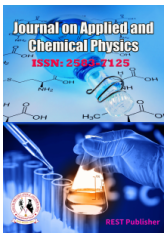
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Evaluating The Impact of Climate Change On Landslide Susceptibility: An Electre Method Approach

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ABSTRACT

Climate Change Impact on Landslides Rising global temperatures contribute to more extreme weather patterns, including intense rainfall events that increase soil saturation and slope instability. Additionally, the melting of permafrost in colder regions due to warming temperatures weakens mountain slopes, heightening the risk of landslides. Deforestation and land-use changes further exacerbate these conditions by reducing natural vegetation that stabilizes soil. Research significance Researching climate change's impact on landslides is critical as rising temperatures, shifting precipitation patterns, and extreme weather events intensify landslide risks globally. Increased rainfall and rapid snowmelt contribute to soil saturation and instability on slopes, while droughts can dry soils, leading to heightened erosion and landslide susceptibility. Methodology Climate models project changes in temperature, precipitation, and extreme weather, which can trigger landslides. Landslide susceptibility maps, created using GIS tools and machine learning algorithms, help identify high-risk zones based on topography, soil type, and vegetation. Historical landslide records are analyzed alongside climate data to detect trends and correlations. Alternative High Rainfall, Low Vegetation, Stable Soil, Steep Slope Evaluation preference Average Rainfall (mm), Vegetation Coverage (%), Soil Stability Index, Community Preparedness (%), Slope Gradient (degrees), Erosion Rate (%) Results High Rainfall is getting top of the table Low Vegetation is getting bottom of the table

1. INTRODUCTION

As global temperatures rise, climate change influences several key environmental factors that directly impact landslide vulnerability. Chief among these factors are precipitation intensity, snowmelt rates, and alterations to soil moisture and vegetation stability, each of which affects the likelihood of landslides in different ways [1]. In cold regions, permafrost layer of permanently frozen ground acts as a stabilizing agent for steep slopes. However, rising temperatures lead to permafrost thawing, which destabilizes the slopes and increases the likelihood of landslides [2]. Warmer temperatures and shorter winters lead to earlier snowmelt, which releases large amounts of water into the soil in a short period [3]. Climate change affects vegetation patterns, altering the type and density of vegetation in different regions. preventing landslides through root networks that bind the soil together. As climate zones shift, native vegetation may struggle to survive, reducing the soil's cohesion and increasing susceptibility to erosion [4]. Climate change contributes to an increase in extreme weather events, including hurricanes, cyclones, and intense storms [5]. Landslides have severe consequences for both human and environmental systems, affecting lives, infrastructure, and ecosystems [6]. Environmentally, landslides alter natural

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landscapes, affecting habitats and biodiversity. For instance, landslides can result in deforestation, soil erosion, and changes in river courses, which disrupt aquatic ecosystems [7]. landslides are particularly pronounced in vulnerable regions, such as mountainous areas and tropical countries with seasonal monsoons. These regions often have high population densities and limited resources for adaptation and risk managemen [8]. Conducting detailed landslide hazard assessments and creating landslide susceptibility maps are essential for understanding [9]. Developing and implementing early warning systems based on meteorological data, such as rainfall intensity and soil moisture levels, can provide communities with valuable time to evacuate or prepare for potential landslides [10]. Educating communities about landslide risks and involving them in preparedness planning can significantly reduce the impact of landslides [11]. The link between climate change and landslides is undeniable, as rising global temperatures lead to increased precipitation, permafrost thaw, snowmelt, and extreme weather events that destabilize slopes [12]. Ultimately, addressing the climate change-induced landslide risk requires a collaborative effort that combines scientific knowledge, technological innovation, and community resilience. By understanding and preparing for these hazards, we can mitigate the devastating impact of landslides and promote safer, more sustainable living environments in a changing climate [13].

