

1 **INDIRECT COSTS OF FLOODS: A CASE STUDY OF HIGHWAYS**

2 **ROAD USERS**

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14 **Abstract.** Hydrometeorological events have a significant impact on road infrastructure and traffic flow. Floods can collapse
15 or weaken bridges, compromise river protection, and flood riverine roads, restricting or halting the traffic. These events incur
16 additional user costs owing to increased travel times from the rerouting and reduced speeds on affected roads. The economic
17 impact of such events on road networks is typically quantified in terms of infrastructure recovery costs, while the expected
18 user cost (EUC) of driving on damaged roads is often neglected. This study estimates flood risk to road networks by integrating
19 a hydrological-hydraulic model with road and bridge vulnerability assessments and traffic assignment models to calculate the
20 EUC. The procedure was applied to the Aconcagua River basin in central Chile, considering floods with return periods ranging
21 from 2 to 100 years, bridges vulnerability to scour, road waterlogging, travel times, and fuel consumption costs. In the 100-
22 year scenario, 7.65 km of roads and 3 bridges were affected. Considering all analysed return periods, the EUC of the network
23 reached 5.7×10^6 US\$ yr⁻¹. These results provide a quantitative basis for flood risk management and support decision-making
24 regarding prioritization of road and bridge interventions in the Aconcagua River basin.

25 **1 Introduction**

26 Hydrometeorological events (HME) originate from atmospheric and meteorological events that result in storms, droughts, heat
27 waves, and floods that modify territory over time and affect the subsistence of people and infrastructure (Sahani et al., 2019).
28 Floods are primarily caused by rainfall and, in mountain watersheds, by rapid snowmelt, which increases river discharge,
29 submerges lowland areas, and generates surface runoff that affects the built environment. Floods recurrently affect road
30 networks and their infrastructure, causing the total or partial destruction of road segments and bridges, and consequently
31 reducing the physical and operational road network performance during and after the event. Floods can cause bridges to
32 collapse or weaken river protection. In some areas, riverine roads may be flooded. Furthermore, flood-scour bridge foundations

33 affect their structural integrity and prevent vehicular traffic (Klinga and Alipour, 2015; Hung and Yau, 2017). Furthermore,
34 road waterlogging reduces traffic speed or prevents passage depending on the water height over the road (Pregolato et al.,
35 2017b; Contreras-Jara et al., 2018). In these cases, the impact on road network performance related to travel time increases
36 because of reduced speed and traffic rerouting. The indirect impacts of non-travel decisions can also reduce the traffic level
37 on the network and induce an alternative cost per non-travel decision. Both impacts involve road users and, depending on the
38 level of damage to the highway network, can be extended during the planning and delivery of repairs for damaged
39 infrastructure.

40 The impact of floods on road network users depends on the magnitude of the HME, infrastructure vulnerability and exposure,
41 and traffic distribution over the affected road network, making it important to estimate the flood risk on roads and bridges.
42 Risk comprises the events that may occur, their consequences and the associated probabilities, with severity characterizing the
43 consequences, commonly expressed as monetary losses (Aven, 2011). Risk analysis in road networks therefore focuses on
44 calculating economic losses in terms of the recovery costs of physical infrastructure. By contrast, economic loss estimation
45 does not always consider road asset fragility or costs incurred by road users. This aspect has drawn interest in risk assessment
46 literature in recent years (Lam and Adey 2016; Hackl et al. 2018; Zhang and Alipour, 2019 and 2020; Wang et al. 2020).

47 Flood risk is the probability of damage to infrastructure over a certain period in interaction with its physical vulnerability and
48 exposure and associated economic losses (Merz et al., 2009; Tsakiris, 2014). This is expressed in terms of the expected annual
49 damage caused by floods during the return period (Penning-Rowsell and Green, 2000).

50 Flood risk modeling of road networks under this approach includes four general steps: (1) hydrological and hydraulic modeling,
51 (2) road asset vulnerability, (3) traffic assignment modeling under normal and damaged conditions, and (4) economic loss
52 estimation. Wisetjindawat et al. (2017) identified the following hydrological modeling approaches: direct flow measurements,
53 remote rainfall and flood perception, rainfall-runoff modeling, and post-event measurements. Arseni et al. (2020) used flow
54 station data for hydrological modeling, which is appropriate if there are sufficient fluviometric stations and data per station to
55 model watersheds or sub-watersheds. Wang et al. (2020) used non-global climate models to model the surface runoff.
56 Vincendon et al. (2016) used hydrological balance-based models to predict flood flow. Hydraulic modeling procedures do not
57 differ significantly and generally use digital elevation models combined with hydrodynamic, one-dimensional (1D), two-
58 dimensional (2D), and ad hoc models. Teng et al. (2017) provided a detailed description of the available hydraulic models.

59 Vulnerability represents the susceptibility of the receiver bodies to damage caused by natural or anthropogenic events (Menoni
60 et al., 2012). Physical vulnerability represents the damage susceptibility of physical assets such as roads, bridges, and cut
61 slopes, which are commonly induced by natural events (Berdica, 2002). This susceptibility is represented by fragility or
62 damage probability models, which estimate the probability of reaching a particular damage state. Each asset has a unique
63 fragility curve for a specific event (Hackl et al., 2018). Traffic assignment modeling determines the travel time and operating
64 speed under normal and damaged road network conditions. Consequently, user costs can be estimated in terms of travel time
65 and additional fuel consumption costs due to rerouting. The Beckmann et al. (1955) model and its updates are frequently used
66 to estimate travel time in road networks in combination with traffic assignment models, assuming no congestion and origin-

67 destination matrices (Hackl et al., 2018). Zhang and Alipour (2019, 2020) used this approach for traffic modeling in flood risk
68 assessments.

69 Generally, flood risk is estimated in terms of the return period without considering the direct or indirect costs to people and
70 their economic activities. Flood effects can be estimated economically; for instance, agricultural and housing losses or the
71 costs of evacuation and attending to the people affected are commonly considered direct costs. In contrast, the effect of floods
72 on highway infrastructure and the cost transferred to road users in terms of travel time increase and additional fuel consumption
73 are not included in the economic loss models. Consequently, the total economic losses for different flood scenarios regarding
74 the return periods were underestimated.

75 In this study, we estimated the road user costs for networks affected by floods. The procedure integrates the vulnerability
76 models of bridges and roads, a locally calibrated rainfall-runoff model for uncontrolled watersheds, and a traffic assignment
77 model. The procedure was applied to a road network 1,823 km in length, located in the lower Aconcagua river basin in central
78 Chile. The flood scenarios included return periods of 2, 10, 25, 50 and 100 years. The discharge was modeled using a rainfall-
79 runoff model calibrated for Chile by Verni and King (1977). Flood maps were obtained by using the HEC-RAS 2D model for
80 each return period. Road network exposure was determined by overlapping flood and road network maps to identify flooded
81 road network sectors and bridges affected by scour.

82 The vulnerability of waterlogged roads was estimated using the traffic interruption model developed by Contreras-Jara et al.
83 (2018). Bridge vulnerability was estimated using the scour probability model developed by Contreras-Jara et al. (2021). Traffic
84 was obtained by combining the travel time model of Nie et al. (2004) with the numerical solution of a static traffic assignment
85 problem implemented by Kumar (2019) under normal and damaged network conditions. Travel time and fuel consumption
86 costs were estimated and combined with the estimated road and bridge vulnerabilities to obtain a proxy for the impact of floods
87 on the road network in the lower Aconcagua River basin in terms of road user cost losses. Finally, the results, discussion, and
88 conclusions are presented.

89 **2 Flood risk in highways networks**

90 **2.1 Quantification of flood risk**

91 Following the definition given in Sect. 1, flood risk comprises the flood events considered, their consequences and the
92 associated probabilities (Aven, 2011; Kron, 2005). Consequences comprise three factors (Gouldby and Samuels, 2005):
93 exposure, vulnerability, and the potential affection on people or damage to infrastructures.

94 According to Hall et al. (2006), risk can be calculated using Eq. (1), where $g(x)$ is the limit state function of a system with “x”
95 characteristics, and $I(\cdot)$ is an indicator whose value is one if $g(x) \leq 0$; otherwise, it is zero. This implies that the system fails
96 when $g(x)$ is less than zero. The term $f(x)$ is the probability density function that describes how the “x” system characteristics
97 vary, and $D(x)$ is the damage function of the system.

$$\text{Risk} = \int I(g(x) \leq 0) f(x) D(x) dx \quad (1)$$

98 A similar definition of risk was provided by Merz et al. (2009), who applied the expected annual damage (EAD) introduced
 99 by Penning-Rowsell and Green (2000) caused by floods. Flood risk is expressed by Eq. (2), where the decision variable is the
 100 water level (h), f(h) is the probability density function of the flood water level, and D(h) is the flood damage. There is a
 101 minimum water level value (h_d) at which the damage increases as the water level rises.

$$\text{Risk} = \int_{h_d}^{\infty} f(h) D(h) dh \quad (2)$$

102 Because flood scenarios are infrequent, Eq. (2) is expressed in discrete terms, as shown in Eq. (3) for the “m” probability
 103 increments and “j” intervals (Merz et al., 2009; Luger et al., 2010; Scorzini and Leopardi, 2017).

$$\text{Risk} = \sum_{j=1}^m \Delta P_j D_j ; D_j = \frac{1}{2} [D(h)_j + D(h)_{j+1}] ; \Delta P_j = (P(h)_j - P(h)_{j+1}) \quad (3)$$

104 where D_j is the average damage, and ΔP_j is the increment in the exceedance probability. Scorzini and Leopardi (2017), Arrighi
 105 et al. (2018), and Ziya and Safaie (2023) applied Eq. (3) Flood damage (D_i) is estimated using three return periods (T_i) to
 106 obtain Eq. (4).

$$\text{Risk} = \frac{1}{T_1} \times D_1 + \left[\frac{1}{T_2} - \frac{1}{T_1} \right] \times \frac{D_1 + D_2}{2} + \left[\frac{1}{T_3} - \frac{1}{T_2} \right] \times \frac{D_2 + D_3}{2} ; \text{Where } T_1 > T_2 > T_3. \quad (4)$$

107 2.2 Flood risk in highway networks modeling

108 Bridges and road segments near rivers are exposed to flooding. Bridge foundations are affected by scouring, which weakens
 109 their structural resistance and limits heavy hauling vehicles and transit traffic. Under extreme conditions, a bridge can be
 110 closed, and consequently, traffic is diverted to other roads in the network. Flooded roads decrease vehicle driving speed and
 111 eventually interrupt traffic, forcing rerouting on the nearby roads. Owing to traffic rerouting, the total travel time and fuel
 112 consumption increase, resulting in higher road user costs. Engineers face challenges in estimating traffic reassignment, and
 113 road user costs increase as a proxy for the expected annual damage (EAD) in flooded highway networks (Pregolato et al.,
 114 2017b; Hackl et al., 2018; Zhang and Alipour, 2019, 2020; Qiao et al., 2023; Rebally et al., 2026). Table 1 summarizes the
 115 state-of-the-art of highway flood risk modeling. The flood risk has been studied using topological, phenomenological, and
 116 hybrid approaches. The topological approach identifies link interactions in the road network and the connectivity loss of a
 117 closed set of links and nodes (Lertworawanich, 2012; Nelson et al., 2019). This phenomenological approach uses climatic or
 118 hydrological-hydraulic models to identify flooded road network links and those that are potentially disabled (Pedrozo-Acuña
 119 et al., 2017; Versini et al., 2010). The hybrid approach integrates topological and phenomenological approaches, as well as
 120 traffic assignment modeling, to determine the user costs induced by floods in highway networks (Pregolato et al., 2017b;
 121 Hakl et al., 2018; Wang et al., 2020; van Ginkel et al., 2021; Zhang and Alipur, 2020, 2022; Moghtadernejad et al., 2022;

122 Shahdani et al., 2022; Papilloud et al., 2024). The hazard is thus modeled using common hydrological and hydraulic models
 123 and their variations, using return periods ranging between 2 and 50 yr, and exceptionally up to 10,000 yr.

