District-level healthcare accessibility under flood-conditioned road network disruption in Pakistan

Ramla Khan[*1], Martin Lauer[2], Muhammad Marwan[3]
1 Health Data Sciences, The University of Oxford, United Kingdom
[2]NDORMS (Nuffield Department of Orthopaedics, Rheumatology and Musculoskeletal Sciences), IT Services, The University of Oxford, United Kingdom
[3]School of Mathematics and Statistics, Linyi University, China
[*] email: ramla.khan@ndorms.ox.ac.uk; ramla3903@gmail.com

Abstract

Floods disrupt healthcare access not only through facility damage but through road network fragmentation. This study quantifies district-level healthcare accessibility loss during the 2025 monsoon floods in Sindh and Punjab, Pakistan, using a flood-conditioned weighted road network model that reveals how network topology, rather than facility availability, governs access collapse. Satellite-derived flood extents were integrated with road network, healthcare facility, and demographic data; segments with ≥60% inundation was classified as unusable. Shortest-path distances from facilities to district headquarters were computed at 5, 10, and 15 km thresholds. Although only 0.6% of major road segments became unusable, their disruption at structurally critical locations fragmented connectivity across entire districts, producing accessibility losses disproportionate to the physical damage sustained. At the 5 km threshold, 84.8% of facilities in Sindh and 75.9% in Punjab were inaccessible, with primary care facilities most severely affected. These findings demonstrate that protecting a small number of critical road corridors could substantially preserve healthcare access during flood events.

Keywords: Flood impacts; Healthcare accessibility; Spatial network analysis; Road network disruption; Health system resilience; Pakistan

1 Introduction

Floods rank among the most frequent and destructive natural hazards globally, disproportionately affecting vulnerable communities and critical infrastructure [1]. Pakistan experiences recurring catastrophic floods, including the 2010 event that claimed 1,985 lives and affected 20 million people [2] and the 2022 monsoon floods, which impacted 33 million people and resulted in combined damages exceeding $30 billion [3]. The 2025 monsoon floods, beginning in late June, claimed nearly 1,000 lives, displaced over one million people, and destroyed thousands of homes, demonstrating persistent flood vulnerability despite ongoing adaptation efforts [4].

Climate change has intensified flood risk across the Indus Basin through altered precipitation patterns, accelerated glacial melt, and modified hydrological regimes [5,6]. Concurrent rapid urbanisation has compounded this vulnerability, with impervious surface expansion significantly increasing pluvial flood severity during high-intensity rainfall events [7]. These compound pressures create conditions in which concentrated monsoon rainfall overwhelms existing drainage infrastructure and water management systems.

Floods generate cascading impacts beyond immediate physical destruction. Hydrological disturbances combined with land-use change degrade groundwater quality, soil vitality, and ecosystem health [8,9]. Machine learning-based mapping of the 2022 floods estimated that approximately ten million people and hundreds of thousands of buildings were directly affected, with widespread cropland inundation disrupting rural livelihoods [10,11]. Such disruptions weaken community resilience while straining fragile health systems.

Despite advances in hydrological modelling and environmental impact assessment, critical knowledge gaps remain regarding flood impacts on healthcare infrastructure accessibility. High-resolution demographic datasets and healthcare facility geolocation data enable unprecedented spatial precision in population exposure assessment [12], yet these resources remain underutilised for evaluating health system disruption during flood events. Similarly, remote-sensing-based flood products allow precise spatiotemporal inundation mapping [13], but their application to healthcare accessibility analysis is limited.

This study addresses these gaps by integrating demographic, healthcare, and remote-sensing data to quantify healthcare facility accessibility during the 2025 Pakistan floods. Specifically, we assess flood impacts on road network connectivity using high-resolution inundation data, calculate network-based distances from district headquarters (DHQ) to healthcare facilities under flood conditions, and classify facility accessibility at multiple distance thresholds. This approach provides spatially explicit evidence of health system vulnerability to inform disaster preparedness and response planning.

This study advances existing research by providing a district-level assessment of healthcare accessibility under flood conditions, integrating high-resolution flood extent data with network-based accessibility modelling. Unlike previous studies that focus on direct flood exposure or general accessibility measures, this approach demonstrates how limited disruption to strategically important road segments can result in disproportionate losses in healthcare access due to underlying network structure.

2 Methods

The analytical workflow followed a structured sequence of four stages: (1) flood extent integration and road exposure assessment, (2) road network pre-processing and construction of a flood-conditioned network, (3) network-based distance calculation between healthcare facilities and DHQ, and (4) accessibility classification and district-level aggregation. This framework enables the systematic evaluation of how flood-induced road disruption affects healthcare accessibility.

All spatial analyses were conducted in R version 4.3.0 (R Core Team, 2023) using sf [14,15] for spatial vector operations, terra [16] for raster processing, sfnetworks [17] for network graph construction and analysis, and dplyr [18] and tidyr [19] for data manipulation. Statistical tests employed the base R stats package [20]. Map production and cartographic visualisation were performed in QGIS version 3.40.9 [21]

2.1 Study Area

Punjab Province and a broader region covering Sindh Province were analysed in this study. They represent Pakistan's flood-vulnerable districts within the Indus Basin system. A 50 km buffer was applied around the union of both flood extents to capture road network connectivity beyond the immediate inundation zone, allowing analysis of alternative routes and network effects outside directly flooded areas.