2. MATERIAL AND METHOD

Alternatives

- **High Rainfall (M1):** High rainfall refers to significant precipitation levels over a short period, leading to flooding, soil erosion, and landslides. It impacts agriculture, infrastructure, and water resources, necessitating effective management strategies.
- **Low Vegetation (M2):** Low vegetation refers to plant life that grows close to the ground, including grasses, mosses, and small shrubs. It plays a crucial role in soil stabilization, biodiversity, and ecosystem health.
- **Stable Soil (M3):** Stable soil refers to soil that maintains its structure and integrity under varying environmental conditions. It is crucial for supporting vegetation, preventing erosion, and promoting sustainable land use practices.
- **Steep Slope (M4):** Steep slopes are inclined landforms characterized by a gradient greater than 15 degrees. They pose risks like landslides, erosion, and runoff, affecting construction, agriculture, and natural ecosystems.

Evaluation Preference

- **Average Rainfall (mm) (C1) :** Average rainfall (mm) refers to the mean amount of precipitation received in a specific area over a defined period, usually calculated annually or monthly, reflecting local climate patterns.
- **Vegetation Coverage (%) (C2):** Vegetation coverage (%) indicates the proportion of land area occupied by plant life, playing a critical role in biodiversity, soil conservation, climate regulation, and providing essential ecosystem services.
- **Soil Stability Index (C3):** The Soil Stability Index (SSI) evaluates soil's ability to resist erosion and maintain structural integrity, factoring in moisture content, soil composition, vegetation cover, and environmental conditions for land management decisions.
- **Community Preparedness (%) (C4):** Community preparedness refers to the percentage of a community that is equipped, trained, and organized to respond effectively to emergencies, ensuring safety and resilience during disasters and critical incidents.
- **Slope Gradient (Degrees) (C5):** Slope gradient, measured in degrees, quantifies the steepness of a slope. It influences water drainage, erosion potential, and stability, crucial for construction, agriculture, and environmental management.
- **Erosion Rate (%) (C6):** Erosion rate (%) measures the loss of soil or rock over time, influenced by factors such as rainfall, vegetation, land use, and climate. It's critical for assessing land degradation and sustainability.

One of the distinguishing features of the ELECTRE method is its pair wise comparison approach. Decision-makers compare alternatives two at a time, assessing how one alternative performs relative to another based on specific criteria [14].This approach simplifies the complexity of evaluating multiple options simultaneously and provides clearer insights into the relative merits of alternatives [15]. ELECTRE employs an outranking relation to determine which alternatives are superior to others. An alternative AAA is said to outrank another alternative BBB if the advantages of AAA over BBB are deemed sufficient when considering the decision-makers' preferences for each criterion [16]. This concept captures the idea that the decision does not necessarily result in a clear ranking of alternatives but rather in an ordered set of preferences based on their relative strengths and weaknesses [15]. The first step involves identifying the decision problem and the criteria relevant to the decision. This includes both qualitative and quantitative factors that will influence the evaluation of alternatives [18]. Each alternative is compared pair wise based on each criterion. Decision-makers evaluate whether one alternative is preferable to another and assign scores or preference values accordingly [19]. Using the decision matrix, the method calculates outranking relations. This involves establishing the degree to which one alternative outranks another based on predefined thresholds or criteria importance weights [20]. The ELECTRE method has been successfully applied in various fields, including environmental management, urban planning, resource allocation, and project selection. [21]. In summary, the ELECTRE method is a powerful multi-criteria decision-making tool that allows for a nuanced evaluation of alternatives based on conflicting criteria [22].

3. RESULT AND DISCUSSION

TABLE 1. Climate Change Impact on Landslides

	C1	C2	C3	C4	C5	C6
M1	200	70	0.75	80	35	2.5
M2	450	55	0.65	60	45	3.2
M3	380	80	0.8	85	30	2
M4	500	50	0.6	70	40	3.5

Table 1 presents the four models (M1–M4) evaluated using six criteria (C1–C6) related to climate change impacts on landslides. Model M1 records values of 200, 70, 0.75, 80, 35, and 2.5, whereas M2 shows higher values for C1 and C5. Model M3 demonstrates comparatively higher values for C2, C3, and C4, indicating potential differences in the characteristics assessed. Model M4 records the highest C1 value of 500 and C6 value of 3.5. These variations illustrate the differences among the models across the selected criteria, the table supports comparative evaluation and helps identify relevant factors for landslide susceptibility assessment and climate-related risk management.