124 **Table 1: State of the art of flood risk models of highway networks. For each study, the table reports the risk modeling approach**
 125 **(type: topological, phenomenological, or hybrid, as defined in Sect. 2.2; Specification: the specific method used), the hazard**
 126 **characterization (type of hazard, flood model used, and return periods, T, considered), and whether the study incorporated road**
 127 **user costs, traffic assignment modeling, and infrastructure vulnerability assessment.**

Author	Risk Model		Hazard			Vulnerability Models		
	Type	Specification	Type	Flood model	Return Periods (T, yr)	Costs	Traffic assignment	Vulnerability
Lertworawanich (2012)	Topological	Travel time increase	Flood	Not used	Not used	Travel time w/BPR	Particle swarm optimization	Not estimated
Nelson et al. (2019)	Topological	Risk matrix in terms of hazard and betweenness centrality	Floods Landslides Mudslide	NOOA climate model	100	Not used	Not used	Not used
Versini et al. (2010)	Phenomenological	Exposure	Floods	<i>Plan d'Intervention aux Crises Hydrologiques</i> inventory	Not used	Not used	Not used	Not used
Pedrozo - Acuña (2017)	Phenomenological	Exposure	Floods	Not used	100	Not used	Not used	Not used
Pregmolato et al. (2017b)	Hybrid	Travel time increase	Floods	Rainfall-runoff model	3 climate change scenarios	Topological model of Ford et al. (2015)	Non declared	Vehicle speed – water depth model and depth threshold
Hackl et al. (2018)	Hybrid	Annual exceedance probability x Consequences = $(1/T)(costs)$	Floods Mudflow	Hydrological-Hydraulic model	2; 5; 10; 25; 50; 100; 250; 500; 1,000; 2,500; 5,000; 10,000	Assets Repairing Travel time w/BPR; Trip Losses Unsatisfied Vehicle operating costs	Deterministic	Theoretical Fragility models
Wang et al. (2020)	Hybrid	Travel time increase	Floods	Flood model + Global climate model	3 climate change scenarios.	Travel time	Multiagent microsimulation	Not used
van Ginkel et al. (2021)	Hybrid	Damage probability = hazard x exposure x vulnerability	Floods	Flood maps	10; 20; 50; 100; 200; 500;	Recovery cost	Not used	Damage curves: cost – water depth
Zhang and Alipur (2020)	Hybrid	Robustness index	Floods	Model not reported	500	Vehicle operating costs Opportunity loss costs	Not used	All-or-nothing Road or bridge closure in

Author	Risk Model		Type	Hazard		Vulnerability Models		
	Type	Specification		Flood model	Return Periods (T, yr)	Costs	Traffic assignment	Vulnerability
Zhang and Alipur (2022)	Hybrid	Annual exceedance probability x Consequences = $(1/T)(\text{costs})$	Floods	Model Not reported	2; 5; 10; 25; 50; 100; 200; 500	Recovery cost Travel time Opportunity loss costs	Wardrop's equilibrium model	terms of water depth tolerance All-or-nothing Road or bridge closure in terms of water depth tolerance
Moghtadernejad et al. (2022)	Hybrid	Cost minimization with simulated annealing, genetic algorithm, particle swarm optimization	Runoff Floods Mudflow	Model Not reported	500	Assets Repairing Trips losses Travel time w/BPR Vehicle operating costs	ODM, 4STM and Optimization w/Franke-Wolf	Fragility models of Lam and Adey (2016) Identification of the most damaged road sections using Scott et al. (2006) model.
Shahdani et al. (2022)	Hybrid	Travel time increase	Floods	Hydrological-Hydraulic model	20; 100; 1,000	Not estimated	Traffic simulation	Vehicle speed – water depth threshold of Pyatkova et al. (2019)

128 3 Methodology for estimating the road network flooding risk

129 3.1 General description of the procedure

130 The result of the procedure is economic losses in terms of costs for road users of road networks affected by floods for return
131 periods between two and 100 years. To estimate the losses, the procedure incorporates hydrological and hydraulic modeling
132 to simulate flood conditions, which then informs road and bridge vulnerability, culminating in a traffic assignment model that
133 estimates the resultant economic impact.

134 Road vulnerability was estimated as a function of the probability of traffic interruption owing to flooding. Bridge vulnerability
135 was calculated as the probability of scour exceedance. The exposure was obtained from overlapping flood maps and the road
136 network under study. Flood maps were obtained using a combination of hydrological and hydraulic models for different return
137 periods.

138 The indirect costs of flooding are estimated in terms of road user costs. These costs are the sum of fuel consumption and travel
139 time costs. They were estimated under normal operating conditions of the road network and for restrained operations under

different road flooding scenarios. Under normal conditions, road user costs are estimated by applying a traffic assignment model. The model assigns traffic to minimize the travel time of road users in an entire road network. Under restrained conditions, fuel consumption and travel time increase owing to rerouting caused by the disabling of total or partial road sectors and bridges or by speed reduction during the flood. The traffic assignment model is applied to estimate the fuel consumption, travel time, and costs for different flood scenarios. The difference in fuel consumption and travel time costs between normal and restricted operations was the net increase in the cost of the entire road network for each flood scenario

3.2 Workflow

Figure 1 shows the step-by-step procedure proposed for road network risk estimation, which comprises (1) hazard modeling (HMH), (2) road network exposure (RE), and (3) road network risk calculation (RM).

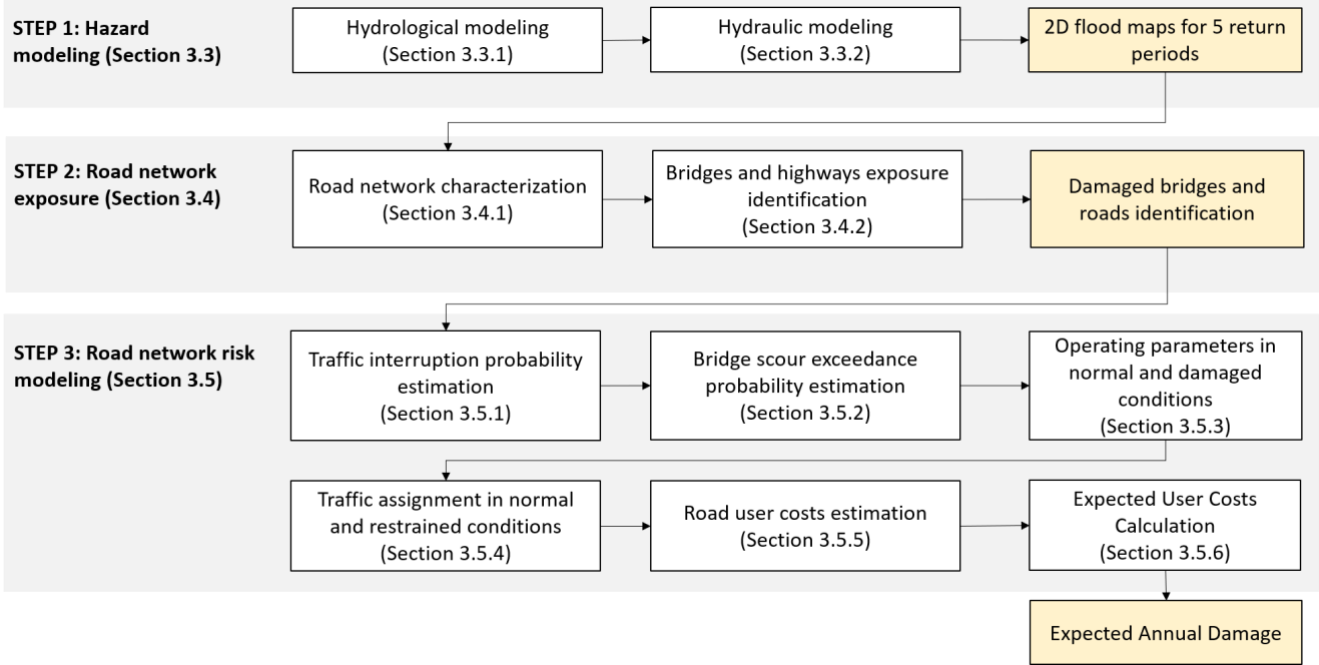


Figure 1: Procedure for calculating road network flooding risk, comprising three steps: (1) hazard modeling (Sect. 3.3), producing 2D flood maps for five return periods; (2) road network exposure analysis (Sect. 3.4), identifying damaged bridges and roads; and (3) road network risk modeling (Sect. 3.5), combining traffic interruption and bridge scour probabilities with traffic assignment and road user cost estimation to obtain the expected annual damage. Yellow boxes indicate the main output of each step; white boxes indicate individual modeling tasks, with the corresponding subsection numbers in parentheses.

The input data for the HMH module were as follows:

- Morphometric data: topography, river network, rainfall-contributing area, main channel length, and average slope
- Hydrological data: maximum rainfall in 24 h for a return period of 10 years and maximum annual discharge.

- Road network data: spatial representation of road links, nodes, and bridges; their physical characteristics, such as cross-section width, pavement type, and capacity; and operational characteristics, such as average speed, traffic volume, and vehicle traffic composition.

3.3 Step 1: Hazard modeling

In the HMM module (step 1), flood maps are obtained as follows: a) estimation of hydrographs at the entrance of each sub-watershed by hydrological modeling and b) spatial representation of flood by 2D hydraulic modeling for each return period. If discharge data are available, flood hydrographs are obtained by tracking floods in the daily maximum discharge registers. If discharge data are unavailable, a hydrograph can be obtained using locally calibrated rainfall-runoff models. The maps indicate the flood surfaces, maximum heights, and maximum flow velocities for various return periods.