2.2 Data Sources

Flood extent data were obtained from the United Nations Satellite Centre (UNOSAT) as binary raster layers at 20 m spatial resolution, indicating inundated areas. The Punjab scenario [22] and the Sindh scenario [23] represent peak flood conditions during the 2025 monsoon season during the first half of July, derived from Sentinel-1 Synthetic Aperture Radar (SAR) and Multispectral Sentinel-2 imagery.

Road network data were extracted from OpenStreetMap (OSM) [24]. The dataset includes spatial geometries, highway classifications, and attributes such as road names and lane count where available.

Healthcare facility locations (point features) were obtained from OSM [25]. Facilities include diverse categories ranging from Basic Health Units (BHU) and Rural Health Centres (RHC) to DHQ Hospitals and specialised facilities.

Administrative boundaries at the district level (Level 2) were obtained from the World Food Programme Spatial Data Infrastructure [26], quality-assured by OCHA Field Information Services.

Demographic data was acquired from WorldPop [12], as multiple raster images, each representing age groups of male or female gender.

This study relies on secondary spatial datasets, including satellite-derived flood extents (UNOSAT), OSM infrastructure data, and WorldPop demographic grids, which are widely used in large-scale disaster and accessibility analyses. Similar approaches have been applied in recent studies assessing flood-induced disruption to healthcare access and critical infrastructure [27,28]. While field validation was not feasible given the spatial extent of the study, the integration of multiple independent datasets enhances the robustness and consistency of the analysis.

2.3 Spatial Data Processing

All spatial datasets were verified for coordinate reference system (CRS) consistency and projected to UTM Zone 42N (EPSG:32642) for accurate distance calculations. Spatial extents of roads, healthcare facilities, and districts were cropped to a 50 km buffer around the union of both flood scenario extents. This buffer ensures the analysis captures potential route diversions around flooded areas while excluding distant infrastructure unlikely to influence district-level accessibility during the flood event.

2.4 Road Network Preparation

Road network pre-processing was performed to ensure topological validity and computational efficiency. Only major road classifications supporting inter-district connectivity and emergency response were retained, including primary, secondary, trunk, motorway, and highway classes, along with their associated link roads (Fig. 1). Minor road types such as residential streets, service roads, and tracks were excluded.

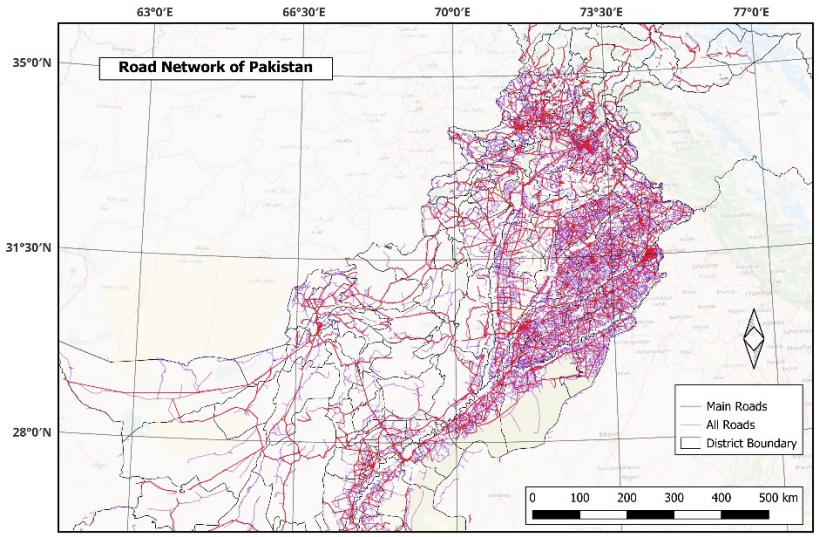

Fig. 1. Road network of Pakistan with main roads represented with magenta colour, while the thinner purple lines represent all roads, inclusive of residential streets, service roads, and tracks.

Duplicate road segments with identical geometries were removed to prevent redundancy in network analysis. Invalid geometries were corrected using standard validation procedures. Road features stored as Multiline-String geometries were converted to individual Line-String segments to ensure each segment functions as a single network edge. Segments shorter than 5 m were removed as digitisation artefacts that could introduce spurious network nodes. Following these pre-processing steps, unique identifiers were assigned to all retained segments, and segment lengths were calculated in meters for use as edge weights in network analysis.

The pre-processing reduced the road network from its original size to a cleaned dataset suitable for graph-based analysis. Road type distribution was verified to ensure adequate representation of major road classes. Total road length in the study area was calculated as the sum of all segment lengths.

2.5 Flood Impact Assessment

The combined flood raster was created by loading both the Punjab and Sindh flood raster, stacking them, and applying a pixel-wise maximum function to produce a unified binary inundation surface. This combined raster was used for all subsequent flood impact assessments (Fig. 2).

