Landslide Susceptibility of Roads in Kyrgyzstan

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1 Introduction

Kyrgyzstan is characterized by its mountainous terrain, with over 90% of its territory covered by mountains. This topography makes the country highly susceptible to natural disasters, particularly landslides [Saponaro et al., 2015]. Until 2009, 5,000 potential active landslide sites have been identified in Kyrgyzstan. Landslides pose a significant risk to the infrastructure as well as the people. Especially the limited road network connecting the northern and southern regions of the country can be severely impacted by only a singular landslide. These roads are critical for transportation, trade, and access to essential services. The country relies heavily on the accessibility of these roads, as they connect rural and urban populations to healthcare facilities and economic centers. Additionally, they facilitate the transport of humanitarian aid deliveries in case of a disaster. Even though the distribution of infrastructure across the country is generally considered adequate [WHO, 2022], limited road access can prevent effective disaster response and relief. Literature highlights that areas with sparse infrastructure, particularly in rural regions, face greater challenges during emergencies, as road blockages caused by landslides can severely impede the transportation of critical resources and aid. Identifying high-risk zones and improving road network resilience are essential for mitigating the impact of such events. While analyzing roads for landslide susceptibility is a common practice [Pacheco Quevedo et al., 2023, Yan et al., 2019], integrating disaster relief and accessibility considerations remains an area with significant potential for further research.

The aim of this analysis is to provide a high resolution map of the landslide susceptibility of all major roads in Kyrgyzstan based on free and open source data and software. Using the map we can provide a recommendation on where to focus anticipatory action and allocate resources to ensure continuous access to as many impacted areas as possible.

1.1 Landslides

Landslides occur when the slope is unstable. Slope (in)stability is influenced by multiple exterior and interior factors. The key factors are of geomorphological (slope, faults), geological (soil and rock properties) or hydrological (water content) nature and are additionally influenced by vegetation, land use, seismic activities, precipitation and human activity [Soeters and van Westen, 1996].

The term landslide refers to different types of gravitative mass movements. The movement types are classified in a scheme developed by Cruden and Varnes [Cruden, 1996], as described in Figure 1.

The dominant landslide types in Kyrgyzstan are Fall (semi-hard and hard rocks), Slide and Flow (soft and semi-hard rocks) movements [Saponaro et al., 2015]. Flow and Slide movements, which maintain contact with the bed during the transport, are typical in permafrost regions due to thaw processes [Patton et al., 2019]. Fall movements occur in Kyrgyzstan's steep cliffs [Saponaro et al., 2015].

1.2 Disaster-impact related terminology

Calculating landslide susceptibility is commonly used to forecast hazard and risk for the area of interest. While in some literature those key terms seem interchangeable, they are clearly distinct and denote different matters. In this chapter, we distinguish the most relevant disaster related terms.

		MATERIAL TYPE		
		Rock (bedrock)	Debris (predominantly coarse soil)	Earth (predominantly fine soil)
MOVEMENT TYPE	Fall	Rockfall	Debris fall	Earth fall
	Topple	Rock topple	Debris topple	Earth topple
	Slide*	Rockslide	Debris slide	Earth slide
	Spread	Rock spread	Debris spread	Earth spread
	Flow	Solifluction flow	Debris flow	Earth flow
	Complex	e.g. rock avalanche	e.g. debris slide-debris flow	e.g. earth slide -earth flow

* Slide includes translational and rotational slides. Slumps are rotational slides.

Figure 1: Landslide classification scheme, adapted from [Cruden, 1996][Clague and Stead, 2012]

Susceptibility refers to the tendency of a region to be affected by a particular hazard, e. g., landslides, without considering the time of its occurrence nor the potential number of victims and economic losses [Domínguez-Cuesta, 2013].

Hazard: "Hazard is the probability that a specific damaging event will happen within a specific area in a particular period of time" ([Clague and Stead, 2012], p. 2). Hazard refers to the likelihood of the event occurring, without regard to impact or effect.