3.4.1 Hydrological modeling

Hydrological modeling was performed using the Verni and King (1977) rainfall-runoff model, calibrated for Chilean basins with areas between 20 and 10,000 km² and mixed nival-pluvial regimes, which was consistent with the watershed considered in the case study. The lower Aconcagua river Basin was divided into eight subwatersheds, each with a control point at its outlet, for which the watershed area, channel length, slope, elevation difference, time of concentration, and 24 h design rainfall were collected. For each PC, peak discharges were estimated for return periods of 2, 10, 25, 50, and 100 years, respectively. Synthetic unit hydrographs were derived and adjusted such that the time to peak matched the concentration time of each sub-watershed. Finally, by convolving these unit hydrographs with the design rainfall, one design flood hydrograph was generated for each return period at each control point. These hydrographs were subsequently used as inflows for the hydraulic simulations.

3.4.2 Hydraulic modeling

Hydraulic modeling was performed with HEC-RAS 2D using the ALOS PALSAR digital elevation model (12.5 × 12.5 m resolution) as terrain input, ensuring consistency with the topographic data used in the hydrological analysis. The Manning's roughness coefficients of each sub-watershed were assigned using land use/land cover information collected from satellite images. For each return period, the design hydrographs obtained at the PCs were imposed as the input flow boundary conditions. The HEC-RAS model simulated flood propagation over the Aconcagua River floodplain and its tributaries, and the outputs were processed to generate maps of flood extent, representing the maximum water depths. Finally, the maximum flood depth at each grid cell and return period was extracted for subsequent intersection with the road networks.

186 **3.4 Step 2: Road network exposure modeling**

187 In step 2 (RE), the flood-affected road network was identified by superimposing the flood maps for each return period on the
188 road network map. The flood maps represent the maximum flood depth at each pixel for every return period. For each road
189 segment, the maximum flood depth along the segment was extracted from these maps and used as input to the traffic
190 interruption probability model (Eqs. 5 and 6), and the speed reduction model (Eq. 7), as it represents the most restrictive
191 condition for traffic operability.

192 **3.4.1 road network characterization**

193 Road network characterization involves the following tasks: specification of a node-arc configuration of the road network
194 potentially affected by floods, identification of road type (multilane, two-lane class 1, and two-lane class 2) and road bridges,
195 and specification of operative parameters (average travel speed, capacity, pavement roughness, and vehicle classes in traffic
196 flow). Finally, these attributes are introduced as properties of each arc of the road network. The obtained road network is then
197 prepared to apply the traffic assignment model and estimate road user costs.

198 **3.4.2. Bridge and highway exposure identification**

199 Bridge and highway exposure was obtained by overlapping the road network and flood maps obtained in the hazard modeling.
200 The resulting maps allow the identification of bridges affected by floods and flooded highway segments. Each segment is cut
201 off from the arc, and a new segment is reconfigured. This step is necessary to assign the operating parameters under the
202 damaged conditions.

203 **3.5 Step 3: Road network risk modeling**

204 In Step 3 (RM module), the traffic interruption probability models (Eqs. (5) and (6)) are exponential functions calibrated for
205 the Chilean vehicle fleet, estimating the interruption probability for light and heavy vehicles as a function of flood depth,
206 accounting for the variability in wading depth across representative vehicle types (Contreras-Jara et al., 2018). The bridge
207 vulnerability model estimates the exceedance probability of the design scour depth as a function of the water depth (Contreras-
208 Jara et al., 2021). The RM module then identifies the road network characteristics and determines the traffic capacity and
209 operating speed at each network link under normal and restrained operating conditions. Under normal operating conditions,
210 no network links are physically affected by floods. In a restrained operation, one or more network links are partially or fully
211 disabled owing to a flood, forcing traffic to reroute, or speed reduction. Restricted operating conditions in flooded links were
212 assumed if the waterlogging probability exceeded a predetermined value. The circulation speed was calculated using the model
213 proposed by Pregnotato et al. (2017). Finally, a traffic assignment model is applied under normal and restrained conditions.

214 3.5.1 Traffic interruption probability estimation

215 The traffic interruption probability model for flooding, given by Eqs. (5) and (6) for light ($P_{\text{int-light}}$) and heavy ($P_{\text{int-heavy}}$) vehicles
216 respectively, were used to estimate road vulnerability. Contreras-Jara (2018) calibrated Eq. (5) and Eq. (6) for Chilean
217 conditions using reliability principles. The models estimate the probability of traffic interruption in terms of the flood height
218 (h , m).

$$P_{\text{int-light}} = 1 - e^{-79.829h^{5.223}} \quad (5)$$

$$P_{\text{int-heavy}} = 1 - e^{-0.137h^{12.917}} \quad (6)$$

219 3.5.2 Bridge scour exceedance probability estimation

220 Bridge vulnerability was calculated using the model proposed by Contreras-Jara et al. (2021). This model estimates the scour
221 exceedance probability of one- or two-span bridges exposed to local scouring. The exceedance probability was estimated based
222 on the maximum water depth and the return period.

223 3.5.3 Operating parameters under normal and restricted traffic conditions

224 The operating parameters under normal traffic conditions are assigned to each bridge and arcs unaffected by floods. The defect
225 parameters were those described in Section 3.4.1. In bridges and road arcs affected by floods detected in Section 3.4.2,
226 operative restraints are introduced, from which the more relevant limit probabilities are estimated using Eqs. (5) and (6), and
227 the speed limits in the flooded road arc were estimated using Eq. (7).

228 For each return period, the probability obtained using Eqs. (5) and (6) set a limit on the water height and determine whether
229 each link operates under normal and restricted conditions. In the flooded links, the limit values of $P_{\text{int-light}}$ and $P_{\text{int-heavy}}$ is set at
230 15%, consistent with the upper calibration limit of the speed reduction model of Pregnotato et al. (2017a, b) for light vehicles
231 at $h = 0.3$ m. The same threshold is applied to heavy vehicles using Eq. (6), yielding a flood depth limit of $h = 1.0$ m. The
232 traffic conditions were as follows:

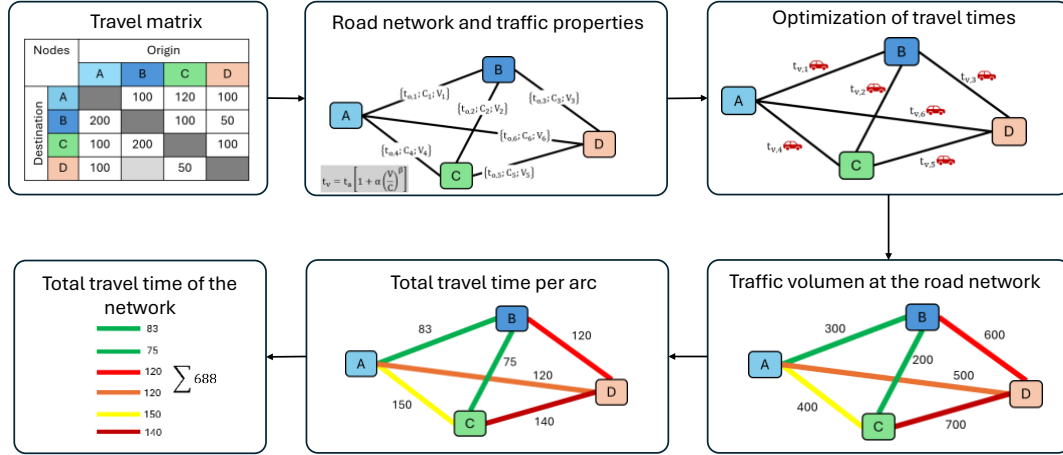
- 233 • If $h < 0.3$ m, light and heavy traffic operate under restricted conditions.
- 234 • If $0.3 \text{ m} < h < 1.0$ m, light traffic is interrupted, and rerouting is required. Heavy traffic operates under restricted conditions.
- 235 • If $h > 1.0$ m, light and heavy traffic were interrupted. Re-routing is needed.

236 Under restricted operating conditions, the traffic speed on roads and bridges is reduced. On flooded road arcs, the speed is
237 calculated using the model calibrated by Pregnotato et al. (2017a, b) (Eq. (7)), which estimates the speed limit of light vehicles
238 in the event of flooding (V_{lim} , km h⁻¹) from the height of the flood on the road (h_R , mm). For larger vehicles, a height limit of
239 1000 mm was used to estimate V_{lim} .

$$V_{\text{lim}} = \begin{cases} 0.0009h_R^2 - 0.5529h_R + 86.9448 & ; \quad h_R \leq 300 \text{ mm} \\ 0 & ; \quad h_R > 300 \text{ mm} \end{cases} \quad (7)$$

240 3.5.4 Traffic assignment model

241 The traffic assignment model (TAM) of Beckmann et al. (1955), extended by Nie et al. (2004), was used. A diagram of this
 242 process is shown in **Figure 2**. The diagram describes the main features of the traditional traffic assignment model described in
 243 Eq. (8) to Eq. (12). The input data were arranged in a travel matrix format. After the road network was characterized (Sections
 244 3.4.1 and 3.5.3), the optimization model estimated the unit travel time and traffic volume for each arc. Finally, the unit travel
 245 time is multiplied by the traffic assigned to each arc and summarized to obtain the total travel time of the network. These
 246 values are used as inputs to estimate the expected user cost (EUC) for restrained and normal traffic operations in the network.



