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Improving the Resilience of Peru's Road Network to Climate Events

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Abstract

This paper proposes a methodology to prioritize interventions in Peru's road network. A network model is built, linking the country's economic and population centers through indicative corridors, which are defined as the least-cost routes to connect origins to destinations. The network's critical links are identified by systematically simulating disruptions and calculating the costs associated with them. The network is then overlaid with natural hazard layers. The average annual losses associated with the hazard disruptions of the critical links are calculated in many scenarios, including climate change uncertainty and different impacts and reconstruction times. A robust decision-making approach is then used to select interventions that decrease hazard disruption costs.

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1. Introduction

In Latin America, economic activity and population mobility are heavily dependent on transport. Many economies rely on commodity exports and populations and economic production are concentrated in urban areas, often far from dispersed rural populations. Thus, connectivity among cities, mining and agricultural production areas, and external markets requires transport networks to move people and goods cost-effectively.

Peru's difficult topography and climate create challenges for businesses and communities, as in much of Latin America, nearly all of the nation's cargo travels by road. Median altitudes range from less than 500 meters above sea level on the coast and the Amazon regions to more than 3,000 meters in mountainous areas. Extreme temperatures, floods and landslides triggered by heavy rains sometimes lead to closures of important roads (MTC, 2005). In 1982-83 and 1997-98, severe El Niño events caused flash floods and landslides, resulting in huge losses. In 1982-83, for instance, most bridges on the northern areas of the Pan Americana road, along the Peruvian coast, were destroyed. Not all bridges have been rebuilt and many temporary structures remain. Such interruptions help explain the high logistics costs for export commodities in Peru.

To support economic growth, policy makers must ensure that as Peru develops, its road network is resilient to future shocks. Obviously, the best solution would be to fully protect the entire network against all possible disruptions. But because resources are limited, policy makers must know which roads are critical -- for instance, those with the most traffic, greatest socio-economic relevance, or most expensive consequences in the event of disruption -- and the best interventions to protect them against the disruption risks they face.

Identifying the most appropriate interventions to prevent or mitigate disruptions linked to natural disasters in a road network is challenging. First, it is difficult (and sometimes impossible) to predict the frequency, severity, and duration of the potential disruptions to which a road segment is exposed. Large data sets and sophisticated modeling are needed to accurately estimate the probability of an extreme event such as extreme rainfall or earthquake to occur in a particular place. In addition, climate change adds considerable uncertainty to the magnitude of mean and extreme changes in precipitation that may occur in a country or region. This uncertainty is even more pronounced at the fine scale needed for road projects – since downscaling climate data tends to amplify rather than reduce uncertainty.

Moreover, the economic impact of natural disasters on a road depends on many local variables that are sometimes unknown to analysts. The impact worsens if the road is not well maintained, if deforestation makes the terrain prone to landslides, or if emergency responses are not dispatched in a timely fashion to make the road operational again in a short time. Whether a critical road can be repaired in a few weeks or months can dramatically change the economic consequences of a disruption, as well as the type of interventions required.

Finally, the economic impact of a disruption in a road network is exacerbated if the road is critical to an economic sector, to a certain community, or to the entire transportation network. Traditionally, economic

analyses of road interventions have been focused on project-level benefits. For instance, Peru's Supervisory Board for Investment in Public Transport Infrastructure (OSITAN) typically asks concessionaries and the Ministry of Transport (MTC) to submit economic analysis for each intervention for which they are seeking funding. The main metrics used to choose projects are financial indicators based on future traffic demand. But this project-centered approach misses the system-wide benefits of some interventions, particularly their impact on resilience.

So, to plan for a resilient road network, it is important to identify the critical links of a network whose rupture the economy cannot afford, and the alternatives available to planners and policy makers to reduce the risks associated with the disruption of those links. This papers aims to help governments solve these challenges. Building on the framework and concepts for accessibility and criticality by (Briceño-Garmendia et al., 2015), this paper proposes a methodology to set priorities within Peru's road network, taking a system-wide approach, and to design robust interventions that may reduce its vulnerability, despite the uncertainties related to hazards and their impacts. Specifically, it helps answer two questions.

What are the most critical roads in the national network, and of these, which are the most exposed to natural disasters? The study finds that because of high traffic and agriculture exports – combined with exposure to floods, landslides, and storm surges – disruption risks could be especially high for three clusters of the Peruvian road network: Carretera Central near Lima, Piura in the north and a southern part of the Pan Americana road.

What are the most robust proactive interventions to reduce the disruption risks of these critical links? The most robust options to mitigate disruption risk vary by link. In Piura and Pan Americana, building a flood-proof road is the most robust option in the face of the many uncertainties considered, since it is the most cost-efficient investment across a large number of scenarios. By contrast, for Carretera Central, building redundancy is the most robust option.

2. Methodology

This paper uses a network approach to evaluate the vulnerability of a subset of the Peruvian road system across a wide range of potential future conditions. Given the size and complexity of Peru's national road network, a systematic assessment of each link is costly in terms of data needs and computational demands, and would not necessarily address decision makers' need to prioritize interventions. Instead, carefully selected criticality criteria can help narrow a road network of tens of thousands of links down to several hundred meriting further analysis.

Accordingly, this study is split into two main parts. First, we built a Geographic Information System (GIS) model of the road network in Peru that captures the physical characteristics and cast aspects of the road, which we use to identify a set of critical links. Critical links are those of utmost importance for the performance of the overall network, which can be defined using different geopolitical, social, and economic criteria. The impact that an individual road (a network segment more generally) has on the aggregate accessibility of the country or region gives a sense of the relative importance of that individual road in the network or, in other words, of its criticality.

Then, for the critical links exposed to floods and landslides, we assessed the disruption risk under many possible scenarios and compared alternative interventions to reduce this risk. We then identified the best intervention to reduce the risk associated with floods and landslides for these links, taking into account the uncertainties around future hazards and vulnerabilities. Here we applied state-of-the-art methodologies to address deep uncertainties related to future conditions and data gaps.

2.1. A network approach for measuring criticality

Ranking corridors based on their criticality can inform prioritization exercises and, ultimately, enable the analysis of the economic and development impacts of specific interventions and policy decisions.

Peru's road network contains 164,411 kilometers of roads, of which we wanted to identify the most critical links. Several criteria can be used depending on the policy goal. For instance, policy makers might decide to prioritize export outlets for agricultural products, mining corridors, or increase access for lagging areas to main cities. Here we measured a link's criticality in terms of the impacts that its removal would have on the overall network. This required building a model of the road network and calculating least-cost routes between Origin-Destination pairs (see annex for a description of the model and data).

Before calculating the impact of link removal, we applied two initial filters to identify the critical links. First, we narrowed the network down by selecting only the least-cost routes between our set of origins and destinations. We call these routes the indicative corridors.[1] Then, we applied a second filter which we used to capture the socio-economic importance of the different routes by looking at their traffic levels. We ranked the links by traffic levels and selected the 10 percent links with the highest traffic – that is with 4,000 or more vehicles per day[2] (Figure 1)**.** This step reduced the analysis to about 1.3 percent of the national network, or 2,274 kilometers – we call these 974 links candidate critical links.

[1] Explicit criteria were imposed to define the corridors of interest to make sure cross-country comparisons were possible. To identify the indicative corridors, we used the Network Analyst, an extension of the ArcGIS software, which allowed us to analyze all routes via their HDM-4 estimated RUCs, which fully reflects the physical characteristics of the existing road network.

[2] The median average daily traffic (ADDT) for Peru is 982 vehicles. Figure 1 is adapted from (Taylor et al., 2006) whose methodology we borrow. These authors first identify the candidate critical links as those that are part of the least-cost route between two locations -- then measure the change in cost or in accessibility associated with the loss of each of these links. For computation capacity reasons, in this study we modified the first step of their application by defining the candidate critical links as those links that are part of the least-cost routes and have the highest traffic.

Figure 1 indicative corridors and candidate critical links (in red). Source: author's calculations based on MTC data.

Once we had narrowed down the number of links, the second step was to measure the criticality of each of the 974 candidate links by estimating the cost for the network when a link is disrupted, lost, or degraded. We used the *interdiction* technique, which solves the network when some of its elements are removed (Lu et al., 2014; Pokharel and Ieda, 2013; Ukkusuri and Yushimito, 2009). We removed each candidate critical link sequentially and each time we recalculated the least-cost routes between all OD pairs. With the new least-cost routes configuration (the "second-best" routes), we calculate the new performance of the network.

The performance of the network and impacts of link removal were calculated along three dimensions: the road user cost for each OD pair, the kilometers driven for each OD pair and the total daily cost of using

the network (using average daily traffic on each link). We aggregated the performance of the least-cost routes at the national level using weights that reflect the importance of each OD pair. Indeed, a simple sum of the road user cost over all the routes in the network would be misleading because some routes are used much more frequently than others.