Vulnerability: This term refers to the social and economical impact of disaster. It is assessed by the number of people injured or killed, along with the loss of shelter and the economic impact of the disaster [European Commission DRMKC, 2024]. Other relevant factors are economic, political, and social characteristics of a community that could be disrupted [European Commission DRMKC, 2024].

Coping Capacity: Coping capacity refers to the ability to manage and respond to the impact of the hazard. Resources, strategies and skills committed by the government and individuals to mitigate damage and recover [European Commission DRMKC, 2024]. This is divided into two categories: institutional and infrastructural. Institutional coping capacity refers to early warning systems and preparedness, the latter to the infrastructure available for emergency response [European Commission DRMKC, 2024].

Risk: Risk, on the other hand, refers to the interrelationships between hazard, vulnerability, coping capacity and exposure [Clague and Stead, 2012]. If there is no physical exposure, there is no risk, regardless of the severity of the event [European Commission DRMKC, 2024]. The other elements, vulnerability and coping capacity, only manifest when a hazardous event occurs [Clague and Stead, 2012].

While the findings of this analysis can be further utilized in hazard and risk assessments, the primary focus is on susceptibility as defined by Domínguez-Cuesta (2013).

1.3 Anticipatory Action and Forecast based Financing

"Anticipatory action refers to actions taken to reduce the humanitarian impacts of a forecast hazard before it occurs, or before its most acute impacts are felt." [Anticipation Hub, 2023] As the name suggests, the timing of the action is of great importance. It is assumed that taking humanitarian action before a disaster actually occurs, or at least before all the impact has been felt, can save lives and livelihoods as well as reduce losses and suffering. Anticipatory action involves implementing short-term measures before a disaster occurs, based on reliable forecasts. Such measures include actions like evacuations, distributing critical supplies, and reinforcing infrastructure. Examples include an evacuation of 1,000 patients in New York City during Hurricane Sandy, and the pre-positioning of search and rescue teams ahead of the storm [Coughlan de Perez et al., 2015].

Forecast-Based Financing (FbF) is an anticipatory action approach which links disaster forecasts, e. g., extreme precipitation forecasts that precede flooding, to financial mechanisms, enabling proactive disaster risk management. FbF allocates funds that are triggered by specific forecast thresholds. These funds support pre-planned, risk-reducing actions, like in Uganda, where the Red Cross piloted FbF by identifying actions like purchasing and distributing water purification tablets before floods, informed by local participation and forecast data. [Coughlan de Perez et al., 2015].

A key component of FbF is the development of accurate forecasting models that can predict potential disasters with sufficient lead time, which enables a shift from reactive to proactive disaster management, using advances in meteorological science and financial innovation to protect vulnerable communities and reduce economic losses. More detailed FbF approaches can be found in [Coughlan de Perez et al., 2015].

2 State of the Art

The use of geographic information systems (GIS) for calculating landslide susceptibility has become widely established and is now a common approach in the field [Assilzadeh et al., 2010, Bandara and Jayasingha, 2018, Maes et al., 2017, Mikoš, 2011, Yordanov et al., 2021].

Assilzadeh et al. aim to improve landslide prevention, prediction, and management by coupling two existing three-dimensional landslide models: the slope-stability model (SCOOPS) and the debris-flow inundation model (LAHARZ) and enhancing it with further information through field-based landslide mapping, analysis of soil properties, and computer modeling of rock slope stability and groundwater impacts. The framework was tested as a pilot project for for Penang Island, Malaysia [Assilzadeh et al., 2010].

Maes et al. and Bandara and Jayasingha are both studying landslides in tropic regions. In their review of landslide disaster risk reduction (LS-DRR) strategies Maes et al. address the challenges of reducing vulnerability to landslides. The paper examines the use of GIS-based models, physical exposure, and Human Development Index (HDI) factors in disaster risk reduction efforts. The paper identifies discrepancies between theoretical recommendations and practical implementation, particularly in the domains of governance, preparedness, and resilience. It underscores the necessity for interdisciplinary research to enhance landslide disaster risk reduction (LS-DRR) measures [Maes et al., 2017].