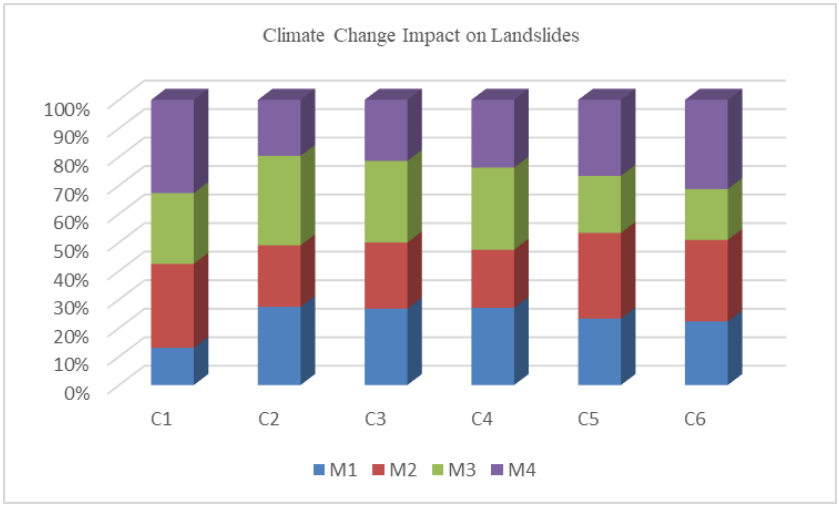


FIGURE 1. Climate Change Impact on Landslides

Figure 1 shows the comparative contributions of four models (M1, M2, M3, and M4) across six criteria (C1–C6) related to climate change impacts on landslides. The 100% stacked columns highlight the relative distribution of each model across the criteria. M1 contributes a larger proportion to C2, C3, and C4, while M2 shows a notable contribution to C5 and C6. M3 has a stronger representation in C1, C2, and C3, whereas M4 contributes substantially to C1 and C6. the figure enables visual comparison of model performance and supports further evaluation of landslide-related climate change factors.

TABLE 2. Sum and Square Root

	C1	C2	C3	C4	C5	C6
M1	40000	4900	0.5625	6400	1225	6.25
M2	202500	3025	0.4225	3600	2025	10.24
M3	144400	6400	0.64	7225	900	4
M4	250000	2500	0.36	4900	1600	12.25
Sum	636900	16825	1.985	22125	5750	32.74
Square Root	798.0601	129.7112	1.4089	148.7447	75.82875	5.721888

Table 2 presents the squared values, sums, and square roots for six criteria (C1–C6) across four models (M1–M4). The sum values indicate the cumulative squared contributions of each criterion, while the square roots provide normalization factors for subsequent analysis. C1 records the highest sum of 636900, followed by C4 at 22125 and C2 at 16825. In contrast, C3 has the lowest sum of 1.985, reflecting its smaller numerical scale. The corresponding square roots are 798.0601, 129.7112, 1.4089, 148.7447, 75.82875, and 5.721888. These results support criterion-wise normalization and comparative evaluation of climate change impacts on landslides.

TABLE 3. Normalized Decision Matrix

Normalized DM	C1	C2	C3	C4	C5	C6
M1	0.250608	0.539660	0.532330	0.537834	0.461566	0.436919
M2	0.563867	0.424019	0.461353	0.403376	0.593442	0.559256
M3	0.476155	0.616755	0.567819	0.571449	0.395628	0.349535
M4	0.626519	0.385472	0.425864	0.470605	0.527504	0.611686

Table 3 presents the normalized decision matrix for four models (M1–M4) across six criteria (C1–C6) related to climate change impacts on landslides. The normalized values enable comparison by converting the original measurements into a common scale. Model M4 records the highest value for C1 (0.626519) and C6 (0.611686), while M3 achieves the highest values for C2 (0.616755), C3 (0.567819), and C4 (0.571449). Model M2 shows the highest value for C5 (0.593442). These differences indicate varying model strengths across the criteria, the normalized matrix provides a foundation for weighting criteria and ranking alternatives in multi-criteria decision-making analysis.

