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Budget Allocation for Emergency Management in Flood-Prone Mining Regions: A System Dynamics Perspective

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Abstract. Local governments face uncertainty when allocating resources for flood risk management, particularly in open-pit mining areas where sediment-laden runoff intensifies floods. Climate variability and increasingly intense precipitation peaks complicate the prioritization of interventions that protect people and infrastructure while safeguarding business continuity under limited budgets. To support this decision-making process a system dynamics model is developed to evaluate local public budget allocation and its effects on prevention, emergency response, and recovery. The model incorporates climate variability as an exogenous disturbance and assesses robustness and resilience through key performance indicators, including response costs, operational requirements, deprivation costs, and business continuity. It is validated through structural tests and expert consultation and applied illustratively to a mining community in Colombia. Computational experiments compare alternative emergency management budget allocation policies. A policy allocating a larger budget share to preventive channel maintenance while sustaining assistance for affected populations yields superior robustness, resilience, business continuity, and lower deprivation costs than alternative strategies. The model supports local decision-makers in public administration and disaster risk management in designing integrated budget allocation policies that balance preventive and reactive spending; jointly account for impacts on people, infrastructure, and business continuity; and strengthen flood risk management.
Keywords: Humanitarian logistics, disaster management, system dynamics, budget allocation, public policy.

1. Introduction

Climate variability intensifies the hydrological cycle and increases the frequency and severity of extreme precipitation and floods. For each additional 1 °C of global warming, very intense short-duration (1–3 hours) rainfall events tend to be on average 7 % more intense (Fowler et al., 2021). This information is consistent with the upward trends in daily precipitation at the global scale, as observed in the annual maxima of daily precipitation (Westra et al., 2013). Between 2022 and 2023, the global mean temperature increased by about 0.29 ± 0.04 °C, partly driven by the El Niño episode (Raghuraman et al., 2024; Global Temperature Report for 2023, 2025), and rainfall patterns have become more irregular, with stronger and more frequent intense events (Gründemann et al., 2022; Nie et al., 2024; Zhang et al., 2024). In open-pit mining contexts, such intense rainfall further increases sediment inputs, alters river-channel morphology, and reduces flow capacity, creating bottlenecks that

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increase the probability of river overflows and raise flood exposure for nearby communities (Koščová et al., 2018; Rentier and Cammeraat, 2022; Thapa et al., 2024; Wang et al., 2018; Zapico et al., 2021). Effective flood risk management in such settings should aim to balance robust risk reduction measures with the continued operation of mining activities.

Against this backdrop, local governments face important levels of uncertainty when allocating and executing budgets for flood prevention and emergency response (Merz et al., 2010a). The combination of limited resources and the need to act quickly turns budget management into a complex task that goes beyond financial analysis and requires integrating risk, impact, and trade-off assessments across alternative allocations (Merz, Kreibich, et al., 2010b). Prioritization involves comparing structural measures (such as levees, channels, or drainage systems) and non-structural measures (such as emergency plans or early-warning systems) using multi-criteria decision-making approaches that consider not only expected tangible losses but also broader effects on population, infrastructure, and economic activities (Hamidifar et al., 2024; Wang et al., 2022). Decisions about where and when to allocate financial resources shape the future trajectory of risk and well-being; it is therefore essential to incorporate multiple criteria and evaluate alternatives under different hydrological, economic, and social risk scenarios (Christopher et al., 2024; Hallegatte, 2009; V. Kumar et al., 2023).

During flood events, immediate assistance to the population must be prioritized to minimize deprivation costs, defined as the losses associated with the interruption or reduction of access to essential goods and services during and after the disaster (Holguín-Veras et al., 2013, 2016). At the same time, it is crucial to keep infrastructure operating at a minimum level to sustain basic services and business continuity, preventing prolonged disruptions that amplify disaster impacts (Ouyang, 2014; Rodríguez-Coca et al., 2024; Wright et al., 2020). This is consistent with the principles of the Sendai Framework for Disaster Risk Reduction, which stresses the need to link public planning with social protection, infrastructure, and service continuity (Aitsi-Selmi et al., 2016; United Nations Office for Disaster Risk Reduction [UNDRR], 2015). Therefore, resource allocation should prioritize interventions that reduce vulnerabilities and strengthen community robustness and resilience (de Brito and Evers, 2016). Robustness refers to the ability to maintain acceptable performance under disturbances, while resilience denotes the capacity to recover after extreme events (Mens et al., 2011; Muñoz et al., 2024; Stricker and Lanza, 2014). Response to and prevention of flooding require a strategic and adaptive approach that balances the protection of individuals, the robustness and resilience of infrastructure, and the functioning of local economic activities and businesses under uncertain conditions (de Brito and Evers, 2016).

System dynamics (SD) models are particularly useful for designing budget allocation policies for flood prevention and emergency response because they simulate the behavior of complex systems over time by integrating variables such as financial resources, preventive and response actions, and interactions among stakeholders (Abdel-Latif et al., 2023). These models can incorporate rules for budget allocation (Peiris, 2025; Poudel, 2019), the prioritization of investments in resilient infrastructure (Jiang et al., 2020; Li et al., 2023), and the activation of emergency protocols (Links et al., 2018; Simonovic and Ahmad, 2005), while explicitly accounting for climate variability scenarios (Li et al., 2024; Zhu et al., 2024).

Although there is a growing body of research that employs SD to assess impacts on population, it has focused on the pre-disaster phase (Ciullo et al., 2017; Coletta et al., 2024; Feofilovs et al., 2020; Li et al., 2023; Perrone et al., 2020), on evacuation

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and emergency response during flood events (Feofilovs et al., 2020; Peiris, 2025; Poudel, 2019; Simonovic and Ahmad, 2005), as well as on infrastructure recovery, predominantly in the post-disaster phase (Coletta et al., 2024; Feofilovs et al., 2020; Kumar et al., 2015; Peiris, 2025; Perrone et al., 2020). However, only a limited number of studies explicitly address business continuity. Existing work has examined the continuity of critical services such as waste collection, energy supply, or transport during an emergency scenario (Cavallini et al., 2014; Phonphoton and Pharino, 2019), but these studies do not explicitly refer to the continuity of business operations. Likewise, some authors analyze business continuity using post-disaster surveys and statistical methods, without applying SD (Watson et al., 2024). In addition, only a few contributions explicitly incorporate climate variability aspects within system dynamics models in the context of budget allocation (Li et al., 2024; Zhu et al., 2024). The existing literature does not explicitly model the causal relationships between mining-sector business continuity variables and deprivation costs in flood situations.

Building on this context, this article seeks to answer the following question: How can the effectiveness of budget allocation strategies for flood prevention and emergency response in mining regions under climate variability be assessed while ensuring population safety, infrastructure protection, and business continuity? To answer this question, a System Dynamics model is proposed. The model represents and evaluates the budget allocation required to prevent and manage flood emergencies, thereby protecting the population, the infrastructure while supporting the continuity of business operations. The proposed model incorporates a methodology for robustness and resilience analysis. Also, the methodology makes it possible to define and measure disturbance parameters, performance indicators, and explicitly account for climate variability (Muñoz et al., 2024; Polo et al., 2019; Tordecilla et al., 2017). Through dedicated performance indicators, the model accounts for the costs associated with flood prevention, emergency response (UNDRR, 2015), and deprivation cost.

These metrics complement conventional physical and monetary damage estimates by incorporating the temporal dimension of well-being, which is crucial for prioritizing resources under conditions of scarcity and delay (Ghahremani-Nahr et al., 2024; Holguín-Veras et al., 2016). To assess the model, a structural analysis was conducted, and a mining community in Colombia was used as an illustrative application. This application enables the evaluation of the model's effectiveness in assessing alternative budget allocation policies designed to support flood-affected populations; restore infrastructure, roads, and critical river channels in mining regions; and ensure the operational continuity of mining activities under changing climate conditions. The paper is organized as follows: Section 2 presents the methods and the proposed SD model; Section 3 the results; Section 4 the discussion; and Section 5 the conclusions.