We thus assigned weights to the different OD pairs based on the importance of the origins and destinations, which we measured in terms of traffic. We did this by:

- Summing the traffic getting in and out of each origin and destination node.
- Calculating for each route – each Origin-Destination pair – a weight *w* based on the gravity model:

$$w = \frac{T_O * T_D}{km_{OD}^2}$$

where T_O is the total traffic getting in and out of the origin, T_D is the total traffic getting in and out of the destination, and km_{OD} is the distance between the origin and destination. We also use these weights to distribute traffic (measured at each link) between the OD pairs in the calculation of the total daily cost of the network.

The impact of a disruption at the national level is then the difference in network performance between the baseline conditions and the new network configuration with second-best routes when a link is removed. The criticality of each link is thus expressed along the three same dimensions: first, by aggregating over the network the average increase in road user cost (dollars per ton-kilometer) when the link is removed, compared with a baseline condition with no disruptions. Second, by aggregating over the network the average increase in kilometers that users have to drive when a disruption occurs. And third, by calculating the total direct economic cost linked to the disruption.

The candidate critical links are ranked according to these impacts on the network when they are disrupted: the higher these three impacts, the higher the criticality of the link.

2.2. Exposure of critical links

Once we have identified the critical links, we overlay the network with hazard layers to identify which ones are also exposed to natural disasters.

We used a database of flood scenarios produced by Global Flood Risk using the IMAGE Scenarios model—GLOFRIS (Ward et al., 2013; Winsemius et al., 2013). This model simulates daily discharge and runoff at a horizontal resolution of 0.5° x 0.5°. Deltares simulated eight return periods – RP5, RP10, RP25, RP50, RP100, RP250, RP500, and RP100. The model was forced using daily meteorological fields of precipitation, temperature, and radiation for four time periods: 1960-99, which represents the baseline climate; 2010-49 representing 2030; 2030-69 representing 2050; and 2060-99 representing 2080. The meteorological data for the baseline climate are WATCH Forcing data (Weedon et al., 2011). The future meteorological data are provided by the ISI-MIP project, and consist of bias-corrected data (Hempel et

al., 2013) for an ensemble of five Global Climate Models (GCMs) from the CMIP5 project (Taylor et al., 2012).[3]

Because Peru's most important highway is along the coast, we also overlay the network with coastal flood data.[4] But since there are no probabilistic data we simply identify the links exposed to coastal floods and do not calculate disruption losses linked to coastal floods.

Finally, some parts of Peru are susceptible to landslides triggered by high rainfall. Thus, we use landslide susceptibility maps provided by Ingemmet to associate landslides to flood events.[5] In places where landslide susceptibility is high, we add landslide impacts to flood impacts for high return period floods.

2.3. Vulnerability of critical links

Here we define the vulnerability of a link as the economic consequences of a hazard event. It is therefore broader than structural damages to the infrastructure and includes impacts on both road users and the government or concessionaries.

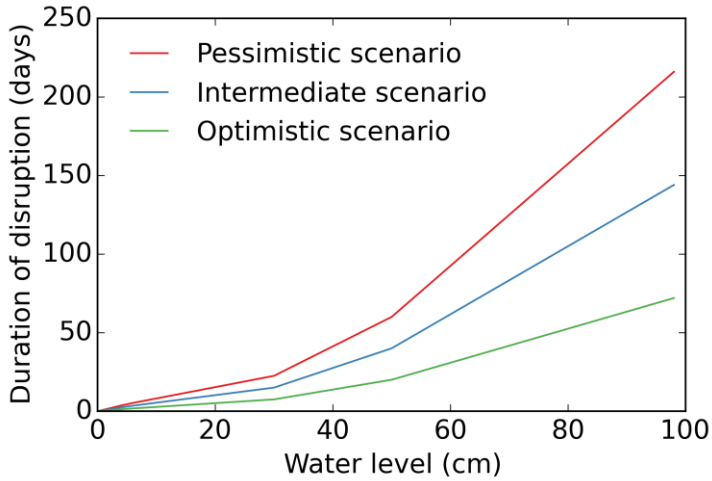
Assessing the vulnerability of exposed roads to floods was the most difficult part of this exercise because of a lack of local data on critical parameters such as flood duration, structural damages, and traffic rerouting. Instead of working with best guesses we built several scenarios for each unknown parameter and relationship.

Flood duration

Data on flood duration and on the relationship between flood duration and depth were not available. This relationship generally depends on many factors other than flood depth, such as water velocity and topography. Thus, we constructed simple curves based on information about past floods on the Carretera Central, the only highway for which data were available (Figure 2). We validated those curves with expert consultations.

[3] The GCMs used are GFDL‐ESM2M, HadGEM2‐ES, IPSLCM5A‐LR, MIROC‐ESM‐CHEM, and NorESM1‐M. For this study, we used climate projections based on one representative concentration pathway (RCP), RCP8.5.
[4] 2013 Dartmouth flood observatory flood extend v2 data set.
[5] http://www.ingemmet.gob.pe/.

Figure 2 Relationship between flood depth and flood duration. Source: authors' calculations



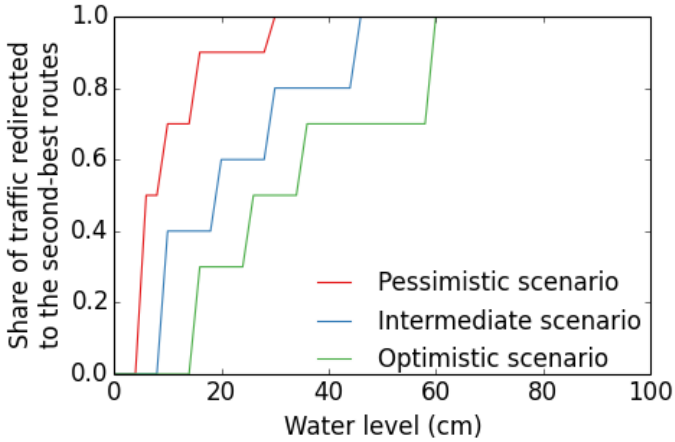
Structural damages

The impact that different water levels may have on a particular road segment depends on many factors and on engineering design – for which we had no local data. After consultations with transport and civil engineers, we assumed that a road would have to be entirely reconstructed if water remained for more than 30 days, or rehabilitated if water stayed 10-30 days. We assumed that for less than 10 days underwater, a road would need only cleaning and minor maintenance. The costs of reconstruction, rehabilitation, and cleaning depend on the characteristics of the disrupted link (Table 6 in Annex). We did not distinguish between primary and secondary roads for the time thresholds.

Traffic rerouting during a disaster and reconstruction

When a disaster hits, different scenarios of traffic rerouting may occur. We assumed that if a landslide hits a road, all traffic is redirected to the second-best routes. But for floods, we assumed that the share of traffic that can drive through the flooded road depends on the water level on the road and created three scenarios (Figure 3).

Figure 3 Relationship between water level and traffic disruption. Source: authors' calculations.



In the optimistic scenario, 30 percent of traffic has to take the second-best route if water is between 15 and 25 centimeters, and 100 percent of traffic has to take the second-best route when water is above 60 centimeters (Figure 3). But in the pessimistic scenario, 100 percent of traffic needs to take the second-best route when water is 30 centimeters deep (that is we assume that all vehicles on that road are too low to drive through 30 centimeters of water). For the share of traffic that can still use the first-best route, despite water on the road, we assume that the maximum speed remains below 30 kilometers per hour and recalculate road user costs (RUCs) accordingly.

Not only during the event, but also during reconstruction or rehabilitation, only some traffic can use the road. Because the exact share of traffic that can use the road during works is also unknown, we develop three additional traffic scenarios. In the optimistic one, 90 percent of traffic can use the link during reconstruction, at a slower pace. In the intermediate one, 80 percent can use the link. In the pessimistic one, 70 percent of traffic can go through. In terms of timing of rerouting, we assumed that reconstruction takes 30 days per kilometer, rehabilitation 10 days per kilometer, and cleaning 2 days per kilometer.

Landslides

In some parts of Peru, intense rainfall can trigger landslides. Where landslide susceptibility is high, we assume that the road is destroyed and 100 percent of traffic has to be redirected to the second-best routes. We also assume that it takes 30 days to clear the debris and reestablish disrupted connectivity.

Total cost of an event

For one flood event, the total costs for users are:

$$L = D * \left((1 - s) * c_{1st\ best} + s * c_{2nd\ best}\right)$$

Where D is the number of days of the disruption, s is the share of traffic redirected to the second-best route, $c_{1st\ best}$ is the cost of using the first-best route adjusted for the increased cost of use when partially disrupted, and $c_{2nd\ best}$ is the cost of using the second-best route.

