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From Snow's map of cholera transmission to dynamic catchment boundary delineation: current front lines in spatial analysis

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The history of mapping infectious diseases dates back to the 19th century when Dr John Snow utilised spatial analysis to pinpoint the source of the 1854 cholera outbreak in London, a ground-breaking work that laid the foundation for modern epidemiology and disease mapping (Newsom, 2006). As technology advanced, so did mapping techniques. In the late 20th century, geographic information systems (GIS) revolutionized disease mapping by enabling researchers to overlay diverse datasets to visualise and analyse complex spatial patterns (Bergquist & Manda 2019; Hashtarkhani *et al.*, 2021). The COVID-19 pandemic showed that disease mapping is particularly valuable for optimising prevention and control strategies of infectious diseases by prioritising geographical targeting interventions and containment strategies (Mohammadi *et al.*, 2021). Today, with the aid of high-resolution satellite imagery, geo-referenced electronic data collection systems, real-time data feeds, and sophisticated modelling algorithms, disease mapping has become a feasible and accessible tool for public health officials in tracking, managing, and mitigating the spread of infectious diseases at global, regional and local scales (Hay *et al.*, 2013).

The visual representation of disease occurrences on geographical maps provides a powerful analytical tool to discern their spatial distribution. This approach is pivotal for identifying clusters, hotspots and emerging trends as well as for investigating drivers of transmission (Firouraghi *et al.*, 2023). When incorporating the temporal dimension, invaluable insights into disease dynamics are revealed (Kiani *et al.*, 2021). Furthermore, mapping technology can be used to investigate potential associations between the occurrence of infectious diseases and a wide array of spatially heterogeneous indicators such as natural and built environments, socio-cultural and socioeconomic elements, vectors and animal reservoirs (Mohammadi *et al.*, 2023). All these factors play significant roles in shaping the dynamics of infectious diseases (Yantzi *et al.*, 2019),with the socioeconomic indicators adding the critical facet of access to healthcare resources (Tizzoni *et al.*, 2022). One of the most crucial points to bear in mind when employing spatial regression models to discern connections between infectious disease outcomes (such as prevalence or incidence) and spatially heterogeneous indicators is that these analyses can only establish 'associations' and should not be construed as indicating 'cause and effect' relationships.

By integrating the intricate interplays of environmental, socioeconomic, built environment and socio-cultural factors, mapping of infectious diseases affords a comprehensive understanding of disease transmission patterns, enabling more effective public health responses and targeted interventions. This holistic approach equips researchers and public health officials with a robust framework for formulating tailored strategies to control and prevent infectious diseases. Various types of maps have different utility in the field of infectious diseases epidemiology. Cluster and hotspot maps provide a visual representation of high-risk areas in terms of disease occurrence across geographical regions (Wangdi *et al.*, 2022), while choropleth maps use colour gradients to represent disease intensity, which allows a clear visualization of disease burdens in different areas (MohammadEbrahimi *et al.*, 2022). Heat maps employ colour intensity to highlight areas with higher disease concentration, providing a smooth perspective of disease distribution (Fagerlin *et al.*, 2017). Additionally, thematic maps overlay disease data with environmental, socioeconomic, or demographic factors, offering insights into potential drivers of disease transmission (Talbi *et al.*, 2020). Flow maps, on the other hand, illustrate the movement of people, goods or vectors, aiding in understanding the spread of infectious agents (Ponce-de-Leon *et al.*, 2021). By incorporating the time dimension, they reveal patterns crucial for tracking disease trends and outbreaks over time (Firouraghi *et al.*, 2022). As pointed out by Mohidem *et al.* (2021), interactive web-based maps enhance decision-making by allowing users to explore and analyse disease data in real-time and filter data by subpopulations of interest, e.g., age and sex. Overall, the diverse range of maps and their applications in infectious diseases epidemiology provide vital tools for researchers, policymakers

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and public health officials in formulating more geographically targeted strategies for disease control and prevention.