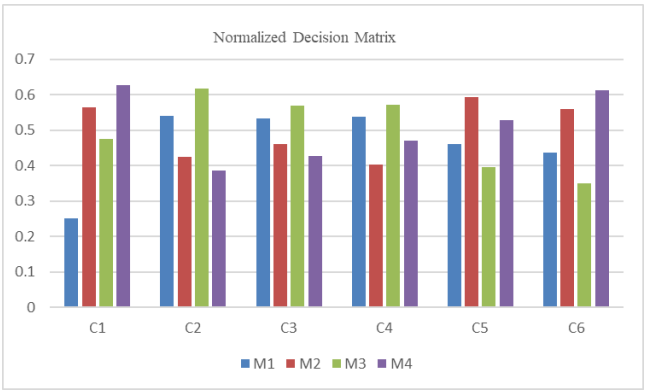


FIGURE 2. Normalized Decision Matrix

Figure 2 shows the normalized decision matrix for four models (M1, M2, M3, and M4) across six criteria (C1–C6) related to climate change impacts on landslides. The bar chart facilitates comparison of the normalized values for each criterion.

M4 achieves the highest value for C1 and C6, while M3 performs strongly in C2, C3, and C4. M2 records the highest value for C5, indicating its relative strength under that criterion. M1 demonstrates moderate values across most criteria, the figure highlights differences among the models and provides a visual foundation for subsequent weighting, evaluation, and ranking in multi-criteria decision-making analysis.

TABLE 4. Weighted Normalized Matrix

	C1	C2	C3	C4	C5	C6
Weights	0.2336	0.1652	0.3355	0.1021	0.0424	0.1212
M1	0.058542	0.089152	0.178597	0.054913	0.019570	0.052955
M2	0.131719	0.070048	0.154784	0.041185	0.025162	0.067782
M3	0.111230	0.101888	0.190503	0.058345	0.016775	0.042364
M4	0.146355	0.063680	0.142877	0.048049	0.022366	0.074136

Table 4 presents the weighted normalized decision matrix for four models (M1–M4) across six criteria (C1–C6) related to climate change impacts on landslides. The matrix is obtained by multiplying normalized values by their corresponding criterion weights. Model M3 achieves the highest weighted value for C2 (0.101888) and C3 (0.190503), indicating strong performance in these criteria. Model M4 records the highest values for C1 (0.146355) and C6 (0.074136), while M2 shows a relatively higher value for C5 (0.025162). These weighted results help compare model performance, reflect criterion importance, and support subsequent evaluation and ranking for effective landslide risk assessment.

TABLE 5. Concordance Interval Matrix and Discordance Interval Matrix

Concordance Interval Matrix		Discordance Interval Matrix	
Pair	C_{ij}	Pair	D_{ij}
12	{2}	12	{1, 3, 4, 5, 6}
13	{3, 5}	13	{1, 2, 4, 6}
14	{2}	14	{1, 3, 4, 5, 6}
21	{1, 3, 4, 5, 6}	21	{2}
23	{1, 3, 5}	23	{2, 4, 6}
24	{1, 4}	24	{2, 3, 5, 6}
31	{1, 2, 4, 6}	31	{3, 5}
32	{2, 4, 6}	32	{1, 3, 5}
34	{1, 2, 4, 6}	34	{3, 5}
41	{1, 3, 4, 5, 6}	41	{2}
42	{2, 3, 5, 6}	42	{1, 4}
43	{3, 5}	43	{1, 2, 4, 6}

Table 5 presents the elements, labeled as CCC and DDD, organized by rows and columns. Each cell entry, such as C12C12C12 or D12D12D12, represents a unique subset of elements. For example, C12=2C12 = {2}C12=2 and D12=1,3,4,5,6D12 = {1,3,4,5,6}D12=1,3,4,5,6, indicating that element 2 is in subset C12C12C12, while the others (1, 3, 4, 5, and 6) are in subset D12D12D12. Each row pairs corresponding CCC and DDD subsets across multiple columns, illustrating different groupings and separations of elements within each context. This structure helps to organize elements based on their respective conditions or classifications across various subsets.