Bandara and Jayasingha compare different strategies for landslide risk reduction in Sri Lanka. One of them being a Hazard Zonation Mapping, in which fieldwork has been combined with GIS methods. Data included geology, slope, hydrology, and land use, which has been analyzed to zone the country into areas of high, medium and low hazard zones with an predictive accuracy of over 90%. Overlying this information with conducted exposure data refines the predictions furthermore enabling local authorities and the public to make informed decisions [Bandara and Jayasingha, 2018].

Highlighting the importance of combining different approaches, Yordanov categorises a variety of methodologies employed in landslide research, into three approaches:

1. Earth Observation (EO),
2. Volunteered Geographic Information (VGI) and
3. Artificial Intelligence (AI) and Machine Learning (ML)

The paper concludes that, individually, every approach has advantages and disadvantages, but by integrating them a better understanding of the overall problem can be achieved. EO provides large amount of data, ML and AI are able to process these data, model a prediction and using crowdsourced information enriches the calculation with local knowledge [Yordanov et al., 2021]

3 Data

The datasets used in this study integrate a variety of sources to ensure comprehensive analysis. Permafrost data were obtained from the ESA Permafrost Climate Change Initiative (Permafrostcci) v4.0 [Westermann et al., 2024], providing detailed information on permafrost extent across the Northern Hemisphere. Elevation data were sourced from the Shuttle Radar Topography Mission (SRTM) at a 30-meter resolution, accessible via the SRTM30m portal [Watkins and JPL, 2000]. Administrative boundaries and road networks were derived from OpenStreetMap (OSM), with the latter retrieved through the Overpass API. Land use and land cover (LULC) information was extracted from the Sentinel-2 10m dataset developed by Esri and Impact Observatory, offering high-resolution classification [Esri and Observatory, 2024]. Rainfall data, critical for assessing precipitation-driven landslides, were derived from the study by [Patton et al., 2020], while datapoints for landslide susceptibility were informed by [Havenith et al., 2015]. This combination of datasets ensures a robust and multi-faceted approach to modeling landslide susceptibility.

4 Methodology

"At the most fundamental level, GIS-MCDA can be thought of as a collection of methods and tools for transforming and combining geographic data and preferences (value judgments) to obtain information for decision making" [Malczewski and Rinner, 2015]. Multi-criteria decision analysis has been used in a variety of cases, especially for site (pre-) selection. We have adapted the methodology to be able to calculate landslide susceptibility of roads based on multiple environmental factors.

4.1 Factors

Each MCDA requires a set of criteria, as the name suggests. We call them *factors* in our analysis. Each factor has the potential to influence the outcome of the analysis. In a real world scenario, factors are often selected and evaluated by a CEO, board of a company or a consulting business that seeks to evaluate relocation or expansion of their business or business partners. As this is a merely an exploratory analysis, we have taken inspiration by scientific literature to choose the factors and assign weights. Each factor data were clipped to a 3 km buffer around the roads taken from OSM. Apart from the steps outlined in the MCDA handbook, we resampled the data to a 30x30m resolution. We briefly describe the factors in this chapter.

4.1.1 Geomorphological

Elevation: Many other factors are associated with elevation [Havenith et al., 2015]. Precipitation typically increases with altitude, as does permafrost occurrence (in the Tien Shan mountain range starting at 3000m), whereas potentially slope stability increasing LULCs, like forests or other deep rooted vegetation, does not occur in high altitudes. Of course, slope also increases statistically in higher altitudes. Still, according to [Havenith et al., 2015] elevation is a key indicator for landslide susceptibility, where, in Kyrgyzstan, instances of landslides have occurred more densely between 1000 and 3000 meters, as compared to other altitudes.