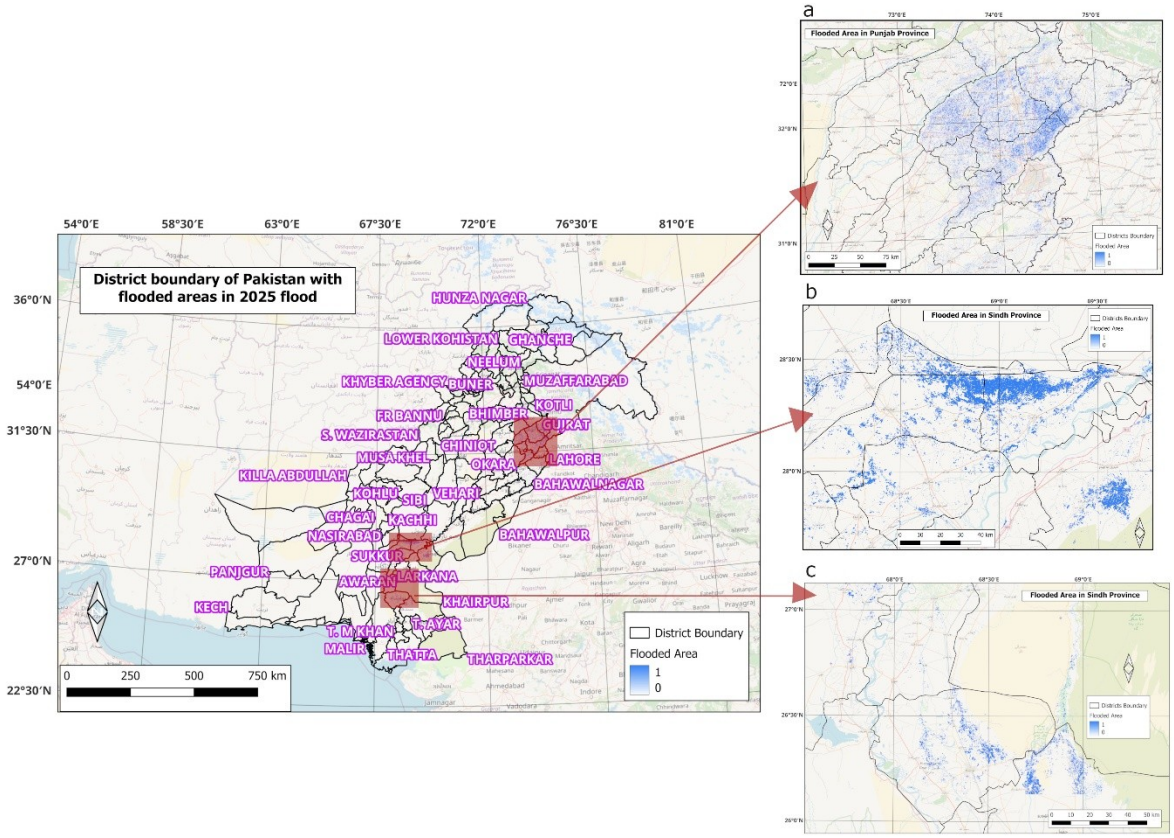

Fig. 2. Flooded areas of Pakistan in the summer of 2025 a) Punjab province, b) Northmost Sindh, c) the middle of Sindh

Road flood exposure was assessed using a point-based sampling approach rather than computationally expensive raster-to-polygon conversion. Sample points were generated along each road segment at 20 m intervals, matching the spatial resolution of the flood raster. This sampling density ensures adequate representation of flood conditions along each segment while maintaining computational feasibility.

Flood values were extracted from the combined flood raster at each sample point location. Points intersecting flooded raster cells (value = 1) were classified as flooded, while those intersecting non-flooded or no-data cells (value = 0 or NA) were classified as non-flooded. For each road segment, the percentage of sample points classified as flooded was calculated, providing a continuous measure of inundation severity.

Road segments were classified as unusable if 60% or more of their sampled length was flooded. This threshold provides a segment-level approximation of loss of operability under flood conditions and reflects functional disruption for emergency and service vehicles. Previous studies have demonstrated that even partial inundation can significantly impair road usability depending on flood depth and vehicle type [29,30]. Sensitivity testing using alternative thresholds (50% and 70%) produced qualitatively similar spatial patterns, supporting the robustness of the selected threshold.

2.6 Network Construction and Accessibility Analysis

Usable road segments were assembled into a weighted, undirected network graph. Nodes represent road intersections and segment endpoints, while edges represent road segments weighted by their length in meters. Road segments classified as unusable due to flooding were excluded, producing a flood-conditioned network representing viable travel paths during the event.

DHQ served as origin points for accessibility analysis, reflecting their role as administrative hubs and focal points for healthcare coordination and emergency response during flood events. This approach is consistent with prior accessibility studies in low- and middle-income settings that model access relative to key service or administrative centres [31]. District polygon centroids were used to represent headquarters locations, reflecting their typical role as administrative hubs and centres for healthcare coordination and emergency response. All district centroids were snapped to their nearest node in the flood-conditioned road network to enable accurate distance calculations.