2 Methods

The proposed model was developed in Vensim® PLE version 10.3.2 software. The construction and validation of the model were conducted in three phases. In the first phase, key variables and causal relationships were identified, forming the basis for the system's causal diagram. The second phase introduced the metrics used to define budget allocation policies and to evaluate system robustness and resilience, along with cost components such as deprivation costs (Holguín-Veras et al., 2013). The third phase involved an illustrative application of the model in an open-pit mining context, with results presented in Section 3.

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Level, flow, and auxiliary variables included in the model can be seen on Table 1. The first column, "Level Variable" contains the stock variables of the model. The second column, "Source" identifies authors who have addressed the level variables, included in the proposed model, using SD. Watson et al. (2024) is an exception since they studied business continuity but did not apply System Dynamics methodology. The third column, "Flow Variable" presents the proposed rates that modify levels. Finally, the "Auxiliary Variables" column lists the main variables used to calculate the states and their corresponding rates.

Table 1: Level and flow variables included in the model

[1]Level Variable	Source	Flow Variable	Auxiliary Variables
Available Funding Level ($): Cumulative funds available to the municipal government for flood-emergency response and infrastructure investment.	(Peiris, 2025; Poudel, 2019; Zhu et al., 2024)	Budget Allocation Rate ($\$/Day$): Rate at which local budget is received based on allocated funding.	– Recurring local government allocation. – Mining budget Contribution.
		Fund Disbursement Rate for Roads ($\$/Day$): Rate at which allocated funds are disbursed for road maintenance.	– % budget roads. – Total funds required for the road. – Information roads delay.
		Fund Disbursement Rate for Channel ($\$/Day$): Rate at which allocated funds are disbursed for channel maintenance.	– % budget channels. – Total funds required for unblockage. – Information channel delay.
		Fund Disbursement Rate for Buildings ($\$/Day$): Rate at which allocated funds are disbursed for building maintenance after a flood.	– % budget buildings. – Total funds required for building. – Information building delay.
		Fund Disbursement Rate for Water Return ($\$/Day$): Rate at which allocated funds are disbursed to restore water flow to its natural channel during flooding events.	– % budget for return water. – Total funds required for water return. – Information water return delay.
		Fund Disbursement Rate for Aid ($\$/Day$): Rate at which allocated funds are disbursed to assist affected populations during flooding events.	– % budget for aid population. – Total cost to assist people. – Information aid delay.
Overflow Water Level (%): Proportion of the potential flood extent that is effectively inundated at a given moment.	(Abebe et al., 2021; Ahmad and Simonovic, 2000; Ciullo et al., 2017; Coletta et al., 2024; Feofilovs et al., 2020; Jiang et al., 2020; Li et al., 2024, 2023; Peiris, 2025; Perrone et al., 2020; Phonphoton and Pharino, 2019; Poudel, 2019; Zhu et al., 2024)	Flood Expansion Rate ($\%/Day$): Rate at which floodwaters advance over identified risk zones.	– Overflow water. – Water flow channel. – Channel flow capacity. – Maximum estimated. – Overflow Water Level.
		Flood Recession Rate ($\%/Day$): Rate at which floodwaters recede, restoring dry conditions.	– Desired level of water level. – Regression delay. – Natural flow regression. – Maximum assisted water Return Rate.
Affected Roads Level (%): Total proportion of roads in poor condition due to direct impact of flooding and mining operations.	(Peiris, 2025; Perrone et al., 2020; Simonovic and Ahmad, 2005; Zhu et al., 2024)	Roads Damage Rate ($\%/Day$): Rate at which road infrastructure deteriorates due to flooding and mining operations.	– Access road density. – Road damage from mining. – Road damage from flooding.
		Roads Recovery Rate ($\%/Day$): Rate at which road segments are restored back into functional status.	– Desired level of roads. – Access road density.

[1]The level variables are expressed as percentages to facilitate interpretation of results and interactions among variables.

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[1]Level Variable	Source	Flow Variable	Auxiliary Variables
			– Maximum road recovery Rate. – Road Repair Delay.
Affected Building Level (%): Total proportion of buildings exhibiting structural damage due to flooding.	(Coletta et al., 2024; Kumar et al., 2015; Peiris, 2025; Perrone et al., 2020)	Building Deterioration Rate ($\%/Day$): Rate at which buildings deteriorate due to flooding.	– Desired level of buildings. – Maximum building recovery. – Building repair delay. – Building density
		Building Recovery Rate ($\%/Day$): Rate at which buildings are restored to functional condition.	– Building density
Channel Blockage Level (%): Total proportion of the channel's flow capacity that is obstructed.	(Ahmad & Simonovic, 2000; Jiang et al., 2020; W. Li et al., 2023; Peiris, 2025; Perrone et al., 2020; Sadeghi et al., 2018; Zapico et al., 2021; Zhu et al., 2024)	Channel Blockage Rate ($\%/Day$): Rate at which the channel becomes blocked due to sediment accumulation.	– Sediment production from mining. – Sediment production from basin. – Sediment accumulation Threshold. – Channel flow capacity
		Channel Clearance Rate ($\%/Day$): Rate at which the channel is cleared following sediment removal.	– Alert level of Channel. – Planned Maintenance Days. – Channel Repair Delay. – Quantity required for full Unblocked.
Affected Population Level (%): Proportion of the exposed population currently affected by flooding.	(Ciullo et al., 2017; Coletta et al., 2024; Feofilovs et al., 2020; Li et al., 2023; Peiris, 2025; Perrone et al., 2020; Poudel, 2019; Simonovic and Ahmad, 2005)	Population Affectation Rate ($\%/Day$): Rate at which individuals become affected due to direct exposure to flooding.	– People in Risk Zone
		Population Recovery Rate ($\%/Day$): Rate at which affected people receive support that helps them overcome the impact.	– Initial People in Risk Zone. – Desired level of Aid fund. – Required Cost per Affected Person. – Population Attention Delay. – Total Deprivation cost.
Operational Disruption Level (%): Cumulative proportion of scheduled business continuity time during which mining operations are suspended due to flood-related blockages.	(Cavallini et al., 2014; Phonphoton and Pharino, 2019; Watson et al., 2024)	Disruption Rate ($\%/Day$): percentage of time periods within the evaluation horizon during which the business experiences total or partial interruption.	– Mining Continuity Robustness Indicator [0:1] – Simulation Horizon. – Population disruption threshold for mining. – Road disruption threshold for mining. – Mining Disruption Cost.

The proposed "level variables", as well as their corresponding impact rates, were grounded both in their individual treatment in other contexts and in the cause–effect relationships established among the model's level, flow, and auxiliary variables. Figure 1 presents the proposed causal diagram, which includes main level and flow variables, as well as the relationships among them. Seven fundamental level variables are defined: (1) allocation of the available budget; (2) population affected by flood impacts; (3) volume of overflow water during flood events; (4–6) infrastructure-related levels encompassing buildings, damaged roads, and river channels; and (7) business continuity.