TABLE 6. Concordance Matrix

0	1	1	1	0	0
0	0	0	0	1	1
0	1	1	1	0	0
1	0	0	0	1	1
1	0	0	0	1	1
0	1	1	0	1	0
1	1	1	1	0	0
0	1	1	1	0	0
0	1	1	1	0	0

Table 6 presents the matrix consists of binary values (0s and 1s) arranged in a grid, where each row and column represent specific conditions or elements. A value of "1" indicates the presence or activation of a condition, while "0" signifies its absence. Patterns emerge across the rows, suggesting different combinations of active and inactive states. For example, rows 1, 3, 8, and 9 have a similar pattern of three consecutive 1s, indicating they share similar conditions. Rows 2, 4, and 5, with alternating 0s and 1s, show different configurations. This binary matrix helps identify unique and shared conditions across each row.

TABLE 7. Concordance Interval Matrix

	M1	M2	M3	M4	Sum
M1	0	0.1652	0.3779	0.1652	0.7083
M2	0.8348	0	0.6115	0.3357	1.7820
M3	0.6221	0.3885	0	0.6221	1.6327
M4	0.8348	0.6643	0.3779	0	1.8770
Sum	2.2917	1.2180	1.3673	1.1230	6

Table 7 presents the concordance matrix presents the pairwise comparison values among four alternatives (M1, M2, M3, and M4) for assessing climate change impacts on landslides. The diagonal entries are zero, indicating no comparison of an alternative with itself. The highest individual value is 0.8348, observed for the comparisons M2–M1 and M4–M1, reflecting strong preference relationships. The row totals indicate that M4 has the highest aggregate value of 1.877, followed by M2 at 1.782, M3 at 1.6327, and M1 at 0.7083. These results support comparative evaluation and help establish preference rankings among alternatives for landslide risk assessment and management

TABLE 8. Concordance Index Matrix

	M1	M2	M3	M4
M1	0	0	0	0
M2	1	0	1	0
M3	1	0	0	1
M4	1	1	0	0

Table 8 presents The Concordance Index Matrix displays binary values (0 or 1) representing the concordance between four categories (M1, M2, M3, and M4). A "1" indicates concordance or alignment between two categories, while a "0" shows no concordance. For example, M2 aligns with M1 and M3, as indicated by "1" values in the corresponding cells. M3 is concordant with M1 and M4 but not M2. M4 shows concordance with M1 and M2 but not M3. The diagonal is all zeros, as categories do not self-align. This matrix reveals relationships between categories based on concordance presence or absence.

TABLE 9. Discordance Matrix

	C1	C2	C3	C4	C5	C6	Index
D12	0.073177	0.019104	0.023813	0.013728	0.005592	0.014827	1
D13	0.052688	0.012736	0.011906	0.003432	0.002796	0.010591	1
D14	0.087813	0.025472	0.035719	0.006864	0.002796	0.021182	1
D21	0.073177	0.019104	0.023813	0.013728	0.005592	0.014827	0.261064
D23	0.020490	0.031840	0.035719	0.017160	0.008387	0.025418	0.891393
D24	0.014635	0.006368	0.011906	0.006864	0.002796	0.006355	0.813533
D31	0.052688	0.012736	0.011906	0.003432	0.002796	0.010591	0.225981
D32	0.020490	0.031840	0.035719	0.017160	0.008387	0.025418	1
D34	0.035125	0.038208	0.047626	0.010296	0.005592	0.031773	1
D41	0.087813	0.025472	0.035719	0.006864	0.002796	0.021182	0.290071
D42	0.014635	0.006368	0.011906	0.006864	0.002796	0.006355	1
D43	0.035125	0.038208	0.047626	0.010296	0.005592	0.031773	0.802253

Table 9 presents the six columns labeled C1 to C6, representing different variables, alongside rows labeled D12 to D43, which likely denote distinct data entries or categories. Each cell contains numerical values, presumably indicating

measurements or observations related to these variables. The last column, with values less than or equal to 1, could signify a computed metric or classification result, indicating the significance or relevance of each data entry. The data may be analyzed to identify trends, correlations, or patterns across the variables, providing insights into the underlying phenomena represented by the dataset.