Healthcare facilities were similarly snapped to their nearest network node. Network distances were calculated using Dijkstra's shortest path algorithm [32–34], computing the minimum cumulative edge weight (in meters) along the flood-conditioned network from each facility to all DHQ. For each facility, the nearest accessible DHQ and corresponding network distance were recorded. Facilities with no valid path to any DHQ were assigned an infinite distance, indicating complete network disconnection.

2.7 Accessibility Classification

Healthcare facilities were classified using three distance thresholds representing different accessibility contexts: 5 km (short-range, typical of urban and peri-urban settings), 10 km (medium-range, representing suburban and accessible rural areas), and 15 km (extended-range, capturing more remote rural contexts). The 5 km threshold is widely recognised in healthcare accessibility studies in low- and middle-income countries (LMICs) as a benchmark for reasonable access to care [35,36], while larger thresholds capture reduced service availability in peri-urban and rural areas. Healthcare utilisation declines with increasing distance, reflecting a well-established distance-decay effect in access to services [31]. The use of multiple thresholds allows accessibility to be evaluated across varying spatial contexts and levels of service availability, consistent with previous flood-related accessibility analyses [27].

For each threshold, facilities were classified into three mutually exclusive categories. Facilities were classified as accessible if a valid network path existed and the distance to the nearest DHQ was less than or equal to the threshold. Facilities were classified as inaccessible if a valid network path existed, but the distance exceeded the threshold. Facilities were classified as disconnected if no valid network path existed due to complete network severance, representing the most critical condition from an emergency response perspective.

Binary accessibility indicators were created for each threshold (5 km, 10 km, 15 km), and categorical status variables were assigned based on the distance and connectivity criteria. Summary statistics were generated by facility category, distance threshold, and accessibility status to quantify the number and percentage of facilities in each classification.

2.8 Statistical Analysis

Descriptive statistics were used to summarise healthcare facility accessibility outcomes across distance thresholds (5 km, 10 km, and 15 km) by facility category, district, and province. Facility accessibility status was classified as accessible, inaccessible, or disconnected based on flood-conditioned network distances to the nearest DHQ.

To assess whether observed differences in accessibility patterns departed from random variation, chi-square tests of independence with Monte Carlo simulation (10,000 replicates) were conducted [37]. Tests were applied in two contexts. First, associations between healthcare facility category and accessibility status were evaluated to examine whether accessibility loss differed systematically by level of care. Second, accessibility status distributions were compared across provinces at each distance threshold to assess whether province-level differences were statistically distinguishable.

Monte Carlo simulation was employed to avoid reliance on asymptotic assumptions given small and uneven cell counts in certain facility categories and districts. Effect sizes were assessed using Cramér's V to support the interpretation of statistically significant results. Statistical analyses were performed in R, with results interpreted as confirmatory evidence supporting descriptive and spatial patterns rather than as primary inferential outcomes.

3 Results

3.1 Flood-Exposed Population by Age and Sex

Flood exposure analysis indicates substantial demographic impacts across Sindh and Punjab provinces (Table 1; Fig. 3). An estimated 1.22 million people resided within the mapped flood extents, with Punjab accounting for approximately 67% of the exposed population (820,950 individuals) and Sindh contributing the remaining 33% (398,084 individuals).

Across both provinces, flood exposure was concentrated among children and working-age adults. Individuals aged 0–14 years constituted 25.1% of the exposed population in Sindh and 27.4% in Punjab. The largest absolute exposure occurred in the 15–34 age range in both provinces, reflecting underlying population structure and the spatial coincidence of densely inhabited districts with flood-prone areas.

Sex-disaggregated estimates showed broadly balanced exposure patterns. Males represented 51.1% of the exposed population in Sindh and 50.1% in Punjab, with minimal differences between sexes across most age groups (Table 1). Minor deviations were observed in older age cohorts, where female exposure slightly exceeded male exposure.

Population pyramids illustrate similar age–sex structures of flood-exposed populations in both provinces, characterised by wide bases and progressively narrowing upper age bands (Fig. 3). Individuals aged 60 years and older accounted for a smaller proportion of total exposure relative to younger age groups in both Sindh and Punjab.

Table 1. Estimated population counts derived from a gridded population raster (100 m resolution) intersected with the flood extent in the Punjab and Sindh provinces of Pakistan in 2025.

Age group (years)	Sindh Female	Sindh Male	Sindh Total	Punjab Female	Punjab Male	Punjab Total
infants	6,584	6,630	13,214	9,451	9,834	19,285
1–4	25,501	25,640	51,142	36,608	38,032	74,640

5–9	29,740	32,384	62,124	44,106	44,920	89,026
10–14	23,406	27,375	50,781	47,640	47,656	95,296
15–19	18,676	21,256	39,932	44,652	45,047	89,699
20–24	14,739	15,646	30,385	40,290	40,146	80,435
25–29	13,900	14,604	28,504	32,722	33,132	65,854
30–34	12,682	13,028	25,709	28,737	28,899	57,636
35–39	11,465	12,218	23,683	25,501	25,647	51,148
40–44	8,918	8,730	17,648	22,035	22,339	44,374
45–49	7,442	7,243	14,685	17,663	17,876	35,539
50–54	5,216	5,174	10,391	15,418	15,625	31,043
55–59	4,933	4,403	9,337	12,616	12,765	25,381
60–64	4,033	3,366	7,399	10,389	10,392	20,780
65–69	3,290	2,703	5,993	8,251	7,410	15,661
70–74	1,927	1,432	3,360	6,160	5,459	11,618
75–79	1,149	781	1,930	4,144	3,731	7,875
80–84	710	467	1,176	2,157	1,910	4,067
85–90	325	204	529	730	597	1,326
90+	104	58	162	159	104	264
All ages	194,741	203,343	398,084	409,430	411,520	820,950