When a disaster strikes, not only private users suffer, but the government or concessionaries also need to reinstate the road. Depending on the severity of the impact, they may rebuild it, rehabilitate it, or clean it. We calculate the cost for the government or concessionaries as the number of kilometers damaged multiplied by the cost of rehabilitation or reconstruction, depending on the structural damages (see Table 6).

We assume that during reconstruction, a share of traffic may continue to use the second-best routes, which adds to users' costs of disruption. Our measure of vulnerability misses indirect effects such as missed hours of work, traffic congestion, costs of missing connections with other transport modes, and losses of perishable goods. For instance, every year, $5.2 billion of agricultural commodities – mainly yellow onions, grapes, quinoa, coffee, and cocoa – are transported by road to the harbors from the Andes and Amazonian regions. Some of these commodities are lost because of road disruptions, but these losses were not taken into account in this paper for lack of data.

2.4. Prioritization and choice of interventions

Decision-makers need guidance on how to reduce the vulnerability of critical links. Should they wait until the disasters strike and simply rebuild or rehabilitate the roads? Or, should they mitigate risks in advance?

Deep uncertainty like climate change, combined with data gaps, challenge decision-makers around the world. How can long-term decisions be made now when the parties to decisions do not know or cannot agree on the system model relating actions to consequences or the prior probability distributions for the key input parameters to those models (Groves and Lempert, 2007)?

Traditional analysis, sometimes called "Predict then Act", hinges on accurately predicting climate and other conditions – then reaching consensus on what the future will bring. This approach does not work well for long-term climate change or project-specific inventions given the multiple challenges noted above.

Innovative methods exist for managing long-term and uncertain project risks. Robust Decision Making (RDM) is one such approach. RDM is an iterative, quantitative, decision support methodology designed to help policy makers identify robust strategies – that satisfy decision-makers' objectives in many plausible futures rather than being optimal in any single best estimate of the future. RDM asks, "What are the strengths and limitations of our strategies, and what can we do to improve them?"

To answer this, RDM rests on a simple concept. Rather than using models and data to evaluate plans under a single or handful of scenarios, RDM stress tests investment choices under hundreds of scenarios. Statistical analyses of these model runs identify the key conditions under which each strategy satisfies or fails to satisfy decision-makers' objectives. Visualizations help decision-makers understand how robust different strategies are by benchmarking those key conditions against the range of plausible outcomes. They also help compare strategies along other dimensions such as cost, technical feasibility, and social acceptability (Lempert et al., 2013).

Importantly, approaches like RDM are not new: they are based on solid traditional decision-making theories. They use existing data and models transparently, revealing critical assumptions often hidden in analyses. Such approaches also promote consensus – decision-makers can agree on a plan without agreeing on predictions of the unpredictable.

Similar approaches have been applied with increasing frequency in the United States and Europe (Haasnoot et al., 2013; Lempert and Groves, 2010). These methods are collectively referred to as "decision making under deep uncertainty" (DMDU). The World Bank has been using DMDU methodologies in various projects, ranging from hydropower investments in Nepal (Bonzanigo et al., 2015a), to water and energy investments in Africa (Cervigni and Morris, 2015), water resources planning in Lima Peru (Bonzanigo et al., 2015b; https://goo.gl/BRojPW), and wetland management. But few papers have applied DMDU tools to road networks (Cervigni et al., 2016; Espinet et al., 2015).

This paper applies RDM techniques to identify the most robust interventions in each critical link – that is, interventions that work well no matter what the future brings.

Available interventions

An RDM analysis typically begins by identifying available options. To reduce losses linked to the disruption of part of the road network because of a disaster, policy makers have two sets of choices: intervene after the disaster hits (reactive), or try to reduce possible impacts with proactive interventions beforehand. Proactive interventions include all those that reduce or eliminate disruption losses, while reactive interventions include rehabilitation or reconstruction of the affected road. The advantage of the latter is that no resources are directed where they may not be needed. But intervening after a disaster may be more costly than preventing it. In particular, rehabilitation can take time, especially for roads managed directly by the government, so the costs for the economy at large may escalate.

We compared several proactive options with a reactive one, in which the government or concessionaries rebuild the same road after a disaster ruined it. We considered the following proactive options:

- *Interventions on the critical road.* The first option is to maintain the road more frequently. Generally, road authorities perform two types of maintenance: routine and periodic. Routine maintenance involves all sorts of small interventions on a road and can be carried out once a year or more often, depending on the weather, on the materials used, and on the traffic. Periodic maintenance generally occurs every five years and includes major rehabilitation works. Proper maintenance and frequent cleaning of drainage structures can significantly reduce the time water remains on a road – and in its turn, reduce the overall damage to the infrastructure. As intervention, we considered doubling the frequency of periodic maintenance, and assumed that it divides by three the length of a disruption due to flood.
  The second option is to upgrade the road, which may involve adding tunnels or elevating a road – depending on the topography of the area. Such work can be very costly, but we assume that it would make the road resistant even to 100-year return period floods. The costs we use are based on discussions with stakeholders.

- *Adding redundancy by upgrading an existing alternative to the first-best route*. For each link disrupted, we already identified second-best routes as alternatives to the lowest-cost routes between all ODs. So, we explored the option of improving the roads most used by these second-best routes. For instance, this could imply transforming an existing secondary road, or an unpaved road, into a primary paved road. We considered two possible ways of adding redundancy: a large-scale increase in redundancy, where all road segments used for second-best routes are upgraded to primary paved roads, and a more targeted increase in redundancy, where only 30 percent of alternative roads are upgraded to primary paved roads.

These interventions have different capital and maintenance costs (see Table 6).

Uncertainties

We considered four types of uncertainties that can affect the choice of the best intervention. Some are related to the impossibility of predicting their values; others to data gaps. The uncertainties are the intensity, frequency, and duration of climate-related events; the structural impact of water levels on the

road; the amount of traffic to be rerouted when a flood or landslide hits; and the time and total cost of reconstructing a road after a disaster.

We then statistically generated 500 futures, each a combination of one value for each uncertainty. These futures are not predictions, and we do not assign any likelihood to their occurrence. We use them to better understand the behavior of our investment options.

Metrics

Metrics describe how we measure the performance of the different interventions. We express this performance as the discounted sum of the difference between the costs of interventions (investment and operations and maintenance) and the avoided average annual losses (AAAL) every year over the life cycle of the investment:

$$P = \sum_{t=1}^{30} \left(\frac{-costs(t) + AAAL(t)}{(1+d)^t} \right)$$

Where *AAAL* is the difference between the average annual losses (*AAL*) with the intervention and *AAL* if we do nothing.

$$AAAL\ (t) = \ AAL(do\ nothing) - AAL(intervention)$$

Average annual losses include the total private cost to users and the cost of reactive investments to reconstruct or rehabilitate the road after a disaster. To calculate average annual losses, we calculate disruption costs for each return period event and aggregate them.

This measure of performance is similar to a net present value in which the only benefits of the intervention that are considered are the avoided disruption losses. Later in this paper, an investment is "profitable" if *P* is positive.

Choosing the most robust option

To choose the most robust option across the futures considered, several criteria can be applied. In this paper, we use the minimum of the maximum regret across all scenarios. The regret of an option *i* is the difference between the performance of the option and the performance of the best option *i'* for a particular scenario *s*.

$$\text{regret}(i, s) = \max_{i'}(P(i', s) - P(i, s))$$

We calculate regret for each option in every future, then identify the option with the lowest possible value of regret – our robust option, which performs well no matter what the future brings.[6]

[6] This metric is dependent on extreme scenarios. One way to avoid that is to compare the regret of each project to the regret of not implementing the project.

3. Results

3.1. The most critical and most exposed roads in the Peruvian road network

Figure 4 visualizes the performance of the network with the three metrics when each of the 974 links is disrupted (each point in the graph represents one link being disrupted):

- The X-axis shows the change in the network length, measured in additional kilometers.
- The Y-axis shows the increase in cumulative road user costs (RUC) over all OD pairs, measured in US dollars per vehicle
- The shape of the plotted links represents the daily additional economic cost – the increase in RUC multiplied by traffic.

Accordingly, the three metrics are correlated. When a link is removed the additional road user cost largely depends on additional kilometers driven, because the conditions of the alternative routes tend to be similar across the network. In addition, we pre-selected links with high traffic and we gave more weight to OD pairs with more traffic, so that when the additional road user cost is high, the total daily economic cost is high as well. This correlation may not hold in different contexts (rural roads for instance) where the cost of the alternative roads depends much more on the quality of the road and where there is little traffic. Here, since the three dimensions of criticality are correlated, we can easily use daily economic cost as a proxy for criticality and lack of redundancy.

For most of the links considered here, the increase in RUC is less than $40 per day, the increase in length is less than 70 kilometers, and the economic cost remains below $2 million a day (Figure 4).

