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# Analytics for Financial Risk Management of Critical Infrastructure in South East Asia:

## Scoping & Feasibility Study

## Final Report

## May 2021

Oxford Infrastructure Analytics Ltd.

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# Table of Contents

## List of Figures

## List of Tables

# Executive summary

Critical infrastructure (CI), including energy and transport networks, is vulnerable to the impacts of natural disasters such as cyclones, floods and earthquakes. Natural disasters can physically damage these costly assets and cause widespread disruption to the essential services that CI provide for people and economies. The impacts of this damage and disruption can propagate far beyond the footprint of the disaster and even beyond national boundaries by impacting supply chains. Several of the most damaging categories of natural disasters (including cyclones, floods, storm surges, droughts, along with associated landslides, coastal erosion and subsidence) are being influenced by climate change, with climate models indicating that these hazards may become more severe or occur more frequently in the future.

The impacts of natural disasters on CI are major risks that need to be managed by governments, infrastructure owners and investors and international organisations. When disasters hit, governments typically take the lead in the response, mobilising emergency relief and assisting infrastructure operators to restore essential services. Governments carry the risks of damage to public assets. People will look to the government for assistance with repair and recovery, so government may carry implicit liabilities beyond the systems for which they are explicitly responsible. The wider economic impacts of natural disasters will include temporary disruptions to supply and shifts in demand. Natural disasters are therefore a major shock to public finances, requiring budget reallocation and potentially impacting loan repayments. Governments' exposure to natural hazards may therefore impact credit ratings and the cost of capital.

There is growing interest in the use of financial instruments, including pre-arranged risk financing, parametric insurance and risk pools to help manage the financial risks to governments from natural disasters. The South East Asia Disaster Risk Insurance Facility (SEADRIF) is one of several regional risk pool facilities that are increasingly specialised in supporting member governments to manage the financial risks from natural disasters.

**This study has aimed to demonstrate the feasibility and limitations of disaster risk analysis of infrastructure networks to inform disaster risk finance and insurance (DRFI), which particular application in the South East Asia region**. **The initial pilot phase of analysis and platform development presented in this feasibility study focuses on the Southeast Asia countries of Myanmar, Cambodia, Laos PDR, Indonesia, Philippines, Vietnam and Thailand. For these countries we have developed a platform that shows the results from analysis of the criticality and risks of infrastructure assets in networks of electricity transmission lines, roads, and railways, due to current and future climate change driven fluvial flooding, coastal flooding and cyclone hazards of different return periods.**

## Answering DRFI relevant questions

The key insights and findings of this study are centered around answering five questions that help develop a better link between infrastructure risk assessments and DRFI solutions. Below we summarize to what extent these questions are answered through this study.

*Whether and how criticality analyses and vulnerability assessments for CI systems can be used to inform financial risk management by governments, and how these efforts can be scaled up nationally?*

This study has established that all forms of DRFI rely upon Quantitative Risk Assessment (QRA) i.e., estimation of the amount of loss that will be incurred under specific disaster conditions, and which on average exceed a certain probability threshold annually (see Section

1.5). The process of risk quantification involves a *vulnerability assessment*, which includes measuring the severity of extreme hazards and their impacts. These impacts might be measured in different ways before linking to the relevant financing protection option and solution, as we have shown in Figure 1.6. *Criticality analysis* involves ranking risks (i.e., vulnerability assessment outcomes) to identify importance and disruptive impact at different spatial scales (see Section 2.2), which would be relevant in the DFRI process to prioritise investments for locations of higher concentrations of risks. Quantified estimates of disaster impacts and their criticality ranking are therefore essential for governments (and insurers) to assess how much finance might be required under specific circumstances and to estimate the fair price for insurance products such as parametric insurance and catastrophe bonds.

While the above explanation makes it clear 'whether criticality analyses and vulnerability assessments for CI systems can be used to inform financial risk management by governments', the main focus of this study is on 'how' this can be done. We note that most DFRI solutions have traditionally been rooted in approaches from the insurance industry, which is experienced at quantifying disaster risks to portfolios of assets like houses and business properties. For this they use catastrophe (Cat) models, into which an insurer can enter the geolocation and value of their insurance portfolio and estimate the expected asset damages for which they would be liable at different return periods of disaster extreme event. The assessment of CI and the wider economic impacts of services that these networks provide is much less developed and is not a part of standard Cat models. Yet CIs are amongst the most important economic assets in a country and are instrumental in systemic risks for governments.

Hence to answer the how this can be done for CI, **the main insight of our study is establishing a generalised methodology framework for CI networks QRA. As explained in detail in Section 2.1 this methodology shows the steps for CI networks QRA that include intersecting: (1) any type of spatial hazard maps of different climate scenarios and return periods; and (2) any type of spatially detailed infrastructure assets and networks with fragility functions**, **asset costs, and economic usage assigned to them. With this framework we have established that there is a well-developed and scalable methodology whose outputs can inform the DRFI design stages (Figure 1-6)**. The outputs of the methodology include the following three *DRFI relevant risk metrics* that apply to any scale (from an individual asset to a whole administrative boundary) (see Section 2.2):

- **Probability of failure** – The total annual probability of failure of an asset when exposed to hazards of different exceedance probabilities (1/return periods).
- **Expected annual damages (EAD)** – This is the integral over the hazard exceedance probabilities and the corresponding direct damage value in US$ calculated with the asset fragility function and reconstruction cost associated with the asset. EAD at the administrative boundary scale are estimated by summing up the EADs of assets within that boundary.
- **Expected annual economic losses (EAEL)** – Estimated for an asset, this is the integral over the hazard exceedance probabilities and the corresponding national-scale economic loss in US$ for a given duration of disruption associated with the failure of the asset. EAEL at the administrative boundary scale are estimated by summing up the EAELs of assets within that boundary.

To answer the third part of the question 'how these efforts can be scaled up nationally' we have:

1. Described the methods in the CI network risk analysis framework for it to be applicable to electricity and transport (road, rail) networks at the SE Asia scale.
2. Assembled globally available open-source datasets for SE Asia, processing these datasets and analysing them to generate the risk metrics that can be used in DRFI.

3. Built a criticality and vulnerability assessment prototype web interface https://tool.oi-analytics.com, which comprises of:
    a. A mapping tool to view infrastructure asset and networks exposure and vulnerability to natural hazards; and
    b. A dashboard displaying aggregate risk metrics.

**The fact that we have been able to successfully demonstrate our methods and model outputs for the whole of SE Asia provides ample proof that the CI risk metrics for DRFI analysis can be scaled geographically from a local asset level to not just at the national scale but at the global (SE Asia) scale. This is a key finding of this study.**

Figure ES-1 demonstrates the platform tool output, where for each asset in the road networks for all SE Asia the three risk metrics were calculated and now can be interrogated through the web-based platform. Similar outputs for the electricity and rail network across SE Asia were created and are displayed in the platform. The results at geographical aggregations (Admin 1 or Province level) and show the total risks (EAD + EAEL) across all three infrastructure assets (electricity, road and railways) within the Admin 1 region. For each Admin 1 region we have also presented as direct damage (EAD) or economic losses (EAEL) or total loss (direct + economic) vs hazard exceedance probabilities. Such results are either hazard specific or show the totals across all hazards and all infrastructure networks, assuming hazard independence.

Figure ES-1 and Figure ES-2 also show the criticality assessment outcomes where the darker colours show the most critical assets and regions ranked by the specific risk metric of interest (EAD, EAEL or EAD + EAEL). **These visualizations highlight key findings of this study, which would be to enable governments to identify and locate the assets (e.g., the top 20 most critical roads in a country) and regions (e.g., the top 5 most affected provinces) where the DRFI solutions can be implemented as a priority.**

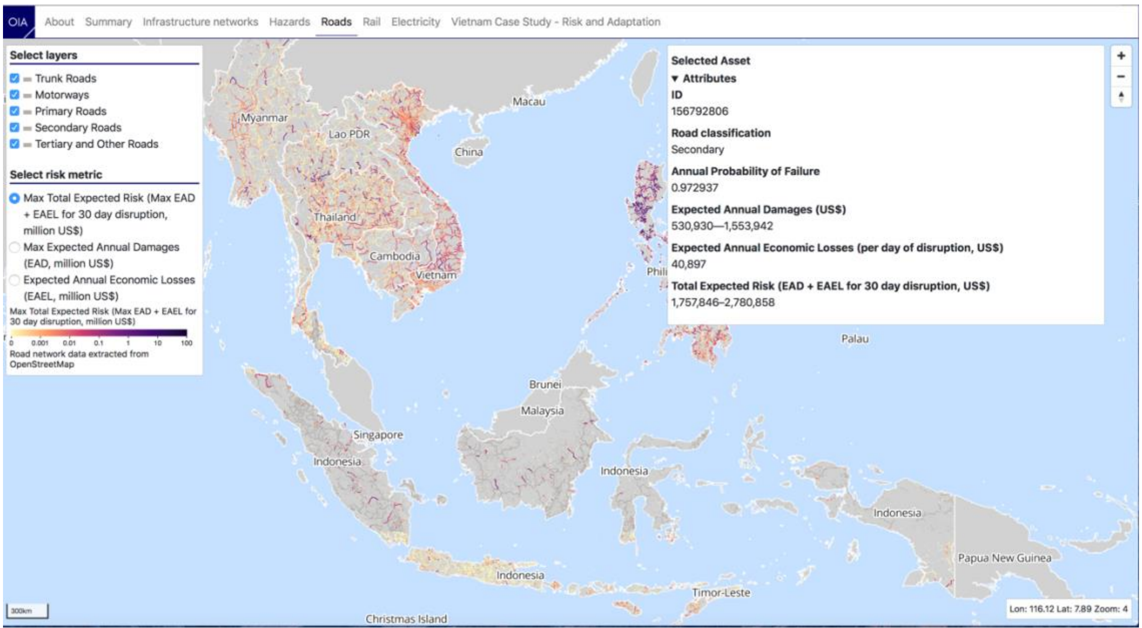


**Figure ES-1: Screen shot of the prototype infrastructure risk analysis tool for South East Asia, which shows the electricity, roads, and railways in the region. For a selected asset the tool outputs are shown, which include the annual probability of failure, the expected annual damages, the expected annual economic losses, and the total expected risks.**

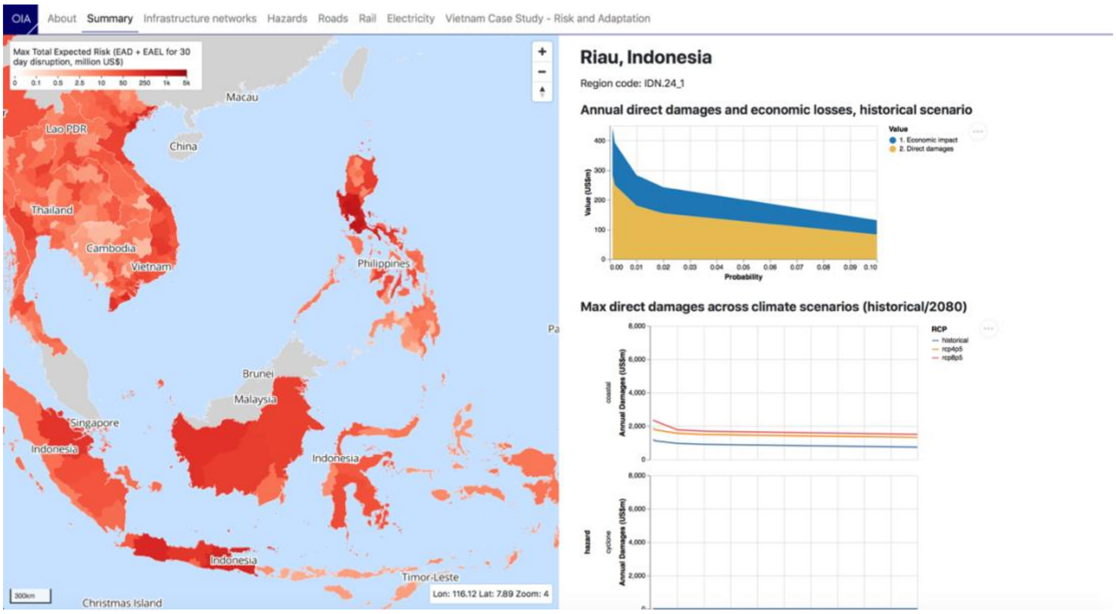


**Figure ES-2: Admin 1 (province) level criticality (choropleth) maps showing the magnitudes of maximum total expected risks for current (baseline) flooding (fluvial, coastal) and cyclone hazards assuming 30-day disruption durations. The darker colours show the regions with highest risks. Also shown on the right are the total damage vs exceedance and economic impact vs exceedance probability curves for a particular region (Riau) in Indonesia. The hazard specific loss vs exceedance probability curves can be seen by scrolling further down.**

*What can be done and cannot be done with globally and publicly available data and methodologies developed to date?*

**A key finding of our study is that existing global and publicly available hazard and infrastructure network datasets can be used for CI QRA useful for DRFI analytics**. In the very limited time of exploring the feasibility of demonstrating a large-scale CI QRA in SE Asia the analysis of data to estimate hazard network intersections and build models to estimate EADs and EAELs to include in the pilot platform has involved a huge volume of computation, and over a terabyte of data has been created in the study and is being provided to the World Bank. The C++ and Python codes for the analysis are available at https://github.com/oi-analytics/seasia. **A key finding of this study is that it has demonstrated that it is feasible to do CI QRA on a very large scale (SE Asia), and hence it is feasible at a global scale and research is already under way to implement methods at a global scale.**

The minimum data requirement for our methodology include having: (1) *Spatial hazards maps* – with exceedance probabilities and hazard magnitudes (e.g., flood depths, cyclone wind speeds); (2) *CI physical and service attributes* – Location and connectivity information for individual point and line assets; (3) *CI costs* – Rehabilitation or construction costs assigned to each asset, based on some general principles; (4) *CI fragility* – Failure or damage probability information that tells us about the percentage of damage an asset due to hazard exposures; (5) *CI economic value* – Measures of (macro)economic usage linked to the CI asset. In Chapter 3 we have described the process of harnessing all this information from globally and publicly available data.

It goes without saying that there are several limitations and gaps in the quality of information harnessed from global and publicly available data. These limitations, discussed in detail in Section 6.2, arise due: (1) Lack of finer scale hazard datasets with spatially correlated event sets and better regional climate model based future scenarios; (2) Missing CI asset location information within networks; (3) Lack of fragility information that incorporates asset design standard, lifetime since construction and rate of deterioration for specific hazard; (4) Lack of better cost information associated with assets; (5) Very little information of CI disruption durations; and (6) Very little information on observable macroeconomic impacts associated with CI failures.

These limitations in data do not methodologically hinder how direct damage (EAD) calculations for CI asset can be done with global and publicly available data. The analytics for direct damage calculations, widely used in the insurance industry, require spatial hazards, CI asset locations, fragility and costs, all of which are harnessed in the global data.

However, the data gaps do influence how economic loss (EAEL) calculations are done. **Currently there is no global scale demonstrable methodology for economic losses calculations of CI assets and networks.** As we have described in Section 1.2 and Section 2.1 the economic losses of CI would involve estimating: (1) Infrastructure service disruption impacts that quantify how economic productivity would be altered when people and businesses will modify, delay or curtail their activities; and (2) Wider economic impacts caused by loss of infrastructure services can propagate through economic networks nationally and indeed globally.

In the absence of the any method we have created our own methods in the pilot platform demonstration for SE Asia using global population, GDP and pollution datasets for allocating GDP to electricity transmission lines, roads segments and railway tracks as a macroeconomic usage and impact metric for EAEL calculations. See Section 3.2.4 for the details of the methods. A key limitation of our methodology for economic loss estimation is that we have not considered network rerouting or redistribution when assets are failed and disrupted, resulting in the assumption that the GDP associated with an asset would be fully lost.

Bearing in mind the limitations in our methodology in estimating economic losses, we would still argue that the question 'what cannot be done with globally and publicly available data and methodologies developed to date' is an unanswered question. The more appropriate question here is '*how fit-for-purpose DRFI analytics for critical infrastructure can be undertaken with less time, resources, and data inputs?*' To the best of our knowledge this study is the first-of-its-kind to attempt estimating economic losses for CI networks at detailed spatial scales, and in the very limited time for the study the full range of global datasets could not be harnessed sufficiently to even understand and develop an implementable[1] method. In Appendix B Tables B-3 to Table B-8 we have presented a review of several global datasets that would be useful to develop a more nuanced economic loss methodology, and in ongoing research activity we are exploring new CI network economic usage and loss estimation model using these datasets.

*What are the challenges, opportunities and next steps for development of full-scale platform for SE Asia?*

We have already highlighted the data and methodology challenges and gaps in the CI QRA process for the SE Asia platform. **We note here that the risk metrics and their estimation (probability of failure, EAD, EAEL, exceedance probability vs loss curves) would remain the same, the difference being in how they are quantified.**

The next steps of such developments again hinge on the objective to produce '*fit-for-purpose DRFI analytics for critical infrastructure can be undertaken with less time, resources, and data inputs.*' Depending upon the investment of effort, different types of criticality analyses and vulnerability assessments (distinguished in the way the direct damages and indirect losses are estimated) for CI network might be suited at various stages of exploring and designing resilience and DRFI solutions by the government. For example, if the quality of data for estimating direct damages is vastly improved, but the data for indirect loss estimations is very bad then we would argue that using only EAD estimations in making DRFI decision would be

[1] Please note the stress here on the word implementable. In Chapter 2 we have outlined the kind of models and the process required to quantify macroeconomic losses.

better than using incorrect data for the sake of completeness. As we have shown in this study (see Section 2.1) the methodology for CI QRA is well developed and scalable to regional and global levels for some of these criticality analyses and vulnerability assessments for DRFI design stages (i.e., estimating the socioeconomic impacts of natural disasters to infrastructure due to damages and disruptions of assets and services) but may require country-by-country and CI-by-CI in depth data gathering and analysis for many of the analytics needed for DRFI solutions design and decision-making.

As we have already noted, the next step in estimating direct damages (EADs) is mainly a data challenge with the methodology is well established. Indirect loss quantifications (EAELs) require more methodological developments. In the web-based platform we also present results of a previous study on transport risks analysis done in Vietnam (Oh et al. 2019, see Chapter 5), in which the EAEL calculations were based on more detailed information using which we were able to model commodity specific freight flows on roads and link them to macroeconomic input-output impact assessment models (see Table 5-2). For roads in particular the OpenStreetMap location and connectivity information is known to be of a very good quality (Koks et al. 2019), so the direct damage calculations in the SE Asia platform could be improved with less time and effort to be more accurate. However more time and is needed for a proper model for indirect loss estimations, as our current method of GDP allocation and estimation is not the ideal solution.

Another further development for the full SE platform is to introduce elements beyond CI QRA, such as adaptation options, their costs, and a cost-benefit analysis to identify the locations and scales of adaptation investments that would be effective in reducing risks (see Figure ES-3). This was done in the Vietnam analysis and has not been explored in the wider SE Asia analysis due to the limited time of this study. Section 5.2 explains the process and data created for this analysis in Vietnam, which considered the very specific adaptation option of improving the civil engineering design standards of existing roads by upgrading them to more climate resilient roads. We believe that the time and effort to include such analysis in the SE Asia platform would be less because it mainly requires construction costs information for based on either considering data on previous projects or consulting with civil construction experts who design new infrastructure. We adopted a similar approach in another project in Argentina (Pant et al., 2019), for which adaptation options and costs were derived for the World Bank's globally available Road Costs Knowledge System (ROCKS) database where detailed information for Argentina was improved by local experts.

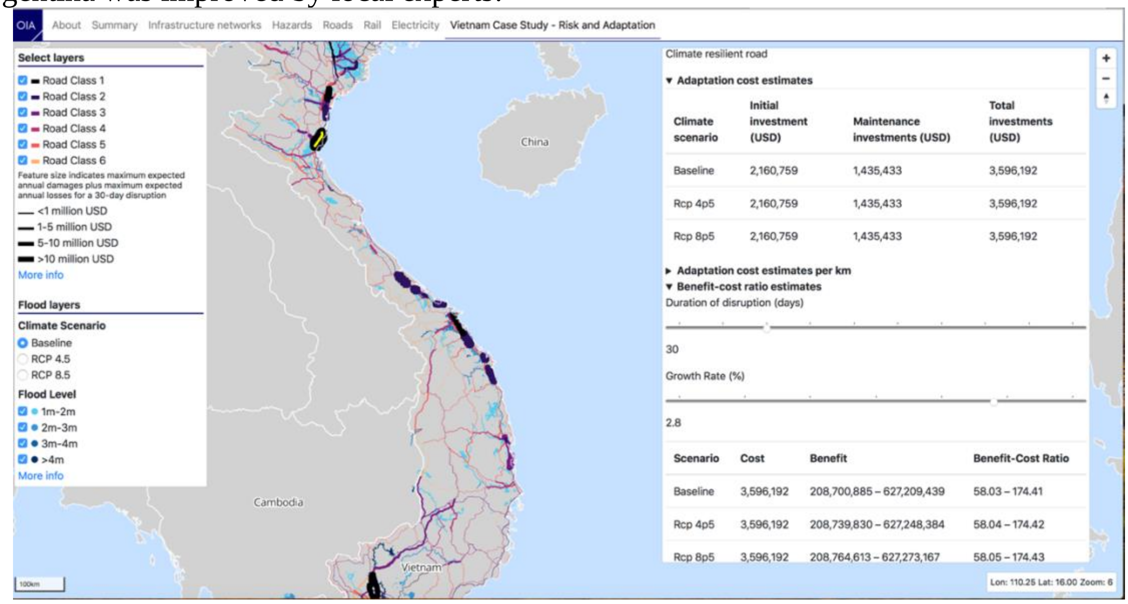


**Figure ES-3: Screen shot of the prototype infrastructure risk analysis tool which shows the adaptation costs and CBA analysis for national roads in Vietnam.**

*Based on globally and publicly available data and methodologies developed to date, to what level of detail and accuracy could we quantify the cost of disaster and climate risks to infrastructure assets and systems, specific and relevant to each country?*

In the absence of any observable data on disaster losses and climate risks associated with CI assets and networks, it would be very difficult to comment here on the accuracy of the EAD and EAEL estimations that are produced in this study. This is a difficult problem in general and based on our experience in other country-specific projects as well we have found there is mostly no data on CI specific direct damages and economic losses for past disaster events.

The analysis we have done here is best suited to provide a high-level estimate of magnitudes of risks, which should be more accurate at aggregated spatial scales. There will be greater errors in estimations at the individual asset level here. For example, the flood hazards maps used in this study are at roughly 1km$^2$ gridded resolution, which means they predict that much larger (or even smaller if the grid cell is not considered flooded) sections of individual roads or railways lines would be flooded than in reality. But over a large administrative area roughly the error would be relatively lower when considering all roads not flooded as well.

For direct damage calculations the cost information we have assigned to assets is derived from known sources that have been complied for past project costs in SE Asia (see Section 3.2). Hence, we can say that such information would provide reasonably accurate estimations of order of magnitudes of direct losses. The economic losses estimates are based on disaggregating administrative level GDP estimation onto assets, which increases the inaccuracy of the assigned GDP at the asset level but then at the aggregated administrative level we sum back up from the asset levels and mostly preserve the accuracy of the original data.

*Based on globally and publicly available data and methodologies developed to date, to what level of detail and accuracy could we provide information needed to design structural and financial ex-ante and ex-post resilience measures, as well as the estimated benefits of these measures in safeguarding assets against climate and disaster risks, specific and relevant to each country or infrastructure investments?*

This study has looked in detail on the CI QRA aspect of DRFI, which forms part of the 'information needed to design structural and financial ex-ante and ex-post resilience measures.' We have already discussed the details and accuracy of the CI QRA methodology and data in responding the previous four questions. We have not explored any global of publicly available data on the specific financial ex-ante and ex-post resilience measures and the benefits of these measures in safeguarding assets against climate and disaster risks. Hence, we cannot comment on this in the study.

Through the previous study in Vietnam, included in the platform and explained in Chapter 5, we have shown how climate resilience measures for CI networks can be quantified and how their benefits can be estimated. Table 5-1 shows how the study's insights could be useful in designing DRFI solutions.