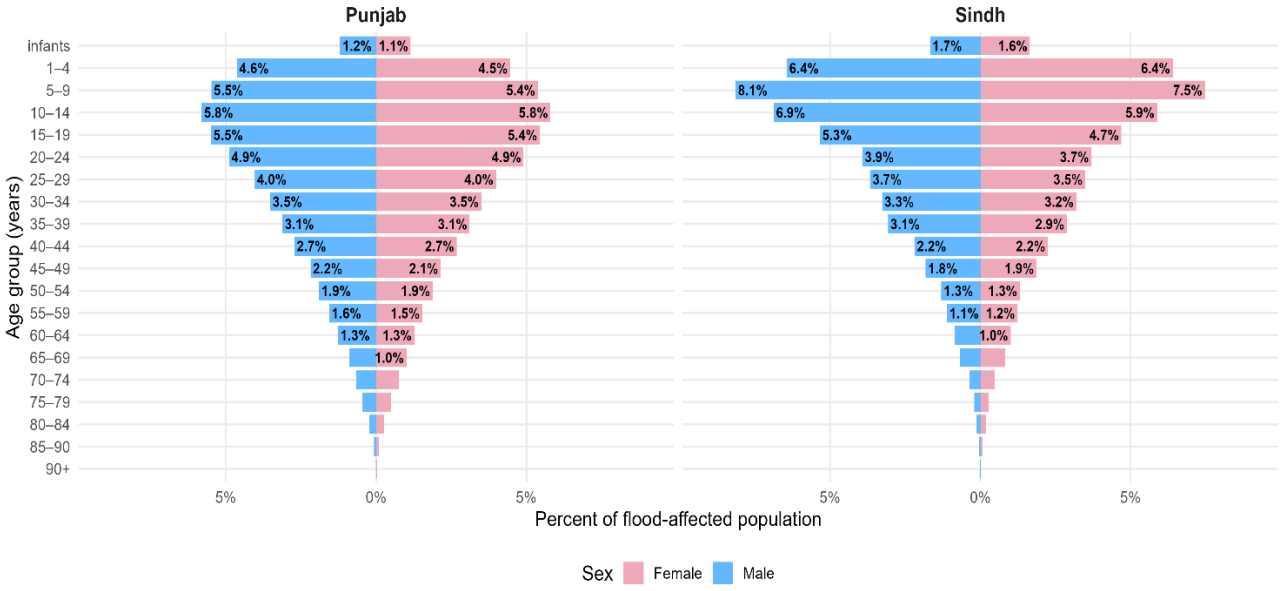

Fig. 3. Population pyramids showing age–sex distribution of flood-exposed populations in Sindh and Punjab provinces of Pakistan in 2025.

3.2 Road Network Disruption Under Flood Conditions

Flood impact assessment revealed limited but spatially concentrated disruption to the major road network across the study area (Table 2). Of the retained road segments, approximately 0.6% were classified as unusable under flood conditions, corresponding to 40 individual segments and a total unusable length of 2.99 km.

All unusable segments were located within the primary set of major road corridors, while elevated structures such as viaducts were not affected. Low-water crossings were not identified as inundated in the dataset; however, this may reflect limitations in flood detection or spatial resolution rather than actual operability.

Although the total length of affected roads represented a small fraction of the overall network, unusable segments were unevenly distributed and occurred at specific low-lying locations.

Lower-order connectors linking rural and peri-urban settlements to district centres were disproportionately represented among unusable segments. Several districts experienced fragmentation of inter-district routes despite limited overall road exposure, reflecting localised network disruption rather than widespread network failure.

Full details of flood exposure and usability classification for all road segments are provided in Supplementary Table S1.

Table 2. Flood impact on different types of roads in the combined Sindh and Punjab

Road classification	Total segments	Usable segments	Unusable segments	% unusable	Total length (km)	Unusable length (km)
Major road segments	6,948	6,908	40	0.6	679.36	2.99
Viaducts	85	85	0	0.0	37.18	0.00
Low-water crossings	2	2	0	0.0	0.06	0.00
Total	7,035	6,995	40	0.6	716.60	2.99

3.3 Spatial Distribution of Healthcare Facility accessibility

Spatial patterns of healthcare facility inaccessibility during the 2025 floods exhibited pronounced geographic heterogeneity across both Sindh and Punjab provinces (Fig. 4; Supplementary Table S2, Supplementary Fig. S1). Across all evaluated distance thresholds, accessibility loss was highly clustered at the district level rather than uniformly distributed, reflecting differences in road network structure and redundancy. Districts with limited alternative routes were more susceptible to disruption, where the loss of a small number of critical segments resulted in disproportionate accessibility decline. The intermediate 10 km threshold exhibits similar spatial patterns and is therefore presented in Supplementary Fig. S1.