247
 248 **Figure 2: Diagram of the traffic assignment model (TAM).** Based on an origin-destination trip matrix and the road network with
 249 the properties of its links (top row), the model iteratively optimizes the travel times for each arc (top right; the red cars indicate
 250 traffic flow) to obtain, for each arc, the total travel time and the assigned traffic volume (bottom row, from right to left) and,
 251 finally, the total travel time for the network. The colours in the “Total Travel Time per Arc” and “Traffic Volume on the Road
 252 Network” panels are for illustrative purposes only and represent a qualitative scale ranging from low (green) to high (red) in
 253 terms of relative travel time and traffic level, respectively; they do not correspond to the actual values from the case study.
 254 TAM assigns traffic to a road network “G” composed of “N” nodes and “A” links, thereby minimizing the total travel time.
 255 The optimization problem is formulated in Eq. (8) to Eq. (13). The optimization problem is typically solved using the Frank-
 256 Wolfe algorithm.

$$\min \sum_{a \in A} \int_0^{f_a} t_a(x) dx \quad (8)$$

257 In Eq. (8), where “a” represents each link of network “G,” “ f_a ” is the traffic in link “a,” and “ t_a ” is the total travel time in link
 258 “a,” calculated using Eq. (13). The “a” links of the network “G” are obtained from national road surveys, with which a
 259 connected network is prepared. The traffic “ f_a ” is obtained from national traffic surveys and is generally expressed as average
 260 annual daily traffic (AADT). The restrictions on the optimization model are as follows (Bar-Gera, 2002; Nie et al., 2004).

$$\text{Total vehicle flows equal to the demand for each origin-destination:} \quad \sum_{p \in P_w} h_p = T_w \quad ; \quad w \in W \quad (9)$$

Traffic in the link is the sum of the flows of all routes that use the link:
$$f_a = \sum_{p \in P_w} \delta_{ap} h_p \quad ; \quad a \in A \quad (10)$$

No traffic negativity on route “p”:
$$h_p \geq 0 \quad ; \quad p \in P_w \quad (11)$$

No negative traffic in link “a”:
$$f_a \geq 0 \quad ; \quad a \in A \quad (12)$$

$$t_v = t_a^0 \left[1 + \alpha \left(\frac{f_a}{c_a} \right)^\beta \right] \quad (13)$$

In Eq. (9) to Eq. (12), where “w” is a travels origin-destination (O-D) pair; “W” is the set of all O-D pairs in the “G” network; “P” represents all possible routes in the road network. It can be obtained from an O-D survey or zoning of the study area, and traffic data from national surveys estimate the traffic (h_p) at each link “a” that connects each zone. “ P_w ” is the set of available routes connecting the O-D pair “w” which are obtained from the network “G”; “ T_w ” is the traffic in the O-D pair “w” that are obtained from the network “G”. “ h_p ” is the traffic in route “p”; and “ δ_{ap} ” is a dummy coefficient ($\delta_{ap} = 1$ if the link “a” belongs to the route “p”; otherwise, $\delta_{ap} = 0$). In Eq. (13), “ t_a ” is the travel time in the link “a” (h); “ t_a^0 ” is the travel time (h) of link “a” in free-flow condition, which is obtained by dividing the length of each link by the average travel speed or by the design speed. “ c_a ” is the capacity of link “a” (pcu h⁻¹ lane⁻¹), which can be obtained from TRB (2016). Generally, the capacity of two-lane rural roads ranges between 1400 and 1800 (pcu h⁻¹ lane⁻¹), and multilane rural roads vary between 2000 and 2200 pcu/h/lane. These variations depend on whether the terrain is flat, rolling, or mountainous. The parameters α and β were obtained from the TRB (2010 and 2016) ($\alpha=1.5$ and $\beta=5$ for multilane and Class 1 roads; $\alpha=1.2$ and $\beta=5$ for Class 2 roads).

3.5.5 Road user costs

The speed, traffic volume, and travel time of each road network link are then determined. These outputs are used to estimate the total road user cost (RUC), which is the sum of the travel time cost (TTC) and fuel consumption cost (FCC), as expressed in Eq. (14). The road user cost (RUC) is the sum of these costs per link and vehicle type. The total costs for the network under normal and restrained conditions are the sum of the road user costs of each link and vehicle type. The cost difference between normal and restrained conditions results in operational losses after flooding.

$$RUC = FCC + TTC = \left[\sum_{a=1}^A \sum_{v=1}^{V_a} d_a FC_v f_v + \sum_{v=1}^V t_v s_v \right] \quad (14)$$

In Eq. (14), where “V” is the traffic assigned; “ V_a ” is all vehicles assigned in the link “a”; “ d_a ” is the length of the link “a” (km); “ FC_v ” is the fuel consumption of vehicle “v” (mL km⁻¹); “ f_v ” corresponds to the unit cost of fuel for vehicle “v” (US\$ L⁻¹); “ t_v ” corresponds to the travel time of vehicle “v” (h) obtained from the TAM; “ s_v ” is the unit cost of the time for vehicle “v” (US\$ h⁻¹). The unit fuel consumptions of light vehicles (FC_{lv} , mL pcu⁻¹ km⁻¹) and heavy vehicles (FC_{hv} , mL pcu⁻¹ km⁻¹) were calculated using Eqs. (15) and (16), depending on the pavement roughness (IRI, m km⁻¹) and operating speed (OS, km h⁻¹). FC_v is then obtained by converting FC_{lv} and FC_{hv} from mL to L.

$$FC_{lv} = (1,255.7 - 1.7735 \cdot IRI) \cdot OS^{-(0.543-0.0009 \cdot IRI)} \quad (155)$$

$$FC_{hv} = (8,308.2 - 10.085 \cdot IRI) \cdot OS^{-(0.3048-0.0004 \cdot IRI)} \quad (16)$$

284

285 3.5.6 Expected user cost

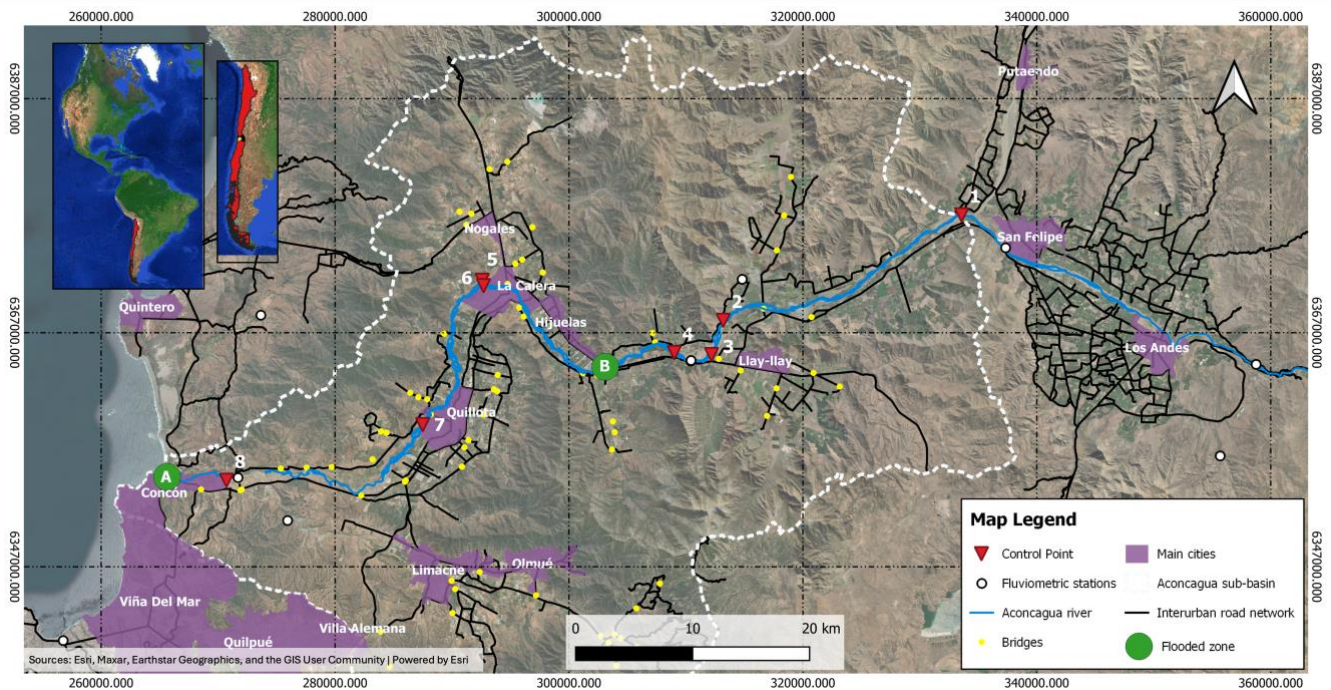
286 The expected user cost (EUC) is used as a proxy for flood risk in road networks. The EUC (in US\$/year) is computed by
 287 integrating the user road cost (RUC) across return periods using the trapezoidal rule, as expressed in Eq. (17), where T_1 – T_5 are
 288 the return periods of 100, 50, 25, 10, and 5 years, respectively, and S_1 – S_5 are the road user costs (RUC) for each return period,
 289 estimated using Eq. (14).

$$EUC = \frac{S_1}{T_1} + \sum_{i=1}^{n-1} \left(\frac{1}{T_{i+1}} - \frac{1}{T_i} \right) \cdot \frac{S_i + S_{i+1}}{2} \quad (7)$$

290 4 Case study and application: Road Network of Aconcagua Basin

291 4.1 Study area

292 The study area is known as lower Aconcagua River Basin (LAB) (Figure 3). The basin originates 4 km downstream of San
 293 Felipe City at the confluence of the Aconcagua and Putaendo Rivers. It belongs to the larger watershed of the Aconcagua
 294 River, located in the central zone of Chile between the coordinates [32-43°37.9" S, 70-46°09.21" W] and [32-55°21.9" S, 71-
 295 30°32.1" W].



296

297 **Figure 3: Location and general characteristics of the study area in the lower Aconcagua River sub-basin, central Chile. Insets (top**
 298 **left) show the regional location within South America and Chile. Numbered red triangles (1–8) indicate the control points (PC1–**
 299 **PC8) used for hydrological modeling (Tables 2–4); yellow dots indicate bridges; white circles indicate fluviometric stations; the**
 300 **blue line indicates the Aconcagua River; black lines indicate the interurban road network; purple polygons indicate the main**
 301 **cities; the dashed white line delimits the Aconcagua sub-basin. Green circles labeled A and B indicate the two zones shown in**
 302 **detail in Figs. 4 and 5, respectively. Base map: Esri World Imagery (Sources: Esri, Maxar, Earthstar Geographics, and the GIS**
 303 **User Community | Powered by Esri). Coordinate system: WGS 84 / UTM zone 19S.**

304 The main watercourse of the LAB is the Aconcagua River, which is 152 km long and flows from the east to the west. The
 305 watershed has an area of 2,625 km² and an average flat slope between 160 and 200 m/km. It has a mixed pluvial-nival regime,
 306 a monthly average discharge between 20 and 50 m³/s, and a maximum rainfall in 24 h between 80 and 110 mm in a return
 307 period of 10 years (MOP, 2004; MOP, 2019a). The road network in the LAB is mainly linear and spatially located on the
 308 margins of the floodplains in the watershed. The road network comprises two multilane roads connecting the cities of Los
 309 Andes, La Calera, Quillota, Concon, and Viña del Mar, and a complementary network composed of two-way, two-lane rural
 310 roads. Two percent of the watershed land use is urban and 13% of the surface is used for forestry and agricultural activities. In
 311 addition, 35% of the land was wooded, 32% was grassland, 4% was water bodies, and the remaining 14% was un-vegetated.
 312 Industrial activity is present in the cities mentioned, and agricultural use occurs in rural areas adjacent to the watercourses
 313 (MOP, 2004).

314 The road network under study is in the ancient floodplain of the Aconcagua River, with the main road network on both banks
 315 of the river. Road networks near towns and cities have subnetworks that provide accessibility between towns, farms, and main
 316 roads. These subnetworks have a geometric design standard that is lower than that of the main route of the network.