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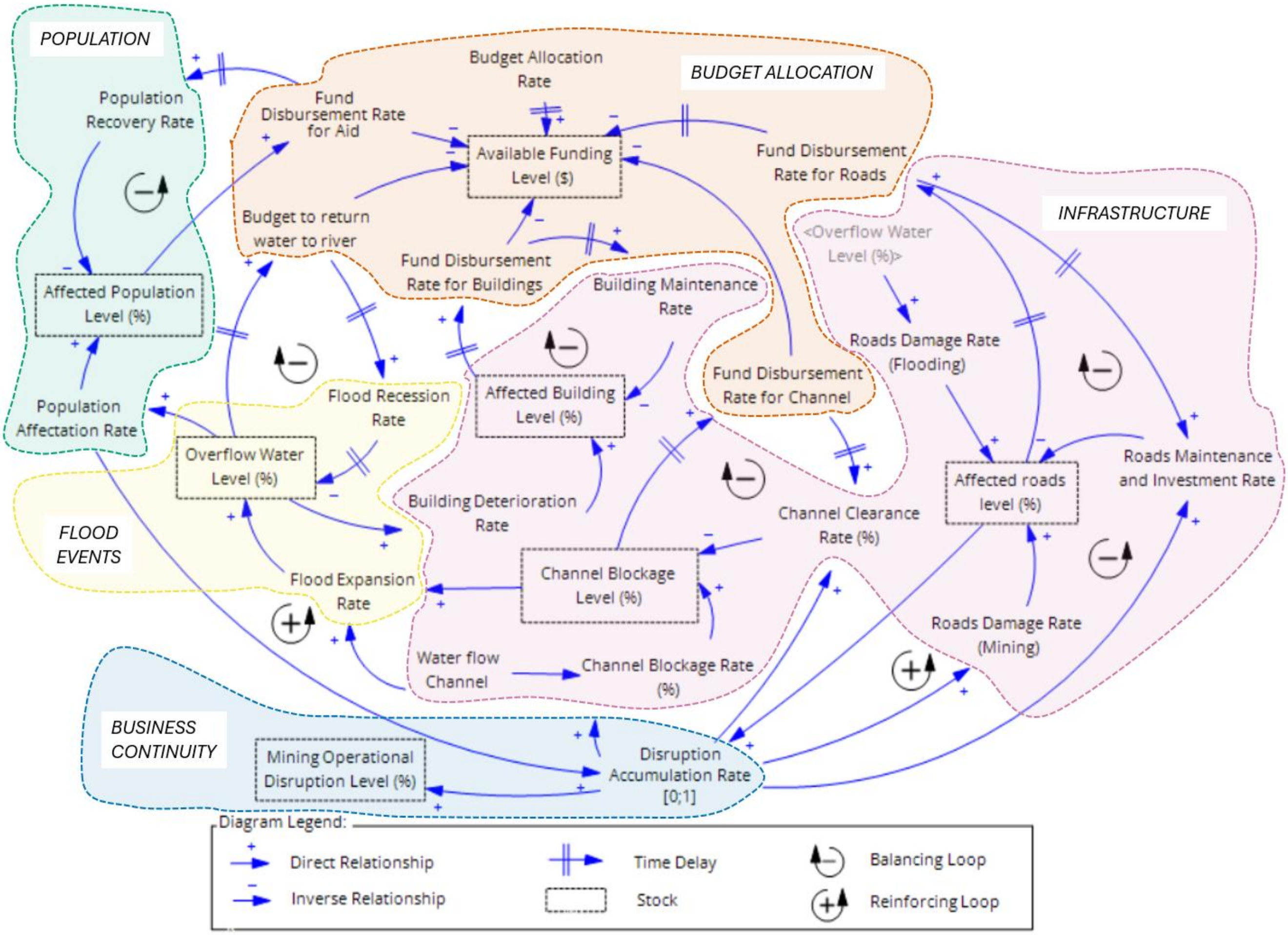

Figure 1. Causal diagram

The model explicitly incorporates delays related to information availability and budget execution, which are critical for flood prevention and emergency management. The Auxiliary Variables column in Table 1 includes parameters that were modeled as time-lag terms to represent information flows and response times (for example: repair delays, attention delays, regression delays). These delays are implemented as time-lag parameters within the stock-and-flow structure and were calibrated following established recommendations for modeling information and decision delays in complex dynamic systems and disaster management (Perrone et al., 2020; Sterman, 2000). Calibration combines literature guidance with structured consultation with local managers, ensuring that time-lag values balance theoretical consistency and operational plausibility.

The robustness analysis methodology proposed by Tordecilla et al. (2017) for logistics systems was adapted by Muñoz et al. (2024) for application to water systems, where resilience metrics were additionally incorporated to complement the robustness framework. Table 2 presents the key performance indicators for the disturbance parameters (exogenous, non-controllable alterations that affect system functioning), operational characteristics, robustness and resilience requirements defined for this

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context. The water levels in river channels are defined as the disturbance parameter (Muñoz et al., 2024). This parameter is linked to precipitation and to the exogenous behavior of climate variability, which affects both the occurrence of floods and the operability of mines due to sediment generation. Operational, robustness, and resilience indicators are proposed to assess system performance. The system operates normally when control variables remain within acceptable bounds of these requirements, which are adaptable to each context given specific geographical conditions and local needs. The proposed bound values are defined based on technical information gathered through structured consultations with five experts possessing operational experience in flood emergency management. Within the SD model, these bounds were implemented as control limits that trigger budget requests and fund disbursement.

Table 2: Key performance indicators for disturbance parameters, operational characteristics, robustness, and resilience requirements

Metric	[2]Indicator	Description	Proposed limit
Disturbance Parameter	Water flow Channel (Mm^3/Day)	Runoff-driven water flow in the basin, which experiences peaks and troughs due to seasonal and climatic fluctuation.	Not applicable (exogenous disturbance).
Operational Characteristics	Available Channel Capacity (%)	Represents the percentage of the channel's maximum capacity that remains unobstructed to allow water flow.	Minimum Operational Requirement for Channel (84%)
	Available Functional Buildings (%)	Indicates the proportion of buildings maintaining operability under flood conditions.	Minimum Operational Requirement for Building (74%)
	Operational Road Availability (%)	It indicates the proportion of roads that remain operable under flooding and mining operation conditions.	Minimum Operational Requirement for Roads (62%)
Robustness Requirements	Overflow Water Level (%)	Proportion of the potentially flood-prone area that is inundated at a given moment.	Critical Flood Tolerance Level (7%)
	Mining Continuity Robustness Indicator [0:1]	Binary indicator representing whether the mine has ceased operations (1) or remains operational (0).	Population Disruption Threshold for Mining (26%); Road Disruption Threshold for Mining (34%)
	Unaffected Population Level (%)	Represents the proportion of the potentially affected population that remains unaffected by flooding.	Minimum Population Robustness Requirement (72%)
Resilience Requirements	Flood Robustness Failure Duration (days)	It indicates the time span in which flood conditions surpass the system's capacity to maintain operational robustness.	No fixed limit (shorter durations indicate better resilience).
	Consecutive Days of Mining Inactivity (days)	It indicates the time span in which flood conditions surpass the system's capacity to maintain operational robustness.	
	Duration of Continuous Population Exposure (days)	Indicates the time span during which mining operations were suspended.	

[2] Inputs: disturbance parameters. Outputs: operational, robustness, and resilience indicators for performance evaluation.

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On the other hand, the model allows estimation of the total crisis management cost. This includes the funds executed through budget allocation, the costs due to disruptions in mining operations, and the costs associated with deprivation experienced by the affected population (Figure 2).