At the 15 km threshold, inaccessibility was concentrated in a limited number of predominantly rural districts. In Punjab, several districts recorded very high proportions of inaccessible facilities, while others experienced a complete loss of accessibility within the threshold. In contrast, major urban and peri-urban districts retained full accessibility despite geographic proximity to flood-affected areas, reflecting higher network redundancy and the availability of multiple alternative routes.

A similar pattern was observed in Sindh, where districts in southern and interior regions exhibited consistently high levels of inaccessibility at the 15 km threshold, whereas several central districts showed little or no accessibility loss. Districts with both high proportions and large absolute numbers of affected facilities accounted for a substantial share of total inaccessibility (Supplementary Table S2).

As distance thresholds were reduced, the spatial extent and severity of inaccessibility increased markedly, reflecting the limited local connectivity of healthcare facilities in many districts. Short-range access was particularly sensitive to network disruption, as even minor increases in travel distance resulted in facilities

exceeding lower accessibility thresholds. Additional districts transitioned from partial to majority inaccessibility, particularly in rural settings where healthcare facilities are more sparsely distributed. At the 5 km threshold, widespread accessibility loss was observed across both provinces, indicating severe constraints on short-range access to district-level healthcare services under flood conditions.

Accessibility loss was not consistently related to the total number of facilities within districts, indicating that connectivity, rather than facility density, was the dominant factor shaping accessibility outcomes under flood conditions. Districts with relatively small facility inventories often experienced near-total inaccessibility, while others with larger numbers of facilities retained access due to differences in network connectivity.

This pattern is consistent with previous studies demonstrating that disruption of a small number of strategically located road segments can significantly reduce accessibility due to network topology effects [38].

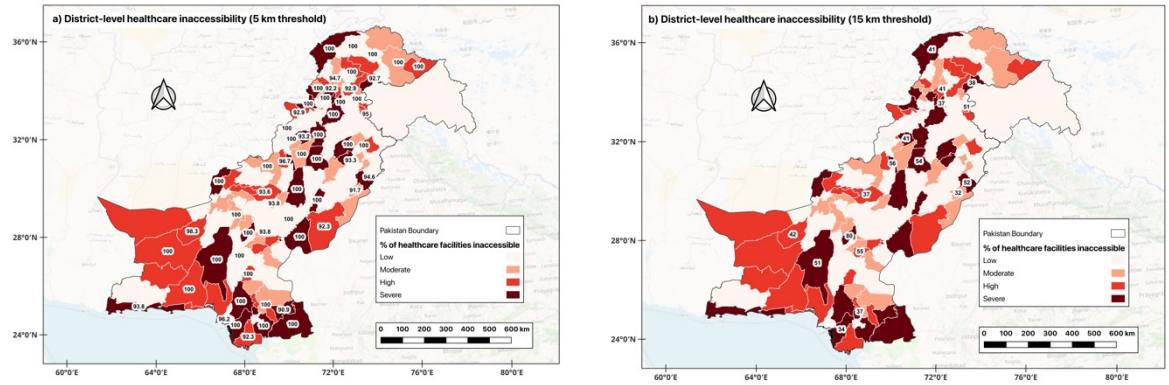

Fig. 4. District-level healthcare inaccessibility under flood conditions in Sindh and Punjab: (a) 5 km threshold; (b) 15 km threshold. Colours represent the percentage of healthcare facilities classified as inaccessible, with darker shades indicating higher inaccessibility and clustering of severe impacts in districts with limited road network connectivity.

3.4 Network Distance to DHQ by Facility Type

Network distance distributions varied substantially by healthcare facility type under flood-conditioned road connectivity (Fig. 5). Primary care facilities, including BHU, Dispensaries, RHC, and Sub-health Centres, exhibited the largest median distances and widest interquartile ranges, with median distances frequently exceeding 20–30 km and upper quartiles extending beyond 50 km.

In contrast, secondary and tertiary care facilities, such as District and Tehsil Headquarters Hospitals and Children's Hospitals, were generally located closer to district centres, with median distances typically below 15 km. Dental clinics exhibited the shortest median distances, consistent with their predominantly urban distribution.