Slope: The existence of slope is the most important factor for landslide occurrence in Kyrgyzstan. Almost all landslides have occurred on slopes of more than 5°. Comparatively, most occurred between 10° and 40° of slope, with an average amount occurring on steeper slopes [Havenith et al., 2015].

Curvature: Curvature refers to the characteristics of a slope, it can be neutral, convex or concave. In Kyrgyzstan, neutral or no curvature is connected to less landslide occurrences, compared to slightly convex or concave slopes. In fact, more landslides occurred in convex slopes, which, according to [Havenith et al., 2015], is caused by a generally higher susceptibility of convex forms, like hill crests, borders of canyons or convex slope breaks to seismic activity.

Seismic activity: The Tien Shan region is a seismically very active region, which features many faults and other seismological hotspots [Havenith et al., 2006], [Havenith et al., 2015], [Saponaro et al., 2015]. Unfortunately, well mapped seismological material is not available. Even if it were, additionally calculating earthquake risk and potential effects on landslide susceptibility would exceed the scope of this project. Hence, we have chosen to focus on more predictable factors that contribute to landslide susceptibility.

4.1.2 Climatic

Precipitation: Precipitation is an important climatic factor for slope instability, as especially soil saturation with water can lead to increased landslide susceptibility [Havenith et al., 2015], [Caine, 1980], [Cannon, 1988], [Iverson, 2000]. Given the complexity of calculating soil stability, we rely on annual precipitation values as a proxy for water-induced soil instability, as more detailed calculations fall beyond the scope of this work. Despite the country's continental climate, heavy rainfall, particularly during the spring, can act as a potential trigger for landslides in areas with loose or unstable ground [Saponaro et al., 2015]. However, Havenith (2015) suggests that since precipitation is heavily influenced by altitude, the elevation factor already accounts for much of the landslide susceptibility, making precipitation of less significance [Havenith et al., 2015]. Additionally, obtaining high-resolution precipitation data remains a challenge.

Permafrost: Permafrost refers to ground with temperatures below 0 °C for at least two following years [Dobinski, 2011]. If permafrost is present in the area, it will affect the stability of the slope. Thawing of it increases the slope's susceptibility to landslides. This results in weak soil cohesion and increased water flow through the ground, which destabilizes the ground and increases the landslide frequency as well as magnitude in the area, see Figure 2. Due to changing climate and rising average temperature, areas with thawing permafrost will likely experience more landslides [Patton et al., 2019]. However, it is important to note, that more landslides occur in discontinuous permafrost regions than in sporadic or isolated permafrost. Although generally more stable, continuous permafrost can host landslides in regions undergoing rapid thaw [Patton et al., 2020], [Morino et al., 2021], [Allen et al., 2011], [Fischer et al., 2012].

4.1.3 Misc

Land use and land cover (LULC): In the literature, LULC analyses regarding landslides mostly consider the LULC classes roads, soil and forest, as the data are comparatively easy to collect and

