Spatial Data Studio (LTOM.02.011)

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Infrastructure-Weighted Analysis of Population Vulnerability to Landslides in KPK, Pakistan

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Abstract

This study assesses community vulnerability to landslides in Khyber Pakhtunkhwa (KPK), Pakistan, with a specific focus on how landslide susceptibility and infrastructure deficiencies affect access to critical healthcare services. By integrating spatial datasets from NASA's LHASA 2.0 landslide susceptibility maps, WorldPop population density data, hospital surge capacity information, and detailed road network attributes, a comprehensive vulnerability framework is developed. The investigation employs the Analytic Hierarchy Process (AHP) to combine exposure, sensitivity, and adaptive capacity indicators—assigning highest importance to infrastructure (53.9%), followed by landslide susceptibility (29.7%) and population (16.4%)—with consistency indicators ($\lambda = 3.007$, CI = 0.004, CR = 0.007) affirming the reliability of the multi-criteria assessment.

Spatial analysis reveals that densely populated regions with high landslide susceptibility, particularly in the mountainous and central areas of KPK, are at greatest risk. The study further utilizes Python-based network analysis, incorporating cost-distance modeling and Dijkstra's algorithm, to quantify healthcare accessibility during disaster scenarios. This integration of hazard evaluation, infrastructure analysis, and population metrics provides critical insights into areas that require urgent intervention, such as enhancing road networks, increasing hospital surge capacities, and implementing disaster mitigation measures.

Overall, the methodology not only highlights the spatial variability of risk but also establishes a robust framework for prioritizing resource allocation and policy planning aimed at enhancing disaster resilience in vulnerable regions of Pakistan.

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1 Introduction

Understanding community vulnerability in Khyber Pakhtunkhwa (KPK), Pakistan is crucial in the context of increasing natural hazards, rapid population growth, and expanding infrastructure. Landslides in this region present a significant threat not only to lives and property but also to essential services such as healthcare, especially in areas where the natural environment and human settlement patterns intersect precariously. This study is designed to assess how the spatial distribution of landslide susceptibility affects population while factoring for accessibility to healthcare facilities.

The investigation is driven by two core questions. First, it asks how the spatial distribution of landslide susceptibility influences densely populated regions. Second, it inquires which parts of the region are most vulnerable to landslides when considering the combined effects of natural hazard conditions and infrastructure. Addressing these questions requires a comprehensive understanding of three key concepts: exposure, sensitivity, and adaptive capacity.

In this study, exposure is defined as the presence of people, infrastructure, or assets in areas prone to landslides. This component is quantified using the NASA Landslide Susceptibility Map (NASA Goddard Space Flight Center, 2020) based on the LHASA 2.0 framework, which identifies “landslide susceptibility zones” where the natural risk is heightened. Sensitivity reflects how severely an exposed population or system is affected by a hazard, and it is measured using population density data from the WorldPop dataset (WorldPop, 2020).

A higher population density indicates a greater number of people who may be adversely impacted by a landslide event. Adaptive capacity, on the other hand, is the ability of a community to prepare for, cope with, and recover from the impacts of a hazard. It is assessed in this analysis through the availability and distribution of critical infrastructure, specifically hospitals and road networks, which play vital roles in emergency response and recovery efforts. By integrating these dimensions through the Analytic Hierarchy Process (AHP), the study develops a composite vulnerability index that provides a detailed picture of how landslide risk interplays with healthcare accessibility and overall community resilience in KPK.

1.1 Study Area

KPK is a geographically diverse region in northwestern Pakistan, characterized by its varied topography that includes towering mountain ranges such as the Hindu Kush in the north and expansive plains in the south. The region's climate varies significantly due to its altitudinal differences. The northern mountainous areas experience cold winters with heavy snowfall and mild summers, while the southern plains are marked by hot summers and relatively mild winters. Seasonal monsoon rains, predominantly affecting the central and southern parts of KPK, contribute to substantial rainfall, particularly from July to September (Ahmed et al., 2020).

KPK is densely populated, with many communities residing in remote and dangerous terrains, especially in the mountainous regions. These areas often lack access to adequate healthcare facilities, which poses significant challenges for the local population, particularly in emergencies and during harsh weather conditions (World Health Organization, 2021). The interplay of challenging geography, climatic variations, and solar exposure makes KPK a unique and critical area for studies focused on climate, public health, and infrastructure development.

Fig 1. Study Area

2 Description of Work

2.1 Exposure: Landslide Susceptibility and Vulnerability

This map, based on the LHASA 2.0 framework, has been critical for understanding regional risks. This dataset originally categorized landslide susceptibility into five classes, with Class 5 representing the highest susceptibility and Class 1 indicating the lowest. To streamline the analysis and integrate it into a vulnerability assessment, these five classes were reclassified into four broader categories: **Very Low**, **Low**, **Moderate**, and **High**.

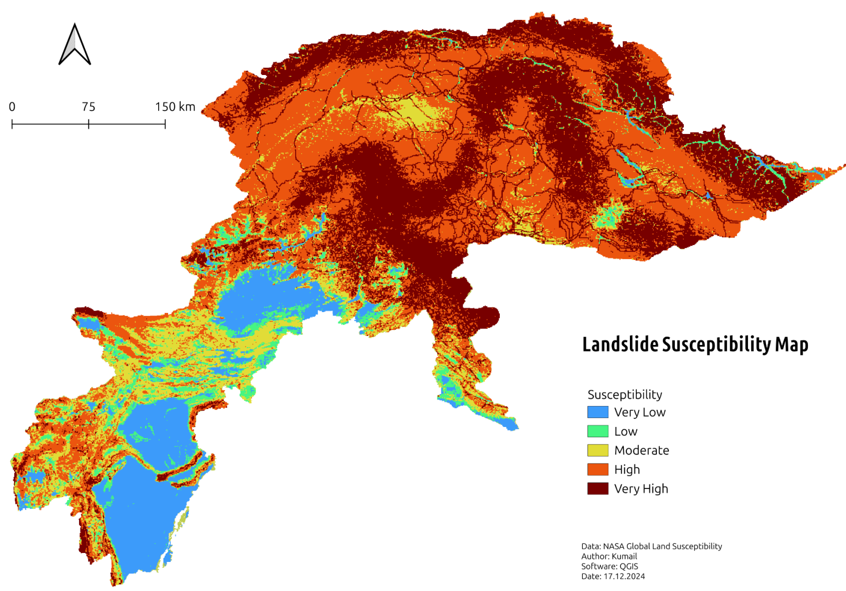

Fig 2. Landslide Susceptibility Map

Figure 2 shows the initial classes and figure three shows it classified according to vulnerability classes. Table 1 displays the mapping of classes used for assessing vulnerability based on susceptibility.