## Key learnings

- This study has demonstrated the feasibility of infrastructure network risk analysis of natural disasters on a very large scale.
- The study has focussed upon electricity and transport (road/rail) infrastructure.
- Future studies will include further elements of CI i.e., water supply, wastewater treatment and telecommunications.

- The analysis is inevitably limited by the availability and accuracy of relevant datasets, namely: hazard maps, asset locations and characteristics, and information on socio-economic use of infrastructure networks.
- The study has piloted methodology and was not intended to produce validated results. Sensitivity analysis and validation are required to estimate the accuracy of risk estimates.
- Noteworthy data gaps relate to the asset condition and standards of hazard severity that specific assets are designed to resist.
- The economic impacts are sensitive to the duration of disruption, which depends upon organisational capacity and resources.
- Notwithstanding these limitations, we have made a significant next step in analysis of natural hazard risks to infrastructure systems.

# Chapter 1. Infrastructure risks analytics to inform Disaster Risk Finance and Insurance (DRFI)

## 1.1 Introduction

Critical infrastructure systems, including energy and transport networks, are particularly vulnerable to the impacts of natural disasters. Infrastructure is often disproportionately exposed to natural hazards: roads and railways links and bridges are built across coastal areas and rivers where they are inevitably going to feel the consequences of storm surges and river flooding; thermoelectric power plants are usually located on the coast or next to large rivers because they need access to cooling water. The impacts of climatic extremes can be propagated through infrastructure networks far away from the places where the extreme event hit. Repairing and replacing infrastructure after a disaster can take months or even years, denying people of essential services and adding to the financial burdens on governments and communities.

The need for expansion and modernization of infrastructure networks is projected at record high levels, with an estimated US$90 trillion of investment in new and existing infrastructure is required worldwide from 2016-2030[2]. Leading private sector firms also estimate US$1 trillion potential losses due to climate impacts between 2018-2022, with 40% of these losses being due to physical risks to assets exposed to extreme climate impacts[3], which raises concerns for those invested in large-scale infrastructures. Infrastructure investments lock in patters of development for decades to come. Plans, designs, and investments made in the next few years will feel the full brunt of climate change. It is therefore essential the climate change is factored into infrastructure planning right from the outset. Moreover, all countries have a large stock of existing infrastructure which has mostly not been designed to cope with the threat of natural disasters. The impacts of natural disasters on energy, transport and water infrastructure networks are already being felt worldwide. For example, analysis for the World Bank[4] and Global Commission on Adaptation[5] estimate that more than 200,000km of roads are currently exposed to climate-related hazards worldwide, which could increase to 237,000km by 2050 because of climate change, without considering the new highway construction that will take place in that period[6]. Studies suggest that timely investments in building climate resilient infrastructures would have an upfront cost of 3% of asset value[4] but would yield average benefits of 4-5 dollars of avoided losses for every 1 dollar spent[5].

The COVID-19 pandemic has been an unexpected test of the resilience of infrastructure systems. Prior to the pandemic, resilience planning and stress testing for energy, transport, digital communications and water systems focussed on natural hazards and cyber threats. Unlike natural hazards, COVID-19 has not physically damaged the lifelines upon which we all depend, but it has profoundly impacted people's use of infrastructure services and has precipitated a hiatus for the organisations that operate infrastructure and deliver new systems for the future. COVID-19 has made many people reluctant to use public transport and has

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[2] New Climate Economy. (2016). The sustainable infrastructure imperative: financing for better growth and development. *London, UK*. http://newclimateeconomy.report/2016/wp-content/uploads/sites/4/2014/08/NCE_2016Report.pdf.

[3] Bartlett, N., Coleman, T., (2019). Major risk or rosy opportunity: Are companies ready for climate change. CDP Worldwide, London, UK. https://www.cdp.net/en/research/global-reports/global-climate-change-report-2018/climate-report-risks-and-opportunities#35505b1e1102af23bcf4bfc4efba2ab3.

[4] Hallegatte, S., Rentschler, J., Rozenberg. J., (2019). Lifelines: The Resilient Infrastructure Opportunity. Sustainable Infrastructure Series. Washington, DC: World Bank. doi:10.1596/978-1-4648-1430-3.

[5] Hall, J.W., et al., (2019). Adaptation of Infrastructure Systems: Background Paper for the Global Commission on Adaptation. Oxford: Environmental Change Institute, University of Oxford. https://cdn.gca.org/assets/2019-12/GCA-Infrastructure-background-paperV11-refs_0.pdf.

[6] Koks, E.E., Rozenberg, J., Zorn, C., Tariverdi, M., Vousdoukas, M., Fraser, S.A., Hall, J.W., Hallegatte, S, (2019). A global multi-hazard risk analysis of road and railway infrastructure assets. *Nature Communications*, 10(1): 2677. DOI: 10.1038/s41467-019-10442-3.

boosted dependence on digital communications infrastructure. The pandemic has reinforced appreciation of the benefits of walking, cycling and green spaces. Infrastructure projects have been put on hold. Governments have had to step in to keep train operators and airports afloat because of the collapse in revenues from rail passengers and aviation. Funds from international financial institutions that were intended for infrastructure are being diverted to budgetary support to cope with the immediate fiscal shock. But as many governments embark upon vast investments in fiscal stimulus, infrastructure is back on the agenda. It is not yet clear whether infrastructure resilience in the face of multiple future threats will be factored into these investment packages. There are several versions of Green New Deals, with low-carbon infrastructure centre-stage[7,8], but there are also signs of an infrastructure construction splurge, fuelled by cheap money, in which sustainability goals are nowhere to be seen.

## 1.2 Disaster risk analytics for infrastructure systems

When natural disasters hit infrastructure systems, they can cause multiple forms of damage and disruption to societies and economies:

- **Direct damage**: Natural hazards directly damage infrastructure assets: floods wash away bridges, earthquakes physically damage structures, hurricanes blow trees onto powerlines. These physical assets were costly to create and are also costly to repair and replace. The costs of these damages fall upon utility owners and operators and often also on governments who carry an implicit contingent liability for the impacts of natural disasters.
- **Infrastructure service disruption**: If infrastructure assets are physically damaged the service they provide will be impacted and may be stopped altogether. Service disruption may also occur in the absence of physical damage: roads that are under water in a flood will be impassible but may be immediately usable once the flooding subsides. When infrastructure services are disrupted people and businesses will usually have to modify, delay or curtail their activities. Road haulers will have to use an alternative (longer) route. People and businesses will be without electricity, water, and/or telephone connectivity. There will therefore be interruptions to economic production.
- **Wider economic impacts**: The economic shock caused by loss of infrastructure services can propagate through economic networks nationally and indeed globally. If a business supplying parts to a manufacturing plant is unable to produce because they do not have an electricity supply, then the manufacturing plant could also be disrupted, depending on how much inventory it holds, even if it is not directly impacted by the disaster. These supply chain impacts may propagate around the world through interconnected global supply chains. Meanwhile, workers may be unable to travel to work. There may be shifts in patterns of demand while households delay expenditure or use their savings to rebuild their homes. Thus, there is a range of wider supply-side and demand-side effects that natural disasters can have, outside as well as within the footprint of the disaster.

Quantifying these impacts and, as far as possible geographically attributing them to infrastructure assets in the network, is fundamental to understanding and managing risks.

We can, in principle, learn a great deal from the observed impacts of past disasters. This teaches us about the potential scale of impacts from natural disasters, the ways in which those impacts have materialized and the time and effort it takes to recover. However, empirical evidence from

7 Hepburn, C., O'Callaghan, B., Stern, N., Stiglitz, J., Zenghelis. D. (2020). Will COVID-19 fiscal recovery packages accelerate or retard progress on climate change? *Oxford Reviews of Economic Policy*, graa015, https://doi.org/10.1093/oxrep/graa015

8 Vivid Economics (2020) Green Stimulus Index: An assessment of the orientation of COVID-19 stimulus in relation to climate change, biodiversity and other environmental impacts https://www.vivideconomics.com/wp-content/uploads/2020/08/200820-GreenStimulusIndex_web.pdf

past disasters is inevitably limited. Collecting data about the impacts of disasters is a challenge when the focus is upon emergency assistance and recovery. Disaster sites are often inaccessible. Where assets are insured, it can take years for claims to be settled and commercial insurers are often reluctant to share their claims data. Moreover, each disaster represents a unique combination of events, for which there is a countless number of counterfactuals – events that could have happened but didn't. Natural hazards (particularly those that are driven by climate change) and infrastructure exposure and vulnerability are changing, so events in the past are only partially relevant to understanding risks in the future. Thus, the (hopefully) small sample of natural disasters that have actually hit a country provides a valuable, but inevitably limited, impression of the risks to which it is exposed, and will be exposed in the future.

Therefore, the insurance industry and others interested in the quantification of risks from natural disasters have over the past three decades developed increasingly sophisticated models and datasets for quantified risk analysis (QRA). Model-based QRA combines probabilistic analysis of natural hazards with geospatial data on asset exposure and engineering knowledge of the vulnerability of these assets, should disaster strike. QRA can test many thousands of synthetic hazards events, with different severities and locations. It can trace the many possible combinations of the ways in which failure can occur and the impacts can propagate through infrastructure networks and supply chains. The analysis can be repeated with hazard event sets whose severity and frequency have been modified to represent the potential impacts of climate change. Asset exposure can be modified to include future infrastructure development and the effects of changing asset vulnerability an also be tested.

Analysis in the insurance industry has focused on the asset portfolios that insurers and reinsurers are liable for. By far the greatest exposure in the insurance industry to natural disasters is in the buildings and other fixed assets that they insure against natural perils. Thus, the focus of QRA within the insurance industry, using catastrophe (Cat) models, has been upon estimating the loss-probability distribution for a given geographically distributed portfolio of exposed assets. Insurers also provide business interruption cover, but a wide range of causes of business interruption tend to be covered, so the insurance industry has invested relatively little effort in quantifying the specific risks of infrastructure service disruption and supply chain interruption that are central to the analysis described in this report.

The growing demand for QRA of infrastructure systems derives from a range of motivations:

- **Risk-based asset management**: It has long been recognized that the optimal way of allocating resources for asset management (e.g. maintenance and rehabilitation of infrastructure networks) should balance operational and capital expenditures against the damage and disruption associated with asset failure. Though this is a well-known theoretical insight, in practice risk-based asset management has been thwarted by lack of data on asset condition and deterioration. Nonetheless, with the new possibilities in data and analytics that are described in this report, there are growing opportunities to achieve the elusive goal of risk-based asset management.
- **Adaptation to climate change**: Infrastructure systems are amongst the most significant assets that are exposed to the impacts of climate change, so they feature highly in climate risk assessments (see Table 1-1). Adapting infrastructure systems to cope with more extreme events that are expected in a changing climate is potentially costly and resources are scarce. It will always be more cost-effective to factor climate change into new infrastructure design and avoid costly retrofits. How much it is worth investing in adaptation depends upon the balance of the costs of adaptation and the benefits of risk reduction that are achieved from adaptation, alongside any co-benefits. QRA, in present and future climatic conditions, is therefore fundamental to infrastructure adaptation decisions.

- **Climate risk reporting and investment pricing**: Infrastructure is an important asset class for private investors, whilst sovereign investment banks and Multilateral Development Banks (MDBs) invest extensively in infrastructure. There are growing calls, for example through the Task Force on Climate-Related Financial Disclosure (FCFD), for more explicit reporting of physical climate risks. Physical climate risks need to be priced into infrastructure investments to enable more efficient capital allocation and incentives adaptation. MDBs need to demonstrate that their infrastructure investments are resilient to climate-related risks.
- **Supply chain risk analysis**: The possibilities for major disruptions to supply chains have been highlighted during the COVID-19 pandemic. Before that there had already been significant instances of supply chain disruption during natural hazards, most notably during the 2011 Thailand flood. Infrastructure networks are often critical in supply chain disruptions, but are an under-researched risk.
- **Disaster Risk Finance and Insurance**: As infrastructure systems are amongst the most exposed assets in natural disasters, and governments usually carry explicit and implicit liability for infrastructure damage and disruption, infrastructure networks are a focus for attention in risk quantification to inform DRFI decisions. The ways in which infrastructure network QRA can inform DRFI are discuss in more detail in Section 1.4.

**Table 1-1: Example of climate hazards to infrastructure sectors (Dawson et al. 2016)[9].**

| | Floods | Droughts | Heatwaves | (Wind) Storms | Geohazards (including subsidence and landslides) | Permafrost melt | Wildfires |
|---|---|---|---|---|---|---|---|
| **Water and waste water** | ✓✓ | ✓✓ | ✓ | | ✓ | | |
| **Transport** | ✓✓ | | ✓ | ✓✓ | ✓✓ | ✓✓ | ✓✓ |
| **Energy generation** | ✓✓ | ✓ | ✓ | ✓ | | ✓✓ | ✓ |
| **Energy distribution** | ✓✓ | | ✓ | ✓✓ | ✓ | ✓✓ | ✓✓ |
| **Flood and coastal defenses** | ✓✓ | | | ✓ | ✓ | | |
| **Solid waste** | ✓ | | ✓ | | | | ✓ |
| **Telecomm-unications** | ✓✓ | | ✓ | ✓✓ | ✓ | | ✓✓ |

**Notes:** A single tick denotes a relationship, a double click denotes a strong relationship. These do not consider interdependencies between infrastructures.

The framework for quantified analysis of natural disaster risk for infrastructure systems is described in detail in Chapter 2 of this report. In summary, disaster risk analysis for infrastructure systems (Figure 1-1) involves combining:

- Natural hazard information e.g., extreme precipitation or the wind speed of possible storms;
- The exposure of infrastructure assets i.e., whether they are located in places that could potentially be impacted by one or more climate hazards;
- The vulnerability of infrastructure assets. In this context, 'vulnerability' refers to the sensitivity of the asset to a hazard of given severity; for example, the depth of flooding an electricity substation can withstand before it ceases to function;
- The connectivity of infrastructure assets to each other to form networks, to other infrastructures to form systems-of-systems and to infrastructure users to deliver services[10];
- Quantified understanding of the ways in which the system might be operated and adapted during disasters: are there back-up facilities; can traffic be rerouted down other roads; how quickly can a damaged asset be brought back on-line;
- Socio-economic data on the use of infrastructure and the services being delivered. For example, how much freight passes through a port each day and how many people does a wastewater treatment plant serve; and
- Data on economic interdependencies which are needed to understand the potential for wider economic disruption, in particular through supply chains to businesses being disrupted, meaning that even though a production site is not directly impacted, it cannot obtain the supplies it needs, or provide customers with its service products.

[9] Dawson, R.J., Thompson, D., Johns, D., Gosling, S., Chapman, L., Darch, G., Watson, G., Powrie, W., Bell, S., Paulson, K., Hughes, P., and Wood, R. (2016) *UK Climate Change Risk Assessment Evidence Report: Chapter 4, Infrastructure*. Report prepared for the Adaptation Sub-Committee of the Committee on Climate Change, London.
[10] Thacker, S., Pant, R., Hall, J.W. (2017). System-of-systems formulation and disruption analysis for multi-scale critical national infrastructures. *In Reliability Engineering and Systems* Safety, 167: 30-41.

Each of these pieces of information can be mapped in order to calculate the economic impact of climate risks for a given scenario[11]. This type of analysis can also help to quantify social impacts e.g., how damaged road transport can affect accessibility of health and social services and facilitate benefit-cost and trade-off analyses for risk management[12,13].

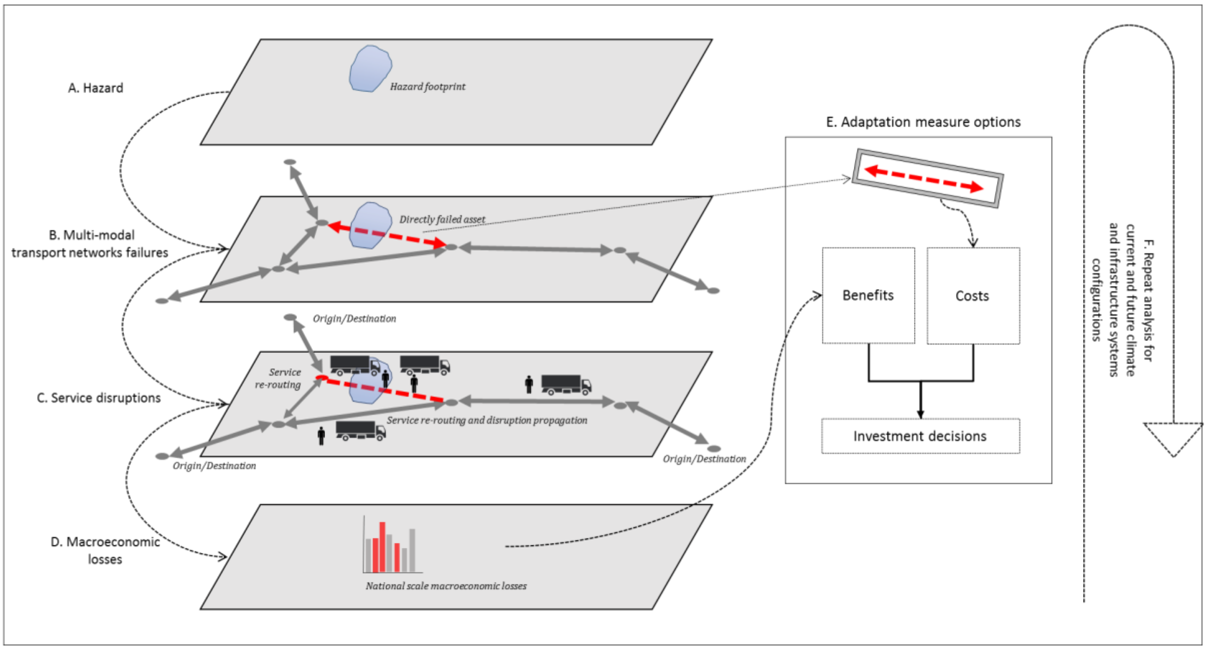



**Figure 1-1: Diagrammatic representation of climate hazards, infrastructure exposure, infrastructure service disruption and economic impacts**

Though the risk analysis framework outlined above in Figure 1-1 shows transport networks, it also applies to other network infrastructure like energy, telecommunications and piped water supplies and sewage systems where the principle of service redistributions is the same though the rules of service redistributions depend upon the operational rules of the specific infrastructure network. Some distributed infrastructures like tube wells for water supply or household/village scale renewable energy do not rely so strongly on physical networks, so can be analyzed as a set of independent point assets. Large water infrastructure, like dams, also operate as systems, but connectivity is provided via river networks and associated hydraulic infrastructure, so the approach to modelling and risk analysis involves explicit representation of the hydrology of river basins as well as the operation of hydraulic infrastructure.

QRA involves repeating many variants of the chain of events from a climate hazard materializing, impacting upon an infrastructure network, and then having wider economic impacts. Analysis of the full range of possible severities and locations of a hazard, particularly its spatial pattern, is required to estimate disaster risk. Whilst exhaustive testing of all combinations is not feasible, a thorough risk analysis will extensively sample plausible scenarios. Examining the statistical dependence between natural hazards in different locations, and between multiple different hazards will provide a more thorough understanding of the spatial and temporal trends of climate risks.

The risk from natural disasters is going to change in the future for a variety of reasons. A risk analysis provides a ‘snap-shot’ of risk that is conditional upon assumed climate and socio-

[11] Pant, R., Koks, E.E., Russell, T. and Hall, J.W. (2018). Transport Risks Analysis for The United Republic of Tanzania – Systemic vulnerability assessment of multi-modal transport networks. Final Report Draft, Oxford Infrastructure Analytics Ltd., Oxford, UK. Doi: 10.13140/RG.2.2.25497.26722.

[12] Oh, J.E., Espinet Alegre, X., Pant, R., Koks, E.E., Russell, T., Schoenmakers, R. and Hall, J.W. (2019). Addressing Climate Change in Transport: Volume 2: Pathway to Resilient Transport. World Bank, Washington DC. Doi: http://dx.doi.org/10.1596/32412.

[13] Pant, R., Koks, E.E., Paltan, H., Russell, T., & Hall, J.W. (2019). Argentina – Transport risk analysis. Final Report, Oxford Infrastructure Analytics Ltd., Oxford, UK.

economic exposure and vulnerability. The analysis can be repeated to demonstrate the effect of potential future changes, like sea level rise, which increases the risk of coastal flooding, or urbanization which can increase exposure to climate hazards. This will help decision-makers to understand how risks can evolve under different scenarios. Disaster risk reduction actions, such as strengthening infrastructure assets, and enable better planning of, for instance, urbanizing floodplains, or managing demand for water, which can be included in the risk analysis to test their effectiveness at reducing flood risk.

## 1.3 Financial protection of critical infrastructure

There is growing recognition of the financial implications of natural disasters, especially for governments[14]. When disasters strike, governments have to mobilise emergency services to assist people and restore services from damaged infrastructure assets. Repairing or replacing damaged infrastructure can take weeks, months or even years. In the meantime, people and businesses have to cope with reduced services and possibly increased costs. For people and businesses, especially in developing countries with limited alternatives/redundancies, the service itself may be cut off and people/businesses may have to cope with lack of services, rather than simply reduced services. Because of the economic disruption, governments will likely receive reduced tax revenues, at the same time as incurring increased costs. To cope financially, governments may reallocate budgets from other purposes, increase borrowing, impose increased taxation and/or look to international aid. These financial arrangements are disruptive, inhibiting development plans and potentially impacting a country's credit rating. Repeated shocks from natural disasters can be even more debilitating for a country's growth trajectory.

Interventions that can practically help to build disaster resilience of infrastructure systems include:

- Strengthening of infrastructure assets;
- Effective maintenance of assets, to limit their rate of deterioration and maintain their performance;
- Ensuring that new infrastructure is built to disaster-resistant standards;
- Building in redundancy (e.g. additional links in power and transport networks) so that services can be rerouted when disaster hits some assets;
- Investment in back-up facilities that can be mobilised in emergencies e.g. back-up generators;
- Building up capacity for emergency repair and recovery, which is often achieved by ensuring that routine maintenance teams are trained to deal with emergencies and can draw upon additional resources during emergencies;
- Pre-arranged contracts with firms in the private sector who can assist with repair;
- Increasing stocks in supply chains, so businesses are more able to cope with short-term disruptions.

These need to be embedded within legal, institutional and policy frameworks for protection. Moreover, all of these activities require financial resources, and some of them need financial resources to be mobilised and efficiently disbursed during disasters (Figure 1-2).