Yet the disruption of some links can lead to an increase of more than 300 kilometers on average for routes of the network, and to more than a $400 daily increase in RUC. The disruption of these links that lead to the longest detours and highest increase in RUC generally present high costs when traffic is accounted for (on average, between $2 million and $4 million a day). One of these links, if disrupted, leads to losses above $4 million per day. Thus, such disruptions have very important consequences for the performance of the network even if they last for a short time.

Figure 4 Ranking the criticality of links in Peru's road network

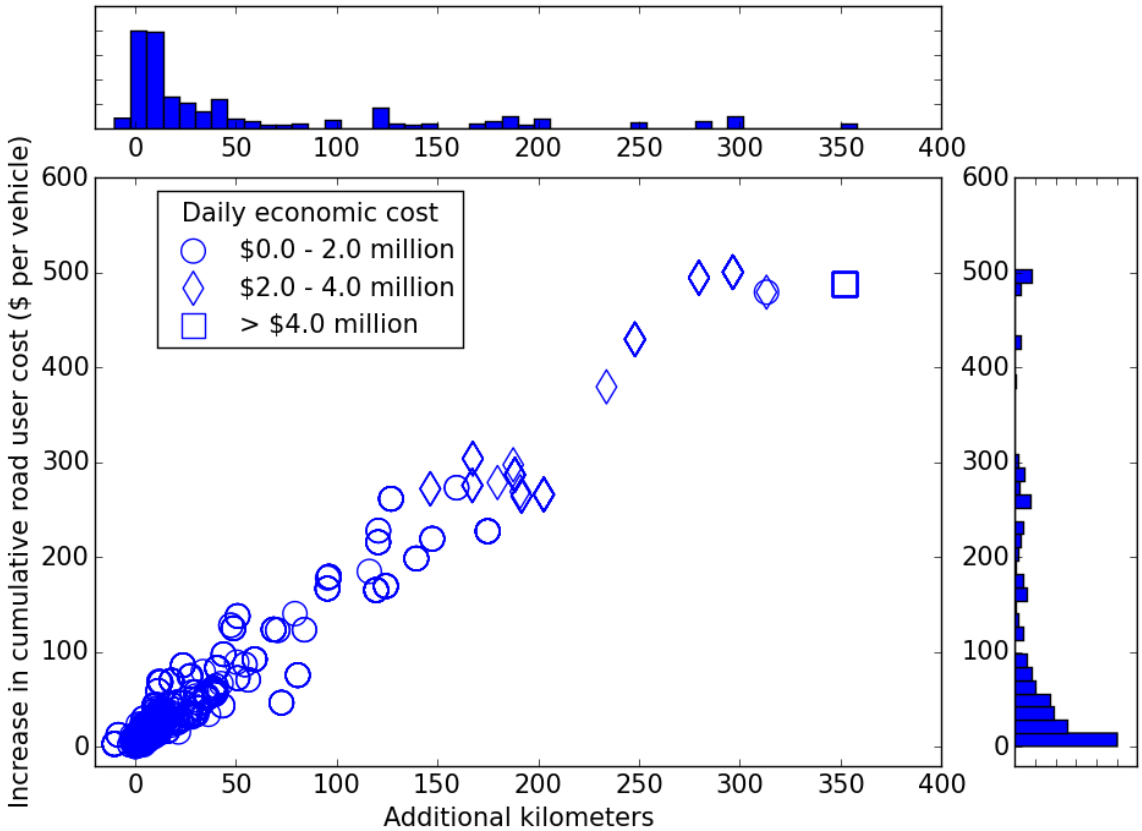


Figure 5 maps the economic costs of disruption over all candidate critical links. The links with daily costs higher than $2 million are shown in red and all are located on the Pan Americana Highway. This is not surprising as this is the road with the highest daily traffic and it is located between the sea and the mountains; thus, it has little redundancy.

Next, we explore the critical links most exposed to disruptions caused by natural disasters.

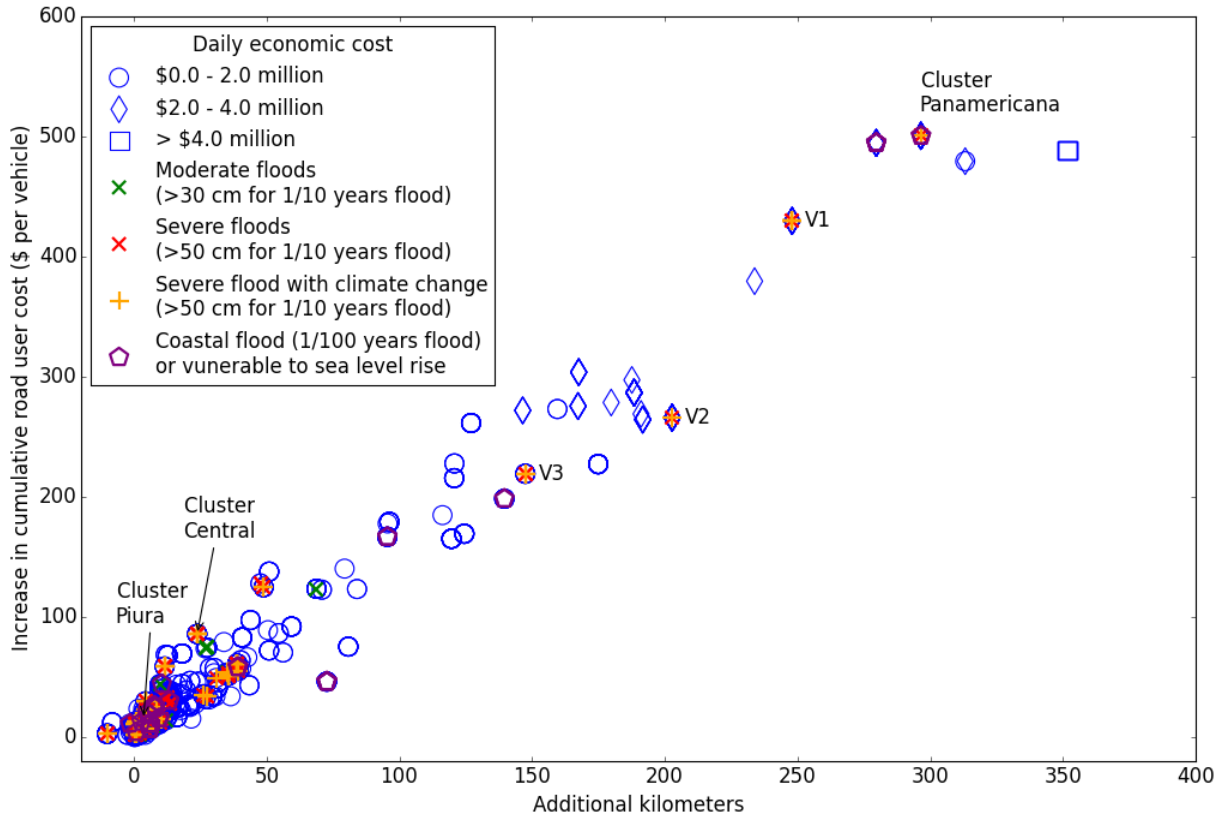
First, we overlay the network with the flood maps described in section 2.2. The links with the highest cost and kilometers increase that are also exposed to floods are all on the Pan Americana highway (Figure 5). The cluster Pan Americana – a set of critical links located on the Pan Americana highway – is exposed to river and coastal floods, and if disrupted costs close to $3 million a day to its users – forcing them to drive an average of 300 additional kilometers. The area North of Arequipa presents the highest economic losses and very low redundancy, so we focus our analysis on this section (cluster Pan Americana in Figure 6).

Figure 5. Economic cost of road disruption in Peru

The other two clusters we considered lay on the Carretera Central, near Lima, and around Piura. The disruption costs in these two clusters are not among the highest (Figure 6). But both clusters are frequently affected by disasters and are strategic export routes for agricultural products. In Carretera Central disruptions occur very frequently – and each time, the road's (partial) closure leads to immediate food price rise in Lima, which affects poor people the most. Policy makers indicated that the most vulnerable cluster is located between Lima and La Oroya.

Finally, disruptions due to floods in the region around Piura can lead to the disconnect of four cities and one airport – and high losses in coffee exports.[7] We focus on one particularly strategic area in the south of the city, on one of the main export routes for coffee.

Figure 6 Critical links exposed to floods in Peru.



Note: V1, V2 and V3 are segments on the Pan Americana (map Figure 5) and the three clusters are the ones for which we will do a full analysis.

3.2. What is the most robust proactive intervention to reduce the vulnerability of critical links?

For the three critical clusters, we first calculated average annual losses with no proactive interventions under a wide range of conditions that combine climate scenarios with different flood depth, structural impact and traffic rerouting scenarios.