Disease mapping and spatial analytics can be conducted at different levels of spatial resolution. For example, catchment area analysis goes beyond predefined geographical boundaries, delving into more intricate dynamics of disease transmission compared to regional-level analysis (Huber *et al.*, 2022). Catchment areas defined by travel time or distance can help delineate transmission zones and the potential reach of an outbreak. From that point of view, responses can be instrumental for understanding the potential extent and pattern of an outbreak, allowing the implementation of targeted interventions to contain spread. In addition, these methods aid in the efficient allocation of healthcare resources. By identifying areas with higher disease burdens, authorities can strategically deploy medical personnel, supplies and facilities where they are most needed. Finally, measuring spatial accessibility to healthcare services to ensure equitable access to those services is a key application of catchment area analysis (Mohammadi *et al.*, 2021, Pereira *et al.*, 2021).

Mapping infectious diseases presents several notable challenges. A key obstacle is the potential limitation with respect to availability and quality of data in resource-constrained regions. Spatial sampling methods represents another consideration as it provides a structured approach to gathering data points across geographical areas and ensures that the spatial distribution and number of data points are appropriate for answering the research question posed. For example, determining an appropriate sampling strategy involves considerations of spatial representativeness, ensuring that sampled locations adequately capture the diversity of the landscape. Additionally, logistical constraints and resource limitations may pose hurdles in the implementation of rigorous spatial sampling protocols. Leveraging advanced modelling techniques, such as geostatistics and machine-learning algorithms, predictive risk mapping enables the extrapolation of disease risk estimates to unsampled locations, offering a comprehensive view of disease distribution across entire landscapes (Restrepo *et al.*, 2023). This approach proves invaluable in ensuring that even regions with limited or no direct data contribute to a holistic understanding of disease dynamics.

Sharing and integration of data across different jurisdictions is not as straightforward as one would wish as privacy concerns and legal regulations often hinder this approach. One solution can be jittering of the data for visualisation purposes but keeping the original data for modelling (Helderop *et al.*, 2023). The dynamic nature of infectious diseases poses another challenge, as factors like changing population densities, human mobility, and evolving pathogens and vectors require continuous data updates and sophisticated modelling techniques. Furthermore, biases in healthcare access and reporting can lead to underestimations or misrepresentations of disease burdens, skewing the accuracy of maps. Inaccurate geospatial information or errors in mapping techniques can also introduce uncertainties. Moreover, the complexity of interactions between environmental, socioeconomic, and cultural determinants demands multidisciplinary expertise for meaningful interpretation, and the geographical scale of the data is always a challenge for researchers, especially in modelling approaches such as multilevel modelling, where a different geographical scale in the hierarchical structure of the data might change the results (Owen *et al.*, 2015). Finally, the task of accurately defining catchment areas is not without hurdles. Considerations such as transportation infrastructure, socioeconomic disparities, and healthcare accessibility might need to be weighed. Emerging techniques, including gravity models and network-based analyses, are poised to better represent real-world scenarios (Kiani *et al.*, 2021). However, there will be greater opportunities for catchment level analysis in the future because of the strong possibility of better data availability. Indeed, the fusion of real-time data streams, machine-learning algorithms and dynamic modelling techniques promises more refined analyses leading to integration of socio-behavioural factors, climate data and genomic information. There is no doubt that our comprehension of infectious disease dynamics within catchment areas will rise further already in the near term.

In an era marked by unprecedented challenges in infectious disease prevention and control, the marriage of infectious disease mapping and catchment area analysis stands as one important tool. Through sophisticated mapping and dynamic catchment boundary delineation, the intricate tapestry of pathogens and populations can be highlighted and explored at higher spatial resolutions. However, as we navigate this terrain, we must remain vigilant in addressing disparities, adapting methodologies and embracing innovative technologies. By doing so, we pave the way for a more resilient and responsive public health infrastructure, better equipped to face the challenges of tomorrow.

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