14 https://www.financialprotectionforum.org/sites/default/files/Financial%20Protection%20of%20Critical%20Infrastructure%20Services_March9_2021.pdf

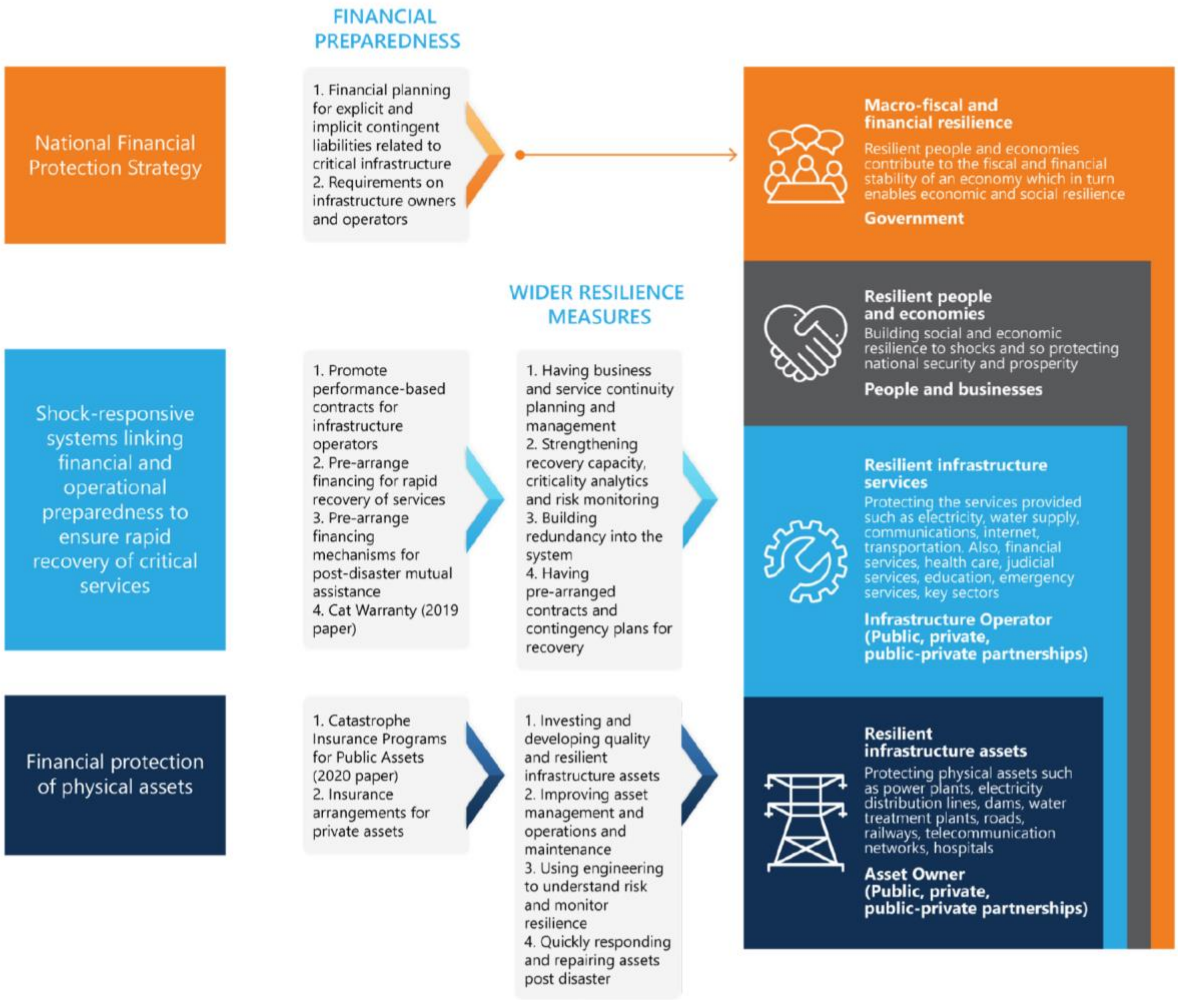



**Figure 1-2: Framework for physical, institutional and financial protection of critical infrastructure (World Bank, 2021)[14].**

The risks to government finances from natural disasters are often not fully understood or quantified. Governments will be liable for the repair of public assets, but there may also be implicit expectations that governments will assist with the repair of disaster-hit infrastructures that are owned or operated by the private sector or state-owned enterprises. There is typically an implicit expectation of government assistance to disaster-hit communities and businesses. There is growing recognition of the need to quantify these contingent liabilities so that governments are better prepared financially to manage the risk[14]. There is also increasing interest in the role that financial protection strategies can have in ensuring that governments are more resilient to the natural disasters.

Prudent public financial arrangements for managing the risks from natural disasters should include adequate allocations of revenue expenditure for infrastructure operation and maintenance. Line ministries may be allocated contingent budgets that can be drawn upon in a disaster, or there may be reserves funds that can be drawn upon in a disaster and rolled over from year to year.

International lenders (in the private sector and MDBs) can provide pre-arranged loans (contingent credit) that can be released when a disaster hits. Risk pools (like the South East Asia Disaster Risk Insurance Facility (SEADRIF)) or private markets can also provide risk transfer, including parametric insurance, which is triggered by a disaster of given magnitude or catastrophe bonds.

## 1.4 Objectives of this study

The objective[15] of this feasibility study is to *demonstrate how criticality analyses and vulnerability assessments for critical infrastructure systems can be used to inform financial risk management by governments*, including potential financial products, and present a prototype analytical platform for South-East (SE) Asian countries. The main questions that are answered through this study include:

- Whether and how criticality analyses and vulnerability assessments for critical infrastructure systems can be used to inform financial risk management by governments, and how these efforts can be scaled up nationally?
- What can be done and cannot be done with globally and publicly available data and methodologies developed to date?
- What are the challenges, opportunities and next steps for development of full-scale platform for SE Asia?
- Based on globally and publicly available data and methodologies developed to date, to what level of detail and accuracy could we quantify the cost of disaster and climate risks to infrastructure assets and systems, specific and relevant to each country?
- Based on globally and publicly available data and methodologies developed to date, to what level of detail and accuracy could we provide information needed to design structural and financial ex-ante and ex-post resilience measures, as well as the estimated benefits of these measures in safeguarding assets against climate and disaster risks, specific and relevant to each country or infrastructure investments?

To answer these questions, the study first outlines the general process of exploring and designing financial risk management options and solutions for critical infrastructure systems, and the various types of information and analysis needed at various stages of this process to assist governments decision-making (see Figure 1-6 and Table 1-2). Through this exercise key questions relevant to informing resilience decision-making at various stages of designing the DRFI solutions for critical infrastructure were identified, as described below:

1. What are the socioeconomic impacts of natural disasters to infrastructure due to damages and disruptions of assets and services?
2. How do we explore and prioritize infrastructure based on criticality?
3. How do we explore resilience measures for priority infrastructures, and the costs and mechanisms (who, when, how) to finance them?
4. How do we understand/assess/compare the economic benefit of the financial solutions?
5. How do we design DRFI solutions?

Through a review of existing data, methodology, and relevant analyses accessible for the target SE Asian countries, the study explores whether and how the five key questions above (numbered 1-5) relevant to informing resilience decision-making at various stages of designing the DRFI solutions can be analyzed and answered quickly and effectively. By doing so, the study aims to stock-take the current status and opportunities, as well as the limitations and gaps for criticality analyses and vulnerability assessments for critical infrastructure systems, especially to inform financial risk management solutions, and to explore whether and how fit-for-purpose DRFI analytics for critical infrastructure can be undertaken with less time, resources, and data inputs to meet the increasing demand for DRFI analytics for critical infrastructure.

[15] From the project's Terms of Reference, Email correspondence with the Client, and discussions during the project.

**We note that Questions 1 and 2 above are answered and demonstrated in this study and through the SE Asia platform and through the previous case-study on transport risks analysis done in Vietnam. The Vietnam case-study is also used to demonstrate resilience measures (Question 3) and how to understand/assess/compare the economic benefits of adaptation options (Questions 4). We do not explore or comment on the aspects of the mechanisms (who, when, how) to finance (Question 3), financial solutions (Question 4) and DRFI solutions (Question 5) anywhere through these studies. The key reason why some questions (1 and 2) are only answered through the SE Asia study and more questions are answered through the Vietnam specific study is the non-availability of appropriate data and models at the SE Asia scale for producing a solution with less time and resources. Table** 4-1 **explains in further detail how Questions 1 and 2 were answered in the SE Asia study and why others were not, and similarly Table** 5-1 **explains the how the Vietnam study outcomes provide answers to the Questions 1-4 and how they could be useful for Question 5.**

Allocating finance to infrastructure resilience (both preparedness and recovery) relies upon dependable risk analytics, which answers the questions 1-5 posed above. The infrastructure systems risk assessment problem is harder than the 'standard' natural hazard risks calculations by insurance industry cat models (even when they contain business interruption) because of the network effects of infrastructure system failure, which mean that wider economic impacts can have large multipliers on direct damages. Understanding infrastructure risks at the system scale, especially during the initial planning and design phase of infrastructure investment can help governments make more informed decisions on how to take cost-effective actions to safeguard their infrastructure investments against disaster and climate risks and put in place plans to ensure rapid recovery of critical services if disasters occur. However, limited data, time, and financial resources have been a barrier to conduct analysis detailed enough to provided sufficient information needed for decision-makers to plan effectively and integrate fit-for-purpose financial protection measures within their infrastructure investments.

This project, led by the Disaster Risk Financing and Insurance Program (DRFIP) of the World Bank with support from the Japan-World Bank Program for Mainstreaming DRM in Developing Countries, which is financed by the Government of Japan and managed by the Global Facility for Disaster Reduction and Recovery (GFDRR) through the Tokyo Disaster Risk Management Hub, aims to scope and develop prototype analyses and tools that can support governments to quantify and manage financial risks related to critical infrastructure disruption, and put in place the right financing arrangements to help speed recovery of services post-disaster. This tool will also inform the scoping of potential financial products to support governments manage the financial risks as part of the Southeast Asia Disaster Risk Insurance Facility (SEADRIF). SEADRIF is an initiative of the ASEAN+3 Finance Ministers and Central Bank Governors. In support of SEADRIF and its member countries, the World Bank is exploring whether and how SEADRIF could support countries to manage financial risks associated with public infrastructure.

The initial pilot phase of analysis and platform development presented in this feasibility study focuses on the Southeast Asia countries of Myanmar, Cambodia, Laos PDR, Indonesia, Philippines, Vietnam and Thailand, as shown in Figure 1-3. Within these countries we have developed the capability of analyzing the criticality and risks of infrastructure points assets and line assets in networks of power plants, electricity transmission lines, roads, railways, ports and airports, due to current and future climate change driven fluvial flooding, coastal flooding and cyclone hazards of different return periods (See Chapter 3 for hazard and infrastructure details). **In the platform we only present the criticality and vulnerability analysis results of line assets - electricity transmission lines, road links, railway links. We also present results in this report and within the platform of a previous study on transport risks analysis done**

**in Vietnam, whose network data is different from the wider SE Asia open-source data, which shows more detailed analysis on risk and adaptation assessment.**

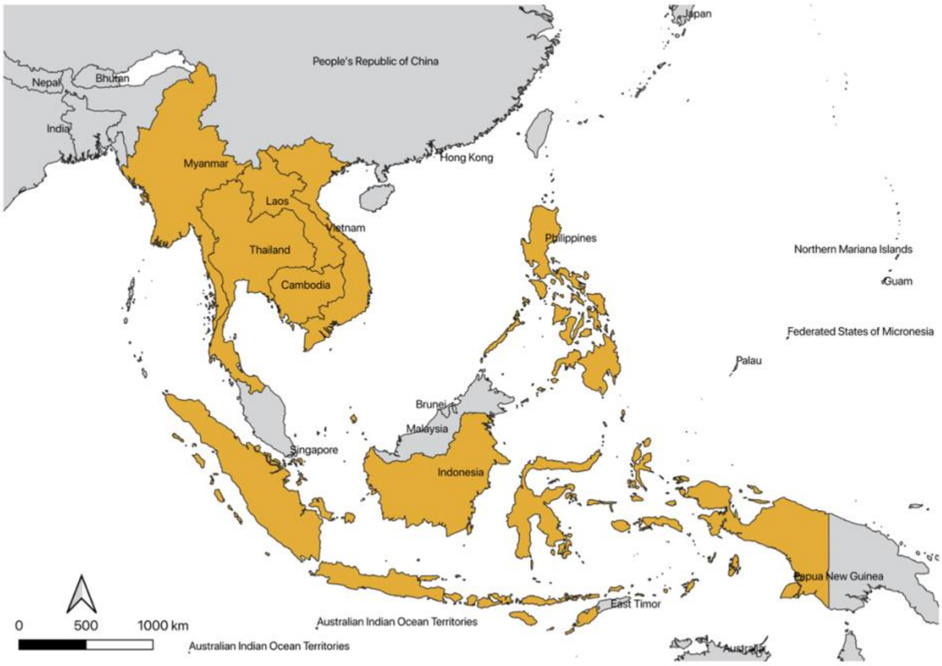



**Figure 1-3: Focus countries for the South East Asia infrastructure risk and climate investment feasibility study - highlighted in yellow.**

## 1.5 Infrastructure climate risk analytics for DRFI

Effective management of risks to public finances, and allocation of disaster risk finance, relies upon quantification of disaster risk. Quantifying disaster risk involves estimating losses at different exceedance probabilities, which are typically expressed as return periods. The losses also need to be expressed in relation to some time frame, typically annually, over which we can calculate statistics like the expected loss (Average Annual Loss (AAL)) and the probabilities of the loss exceeding some value (Figure 1-4).

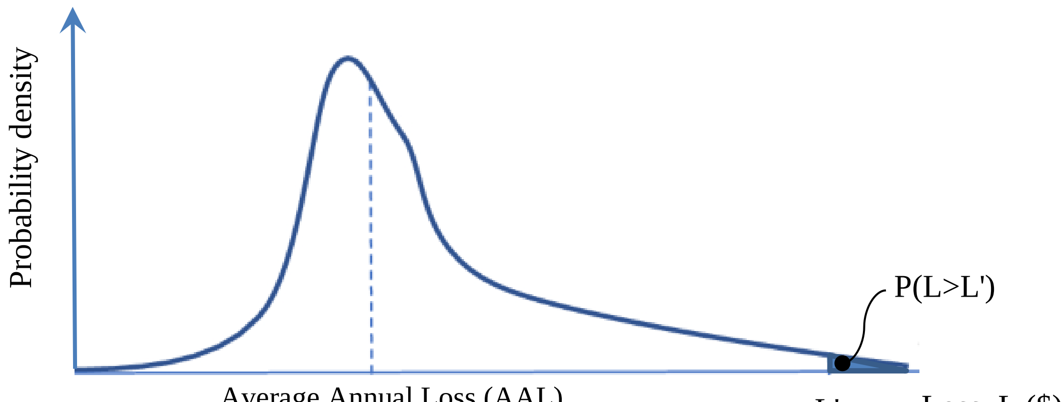



**Figure 1-4: Probability density function of disaster losses**

Different strategies will be adopted for different exceedance probabilities of losses (Figure 1-5). Infrastructure asset damage from fairly frequent events like storms and floods needs to be dealt from within regular operation and maintenance (O&M) budgets. Contingency budgets should be accessible to finance the costs to government from moderately severe disasters i.e., governments self-insure from their own budgets to cover these losses. However, the most damaging catastrophes could result in losses that are financially destabilising for governments, in which case they may wish to arrange contingent credit or insurance, through risk pools, international financial institutions or the private capital/insurance markets. Estimating the losses associated with each layer requires QRA. For example, the fair price for a *parametric insurance* that pays out when a disaster exceeds a given severity, is the expected annual loss from disasters that exceed that severity, plus some reasonable mark-up. The fair price for an *indemnity insurance* is calculated based on the expected losses that are covered by the policy, taking account of the deductibles and other exclusions.

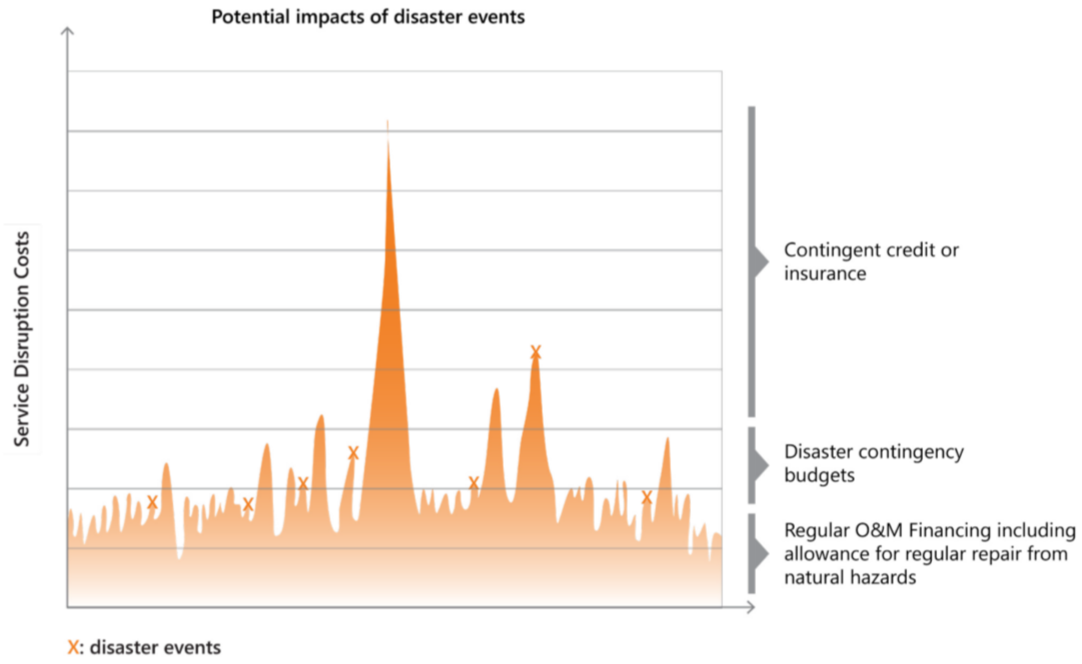



**Figure 1-5: Layering of disaster financial protections (World Bank, 2021)[14]**

As well as quantifying losses at different exceedance probabilities, QRA needs to scrutinise the ownership of risks i.e., who is liable for the losses.

- **National economic losses** are estimated by taking a national social accounting perspective, which seeks to estimate the overall economic loss, factoring out transfer between different actors within the scope of the national accounts. Estimates of the scale of national economic losses provide an overall picture of the economic risks to a country.
- **Government's financial liabilities** cover public assets and explicit or implicit liabilities for private losses. It also needs to incorporate the fiscal impacts of private losses for which the government is not liable, for example the impacts on tax revenues, employment and hence welfare payments. Fiscal risk assessments are needed for sovereign credit rating and macro-prudential regulation.
- **Financial liabilities for private actors and IFIs**: Private actors and IFIs need to assess the disaster risks to their portfolios of assets in a given country. This may include infrastructure investors who will need to quantify the risk of direct damage and loss of revenue from natural disasters. Insurers will need to quantify the loss-probability distribution for their liabilities in country in order to manage their capital allocation and reinsurance arrangements.

Each of these use cases of disaster risk analysis implies estimating the probability distribution of losses for different exposed portfolios. In addition, QRA provides the basis for decision making about measures that are intended to reduce risk, like maintenance, strengthening of assets or measures to speed up repair and reconstruction. To answer these risk management questions requires two further crucial pieces of information:

1. The cost of the intervention, which may be incurred over years in the future e.g., regular annual maintenance and periodic rehabilitation.

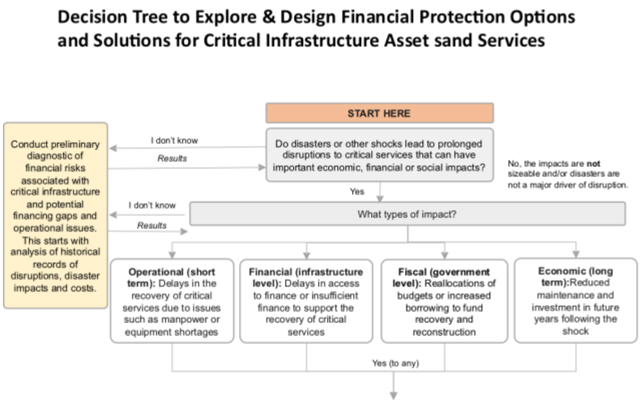
2. The residual risk associated with the asset or system once the intervention has been implemented. In other words, how effective is the intervention at reducing risk?

Given these two pieces of information alongside a baseline estimate of disaster risk and how it will change in the future, it is possible to estimate optimal investments in interventions like maintenance and upgrades. However, whilst straightforward in theory, these calculations are fraught with uncertainties due to limited data (e.g., on asset condition) and epistemic uncertainties (e.g., about rates of asset deterioration, and future climatic changes). Moreover, the optimal decision will be sensitive to the discount rate that is applied.

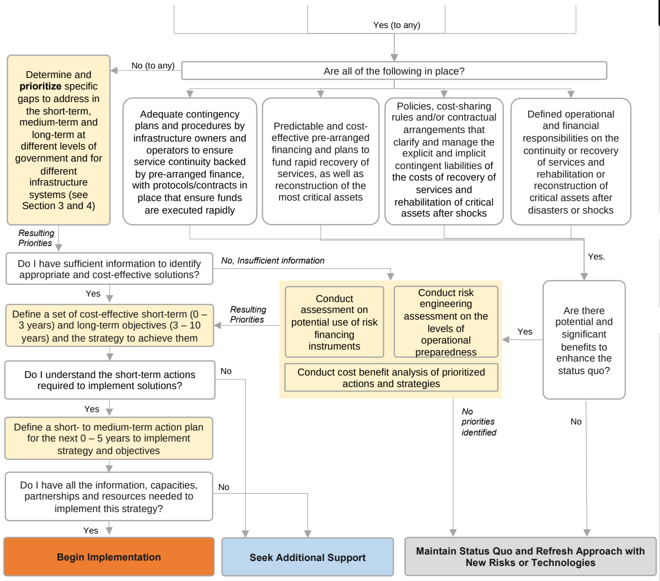
This study for SE Asia **does not** assess the costs of disaster risk management interventions or the benefits, in terms of risk reduction, of these interventions. A previous study on transport risks analysis in Vietnam answered these questions and has been included in this report and the platform tool developed in this project. This previous study done in Vietnam **does** demonstrate how crucial information that forms the basis for DRFI could be provided in SE Asia. The reason why the costs of disaster risk management interventions or the benefits were not assessed in the SE Asia analysis is simply to do with the unavailability of climate resilient design options and data at the global scale, which was created for the Vietnam specific study. This is data gap is pointed out in Table 4-1 for the SE Asia analysis and in Table 5-1 for the Vietnam study elaborates what kind of data was created to assess .

Figure 1-6 shows a decision-tree framework for creating a product of financial protection options and solutions for critical infrastructure assets and services. **The text shown in red in the figure indicates where and how the risk analytics being developed in this study fits into the broader decision-tree process**. This text is specific to the SE Asia analysis, where the focus is on open-data resources.