Class (Original)	Description (Original)	Reclassified Value	Description (Reclassified)
5	Highest Susceptibility	4	High
4	High Susceptibility	4	High
3	Moderate Susceptibility	3	Moderate
2	Low Susceptibility	2	Low
1	Very Low Susceptibility	1	Very Low

Table 1. Landslide Vulnerability Mapping

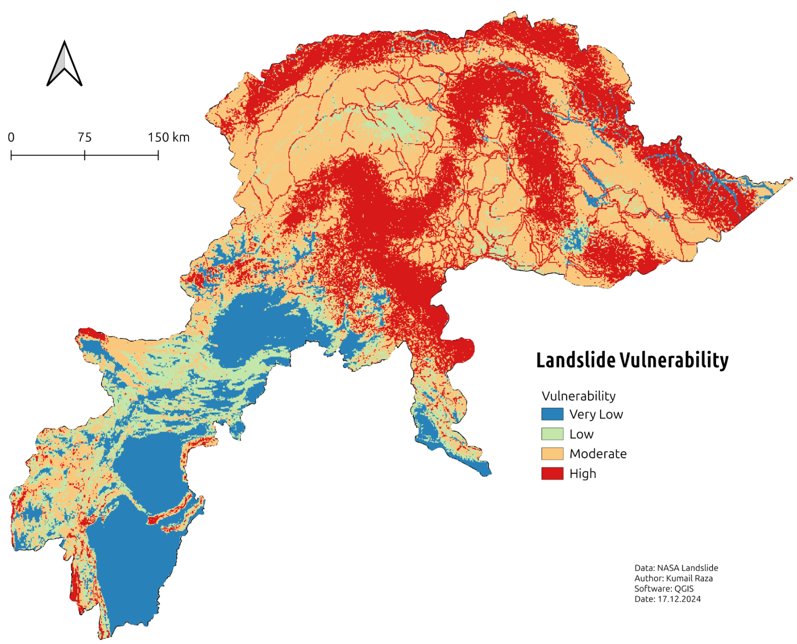

Fig 3. Landslide Vulnerability Classes Map

The landslide vulnerability map of KPK as shown in Figure 3 highlights regions classified into four categories: Very Low, Low, Moderate, and High, based on the NASA Landslide Susceptibility data. Areas marked in red represent zones with high vulnerability, primarily concentrated in northern and mountainous regions, indicating a significant risk of landslides due to steep slopes and environmental conditions. The moderate zones, shown in yellow, cover transitional areas with moderate susceptibility, often adjacent to the high-risk regions. Low and very low vulnerability zones, depicted in green and blue, dominate the southern plains and flatter regions, where the risk of landslides is minimal due to favorable topography. This map provides crucial insights for identifying high-risk areas requiring focused disaster management and infrastructure planning efforts to reduce vulnerability.

2.2 Sensitivity: Vulnerability based on Population Density

In assessing population vulnerability within the region, we utilized the WorldPop(WorldPop, 2020) dataset to analyze population density and incorporated the Pakistan Health Facilities dataset, sourced from ALHASAN Systems' Open Data/Open Access initiative, to evaluate healthcare accessibility (ALHASAN Systems, n.d.).

2.2.1 Population Density

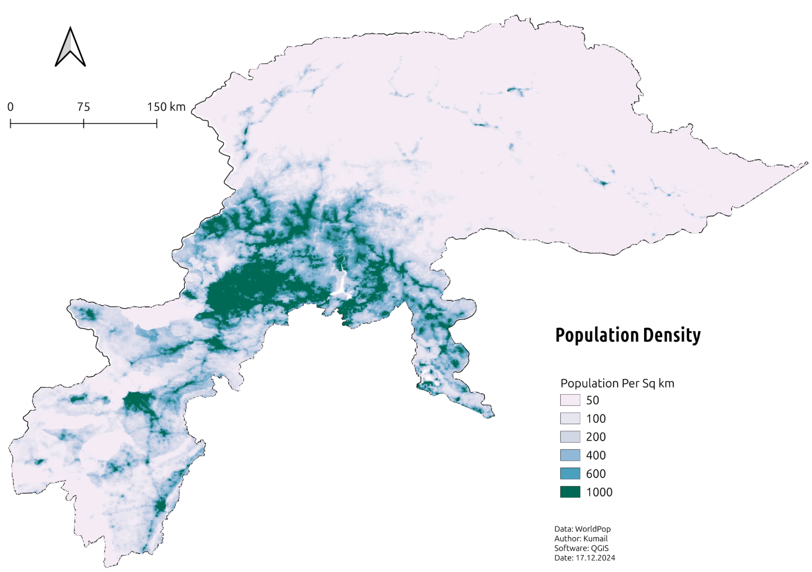

Fig 3.Population Density Map Classified.

Figure 3 illustrates the spatial distribution of population concentrations across the region. Areas with darker shades represent higher population densities, reaching up to 1,000 people per square kilometer, primarily concentrated in urban centers and densely populated valleys. In contrast, lighter shades correspond to sparsely populated regions, typically found in the mountainous and rural northern areas. This distribution highlights significant population clustering in certain areas, which may increase vulnerability to natural hazards like landslides due to the concentration of people and infrastructure in high-risk zones. The map provides crucial insights for assessing population exposure and guiding resource allocation for disaster risk reduction efforts.