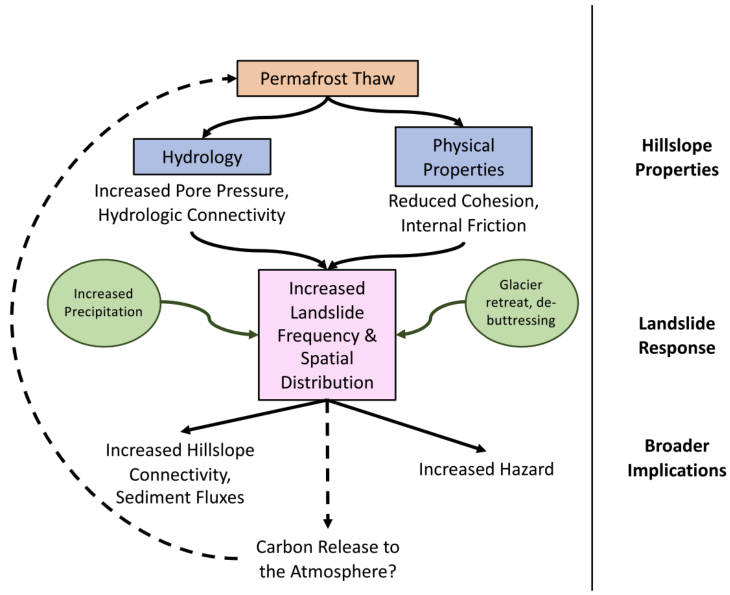


Figure 2: "Known effects of permafrost thaw in high-relief permafrost terrain and some of the implications for geomorphic, ecological, and human systems. Dashed lines indicate uncertainty regarding the direction or magnitude of response." ([Patton et al., 2019], p. 117)

objective [Pacheco Quevedo et al., 2023]. Generally speaking, road construction and use changes the slope, and therefore surface water runoff , which changes landslide susceptibility in these areas [Vuillez et al., 2018], [Pacheco Quevedo et al., 2023]. Regarding soil, many studies focus on exposed parts of soil or less vegetated ground, but rarely focus on soil types. However, those studies have found that "deforestation or logging exposes soil to erosion processes and slope instability" [Pacheco Quevedo et al., 2023] (p. 977), (e. g. [Reichenbach et al., 2014], [Cohen and Schwarz, 2017], [Persichillo et al., 2017]). Research on forest has behaved similarly, where it is rather common knowledge, that deforestation increases landslide susceptibility [Dai et al., 2002] [Cohen and Schwarz, 2017], [Pacheco Quevedo et al., 2023].

5 Results

5.1 Landslide susceptibility in Kyrgyzstan

The landslide susceptibility map (Fig. 3) highlights areas of varying susceptibility along the road network, providing valuable insights for disaster preparedness and infrastructure management. Susceptibility values range from 0.15 (indicating very low susceptibility) to approximately 1.5 (highest susceptibility). High and low elevation areas show lower susceptibility than medium elevation areas. Mainly transitional regions between high mountainous areas and lower areas exhibit a higher susceptibility to landslides. Especially in the Osh and Jalal-Abad region, in the outskirts of the large Ferghana Valley in the West, where the majority of historical landslides have been reported, a high susceptibility can be observed. Additionally, in the bordering mountain ranges of the lake Issyk-Kul the roads have a high susceptibility. Similarly to the Ferghana Valley, the transition from the Chüy Valley in Kyrgyzstan's North to the Ala-Too mountain range seems to be very susceptible, as well. Kyrgyzstan's central Naryn region exhibits high susceptibility, especially along the Naryn river.

5.2 Recommendations for FbF

Based on the findings of landslide susceptibility along major roads, implementing a forecast-based financing approach could significantly enhance disaster preparedness and resilience. Reinforcing infrastructure in high-risk areas through anticipatory investments can reduce long-term vulnerability. We