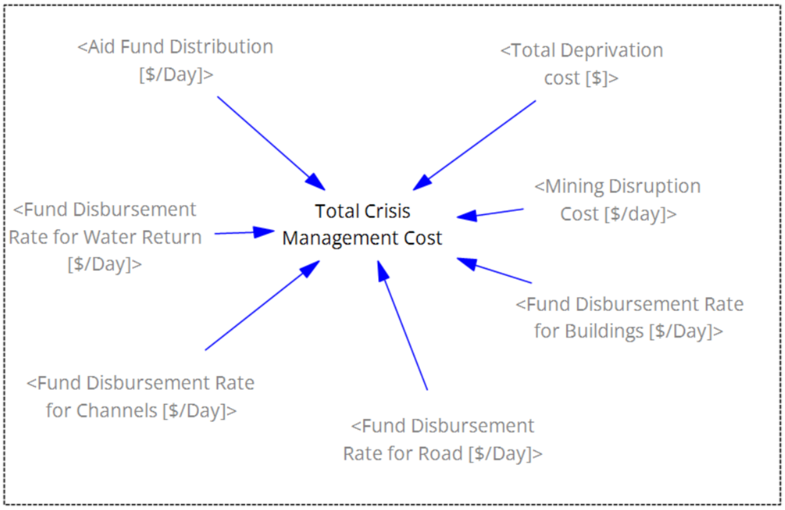

Figure 2. Representation of the Costs in the Model

The crisis management cost elements allow local governments to gain insight into the budget management policies aimed at flood prevention and emergency response. This is relevant because the cost components may have a great economic impact over time. For instance, deprivation costs are indirect losses such as forgone income, prolonged service disruptions and reduced productivity. These losses accumulate over time and can exceed immediate repair expenditures, leading to larger long-term economic and fiscal burdens (Holguín-Veras et al., 2013).

2.1 Model validation through illustrative application

The model was applied and validated using data from a community in the municipality of Tocancipá, Colombia, which reported a flood event in 2023 caused by overflows of the Esmeralda Stream (Municipal Mayor's Office of Tocancipá, 2023). This community is in a mining area covering more than 420 acres and is exposed to persistent flood risk driven by climate variability and the characteristics of open pit mining operations, making it a suitable case for model validation. The community has an approximate population of 2,125 inhabitants (Municipal Mayor's Office of Tocancipá, 2017), of whom 297 have been identified as directly vulnerable to flood events (National Administrative Department of Statistics [DANE]., 2024). In addition, two access roads were identified within the study area, with a total length of 3.4 km. These road sections are used by vehicles associated with the mining operation. Some sections of the road are at risk of being affected by river overflows, which block access to both the mines and the community. Furthermore, more than 33 buildings in vulnerable condition are located within the flood-risk zone. The wet-year rainfall profile incorporating annual rainfall peaks data from the Bogotá River Basin

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Management Plan (Plan de Ordenación y Manejo de la Cuenca hidrografica del Río Bogota - POMCA, 2019) estimate peaks of rainfall of 3.49 m^3/s and lows of 1.48 m^3/s.

The stream channel in the area exhibits a reduced hydraulic section, where sediment accumulation limits water conveyance capacity. This reduction is exacerbated during intense rainfall in the rainy season (Municipal Mayor's Office of Tocancipá, 2023). Based on Manning's equation (Chow et al., 2013), the hydraulic capacity of this section was estimated at $4.13\ m^3/s$. Sediment deposition originating from mining operations can further decrease this capacity, especially under heavy rainfall, thereby increasing the risk of overflow. The average suspended-sediment concentrations reported ($0.365\ a\ 0.408\ Kg/m^3$) for the Trishuli River (Nepal) under sand-mining conditions (Pant et al., 2025) were taken as reference values to parameterize sediment dynamics in the model. Figure 3 provides a detailed representation of the community used in the model's validation.

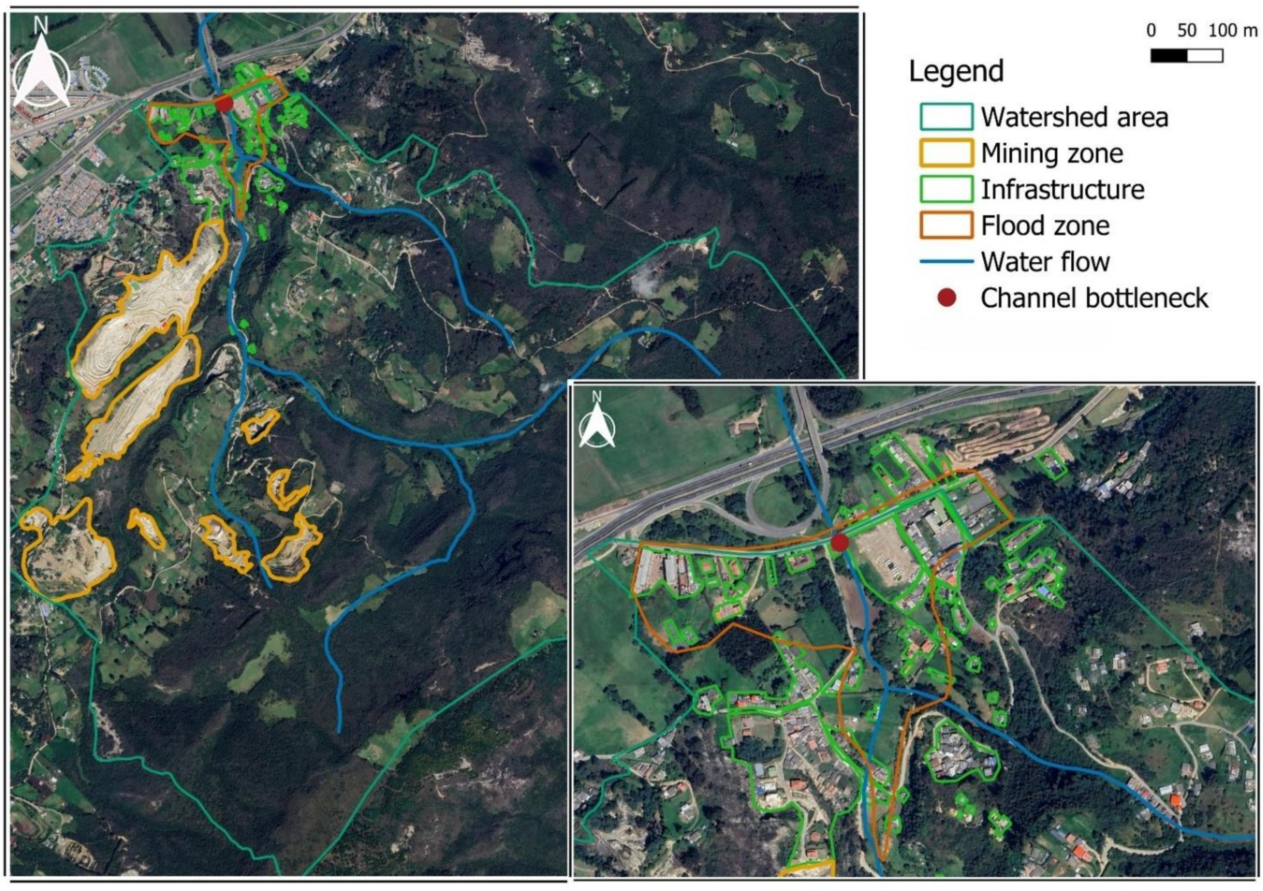

Figure 3. Illustration of the flood risk zone used in the model's validation

Source: Adapted from the work (Corriente de Agua. Bogotá D.C, 2023; Plan de Ordenación y Manejo de la Cuenca hidrograficahidrográfica del Río Bogota - POMCA, 2023; Tocancipá Escala 1:10.000, 2025; Densidad de vivienda. Bogotá más 20 municipios, 2025; Tocancipá La Esmeralda Escala 2000, 2025)

The 2025 budget for the municipality of Tocancipá allocated COP 7,592 million (≈ USD 1,973,288) to environmental management and disaster risk reduction measures. This amount, distributed uniformly throughout the year, is limited compared to the high costs of infrastructure adaptation and emergency response, highlighting the need for efficient allocation (ACUERDO 020 DE 2024, 2025).

In budget allocation policies, three universal operational priorities in emergencies are considered: life safety, incident stabilization, and property and infrastructure conservation (U.S. Fire Administration [USFA], 2024). In addition, the proposed budget allocation policies must also prevent future risks through the prioritization of critical infrastructure (Maryland Department of Emergency Management, 2009; Sphere Association, 2018). Thus, all budget allocation policies include a preventive maintenance schedule for the stream channel during the period of most intense rainfall.