2.2.2 Health Facilities

A critical component of this assessment was the calculation of hospital surge capacity, which refers to a hospital's ability to manage a sudden influx of patients during disasters and emergencies. According to the systematic review by Hasan et al. (2023), surge capacity encompasses four key domains: staff, stuff (supplies), space, and systems For our analysis, we focused on the 'space' domain, specifically the availability of hospital beds. We adopted an assumption that each hospital bed could accommodate up to four patients per day during a disaster scenario, reflecting rapid turnover rates necessitated by emergency conditions. This assumption aligns with the strategies discussed in the aforementioned systematic review, which emphasizes the importance of optimizing existing resources to enhance surge capacity. It is somewhat oversimplified but is considered sufficient for the scope of this project.

Subsequently, we identified hospitals with a calculated surge capacity exceeding 16 patients per day, indicating facilities better equipped to handle increased patient loads during emergencies. This threshold was set to pinpoint healthcare facilities capable of providing critical services under strained conditions, thereby informing targeted interventions to bolster healthcare resilience in high-risk areas.

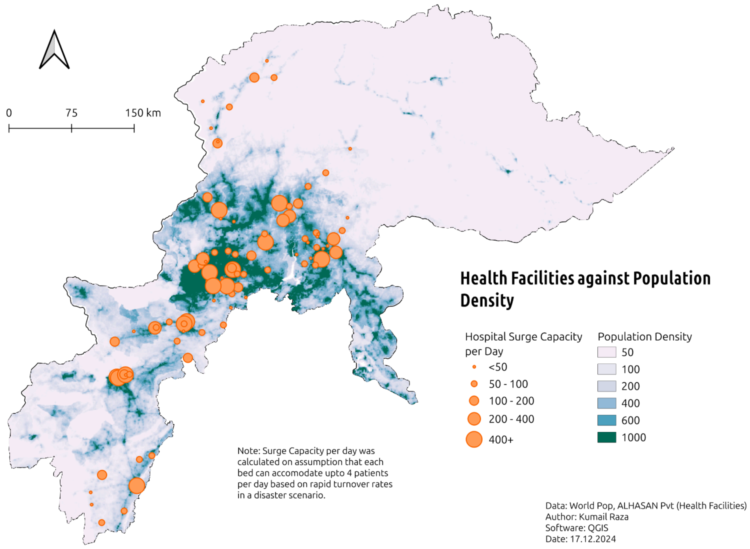

Fig 4.Hospital Surge Capacity against Population Density.

Figure 4 shows that high-capacity facilities are concentrated in densely populated areas, shown in dark green. This highlights a disparity, with rural and sparsely populated regions lacking adequate healthcare infrastructure, emphasizing the need for improved resource allocation in these vulnerable zones.

2.2.3 Population Vulnerability

Population Density (per sq km)	Reclassified Value	Description
1–50	0	Very Low
51–150	1	Low
151–300	2	Moderate
>300	3	High

Table 2. Classes According to Population Density

As shown in Table 2, population density values were reclassified into four categories to represent varying levels of vulnerability. Areas with 1–50 people per sq km were classified as "Very Low" (0), indicating sparsely populated regions. Zones with a population density between 51–150 people per sq km were assigned "Low" (1). Densities between 151–300 per sq km were classified as "Moderate" (2), and areas with a density greater than 300 per sq km were marked as "High" (3), representing densely populated areas with potentially higher vulnerability due to increased human presence. This classification simplifies the analysis by grouping population density into meaningful categories that can be correlated with other vulnerability layers.

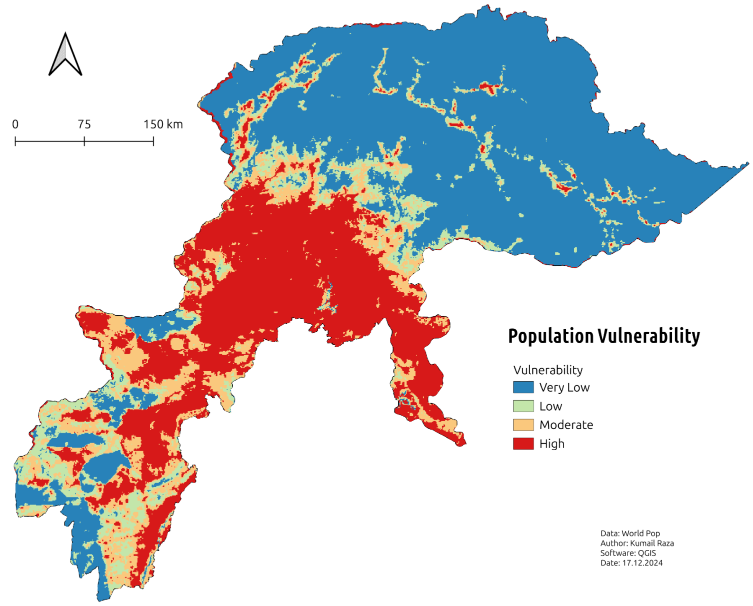

Fig 5.Population Vulnerability based on Density

Figure 5 shows areas marked in red which represent regions of high vulnerability, where high population densities overlap with significant landslide susceptibility. These zones are primarily concentrated in central and southern areas with steep terrain and dense populations. Yellow regions indicate moderate vulnerability, reflecting a balance between population density and susceptibility. Blue and light blue zones denote low and very low vulnerabilities, typically in sparsely populated areas or regions with minimal landslide risk. This visualization provides critical insights for identifying high-risk areas that require prioritized intervention and disaster management planning.

2.3 Adaptive Capacity: Infrastructure Vulnerability

In areas with a poor or inadequate road network, accessibility is significantly hindered, which in turn increases the vulnerability of the population to hazards like landslides. Conversely, a well-connected road network enhances the ability of communities to respond and recover from disasters effectively, reflecting an important aspect of **adaptive capacity**. Adaptive capacity is a measure of how well a population or system can prepare for, cope with, and recover from hazardous events. In this context, the presence of an efficient and accessible road network strengthens adaptive capacity by enabling timely disaster response and resource distribution, reducing the overall vulnerability of the affected population.