317 The road network in the study area and its specific characteristics were obtained from the geodatabase of roads of the Chilean
318 Ministry of Public Works (MOP 2020a, 2020b). The roads were classified into three categories according to the average speed
319 and road capacity: multilane, two-way, and two-lane Class 1 roads; and two-way and two-lane Class 2 roads (see Table 6).
320 The principal road network consisted of 307 km of multilane roads and 1516 km of two-way, two-lane Class 1 and Class 2
321 roads, all of which were paved. On multilane roads, each carriageway cross-section consists of two lanes (3.5 m wide each), a
322 2.5 m-wide shoulder, and a 6 m wide median. On two-way, two-lane roads, the cross-section consists of one lane per traveled
323 way, a lane width of 3.5 m, and shoulders of 1.5 m.
324 The road network has 79 bridges, with lengths ranging between 10 and 530 m. Nine bridges cross the main watershed river
325 (Aconcagua River). Of these, 75% are one-span bridges, and the remaining 25% are two or more span bridges. The annual
326 average daily traffic (AADT) and its composition were estimated using the traffic database of the Chilean Ministry of Public
327 Works (MOP, 2020c) available online. On multilane roads, the AADT varied between 4,670 and 17,670 vehicles/day-year.
328 On Class 1 roads, the AADT varied between 605 and 9,449 vehicles/day-year. On Class 2 roads, the AADT varied between
329 1,105 and 8,015 vehicles/day-year.

330 4.2 Flood hazard modeling

331 4.2.1. Flow modeling by return period

332 Hydrological modeling was performed using a rainfall-runoff model calibrated for Chile by Verni and King (1977) in
333 watersheds between 20 and 10,000 km², with return periods of less than 100 years and a mixed nival-pluvial regime. In the
334 case study, the watersheds had areas between 1638 and 3860 km², and modeling was performed for return periods of up to 100
335 years; therefore, the model of Verni and King (1977) is applicable to the situation represented in the case study.
336 Regarding the input parameters used, the topography was obtained from the ALOS PALSAR digital elevation model developed
337 by the Japanese Aerospace Exploration Agency in its JAXA 2011 mission (ASF DAAC, 2014). The resolution was 12.5x12.5
338 m. Hydrographic data were obtained from the Chilean Ministry of National Land (MOP, 2017). Geomorphological data of the
339 watershed were obtained from post-process topography, hydrographic information, and the contributing areas. The model of
340 Verni and King (1977) used as input data the maximum rainfall in 24 h for a return period of 10 years (P_{24}^{10} , mm), watershed
341 area, duration factors, and return period factor to adjust the maximum flow in every watershed without fluviometric data.
342 Parameter P_{24}^{10} , was obtained from the online Hydrometric System of the General Directorate of Waters of the Ministry of
343 Public Works of Chile (MOP 2019a). All the data are freely accessible.
344 Hydrologic modeling was performed using a rainfall-runoff analysis owing to the lack of flow information for the entire
345 Aconcagua Basin. For this purpose, flood routing was performed by dividing the basin into eight sub-basins, each with its own
346 attributes and precipitation data. In addition, eight checkpoints (PC) were set at the end of each sub-watershed, including the
347 main channel of the Aconcagua River (Figure 3). Each PC had a specific data input depending on the runoff-contributing area
348 (Ap). Table 2 shows the input data of each PCi.

349 As the first step of the modeling, using the model of Verni and King (1977) as a function of the parameters described in Table
350 2, the flow rates for return periods of 2, 10, 25, 50, and 100 years were obtained (Table 4). Then, based on the parameters in
351 Table 3, the synthetic unit hydrograph of each sub-basin was obtained and adjusted according to the flow obtained using the
352 Verni and King (1977) model and the time of concentration “tc” of each sub-basin. The criterion used was that the
353 concentration time was equal to the time required to reach the peak value. As a result of hydrologic modeling, five hydrographs
354 for each return period were obtained for the eight sub-basins.

355 **Table 2: Morphometric and hydrological input data used in the rainfall–runoff model (Verni and King, 1977) at each of the eight**
356 **control points (PC1–PC8, Fig. 3).**

Input data	PC ₁	PC ₂	PC ₃	PC ₄	PC ₅	PC ₆	PC ₇	PC ₈
Ap (km ²)	1636.8	2154.3	313.4	574.2	2452.7	418.5	2983.2	3860.4
Ls (km)	63.5	89.9	30.1	96.4	115.1	22.3	130.7	152.2
Lg (km)	17.0	33.1	12.2	43.0	43.7	10.2	44.8	52.6
S (m/m)	0.4	0.4	0.4	0.3	0.4	0.4	0.4	0.4
D (km)	5.3	4.3	1.9	3.6	4.3	2.1	4.4	4.5
tc (h)	4.2	6.8	2.6	8.0	9.1	1.8	10.4	12.3
P ₂₄ ¹⁰ (mm)	80.0	83.3	80.0	120.0	88.2	100.0	100.0	110.0

357 Ap: basin area; Ls: length of the channel upstream of PC_i; Lg: distance between the center of gravity of the basin and the
358 location of the PC_i; S: average slope of each basin obtained from the digital elevation model (DEM) using the QGIS Slope
359 tool (QGIS Development Team, 2021); D: maximum height difference between the highest point of the basin and the PC_i; tc:
360 time of concentration in each virtual sub-basin; P₂₄¹⁰: maximum rainfall in 24 h for a 10-years return period (T).

361 **Table 3: Synthetic unit hydrograph parameters derived for each control point (PC1–PC8, Fig. 3), used together with the design**
362 **rainfall to generate the flood hydrographs for each return period**

Parameter	PC ₁	PC ₂	PC ₃	PC ₄	PC ₅	PC ₆	PC ₇	PC ₈
t _p (h)	7.52	11.57	4.73	11.09	14.64	4.01	15.56	17.87
t _b (h)	27.28	38.60	18.77	37.30	46.64	16.44	48.98	54.76
q _p (m ³ /s/km ²)x10 ⁻³	28.93	20.53	41.87	21.24	17.02	47.75	16.22	14.53

363 t_p: time to peak discharge; t_b: base time; q_p: peak discharge.

364 **Table 4: Peak discharge Q(T) (m³/s) estimated at each control point (PC1–PC8, Fig. 3) for return periods T = 2, 10, 25, 50, and 100**
365 **years, obtained from the synthetic unit hydrographs in Table 3.**

PC _i	Q(T) (m ³ /s)				
	T = 2 years	T = 10 years	T = 25 years	T = 50 years	T = 100 years
PC ₁	420.3	676.7	822.1	946.2	1066.2
PC ₂	562.8	906.1	1100.8	1267.0	1427.6
PC ₃	11.8	64.5	96.9	138.2	185.8

PC ₄	276.4	445.0	540.8	622.3	701.2
PC ₅	677.3	1090.2	1324.6	1524.5	1717.7
PC ₆	778.0	1252.3	1521.5	1751.2	1974.2
PC ₇	940.2	1513.5	1838.7	2116.3	2384.6
PC ₈	542.2	2137.0	2596.4	2988.3	3367.1

366 4.2.2 Flood map estimation

367 HEC-RAS 2D software (USACE, 2016) was used for hydraulic modeling. The same ALOS PALSAR digital elevation model
368 (12.5×12.5 m resolution, ASF DAAC, 2014) used for hydrological modelling was used as the terrain input for the HEC-RAS
369 2D hydraulic simulations. Manning's roughness coefficients, assigned to each sub-watershed based on land use/land cover
370 classification derived from satellite imagery following Chow (1988), were used as the surface roughness input. Flood
371 hydrographs estimated from hydrological modeling for each return period were used as the boundary conditions for the HEC-
372 RAS 2D model. The same return period was simulated for the entire lower Aconcagua River Basin. The floodable area was
373 identified and assigned roughness and slope, and the input and output hydrographs were obtained from the DEM used for
374 hydrologic modeling. These data were used to estimate the flood surface, flood height, and flow depth of the bridges, roads,
375 and riverbanks in the area. The hydraulic model output represented the maximum flood depth for each return period in the
376 eight sub-watersheds. Figure 4 and Figure 5 show the flood surface and maximum flood depth in zones A and B, Figure 3.

377 The significant scarcity of comprehensive real-time precipitation data across the entire Aconcagua Basin, with reliable records
378 limited to only two stations situated in the headwaters, precludes the direct use of actual rainfall for the comprehensive
379 hydraulic model calibration and validation. Consequently, the Verni and King (1977) hydrological model was employed to
380 estimate the discharge. Full model calibration or validation using actual distributed rainfall was not feasible under these data
381 constraints; rather, the estimated flows were verified against limited fluvimetric station data.

382 Data from two available fluvimetric stations (San Felipe and Llayllay) were used to verify discharge over a 25-year return
383 period. However, insufficient discharge and correspondingly low water height records at these stations precluded the validation
384 of simulated flows. Consequently, verification must be conducted at specific locations using sufficient data. Therefore, PC1
385 can only be verified for a 25-year return period. The maximum measured discharge at this control point was $800 \text{ m}^3/\text{s}$, which
386 was associated with $T=25$ years (Alvarez-Garretón et al., 2018). The discharge modeled for this return period was $822 \text{ m}^3/\text{s}$,
387 which was 3% greater than the measured value.

388 Similarly, the specific discharge reported by Alvarez-Garretón et al. (2018) was $0.153 \text{ m}^3/\text{s}/\text{km}^2$, and the model was 0.147
389 $\text{m}^3/\text{s}/\text{km}^2$, which is 4% less than the former. Therefore, the modeled flows were assumed to be valid for 25 years. In addition,
390 water height data were compared with data from an existing fluvimetric station in the lower Aconcagua River basin. The data
391 from the fluvimetric station showed water heights between 4.4 and 4.8 m for a maximum discharge of $800 \text{ m}^3/\text{s}$. The modeled
392 water height resulted in values between 4.7 and 5.2 m for a return period of 25 years. The maximum difference was 8%.

393 **4.3. Road network exposure to floods**

394 The road network was overlaid on the flood maps obtained from the hydrological–hydraulic simulation to identify flood-
395 affected road infrastructure. The flooded road segments, lengths, and maximum flood depths were identified for each return
396 period. Road surface elevations were obtained from the ALOS PALSAR DEM (12.5 × 12.5 m, ASF DAAC, 2014) extracted
397 at the centerline of each road segment. Given the vertical margin of error of the DEM, more precise road surface elevations
398 cannot be derived from this data source. Bridges with a probability of scour design exceedance greater than zero were also
399 identified. Table 5 summarizes the results. Figure 4Figure 4 and Figure 5 highlight the flood surface and water depth in zones
400 A and B in Figure 3.

