveys already exist for specific tasks such as user geolocation (Xu et al., 2020; Luo et al., 2020) and mentioned-place extraction (Hu et al., 2023).

RESULTS

In this section, we describe the goals, approaches and data sources, methods of location extraction and inference, and evaluation strategies of the 46 reviewed studies.

Geolocation Goals and Methods

Figure 2 summarizes the frequency of the geolocation goals and methods observed among the 46 reviewed studies. These goals include:

Mentioned geolocation (n=9) aims to infer locations that users explicitly name in social media posts. In these studies, geolocation is operationalized as extracting explicit spatial references from post content, typically toponyms or named entities, and linking them to geographic coordinates. For example, Espinosa et al. (2022) infer locations of symptomatic individuals and mass gatherings by extracting toponyms from X/Twitter posts to detect public health threats. Elsewhere, Osorio-Arjona et al. (2021) extract and geocode metro station names from non-geotagged tweets to analyze the experiences Madrid Metro commuters. Across these studies, mentioned-location geolocation relies on explicit place references (toponyms and named entities), with accuracy contingent on correct extraction and disambiguation.

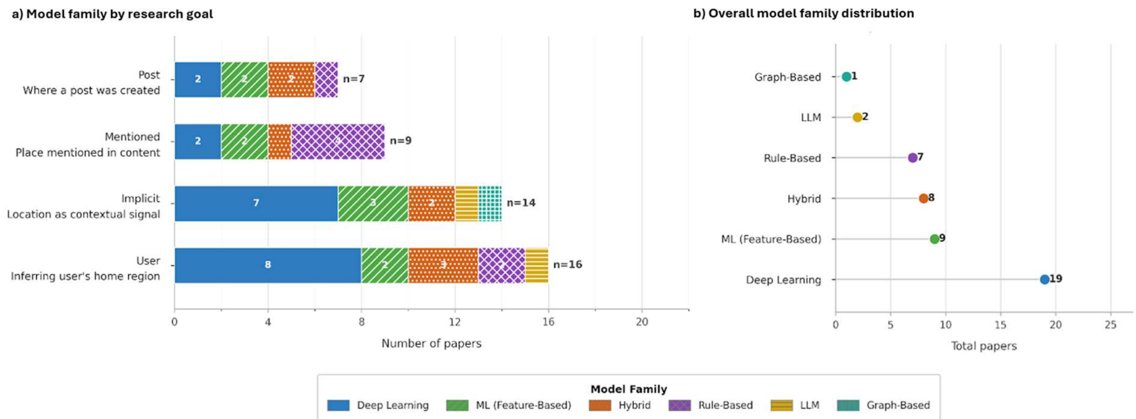

Figure 2. Goals and methods of social media geolocation in the reviewed papers

Implicit geolocation (n=14) aims to infer a location not explicitly named in a social media post using cues such as semantic context, descriptive language, or visual features extracted from images. Several studies infer event locations from multimedia content. Panagiotopoulos et al. (2022) define image geolocation as inferring GPS coordinates from visual elements alone. Others use implicit geolocation for misinformation detection by verifying whether images correspond to a claimed place (Lucas et al., 2022). In this work, geolocation depends on recognizing multimodal cues that imply location without explicitly naming it. As Zhang et al. (2022) note, location prediction requires capturing words that indicate place. Implicit geolocation is thus defined by the absence of explicit toponyms and reliance on multimodal inference.

User geolocation (n=16) aims to infer home or resident location of users or, less often, trace their movements over a specified timeframe. These methods typically rely on long-term posting activity rather than the content and/or metadata of individual posts. These methods typically operate at coarse spatial resolutions, often the city level. Zheng et al. (2020) infer user locations by jointly modeling post content and social networks, treating geolocation as a user-level task based on aggregated behavior rather than individual posts. Similarly, Meteriz-Yildiran et al. (2024) demonstrate that limited workout metadata (e.g., elevation profiles) can predict a user's home city with high accuracy, underscoring associated privacy risks.