For simplified understanding, when discussing infrastructure, we utilized a road network dataset obtained from HOTOSM Roads (OpenStreetMap). While real-case scenarios involve complex interactions of multiple factors, for the purposes of this project, we considered the road network as a critical element of infrastructure that facilitates accessibility during disasters. In this framework, the road network represents the ability of communities to access essential services such as healthcare, evacuation points, and emergency relief during and after a disaster.

2.3.1 Road Network Dataset

Category	Subcategory	Penalty
Highway Types	motorway, motorway_link, primary, primary_link	1
Highway Types	secondary, secondary_link, tertiary, residential, living_street, trunk, trunk_link	2
Highway Types	track, service	3
Highway Types	path, footway, bridleway, construction	4
Surface Types	asphalt, concrete, paved	0
Surface Types	gravel, cobblestone, compacted, fine_gravel	2
Surface Types	unpaved, ground, wood	3
Surface Types	dirt, sand, mud	4
Surface Types	ice, water	5
Smoothness	Excellent, Good	0
Smoothness	Intermediate	1
Smoothness	Medium	2
Smoothness	Bad, No	3
Smoothness	Very Bad	4
Smoothness	Horrible	5
Smoothness	Very Horrible	6
Road Width (meters)	Less than 3	3

Road Width (meters)	3 to 5 (inclusive)	1
Road Width (meters)	Greater than 5	0
Oneway	Yes	1
Oneway	No	0

Table 3. Road Network Penalties

Table 3 presents the penalties assigned to various attributes in the dataset, which were derived based on domain knowledge and an understanding of their impact on accessibility and vulnerability in a disaster scenario. These attributes include highway types, surface types, smoothness categories, road width, and whether the road is one-way. Each attribute was assigned a penalty value, with higher penalties reflecting increased difficulty or reduced accessibility in disaster conditions.

The Highway Types were categorized based on their functional importance, where motorways and primary roads (e.g., highways) received lower penalties, as they provide better connectivity and accessibility. Secondary and residential roads were assigned moderate penalties, while tracks and footpaths, which are less reliable for access, received higher penalties.

For Surface Types, penalties were assigned based on the quality of the road surface. Paved roads, such as asphalt and concrete, received the lowest penalty, while unpaved surfaces, including dirt and mud, were given higher penalties to account for their limited usability in adverse conditions.

The Smoothness Categories reflect the quality of the road's surface, where penalties increase as smoothness decreases. For example, roads labeled "Excellent" or "Good" were assigned the lowest penalty, while those categorized as "Very Horrible" received the highest penalty due to their poor condition and reduced usability.

For Road Width, narrower roads received higher penalties, as roads less than 3 meters wide pose significant challenges for accessibility, particularly for emergency vehicles. Roads between 3 to 5 meters were moderately penalized, and roads wider than 5 meters received no penalty.

Lastly, One Way roads were penalized to account for the reduced flexibility in traffic flow during disaster scenarios, where two-way accessibility is critical.

This penalty-based classification provides a structured approach to integrating infrastructure attributes into the analysis, helping to quantify their contribution to overall accessibility and vulnerability. By assigning these penalties, the analysis aligns with the project's objectives to identify areas of high vulnerability and prioritize them for intervention.

Profile analysis was employed to incorporate penalties into the road network data based on landslide susceptibility classes. This process aimed to quantify the relationship between landslide susceptibility and road accessibility, ensuring that areas with **higher susceptibility are less preferred for use during a disaster** scenario. The penalties were assigned directly based on the default susceptibility classes, where a class of 1 corresponded to a penalty of 1, and a class of 5 was assigned a penalty of 5.

This straightforward approach ensured that roads located in areas of higher landslide susceptibility (class 5) were assigned the highest penalties, making them the least preferred routes for accessibility. Conversely, roads in low susceptibility areas (class 1) received the lowest penalties, indicating their higher reliability during disaster conditions.