401 **Table 5: Flood-affected roads and bridges for each return period (T = 2 to 100 years), by road category (Multilane, Two-way Two-**
402 **lane Class 1, Two-way Two-lane Class 2) and bridge type (1-span, +1-span).**

Road Element		Return period (years)				
		2	10	25	50	100
Multilane	# Sections	2	4	4	4	4
	H _{av} (m)	0.45	1.25	1.57	1.75	2.18
	L (m)	1846	3182	3182	3182	3182
Two-way	# Sections	5	9	10	10	10
Two-lane Class 1	H _{av} (m)	1.23	1.25	1.43	1.73	2.35
	L (m)	960	3426	3512	3512	3512
Two-way	# Sections	1	2	2	2	2
Two-lane Class 2	H _{av} (m)	0.02	0.75	1.6	1.7	3.7
	L (m)	439	960	960	960	960
1-span	# bridges	0	0	0	0	0
Bridge	Exceedance	0	0	0	0	0
	Probability					
+1-span	# bridges	0	1	2	3	3
Bridges	Exceedance	0	0.73	[0.07–0.83]	[0.07–0.83]	[0.08–0.90]
	Probability					

403 Hav: average water depth in flooded roads (m); L: total length of flooded roads (m)

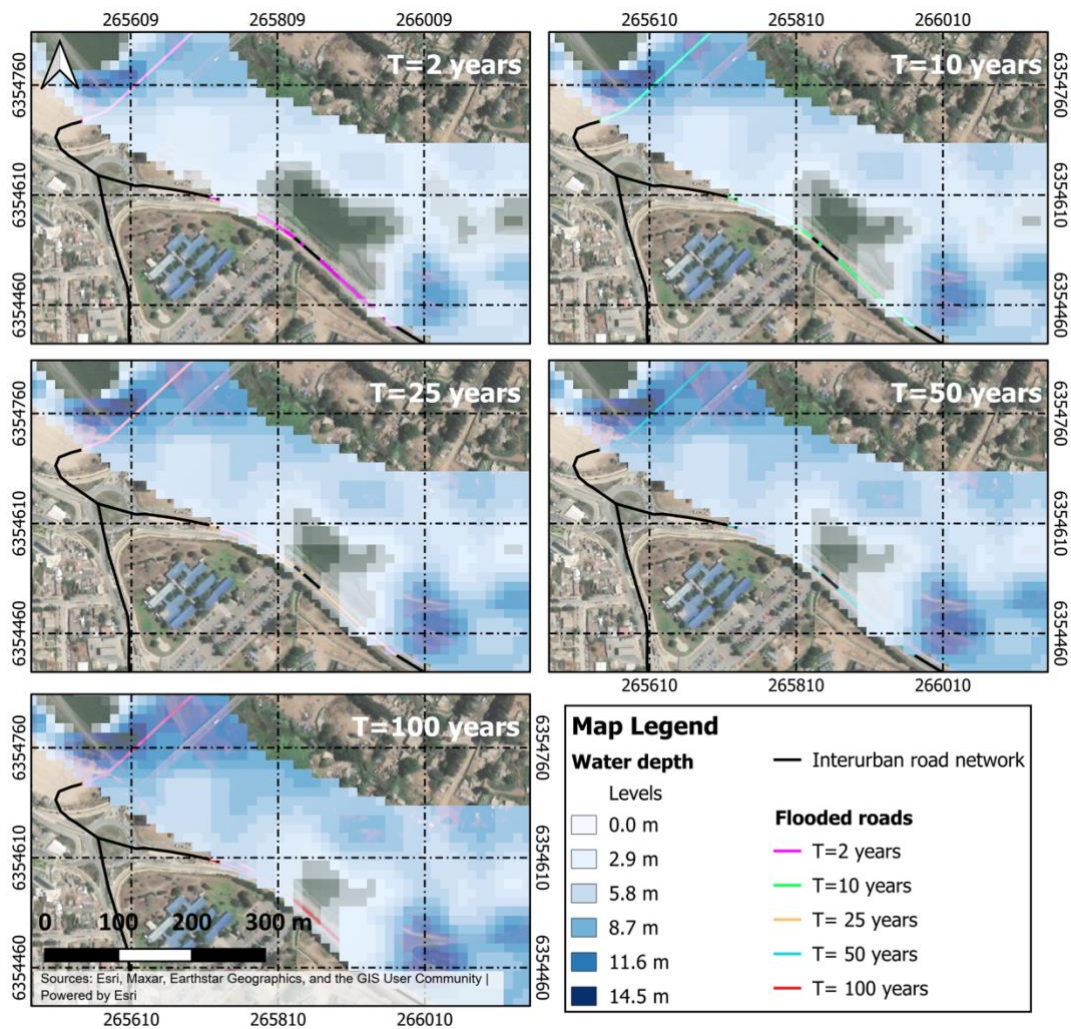


Figure 4: Zone A (see Figure 3): flooded roads and bridges, their lengths, and flood heights for each return period (T = 2, 10, 25, 50, and 100 years). Shaded blue tones indicate water depth in meters (see legend); coloured lines indicate flooded road segments for each return period. Base map: Esri World Imagery (Sources: Esri, Maxar, Earthstar Geographics, and the GIS User Community | Powered by Esri). Coordinate system: WGS 84 / UTM zone 19S.

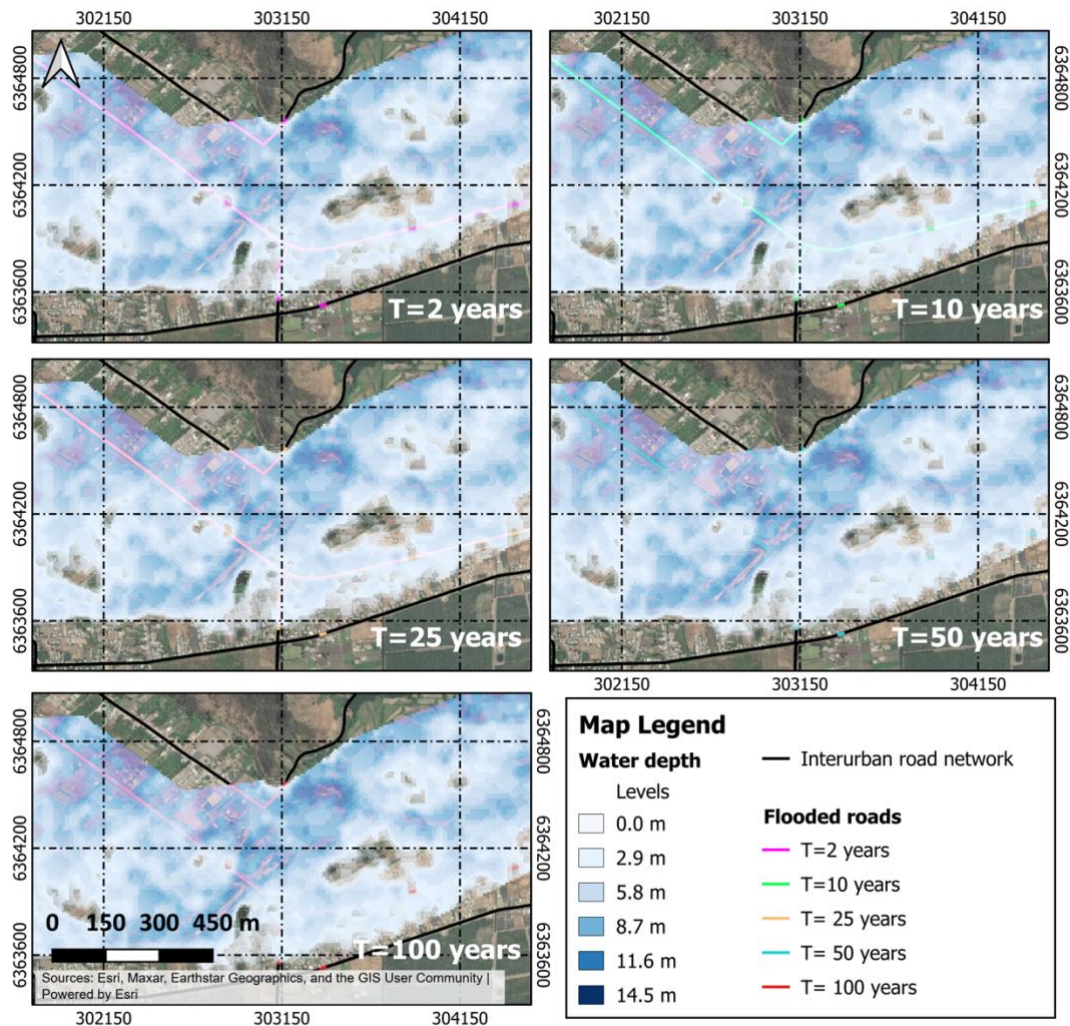


Figure 5: Zone B (see Figure 3): Flooded roads and bridges, their lengths, and flood heights for each return period (T = 2, 10, 25, 50, and 100 years). Shaded blue tones indicate water depth in meters (see legend); coloured lines indicate flooded road segments for each return period. Base map: Esri World Imagery (Sources: Esri, Maxar, Earthstar Geographics, and the GIS User Community | Powered by Esri). Coordinate system: WGS 84 / UTM zone 19S.

4.4 Road network risk modeling

4.4.1 Modeling parameters

Road network risk modeling considers the reduction of expected costs for network users under normal and restricted conditions. Table 6 lists the parameters under normal and restricted conditions for each road type and vehicle class. The design speed and highway capacities under normal operation were obtained from MOP (2019b). For bridges, the operating speed was set to 20 km/h when the scour design exceedance probability was 0.3 and 0.6. Total traffic disruption was assumed for

420 exceedance probabilities higher than 0.6 with an operating speed of 0 km/h. We assumed that the capacity of the flooded roads
 421 remained constant at different flood heights and that only the speed changed, according to the model proposed by Pregnotato
 422 et al. (2017a). Above these values, the capacity is zero owing to traffic interruptions. For bridges, it was assumed that scour
 423 probabilities between 0.3 and 0.6 are in such a state of damage that traffic and structural capacity are reduced (Hackl et al.,
 424 2018). Under these conditions, the reduction in bridge capacity was estimated to be 20%, assuming normal conditions for
 425 vehicles (Bocchini and Frangopol, 2011). For exceedance probabilities greater than 0.6, traffic interruption was assumed;
 426 therefore, the traffic and structural capacities of the bridge were considered zero.