Post geolocation (n=7) aims to infer the location from which a media post was uploaded. This goal targets where users make individual social media posts, distinguishing it from user geolocation, which infers a user's residence or habitual location (e.g., home city). Several studies define post geolocation as inferring where content was created. Mostafa et al. (2020) describe tweet location as "the place where a user posts his tweet," while Li et al. (2023) define it as estimating the originating location of posts for applications such as emergency response. However, many studies do not clearly distinguish posting location from locations referenced in content, obscuring the underlying inference task. Some acknowledge but analytically collapse this distinction; for example, Dimitrov et al. (2022) compare user- and post-level models by assigning users' home locations to individual tweets.

Eyewitness geolocation (n = 0) aims to infer both (a) the mentioned or implicit location a post refers to and (b) the location from which the post was made, with the additional requirement that these locations are co-located. This goal integrates mentioned/implicit and post/user geolocation to verify that content originates from on-the-ground presence at the referenced location. Although several studies invoke social media users as eyewitnesses, none satisfied both criteria. For instance, Peng and Zhang (2024) describe Sina Weibo users as "social sensors" and extract toponyms and event times to identify flooding locations, but they do not infer posting locations or verify co-location between the user and the referenced event. Their study therefore addresses implicit event geolocation rather than eyewitness geolocation as defined here.

Platforms and Data Sources

Overall, 34 (74%) of 46 studies geolocated social media posted on Twitter/X, while 19 (41%) utilized another platform. Only three studies analyzed data from multiple platforms (Li & Chen, 2024; Fiallos, 2025; Zhang et al., 2022). However, different platforms appeared across geolocation goals:

- *Mentioned:* Twitter/X (8), Facebook (1), PTT Bulletin Board System (1)
- *Implicit:* Twitter/X (6), Flickr (3), Facebook (1), Foursquare (1), Instagram (1), Reddit (1), Weibo (1), Unknown (2)

- *User:* Twitter/X (13), Brightkite (1), Runkeeper (1), Instagram (1), YouTube (1), Weibo (1)
- *Post*: Twitter/X (7), Flickr (1)

These platform distributions align with the types of data available on each platform and can be directly compared to the data sources leveraged for each geolocation goal.

Figure 3 displays the data sources used across geolocation goals. Across all studies (n=46), text is the dominant data source for all geolocation goals—used in all Mention (9/9) and Post (7/7) studies, and in the majority of User (13/16) and Implicit (10/14) studies—while network, user profile, metadata, and images are used inconsistently, often for specific goals. Over half of the studies (n=25) rely on a single data source. These single-view studies overwhelmingly use text across geolocation goals, while Implicit geolocation studies split between text and images (4/8 each), and User geolocation studies occasionally rely on network, user profile, or metadata signals. Lastly, multi-view studies (n=21) utilize multiple data sources. These studies all use text (21/21), but use of network data is concentrated in User geolocation studies (6/8) and nearly absent elsewhere. Post geolocation studies show the strongest reliance on metadata (5/6) and substantial user profile use (4/6), while network and image data are entirely absent in this group