TABLE 10. Discordance Interval Matrix

	M1	M2	M3	M4	Sum
M1	0	1	1	1	3
M2	0.261064	0	0.891393	0.813533	1.965989
M3	0.225981	1	0	1	2.225981
M4	0.290071	1	0.802253	0	2.092324
Sum	0.777116	3	2.693646	2.813533	9.284294

Table 10 presents the Discordance Interval Matrix illustrates the pair wise discordance levels among four matrices (M1 to M4). The diagonal entries represent the discordance of each matrix with itself, which is zero, while off-diagonal values indicate the degree of discordance between different matrices. The last row aggregates discordance values, totaling 9.284294, and indicates relationships among the matrices. The d bar value of 0.773691 provides an average discordance measure across the matrices. This matrix aids in understanding discrepancies in data interpretations or performances among the matrices, which can be crucial for decision-making processes or comparative analyses.

TABLE 11. Discordance Index Matrix

	M1	M2	M3	M4
M1	1	0	0	0
M2	1	1	0	0
M3	1	0	1	0
M4	1	0	0	1

Table 11 presents the Discordance Index Matrix quantifies the discordance relationships among four matrices (M1 to M4) using binary values. Each cell indicates whether a discordance is present (1) or absent (0) between the corresponding matrices. The diagonal entries are all 1, reflecting self-discordance, while the off-diagonal entries show the presence or absence of discordance between different matrices. For instance, M2 exhibits discordance with M1 and M2 but not with M3 or M4. This matrix serves as a tool to assess the consistency of data interpretations, highlighting areas where matrices diverge in their assessments or classifications.

TABLE 12. Net Superior Value and Rank

	Net Superior Value		Net Inferior Value	
Alternative	Value	Rank	Value	Rank
High Rainfall	-1.5834	4	2.222884	1
Low Vegetation	0.564	2	-1.03401	4
Stable Soil	0.2654	3	-0.46766	2
Steep Slope	0.754	1	-0.72121	3

Table 12 presents the comparison of environmental factors based on their Net Superior Value and Net Inferior Value, along with their respective ranks. The factors are High Rainfall, Low Vegetation, Stable Soil, and Steep Slope. A higher Net Superior Value indicates a more favorable condition, with Steep Slope ranked highest at 1, while High Rainfall has the lowest at -1.5834, ranked 4. Conversely, the Net Inferior Value shows adverse effects, where Low Vegetation is ranked 1 (most negative impact), and Stable Soil is ranked 2. This matrix helps in assessing and prioritizing environmental factors based on their contributions and detriments.

Figure 3 shows the net superior value, rank, and net inferior value for four landslide-related factors: high rainfall, vegetation, stable soil, and steep slope. High rainfall exhibits the highest value, indicating its potential importance in landslide

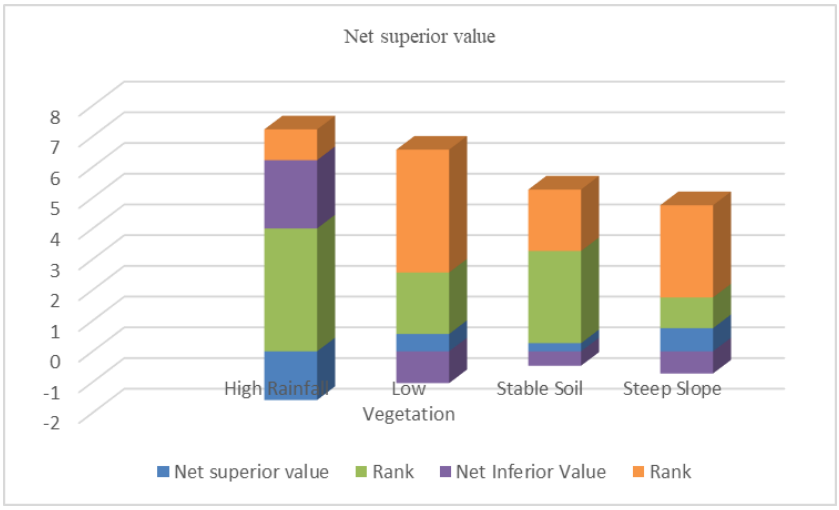


FIGURE 3. Net Superior Value

susceptibility assessment. Vegetation also demonstrates a substantial contribution, suggesting its influence on slope stability and erosion control. Stable soil shows a moderate value, reflecting its role in reducing landslide occurrence. Steep slope presents comparatively lower values in the displayed distribution. the figure enables visual comparison of these factors and supports prioritizing relevant environmental conditions for effective landslide risk evaluation and climate change impact management.