427 **Table 6: Operating parameters of the road networks under normal and flood-restricted conditions, by road category, road asset**
 428 **(roads and bridges), and vehicle class, used as input to the traffic assignment model.**

Operating Condition	Road category		Road asset		Vehicle class	Average travel speed (km/h)	Capacity (pcu/h/lane)	Pavement Roughness (m/km)
Normal	Multilane		Roads and bridges		All	100	2200	2.0
	Two-way Class 1	two-lane	Roads and bridges		All	70	1800	5.0
	Two-way Class 2	two-lane	Road and bridges		All	50	1400	5.0
Restricted	All road's categories		Roads		Light	10	2200	10.0
					Heavy	10	1800	10.0
					All	0	1400	10.0
	Multilane		Bridges		All	100	2200	2.0
					All	30	1760	10.0
					All	0	--	10.0
	Two-way Class 1	two-lane	Bridges		All	70	1800	5.0
					All	30	1440	10.0
					All	0	--	10.0
	Two-way Class 2	two-lane	Bridges		All	50	1400	5.0
					All	30	1120	10.0
					All	0	--	10.0

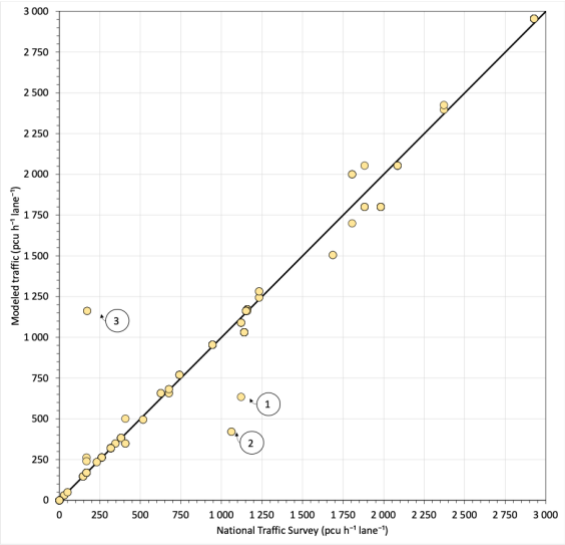
429 **4.4.2 Traffic assignment to the road network**

430 The traffic assignment model applied in this study was solved using the Kumar (2019) code, aiming to optimize traffic flow
 431 across the network and minimize travel time under both normal and flood-affected conditions. This model leverages national

432 traffic data and road network characteristics to simulate how floods reroute traffic and increase the user costs. The traffic
 433 assignment model uses road and traffic data obtained from national road and traffic surveys conducted by the Chilean Ministry
 434 of Public Works (MOP): the National Road Network geodatabase (MOP, 2020b; available at <http://www.mapas.mop.cl/>), its
 435 dimensions and characteristics (MOP, 2020a), and the National Traffic Survey 2019 (MOP, 2020c; available at
 436 <https://vialidad.mop.gob.cl/plan-nacional-de-censo-vial/>). All datasets were freely accessible online. It also uses a travel time
 437 function that considers the capacity and traffic of different road types. The model was applied successively for each return
 438 period to obtain the cost-return period pairs with which the loss model was prepared.
 439 The network was built with 154 links and 129 nodes using GIS. Six modeling networks were considered: one representing the
 440 normal operating conditions and one for each of the five return periods. The operational physical attributes for the normal and
 441 restricted operating conditions were assigned to each link according to the following rules:

- 442 • Physical attributes under normal conditions, road class, and length of each link.
- 443 • Physical attributes under restricted conditions, road class, length of each link, flooded segment, flood height, and the link
 444 to which the flooded segment belongs.
- 445 • Operating attributes under normal and restricted conditions are shown in Table 6.

446 Traffic data were obtained from the National Traffic Survey, issued for two years each, and are freely available on the Chilean
 447 Ministry of Public Works website (MOP, 2020c). These data were used to estimate the origin destination matrix. After applying
 448 TAM, the modeled traffic was compared with the existing flows in the road network. Figure 6 shows the correlation between
 449 the modeled and actual traffic data. Traffic was expressed as passenger car units per hour per lane (pcu/h/lane). The outlier
 450 data points represent traffic in the cities of Hijuelas (Point 1) and Limache (Points 2 and 3).



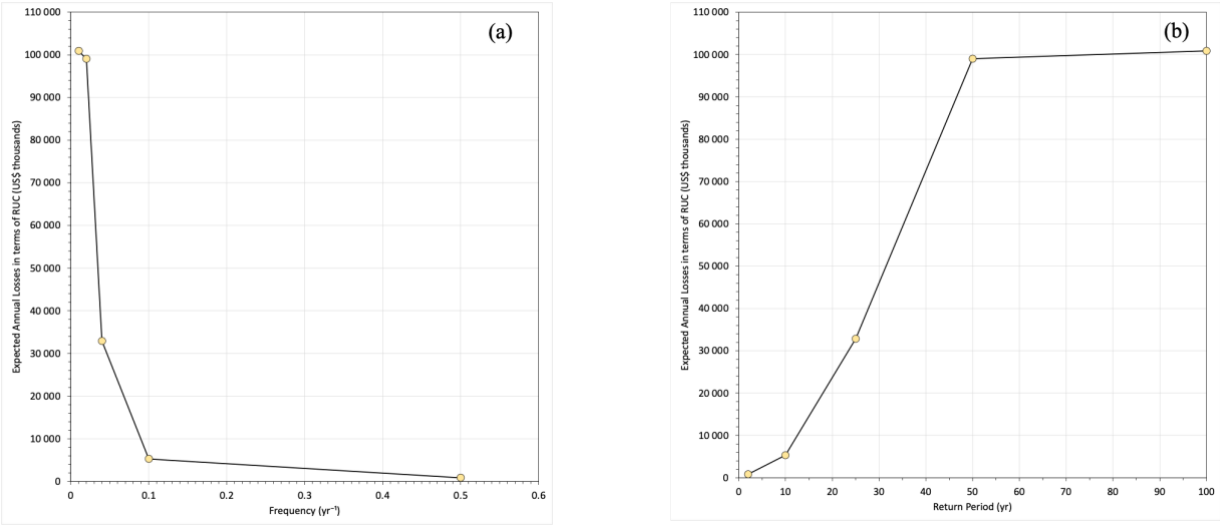
451
 452 **Figure 6: Traffic assignment model calibration results under normal operating conditions: modeled traffic ($\text{pcu h}^{-1} \text{ lane}^{-1}$) versus**
 453 **traffic from the National Traffic Survey ($\text{pcu h}^{-1} \text{ lane}^{-1}$). Each point represents one road segment (link) of the network ($R^2 = 0.98$).**
 454 **The solid black line indicates the 1:1 correspondence between modeled and surveyed values. Labeled outlier points correspond to**
 455 **Hijuelas (1) and Limache (2, 3).**

456 **4.4.3 Road user costs**

457 The road user cost (RUC) was estimated using Eq. (14) for each return period. The fuel consumption models in Eqs. (15) and
458 (16) were obtained from the HDM-4 model calibration developed by the Chilean Ministry of Public Works (MOP, 2018). A
459 travel time unit cost of US\$ 18.6 h⁻¹ per light vehicle and US\$ 64.0⁻¹ per heavy vehicle was used. The unit fuel costs are US\$
460 0.5 L⁻¹ and US\$ 0.6 L⁻¹ for light and heavy vehicles, respectively (MDS, 2020). These values correspond to the social prices
461 published by the Chilean Ministry of Social Development for 2020 and were converted from Chilean pesos at the average
462 exchange rate of that year (800 CLP per US\$). All monetary values in this study are therefore expressed in 2020 US dollars,
463 and no inflation adjustment was applied.

464 **4.4.4 Road network risk obtained**

465 The total EUC obtained was 5.7×10^6 US\$ yr⁻¹. This cost represents the additional travel time and fuel consumption costs
466 owing to vehicle rerouting in the network caused by flooded road segments, bridge closures, or heavy traffic restrictions on
467 damaged or weakened bridges in the road network under consideration. The accuracy of the estimated EUC increased when
468 additional floods with different return periods were added to Eq. (17). Figure 7 shows the expected losses in terms of the road
469 user costs of the network and each return period.



470 **Figure 7: Expected annual losses in terms of road user cost (RUC, US\$ thousands) for the road network, plotted against (a) the**
471 **annual exceedance frequency (T, yr⁻¹) and (b) the return period T (yr). Points indicate the RUC estimated for each of the five**
472 **return periods analyzed (R=2, 10, 25, 50, 100 years); the area under the curve in (a) correspond to the expected user cost (EUC)**
473 **obtained via trapezoidal integration (Eq. 15).**

474 Figure 7 shows the estimated benefits of flood abatement on the road network. According to Penning-Rowsell and Green
475 (2000), if abatement measures are set for a return period of 100 years, then the expected annual benefits are approximately

476 equal to the EUC obtained in this case study. However, to estimate the net benefit, it is necessary to assess higher return
477 periods, estimate the abatement costs at each bridge and road segment affected by floods, and apply the TAM to recalculate
478 the road user and fuel consumption costs for new rerouting schemes. In addition, it shows the avoided costs when implementing
479 risk abatement measures on roads and bridges to ensure the operational continuity of the road network after flooding. The
480 results also allow for the assessment of the benefits of keeping roads open after a flood to permit evacuation and pay attention
481 to people affected by floods.

482 **5 Results discussion**

483 This study extends current practice in three respects. First, risk is expressed as an expected user cost rather than as a
484 reconstruction cost, so that the additional travel time and fuel consumption borne by users are integrated over the event
485 probabilities within the same expected-damage framework used for physical damage. Second, hazard, exposure, vulnerability,
486 and traffic assignment are linked in a single workflow, in which the flood depth for each return-period condition the disruption
487 and scour probabilities of road segments and bridges, and these, in turn, condition the traffic assignment. Third, the procedure
488 relies on open-access data and open-source models, which makes it applicable in basins with limited hydrological monitoring.
489 It thus complements studies that express the consequences of flood-induced road disruption as a loss of accessibility rather
490 than as a cost (Coles et al., 2017; Arrighi et al., 2019; Papilloud et al., 2024).

491 The flow rates estimated by the Verni and King (1977) model were compared with the available data. This verification
492 indicated that the flows estimated with this model, compared with those available from the PC1 fluvimetric station (the only
493 spot check located at the head of the lower Aconcagua River basin), overestimated the 25-yr return period by 3%. This
494 discrepancy subsequently affected the hydraulic modeling results, resulting in an 8% increase in the estimated flood extent and
495 maximum water height compared with the locally reported values. Such variations may stem from multiple factors, including
496 hydrological model calibration, input topographic data quality, and roughness coefficients. Nonetheless, the values obtained
497 were acceptable for regional-scale simulation.

498 For the range of analyzed return periods, the following patterns were identified: a) between 2 two to four sections of flooded
499 multilane roads, with a total affected length of 1.8 to 3.2 km and water heights between 0.5 and 2.2 m; b) five to ten flooded
500 sections of Class 1 roads with a total affected length between 960 and 3,512 m, and flood heights between 1.2 and 2.3 m; and
501 c) up to two flooded sections of Class 2 roads with a total affected length between 439 and 960 m and flood heights up to 3.7
502 m. In addition, between one and three bridges with two or more spans affected by flooding were identified, mainly belonging
503 to the multilane and Class 1 two-way two-lane roads.