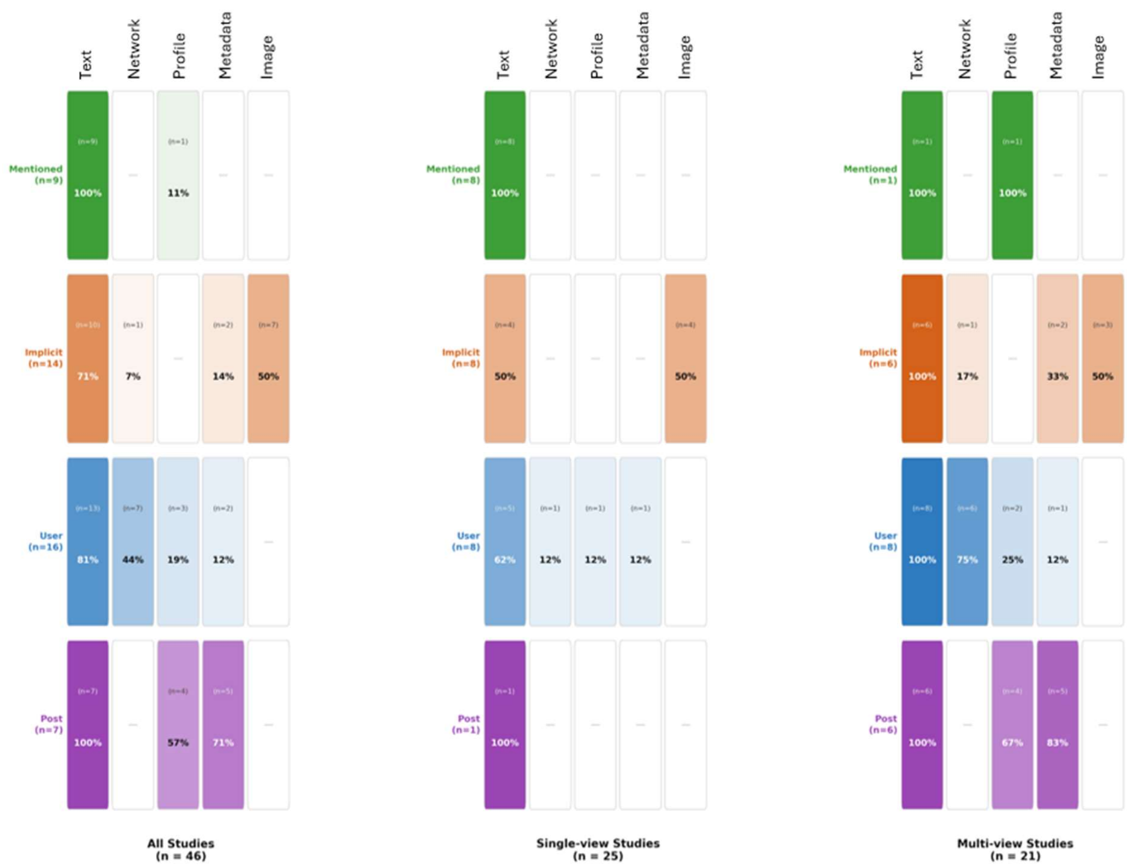

Figure 3. Data sources used across geolocation inference goals

Geolocation Resolution

Figure 4 displays the spatial resolution span achieved by studies by geolocation goal. Spatial resolution span captures the range between the finest and coarsest geographic outputs supported by a method, reflecting the breadth of spatial inference it enables rather than its accuracy. As Figure 4 shows, most approaches target a fine-grained prediction, but fall back to coarser levels when available data is sparse. While mentioned geolocation studies tend to achieve the highest spatial resolution across the geolocation goals, these approaches also have broad spatial resolution spans, returning locations that range from fine-grained points of interest (<100m) to course-grained regions (<25km). In contrast, user geolocation studies have narrow spatial resolution spans, but typically return course-grained locations at the city or regional-levels as the inferred home locations of social media users.