Figure 7 shows average annual losses (AAL) for the three selected clusters, with no proactive interventions, under a range of future conditions. AAL are broken down into private losses (Figure 7, panel a) and cost of reconstruction and rehabilitation (Figure 7, panel b). The highest AAL for users are on the

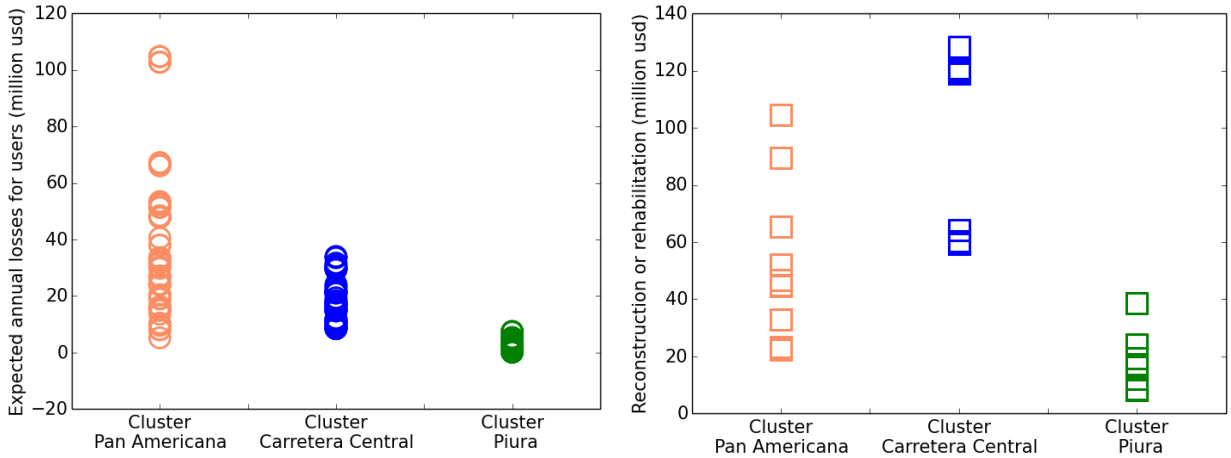
[7] About 58% of Peru's coffee exports move through the Paita harbor in this area. (Briceño-Garmendia and Guasch, 2015) finds that the time that coffee takes from the production site to the toasting site (in our critical area) is what most affects the competitiveness of coffee producers and exporters. Delays in reaching the toasting site can also lead to severe losses – particularly if the raw product remains exposed to changes in temperature before being toasted.

Pan Americana highway, where traffic is the highest. For Carretera Central, ex-post costs are higher because rainfall triggers landslides that require rebuilding the road more often.

The range of possible AAL is large because of the uncertainty considered, and we cannot attach specific probabilities to these scenarios. Instead we perform analyses of variance to identify the main drivers behind the range of AAL.[8] For the Pan Americana, the uncertainty on future AAL mainly depends on the impacts of climate change on flood frequency and on the uncertainty of flood duration. For Piura and Carretera Central, the range of AAL mostly depends on the duration of the disruption. For at least these two latter clusters, our results indicate that the high losses could be reduced if the duration of the disruption were contained.

Figure 7. Total disruption costs (AAL) for three road clusters in Peru

(a) Private costs (for users) *(b) Reactive intervention costs*



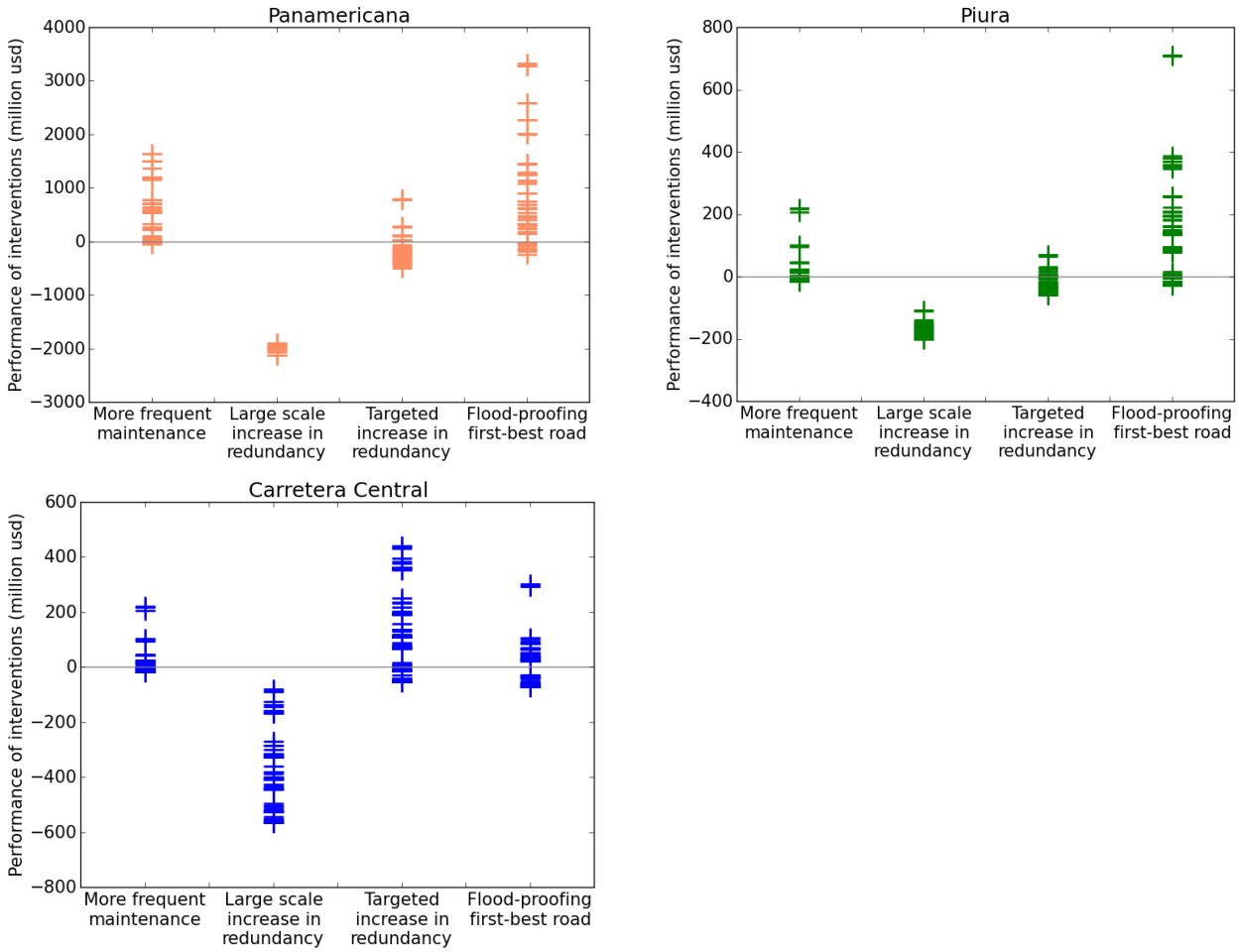
To decide what proactive intervention protects the road the best against uncertain disruption losses, we calculated the economic performance of each possible intervention in the three clusters for all possible scenarios of AAL. We consider four options:

- increased maintenance, which allows reducing disruption length,
- large-scale increase in redundancy, where we assume that most of the road segments used for second-best routes are upgraded to primary paved roads,
- targeted increase in redundancy, where only 30 percent of the alternative roads are upgraded to primary paved roads, and
- flood-proofing the first-best road, where we assume the road is elevated or drainage is highly improved to avoid flood losses for all events with a return period of 100 years or less.

[8] The analysis of variance partitions the observed variance of a variable into components attributable to different sources of variation. In other words, we are explaining the variance of the outputs of our average losses model by the variance of the inputs (the sources of uncertainty identified previously). Doing so tells us about the drivers that are the most important to increase or decrease average annual losses.

Figure 8 shows how these four options perform, under all scenarios for the three clusters. The performance is calculated as described in the section on Metrics, and incorporates, in the avoided losses, both user costs and the cost of rehabilitating the road after a disaster.

Figure 8. Performance of different interventions over 30 years, for different scenarios, for the three Clusters



Note: These performance metrics are calculated over 30 years, with a discount rate of 3 percent and with the assumption that traffic will not increase in the next 30 years.

Here we assumed that the traffic on the roads analyzed does not increase in the next three decades. This is a conservative assumption that tends to reduce the benefits of the interventions. We vary these assumptions in the annex (with a 6 percent discount rate and a 3 percent growth rate in traffic), but these alternative assumptions do not change the order of preference of the different interventions.

Because reactive interventions are included in the performance, whenever the performance of a proactive intervention is negative, it means that reactive interventions are more profitable.

We then measure the robustness of interventions by calculating the maximum regret for each option in each cluster (Table 1).