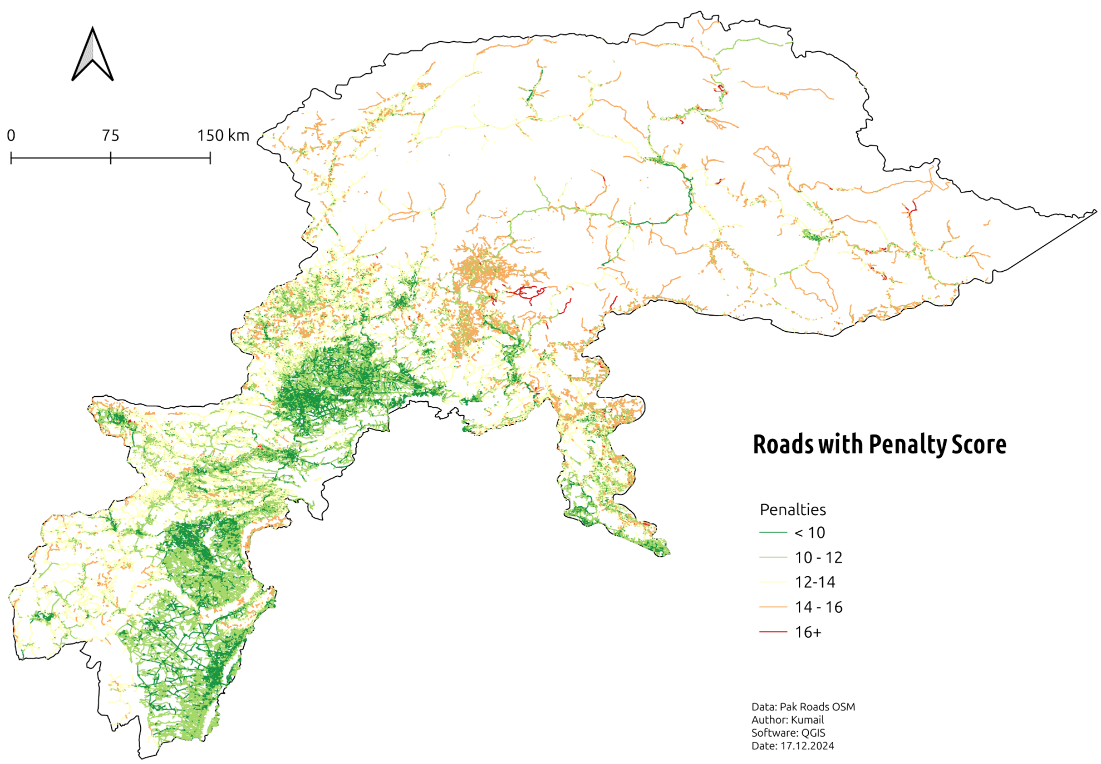

Fig 6.Road Network with Penalties

Figure 6 shows roads with **lower penalties** (green, <10) represent the most preferred routes, typically found in regions with low landslide susceptibility and better road infrastructure. As the penalty scores increase (yellow to red, >16), the roads are less favorable, indicating higher vulnerability due to factors like poor surface conditions, narrow widths, or high susceptibility to landslides.

The penalty scores were assigned by integrating road attributes (e.g., type, surface, width) with landslide susceptibility classes, where roads in highly susceptible zones (class 5) received the highest penalties. This approach ensures that the map highlights routes that are safer and more accessible during disaster scenarios, helping prioritize infrastructure improvements and disaster response planning in vulnerable areas.

2.3.2 Network Analysis of Roads

I wrote a Python-based code for network analysis using libraries like `rasterio`, `numpy`, `scipy`, and `geopandas` to calculate accessibility to healthcare facilities in disaster scenarios. The code integrates hospital locations, a raster-based cost surface, and a graph-based representation of the road network to compute the least-cost paths to the nearest hospital. The cost surface, read from a raster file, represents travel difficulty based on our road penalty dataset, with areas outside the study region assigned infinite cost to exclude them from the analysis. This approach aligns with established methodologies in geographic information science, where cost surfaces are crucial for modeling accessibility and movement across a landscape (Adams & Levine, 2020).

Hospital locations were extracted from converted into raster indices, and used as source points for the shortest-path calculation. This ensures that only hospitals within the raster bounds are considered:

The raster was transformed into a sparse graph, where each cell represents a node, and edges connect neighboring cells. The cost of traversing between cells was calculated as the average of the two cells' values, ensuring travel costs reflect local conditions. Using Dijkstra's algorithm, the shortest paths from multiple hospital sources to all other locations were computed efficiently, minimizing computational load by leveraging sparse matrix operations (Newman, 2003). The algorithm iteratively calculated the accumulated cost to the nearest hospital for each cell, producing a cost-distance raster. This raster was then processed to replace unreachable areas with a NoData value and saved as a GeoTIFF file for visualization and further analysis.

The approach combines cost-distance modeling and network analysis, widely recognized in spatial and disaster research for assessing accessibility and resilience (Higgs, 2004).

The decay factor (1/surge) modifies the initial distance of each hospital, prioritizing hospitals with higher capacities by reducing their effective distance.

```
for _, h in hospitals.iterrows():
    hx, hy = h.geometry.x, h.geometry.y
    surge = h["normalized_surge_costs"]
    hn = nearest_node(hx, hy)
    G.add_edge(super_source, hn, weight=(1/surge))
```

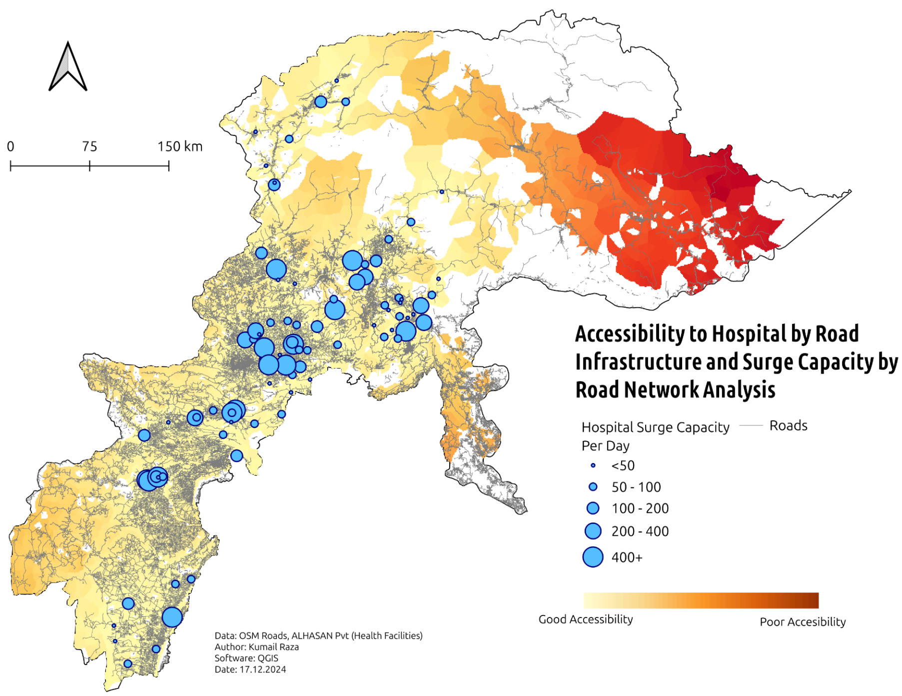

Fig 7.Road Network with Penalties

This analysis combines road quality, landslide susceptibility, and hospital capacity into a single accessibility model. Regions with poor accessibility often overlap with areas lacking sufficient road networks or with hospitals of lower capacities. Figure 7 emphasizes the importance of integrating healthcare capacity and infrastructure quality for disaster management and highlights regions that require infrastructure improvement or additional healthcare facilities to enhance accessibility during emergencies. Areas with no value are not accessible by road. **The penalties were normalized between 0-1 for later calculations.** The code is available on Github and the link is attached in Annex 1.