504 The vulnerability estimation of roads and bridges was conducted using models calibrated for Chile, considering the
505 characteristics of the local vehicle fleet and the climatic conditions. Therefore, the results for the probabilities of disruption
506 and scour exceedance were suitable for this case study. However, it is crucial to acknowledge that these results are conditioned
507 by the quality of the input data, particularly the digital elevation model and flood map used for each return period.

508 The traffic assignment model assumes a constant road capacity and static interruption states for each flood scenario based on
 509 the maximum flood depth for each return period. The temporal variability of flood depth during an event, which could result
 510 in variable capacity and transient interruption states, was not considered in this study.

511 The traffic modeling results were validated using data from the Chilean Ministry of Public Works. The traffic model calibrated
 512 for normal operating conditions demonstrated a solid statistical fit with a coefficient of determination of $R^2=0.98$, underscoring
 513 its accuracy and representativeness. However, this calibration was not performed under restrained traffic conditions after
 514 floods, because of unreliable traffic data. Calibration under these conditions requires counting traffic in extensive road
 515 networks before and immediately after floods, which is very difficult to achieve. In addition, it should be noted that the 15%
 516 interruption threshold for $P_{\text{int-light}}$ and $P_{\text{int-heavy}}$, based on the calibration range reported by Pregnotato et al. (2017a, b), is
 517 considered a fixed value in this study. In practice, this threshold is uncertain and could be represented as a distribution of
 518 damage states, rather than a single criterion, calibrated using field measurements, studies, or other empirical data. The analysis
 519 of this sensitivity is left as a line of research for future studies.

520 EUC estimation implies the combination of datasets, models, and procedures from different origins, which, when combined,
 521 introduces errors that propagate throughout the process and affect the results of the study. This study did not include a
 522 sensitivity assessment or error identification. However, this type of analysis can be performed using procedures such as those
 523 used by Allen et al. (2022), who assessed the sensitivity of the seismic risk assessment of road networks and identified the
 524 effect of different error sources on the EUC results.

525 EUC estimation relies on the following data inputs: digital elevation models, traffic and road network data, and hydrological
 526 data (such as discharge and water height). Among these, the resolution of the DEM is a determinant of the accuracy of flood
 527 extent and water level modeling. The resolution of the DEM can directly impact vulnerability quantification, as a coarser grid
 528 (e.g., 12.5×12.5 m) may identify more potentially affected road assets owing to less detailed terrain and channel bathymetry,
 529 leading to potentially overestimated flood extents and depths. Although such a DEM is suitable for preliminary analyses to
 530 pinpoint potential flood hotspots, transitioning to a higher resolution (e.g., $5 \text{ m} \times 5 \text{ m}$ or $1 \text{ m} \times 1 \text{ m}$) is crucial for a more accurate
 531 assessment of vulnerability and, consequently, more reliable indirect cost estimations. This finer resolution allows for detailed
 532 site-specific studies in identified high-risk zones, enabling a more precise analysis of the impacts, especially considering that
 533 infrastructure dimensions, such as road lane widths (typically 3.5 m), are better represented, leading to a more accurate risk
 534 profile for specific assets. Discharge and water height data are required to calibrate hydrological and hydraulic models.
 535 However, these data are not always available in terms of their quantity or quality. This situation arises in the studied basin,
 536 where only two stations in the basin headwaters provided sufficient data for analysis. Consequently, Verni and King's (1977)
 537 hydrological model calibrated for Chile was used. The model relies on the maximum precipitation isohyets to estimate flows.
 538 However, the results obtained by the model were generally more significant than the data available for validation, which may
 539 have propagated errors in downstream flow modeling and, consequently, in flood map simulation.

540 Regarding hydraulic simulation, it is important to note that the flood map representation assumes a time-less scenario,
 541 graphically displaying only the maximum depth obtained from the simulation for each return period. Consequently, the model

542 does not consider the temporal dynamics of flooded areas, including their appearance and disappearance over time, which can
543 significantly affect traffic assignments. Furthermore, the deterministic approach adopted in this study does not account for the
544 uncertainty inherent in the hydraulic modeling and simulation process, including uncertainty in the model inputs, calibration
545 metrics, and flood predictions. Probabilistic flood mapping approaches are recognized as a more robust alternative and a
546 valuable direction for future work according to the proposal of Huang & Merwade (2022, 2024) and Gomez et al. (2024)
547 Other aspects affecting the results were road and bridge vulnerability and the RUC models. Both models depend on local
548 conditions and infrastructure design, which are based on design standards. Therefore, models from literature are not
549 recommended for this type of analysis. This study used previously calibrated models for Chilean conditions to represent
550 vulnerability and RUC.

551 Future research should focus on enhancing hydraulic modeling by moving beyond the current reliance on static flood maps,
552 which typically represent only the maximum inundation depths. For example, this study assumed a constant flood duration of
553 two hours. However, the development of dynamic models that can simulate the complete temporal evolution of flood events,
554 including their initiation, duration, and recession, is crucial. Such advancements, even when utilizing a DEM of the same
555 resolution, would enable a more qualified representation, differentiating between areas experiencing brief transient inundation
556 and those subjected to prolonged periods of significant water depth. This dynamic perspective reveals that the vulnerability of
557 road assets is not static but varies over the duration of an event. Consequently, traffic reassignment also becomes a dynamic
558 process as network accessibility changes over time. This, in turn, would require corresponding improvements in traffic
559 modeling to accurately capture and respond to this temporal variability in flood impacts and network conditions, thereby
560 providing a more realistic understanding of overall system resilience.

561 Furthermore, given that Expected User Cost (EUC) estimation integrates outputs from sequential hydrological, hydraulic,
562 vulnerability, and traffic models, understanding the propagation of uncertainties is vital. Errors introduced at any stage can
563 cascade through the modeling chain and affect the results of the study. A critical area for investigation is the implementation
564 of a comprehensive sensitivity analysis, such as the approach employed by Allen et al. (2022), which covers the entire
565 workflow. Such an analysis would identify the most influential parameters and data sources contributing to uncertainty and
566 quantify how these errors propagate and impact the final EUC estimation, thereby strengthening the reliability of the risk
567 assessment.

568 **6 Conclusions**

569 This study presents a method for estimating the expected user cost of a network affected by floods in terms of the return period
570 and the costs involved in traffic rerouting owing to total or partial traffic interruption of roads and bridges. This method was
571 applied to a case study of the road network of the lower Aconcagua River basin in central Chile. Flood hydrographs were
572 generated using rainfall-runoff models calibrated for Chile. An open-source digital elevation model and traffic assignment
573 model were also used. This study contributes to the existing literature by providing a comprehensive model that integrates

574 hydrological-hydraulic analysis with road and bridge vulnerability assessments to estimate the EUC, a perspective that has not
575 been thoroughly explored in previous studies.

576 The effects of floods on bridges and roads were analyzed, mainly because the road network is located on flat ground without
577 cut slopes and embankments of significant heights in the area's natural terrain. However, analyzing the hydrometeorological
578 hazards on road networks located on undulating or mountainous terrain requires including the effects of slopes, sliding slopes,
579 debris flows, and more detailed digital elevation models than the one used. Furthermore, vulnerability and traffic interruption
580 models must be considered natural hazards in steep or undulating terrains.

581 The traffic assignment was made considering that the origin-destination matrix was not modified by the effect of the modeled
582 flood owing to its duration. An important aspect of future research is the analysis of the effect of flood road interruptions on
583 non-travel decisions and their costs, as well as the modeling of traffic reassignment from flood onset to lowering water levels
584 to normal values. Such research requires a dynamic traffic assignment model and in-depth analysis of how the travel matrix
585 evolves during floods.

586 The expected user cost was aggregated on the network because the traffic assignment model does not identify the proportion
587 of traffic that reroutes from one link to another in the road network or to which link it reroutes. Resolving this situation requires
588 a traffic allocation model using an agent-based microsimulation model that enables the identification of individual behavior
589 patterns in the network and the calculation of the risk level per link.

590 Network redundancy refers to the existence of more than two links connecting two nodes or origin-destination pairs.
591 Redundancy exists if the links are similar in length, platform materials, traffic capacity, and bridges without load restrictions,
592 and satisfy topological conditions based on centrality measures, such as betweenness or closeness. If these conditions are
593 satisfied, two or more links provide redundancy to the road network. In contrast, a road network is non-redundant if the links
594 are significantly different. Under this framework, the lack of redundancy reduces the possibility of traffic rerouting when a
595 flood partially or totally interrupts a link, thereby increasing the travel time in the road network and risk. A detailed analysis
596 of this effect enables decision makers to identify the investments needed in specific road network links to increase redundancy.
597 However, this aspect of road networks was not examined in this study, which offers a research opportunity to improve the
598 flood risk of road networks in the future.

599 The proposed method integrates the existing procedures to estimate hazards, traffic assignments, and road user costs. This
600 method can be applied directly to other watersheds by considering local parameters. The traffic assignment algorithm depends
601 only on road network properties, traffic data, and origin-destination matrices that can be estimated locally. The road-user cost
602 parameters were obtained from the literature. Only models that estimate traffic interruption and scour exceedance probability
603 must be locally developed and calibrated for each bridge. Therefore, considering local conditions, this procedure can be easily
604 applied to other study areas in the future. The transferable elements are therefore the workflow and the definition of risk as an
605 expected user cost, not the numerical results, which are specific to the Aconcagua Bajo network, its vehicle fleet and its cost
606 parameters. The main weakness of hydrological-hydraulic issues is data availability, which depends on the availability and
607 number of stations for measuring discharge and height over a significant period. Similarly, the availability of detailed land-

608 use information in the watershed is required to estimate the concentration time comprehensively. Regarding traffic, the main
609 challenge is dealing with changes in origin-destination travel, travel not carried out, and the differentiated effect on cargo and
610 passenger travel.
611 This study did not examine the effect of the lack of redundancy on risk valuation, considering the road network as input data.
612 However, we expect to assess the impact of increasing or reducing alternative routes on risk in future studies. Another relevant
613 challenge is the establishment of error propagation throughout the procedure. This novel research field requires the
614 development of more reliable risk estimations by identifying sources of uncertainty and their propagation.

615 **Data and code availability**

616 The underlying data for this study, including the road network baseline information and the traffic simulation results for the
617 Aconcagua River Basin, are openly available in Datos de Investigación UC (Contreras-Jara et al., 2026) at
618 <https://doi.org/10.60525/04teye511/FHGMNE>. The traffic assignment code used in this study is openly available in Kumar
619 (2019) at <https://doi.org/10.5281/zenodo.3479554>.

620 **CRedit authorship contribution statement**

621 Manuel Contreras-Jara: methodology, formal analysis, visualization, writing (original draft preparation); Tomás Echaveguren:
622 conceptualization, investigation, writing (review and editing); Eduardo Allen: methodology, formal analysis; Alondra
623 Chamorro: conceptualization, writing (review and editing); José Vargas-Baccheler: conceptualization, methodology.

624 **Competing Interests**

625 The authors declare that they have no conflict of interest.

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