Table 1. Maximum regret in the three clusters, discounted over 30 years (billions of US dollars)

	More frequent maintenance	Large-scale increase in redundancy	Targeted increase in redundancy	Flood-proofing first-best road	Do nothing (ex-post intervention only)
Pan Americana	2.1	5.4	2.5	**1.9**	7.4
Piura	0.50	0.82	0.64	**0.040**	4.8
Carretera Central	0.37	0.55	**0.037**	0.32	4.5
In bold, the option that in each cluster minimizes the maximum regret.					

For all three clusters the option of doing nothing and relying only on ex-post interventions is the one with the highest possible regret, and this regret increases as traffic increases.

For Pan Americana and Piura, the most robust option would be flood-proofing the first-best road (Table 1). Assuming that it is possible to build a flood-proof road at the costs we have used, this option provides the greatest benefits in most scenarios. Moreover, the flood-proof road remains a better option than the others even in some scenarios where it has negative performance – that is, in which being reactive is better, due to lower rainfall and optimistic assumptions about the duration of disruptions. Note that if we assume that traffic will increase at 3 percent per year in the next 30 years, there are no scenarios in which being reactive is better than investing in flood-proof roads, and this option always performs better than the others. In other words, there is no regret in investing in a flood-proof road (Figure 13 in the Annex).

If the option of a flood-proof road were not available for the Pan Americana and Piura clusters, in both, the second most robust option would be more frequent maintenance (Table 1). Here the scenarios that lead to a negative performance are those with an optimistic assumption on flood duration – that is, where water recedes rapidly. Since the main benefit of improved maintenance is the reduced duration of a flood because of cleaner drainage, for instance, if a flood lasts a short time, improved maintenance is not as useful.

In neither of these two clusters is the option of improving redundancy profitable, but for different reasons. For Pan Americana, the number of kilometers of roads that would need to be upgraded to improve redundancy is very high (840 kilometers), so even if the potential disruption costs are very high (Figure 7), they do not offset the cost of upgrading all those roads. For Piura, the number of kilometers to upgrade is smaller (400 kilometers) but the potential disruption losses are also lower, hence the upgrading of the second-best routes is not profitable. This may change if we included the export losses linked to even shorter disruptions. Note that if only a portion of the second-best routes were upgraded (third intervention in Figure 8), this option becomes profitable in those scenarios with the highest expected losses. These results suggest that a further, more detailed analysis about which segments of the second-best routes would be most critical to upgrade may be useful.

For Carretera Central, targeted upgrading of second-best routes is the most robust option (Table 1). This occurs because Carretera Central suffers from landslides in addition to floods, so more frequent maintenance and flood-proofing the first-best route are not as efficient. Here again, the regret of targeted increased redundancy becomes null if traffic increases by 3% per year (Figure 13 in the Annex), so this intervention should be implemented no matter what happens.

The Ministry of Transport is currently upgrading two roads to increase the redundancy of Carretera Central.[9] To dive deeper into the performance of the best option for the Carretera Central, we explored in greater detail the profitability of these two projects. To simplify the analysis, we calculated the performance of increasing redundancy only considering losses from landslides (which cause the biggest losses in this cluster). Moreover, we varied the probability of occurrence (and duration of disruption) of landslides every year and the discount rate, as before.

Figure 9. Profitability of increased redundancy around Carretera Central for different probabilities of occurrence of events and different discount rates.

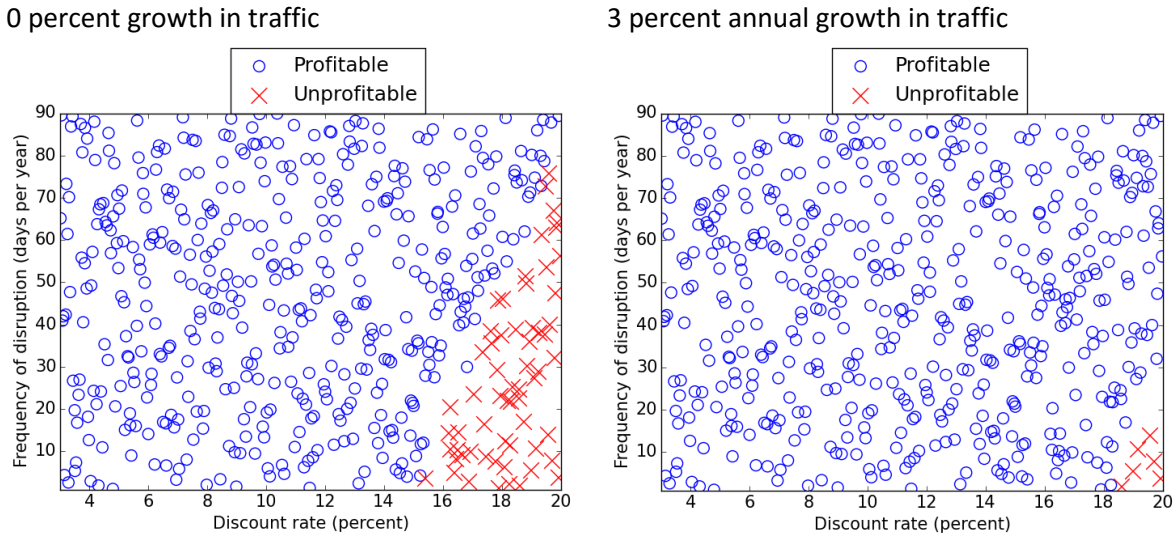
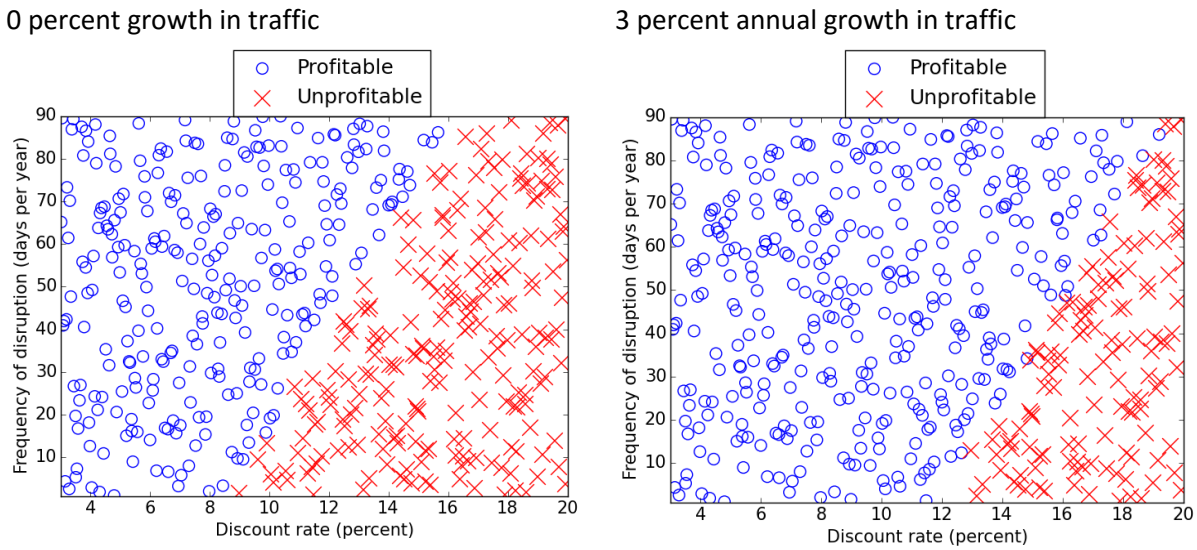


Figure 9 shows the profitability of the investment (that is, whether or not the performance of the investment is positive) for different probabilities of occurrence of landslides and different discount rates. The left panel calculates performance assuming there is no increase in traffic while the right panel assumes there is an annual growth rate of 3 percent for traffic. According to these results, for any discount rate lower than 15 percent, the investment makes sense even if traffic is disrupted for one day because of a small landslide and even if traffic does not increase for the next 30 years. If traffic does increase, the investment makes sense even with an 18 percent discount rate for any frequency of landslides.

[9] Road 1: Huaura – Sayán – Churin – Oyon – Ambo = 283.5 km. Road 2: Lima (Puente Santa Anita) – Canta – Unish (Vicco) = 239.3 Km. Cost: around $700 million.

Finally, we evaluate a more challenging investment to avoid landslides on the Carretera Central: a tunnel. We repeat the analysis assuming that the tunnel avoids all losses but costs $33 million per kilometer.

Figure 10. Profitability of a tunnel on Carretera Central for different probabilities of occurrence of events and different discount rates.