The decision-tree links to the five questions, relevant to DRFI, posed in Section 1.4, which is described in first column of Table 1-2. The second column of the table also shows the outcomes or metrics that are relevant in responding to DRFI decision-tree process. The third column of Table 1-2 explains which aspects of the decision-tree process are covered in the analysis done in this study, and the same information is presented in again in more detail when presenting the results of the SE platform tool (see Table 4-1) and the results of the Vietnam transport risk analysis case study (see Table 5-1).




| Analysis | Open data sources (facts/data) | Country data (may exist, not public) | Analytics and proxies |
|---|---|---|---|
| **Historic records of losses**<br>- Economic losses<br>- Insured losses<br>- Infrastructure failure | • EMDAT | • Disaster records<br>• Previous insurance claims | |
| **RELEVANCE TO TOOL** | ↓ | | |
| **Asset exposure**<br>**a) Basic Asset Fragility:** location, asset value, capacity, population served<br>**b) Detailed Asset Fragility:** other COPE characteristics<br>**c) Criticality:** % of total/regional capacity, GDP or population dependencies | • Georeferenced infrastructure assets (from open data sources)<br>• Asset fragility from generalised curves<br>• Economic representation (e.g. Capacity as percentage of total, GDP and Population data) | • Infrastructure inventory or registry<br>• Asset owners may have COPE characteristics | • Interconnectivity<br>• Network flows<br>Useful Functions:<br>• Layering of different infrastructure (together and separate)<br>• Heatmapping of higher criticality assets based on criteria |
| | ↓ | | |
| **Vulnerability**<br>• **Types of hazards:** current and future expected frequency and severity | • Climate hazard layers, current and future<br>**Impacts**<br>A – Damage costs<br>B – GDP loss<br>C = A+B | • Previous insurance claims<br>• Previous O&M costs<br>• Previous financial budget allocation to DRR<br>• Budgetary adjustments to future investments | **Functions:**<br>Estimation of A, B and C based on inputs, using proxies if needed.<br>**Useful Proxies:**<br>• Delay periods by infrastructure types and event severity, adjust by age.<br>• Economic impact of affected geographical location (GDP) |




| Analysis | Open data sources (facts/data) | Country data (may exist, not public) | Analytics |
|---|---|---|---|
| **Option analysis and cost-benefit assessment**<br>a. Increased structural resilience<br>b. Increased O&M spending<br>c. Improved pre-arrangements (contracts, plans, finance) | • Global information on generalised costs from previous projects<br>• Assumptions on investments as a percentage of asset value | Costings for different engineering options<br>**Inputs:**<br>O&M budget<br>Selected infrastructure | **Useful Proxies:**<br>a. Reduced damages under higher design standards (return periods)<br>b. Adjusted 'depreciation'<br>c. Reduced delay periods by infrastructure types and event severity |
| | ↓ | | |
| **Residual risks**<br>**Status quo vs. options** | | | Loss-probability curves before vs. after<br>AAL |
| | ↓ | | |
| **DRF options/ implications?**<br>• Asset indemnity<br>• Parametric for recovery<br>• Parametric for business interruption<br>• O&M funds | | | AAL / LP curves to show<br>• Asset indemnity: asset damage functions<br>• Parametric for recovery: short term direct impacts<br>• Parametric for business: short term direct impacts interruption<br>• O&M funds: % O&M to match specific outcomes |

**Figure 1-6: Decision-tree showing the process of integrating the risk and resilience analysis (shown in red text) within a broader framework for creating financial protection products for infrastructure and asset investments.**

**Table 1-2: Different DFRI outcomes that can be informed from this study.**

| Key DRFI Steps and Process | Types of Information Outputs Needed for DRFI | Scope as described in this study |
|---|---|---|
| **1. Understand the socioeconomic impacts of natural disasters to infrastructure due to damages and disruptions of assets and services** [Decision Tree - Asset exposure] | 1.1 **Probability of failure –** at asset scale<br>1.2 **Expected annual – damages, losses and totals (damages + losses) –** at asset scale<br>1.3 **Damage and Loss vs exceedance probability curves –** at aggregated spatial scales | **1.1** By intersecting hazards and assets and combining hazard probabilities with asset fragility functions. **See Chapter 3 for hazard probabilities (Section 3.1) and asset fragility functions (Section 3.2.3)**.<br>**1.2** By combining failure probabilities with generalised estimations of asset costs and GDP estimations assigned to assets. **See Chapter 2 for the formulation of expected risks (Section 2.3) and Chapter 3 for the data on costs (Section 3.2.2) and GDP (Section 3.2.4) assignment to assets.**<br>**1.3** By adding up asset direct damages and losses for different hazard probabilities at regional scales. **See Chapter 2 Section 2.3.3 for formulation of aggregated risks and Chapter 4 for results.** |
| **2. Explore and prioritize infrastructure based on criticality** [Decision Tree - Asset exposure] | 2.1 Classification of **criticality / priority** infrastructure – at asset scale<br>2.2 Classification of **aggregated criticality –** at spatial scales | **2.1** Identifying assets by their failure probabilities expected annual damages and losses. **See the platform tool (Chapter 4 and Chapter 5) for results.**<br>**2.2** Identifying and highlighting regions by their expected annual damages and losses. **See the platform tool (Chapter 4) for results.** |
| **3. Explore resilience measures for priority infrastructures, and the costs and mechanisms (who, when, how) to finance them** [Decision Tree - Vulnerability] | 3.1 **Cost of developing new resilient infrastructure** - Infrastructure costs (development, O&M) + additional costs for resilience<br>3.2 **Cost of resilience upgrade** (retrofitting) of infrastructure<br>3.3 **Response and recovery cost** (i.e., freight / power redistribution costs) due to service disruptions from natural hazards<br>3.4 **Reconstruction cost** due to asset damages from natural hazards | **3.1 Not considered in the study**<br>**3.2** Not included in the SE Asia analysis. **Considered in Vietnam study in Chapter 5 (Section 5.4)**.<br>**3.3** Not considered in SE Asia analysis. **Considered in Vietnam study in Chapter 5 (Section 5.3).**<br>**3.4** Reconstruction costs are **considered and listed in the SE Asia analysis in Chapter 3 (Table** 3-3). |
| **4. Understand / assess / compare the economic benefit of the financial solutions** [Decision Tree - Option analysis and cost-benefit assessment | **4.1 CBA of resilience measures for priority infrastructure** | **4.1** No CBA analysis is done for the SE Asia analysis, though **a methodology is described in Chapter 2 (Section 2.3.4) and** |

| | | |
|---|---|---|
| & Residual risks / Status quo and under options] | | **demonstrated for Vietnam in Chapter 5 (Section 5.4)**. |
| **5. Design DRFI solutions** [Decision Tree - DRF options] | 5.1 Total cost of asset indemnity insurance (informed by 3.4)<br>5.2 Total cost for parametric for recovery (informed by 3.3)<br>5.3 Total cost for parametric for business interruption; (informed by 3.3)<br>5.4 Total cost for O&M funds (informed by 3.1) | Beyond the scope of this report. |

# Chapter 2. Methodology with global datasets

The focus of this study is on infrastructure assets and networks of electricity, roads, railways, ports and airports in SE Asia. Here we develop the QRA methodology to analyse the risks to these infrastructures from fluvial flooding, coastal flooding and cyclone hazards. **We note that the methodology includes more steps than what have been implemented in the SE Asia analysis. The aim of presenting this methodology is to show the complete scope of the infrastructure risk and adaptation analysis**. The methodological framework created for this study is consistent with our spatial systems modelling approaches previously applied to United Kingdom (UK)[16] to inform infrastructure vulnerability and extreme hazard risk assessment at local[17], national[18] and global[6] scales. The general methodology for estimating risks of disaster impacts to critical infrastructures from global datasets is the same across infrastructure type and hazards, which is elaborated below.

## 2.1 Methodology framework

Figure 2-1 shows a coherent framework outlining the steps in undertaking a QRA and adaptation assessment of infrastructure networks. This framework can be applied to a probabilistic risk analysis approach with events sets (spatially coherent maps with different exceedance probabilities at different locations) or with static hazard layers (maps with no spatial coherence and same exceedance probabilities everywhere). The methodological steps in this system-of-systems framework for climate vulnerability, risk and adaptation assessment of infrastructure networks involve[19]:

1) **Hazards** – Climate hazard information that includes spatially correlated probabilities, magnitudes, and extents of hazard events under current and future climate scenarios – In this study this means collecting gridded static hazard layers with exceedance probabilities and intensities assigned at the grid scale. The grid sizes in global hazard datasets are variable – for example in global flood maps are the whole world is roughly divided in grids of roughly 1km$^2$ resolution. See Chapter 3 for the details on the grid sizes of the datasets used in this study.
2) **Networks –** Spatial representations of network point and line assets to create topologically connected networks with attributes necessary for failure, damage and disruption analysis – In this study this means collecting or inferring all locations information of point assets (ports, airports, railway stations, power plants) and geometries of line assets (roads, railway lines, electricity cables), inferring structural condition of assets (e.g. paved or unpaved roads), and associating fragility curves with different asset types, getting construction or rehabilitation costs of assets for quantifying direct damages, linking the assets to population and economic activities.
3) **Exposure** – Intersection of hazards with networks provides quantified estimates of the quantity and location of assets that are exposed to given hazards. These are not risk estimates, but they provide useful information for comparison across different geographies.
4) **Vulnerability** – Vulnerability relates to how sensitive an asset is to the hazard to which it is exposed. This involves finding the degree of damage (fraction or percentage of the asset

[16] Thacker, S., Pant, R., Hall, J.W. (2017). System-of-systems formulation and disruption analysis for multi-scale critical national infrastructures. *In Reliability Engineering and Systems* Safety, 167: 30-41.
[17] Pant, R., Thacker, S., Hall, J.W., Alderson, D. and Barr, S. (2016). Critical infrastructure impact assessment due to flood exposure. *Journal of Flood Risk Management*. DOI: 10.1111/jfr3.12288.
[18] Thacker, S., Barr, S., Pant, R., Hall, J. W. and Alderson, D. (2017). Geographical Hotspots of critical national infrastructure. *In Risk Analysis*, DOI: 10.1111/risa.12840.
[19] Pant, R., Russell, T., Zorn C., Oughton, E., and Hall, J.W. (2020). Resilience study research for NIC – Systems analysis of interdependent network vulnerabilities. Environmental Change Institute, Oxford University, UK. https://www.nic.org.uk/wp-content/uploads/Infrastructure-network-analysis.pdf.

that is damaged) to the asset based on its fragility curve with respect the given hazard intensity. This gives several values of the direct damage costs (*direct vulnerability*) to assets for different hazards of varying exceedance probabilities across current and future climate scenarios.

5) **Services –** Assigning service capacity and usage of network assets – For example the capacities and service demands of ports, airports, roads, railway lines in vehicles/day or tons/day, power plant capacities in MW, voltages of substations and transmission lines in KV, electricity demands during peak hours in Kwh. Network service mapping helps in estimating the knock-on effects of asset disruptions in terms of the amount of service capacity or usage that is lost and can be linked to socio-economic indicators discussed in the next step.

6) **Δ Service provision – Criticality –** Estimating the *indirect vulnerability* as the network failure effect (from network and service mapping in step 2 and step 3) associated with an individual failed asset – If more complete network flow assignment information were available (as would be created in step 2 and step 3), this step would involve flow rerouting assessments, which is not done in this study. Combining the direct and indirect vulnerability metrics and comparing them across all assets provides a more complete criticality assessment of the relative severity of impacts between different assets.

7) **Probability x Loss = Risk –** Estimating risks as the product of the hazard exceedance probabilities, and direct and indirect vulnerabilities summed over all possible hazard (climate or any shock event) and network failure and disruption scenarios– In this study the risk results are presented in terms of the direct damage vs exceedance probability curves, indirect losses vs exceedance probability curves, and total (direct + indirect) losses vs exceedance probability curves aggregated at the admin 1 levels, while at the individual asset level we estimate the expected annual damages, expected annual economic (indirect) losses and expected annual total risks.

8) **Socio-economics –** Socio-economic metrics of infrastructure service usage means associating the number of people and businesses using infrastructure services to larger economic activity at the macroeconomic scale using supply and use tables developed in national accounts – In this study we link the network services provided by individual assets to the population and GDP which is a macroeconomic indicator.

9) **Macroeconomic –** Estimating losses to industry supply chains that affect the macroeconomic industry outputs mapped in step 5 and 8 – In this study we skip this step, but we measure the economic losses in GDP/day associated with a failed network asset as a suitable proxy for measuring macroeconomic scale losses.

10) **Adaptation options –** Quantifying adaptation options in terms of their costs and benefits (as the value of avoided risks) and doing a cost-benefit analysis to prioritise assets – This step is not implemented in this study because of the lack of data on adaptation options. In Chapter 4 the analysis from a previous study in Vietnam is shown. In general, this step would include quantifiable options and cost for building resilience (to climate shocks) of individual assets and the networks that include, but are not limited to, upgrading existing design standards of assets to withstand more extreme shocks and speeding up the recovery of damaged assets to bring back the networks to normal levels of service. This would be followed by a cost-benefit analysis for prioritization of climate-proofing of assets (see Section 2.3.4).

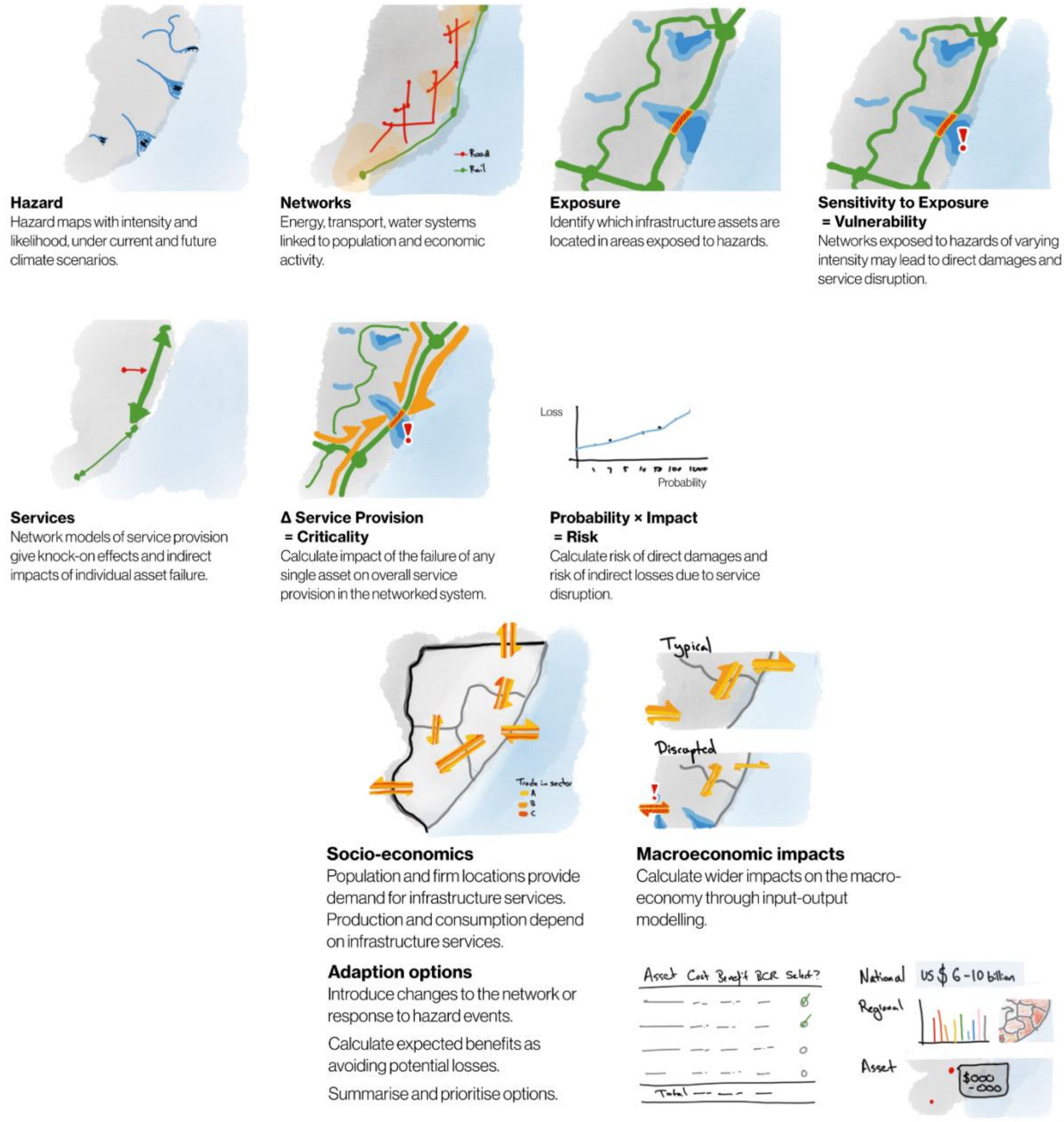



**Figure 2-1: Framework for risk and climate adaptation assessment of infrastructure networks applicable to SE Asia.**

## 2.2 Framework outcomes and links to DRFI

As noted in Section 1.4, the methodology framework developed for this study is implemented to create a platform focusing on the Southeast Asia countries of Myanmar, Cambodia, Laos PDR, Indonesia, Philippines, Vietnam and Thailand. This platform presents the criticality and vulnerability analysis for line assets – electricity transmission lines, road links, railway links – exposed to fluvial flooding, coastal flooding and cyclone hazards of different return periods under current and future climate scenarios over different time epochs (e.g., 2030, 2050, 2080) (See Chapter 3 for hazard and infrastructure datasets used in this study).

The main outputs from the implementation of the framework are presented in terms of the three metrics:

- **Probability of failure** – The total annual probability of failure of an asset when exposed to hazards of different exceedance probabilities (1/return periods). This is estimated by multiplying the asset fragility for a given hazard exceedance probability, and then summing over all the products of the fragilities and hazards exceedance probability for a given climate scenario and time epoch.

- **Expected annual damages (EAD)** – Estimated for an asset, this is the integral over the hazard exceedance probabilities and the corresponding direct damage value in US$ calculated with the asset fragility function and reconstruction cost associated with the asset.
- **Expected annual economic losses (EAEL)** – Estimated for an asset, this is the integral over the hazard exceedance probabilities and the corresponding GDP loss in US$/day associated with the failure of the asset.

**We note that these 3 metrics apply of an asset at any scale in the analysis**, by taking into account that there will be difference in the way each asset is exposed to hazards, has its own fragility function, costs, and GDP assigned to it. These details are covered in Chapter 3. For example, whether we are analysing an electricity transmission line or a road section in the end we will create the same 3 output metrics associated with each type of asset. Chapter 4 explains this further with some results.

**We also aggregate the asset level estimations of EAD and EAEL to the Admin 1 (Province) level in a country, by simply adding up the values**. Here again the process of aggregation is the same across every hazard and asset EAD and EAEL calculation. Also, we know the aggregated asset damages and GDP losses corresponding to each hazard exceedance probability, which allows us to create (damage or loss or damage + loss) vs exceedance probability curves at the Admin 1 level. See Chapter 4 explains this further with some results.

**Criticality assessment** simply involves ranking (or colouring on a map) the assets (or a region) in a network based on their relative risk metrics – EAD or EAEL or EAD+EAEL – to identify importance and disruptive impact on an asset or region at a wider (national) scale[20].

Linking the output metrics of the study to the DFRI questions posed in Section 1.4, Table 2-1 lists the output metrics, the process of estimating the metrics in the study and link with the DRFI decision-tree process shown in Table 1-2.

**Table 2-1: Outputs metrics and the process of estimating the metrics in the study.**

| Infrastructure | Spatial scales | Analysis (hazard type + combined) |
|---|---|---|
| All | • By asset<br>• Aggregated to Admin 1 level within country | Potential **socioeconomic impacts of natural disasters to infrastructure due to damages and disruptions of assets and services** [Decision Tree - Asset exposure]:<br>• Direct damages of assets:<br>▪ Hazard magnitude (flood depth or cyclone wind speed)<br>▪ Asset located in hazard area and exposed to hazard magnitudes (flood depth and wind speed)<br>▪ US$ asset damage based on direct damage fragility functions and costs<br>▪ EAD of asset by integrating over all hazard exceedance probabilities and asset damages<br>• Indirect losses of assets:<br>▪ GDP in US$/day assigned to assets is assumed to be lost<br>▪ Assume a duration of disruption and scale up GDP/day losses linearly by that duration of disruption<br>▪ EAEL of asset by integrating over all hazard exceedance probabilities and GDP loss associated with the asset<br>• Damages & economic losses at Admin 1 levels:<br>▪ Sum up asset level EAD and EAEL values |

[20] Arga Jafino, B. (2017). Measuring Freight Transport Network Criticality: A Case Study in Bangladesh. TU Delft.

| | | |
|---|---|---|
| | | **Explore and prioritize infrastructure based on criticality** [Decision Tree - Asset exposure] - **criticality/priority infrastructure** based on:<br>• EAD (by segment of line asset or by point asset or Admin 1 total)<br>• EAEL (by segment of line asset or by point asset within subnational boundaries or Admin 1 total)<br><br>**Response and recovery cost** due to service disruptions from natural hazards [Decision Tree - Vulnerability]:<br>• Understood in terms of durations of disruptions of GDP<br><br>**Reconstruction cost due to asset damages from natural hazards** [Decision Tree - Vulnerability]:<br>• Quantified in terms of the direct damage costs<br>• Values added up to admin 1 levels for different hazard return periods can inform how much is the scale of costs by each asset type and in total |

## 2.3 Formulation of risks and cost-benefit assessment with global datasets

| Symbol | Explanation |
|---|---|
| | All scalar variables are in lower- or upper-case *italics* |
| | All vectors or sets are in lower- or upper-case **bold** |
| $\mathbb{P}$ | Notation for probability |
| $d$ | Direct damage loss associated with an asset |
| $e$ | Indirect economic loss associated with an asset |
| $g$ | Probability density function of hazard intensities over space |
| $i$ | Index of an asset, which goes from $1, \ldots, n$ |
| $j$ | Index of a network failure state, which goes from $1, \ldots, 2^n - 1$ |
| $l$ | Loss associated with a network over several failure states for a given hazard event or return period |
| $m$ | Number of hazard maps of different exceedance probabilities |
| $n$ | Number of assets in a network |
| $p$ | Exceedance probability (1/return period) of a static hazard map layer |
| $r$ | Discounting rate in % used in the CBA analysis |
| $s$ | Asset state variable |
| $t$ | Time in years used in the CBA calculations |
| $T$ | Time-horizon in years used in the CBA calculations |
| $y$ | Index of time in years |
| $z$ | Loss associated with a network state |
| $Z$ | Random variable of loss associated with a network state |
| $BCR$ | Benefit-Cost ratio in CBA analysis |
| $Benefit$ | Net present value of benefit (avoided losses) in CBA analysis |
| $CI$ | Initial investment cost in CBA analysis |
| $Cost$ | Net present value of costs in CBA analysis |
| $CP$ | Period maintenance costs in the CBA calculations |
| $CR$ | Routine maintenance costs in the CBA calculations |
| $EAD$ | Expected annual damages for direct losses |
| $EAEL$ | Exceedance annual economic losses for indirect losses |
| $EP$ | Exceedance probability curve value |
| $\mu$ | Expected risk over different hazard probabilities and network failure states |

| | |
|---|---|
| $\tau$ | Duration of disruption in days assigned to an indirect economic loss |
| $\Delta GDP$ | Annual rate of change of GDP in % for the CBA analysis |
| $\mathbf{x}$ | Vector of spatial coordinates |
| $\mathbf{h}$ | Vector of hazard intensities over space |
| $\mathbf{h}_{tr}$ | Vector of threshold values for hazard intensities over space |
| $\boldsymbol{H}$ | Random vector for hazard intensities |
| $\mathbf{s}$ | Vector of a network states, which is the collection of individual asset states |

*Spatial risk* is estimated over a 2D surface area $\mathbf{x}$ when a continuous hazard load $\mathbf{h}(\mathbf{x}) \equiv \mathbf{h}$, sampled from a joint multi-variate probability density function $g_{\boldsymbol{H}}(\mathbf{h})$, introduces failures to infrastructure assets also spread over space. *Failure* here refers to the asset becoming physically damaged and ceasing to deliver its desired services, for example a bridge being washed away by flooding resulting in no traffic along the bridge. An individual infrastructure asset's failure state is represented by a binary state function $s_i = \{0,1\}$, where $s_i = 0$ means the asset has failed and $s_i = 1$ means no failure, though in principle this arrangement could be extended to a continuous [0,1] damage function that represents partial performance. Since infrastructure assets function collectively as a network, there are $2^n - 1$ possible failures states in a network of $n$ assets, with each failure state denoted as $\mathbf{s} = (s_1, \dots, s_n)$. Failure of an asset will entail some direct damage to the asset. Failure of one or more assets will also typically be associated with some additional losses due to the disruption of infrastructure services. The *loss* associated with the failure state $\mathbf{s}$ is quantified as $z(\mathbf{s})$.The conditional probability $\mathbb{P}[\mathbf{s}|\mathbf{h}]$ of the network being in the failure state $\mathbf{s}$ for a given hazard load $\mathbf{h}$ is also known as the *fragility*. The risk with respect to each network state is estimated from the spatial intersection of the hazard and asset locations.

$$\mu(\mathbf{s}) = \int_{\mathbf{h}} z(\mathbf{s}) \mathbb{P}[\mathbf{s}|\mathbf{h}] g_H(\mathbf{h}) d\mathbf{h} \qquad (1)$$

The total risk across all hazards and network failure states is estimated by summing over all possible failure states $\{\mathbf{s}_j, j = 1, \dots, 2^n - 1\}$ the product of the losses incurred $z(\mathbf{s}_j)$ across different failure states, the conditional probability $\mathbb{P}[\mathbf{s}_j|\mathbf{h}]$ of the network being in the failure state $\mathbf{s}_j$ for a given hazard load $\mathbf{h}$, and the hazard probability function $g_H(\mathbf{h})$.

$$\mu = \int_{\mathbf{h}} \left\{ \sum_{j=1}^{j=2^n-1} z(\mathbf{s}_j) \mathbb{P}[\mathbf{s}_j|\mathbf{h}] \right\} g_H(\mathbf{h}) d\mathbf{h} \qquad (2)$$

The above formulation of risk gives one expected score across several hazards and losses, thereby stripping away information of the uncertainty associated with losses associated with different event probabilities. This is captured through loss-probability distributions where the network losses $z(\mathbf{s}_j) \equiv z_j$ are calculated and the loss-probability curve is derived as an exceedance probability (EP) curve (see Figure 1-4), which shows the probability of the loss being above a certain value:

$$EP(z_j) = \mathbb{P}[Z > z_j] = 1 - \mathbb{P}[Z \le z_j] \qquad (3)$$

### 2.3.1 Risks estimation approaches based on different hazard datasets

Realistically at the global scales having hazard loads modelled from a continuous joint multi-variate probability density function has not been done. Such approaches have been applied in a very few national scale studies. Quinn et al. (2019)[21] estimated annual flood risks in the United States (US) by simulating 1,000 years of spatially realistic flooding comprising more

[21] Quinn, N., Bates, P. D., Neal, J., Smith, A., Wing, O., Sampson, C., et al. (2019). The spatial dependence of flood hazard and risk in the United States. Water Resources Research, 55, 1890–1911. https://doi.org/10.1029/2018WR024205.

than 63,000 individual events. Lamb et al. (2019)[22] estimated flood risks on the railway network in Great Britain due to railway bridge failures by simulating 43,000 flood events representing 10,000 years of flooding. The more traditional approach followed at global (and national and sub-national) scales has involved using static hazard exceedance probability layers where the hazard is assumed to occur everywhere over its spatial coverage simultaneously with the same exceedance probability (1/return period).