More than 30 budget allocation policies were evaluated reflecting different priorities combinations for life safety, incident stabilization, and future risk reduction. This paper presents the results for three policies that showed the best performance in the robustness and resilience indicators evaluated. Table 3 summarizes these budget allocation policies.

Table 3: Top 3 budget allocation policies

	Policy		
	N°1	N°2	N°3
Policy description.	**Life first:** Give high priority to assisting people while access to the risk area is still possible.	**Life and stabilization:** Give a balanced priority between assisting people and stabilizing the risk area.	**Life and future risk reduction:** Give priority to assisting people while maintaining or restoring infrastructure.
% of Fund Disbursement Rate for Aid	80%	50%	65%
% of Fund Disbursement Rate for Water Return	5%	30%	5%
% of Fund Disbursement Rate for Buildings	5%	10%	5%
% of Fund Disbursement Rate for Roads	5%	5%	10%
% of Fund Disbursement Rate for Channel	5%	5%	15%

The percentages shown in Table 3 are fixed and do not change when new funds enter the system. However, funds are allocated monthly.

3 Results and analysis

The model is applied to explore its performance as a decision-support tool for evaluating local government budget allocation policies. In this application, the model is used to prioritize the allocation of resources to support affected people, restore conditions in the area by returning overflowed water to its normal channel, and carry out maintenance on infrastructure such as channels, buildings, and roads, as well as to assess business continuity in mining operations. First, the behavior and analysis

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of the operational, robustness, and resilience requirements presented in Table 2 are shown for each policy evaluated. This is followed by a summary of the policy assessment and its implications for budget execution.

In Figure 4, the behavior of the "Available Channel Capacity" indicator is shown, with an operational limit set at 84%. This value represents the minimum threshold of available channel capacity below which an alert is triggered, requiring the immediate allocation of resources to avoid overflow conditions. When comparing the resulting curves, Policy 3 (Life and future risk reduction) maintains channel capacity above the threshold for almost the entire year, with only brief drops followed by rapid recovery. In contrast, the available channel capacity under policies 1 and 2 remain below 84% for several days (particularly between 250 and 320 days), which implies a higher probability of overflow. Therefore, policy 3 is considered the alternative with the best operational performance, as it represents a lower flood risk for the system.

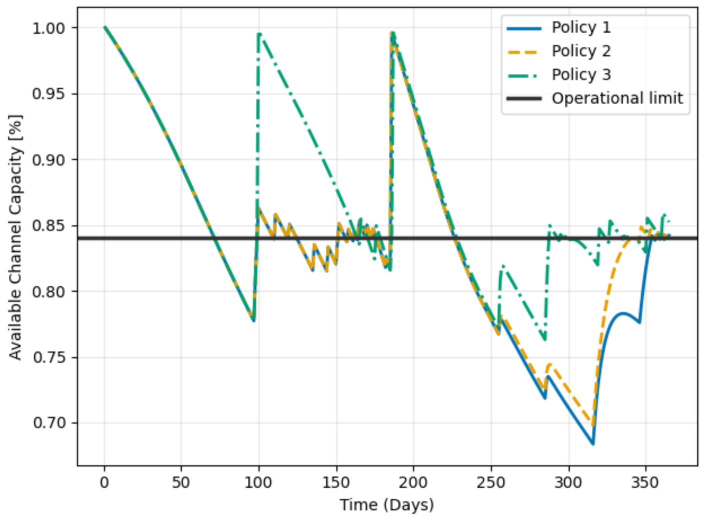

Figure 4. Evolution of available channel capacity under evaluated policies

In Figure 5, the "Available Functional Buildings" indicator is shown, with an operational limit set at 74%. Results show that none of the policies manage to keep building infrastructure above this limit throughout the year. Policies 2 and 3 offer the best operational performance, as they maintain the highest proportion of functional buildings during the evaluation period. Policies 2 and 3 exhibit similar behavior in terms of remaining within control limits. Nevertheless, policy 2 shows the deepest drop, reaching values close to 55%, but it also recovers more quickly than policy 3. In contrast, policy 3 displays better initial performance, yet its recovery after the critical event is slower and does not reach the final levels achieved by policy 2.

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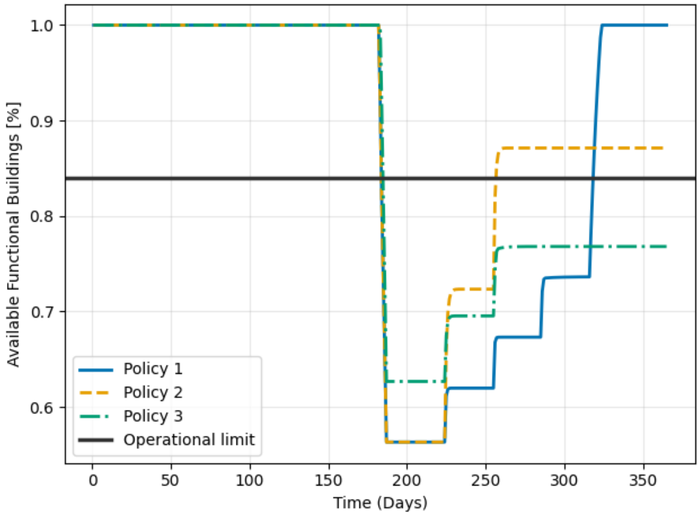

Figure 5. Percentage of buildings functional across evaluated policies

In Figure 6, the "Operational Road Availability" indicator is shown, with an operational limit set at 62%. All three policies keep this indicator above the limit throughout the entire evaluation period, remaining well above the threshold. This result illustrates that road infrastructure maintains an important level of operational availability under the evaluated alternatives. Policy 2 shows the lowest relative performance, with a sharper drop around day 180, linked to lower budget availability at that time of the year. Although this deviation does not compromise the operational limit, it points to the importance of monitoring allocation timing to avoid temporary reductions in road availability.

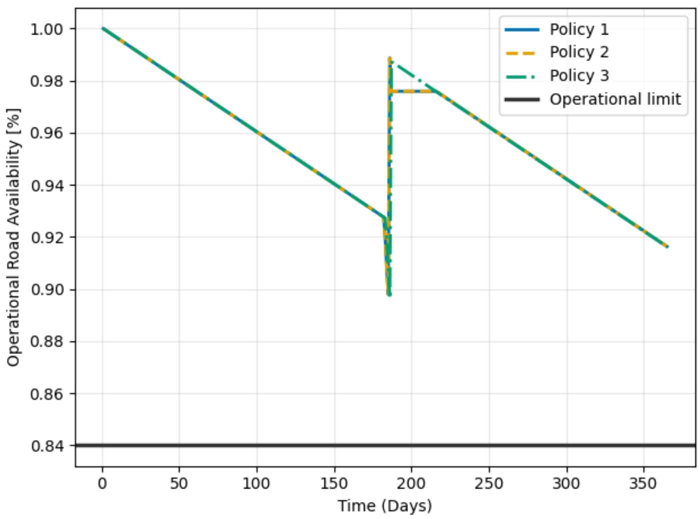

Figure 6. Operational road availability under evaluated policies

In Figure 7, the robustness indicator "Overflow Water Level" is shown, with a maximum limit set at 7%. None of the three policies fully prevents overflow, since all curves rise above the limit around day 185. Policies 1 and 2 display two distinct

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peaks, visible near days 183 and 186, reaching approximately 11.76% and 13.21%. Policy 3, by contrast, shows a single crest close to 13.42% on day 186. Although the maximum levels are similar, Policy 3 stands out for concentrating the overflow in one event, which implies fewer critical interventions compared to the double peaks in Policies 1 and 2. This highlights the usefulness of the model in distinguishing not only the magnitude but also the frequency of overflow events when evaluating management policies in flood risk contexts.