2.3.3 Vulnerability Classes based on Infrastructure

The analysis reveals varying levels of accessibility to healthcare facilities, categorized into four distinct classes based on the calculated accessibility index “y”. This index combines the cost of traveling across a road network, the distance to the nearest healthcare facility, and the hospital's surge capacity as shown in the formula to provide a comprehensive measure of access. Each class reflects unique accessibility conditions, highlighting the interplay between infrastructure quality, travel distance, and hospital capacity.

$$y = \sum(\text{cost} \times \text{distance}) + \frac{1}{\text{surge}}$$

The High Accessibility class where y is 10,000 or less, represents the most favorable conditions for healthcare access. In this category, individuals benefit from short travel distances, well-maintained road networks, and access to hospitals with significant surge capacities. For example, a 5 km journey on a smooth road with a minimal penalty (e.g., 0.5) to a major hospital with a capacity of 1,540 beds would fall under this class. Similarly, a 10 km journey on a perfect road (penalty near zero) to the same hospital would yield a comparable cost. These conditions are typically observed in urban areas with robust infrastructure and well-equipped healthcare facilities, ensuring rapid access to advanced medical care.

The Moderate Accessibility class where y is from 10,000 to 25,000 reflects conditions that are slightly less favorable but still reasonable for accessing healthcare. In this category, travel distances are longer, and road quality may vary, but the overall accessibility remains manageable. For instance, a 25 km journey on a well-maintained road with a penalty of 0.5 to a hospital with a surge capacity of 800 beds would be classified as moderately accessible. Alternatively, a shorter 12.5 km drive on a road with a higher penalty to a hospital with excellent facilities may also fall under this class. These conditions are often observed in peri-urban or semi-urban regions where infrastructure is present but may require some improvements to enhance accessibility.

The Low Accessibility class where y is from 25,000 to 60,000 represents more challenging conditions for reaching healthcare facilities. Individuals in this category face significant barriers, such as longer travel distances, poor road quality, or limited hospital capacity. For example, a 60 km journey on rough terrain to a clinic with a surge capacity of only 300 beds would be classified as low accessibility. Similarly, a 30 km drive on a road with a penalty factor of 0.8 to a hospital with moderate resources would result in a high accessibility cost. These conditions are typical of rural or remote areas where infrastructure deficiencies and limited healthcare facilities combine to hinder access.

Finally, the Very Low Accessibility class where y is 60,0000 to 120,000 or more represents the most unfavorable conditions for accessing healthcare. These situations involve extremely long travel distances, highly penalized roads, and minimal hospital capacity. For instance, a 120 km journey over difficult terrain to a remote clinic with a surge capacity of 100 beds would fall into this category. Alternatively, a 60 km journey on roads with severe penalties (e.g., penalty = 0.9) to a clinic with basic facilities would result in a similar cost. These conditions lead to significant delays in accessing healthcare and are characteristic of isolated regions with minimal infrastructure and healthcare availability. This is **summarised** in table 5.

Y [Cost]	Vulnerability Class
0-10,000	Very Low (1)
10,000 - 25,000	Low (2)
25,000 - 60,000	Moderate (3)
60000 +	High (4)

Table 4. AHP Assigned Weights

This classification provides critical insights into the spatial variability of healthcare accessibility, highlighting areas that require urgent attention for infrastructure development and healthcare investment. By integrating cost, distance, and hospital capacity, this analysis offers a comprehensive framework for evaluating and addressing accessibility challenges, particularly in disaster-prone or underserved regions.