Unlike with the option of upgrading alternative roads, if traffic does not increase the option of the tunnel is only profitable for relatively low discount rates (lower than 10 percent), or higher discount rates and high probabilities of occurrence of landslides. If traffic increases by 3 percent a year, the tunnel is profitable with a discount rate of up to 12 percent. But discount rates are usually lower than 10 percent for public infrastructure investments so this option is still quite robust and should be considered by the local authorities or the government. Indeed, one advantage of tunnels is that they do not need to be rebuilt after an extreme event – unlike upgrading alternative roads.

Again, these results consider only private losses. If we included commercial costs, tunnels would probably make even more economic sense on roads subject to frequent landslides.

4. Conclusions and Policy Recommendations

Faced with the challenge of allocating resources efficiently and prioritizing the most urgent investments on road networks, decision-makers struggle to identify the most critical links and evaluate their vulnerability in the face of uncertain future events and uncertainties about their impact. This paper sought to answer two key questions. First, what are the most critical roads in Peru's national network, and which are the most exposed to natural disasters? Second, what are the most robust proactive interventions to reduce the vulnerability of critical links?

To help answer these questions, the paper shows how to effectively combine traditional transport models, like HDM-4, with innovative network analysis and state-of-the-art methods for managing uncertainties about the future.

By using the interdiction technique on thousands of links, this paper shows how to select the most critical links. Ideally this phase would be conducted in close collaboration with policy makers, who are generally well aware of the most critical links and can bring nuances to the selection. Analysts can easily take into account additional qualitative information on the strategic or economic relevance of some links to improve the decisions. The combination of quantitative information on disruption costs and knowledge of the local challenges allows the identification of the most important areas of the network for further analysis.

This paper then demonstrates how to identify the most exposed of these links to natural hazards by overlaying the network with hazard data and factoring in different parameters of their vulnerability – such as flood depth and duration, traffic rerouting, and structural damage. Finally, by running hundreds of scenarios of possible events and their impacts, it applies a robust decision-making approach to guide an analysis of policy options available when a road network is exposed to unpredictable climate events.

More data are needed to evaluate the full economic and social costs of disruptions and improve the economic analysis on the most vulnerable links of Peru's road networks. In addition, other non-engineering solutions exist to reduce the vulnerability of the critical links that could be as effective, if not more, as the options explored in this paper. They include reforestation, traffic management, and multimodality. Reforestation, for instance, could significantly reduce the risk of landslides. Finally, traffic management, particularly if linked to early warning systems, could reduce losses during a disaster, by redirecting traffic to alternative routes and lowering the costs of a disruption afterwards by avoiding congestion.

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Authors contributions: JR contributed to the design of the analysis, carried out the economic analysis and wrote the paper. CBG was the TTL of the Regional Study, contributed to the design of the analysis and led the discussions with the clients in Peru. XL did the network modeling. LB contributed to the analysis and discussions with the clients and helped write the paper. HM worked on the HDM4 model and helped with the Regional study.

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6. Annex

6.1. The road network

We constructed a GIS road network for Peru and allocated the RUC and the vehicle speed (km/hour) produced by HDM-4 based on the roads' attributes—class, condition, type of pavement, number of lanes, terrain and traffic level. For road segments in urban areas, we recalculated speed with the Google Directions Application program interface (API) to capture the impact of congestion.

Table 2. Coverage of GIS Road Data

Network Type	GIS Coverage of Reported Network KMs %	Surface Type (Paved/Unpaved)	Condition (Good/Fair/Poor)	# of Lanes	Traffic
Primary	100	√	√	----	√
Secondary	100	√	√	----	Some
Tertiary	100	√	√	----	----

Source: Ministerio de Transportes y Comunicaciones (2013).
Note: GIS = geographic information system.

Table 3. Condition as a percent of the total primary network

	Good %	Fair %	Bad %	No info %
Peru	55	20	16	9

Source: World Bank based on GIS data.

Table 4. Surface type as a percent of the total primary network

	Paved %	Not Paved %	No info %
Peru	85	8	7

Source: World Bank based on GIS data.

The Ministry of Transport and Communication (MTC) provided a georeferenced road network data set that contained data on surface type and road condition for 93 percent of the country's roads, updated in May 2015. However, it lacked information on terrain, which is an input to HDM-4. Thus, we used a Digital Elevation Model (DEM) to classify the country into 15 geographies and extracted elevation data at fixed intervals along the line of the road network. We calculated terrain class for each link and grouped them into the seven terrain types used by the HDM-4 model. Though we obtained traffic volume data (AADT) from the MTC, it was not georeferenced or included as one of the attributes in the GIS network. Hence, based on the origin and destination pair of the AADT, we identified the location of origin and destination (OD) and attributed the primary roads that can connect the OD with the shortest distance (the simulation is based on the shortest path routing algorithm). Once we had all the needed information to match the physical characteristics of the GIS network with the outputs of HDM-4, we appended the corresponding road user cost and vehicle speed to each link.

We then selected ODs using national and provincial capital cities, population centers of over 25,000 inhabitants, main ports and airports, and border crossing, generating a total of 93 nodes total. Based on

the GIS road network and the 93 nodes, we used the shortest path routing algorithm to compute number of kilometers, travel time, and total road user cost for each origin-destination pair (or route).

Table 5. Terrain Classes and Percentage of Land Area Peru

Class	Description	Peru
1	Plains	0.11
2	Mid-altitude plains	0.00
3	High-altitude plains	0.00
4	Lowlands	10.92
5	Rugged lowlands	17.41
6	Platforms (very low plateaus)	1.48
7	Low plateaus	0.05
8	Mid-altitude plateaus	0.00
9	High plateaus	0.72
10	Very high plateaus	0.14
11	Hills	20.83
12	Low mountains	7.44
13	Mid-altitude mountains	10.37
14	High mountains	16.81
15	Very high mountains	13.70

Source: Authors' calculations.

6.2. GIS Data Limitations

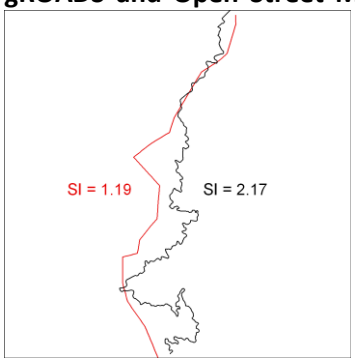
A number of limitations associated with the input data sets and the methods used in this analysis should be taken into account in the interpretation of results.

Scale of roads. The scale of the source data (that is, the level of detail) for roads is unknown, but there are obvious differences between the countries and in comparison with large-scale data sets such as Open Street Map. The smaller the scale, the less likely the features in the geographic information system (GIS) data will accurately represent the geometry of the roads on the ground. As a result, the total kilometers calculated based on the GIS data will deviate, to some degree, from the officially reported statistics. In figure 11 below, scale makes a big difference in the calculated sinuosity index value.

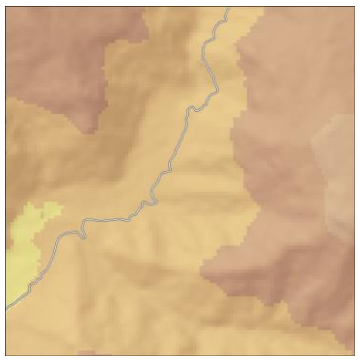
Spatial resolution of the elevation model. The spatial resolution of the elevation model also presents a challenge, particularly with respect to the average width of roads. Figure 11 below shows a road drawn with a width of 7 meters, approximately one-third of the size of an elevation cell. In this case, extracted z-values will be affected by roadside features, particularly in areas of high relief.

Segmentation. In the terrain analysis, road characteristics are calculated by segment, which is defined somewhat arbitrarily according to the network geometry. While the start and end of a segment may not necessarily define a homogenous feature, errors in network geometry only exacerbate the problem.

Scale difference between gROADS and Open Street Map



Spatial resolution of Digital Elevation Model



Segmentation example

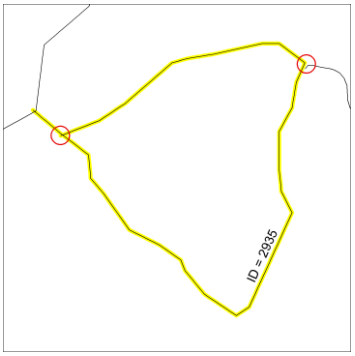


Figure 11 Examples of Challenges with Input Datasets

6.3. The Highway Development and Management Model, HDM-4

Road user costs (RUC)[10] and speed (km/hour) are calculated for roads of different attributes using the World Bank's Highway Development and Management Model (HDM-4). This software package was built to evaluate and assess road maintenance, improvement, and investment projects. Inputs into HDM-4 include both road characteristics (network type, terrain, surface, and pavement condition) and vehicle fleets information (traffic classes). For the purposes of this study, the vehicle fleet data were collected at the country level with a heavy truck taken as the representative vehicle. For each of the possible combinations of road characteristics and traffic class (6,804 in total), we calculated in HDM-4 a unique road user cost and travel speed estimate.