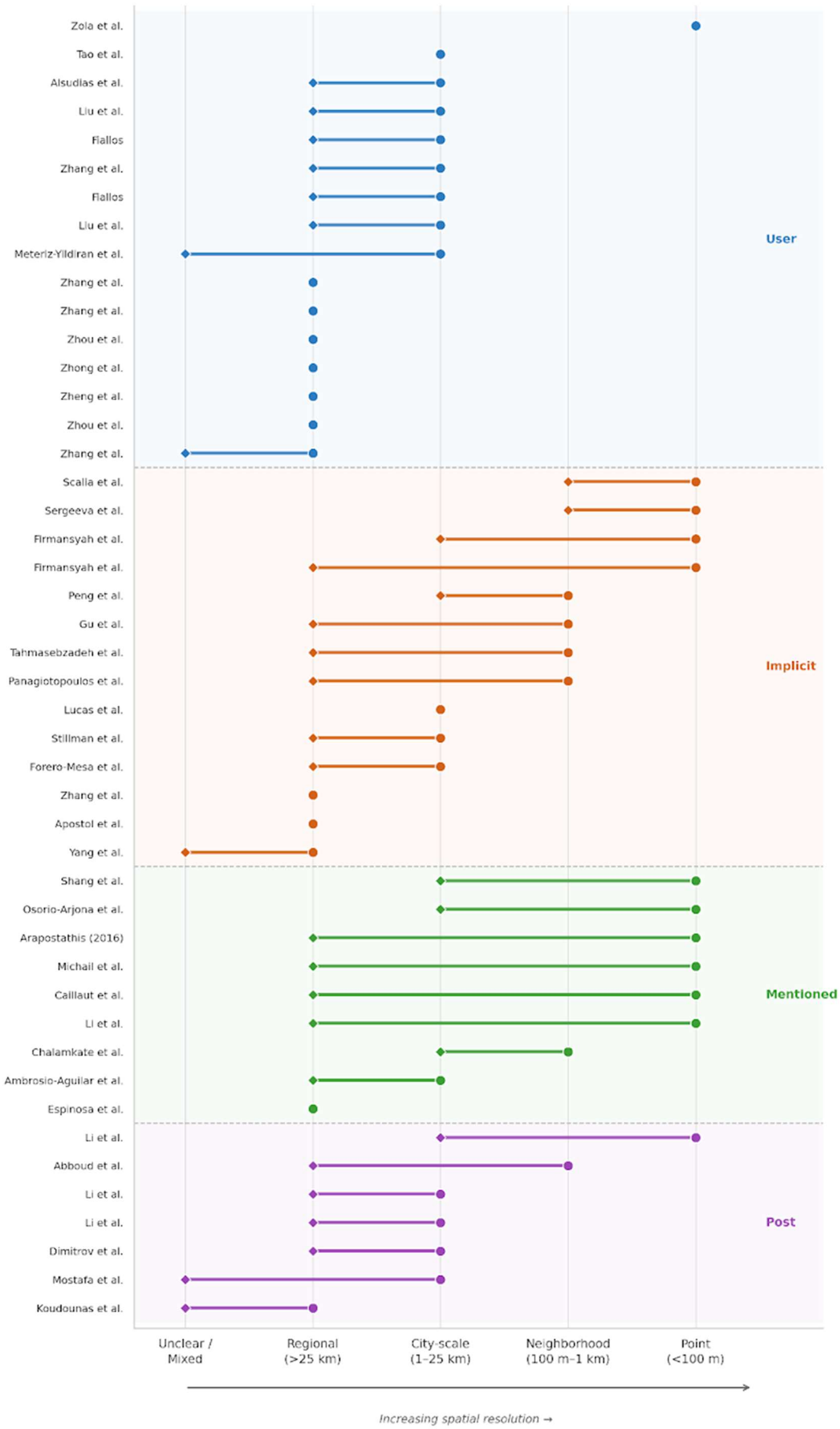

Figure 4. Spatial resolution range of geolocation studies by goal.

DISCUSSION

In contrast to prior method-specific surveys Ajao et al., 2015; Jurgens et al., 2015; Hu et al., 2023; Luo et al., 2020; Singh et al., 2019; Xu et al., 2020; Zheng et al., 2018), this SLR introduces a standardized framework for social media geolocation goals and spatial resolution classes to clarify what location is being inferred and at what spatial scale. Developing this framework based on a synthesis of studies published between 2020-2024, we summarize our findings for our research question below:

- *Geolocation goals (RQ1):* Studies attempted to accomplish four distinct geolocation goals—Implicit (14), User (16), Mentioned (9), and Post (7). Notably, some studies suggested the geolocation of "eyewitness" but lacked methods to co-locate both the location explicitly or implicitly referenced in a social media post and the location where the message was posted and/or the user resides.
- *Methods (RQ2):* Methods tend to be goal-contingent: Deep learning dominates overall (19/46), especially for User (8/16) and Implicit (7/14) geolocation, whereas Mentioned geolocation still relies heavily on rule-based pipelines (4/9). LLM methods are rare (2/46) in the study period, appearing only in Implicit and User geolocation studies.
- *Platforms & Data sources (RQ3):* The field remains Twitter/X-centric (34/46; 74%), predominantly text-reliant (39/46; 85%), and frequently single-view (25/46; 54%). Non-text sources—network, user profile, metadata, and images—are used selectively for specific geolocation goals, rather than commonly integrated in multimodal and multi-view approaches.
- *Spatial resolution (RQ4):* Geolocation inference methods commonly target fine-grained outputs at the point of interest (12/46; 26%) or neighborhood (6/46; 13%) levels but fall back to coarser resolutions when data is sparse (e.g., city and regional levels), reflecting a persistent tradeoff between spatial resolution and coverage. Mentioned geolocation studies achieve the finest resolutions yet exhibit broad spans (point of interest to regional outputs), whereas User geolocation studies typically return municipal or regional home locations with narrower spans.