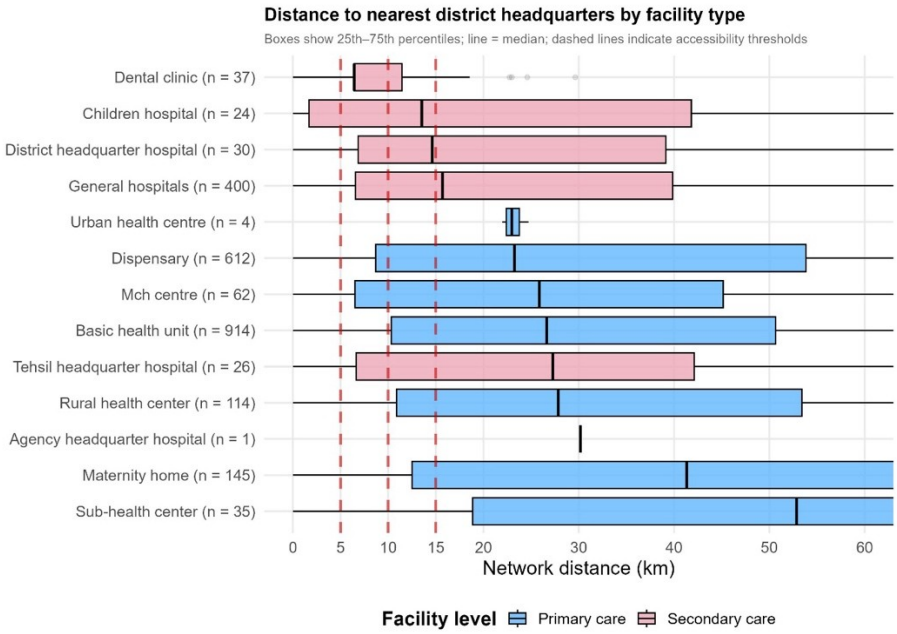

Fig. 5. Network distances from healthcare facilities to the nearest DHQ under flood-conditioned road connectivity, stratified by facility type and level of care. Dashed vertical reference lines indicate accessibility thresholds at 5 km, 10 km, and 15 km.

3.5 Accessibility Loss Across Distance Thresholds

Aggregated province-level results indicated a consistent decline in the proportion of accessible facilities as distance thresholds decreased (Fig. 5). At the 5 km threshold, 84.8% of facilities in Sindh and 75.9% in Punjab were classified as affected. This proportion declined to 66.0% and 68.1% at the 10 km threshold, and to 62.5% and 56.5% at the 15 km threshold, respectively.

Monte Carlo chi-square testing indicated that observed provincial differences were statistically distinguishable at the 5 km threshold ($p = 0.002$), with a weak association strength (Cramér's $V = 0.11$). No statistically significant differences were detected at the 10 km or 15 km thresholds ($p = 0.53$ and $p = 0.09$), indicating convergence in accessibility outcomes as acceptable travel distances increased.

4 Discussion

A key contribution of this study is the demonstration that minimal physical disruption to road networks can produce disproportionate losses in healthcare accessibility due to underlying network structure. While more advanced network metrics such as centrality-based prioritisation frameworks have been applied in previous studies, the present analysis focuses on distance-based accessibility to provide a scalable and interpretable framework under data-constrained conditions.

This study provides a network-based assessment of healthcare accessibility during the 2025 monsoon floods in Pakistan, revealing substantial and spatially uneven disruption across flood-affected districts. Although more than one million people were exposed to flooding, the resulting loss of healthcare access was not uniformly distributed across provinces or districts. Instead, accessibility loss was highly localised, with a limited number of predominantly rural districts accounting for a disproportionate share of inaccessible facilities. The finding that a small but strategically critical fraction of major road segments became unusable during flood conditions

provides an explanation for these patterns, demonstrating that network severance, rather than facility scarcity alone, drove accessibility outcomes [39].

Short-range access was most severely affected. At a 5 km threshold, more than three-quarters of healthcare facilities in both Sindh and Punjab were classified as inaccessible, indicating widespread collapse of local access during flood conditions. This finding highlights the sensitivity of short-distance accessibility to disruptions in road connectivity, particularly in settings where alternative routes are limited.

Primary care facilities experienced the greatest disruption, whereas secondary and tertiary facilities were generally more accessible due to their concentration near district centres. The disproportionate impact on lower-order road infrastructure, particularly secondary roads serving rural areas, directly contributed to the observed accessibility loss for primary care facilities, which are predominantly located in peri-urban and rural settings.

Importantly, districts with large numbers of facilities were not necessarily more resilient, underscoring that healthcare accessibility during floods is governed by network connectivity rather than facility availability alone. Similar patterns have been observed in previous flood events in Pakistan [3]. Disruptions to healthcare access during floods can delay treatment for chronic conditions, maternal care, and routine immunisation, with disproportionate impacts on vulnerable populations [40,41].

The strong spatial clustering of both road network disruption and healthcare inaccessibility highlights pronounced inequalities between rural and urban districts. Rural districts in southern and western Punjab and interior Sindh experienced near-total loss of access within commonly used distance thresholds, whereas major urban centres retained substantial connectivity despite geographic exposure to flooding.

These contrasts reflect differences in road network structure, particularly the limited redundancy of transport routes in rural areas. Where few alternative paths exist, disruption to even a small number of road segments can isolate entire districts. This pattern further highlights the role of network structure in amplifying accessibility loss under flood conditions. Similar dynamics have been observed in previous studies of flood-related network disruption and accessibility loss [42].