Road conditions definition in HDM4
(http://siteresources.worldbank.org/EXTAFRSUBSAHTRA/Resources/SSATPWP89A-RONET.pdf)

For paved roads, the road condition classes are defined as follows:

- Very Good: Roads in very good condition require no capital road works.
- Good: Roads in good condition are largely free of defects, requiring some minor maintenance works, such as preventive treatment or crack sealing.
- Fair: Roads in fair condition are roads with defects and weakened structural resistance, requiring resurfacing of the pavement (periodic maintenance), but without the need to demolish the existing pavement.

[10] RUCs are defined as the unit cost of using a road expressed in dollars per ton-kilometer and consist of vehicle operating costs (VOCs), which reflect the cost of operating a vehicle, and value of time costs (VOTs), which reflect the cost of time associated with using a vehicle. VOCs include the costs of fuel, lubricants, tires, maintenance parts and maintenance labor, crew time, depreciation, interest, and overhead. The VOTs include the cost of passenger time and the cargo time. Each of these components is calculated separately as an output of the HDM-4 model.

- Poor: Roads in poor condition require rehabilitation (strengthening or partial reconstruction).
- Very Poor: Roads in very poor condition require full reconstruction, almost equivalent to new construction.

For gravel roads, the road condition classes are defined as follows:

- Very Good: Roads in very good condition require no capital road works.
- Good: Roads in good condition are roads that require only spot regraveling.
- Fair: Roads in fair condition require regraveling (periodic maintenance).
- Poor: Roads in poor condition require partial reconstruction.
- Very Poor: Roads in very poor condition require full reconstruction, almost equivalent to new construction.

For earth roads, the road condition classes are defined as follows:

- Very Good: Roads in very good condition require no capital road works.
- Good: Roads in good condition are roads that require only spot repairs.
- Fair: Roads in fair condition require heavy grading (periodic maintenance).
- Poor: Roads in poor condition require partial reconstruction.
- Very Poor: Roads in very poor condition require full reconstruction, almost equivalent to new construction.

6.4. Accounting for Urban Friction

Due to higher traffic, urban centers tend to suffer from congestion problems (referred to as higher friction in the urban center in GIS terms). The average speeds of vehicles in the city are expected to be lower than in intercity corridors and even rural areas assuming all other conditions are equal. HDM-4 can be used to model congestion effects by inputting a reduced speed based on travel time and speeds calculated using Google's Directions Application Program Interface (API), which takes congestion into account.

First, urban areas must be defined. This is done based on three criteria: percentage of built-up land; population; and status as a national or provincial capital. Roads which intersect the urban cluster mask are identified and considered "urban" for the purposes of analyzing urban friction. Travel time and speeds are then calculated for these roads using Google's Directions API.

An "urban friction coefficient" can be defined to provide a sense of congestion effects:

$$Urban\ Friction\ Coefficient_i = 1 - \frac{Google\ Speeds_i}{Original\ HDM4\ Speeds_i}$$

The urban friction coefficient can be interpreted as the percentage speed reduction of the original HDM-4 speed estimates. For the urban road links in Colombia, Ecuador, and Peru, the average friction coefficients are 0.50, 0.36, and 0.39 respectively. In other words, there is on average a 50 percent speed reduction in Colombia, 36 percent speed reduction in Ecuador, and 39 percent speed reduction in Peru in the urban centers defined by the study.

For the calculation of road user costs in HDM-4, the speeds derived from Google were inputted directly to the model and calculated as an additional road characteristic for all urban roads. That is, in the case of urban roads, HDM-4 was used to calculate the road user cost associated with an existing road link rather than the road user costs associated with a type of road based on the seven road characteristics.

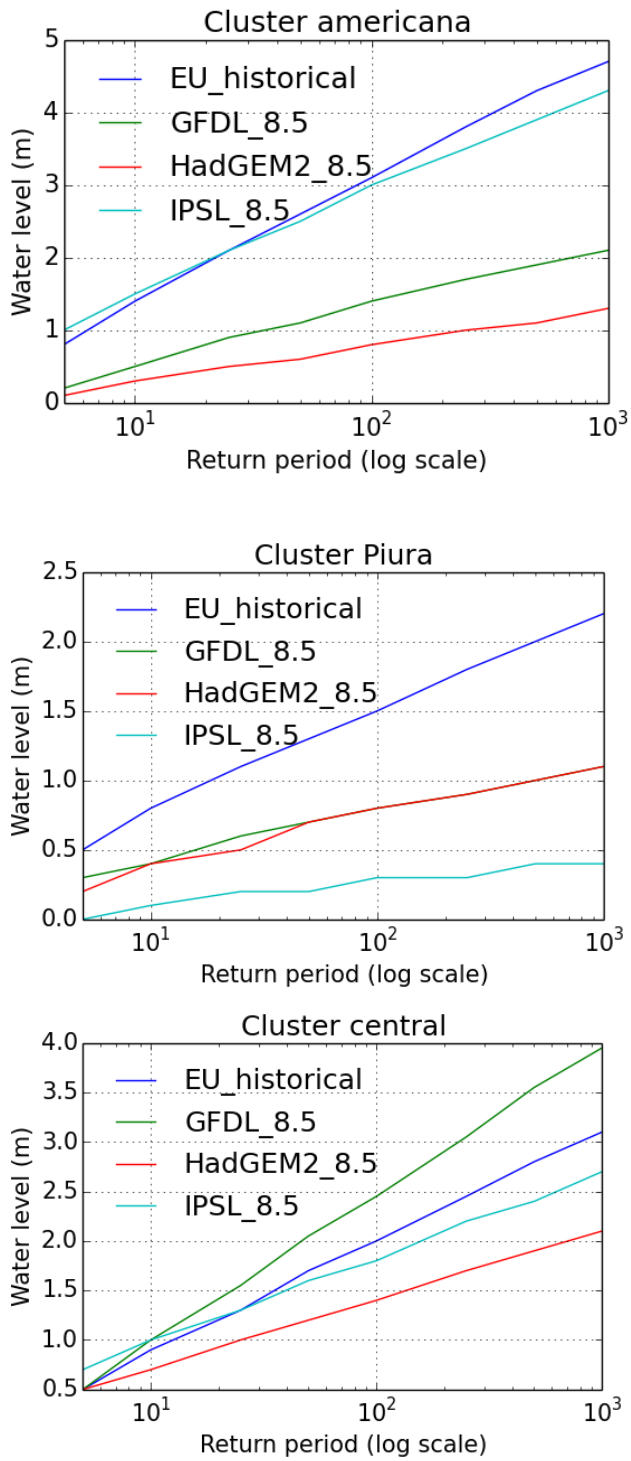
6.5. Costs of interventions

Table 6 Costs of different interventions, per road type (thousands of US dollars per kilometers). Source: Colombia and MTC, Peru

CLASS	Surface	Terrain	Flood Proof 1m	Routine Mainte-nance	Rehabili-tation	Construc-tion	Upgrade to primary	Bridge	Tunnel
Primary	Paved	Flat	2,500	13	1,300	2,500	-	28,000	33,000
Primary	Paved	Hilly	2,804	16	1,328	3,117	-	-	-
Primary	Paved	Mountain	2,944	10	1,212	3,867	-	-	-
Primary	Paved	Steep	3,573	19	1,531	4,712	-	-	-
Secondary	Paved	Flat	2,137	15	850	1,563	1,650	-	-
Secondary	Paved	Hilly	2,357	16	775	2,000	1,970	-	-
Secondary	Paved	Mountain	2,647	13	844	2,617	2,236	-	-
Secondary	Paved	Steep	3,126	15	978	3,260	2,658	-	-
Secondary	Unpaved	Flat	1,646	6	243	840	3,163	-	-
Secondary	Unpaved	Hilly	1,974	7	301	1,057	3,598	-	-
Secondary	Unpaved	Mountain	2,265	9	372	1,433	4,072	-	-
Secondary	Unpaved	Steep	2,706	-	457	1,924	4,855	-	-
Tertiary	Unpaved	Flat	1,566	3	144	312	3,955	-	-
Tertiary	Unpaved	Hilly	1,874	4	177	621	4,398	-	-
Tertiary	Unpaved	Mountain	2,162	5	244	909	5,106	-	-
Tertiary	Unpaved	Steep	2,600	7	326	1,329	6,088	-	-

6.6. Flood depth on the three clusters

Figure 12. Water Levels on the Three Clusters we analyzed, for Different Frequency of Floods, according to different models (Return Period in Years). EU_historical is historical rainfall data while the other 3 curves are based on the outputs of Global Circulation Models taking into account climate change (with a RCP8.5 scenario).



6.7. Sensitivity analysis on traffic

Figure 13. Performance of different interventions, for different scenarios, for the three groups of links and with an annual 3% growth rate in traffic over the next 30 years