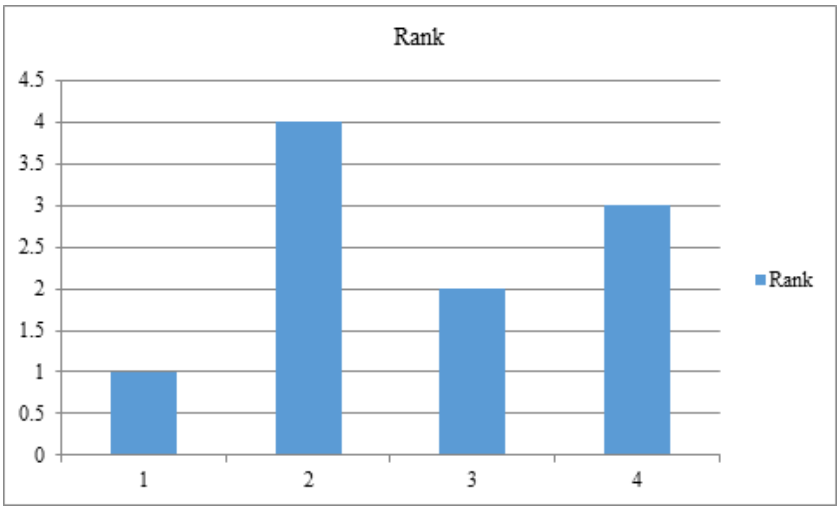


FIGURE 4. Rank

Figure 4 presents the ranking of four alternatives based on their evaluated performance in landslide risk assessment. Alternative 1 receives a rank value of 1, indicating the highest priority, while Alternative 2 records a value of 4, representing the lowest priority. Alternative 3 obtains a rank value of 2, and Alternative 4 receives a value of 3. The bar chart clearly illustrates the differences in ranking among the alternatives. These results help identify the most preferred option for further consideration. the ranking supports systematic decision-making and assists in prioritizing suitable alternatives for evaluating climate change impacts on landslides and developing effective risk management strategies.

4. CONCLUSION

Climate change is increasingly influencing global weather patterns, leading to more frequent and intense rainfall, drought, and extreme weather events. These changes amplify natural hazards, such as landslides, which are particularly susceptible to climate variability. Examining the connection between climate change and landslides, we exacerbating landslide

occurrences, especially in mountainous and heavily populated areas. Climate change has intensified rainfall patterns, with extreme storms becoming more frequent. Heavy rainfall is a primary trigger for landslides, as it saturates soil, destabilizing slopes and leading to failures. In regions experiencing increased precipitation, landslides are occurring more frequently and with greater intensity. Warmer temperatures are causing glaciers and permafrost to melt, especially in high-altitude and Polar Regions. Permafrost acts as a natural "glue" that holds soil and rock in place; its thawing destabilizes terrain, making it more vulnerable to landslides. Glacial retreat exposes steep rock faces, which, without the stabilizing pressure of ice, become susceptible to landslides. While increased precipitation is a significant factor, prolonged droughts are also becoming more common. Droughts lead to vegetation die-off, reducing root structures that stabilize the soil. The weakened soil structure is more prone to landslides when rainfall eventually does return. Rising sea levels, another consequence of climate change, contribute to coastal erosion. Waves erode cliffs and destabilize coastlines, leading to landslides in coastal regions. This risk is amplified in areas where human populations and infrastructure are close to eroding coastlines. Landslides pose a significant risk to communities, particularly those in mountainous, coastal, and deforested areas. As landslides become more frequent and severe due to climate change, the threat to lives, property, and infrastructure grows, creating an urgent need for adaptation and mitigation strategies. Effective solutions include improved land-use planning, reforestation, and the development of early-warning systems. Building infrastructure that can withstand landslides or redirect their flow can reduce the risk of damage.

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