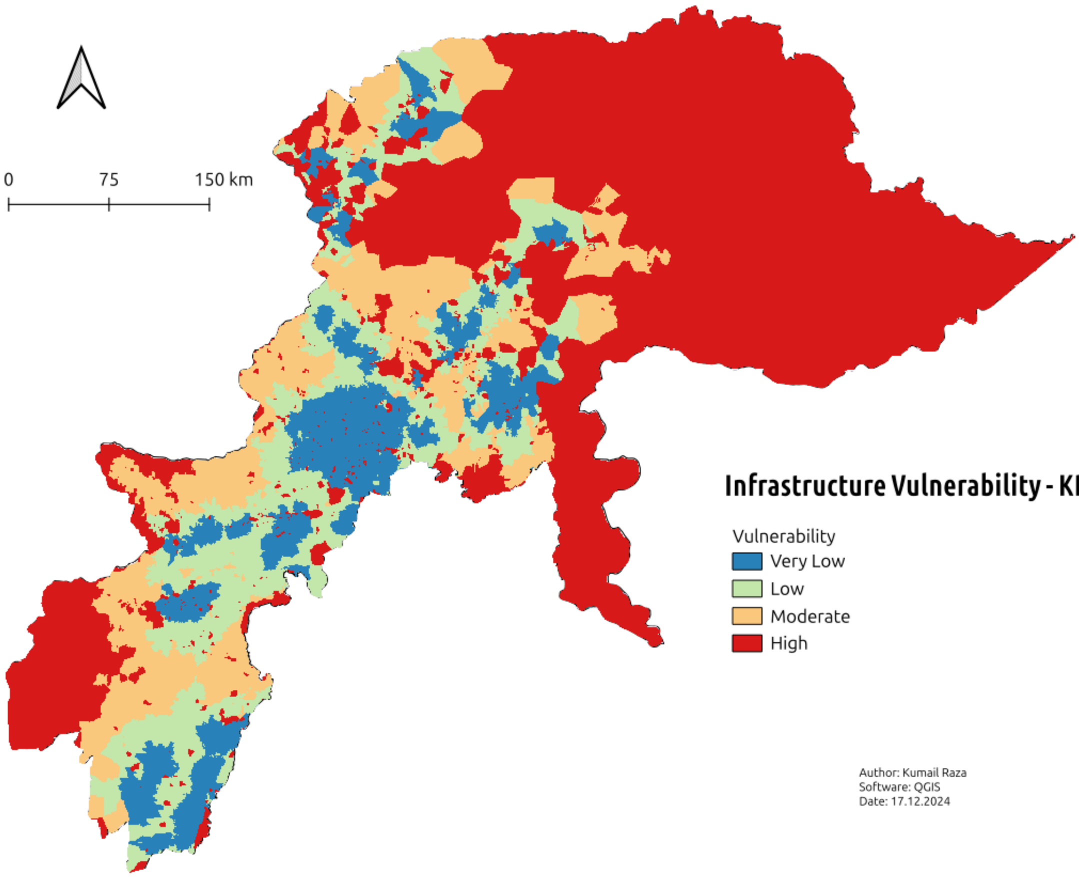

Fig 8. Infrastructure Vulnerability Classes

Figure 8 illustrates the vulnerability across the study area. Areas marked in blue reflect regions with favorable conditions, including well-connected road networks, shorter travel distances, and proximity to hospitals with high surge capacities. These regions are typically concentrated in urban and semi-urban centers where infrastructure investments and healthcare services are robust. Green regions indicate reasonable but slightly constrained access. These areas are often characterized by longer travel distances or intermediate road conditions. While hospitals in these regions may have moderate capacities, they still provide accessible healthcare for surrounding communities. Low Accessibility (yellow) is observed in areas where infrastructure and healthcare resources are limited. These regions typically feature poorly maintained roads, longer travel distances, and hospitals with lower surge capacities. Accessibility is notably impacted in such areas, requiring significant improvement in infrastructure and healthcare capacity.

Finally, Very Low Accessibility (red) areas dominate the map in remote and underserved regions. These regions suffer from severe accessibility challenges due to inadequate road networks, long distances to healthcare facilities, and hospitals with minimal surge capacity. These areas are at the highest risk during disasters, as delays in accessing healthcare can exacerbate vulnerability and reduce the chances of effective emergency response.

This classification underscores the stark disparities in healthcare accessibility across KPK, emphasizing the need for targeted infrastructure improvements and strategic healthcare investments in low and very low-accessibility areas to enhance resilience and equity.

2.4 Analytical Hierarchy Process For Vulnerability Assessment.

The Analytic Hierarchy Process (AHP) is widely utilized in vulnerability assessment because it provides a systematic and flexible framework for integrating multiple criteria and expert judgment to quantify complex phenomena such as vulnerability. In the context of disaster risk assessment, AHP allows the evaluation of diverse factors—such as exposure, sensitivity, and adaptive capacity—by assigning weights to each criterion based on their relative importance (Saaty, 1980). This method is particularly valuable for integrating quantitative data (e.g., population density, road network quality) with qualitative assessments (e.g., infrastructure resilience) to derive a composite vulnerability score. AHP's ability to handle both objective and subjective inputs ensures that it captures the multifaceted nature of vulnerability, making it a robust tool for prioritizing areas and resources for disaster mitigation and planning (Dodgson et al., 2009).

Criterion	Infrastructure	Landslide	Population
Infrastructure	1	2	3
Landslide	0.5	1	2
Population	0.333	0.5	1

Table 5. AHP Assigned Weights

Table 4 presents the pairwise comparison matrix used in the Analytic Hierarchy Process (AHP) to determine the relative importance of three criteria: **Infrastructure**, **Landslide Susceptibility**, and **Population**. The values in the table represent how much more important one criterion is compared to another, based on expert judgment or domain understanding. **Infrastructure** is assigned the highest importance, reflecting its critical role in accessibility and disaster response. It is considered twice as important as Landslide Susceptibility and three times as important as Population, given its direct influence on adaptive capacity and recovery during disasters. **Landslide Susceptibility** holds moderate importance, as it directly represents the hazard level in the region, being equally important as Infrastructure but twice as significant as Population in influencing vulnerability. Finally, **Population** is assigned the lowest importance, representing sensitivity rather than direct mitigative or adaptive capacity, and is considered three times less important than Infrastructure and half as important as Landslide Susceptibility. These comparisons are normalized during the AHP process to calculate final weights, ensuring that each criterion contributes proportionally to the overall vulnerability assessment.

The AHP indicators (λ=3.007 , CI=0.004, and CR=0.007) provide a quantitative measure of the consistency in the pairwise comparisons used in the Analytic Hierarchy Process (AHP).

- **λ:** A value of 3.007 indicates that the matrix is nearly consistent, with minimal deviations.
- **Consistency Index (CI):** A CI of 0.004 suggests excellent consistency, as values close to zero indicate minimal inconsistency.
- **Consistency Ratio (CR):** The CR value of 0.007(less than 0.1) indicates that the judgments are acceptably consistent, meeting the standard threshold for reliability in AHP.

These indicators confirm that the pairwise comparisons made for Infrastructure, Landslide Susceptibility, and Population are highly consistent, validating the reliability of the resulting weights used in the vulnerability assessment.

Criterion	Weight
Infrastructure	0.539
Landslide Susceptibility	0.297
Population	0.164

Table 6. AHP Calculated Weights

These weights in Table 4 reflect the relative importance of each criterion in the vulnerability assessment. **Infrastructure** is the most critical factor, accounting for 53.9% of the total importance, followed by **Landslide Susceptibility** (29.7%) and **Population** (16.4%).