Figure 2-2 from Quinn et al. (2019)[21] shows on the left panel how risks are estimated from a series of static hazard layers for a region (a single basin in this case), by intersecting with asset data and fragility functions to estimate losses for each return period. Using the static hazard layers the integral of the loss-probability curve can be calculated as the Average Annual Loss (AAL). As no information is known relating to likely events and their spatial pattern it is impossible to know the range of losses one might experience over a given time period. The right panel simulates many thousands of individual synthetic flood events that have realistic spatial patterns. Event losses are then assigned to the years in which they occur to provide a distribution of annual (sum) losses. This distribution reveals the full annual loss-probability curve and, therefore, the likelihood of any given year exceeding a particular loss threshold.

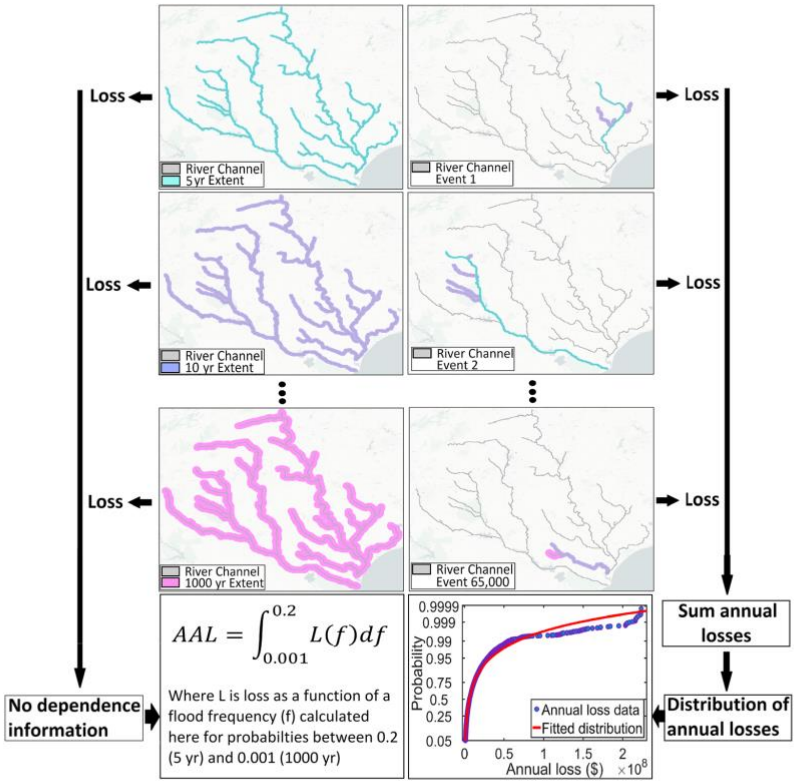



**Figure 2-2: A schematic visualisation of the difference in approaches of estimating flood risks using static hazard layers (left panel) and probabilistic event sets (right panel). AAL = Average Annual Loss. (source: Quinn et al. 2019[21]).**

**For the SE Asia region there are no spatially coherent event sets and only static hazard maps are available, which means we cannot build a full loss-probability distribution for infrastructure failures at any spatial scale. Hence, we use static hazard map layers in this study**. In Chapter 3 we discuss these datasets in greater detail. The static hazard layers are still useful for estimating risks, if the spatial scale is small (a few tens of kilometres) enough to

[22] Lamb, R., Garside, P., Pant, R. and Hall, J.W. (2019). A Probabilistic Model of the Economic Risk to Britain's Railway Network from Bridge Scour During Floods. *Risk Analysis*, *39*(11), pp.2457-2478. Doi: https://doi.org/10.1111/risa.13370.

justify that the return periods of the hazards will be the same over their entire spatial coverage. For example, at the Admin 1 level (i.e., province level boundaries) we can assume that cyclones or floods will occur everywhere with the same return period.

Each static hazard map is created for a given exceedance probability (1/return period) based on the hazard loading ($\mathbf{h}$) being above a certain threshold value ($\mathbf{h}_{tr}$). We generally have a discrete set of such static hazard maps denoted by their spatial loading $\mathbf{h}_k$ and exceedance probabilities $p_k \equiv EP(\mathbf{h}_k > \mathbf{h}_{tr}), \forall k = \{1, \dots, m\}$. For example, a 1/10-year cyclone map shows the spatial coverage of wind speeds that have a 10% probability of being exceeded every year. Each hazard map and the expected losses to the infrastructure networks exposed to them are quantified across all failure states and failure probabilities as $l_k = \sum_{\forall j} z(\mathbf{s}_j)\mathbb{P}[\mathbf{s}_j|\mathbf{h}_k]$. The risk for a discrete set of static hazards with increasing hazard exceedance probabilities $p_1, \dots, p_m$, and losses $l_1, \dots, l_m$ (in US$) is estimated, as the average annual losses, by summing the discrete loss-probability estimates using the trapezoidal summation as following:

$$\mu = \frac{1}{2}\sum_{k=1}^{m}(p_{k+1} - p_k)(l_k + l_{k+1}) \qquad (4)$$

We also plot a loss ($l_k$) vs hazard exceedance probability ($p_k$) curve with the above estimates.

### 2.3.2 Estimating network failures states for risk calculations

The network conditional probability of failure from given hazard loading $\mathbb{P}[\mathbf{s}|\mathbf{h}]$ depends upon the fragility of individual assets exposed to hazard loading at different network locations. In theory, $\mathbb{P}[\mathbf{s}|\mathbf{h}]$ shows that the network asset failures are not independent given that the hazard loading is spatially correlated over a geographic area. We might also have the possibility that the physical failure of one asset could depend upon the failure of another. For example, an electricity overhead line might be damaged by a cyclone and fall on an electricity substation and in turn cause the substation to blow up. Or more likely a bridge might have electricity cables and water pipes going underneath it and the destruction of this bridge by river flooding might wash away the electricity and water asset as well.

However, the fragilities of individual assets in a network can be assumed to be independent of each other, bearing in mind that fragility is simply the conditional probability of failure with respect to hazard loading. For example, a bridge being damaged by the currents of overflowing rivers depends upon the strength of the water currents and not whether another bridge failed somewhere else. Of course, one can argue that maybe there is a case where some asset upstream failed (e.g., a dam) and released a lot of water with force which damaged everything downstream. This should be reflected in the change in the hazard loading at different locations given a failure upstream or it can be accounted for in the assumption of failure states of the system under consideration. Doing the former is more complex because it means we need a dynamic hazard model (in this case a river routing model) that updates in real-time to reflect the cascading effects due to infrastructure failures. This is not possible when using static hazard maps or even when we have an extensive ensemble of event sets to be tested over large spatial areas. The latter case is a more feasible proposition, where we can assume certain failure states will happen and can quantify their probabilities and consequences. For example, if we had a hypothetical network connecting a dam and a bridge, and we know that if the dam fails then bridge fails as well. So, one of the network failure states is $\mathbf{s} = (s_{Dam} = 0, s_{Bridge} = 0)$, and the network fragility here would be estimated as $\mathbb{P}[\mathbf{s}|\mathbf{h}] = \mathbb{P}[s_{Dam} = 0|\mathbf{h}_{Dam}]\mathbb{P}\left[s_{Bridge} = 0\middle|\mathbf{h}_{Bridge}\right]$. In words it means the probability of the network being in the state $\mathbf{s}$ is the result of the dam failing and the bridge failing as well. We note that the $\mathbf{h}_{Dam}$ and $\mathbf{h}_{Bridge}$ show the hazard loading areas at the locations of dam and bridge respectively which are spatially correlated.

The above ideas can be generalized to any network fragility calculation, using a fault-tree method of estimating failure probabilities. The spatial intersection of a given hazard $\mathbf{h}_k$ with infrastructure assets $i = \{1, \dots, n\}$ over space results in hazard loading $\mathbf{h}_k = (\mathbf{h}_{i,k})$ and a failure state $\mathbf{s}$ whose fragility is measured as:

$$\mathbb{P}[\mathbf{s}|\mathbf{h}_k] = \prod_{\forall s_i=0} \mathbb{P}[s_i = 0|\mathbf{h}_{i,k}] \qquad (5)$$

From the above we can see that the contribution towards overall risk of higher states of failure – with several assets failing simultaneously – will start becoming very negligible because the product of individual fragilities will become quite small very quickly. Hence, sampling different failure combinations beyond a certain number of network failure states would not be very effective, while also being computationally expensive. Lamb et al. (2019)[22] looked at the *first-order failure states* by sampling and testing for only individual asset failures, which have the highest failure probabilities, and then tested a limited number of higher failure states based on those combinations of the single state failure state that results in largest losses.

At the SE Asia scale, where the number of assets in the national-scale network could be of the order of several thousand or even million (e.g., roads) estimating first-order failure states is only viable. Koks et al. (2019)[6] adopted this approach in their global scale analysis of transport network damages due to the multiple static hazards layers and reported the transport risks at the national scales by adding up the single asset risks. Similarly, transport risks analysis studies in Vietnam[23] and Argentina[24] adopted the same principle of assessing single assets (i.e., sections of roads) for failures and in this study at the SE Asia scale we will follow a similar approach where:

1. We test the failures of every single asset exposed to different hazard return periods and estimate their risks.
2. We estimate the risks at the national scale (or at sub-national scale) as the sum of the single asset risks.

The overall loss estimation in the risk calculation now becomes:

$$l_k \approx \sum_{\forall i} z(s_i = 0)\mathbb{P}[s_i = 0|\mathbf{h}_{i,k}] \qquad (6)$$

The aggregated risk then also is the sum of individual asset risks:

$$\mu = \frac{1}{2}\sum_{k=1}^{m}(p_{k+1} - p_k)\left(\sum_{\forall i} z(s_i = 0)\mathbb{P}[s_i = 0|\mathbf{h}_{i,k}] + \sum_{\forall i} z(s_i = 0)\mathbb{P}[s_i = 0|\mathbf{h}_{i,k+1}]\right)$$

$$= \frac{1}{2}\sum_{\forall i}\sum_{k=1}^{m}(p_{k+1} - p_k)(z(s_i = 0)\mathbb{P}[s_i = 0|\mathbf{h}_{i,k}] + z(s_i = 0)\mathbb{P}[s_i = 0|\mathbf{h}_{i,k+1}])$$

$$\mu = \sum_{\forall i} \mu_i \qquad (7)$$

### 2.3.3 Estimating network losses

We consider two types of losses associated with infrastructure failure, the *direct damages* and the *indirect economic losses*, which are also measures of *vulnerability*.

1. The direct damage to the physical infrastructure asset itself is quantified as the cost of reinstating or rehabilitating an asset to the state it was in before it was damaged. Ideally

[23] Oh, J.E., Espinet Alegre, X., Pant, R., Koks, E.E., Russell, T., Schoenmakers, R. and Hall, J.W. 2019. *Addressing Climate Change in Transport: Volume 2: Pathway to Resilient Transport*. World Bank, Washington DC, USA. doi: http://dx.doi.org/10.1596/32412.

[24] Pant, R., Koks, E.E., Paltan, H., Russell, T., and Hall, J.W. 2019. *Argentina – Transport risk analysis. Final Report*. Oxford Infrastructure Analytics Ltd., Oxford, UK.

detailed cost information of the damaged assets would be needed to quantify direct damages, some of which might come of insurance claims. But such information is not available openly for a global scale or SE Asia scale analysis. Instead, direct damages are estimated based on multiplying the fraction (or extent) of the asset damaged by some unit costs based on different asset types, which are then applied generally to the whole asset base of similar type. For example, rehabilitation costs of line assets (roads, railways) in US$/km of point assets (power plants, airports) in US$ is are generally derived from global project costs estimates. The fractions of asset damages are estimated from hazard-damage curves (e.g., flood-depth-damage curves) that are also derived from very generalised studies based on very little empirical evidence or expert opinion. The unit costs and hazard-damage curves considered in this study are described later in Chapter 3.

2. The indirect losses are estimated due to interruption of service to the customers (households, businesses, government) who depend upon the whole infrastructure network. The losses associated with network failure are the aggregate, over some appropriate disruption duration, of the difference between the welfare that would have accrued had the network continued to function and the welfare in the case when the network assets fail. We note that these losses are associate with total system state, whereas direct damages are summed over individual assets. In the case of indirect losses, we consider the consequences of failure (damage) to be determined by the overall functionality of the network. Determining indirect losses is broadly a two-step process:
    a. First, we need to estimate how the existing flows on the network are disrupted based on detailed understanding of supply and demand requirements at different locations of the network. In power networks the capacities of power plants in MW of power generated or in Gwh of energy produced has to be balanced by the energy demands in MW or Gwh at different substation locations serving different customers. In transport networks trip assignment models based on origin-destination information associated with passenger or freight travel patterns are needed to determine the volumes and costs associated with traffic along different routes. Following failures, these flow assignments have to be re-estimated based on rerouting or redistributing the resources to satisfy demand, though at an increased cost. Transport studies in Vietnam[23] and Argentina[24] adopted this approach by collecting data on origin-destinations at a zonal-level or asset level (where possible) from government agencies in the Ministries of Transport and creating trip assignment models for freight tonnages based on a cost function (in US$). The pre-failure flows and routes choices were determined by selecting the least cost routes across the whole network. In the post-failure state, the disrupted flows were rerouted along the remaining non-failed network to determine the new costs of transport. The overall network losses for each failure state was the difference between the post and pre-failure transport costs. We discuss the Vietnam study into more detail in Chapter 4.
    b. In cases where the infrastructure failures lead to complete cut-off of assets and services from the rest of the network, there are further indirect losses to the supply chain of commodities and industries that rely on goods and services being provided by the infrastructures. We model these losses at the macroeconomic level based on input-output (IO) impact assessment models. Explaining the details of an IO model are beyond the scope of this report, but in brief the main principle of the model is the determine an economic equilibrium where the industry sector outputs (supply) satisfy demands of other industry sectors, households, and government services. Following disruptions in supply or demand due to infrastructure failures, the IO model finds a new economic equilibrium where reduced supply meets reduced demand. The macroeconomic losses are then the difference between pre- and post-disruption economic outputs of the industry sectors. While IO based impact assessment models have been widely used in literature at aggregated regional

scales[25], linking the spatial network characteristics of the underlying infrastructure with an IO based approach is generally missed in most studies. There are now global datasets on multi-regional input-output tables (MRIO)[26] that have been used to estimate macroeconomic impacts of global trade flow disruptions due to Covid-19 based on very aggregated country-level assumptions[27]. But when validated with real-time data on global shipping during Covid-19 the results of the study were found to be overestimating global trade impacts on countries[28]. Our studies in Vietnam[23] and Argentina[24] have integrated transport freight flows disruptions and macroeconomic IO models, to provide a more realistic understanding of the scales of economic impacts within countries. Another study in Tanzania adopted a similar approach of integrating freight flow disruptions with IO models[29]. The results of this study were used in another study that integrated freight disruptions with firm-level survey data on post-disaster response in a hybrid agent-base-IO model to quantify macroeconomic losses over different durations of disruptions[30]. Apart from transport failures, Koks et al. (2019)[31] linked electricity substation failures to business disruptions (based on land-use data) and IO losses in UK, to produce realistic estimates of the multiplier effects on IO losses when factoring in infrastructure failures. All these studies are specific to the national context they were built for and generalising them to a SE Asia or global scale requires more research effort. Hence, **we do not include an IO modelling in this study**.

As we have explained above, there are several challenges in estimating direct damages and indirect losses using publicly available global datasets for SE Asia. While the direct damages can be estimated through some generalised cost and hazard-damage assumptions (discussed in Chapter 3) for indirect losses we use population and GDP measures as a proxy for quantifying economic disruptions and resulting macroeconomic losses (again discussed in Chapter 3).

We account for only first-order failures – failure of individual assets $i = \{1, \ldots, m\}$ – and estimate the direct damages ($d_{i,k}$) and indirect losses as the economic loss per unit time (per day) ($e_{i,k}$= GDP loss/day) associated with an asset that fails when intersected with different static hazard layers of increasing exceedance probabilities $p_1, \ldots, p_m$. We estimate the asset level risks as the Expected Annual Damages (EAD) and Expected Annual Economic Losses (EAEL) formulised as:

$$EAD_i = \frac{1}{2}\sum_{k=1}^{m}(p_{k+1} - p_k)\left(d_{i,k} + d_{i,k+1}\right) \quad (8)$$

$$EAEL_i = \frac{1}{2}\tau\sum_{k=1}^{m}(p_{k+1} - p_k)\left(e_{i,k} + e_{i,k+1}\right) \quad (9)$$

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25 Koks, E.E., Pant, R., Husby, T., Többen, J., and Oosterhaven, J. (2019). Multiregional disaster impact models: Recent advances and comparison of outcomes. In: Okuyama, Y. and Rose, A(eds.), *Advances in Spatial and Economic Modeling of Disaster Impacts* (pp. 191-218). Springer, Cham. doi: https://doi.org/10.1007/978-3-030-16237-5_8.

26 Lenzen, M., Moran, D., Kanemoto, K. and Geschke, A., 2013. Building Eora: a global multi-region input–output database at high country and sector resolution. *Economic Systems Research*, *25*(1), pp.20-49.

27 Guan, D., Wang, D., Hallegatte, S., Davis, S.J., Huo, J., Li, S., Bai, Y., Lei, T., Xue, Q., Coffman, D.M. and Cheng, D., 2020. Global supply-chain effects of COVID-19 control measures. *Nature human behaviour*, pp.1-11.

28 Verschuur, J., Koks, E.E. & Hall, J.W. Observed impacts of the COVID-19 pandemic on global trade. *Nat Hum Behav* (2021). https://doi.org/10.1038/s41562-021-01060-5.

29 Pant, R., Koks, E.E., Russell, T. and Hall, J.W. 2018. Transport Risks Analysis for The United Republic of Tanzania – Systemic vulnerability assessment of multi-modal transport networks. Final Report Draft, Oxford Infrastructure Analytics Ltd., Oxford, UK. doi: 10.13140/RG.2.2.25497.26722.

30 Colon, C., Hallegatte, S. and Rozenberg, J., 2020. Criticality analysis of a country's transport network via an agent-based supply chain model. *Nature Sustainability*, pp.1-7.

31 Koks, E.E., Pant, R., Thacker, S. and Hall, J.W. 2019b. Understanding business disruption and economic losses due to electricity failures and flooding. *International Journal of Disaster Risk Science*, *10*(4), pp.421-438.

We note here that the economic losses are multiplied by a constant $\tau$ for the time duration of disruption (in days). As noted, with static hazard layers we do not have any information on hazard event and disruption duration, so we have to assume such a linear scaling.

We also aggregate the EAD and EAEL estimate to the Admin 1 (province level) by adding the estimate for each asset, as shown in Equation (10) where $\mu$ is estimated by only summing the damages and losses associated with assets within the Admin 1 level. This links to the formulations of Equations (6)-(7) where the failure states of the system is estimated as the sum of all those states with only one asset failed and the rest not failed.

$$\mu = \sum_{\forall i} EAD_i + \sum_{\forall i} EAEL_i \qquad (10)$$

For each hazard layer we also estimate the total direct damages and indirect losses at the Admin 1 levels by summing up individual asset level damage and loss estimates. Hence, given hazard exceedance probabilities $p_1, \dots, p_m$ we get Admin 1 level direct damage losses $EAD_1, \dots, EAD_m$ and indirect economic losses $EAEL_1, \dots, EAEL_m$. We can generate the loss-probability curves from these values.

### 2.3.4 Linking risk estimations with cost-benefit analysis

The risk information (i.e., with infrastructure and the economy in its current state) is the starting point for all of the decision that this analysis inform, and links to some version of a cost-benefit analysis (CBA) for understanding the effectiveness of adaptation options. In such analysis the costs of an intervention are compared with the benefits that are measured as risk avoided i.e. baseline risk - residual risk remaining after the intervention.

**We note that we have not done and adaptation options assessment and CBA in the SE Asia prototype tool development, simply because we do not have the data and time to do such analysis. The discussion presented here links to the Step 9 of the framework Figure** 2-1 **and a previous case-study done in Vietnam. It also serves to show that it is possible to develop an adaptation CBA using our models and methods. We recognise that structuring DRF products requires more than the risk and cost information from the result of a CBA. For example, design of parametric insurance requires consideration of existing fiscal headroom in order to decide upon an appropriate trigger level and sum insured.**

The most challenging question in a CBA is:

> '*What is the risk reduction with respect to a certain level of adaptation investment being made?*'

Answering this would require more data on costs and residual risks related to:

1. Maintenance – which requires detailed information on the impacts of different maintenance practices on asset deterioration and reliability. From a risk calculation point of view the maintenance costs would shift the asset fragility curves (or hazard-damage curves) downwards.
2. Repair and recovery – which would require more information of alternative scenarios of the time to repair the asset and the costs associated with that repair. In the risk calculation this means reducing the days of disruption durations and hence indirect economic losses.
3. Strengthen and protect – which requires detailed information on the different strengthening and protection measures that could reduce the risks for certain levels of hazards. It could mean that asset would be upgraded or designed to a higher standard such that only hazards over a certain return period would cause failures, while there would be no failures below the design standard return period.
4. New assets and new resilient assets – which would require detailed information on locations of new construction projects and whether the new constructions would be built to existing

design standards or whether they would be built to better standards based on an understanding of current and future hazard exposures.

While some of the above issues could be tackled with scenario analysis, we regard obtaining realistic information as being a challenge. In our studies on building climate resilience of road sections and bridges in Vietnam[23] and Argentina[24] we considered the 'strength and protect' type of options that resulted in upgrading assets to very high standards that would completely eliminate all risks. In Vietnam[23] we collected data on construction costs and estimated some general prototype costs in US$/km of upgrading to climate resilient roads of different types (national roads, province roads) and terrains (mountain roads or coastal flat roads). Every road was then assigned the option and upgrading cost of the prototype design it most related to (see the Chapter 4 and report for more details). It is possible to use the same options and costs in a wider SE Asia analysis, assuming that roads in the region are built to similar standards. But due to the lack of any information of existing and new flood protection standards for roads in Vietnam this approach did not consider whether there were any residual risks > 0 before and after upgrading roads.

Within the hazard layer-based risk analysed we are conducting for SE Asia one would need general assumptions on existing protection standards of infrastructure assets and the costs to improve these assets to higher engineering standards/larger return periods. Koks et al. (2019)[6] applied this approach in their global scale analysis, by considering existing road assets were built to a certain flood protection (1/10 years or 1/50 years in their study) and an investment of 2% of asset values (by increasing flood barriers or widening drainage) would result in doubling the level of protection (i.e., 1/50-year protection would be upgraded to 1/100). For this study such generalised assumptions would be more applicable.