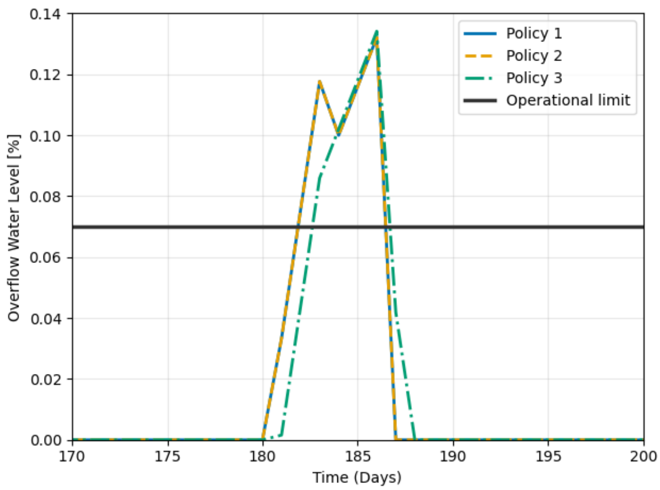

Figure 7. Observed overflow levels under evaluated policies

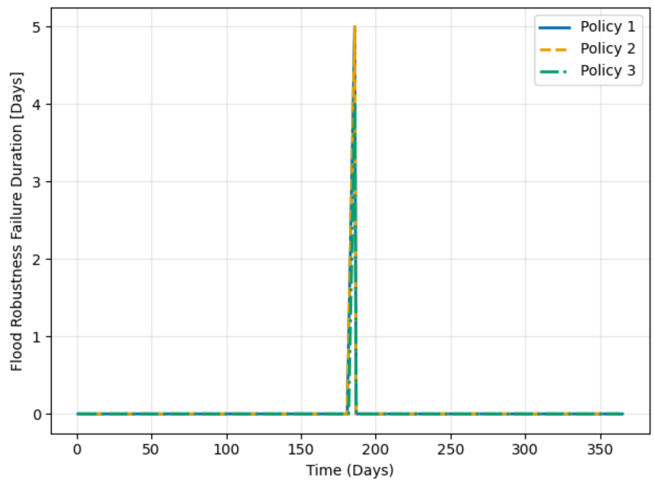

Figure 8. Duration of flood robustness failure under evaluated policies

Regarding the duration of flood events (denoted with the variable "*Flood Robustness Failure Duration*"), Figure 8 shows the time the system takes to recover and return below the control limit. The event's duration is 5 days for policies 1 and 2, whereas for policy 3 it is 4 days, indicating a slightly faster recovery. This behavior suggests that policy 3, in which a larger share of the budget is allocated to channel maintenance, can reduce the time during which flooding remains active. Considering both the magnitude and the duration of the events, policy 3 exhibits the best combined robustness and resilience performance against flooding.

In Figure 9, the "Mining Continuity Robustness" indicator is shown, where it can be observed that none of the three policies fully prevents interruptions in mining operations; all of them exhibit a disruption around day 183, coinciding with the previous flood event.

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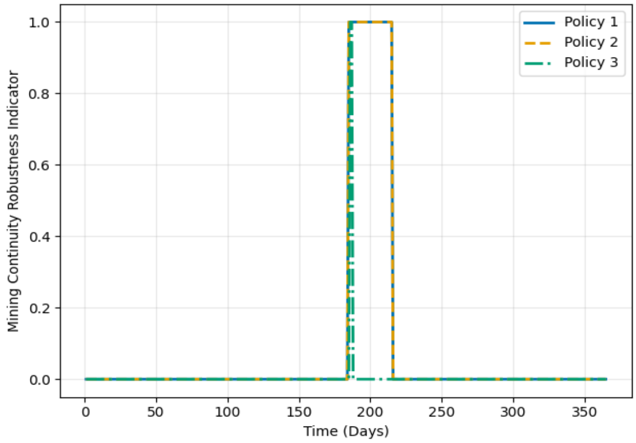

Figure 9. Robustness of Operational Mining continuity under evaluated policies

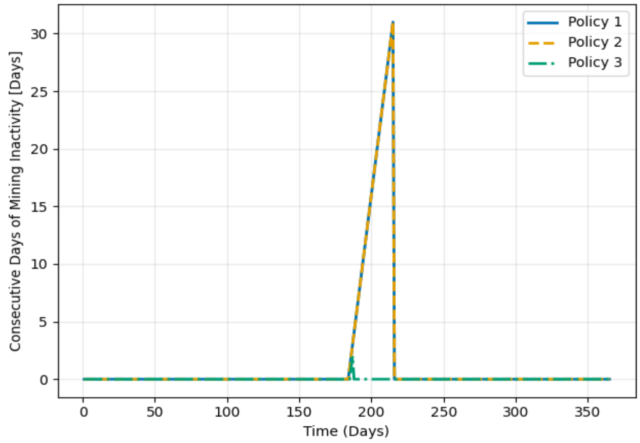

Figure 10. Consecutive days of mining inactivity under evaluated policies

The difference between policies lies in the speed of recovery, as shown in Figure 10. Policies 1 and 2 can lead to prolonged interruptions of up to 31 consecutive days, whereas policy 3 limits inactivity to approximately 2 days. This difference suggests that higher investment in infrastructure maintenance substantially reduces the duration of the impact on business continuity. Although all three policies allow the initial disruption to occur, policy 3 shows the best performance by minimizing downtime and reducing the operational impact caused by the flood.

Figure 11 shows the "Unaffected Population Level" indicator. The three policies lose robustness during the same period, but with different behaviors. When the flood reaches its most critical point, policy 3 maintains the highest percentage of unaffected population and is also the first to recover the 72% threshold and approach 100% again. This better performance is explained by the way the budget is allocated in policy 3, where a larger share of resources is devoted to channel maintenance, which reduces the number of affected people from the beginning.

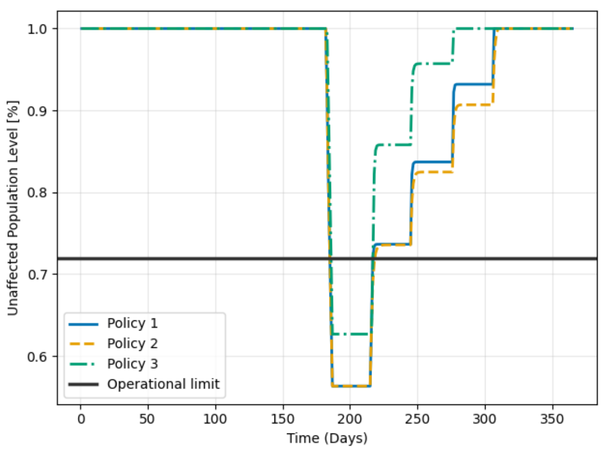

Figure 11. Proportion of population unaffected by flooding under evaluated policies

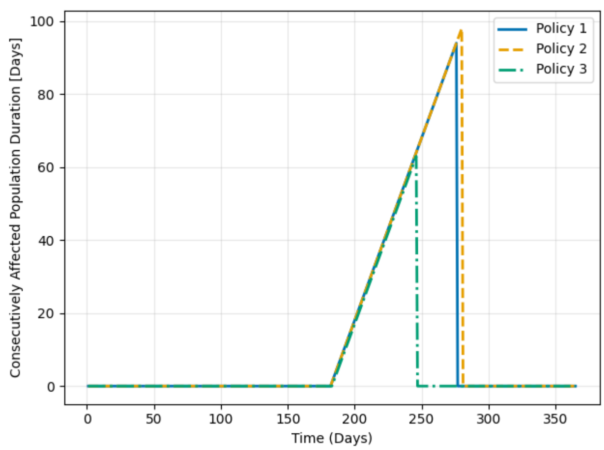

Figure 12. Duration of population impacted under evaluated policies.