3 Results

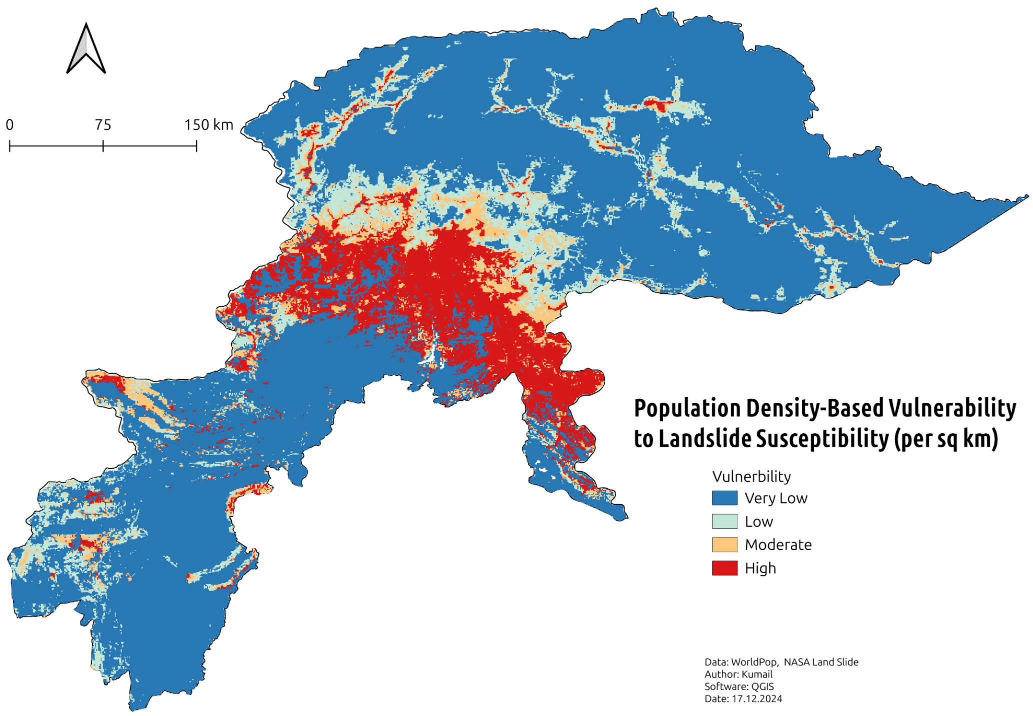

Fig 9. AHP Results: Population Density Based Vulnerability to Landslide Susceptibility

Figure 9 illustrates population density-based vulnerability to landslide susceptibility across our study area, categorizing regions into Very Low, Low, Moderate, and High vulnerability. This classification combines population density with landslide susceptibility to highlight areas at varying levels of risk. High Vulnerability zones, marked in red, represent areas where dense populations coincide with steep terrain and high susceptibility to landslides. These zones are predominantly found in the northern and central parts of KPK, where communities are often situated along unstable slopes, increasing the likelihood of human and infrastructural damage during landslide events. Such areas are critical hotspots that require immediate attention for disaster preparedness and mitigation.

Moderate Vulnerability zones, shown in orange, represent areas with a balance of population density and landslide susceptibility. These regions are typically semi-urban or peri-urban areas where the risk is significant but not as critical as in high-vulnerability zones. While these areas are less likely to experience catastrophic impacts, they still face considerable challenges during landslides, such as disrupted transportation, delayed emergency responses, and localized property damage. Addressing risks in these areas involves strengthening infrastructure, improving road networks, and increasing community awareness.

Low Vulnerability regions, marked in yellow, are areas with lower population densities and reduced landslide susceptibility. These areas generally represent safer zones where the risk of widespread damage is minimal. However, low vulnerability does not eliminate risk entirely. Infrastructure improvements, such as better connectivity to high-risk areas, and strategic resource allocation can enhance resilience even in these relatively safer regions.

Very Low Vulnerability areas, depicted in blue, are the least affected by landslides, owing to their sparse populations and stable terrain. These zones are typically found in the southern plains of KPK, where flat landscapes minimize the impact of landslide hazards. While these areas face minimal risk, they are often isolated and may still benefit from improved road access and disaster response plans to support neighboring higher-risk regions.

In real-world scenarios, this spatial analysis is essential for prioritizing interventions and resource allocation. High-risk areas require immediate investments in slope stabilization, early warning systems, and evacuation planning to mitigate potential disasters. Moderate-risk zones can benefit from enhanced infrastructure and adaptive capacity measures, while low-risk areas require maintenance of existing resources to prevent future vulnerability. This analysis underscores the importance of integrating population exposure with hazard susceptibility to identify and address vulnerability in a targeted and effective manner.

4 Discussion

This study provides an important foundational understanding of vulnerability assessment by integrating population density, landslide susceptibility, and infrastructure data. However, it is crucial to acknowledge that the analysis oversimplifies the real-world complexities to focus on providing a base framework. The road network, hospital data, and vulnerability criteria used in this study are simplified representations designed to closely approximate how real-world systems function but may differ significantly in practice. For example, road conditions and hospital surge capacities vary dynamically during disasters, and these nuances are not fully captured here.

Moreover, the study does not consider healthcare facilities located outside the defined study region, which may still provide critical services to communities near the border. While this limitation is significant, the chosen scope is deliberate and sufficient for the objectives of this project. It allows for a focused exploration of the vulnerabilities within Khyber Pakhtunkhwa (KPK) without introducing excessive complexity.

Future work could expand upon this foundation by incorporating a broader dataset, including inter-regional healthcare accessibility, dynamic infrastructure conditions, and real-time hazard data. Additionally, advanced modeling techniques, such as agent-based simulations or time-sensitive accessibility modeling, could provide a more nuanced understanding of how real-world scenarios may unfold during disasters. Despite its limitations, this study serves as a valuable starting point for understanding vulnerability and offers a basis for more detailed and expansive analyses in the future.

5 Conclusion

In conclusion, this study highlights the critical interplay between population density, landslide susceptibility, and infrastructure in determining vulnerability across KPK. By integrating these factors through a systematic framework, including the AHP, the analysis identifies areas of varying vulnerability, ranging from Very Low to High. The findings underscore that regions with high population density and significant landslide susceptibility, predominantly in the central and northern parts of KPK, are the most vulnerable. These areas require urgent attention for disaster preparedness, including slope stabilization, improved road networks, and enhanced healthcare infrastructure.

Moderately vulnerable regions present a balanced risk, often necessitating targeted improvements in adaptive capacity, such as resilient infrastructure and community disaster education. Low and Very Low Vulnerability zones, while safer, still benefit from strategic resource planning to ensure they remain resilient and can support nearby high-risk regions during emergencies.

This assessment provides a robust foundation for policymakers and disaster management authorities to prioritize interventions, allocate resources effectively, and enhance resilience across KPK. The methodology applied, combining population density, landslide susceptibility, and infrastructure data, demonstrates the importance of integrating spatial and quantitative tools for vulnerability assessment. By addressing the identified high-risk areas, KPK can significantly reduce the adverse impacts of landslides and build a more disaster-resilient future.

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Annex 1

https://github.com/mohnark/ntwrk-analysis-rd