The effectiveness of different adaptation options is evaluated and compared through a cost-benefit analysis (CBA), which is a well-established technique to compare the costs of an option with its benefits[32]. The planning for an adaptation option is done on an annual time-scale $t_0, \ldots, t_T$, starting at the time $t_0$ when the adaptation option is implemented and continues over its planned time horizon $T$. Assuming $r$ is the rate for discounting costs and benefits over time in %, and $y$ is the index for the years over which the value of adaptation is evaluated, the effectiveness of this adaptation option is quantified in terms of the:

1. *Costs* – which includes the initial cost of investment ($CI_{t_0}$) of implementing the adaptation option at the start year $t_0$, and the costs of routine ($CR_{t_y}$) and periodic maintenance ($CP_{t_y}$) and routine) investments needed to maintain the adaptation option over the time horizon. The total net present value of the investment cost of the adaptation options over the project timeline is therefore given by Equation (11).

$$Cost = CI_{t_0} + \sum_{y=0}^{y=T} \frac{CR_{t_y} + CP_{t_y}}{\left(1 + \frac{r}{100}\right)^y} \qquad (11)$$

2. *Benefits* – which include the avoided losses, in terms of the direct damage risks (EAD) and the indirect economic risks (EAELs), were the adaptation option not implemented. Over time the EAELs are also assumed to grow (or decline) based on annual % GDP growth rates $\Delta GDP_j$ over the years. The total net present value of the benefits over the project timeline is therefore given by Equation (12).

$$Benefit = \sum_{y=0}^{y=T} \left( \frac{EAD_{t_y} + \left(1 + \frac{\Delta GDP_y}{100}\right)^y EAEL_{t_y}}{\left(1 + \frac{r}{100}\right)^y} \right) \qquad (12)$$

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[32] Pearce, D., Atkinson, G. and Mourato, S., 2006. *Cost-benefit analysis and the environment: recent developments*. Organisation for Economic Co-operation and development.

3. The *benefit-cost ratio* ($BCR$) of adaptation given as:

$$BCR = \frac{Benefit}{Cost} \qquad (13)$$

The above CBA analysis helps identify the effectiveness of adaptation options at the asset level, which can also be used to prioritise assets and locations for investments by either focusing on all assets with BCR≥1 or only targeting the few assets with the highest BCR. At the aggregated regional levels, we can use this analysis to estimate the total budget need for investing in climate adaptation for assets with BCR≥1.

Again, generalised cost assumptions are needed for doing CBA analysis. In Koks et al. (2019)[6] global roads analysis, periodic maintenance was assumed to be occurring yearly with a cost of 0.075% of the road value, and the routine maintenance was assumed to happen every 6 years with a cost of 5% of the road value. These assumptions were taken from several calibrations of the HDM4[33] model for various countries in which the World Bank recently invested in road projects. Primary roads were assumed to last 20 years, secondary roads 15 years and tertiary roads 6 years. Different discount rates were set based on income group classifications of countries – 12% for Low Income countries, 9% for lower middle-income countries, 6% for upper middle-income countries and 3% for high income countries. In this study we will consider similar assumptions for roads.

Based on the modelling assumptions taken in this study Table 2-2 shows how we can introduce sensitivity into different modelling parameters based on different types of changes in resilient critical infrastructure investment decisions and socio-economic development forecasts for the future.

**Table 2-2: Types of resilient critical infrastructure investments and their effect on the sensitivity of the risk/benefit model parameters considered in this study.**

| **Resilient critical infrastructure investment option** | **Risk/Benefit parameter sensitivity** |
|---|---|
| Speedy repair and recovery | Change duration of economic losses – $\tau$ |
| Maintain or strengthen the asset | Change the fragility of the asset - $\mathbb{P}[s_i = 0 \vert \mathbf{h}_{i,k}]$ |
| Protect the asset | Eliminate risks to certain return period events – $\mu_{p_{design} > p_i}$ |
| **Non-climate factors** | **Risk/Benefit parameter sensitivity** |
| GDP and population growth scenarios | Change in $\Delta GDP$ |
| Development of income groups | Change the discount rates – $r$ |

[33] Kerali, H.G., Odoki, J.B. and Stannard, E.E., 2000. Overview of HDM-4. *The highway development and management series, Volume one, World Road Association, PIARC. World Bank, Washington DC, USA.*

# Chapter 3. Creating SE Asia datasets for analytics

Here we highlight the different datasets collected and created and the type of analytics we will be performing in SE Asia. The infrastructure relevant information presented in this chapter covers roads, railways, ports, airports, ports, power plants, and electricity transmission lines.

## 3.1 Hazard datasets

The different open-source static hazard layer datasets, their relevant attributes, climate scenarios and limitations are explained in Table 3-1. In the flooding datasets the future flooding scenarios are modelled based on five Global Climate Models in the CMIP5 project – GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR, MIROC-ESM-CHEM, and NorESM1-M. Two future climate conditions are considered, based on the Representative Concentration Pathways (RCP) that provide a range of possible future for atmospheric conditions, as defined by the Intergovernmental Panel on Climate Change (IPCC)[34,35]: (1) RCP 4.5 – In simplistic terms this is a stabilizing scenario where global greenhouse gas emissions would peak by the 2040s and start declining for the rest of century resulting in the earth's radiative forcing[36] being stable at 4.5 Watts/m$^2$ by 2100 and global temperature increases of 1.7-3.2$^o$C from pre-industrial levels; and (2) RCP 8.5 – This is generally taken as a worst-case climate scenario where global greenhouse gas emissions would continue growing till 2100 and the earth's radiative forcing would reach 8.5 Watts/m$^2$ and global temperature would increase by 3.2-5.4$^o$C from pre-industrial levels. The modelling assumptions and details of these datasets are explained in Ward et al. (2017)[37] and Hofste et al. (2019)[38]. The tropical cyclonic wind hazard model uses information from 2,594 historical tropical cyclones, topography, terrain roughness, and bathymetry, and further details of the dataset are explained in Bloemendaal et al. (2020)[39] and Knapp et al. (2010)[40].

**Table 3-1: Description of open-source hazard datasets considered in the SE Asia analysis.**

| Hazard type (data source) | Probabilities | Intensities and spatial extents | Climate scenario information | Limitations |
|---|---|---|---|---|
| Fluvial (river) flooding (WRI aqueduct tool)<br><br>Coastal flooding with subsidence (median value) (WRI aqueduct tool) | 1/2, 1/5, 1/10, 1/25, 1/50, 1/100, 1/250, 1/500, and 1/1000 | Flood depths in meters over 30 arc second grid squares. | • 1 current + 5 future climate models<br>• RCP 4.5 & 8.5 emission scenarios<br>• Current + future maps in 2030, 2050, 2080 | • Static hazard layers<br>• Coarse resolution<br>• Based on global climate models rather than regional climate models<br>• Baseline created from only 30 years of flow records till 2010, so misses recent historical |

[34] Meinshausen, M., Smith, S.J., Calvin, K., Daniel, J.S., Kainuma, M.L., Lamarque, J.F., Matsumoto, K., Montzka, S.A., Raper, S.C., Riahi, K. and Thomson, A.G.J.M.V., 2011. The RCP greenhouse gas concentrations and their extensions from 1765 to 2300. *Climatic change*, *109*(1), pp.213-241.
[35] Riahi, K., Rao, S., Krey, V., Cho, C., Chirkov, V., Fischer, G., Kindermann, G., Nakicenovic, N. and Rafaj, P., 2011. RCP 8.5—A scenario of comparatively high greenhouse gas emissions. *Climatic change*, *109*(1), pp.33-57.
[36] Radiative forcing is the difference between the sunlight absorbed by the earth and the energy radiated back into space.
[37] Ward, P.J., Jongman, B., Aerts, J.C., Bates, P.D., Botzen, W.J., Loaiza, A.D., Hallegatte, S., Kind, J.M., Kwadijk, J., Scussolini, P. and Winsemius, H.C., 2017. A global framework for future costs and benefits of river-flood protection in urban areas. *Nature climate change*, *7*(9), pp.642-646.
[38] Hofste, R.W., Kuzma, S., Walker, S., Sutanudjaja, E.H., Bierkens, M.F., Kuijper, M.J., Sanchez, M.F., Van Beek, R., Wada, Y. and GALVIS, S., 2019. Aqueduct 3.0: Updated Decision-Relevant Global Water Risk Indicators. *Technical Note https://www. wri. org/publication/aqueduct-30 (World Resources Institute, 2019)*.
[39] Bloemendaal, N., de Moel, H., Muis, S. *et al.* Estimation of global tropical cyclone wind speed probabilities using the STORM dataset. *Sci Data* **7,** 377 (2020). https://doi.org/10.1038/s41597-020-00720-x.
[40] Knapp, K.R., Kruk, M.C., Levinson, D.H., Diamond, H.J. and Neumann, C.J., 2010. The international best track archive for climate stewardship (IBTrACS) unifying tropical cyclone data. *Bulletin of the American Meteorological Society*, *91*(3), pp.363-376.

| | | | | |
|---|---|---|---|---|
| | | | | flows are not accounted for and higher return period model estimates are very uncertain |
| Cyclones (STORM IBTrACS model) | 28 different probabilities from 1/10 to 1/10000 | 3-hour time step wind gust speeds in m/s at 0.1-degree grid squares. | None | • Static hazard layers<br>• Very coarse resolutions<br>• No climate scenarios<br>• Dataset created from historical records over 38 years, so higher return period model estimates are very uncertain |

## 3.2 Infrastructure sector asset information

The relevant infrastructure asset information for this study include:

1. *Physical and service attributes* – Location and connectivity information for individual point and line assets.
2. *Cost* – Rehabilitation or construction costs that can be assigned to each asset, based on some general principles.
3. *Fragility* – Failure or damage probability information that tells us about the percentage of damage an asset would sustain due to hazard exposures.
4. *Economic value* – Measures of usage that could be linked to the GDP dependent upon the asset.

### 3.2.1 Physical and service attributes

The physical and service attributes are described in Table 3-2 below. We have mostly taken existing open datasets and cleaned their features and geometries and merged different data sources together.

**Table 3-2: Description of the physical attribute information collected and derived from open data sources used in this study.**

| Assets (data source) | Physical and service attributes | Assumptions |
|---|---|---|
| Road links (OpenStreetMap + OSRM) | *Connected geometries* – **From data**<br>*Road class* – Motorway, Trunk, Primary, Secondary, Tertiary, Other – **From data**<br>*Paved condition* – Paved (Motorway, Trunk, Primary) and Unpaved (Secondary, Tertiary, Other) – **Our Assumption**<br>*Road speeds* – **From OSRM tool** (https://github.com/Project-OSRM/osrm-backend/blob/master/profiles/car.lua) | We assume that all Motorway, Trunk, and Primary roads in the OSM data are paved and all road classified into Secondary, Tertiary, and Other categories are unpaved. |
| Railway stations + Railways links (OpenStreetMap) | *Connected link geometries between stations* – **From data + our cleaning**<br>*Rail gauges* – Single gauge – **Our assumption** | We assume all rail lines are single gauge |
| Airports (Mao et al. 2015[41]; Bombelli et al. 2020[42]) | *Location* – **From data**<br>*Annual passengers* – **From data**<br>*Annual freight tons* – **From data + our cleaning** | The airport passengers are included in the dataset and represent estimated annual passenger flows for approximately 3500 airports globally. The airport annual freight estimates are derived from a dataset of air cargo lines[43] and the frequency of airport visits. This excludes freight included in normal passenger planes and is therefore a lower bound of air freight. |
| Ports (Verschuur et al. 2021[44]) | *Location* – **From data**<br>*Boundary area* – **From data**<br>*Annual freight tons* – **From data** | The port boundaries are manually mapped port areas (from satellite imagery), including all individual terminals. Only the 1400 largest ports globally are included in this dataset. Annual freight flows per port are estimated based on a trade downscaling |

[41] L. Mao, X. Wu, Z. Huang, A. J. Tatem, Modeling monthly flows of global air travel passengers: An open-access data resource. *J. Transp. Geogr.* **48**, 52–60 (2015).

[42] A. Bombelli, B. F. Santos, L. Tavasszy, Analysis of the air cargo transport network using a complex network theory perspective. *Transp. Res. Part E Logist. Transp. Rev.* **138**, 101959 (2020).

[43] https://data.4tu.nl/articles/dataset/Air_Cargo_Transport_Network_ACTN_Dataset/12694730.

[44] Verschuur, Koks and Hall (2021), Port's criticality in international trade and global supply-chains, Nature Communications, under review.

| | | |
|---|---|---|
| | | algorithm, as described in Verschuur et al. (2021). |
| Power plants (WRI global powerplants database) | *Location* – **From data + our cleaning**<br>*Usage* – Capacity (MW) – **From data** | |
| Electricity lines (Gridfinder) | *Connected link geometries* – **From data + our cleaning** | |

### 3.2.2 Costs

We have relied on very generalised asset costs information for global datasets, which are described in

Table 3-3. In some instances, we have assumed a ±25% uncertainty in our cost estimations in line with the assumptions from Koks et al. (2019).

**Table 3-3: Asset level rehabilitation/construction cost information used as a proxy for estimating direct damages. The costs are derived from global datasets and studies.**

| Asset | Rehabilitation = Construction Cost | Source | Assumption |
|---|---|---|---|
| Roads – Paved 4Lane | US$3,570,087 /km (±25%) | Koks et al. (2019)[6], World Bank ROCKS database[45] - Based on South Asia average costs | Apply to a motorways and trunk roads |
| Roads – Paved 2Lane | US$ 843,122 /km (±25%) | | Apply to all primary roads |
| Unpaved – Gravel | US$ 19,448 /km (±25%) | | Apply to all secondary and tertiary roads |
| Rail lines | US$ 3,750,000 /km (±25%) | | Apply to all railway lines |
| Electricity lines | Costs in US$/km. Depends upon country and income groups | World Bank PPI database[46]. See Table 3-4 for sample data. | Get the mean and standard deviation of costs based on income groups and apply to all electricity lines of similar income group country. Reconstruction costs are assumed to be 60% of construction costs. |
| Rail stations | - | - | No credible information on costs. Will not include in the loss estimation |
| Power plants | Costs in US$/MW. Based on country, income group, fuel type and capacity. | World Bank PPI database[46]. See Table 3-5 for sample data. | Get the mean and standard deviation of costs for each power plant in a country, fuel type, income group and capacity range. Match the GIS data with the cost data based on country, fuel type, capacity. If no match, then use value from another country with similar income group, fuel type and capacity. |
| Ports | US$ 400/m$^2$ | World Bank PPI database[46] + Expert input. Only construction of | This cost estimate is scaled from a more generalised cost estimate after finding that port construction per m2 is |

[45] World Bank, 2018. Road Costs Knowledge System (ROCKS) - Doing Business Update. World Bank, Washington DC.
[46] https://ppi.worldbank.org/en/ppi.

| | | | |
|---|---|---|---|
| | | Asian ports taken into account. | often less expensive in Asia. Damage values are confirmed by expert input. |
| Airports | US$ 600 million (Mean cost) | World Bank PPI database[46]. Only construction of Asian airports taken into account. | Assume this is average cost of an airport in SE Asia that handles average number of passengers in the region. The cost of an airport is then scaled up or down in proportion of the numbers of passengers it handles. |

For electricity transmission costs a sample of The World Bank PPI database are shown in Table 3-4. The costs are converted to 2021 values by assuming 3% inflation rate for the US$. Amongst the SE Asia countries only projects from Cambodia are included in the database. Hence, we assume costs of other countries based on similar income groups and apply them to other SE Asia countries.

**Table 3-4: Sample of data on electricity transmission projects and costs in US$/km extracted from World Bank PPI database[46].**

| Country | Income Group | Financial closure year | Subtype of PPI | USD/KM | USD/KM (2021) |
|---|---|---|---|---|---|
| Cambodia | Low income | 2007 | Build, operate, and transfer | 375,497 | 551,430 |
| Cambodia | Low income | 2010 | Build, operate, and transfer | 968,182 | 1,301,155 |
| Cambodia | Low income | 2018 | Build, operate, and transfer | 455,500 | 483,240 |
| Cambodia | Low income | 2020 | Not Available | 550,000 | 550,000 |
| Argentina | Upper middle income | 1997 | Merchant | 335,821 | 662,772 |
| Argentina | Upper middle income | 1998 | Build, own, and operate | 201,550 | 386,191 |
| Argentina | Upper middle income | 2000 | Build, own, and operate | 668,633 | 1,207,626 |
| Argentina | Upper middle income | 2004 | Build, own, and operate | 208,108 | 333,952 |
| Argentina | Upper middle income | 2006 | Build, operate, and transfer | 268,000 | 405,374 |
| Argentina | Upper middle income | 2006 | Build, operate, and transfer | 292,642 | 442,647 |
| Argentina | Upper middle income | 2006 | Build, operate, and transfer | 355,655 | 537,960 |
| Argentina | Upper middle income | 2006 | Build, operate, and transfer | 660,000 | 998,309 |
| Belize | Upper middle income | 2019 | Not Available | 826,923 | 851,731 |
| Bolivia | Lower middle income | 2005 | Build, own, and operate | 128,311 | 199,905 |
| Brazil | Upper middle income | 2000 | Build, own, and operate | 668,633 | 1,207,626 |

The electricity generation sample projects and costs for SE Asia extracted from the World Bank PPI database are shown in Table 3-5. The costs are converted to 2021 values by assuming 3% inflation rate for the US$. Projects from all SE Asia countries are in the database, so we use the values most applicable to the type of power generation and capacity as applicable to a given country. Where we do not have any costs for a particular fuel type, we look at similar capacity projects in other countries.

**Table 3-5: Sample of data on electricity generation projects and costs in US$/MW extracted from World Bank PPI database[46].**

| Country | Income Group | Financial closure year | Subtype of PPI | Technology | Capacity (MW) | USD/MW | USD/MW (2021) |
|---|---|---|---|---|---|---|---|
| Cambodia | Low income | 1997 | Build, own, and operate | Diesel | 60 | 1,366,667 | 2,697,235 |
| Cambodia | Low income | 1997 | Build, operate, and transfer | Diesel | 35 | 1,285,714 | 2,537,468 |
| Cambodia | Low income | 1999 | Build, operate, and transfer | Diesel | 15 | 666,667 | 1,240,196 |
| Cambodia | Low income | 1999 | Build, operate, and transfer | Diesel | 22 | 95,455 | 177,574 |
| Cambodia | Low income | 1999 | Build, own, and operate | Diesel | 15 | 400,000 | 744,118 |
| Cambodia | Low income | 1999 | Build, own, and operate | Diesel | 22 | 90,909 | 169,118 |
| Cambodia | Low income | 2001 | Build, operate, and transfer | Diesel | 20 | 400,000 | 701,402 |
| Cambodia | Low income | 2004 | Build, own, and operate | Diesel | 32 | 781,250 | 1,253,677 |
| Cambodia | Low income | 2005 | Build, own, and operate | Diesel | 15 | 1,666,667 | 2,596,612 |
| Cambodia | Low income | 2007 | Build, own, and operate | Biomass | 2 | 3,165,000 | 4,647,909 |
| Cambodia | Low income | 2007 | Build, operate, and transfer | Hydro, Large (>50MW) | 193 | 1,450,777 | 2,130,515 |
| Cambodia | Low income | 2007 | Build, operate, and transfer | Hydro, Large (>50MW) | 120 | 2,127,500 | 3,124,305 |
| Cambodia | Low income | 2010 | Build, operate, and transfer | Hydro, Large (>50MW) | 338 | 1,650,888 | 2,218,655 |
| Cambodia | Low income | 2010 | Build, operate, and transfer | Hydro, Large (>50MW) | 338 | 1,218,935 | 1,638,147 |
| Cambodia | Low income | 2010 | Build, operate, and transfer | Hydro, Large (>50MW) | 246 | 2,195,122 | 2,950,060 |
| Cambodia | Low income | 2017 | Build, own, and operate | Solar, PV | 10 | 1,250,000 | 1,365,909 |

### 3.2.3 Fragility

Creating conditional failure probability curves ($\mathbb{P}[\mathbf{s}|\mathbf{h}]$) for hazard failures is a very complex process. Instead, there are several studies that have created or adopted generalised curves for presenting percentages (or fractions) of direct damages vs hazard magnitudes. We adopt these hazard-damage curves in this study and use them in the calculation of direct damages and $EAD$ values. Figure 3-1 shows direct damage (fragility) curves for assets from different studies. Since having one fragility curve is not ideal for such a generalised context, Koks et al. (2019) suggested adding uncertainty to the fragility information and used five curves (derived from the original) to test the sensitivity of damage estimates to different fragility values. We suggest using a similar approach for the SE Asia scale analysis as well.

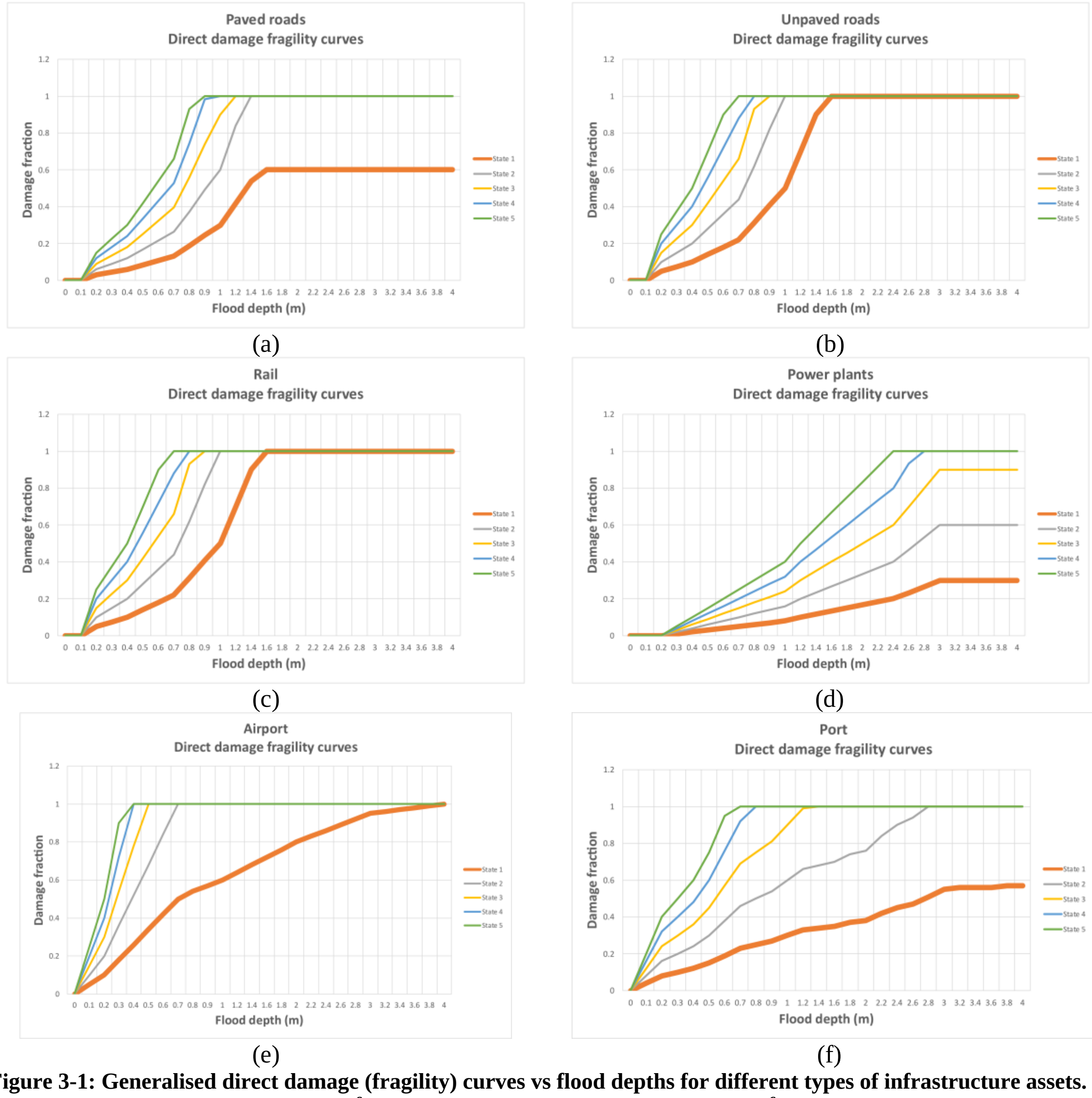


**Figure 3-1: Generalised direct damage (fragility) curves vs flood depths for different types of infrastructure assets. (a) paved roads (from Koks et al. 2019[6]); (b) unpaved road (from Koks et al. 2019[6]); (c) railway lines (from Koks et al. 2019[6]); and (d) power plants (from Miyamoto et al. 2019[47]); (e) airports (from Habermann and Hedel 2018[48]), (f) ports (based on expert judgment). The fragility curve for airports mainly represents flood damage to runways. The fragility curve for ports is based on expert input from a large port authority, details of which we cannot disclose. The boldest lines (State 1) are used in the original studies while the other curves (State 2 – State 5) are derived from the original curve by multiplying by 2, 3, 4, 5.**

[47] Miyamoto International, 2019. Overview of Engineering Options for Increasing Infrastructure Resilience (No. #7183546). The World Bank & GFDRR, Washington DC.