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Figure 12 presents the "Duration of Continuous Population Exposure" indicator. Under policy 3, the system takes around 60 days to be considered robust again. For policies 1 and 2, the impacts last for 94 and 97 days, respectively. In the case of policy 1, higher budget allocation to supporting affected people and a lower investment in channel maintenance translates into a larger affected population and a slower recovery. Policy 2, with even fewer resources allocated to the population, exhibits the slowest recovery. These results show that policy 3 achieves better robustness and resilience because its budget allocation scheme favors a reduction in the number of affected people from the prevention phase.

Figure 13 illustrates the behavior of the total crisis management cost under the three policies evaluated. Figure 13A shows the costs including deprivation costs for the affected population. A marked increase in total costs can be observed compared with the version without deprivation costs (Figure 13B), which reinforces the importance of incorporating these indirect effects into the economic evaluation of floods. When comparing the policies, policy 3 shows the lowest cost peaks when deprivation costs are considered, which is consistent with the previous results. By allocating a larger share of the budget to preventive activities, such as channel maintenance, the number of affected people is reduced and, consequently, the associated deprivation costs decrease. By contrast, when only the direct response costs are considered (Figure 13B), the three policies display similar behavior, which is strongly conditioned by the monthly budget availability. Thus, policy 3 shows slightly better performance than policies 1 and 2, mainly driven by the costs associated with mining business continuity.

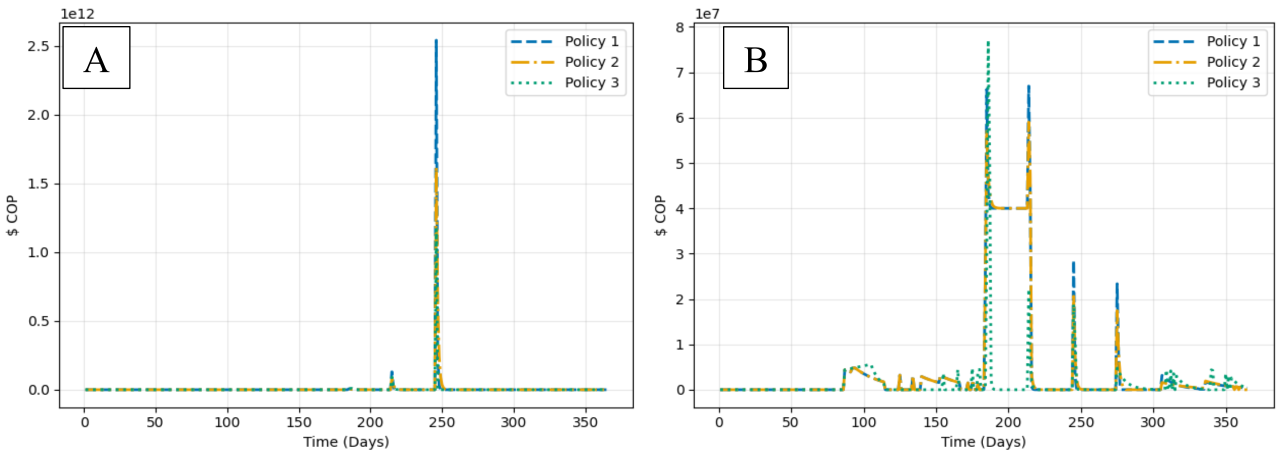

Figure 13. Total crisis management costs under evaluated policies: (A) including deprivation costs, (B) excluding deprivation costs

Finally, Table 4 summarizes the ranking to each operational requirement and to the robustness and resilience criteria, to visualize the advantages of each policy with respect to these metrics. In this scale, a value of 3 corresponds to the best performance for the metric analyzed, whereas a value of 1 represents the worst. When several policies produce the same effect on a metric, they are assigned the same ranking value. This scoring approach facilitates a clearer, more objective and traceable analysis of each policy.

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Table 4: Ranking of budget allocation policies.

Criteria	Policy 1	Policy 2	Policy 3
Available Channel Capacity	3	2	3
Available Functional Buildings	1	2	2
Operational Road Availability	3	2	3
Overflow Water Level	1	1	2
Flood Robustness Failure Duration	2	2	3
Mining Continuity Robustness Indicator	1	1	2
Consecutive Days of Mining Inactivity	2	2	3
Unaffected Population Level	1	1	2
Duration of Continuous Population Exposure	1	1	2
Total crisis management costs under the evaluated policies	1	2	3
Total value	16	16	25

Policy 3 dominates in most metrics: it shares the best result in channel capacity and road availability, and clearly improves performance in terms of overflow, flood duration, mining continuity, and population impact. In this case, this confirms that prioritizing preventive channel maintenance not only reduces the physical flood risk, but also decreases the number of affected people, shortens interruptions in mining activity, and reduces deprivation and crisis-management costs. Policies 1 and 2 achieve similar scores, but with different profiles. Policy 1 concentrates most of the budget on direct assistance to people and leaves only a small margin for preventive actions on the channel and infrastructure. Although one might expect this priority to improve outcomes for the population, Table 4 shows the opposite: the lower effort in prevention increases the number of affected people and lengthens recovery times, which also raises total costs. Policy 2 distributes the budget more evenly between assistance and stabilization, but ultimately delivers intermediate results, without standing out in any key indicator. Overall, Table 4 illustrates how the model enables an integrated comparison of policies in terms of operational performance, robustness, costs, and resilience, explicitly incorporating the impact on people, critical infrastructure, and the continuity of mining business operations.

4. Discussion

The results show that budget allocation in mining contexts under climate variability should be assessed from a holistic perspective that goes beyond direct physical damage or an exclusive focus on annual budget limits. The proposed SD model evaluates budget policies that simultaneously aim to protect people, sustain infrastructure, and preserve business continuity (Aitsi-Selmi et al., 2016; de Brito and Evers, 2016; United Nations Office for Disaster Risk Reduction (UNDRR), 2015). Relationships between social factors, infrastructure performance, and continuity of mining operations, incorporating hydrological variability as an exogenous disturbance were considered in the model.

From the results of the simulated policies, there is evidence that shows that prioritizing direct assistance to people alone, as in policy 1 (“life first”), does not guarantee better social outcomes when preventive allocation to infrastructure is limited. Despite allocating 80% of the budget to supporting people, this policy leads to a larger number of affected individuals, longer recovery times, and higher total costs, due to the low investment in the maintenance of key infrastructure to prevent floods. In contrast, policy 3 (Life and future risk reduction), which combines support to the population (65%) with a stronger preventive effort on infrastructure (mainly the channel), reduces the magnitude and duration of floods, maintains a higher share of the unaffected population, and shortens the disruption of mining operations. This shows that, in highly interdependent systems, the protection of life is strengthened when investment is made in advance in infrastructure robustness, and not only in reactive response (Jiang et al., 2020; Li et al., 2023; Rodríguez-Coca et al., 2024).

On the other hand, the model explicitly integrates the mining business continuity dimension with social and infrastructure metrics. The results show that none of the policies fully prevent interruptions to mining operations during the flood event, but the duration of inactivity changes substantially across policies: up to 31 days for policies 1 and 2, compared with only 2 days for policy 3. This difference does not arise from an isolated "economic" module, but from the interaction between channel capacity, road accessibility, and the recovery of the affected population, confirming that business continuity is the cumulative outcome of prior prevention and response decisions (Cavallini et al., 2014; Phonphoton and Pharino, 2019). The model highlights this relationship and provides a tool to analyze operational continuity in a disaster risk management setting, an aspect that has been little explored in the literature (Cavallini et al., 2014; Phonphoton and Pharino, 2019; Watson et al., 2024).