Overall, the review highlights the field's attempts to address different geolocation problems, while revealing patterns across geolocation goals: persistent focus on Twitter/X shaped by historical data access constraints, uneven integration of multimodal data sources, and ongoing tradeoffs between fine-grained spatial resolution and social media coverage.

Implications for Crisis Management

In crisis management, social media can support multiple operational functions, including damage assessment (identifying and mapping physical impacts to infrastructure and communities), rapid needs assessment (detecting and locating requests for assistance and unmet humanitarian needs), and public response monitoring (analyzing how communities react to hazards and official communications) (Imran et al., 2020). Realizing these functions requires geolocation methods that are explicitly designed around operational decision needs rather than abstract inference tasks.

Aligning Inference Goals with Operational Goals

Our review shows that existing geolocation inference goals—mentioned, implicit, user, post, and eyewitness—must be deliberately mapped to operational goals in crisis management. Prior surveys scope research according to particular inference goals (Xu et al., 2020; Zheng et al., 2018) and methods (Hu et al., 2023), treating inference goals as isolated, self-contained technical tasks divorced from applied needs. Instead, research aiming to apply geolocate social media for crisis management must explore combinations of inference goals and methods in hybrid configurations that align with specific operational objectives. For example, damage assessment likely requires both mentioned and implicit geolocation to capture reports of impacts that include and lack explicit place names, respectively. Rapid needs assessment may require post geolocation and user geolocation to contextualize population vulnerability and mobility. Because multiple model families can achieve each inference goal, operational alignment likely necessitates hybrid inference goals and hybrid methods that expand accuracy and coverage.

Importantly, we observe that studies suggest approaches for locating eyewitnesses when developing inferencing methods that only identify locations that users' mention or implicitly reference in social media content, not the poster's physical location at the time of posting or home residence. These studies can imply that users post about co-located events—an assumption we characterize as *eyewitness bias* or "subject-object displacement" (Robertson & Feick, 2018). For example, Gu et al. (2022) rely exclusively on visual features to geolocate images yet describe their task as identifying where tourists "take" photos. Firmansyah et al. (2023) infer locations from image-extracted text to map disaster impacts when attempting to infer "the location where the images were taken" (p. 71). Sergeeva et al. (2022) set for themselves a post geolocation goal to infer locations "related to the social network post when the user posted it," but operationalize the geolocation task as reconstructing locations depicted in Instagram content using OpenStreetMap data (p. 410). As Caillaut et al. (2024) emphasize, distinguishing between direct and indirect witnesses is critical in crisis management contexts. Without explicitly establishing user co-location, referent geolocation cannot be assumed to support operational goals such as locating requests for assistance. In this sense, our review frequently observed eyewitness bias across studies, yet identified no papers that explicitly articulated eyewitness geolocation as a distinct inference goal. This pattern underscores a misalignment between academically defined geolocation inference goals and the operational requirements of crisis management.

Aligning Spatial Resolution with Operational Requirements

Our review further suggests that aligning spatial resolution targets with operational requirements must be deliberate rather than incidental. Spatial resolution is not merely a performance characteristic; it determines the actionability of geolocated outputs in operational contexts (Zade et al., 2019). Target resolution must match the requirements extracted from operational uses cases context: long-term public response monitoring may tolerate coarse regional estimates, whereas emergency dispatch operations require point-of-interest precision.

However, resolution alignment also requires attention to *target-resolution coverage*. Across the reviewed studies, spatial resolution spans often range from fine-grained to extremely coarse outputs. While this breadth improves overall geolocation coverage, it also means that approaches often cannot consistently produce outputs at the resolution required for specific crisis use cases. High accuracy at coarse resolution or sporadic fine-grained outputs stand to limit operational effectiveness. Building on prior calls to report coverage (Jurgens et al., 2015), we suggest that applied geolocation research should explicitly evaluate the proportion of social media posts or for which a method produces outputs at a targeted spatial resolution, which should be aligned with crisis responders' operational requirements for actionable information. Without adequate target-resolution coverage, even sophisticated models remain ineffective for many crisis management applications.