These findings highlight structural vulnerabilities in Pakistan’s healthcare delivery system during flood emergencies. The disproportionate impact on primary care facilities indicates that first-line health services, which play a critical role in early treatment and referral, are particularly fragile under conditions of network disruption. Floods in Pakistan frequently damage healthcare infrastructure, disrupt medical supply chains, and contaminate water sources, triggering secondary public health crises. During recent flood events, millions of people lacked access to safe drinking water, leading to outbreaks of diarrhoeal disease, while stagnant floodwaters facilitated the spread of malaria and dengue. The World Health Organisation has reported that approximately 10% of healthcare facilities were damaged or destroyed during the 2022 floods, with over 2,000 facilities affected in a system where baseline access is already limited. The observation that network fragmentation occurred even in districts with moderate overall road flooding underscores the sensitivity of healthcare accessibility to the failure of strategically located network segments. This finding has important implications for infrastructure planning, suggesting that targeted protection or redundancy at critical road corridors could yield substantial benefits for maintaining healthcare access during flood events.

From a planning perspective, these results emphasise the need for district-specific preparedness strategies that prioritise maintaining connectivity to primary care facilities in flood-prone areas. Interventions such as pre-positioned mobile health units, flood-resilient upgrades to critical road segments, and alternative transport

planning could substantially reduce accessibility loss during future flood events. This framework could be extended to identify and prioritise critical road segments whose failure would disproportionately affect access, supporting targeted infrastructure investment. Previous studies have demonstrated the utility of network centrality measures for identifying such critical infrastructure, enabling prioritisation of both primary and backup routes. Despite the recurrent and increasingly predictable nature of flooding in Pakistan, disaster response remains largely reactive, with limited emphasis on anticipatory planning. Districts, which are central to operational response, remain among the most neglected administrative tiers in climate preparedness efforts. Strengthening district-level planning, safeguarding essential infrastructure, and ensuring continuity of services such as water, power, and communications are critical to maintaining healthcare functionality during flood events. Locating health facilities on elevated terrain, ensuring secure pharmaceutical storage, and retrofitting existing facilities can further reduce vulnerability to flood-related damage.

Importantly, province-level planning alone risks obscuring critical sub-regional vulnerabilities revealed by this analysis. By integrating high-resolution flood extent data with network-based accessibility modelling, this study captures dimensions of healthcare access loss that are not observable through straight-line distance measures or facility counts alone. Euclidean proximity tends to overestimate functional access, particularly in regions with fragmented infrastructure and significant natural barriers [41]. The use of multiple distance thresholds enables interpretation across diverse urban and rural contexts and supports more nuanced planning decisions. The methodological framework is transferable to other flood-prone regions, particularly in LMICs where healthcare access is strongly mediated by road infrastructure and where reliable travel-time data are often unavailable. Similar applications following recent flood events, such as Cyclone Idai in Mozambique, have demonstrated the value of such approaches for identifying critical infrastructure and assessing accessibility loss. As climate change continues to intensify flood hazards and expand the geographic range of disease vectors, health systems in South Asia face increasing strain. Incorporating network vulnerability into disaster risk reduction and health system planning will therefore be essential to reducing preventable health impacts during future flood events.

Several limitations should be acknowledged. Travel time and flood depth were not explicitly modelled due to data constraints, and network distance was used as a proxy for accessibility. While this simplifies real-world conditions, it may lead to over- or under-estimation of functional access in areas with variable road conditions or flood severity. In Pakistan's flood context, this is particularly relevant where road surface conditions and flood depth vary significantly, meaning some nominally 'usable' segments may in practice be impassable, suggesting our estimates of accessible facilities could be optimistic. Flood extent was treated as static, and potential behavioural adaptations such as boat travel or informal routes were not considered. The analysis also did not account for facility capacity or service quality. Future research could integrate dynamic flood modelling, travel-time estimation, and facility-level service data to refine accessibility assessments. Linking network disruption directly to health outcomes would further strengthen understanding of the public health consequences of flood-related access loss. Developing multimodal network approaches and further testing network centrality indicators across different hazards and geographic contexts would help advance this field of research.

5 Conclusion

This study provides a spatially explicit assessment of healthcare accessibility during the 2025 monsoon floods in Pakistan. It shows that flood impacts on health systems are strongly mediated by road network disruption and

exhibit substantial geographic heterogeneity. While more than one million people were exposed to flooding, the resulting loss of healthcare access was highly localised, with a small number of districts accounting for a disproportionate share of inaccessible facilities.

These findings underscore the importance of considering network vulnerability and spatial configuration, rather than facility availability alone, when evaluating health system resilience to flood hazards. From a planning perspective, the results highlight the need for district-specific preparedness strategies that prioritise maintaining connectivity to primary care facilities in flood-prone areas. Interventions such as pre-positioned mobile health units, flood-resilient upgrades to critical road segments, and alternative transport planning may help reduce accessibility loss during future flood events.

Network-based accessibility analysis provides a valuable tool for disaster preparedness by identifying critical road segments whose failure would significantly impact population access to healthcare. By combining high-resolution flood extent data with network-based accessibility modelling, this study captures aspects of healthcare access loss that are not observable through straight-line distance measures or facility counts alone.

From a policy perspective, this approach enables the identification of priority road segments for targeted intervention, supporting more effective allocation of resources in flood-prone regions. Integrating such analyses into district-level planning can help maintain connectivity to essential healthcare services during extreme events, particularly in LMICs where access is strongly dependent on road infrastructure.

6 Acknowledgements

Not applicable

7 References

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9 Conflict of interest:

The authors declare that they have no conflict of interest.