[48] Habermann, N. and Hedel, R. (2018) 'Damage functions for transport infrastructure', *International Journal of Disaster Resilience in the Built Environment*, 9(4–5), pp. 420–434. doi: 10.1108/IJDRBE-09-2017-0052.

Figure 3-2 shows a suite of fragility curves for extreme wind speeds, that have been used to quantify the risks arising from cyclones to linear assets of road sections, railway lines and power transmission lines. The fragility curves have been developed from first-principles, by considering the degree to which trees are understood to be damaged by wind-events as a function of extreme wind-speed, the percentage tree-cover (assumed to be ~31%, in-line with mean global tree-coverage[49]), and general exposure to wind (taken to be a function of the mean 10m wind speed at the location of the asset, proportional to the kinetic energy).

The cyclone fragility curves express the likelihood that any tree in the vicinity of an asset will be damaged as a function of wind-speed and local asset exposure, and that the resulting falling branches, limbs or trunk(s) will materially impact a local asset, causing damage.

The fragility curves have been tested against a simple published numerical model (The Forest Impact Model[50]) as well as recorded observations of tree-loss during hurricane and cyclone events.

The cyclone fragility curves are used in practice by identifying the mean 10m wind speed for each asset from in-country Global Wind Atlas data[51], and calculating an exposure level (EL) by comparing this speed to the global average of 3.28m/s: Thresholds have been developed that give upper and lower bands of exposure from EL1 (sheltered, <0.5(mean 10m wind speed)), EL2 (somewhat sheltered/less exposed , ≥0.5(mean 10m wind speed), < mean 10m wind speed), EL3 (global average exposure, = mean 10m wind speed), EL4 (more-exposed, ≥ mean 10m wind speed, < 2(mean 10m wind speed)) to EL5 (fully-exposed, > 2(mean 10m wind speed)). Once an EL curve has been assigned to an asset, the percentage tree cover is identified from Copernicus LandSat data[52,53], and this is used to scale the fragility curves to account for tree density relative to global mean tree-cover.

The likelihood of an asset failing by tree-fall during a cyclone event can then be extracted directly from the fragility curve for any given wind-speed. The curves have been applied to all infrastructure assets used in this study.

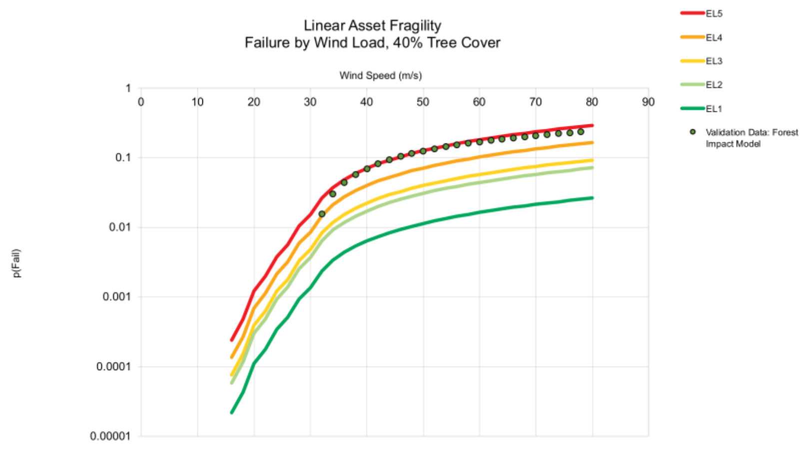


**Figure 3-2: Generalised damage probability (fragility) curves vs wind speeds for different types of assets.**

49 https://www.forestresearch.gov.uk/tools-and-resources/statistics/forestry-statistics/forestry-statistics-2018/international-forestry/forest-cover-international-comparisons/

50 Zeng, H., Chambers, J.Q., Negrón-Juárez, R.I., Hurtt, G.C., Baker, D.B. and Powell, M.D., 2009. Impacts of tropical cyclones on US forest tree mortality and carbon flux from 1851 to 2000. *Proceedings of the National Academy of Sciences*, *106*(19), pp.7888-7892.

51 https://globalwindatlas.info.

52 https://land.copernicus.eu/imagery-in-situ

53 Ottosen, T.B., Petch, G., Hanson, M. and Skjøth, C.A., 2020. Tree cover mapping based on Sentinel-2 images demonstrate high thematic accuracy in Europe. *International Journal of Applied Earth Observation and Geoinformation*, *84*, p.101947.

### 3.2.4 Economic value

The GDP assignment onto individual assets is needed for estimating the economic values attached to them. We propose initial thoughts on how this will be done. There are three steps to this process:

1. Assign some importance weightage to assets based on their usage statistics.
2. Take a GDP dataset and allocate it to infrastructure assets in proportion to the weights assigned to them.

For calculating GDP assignments two datasets were used across all networks, as shown in Table 3-6.

**Table 3-6: Description of population and GDP datasets applicable to the SE Asia study.**

| Data type (source) | Details | Comments |
|---|---|---|
| Grided Population Density/Count (WorldPop Population Data) | 30 arc second gridded resolution with population estimates for 2020 | The GDP estimates are downscaled to the population layer resolution. |
| Gridded GDP per capita (DRYAD Gridded GDP) | 5 degrees gridded resolution with GDP per capita estimates for 2015 | |

**We note that the GDP estimates from above two datasets are in annual values. We converted them to daily GDP estimates by simply dividing by 365.**

**In the demonstration of the platform, we have only estimated the GDP for the line assets of road links, railways lines and electricity transmission lines, which we explain below.**

***Road links***

- The aim was to assign a GDP associated with each road link in a country's road network.
- To estimate the GDP, we first estimated how much traffic (passenger and freight) could be allocated to a road link, which was not that straightforward due to the lack any open-source data resource on actual numbers of vehicles on roads.
- Instead, we used the Emissions Database for Global Atmospheric Research (EDGAR)[54] gridded pollutant dataset to infer the number of road journeys made per year. This dataset provided a global map of 0.1-degree by 0.1-degree grid of Nitrogen Oxide (NOx) emissions attributable to road transport.
- We mapped the roads in the study area onto the 0.1-degree by 0.1-degree grid of Nitrogen Oxide (NOx) emissions to obtain the total length of roads of all different classes (trunk, primary, secondary, etc.) has been calculated.
- For each country in the study region, the size of the passenger and commercial vehicle fleet was identified from the most recently available trade-industry data[55].
- Representative NOx emissions curves were identified[56] for three classes of generic passenger and commercial vehicle – "old", "medium" and "new" – that relate NOx production to vehicle speed. Each of the three classes were matched to an appropriate Euro emissions rating – Euro 6, Euro 4, Euro 2 respectively.
- A distribution of vehicles between the three age-classes was assumed for each of the World Bank income-groups[57] – High, Upper-middle, Lower-middle, Low. A distribution was chosen that yielded an average age of 11.4 years for High income countries, which is known to be consistent with the European average car age of ~11 years[58].
- For every road segment in the network, the total emissions of the entire fleet travelling the full length of the segment at the predicted speed-limit was calculated and weighted

[54] https://edgar.jrc.ec.europa.eu/dataset_ap50
[55] https://www.oica.net/category/vehicles-in-use/
[56] Updated Vehicle Emissions Curves for Use in the National Transport Model, Li et. Al (https://uk-air.defra.gov.uk/assets/documents/reports/cat07/aeat-env-r-0920.pdf)
[57] https://datatopics.worldbank.org/world-development-indicators/the-world-by-income-and-region.html
[58] https://www.acea.be/statistics/tag/category/average-vehicle-age

according to the relative attractiveness of the road[59]. These values were produced for every grid-cell in the EDGAR dataset covering the SEA region.

- The total number of vehicles using the road in any grid-cell have been estimated by scaling the fleet-emissions associated with the full complement of road segments in each grid-cell to match the total NOx output in the gridded EDGAR dataset.
- The total number of freight-km and passenger-km associated with both road and rail were identified for each country[60]: These totals were used to estimate the proportion of GDP flowing through the road network, and the proportion flowing through the railway network.
- The number of commercial vehicle-km that, together with the passenger vehicle km, reproduced the predicted EDGAR NOx emissions in each grid-cell were calculated and summed across the entire network. The total contribution to GDP of each commercial vehicle-km and passenger vehicle-km in the network was calculated and assigned to each road-segment in the road network, in each country, to account for 100% of the GDP transported by road within country.
- The total contribution to GDP associated with each road-link was stored as the final output.

***Rail Lines***

- The OpenStreetMap rail network was manually cleaned to ensure that only currently-functioning railway lines remain.
- The fraction of GDP associated with the rail network (as calculated for the road-transport assignment of GDP, above) was attributed to the cleaned linear assets within the network.
- It was assumed that per kilometre length of railway main-line would make an equal contribution to GDP, and that sidings, yards and spurs made a contribution that was 10% that of an equivalent length of main-line.
- The total number of passenger-km and freight-km were calculated by summing up the total weighted-length of all rail assets in each country, and the relative contributions of each asset in the network was calculated in proportion to its length and stored on each asset as total contribution to GDP based on the railway network.

***Electricity lines***

- For electricity lines, The Gridfinder data[61] provides information on “target” areas, which show the gridded locations predicted to be connected to the electricity grid.
- We take these target areas and intersect them with the population layers and the GDP per capita layers to assign the GDP associated with each target area.
- We combine the Gridfinder data with the power plants database connecting each power plant to its nearest transmission line, and create a network graph of nodes and edges, where the nodes are classified into: (1) *sources* – power plants; (2) *intermediates* – ends points of each transmission line segment; and (3) *sinks* – target areas.
- We then split the network graph into connected components, where each connected component shows the set of nodes and edges such that any two nodes can be reached from each other by travelled on the graph.
- Within each connected component we have a set of power plants and a set of target areas.
- Each target area ($a$) GDP in a connected graph is then split between the set of power plants ($\boldsymbol{p}(a) = \{p_1, \ldots, p_z\}$) connected to that area, in proportion to their capacities.
- The graph shortest route (least-distance) from target area ($a$) to each power plant ($p_l \in \boldsymbol{p}(a)$) over the transmission network is found and that GDP value is added to each of the lines along the route.

[59] https://github.com/Project-OSRM/osrm-backend/blob/master/profiles/car.lua
[60] https://data.worldbank.org
[61] Arderne, C., Zorn, C., Nicolas, C. and Koks, E.E., 2020. Predictive mapping of the global power system using open data. *Scientific data*, *7*(1), pp.1-12.

- The GDP value of a given transmission line is the sum of the shortest-path flows of GDP from each of the target areas (*sinks*) to each power plant (*sources*), in each connected component of the Gridfinder network.

# Chapter 4. Results from the prototype tool

The prototype tool developed in this project shows the results of the methodology and data creation explained throughout Chapter 2 and Chapter 3. The prototype tool is a web-based interface to visualise the outputs and is available at - https://tool.oi-analytics.com – with login and password access given only to people approved by the World Bank team.

In addition to the platform tool a Python analysis package hosted in GitHub is also provided, which is where the backend analytics is done. This GitHub resource is open-source and is available at - https://github.com/oi-analytics/seasia.

This Chapter presents the outcomes of the platform tool and shows how they link to the DRFI decision-tree process outlined in Table 1-2, which is shown in Table 4-1. **The readers, if given access to the prototype tool, can access these outputs in detail and see further explanations provided in the tool itself.**

**A key assumption in the results is that the total risks are estimated by adding up the risks due to each type of hazard, which means we are assuming hazard independence in our results.**

**Table 4-1: Different DFRI outcomes that can be informed from the SE Asia platform.**

| Key DRFI Steps and Process | Types of Information Outputs Needed for DRFI | Scope as described in this study |
|---|---|---|
| **1. Understand the socioeconomic impacts of natural disasters to infrastructure due to damages and disruptions of assets and services** [Decision Tree - Asset exposure] | 1.1 **Probability of failure –** at asset scale<br>1.2 **Expected annual – damages, losses and totals (damages + losses) –** at asset scale<br>1.3 **Damage and Loss vs exceedance probability curves –** at aggregated spatial scales | **1.1** By intersecting hazards and assets and combining hazard probabilities with asset fragility functions. **See Figure 4-1 for roads. Similar results are created for railways and electricity lines in the platform.**<br>**1.2** By combining failure probabilities with generalised estimations of asset costs and GDP estimations assigned to assets. **See Figure 4-1 for roads. Similar results are created for railways and electricity lines in the platform.**<br>**1.3** By adding up asset direct damages and losses for different hazard probabilities at regional scales. **See Figure 4-3.** |
| **2. Explore and prioritize infrastructure based on criticality** [Decision Tree - Asset exposure] | 2.1 Classification of **criticality / priority** infrastructure – at asset scale<br>2.2 Classification of **aggregated criticality –** at spatial scales | **2.1** Identifying assets of different colours by their **maximum total expected risks assuming a 30-day duration of disruption**. **See Figure 4-2 for roads. Similar results are created for railways and electricity lines in the platform.**<br>**2.2** Identifying and **highlighting regions by their expected annual damages and losses. See Figure 4-3.** |

| | | |
|---|---|---|
| **3. Explore resilience measures for priority infrastructures, and the costs and mechanisms (who, when, how) to finance them** [Decision Tree - Vulnerability] | 3.1 **Cost of developing new resilient infrastructure** - Infrastructure costs (development, O&M) + additional costs for resilience<br>3.2 **Cost of resilience upgrade** (retrofitting) of infrastructure<br>3.3 **Response and recovery cost** (i.e., freight / power redistribution costs) due to service disruptions from natural hazards<br>3.4 **Reconstruction cost** due to asset damages from natural hazards | **3.1** Not considered in the study due to lack of data on any new infrastructure developments.<br>**3.2** Not included in the SE Asia analysis because of the limited time of the study.<br>**3.3** Not considered in SE Asia analysis because of the limited time of the study.<br>**3.4 Direct damage calculations at the asset level are done in terms of reconstruction costs (Table 3-3) and the results are shown through Figure 4-1- Figure 4-3.** |
| **4. Understand / assess / compare the economic benefit of the financial solutions** [Decision Tree - Option analysis and cost-benefit assessment & Residual risks / Status quo and under options] | **4.1 CBA of resilience measures for priority infrastructure** | **4.1** No CBA analysis is done for the SE Asia analysis and in the platform because we did not have any data on resilience options and their costs. |
| **5. Design DRFI solutions** [Decision Tree - DRF options] | 5.1 Total cost of asset indemnity insurance (informed by 3.4)<br>5.2 Total cost for parametric for recovery (informed by 3.3)<br>5.3 Total cost for parametric for business interruption; (informed by 3.3)<br>5.4 Total cost for O&M funds (informed by 3.1) | Beyond the scope of this report, because this study is specifically looking at the criticality and vulnerability outcomes that inform DRFI solutions. |

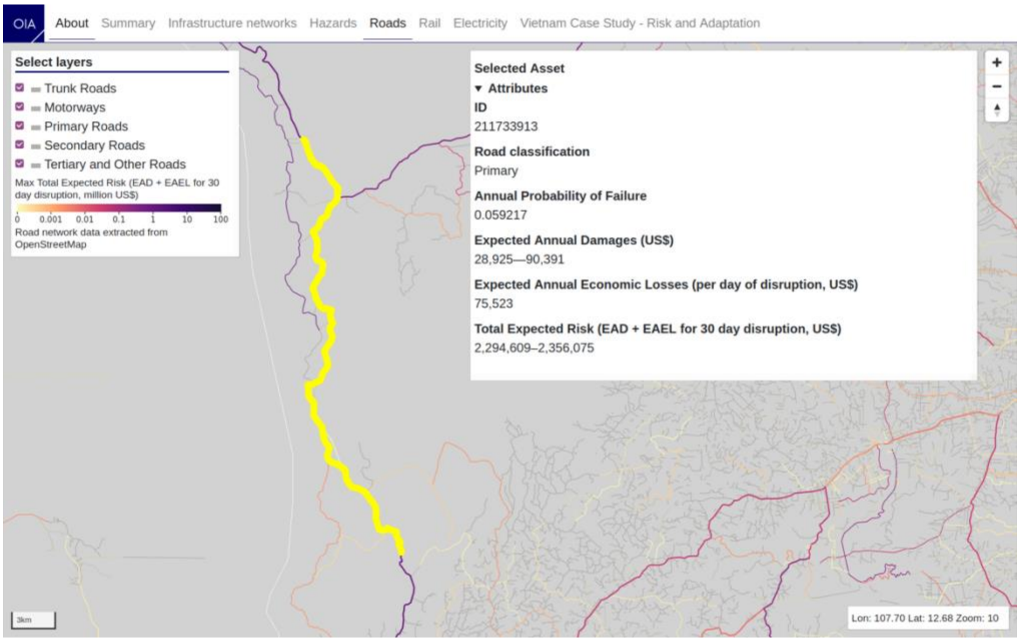


**Figure 4-1: Risk metric outputs of probability of failures, EAD, EAEL and total risk at the asset scale, for an example road section, as shown by the platform.**

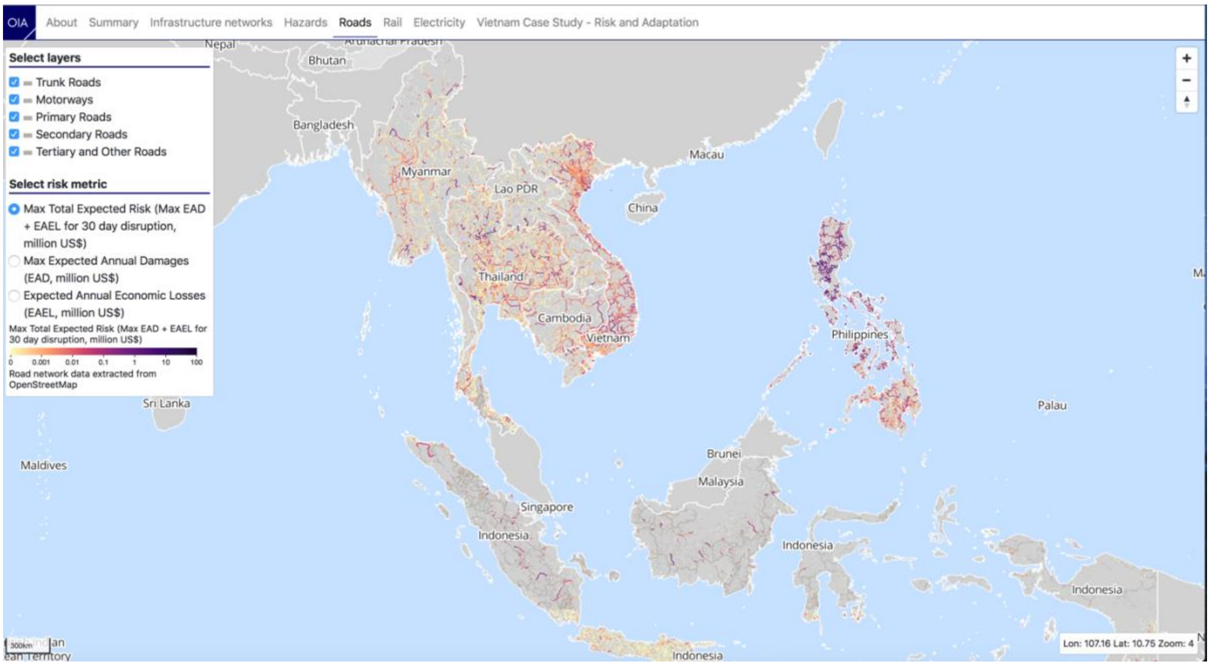


**Figure 4-2: Criticality map of road networks in SE Asia showing the different colours on critical roads based on their estimated maximum total expected risks assuming a 30-day duration of disruption.**

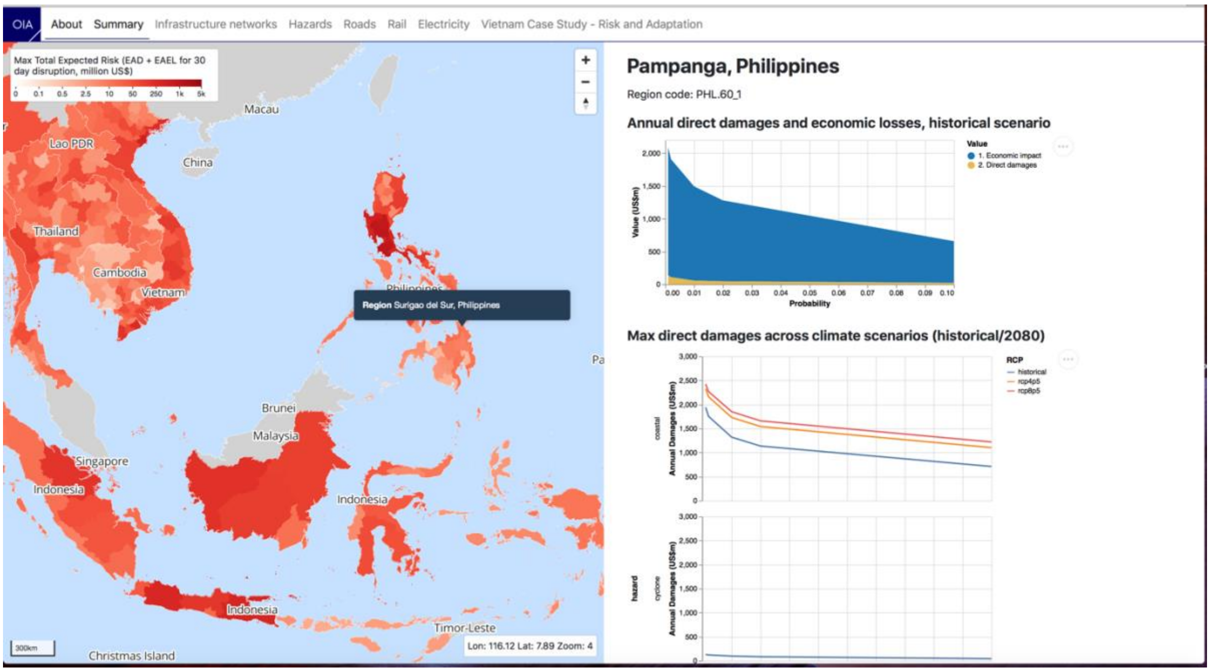


**Figure 4-3: Admin 1 (province) level criticality (choropleth) maps showing the magnitudes of maximum total expected risks for current (baseline) flooding (fluvial, coastal) and cyclone hazards assuming 30-day disruption durations. The darker colours show the regions with highest risks. Also shown on the right are the total damage vs exceedance and economic impact vs exceedance probability curves for a particular region (Pampanga) in Philippines. The hazard specific loss vs exceedance probability curves can be seen by scrolling further down.**

# Chapter 5. **Infrastructure resilience prioritization in Vietnam**

## 5.1 Overview of Vietnam study and links to DRFI

A previous study on multi-modal transport risk analysis (national roads, railways, ports, airports at one scale and province roads at another scale) done in Vietnam demonstrates the results and results that could be produced by following the framework outlined in Figure 2-1 and how this informs some of the questions asked in this study. *The main objective of the Vietnam study was to provide a methodological framework to analyse network criticality and vulnerability, and to prioritize investments to enhance resilience.*

The Vietnam study answers the following question posed in Section 1.5:

> Whether and how criticality analyses and vulnerability assessments for critical infrastructure systems can be used to inform financial risk management by governments, and how these efforts can be scaled up nationally?
>
> What are the socioeconomic impacts of natural disasters to infrastructure due to damages and disruptions of assets and services?
>
> How do we explore and prioritize infrastructure based on criticality?
>
> How do we explore resilience measures for priority infrastructures?
>
> How do we understand/assess/compare the economic benefit of the financial solutions?