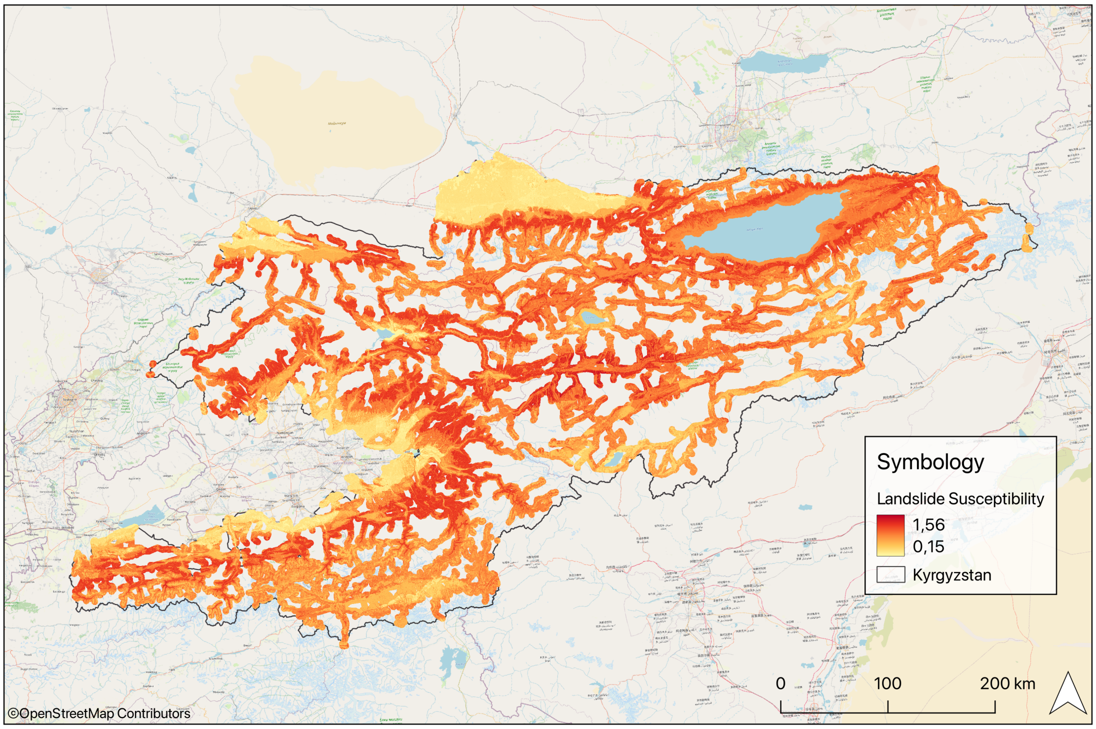


Figure 3: Landslide susceptibility of roads in Kyrgyzstan.

recommend prioritizing resource allocation to areas with high susceptibility to ensure rapid disaster response and minimized disruption. Specifically:

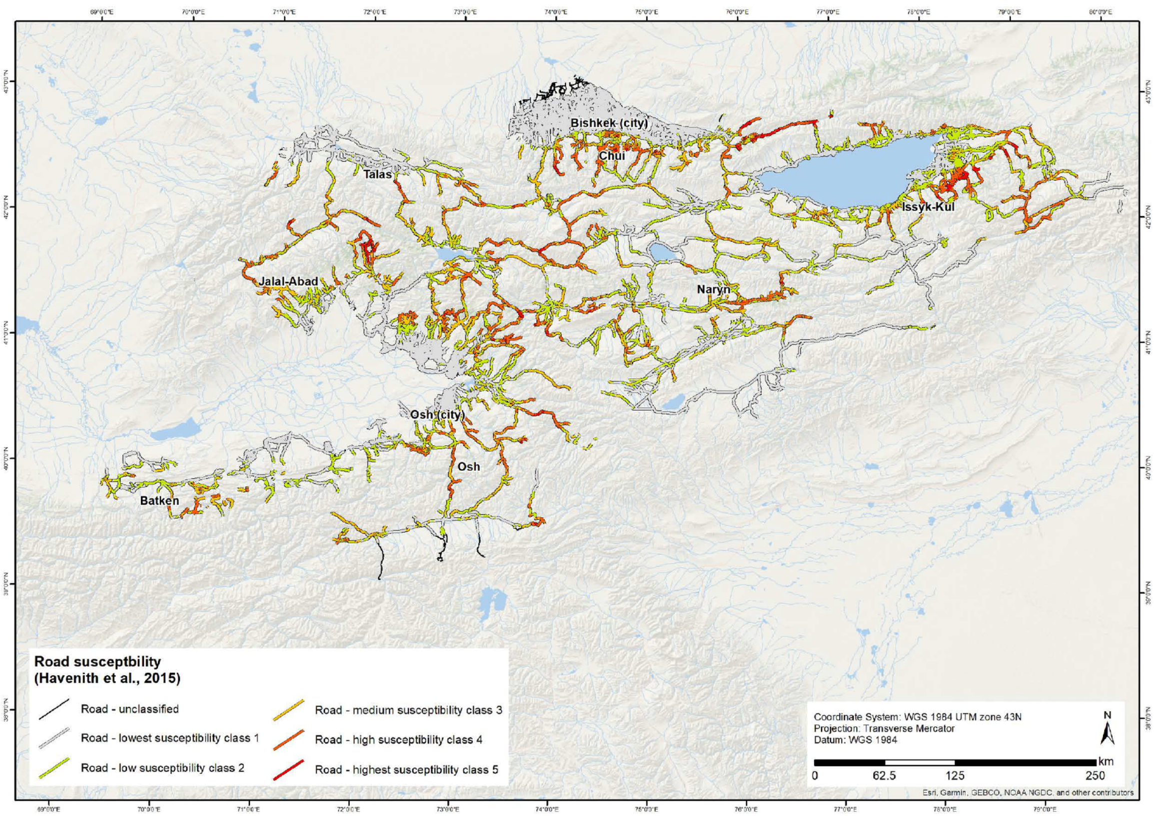
1. **Strategic Resource Placement**: Pre-position emergency response equipment and materials, such as excavation tools and temporary road repair kits near high-risk road segments to reduce delays caused by road blockages.