Across the ten crisis management studies included in the review, most studies (7/10) target fine-grained, point-level resolution (<100 m), reflecting an ambition to support crisis-relevant spatial specificity (e.g., Firmansyah et al., 2023, 2024; Scalia et al., 2022; Arapostathis, 2021). However, target-resolution coverage within these studies is typically wide, often degrading from point- to regional-level outputs (>25 km) under sparse or ambiguous data conditions. Only CIME (Scalia et al., 2022) constrains coverage between point and neighborhood levels (100 m–1 km), while systems such as Epitweetr (Espinosa et al., 2022) and ContCommRTD (Apostol et al., 2024) operate at coarse, regional resolutions for population-level monitoring. Taken together, these findings suggest that while prior studies demonstrate progress in fine-grained geolocation under certain conditions, their target-resolution coverage likely degrades under real-world conditions and, as a result, their operational utility falls short of the spatial resolution thresholds—such as street- or neighborhood-level precision—that often make information actionable for responders (Zade et al., 2019).

Implications for LLM-Based Geolocation

These alignment challenges are particularly salient as LLM-based geolocation methods emerge. LLMs offer capabilities well suited to crisis contexts, including interpreting informal and multilingual text, reasoning over implicit spatial references, and integrating multimodal cues. However, without explicit alignment between inference goals and operational objectives, LLM-based approaches risk reproducing the same conceptual ambiguities observed in pre-LLM research—particularly conflating referent and posting location or optimizing for geolocation goal and/or method-centric geolocation accuracy without regard to operational requirements.

In this respect, the framework introduced in this review provides initial scaffolding for structuring existing methods and LLM-based geolocation more deliberately. By distinguishing inference goals (e.g., mentioned, implicit, user, post, and eyewitness) and formalizing spatial resolution classes, we create a basis for mapping model capabilities to operational tasks. For crisis applications, LLM-based systems should therefore be designed around inference goals explicitly linked to use cases and evaluated against deliberate spatial resolution targets and target-resolution coverage thresholds tied to operational requirements. Such research can make previously un-geolocated social media content actionable while also identifying misleading or incorrectly geolocated content that may distort situational awareness. Aligning inference goals and spatial resolution with operational use cases supports verification of place-based claims, as reflected in studies targeting misinformation (e.g., Apostol et al., 2024; Lucas et al., 2022).

LIMITATIONS

This study has several limitations. First, the review is temporally bounded to publications from 2020–2024 and therefore does not capture earlier foundational work or the most recent advances. Additionally, our search strategy relied on a relatively narrow query ("geolocat* AND social media"), which may have excluded relevant studies that use alternative terminology. Second, we focus on general geolocation inference approaches in both crisis and non-crisis contexts, rather than reviewing applied research organized around specific operational tasks (e.g., damage assessment or rapid needs assessment). As a work-in-progress paper, we do not provide exhaustive technical detail for each method. Importantly, the scope of the review does not include systematic evaluation of model performance. Future research can build on the inference goal and resolution framework introduced here to compare, benchmark, and evaluate geolocation approaches in relation to operational requirements. This also requires more explicit and context-sensitive definition of those requirements, which vary across responder agencies and missions, shift across mitigation, preparedness, response, and recovery phases, and must account for infrastructure constraints and platform biases that overrepresent younger, urban users and organizational accounts (Hecht & Stephens, 2014; Huang & Carley, 2019; Grace, 2021; Shelton et al., 2014).

CONCLUSION

To assess the state of social media geolocation research and inform its application to crisis management, we reviewed 46 peer-reviewed studies published between 2020–2024, establishing a pre-generative AI baseline. The review identifies inconsistently defined inference goals, variable spatial resolution targets, and platform- and method-contingent designs that limit operational applicability. In response, we introduce a standardized framework for classifying geolocation inference goals and spatial resolutions, enabling consistent comparison across pre-LLM and emerging LLM-based approaches and advancing alignment with crisis management requirements.

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