The inclusion of deprivation costs reinforces this holistic perspective. When comparing the results with and without these costs, Figure 13 showed that the total costs of the emergency increase significantly when the suffering associated with the temporary lack of essential goods is taken into account (Holguín-Veras et al., 2013; Shao et al., 2020). In this comparison, policy 3 again emerges as the best alternative, as it reduces both the number of affected people and the duration of their vulnerable condition. If only immediate emergency response costs were considered, the differences between policies are smaller, and biased conclusions are achieved showing that different budget allocation policies produce equivalent effects. Incorporating deprivation costs captures the temporal effects on population wellbeing and provides an additional criterion to justify the prioritization of preventive policies that reduce both exposure and impact duration (Ghahremani-Nahr et al., 2024; Holguín-Veras et al., 2013; Shao et al., 2020).

From a methodological perspective, the SD models represent the delays in budget execution, the feedback loops between infrastructure and population, and the cumulative effects of hydrological variability on management decisions (Abdel-Latif et al., 2023; Feofilovs et al., 2020; Naugle et al., 2024; Naumann et al., 2019). Unlike static econometric approaches, the model simulates how information on the infrastructure state and the population reaches decision-makers with a delay, and how these delays condition the effectiveness of interventions, as documented in SD applications to emergency management and complex social systems (Abdel-Latif et al., 2023; Feofilovs et al., 2020; Perrone et al., 2020). The use of robustness and resilience metrics, adapted from previous applications in logistics and water systems (Muñoz et al., 2024; Tordecilla et al., 2017), provides a common language to translate dynamic trajectories (such as flow time series or levels of impact) into operational indicators that local governments can use to trigger or adjust intervention policies. In addition, the model connects with recent work that employs SD to assess flood resilience (Perrone et al., 2020; Zhu et al., 2024), but does so by incorporating business

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continuity and budget allocation as central components of the simulation (Cavallini et al., 2014; Phonphoton and Pharino, 2019).

On the other hand, the validation of the model in the mining community suggests that it can be parameterized using information available in land-use plans, municipal records, and environmental agency data, which facilitates its adoption by local governments with limited technical capacity (Coletta et al., 2024; Perrone et al., 2020). However, limitations were also identified. First, the operational limits and robustness and resilience thresholds were defined based on expert judgement, which may introduce biases and reduce comparability across contexts. Therefore, the thresholds used need to be re-evaluated and adjusted in line with the specific characteristics of each case (Beaudrie et al., 2011; Maranzoni et al., 2023). Second, in this study the behavior of the model was illustrated using a single mining community, with a specific budget structure and hydro morphological configuration; however, rather than being a limitation, this opens the door to replicating the model in other mining and flood contexts with their own climatic, physical, and governance conditions, in line with evidence highlighting the strong context dependence of flood vulnerability and risk (Merz et al., 2010a; de Moel et al., 2015). Third, although the model incorporates sediment generation and its effects on the channel in an aggregated way, it does not represent in detail the environmental impacts of mining or the long-term effects on water quality and ecosystems. This opens a line of future work to integrate more specific environmental modules that are consistent with the available evidence on the effects of mining waste (Lottermoser, 2010; Rentier and Cammeraat, 2022).

In summary, the practical application of the proposed model can help local governments to formulate more adaptive and transparent policies, capable of prioritizing interventions on the basis of operational thresholds, social impacts, and total crisis costs, rather than relying only on short-term accounting constraints (de Brito and Evers, 2016; Feofilovs et al., 2020; Merz et al., 2010a, c; United Nations Office for Disaster Risk Reduction (UNDRR), 2015)

5. Conclusions

This study shows that a SD approach can support local decision makers in mining contexts under climate variability by providing a holistic view of budget allocation for flood prevention and emergency response. The proposed model brings together, in a single framework, operational indicators (channel capacity, functional buildings and roads), robustness and resilience metrics (magnitude and duration of overflow and disruption), business continuity (mining operations), and deprivation costs for the affected population. By doing so, it translates complex time series into traceable metrics such as thresholds, durations, and maximum values, which help local authorities understand how alternative budget policies shape system performance over the course of the time.

Under the conditions evaluated, policy 3 consistently exhibited the best overall performance among the more than thirty policies explored. This policy, which combines support to the population with a stronger preventive effort focused on channel maintenance, reduced the frequency and duration of overflow events, maintained a higher proportion of the unaffected population, shortened interruptions in mining operations, and lowered total crisis management and deprivation costs. In contrast, policy 1, which concentrates most of the budget on direct assistance to people, and policy 2, which distributes resources more evenly but with a weaker preventive component, led to more affected people, longer recovery times, and higher or intermediate total costs. These results highlight that prioritizing only reactive response, without sufficient preventive investment in critical infrastructure, does not necessarily improve social outcomes and can prolong the impacts of floods on both communities and economic activities.

The analysis also shows that the way the budget is allocated across channel maintenance, support to the population, and infrastructure repair has direct and cumulative effects on the number of affected people, the functionality of buildings and roads, the continuity of mining operations, and deprivation costs. Policy 3 illustrates that strengthening critical infrastructure (in this case, the river channel) can simultaneously reduce the magnitude and duration of floods, limit the size of the affected population, shorten business interruptions, and decrease total costs. Incorporating deprivation costs reinforces this integrated perspective: when these costs are considered, differences between policies become more evident, and preventive policies that reduce exposure and the duration of impact emerge as more desirable than policies assessed only based on direct response costs.

Overall, the results indicate that the proposed model is a useful decision support tool for comparing budget allocation policies for flood prevention and emergency response in mining contexts. It makes the tradeoffs between population protection, infrastructure performance, and business continuity explicit and quantifiable, offering local governments a structured way to design, test, and adjust more adaptive and transparent budget strategies. By linking hydrological variability, infrastructure performance, social impact, and budget execution within a single dynamic framework, the model provides a basis for moving beyond short-term, purely accounting based decisions towards policies that more systematically support disaster risk reduction, business continuity, and community wellbeing.

6. Recommendation and future research

The operational limits and robustness and resilience thresholds used in this study were derived from expert judgement for a specific mining community. Although this was adequate for an initial application, future studies should re-estimate and refine these thresholds using broader expert panels, participatory processes with local stakeholders, and sensitivity analyses. This would help reduce potential biases, improve comparability across cases, and better align the indicators with local risk tolerances and policy priorities.

The model was illustrated using a single open pit mining context with a particular budget structure and hydro morphological setting. Applying and adapting the model to other mining regions and to non-mining flood-prone areas with different climatic, physical, and governance conditions would help test its transferability and limits. Comparative applications across multiple sites could also clarify which model components are context-specific and which can be generalized as a reusable decision-support template for local governments.

Appendices

Appendix A presents the Forrester-style stock-and-flow diagrams associated with the main level variables described in the manuscript. The diagrams complement the causal loop diagram and the definitions in Tables 1 and 2 and correspond to the implementation of the model in Vensim (Muñoz Pinzón et al., 2025).

Code availability

The system dynamics model was implemented in Vensim. The Vensim model file (.mdl) and the supplementary stock-and-flow diagrams used in this study are openly available from Zenodo (Muñoz Pinzón et al., 2025). The case-specific input data are summarized in the manuscript and were obtained from publicly available municipal and national sources cited in the text.

Author contributions

Dairo Steven Muñoz Pinzón conceived the study, developed the system dynamics model, performed the simulations and analysis, and wrote the manuscript. William Javier Guerrero Rueda and Diana Rodríguez Coca supervised the research, contributed to the study design and interpretation of the results, and provided critical revisions to the manuscript. Leonardo González contributed to the validation of the model, supported the interpretation of the results, and contributed to the revision of the manuscript. All authors read and approved the last version of the paper.

Competing interests

The authors declare that they have no competing interests.

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Ethical Aspects

To support the writing, text analysis, and translation of the manuscript, generative artificial intelligence tools were used, ChatGPT (version GPT-5.0) and GitHub Copilot. These tools were employed as linguistic and stylistic support; all decisions related to the scientific content, the interpretation of the results, and the conclusions are the sole responsibility of the authors.

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