2. **Early Warning Integration**: Establishing clear thresholds, as is best-practice in FbF-projects, within early warning systems would ensure timely activation of these resources, enabling more efficient and effective disaster response measures.

3. **Targeted Infrastructure Investments**: Allocate funds to reinforce or redesign critical road infrastructure in highly susceptible areas, reducing vulnerability and maintenance costs over time.

6 Discussion

The landslide susceptibility map (Fig. 4) shows a high resolution (30x30m) geospatial analysis of landlside susceptibility along the road network of Kyrgyzstan, utilizing MCDA to integrate factors like elevation, slope, and precipitation. The susceptibility values align with the distribution of historical landslides recorded in the official inventory [Havenith et al., 2015, Asian Development Bank, 2023]. High-susceptibility zones, particularly in transitional areas like the Ferghana Valley's outskirts, the Issyk-Kul border ranges, and the Chüy Valley's transition to the Ala-Too mountains, corroborate the historical data. MCDA proves to be a practical and adaptable method for assessing landslide susceptibility, allowing the weighting of key factors to fit the contexts. This consistency underscores the reliability of the MCDA approach for identifying areas at risk. While the chosen weights provided a balanced representation of landslide risk, future applications should consider site-specific data or expert elicitation to refine these parameters further. Additionally, the current model does not incorporate certain dynamic factors, such as seismic activity which could further improve its predictive accuracy. Ground validation and stakeholder feedback could also help ensure that the susceptibility map aligns



Sources: Basemap: Esri, Garmin, GEBCO, NOAA NGDC, and other contributors. Roads: OpenStreetmap. Susceptibility: H. Havenith et al. 2015. Tien Shan Geohazards Database: Landslide Susceptibility Analysis. *Geomorphology*. 249. pp. 32–43.

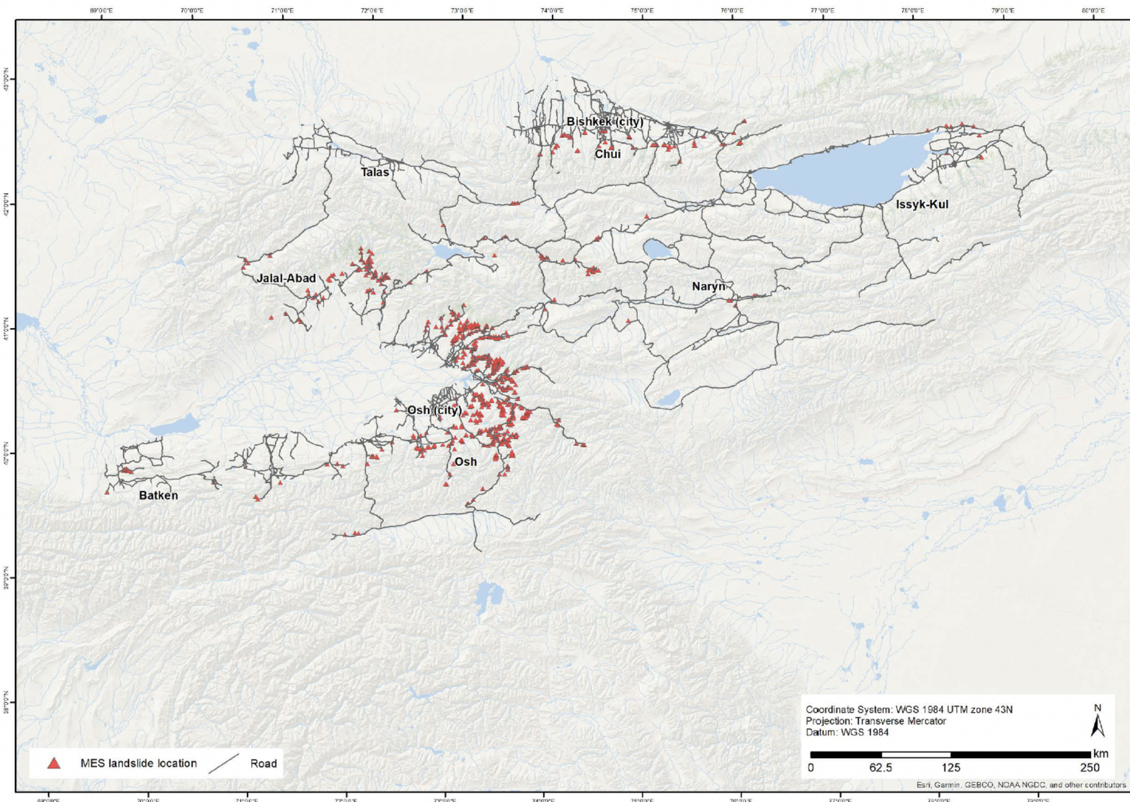
Figure 4: A similar analysis done by [Havenith et al., 2015, Asian Development Bank, 2023]

with on-the-ground realities and is practically applicable for mitigation planning. The reliance on open-source data and software supports accessibility and reproducibility, which we consider crucial for scalability and actual application in regions with limited access to geoinformation resources.

It must be noted, that the official Atlas of Landslides [Asian Development Bank, 2023], which includes the landslide inventory also has significant gaps in anticipatory disaster management. Despite accurately documenting past events, the report lacks actionable strategies for proactive mitigation, such as Forecast-Based Financing (FbF). FbF could allocate resources to high-susceptibility zones identified in this analysis, enabling preemptive measures like equipment staging, infrastructure reinforcement, and community preparedness. The absence of anticipatory action in current frameworks risks reactive responses, which are often less effective and more costly. Integrating susceptibility maps with FbF mechanisms offers a pathway to enhance resilience and reduce the socio-economic impacts of landslides. This analysis not only validates the model but also underscores the urgent need for forward-looking policies in disaster risk management.

Overall, the comparison with the landslide inventory data underscores the accuracy of the analysis. Merely in the Naryn region, the analysis differs from the inventory, as in there have been only few landslides reported in that area.

Figure 4: Landslide Locations in the Kyrgyz Republic, Occurring over 2003–2016
(Based on the MES Landslide Inventory)



MES = Ministry of Emergency Situations.
Sources: Basemap: Esri, Garmin, GEBCO, NOAA NGDC, other contributors; Roads: OpenStreetMap; MES landslide locations: MES landslide inventory.

Figure 5: MES Landslide inventory [Asian Development Bank, 2023]

This study utilized ChatGPT [OpenAI, 2023], an AI language model developed by OpenAI, to assist with the revision of the text. All outputs were reviewed and edited by the authors to ensure accuracy and appropriateness.

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