Figure 5-1 shows a snapshot of the Vietnam study results included in the SE Asia platform, and Table 5-1 shows how the above question was answered by the study, by linking its scope and outputs to the different DRFI steps and process highlighted in the decision-tree process shown in Table 1-2.

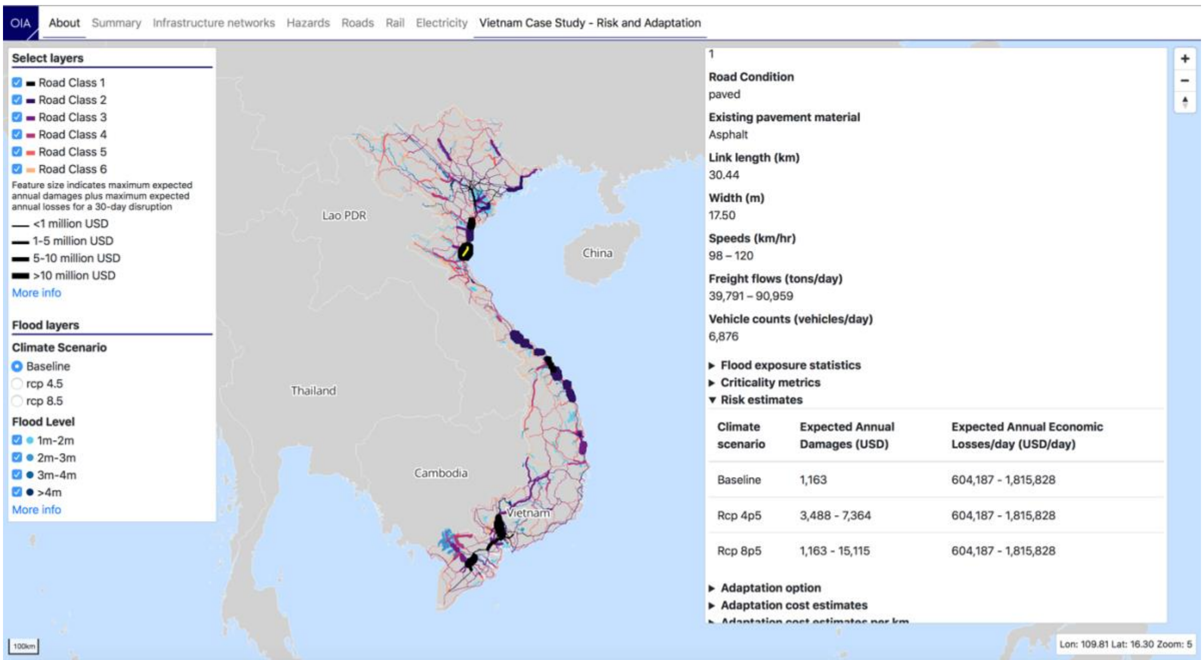


**Figure 5-1: Snapshot of Vietnam study outcomes in the risk platform.**

**Table 5-1: Different DFRI outcomes informed from the Vietnam study.**

| Key DRFI Steps and Process | Types of Information Outputs Needed for DRFI | Scope as described in this study |
|---|---|---|
| **1. Understand the socioeconomic impacts of natural disasters to infrastructure due to damages and disruptions of assets and services** [Decision Tree - Asset exposure] | 1.1 **Expected annual – damages, losses and totals –** at asset scale<br>1.2 **Loss vs exceedance probability curves** at national scale | 1.1 See Figure 5-2 results which show the EAD, EAEL, and total risks estimated for roads exposed to fluvial flooding.<br>1.2 See Figure **5-4** curves of national totals of direct, indirect and summed losses for different flood return periods. |
| **2. Explore and prioritize infrastructure based on criticality** [Decision Tree - Asset exposure] | 2.1 Classification of **criticality / priority** infrastructure – at asset scale<br>2.2 **Criticality** regions – at admin scale | 2.1 See Figure 5-2 which highlights the criticality of roads in terms of the EAD, EAEL, and total risks associated with them. From such analysis we were able to identify the roads in the country with the highest risks to be able to prioritize risk investments. |
| **3. Explore resilience measures for priority infrastructures, and the costs and mechanisms (who, when, how) to finance them** [Decision Tree - Vulnerability] | 3.1 **Cost of developing new resilient infrastructure** - Infrastructure costs (development, O&M) + additional costs for resilience<br>3.2 **Cost of resilience upgrade** (retrofitting) of infrastructure<br>3.3 **Response and recovery cost** (i.e. freight / power redistribution costs) due to service disruptions from natural hazards<br>3.4 **Reconstruction cost** due to asset damages from natural hazards | **3.1** – New infrastructure development were not considered in the study due to lack of any spatial information on new constructions. However additional cost of resilience for existing roads was quantified (see Table 5-4).<br>**3.2 –** The study considered the initial investment costs of resilience upgrades of roads (see Table 5-3 and Table 5-4).<br>**3.3 –** The response costs in terms of transport redistribution costs were estimated in the study and are included in the economic loss estimation result of Figure 5-2. The recovery costs were estimated by linearly scaling the economic losses/day by some assumed duration of disruption.<br>**3.4** – Reconstruction costs were considered and these were used in estimating the EADs shown in Figure 5-2. |
| **4. Understand / assess / compare the economic benefit of the financial solutions** [Decision Tree - Option analysis and cost-benefit assessment & Residual risks / Status quo and under options] | 4.1 CBA of resilience measures for priority infrastructure | 4.1 The CBA analysis of the study is explained in Section 4.4 and the CBA results are shown in Figure 5-3. The results mainly show the roads which were the priority infrastructure for resilience investments, based on the |

| | | |
|---|---|---|
| | | assumed costs shown in Table 5-3. |
| **5. Design DRFI solutions**<br>[Decision Tree - DRF options] | 5.1 Total cost of asset indemnity insurance (informed by 3.4)<br>5.2 Total cost for parametric for recovery (informed by 3.3)<br>5.3 Total cost for parametric for business interruption; (informed by 3.3)<br>5.4 Total cost for O&M funds (informed by 3.1) | These assessments were beyond the scope of the study. However, from the analysis we can get an estimate of the scale of investment needs.<br><br>The analysis suggested that, for some national-scale roads, upgrading to climate-resilient designs could cost up to US$3.4 million per kilometre—very high and comparable to costs of constructing high-standard new highways.<br><br>When the top 20 road links with highest maximum BCRs were selected, the analysis shows that cumulative climate adaptation investments amounted to approximately US$95 million initially, and over 35 years total approximately US$153 million. The cumulative benefits over 35 years of such investments—estimated by adding the benefits from individual links—were substantial, ranging between US$651 million and US$3.66 billion. |

## 5.2 Data assembled and resources for the study

Details of the study and the models are provided in the three resources below, and here we only summarise some results that informed disaster risk investments.

1. The detailed report is provided here - Oh, J.E., Espinet Alegre, X., Pant, R., Koks, E.E., Russell, T., Schoenmakers, R. and Hall, J.W. (2019). Addressing Climate Change in Transport: Volume 2: Pathway to Resilient Transport. World Bank, Washington DC. Doi: http://dx.doi.org/10.1596/32412.
2. All codes are provided here - https://github.com/oi-analytics/vietnam-transport
3. All background data requirements and backend analytics are explained here - https://vietnam-transport-risk-analysis.readthedocs.io/en/latest/

**Table 5-2: Description of all datasets collected, cleaned and integrated together for transport risk analysis study done in Vietnam (Oh et al. 2019[23]).**

| Dataset | Data scope | Source | Year |
|---|---|---|---|
| **Fluvial flooding** | National current and future with RCP 4.5 and 8.5 scenarios (*Older version of the dataset used in this study*) | GLOFRIS | 2016, 2030 |
| **Typhoon flooding** | 28 coastal provinces (*100m resolution with flood depth and probabilities*) | Ministry of Agriculture and Rural Development in Vietnam | 2016 |
| **Landslide susceptibility** | 8 Central provinces (*30m gridded resolution with qualitative values (3- high, 4/5- very high) of hazard, RCP 4.5 and 8.5* ) | Ministry of Natural Resources and Environment in Vietnam | 2016, 2025, 2050 |
| **Flash flood susceptibility** | 15 Northern provinces (*30m gridded resolution with qualitative values (3- high, 4/5- very high) of hazard, RCP 4.5 and 8.5 scenarios*) | Ministry of Agriculture and Rural Development in Vietnam | 2016, 2025, 2050 |
| **Administrative boundary and statistics** | Commune, district and province levels | General Statistics Office of Vietnam, World Health Organisation | 2016 |
| **Economic input-output data** | National scale (*Input-Output accounts of167 industries, converted to multi-regional tables to show trade between 63 provinces*) | General Statistics Office of Vietnam | 2012 |
| **National roads** | National (*Name, Class, Surface type, Terrain, Width, Speeds, Geometries, Connectivity*) | Transport and Strategy Development Institute, Vietnam | 2018 |
| **Origin-Destination (OD) flows** | Inter-province ODs for 13 commodities for each transport mode | VITRANSS II[62] | 2009 |
| | Crop production locations at 1km gridded resolution for 10 crops | International Food Policy Research Institute | 2016 |
| **Transport Costs** | National (*Vehicle operating costs, Commodity tariffs*) | VITRANSS II[62] reports (projected to 2016 values) | 2009–2016 |
| **Damage and Adaptation costs** | Roads (*Costs in US$/km*) | Our team, Ministry of Transport data | 2018 |

[62] Ministry of Transport (MoT). (2000). The Study On The National Transport Development Strategy In The Socialist Republic Of Vietnam (VITRANSS): Technical Report No. 3 Transport Cost And Pricing In Vietnam. Japan International Cooperation Agency (JICA), Ministry of Transport, Socialist Republic of Vietnam (MoT), Transport Development and Strategy Institute (TDSI), Vietnam.

## 5.3 Direct and indirect risk calculations and criticalities

Using the datasets described in Table 5-2 we were able to estimate the *direct (EAD) and indirect (EAEL)* risks at the level of each individual road segment that was exposed to different hazards. We note that there were two limitations in this analysis: (1) Not all hazard information was probabilistic; (2) We did not have any fragility information on roads in the country so, following consultations with country experts, we assumed assets exposed to hazard only failed if the hazard was above a certain threshold – for example, only those roads exposed to ≥ 1-meter flooding were considered to have failed. The process of estimating the risks *for probabilistic fluvial flooding hazards*, in line with the Figure 2-1 framework, is summarised below:

1. Intersect static hazard layers with the network to identify all roads exposed to flooding.
2. Assume roads exposed to ≥ 1-meter flood depth are damaged.
3. Estimate the lengths of all damaged road segments at each flood probability, climate model and scenario.
4. Combine damaged lengths with the rehabilitation/construction cost information of the roads.
5. Apply EAD calculation of Equation (8) to get *direct risks* in US$ *for each road segment*.
6. From a least-cost flow assignment model – built using the OD data, crop data and transport costs – track all commodities types, freights and transport costs along the whole network.
7. Select each damaged road and remove it from the network. Re-calculate all flow assignments involving the damaged road. Find the increased costs of rerouting the freight and estimate the losses as the difference between post- and pre- damage of the road segment.
8. If flow cannot be rerouted, assume the commodity and industry supply chains are affected. Match a disrupted commodity to the Input-Output (IO) industry in the province that produces it. Assume this creates supply-side shocks in IO trade balances and estimate the total industry output losses in the macroeconomy through a multi-regional impact assessment (MRIO)[63] model.
9. From steps 7-8 get the total economic losses in US$/day attributed to *each road segment*.
10. Apply EAEL calculation of Equation (9) to get *direct risks* in US$/day (or in US$ with some assumed duration of disrupted that linearly scales US$/day losses) *for each road segment*.
11. Estimate total risk by adding up the direct EAD and indirect EAEL values (Equation (10)).

Figure 5-2(a)-(c) shows one sample of many results generated from the Vietnam study, highlighting the maximum direct EADs, indirect EAELs (for an assumed 10-day disruption for each flood exposure that leads to failure) and total risks due to individual national road network segment failures from current fluvial flooding hazards. These results align with the *criticality assessment* outputs useful for SE Asia platform, where the aim would be to highlight locations of risks on infrastructure networks.

We note that the results show *maximum* values, because we accounted for uncertainties in our estimations of network attributes like speeds and costs, and in the OD flow estimations. This resulted in a lower and upper bound estimation of flows assignment and hence economic losses due to flow disruptions. In the future flood maps, there were future uncertainties accounted for due to different flood models and climate scenarios, which affected both the direct and indirect risk calculations. All details are provided in the report listed above.

[63] Koks, E., Pant, R., Thacker, S. and Hall, J.W. (2019). Understanding business disruption and economic losses due to electricity failures and flooding. *International Journal of Disaster Risk Science*, *10*(4), pp.421-438. Doi: http://dx.doi.org/10.1007/s13753-019-00236-y.

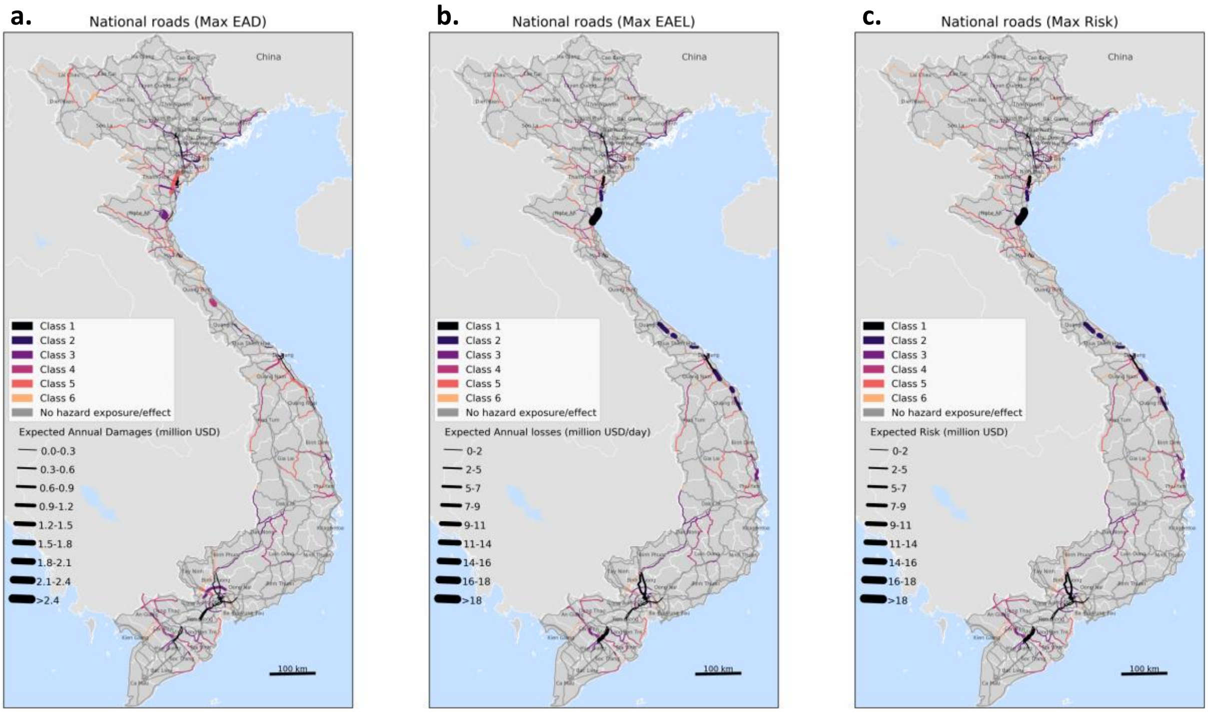


**Figure 5-2: Results from the Vietnam transport risk analysis study showing the (a) Expected Annual damages; (b) Expected Annual losses over 10 days; and (c) Total risks due to fluvial flooding under current conditions. These maps highlight the criticalities of individual road segments.**

## 5.4 Adaptation options and cost-benefit analysis to inform investments

The study also considered possible *climate resilient road design upgrades* that would *eliminate all risks* if implemented. In line with the process described through Equations (11), Table 5-3 shows the summary of the initial investments (CI) in US$/meter that we estimated for prototype climate resilient road and bridge design upgrade requirements in Vietnam. Table 5-4 shows the details for one prototype road design upgrades that would be needed for an existing national road in coastal/flat conditions in Vietnam. In addition to initial investments, we also collected information on routine (assumed every year) and periodic maintenance (assumed every 4 years) costs for each component shown in Table 5-4. These are not shown in this report.

**Table 5-3: Summary of cost of initial adaptation investment for building prototype climate resilient roads in Vietnam (source: Oh et al. 2019[23]).**

| Prototype road | Terrain | Cost of adaptation investment (CI) (US$/meter) |
|---|---|---|
| National road – 2-lane – 22.5 meters wide | Flat | 15,350 |
| | Mountain | 18,285 |
| District road – 1-lane – 6.5 meters wide | Flat | 8,080 |
| | Mountain | 14,390 |
| Bridge | All | 101,790 |

**Table 5-4: Bill of quantities for building a climate resilient 100m section of 22.5 meters wide national flat road in Vietnam.**

| Adaptation group | Item | Estimated length (m) | Unit | Factor | Factor unit | Rate | Rate unit | Total cost (USD) | Design assumptions |
|---|---|---|---|---|---|---|---|---|---|
| Pavement | Gravel | 0 | M | 0.001 | | 20,000 | USD/km | 0 | |
| | Sealed | 200 | M | 0.001 | | 300,000 | USD/km | 60,000 | Existing road should already be paved, so double coat of sealing required to prevent water seepage |
| | Concrete | 0 | M | 0.001 | | 125,000 | USD/km | 0 | |
| | Concrete FW | 0 | M | 0.001 | | 150,000 | USD/km | 0 | |
| Pavement Drain | Line Drain total | 0 | | 0.41 | m3 | 75 | USD/m3 | 0 | Existing road should already have drainage |
| Earthwork | Embankment Construction | 200 | m3 | 13 | m3 | 6 | USD/m3 | 15,600 | Embankments required on either side of road, factor = 13m3 comes from design |
| | Cut slope Formation | 0 | m3 | 1 | m3 | 6 | USD/m3 | 0 | |
| Slope Protection | Cut slope Toe Retaining Gabions | 0 | M | 4.5 | m3 | 80 | USD/m3 | 0 | |
| | Embankment Retaining Gabions | 200 | M | 2.1 | m3 | 80 | USD/m3 | 33,600 | 200 m of toe gabions; factor = 2.1m3 of gabion/m |
| | Concrete/block Face | 200 | M | 3 | m2 | 21 | USD/m2 | 12,600 | 200m of concrete blocking over 3m face, so 3m2 area factor |
| | River bank | 10 | M | 4 | m3 | 80 | USD/m3 | 3,200 | 10 m of river bank protection; factor 4 m3 gabion/m |
| | Face Drain | 0 | M | 1 | M | 15 | USD/m | 0 | |
| | Bioengineering | 200 | m2 | 3 | m2 | 8 | USD/m2 | 4,500 | 200m of bioengineering of 3m face, so 3m2 area factor |
| Culverts | 1m pipe culvert | 1 | No. | 24 | | 400 | USD/unit | 9,600 | 1 pipe culvert for every 200m of road section |
| | Box 1c (3x1.5) | 1 | No. | 24 | | 600 | USD/unit | 14,400 | 1 box culvert for every 1000m of road section |
| | | | | | | **Total** | | **USD153, 500** | |

Using the EAD and EAEL estimations and the climate resilient road design upgrade options we conducted a CBA in line with the Equations (11)-(13) calculations.

1. The timeline of any adaptation intervention was chosen to be from 2016-2050, which is 35 years. Over this time the annual GDP growth rate was assumed to be 6.5%.
2. A discount rate of 12% was assumed based on existing cost-benefit analysis tools assumptions for Vietnam.

Figure 5-3(a) shows adaptation criticality assessments of road links protected against fluvial flooding risks till 2050 under RCP8.5 climate scenarios for Vietnam, showing the total Net Present Values (NPV) of benefits (assuming 10-day disruptions), costs and BCRs. Such analysis helped identify the locations where climate investment should be prioritized based on highest BCRs. The study also showed a significant uplift of BCRs of adaptation when climate resilience investments were made to avoid future levels of extreme river flooding driven risks, while accounting for the uncertainties associated with such estimates. As shown in Figure 5-3(b), the BCRs of adaptation for future RCP4.5 and RCP8.5 climate scenario driven river flooding hazards, were higher than the BCRs under current flood hazard conditions in Vietnam. Significantly, in comparison to the current scenarios, large percentiles of road links had BCRs >1 when adapting to future climate scenarios.

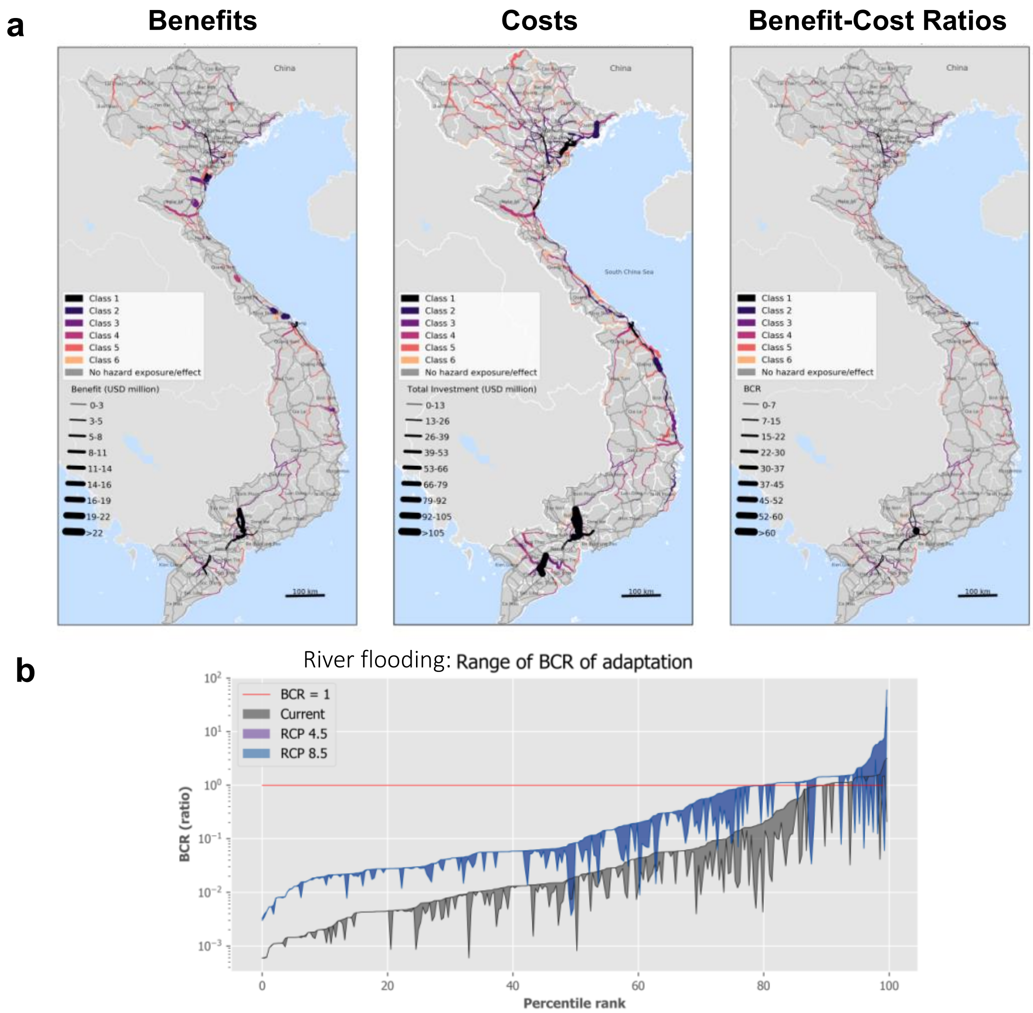


**Figure 5-3: (a) Comparisons of NPVs of benefits (avoided risks), climate adaptation investment costs and BCRs of adaptation options for national-scale road network links exposed to river flooding hazard under RCP8.5 emission scenarios from 2016-2050 in Vietnam (b) Ranges of adaptation BCRs for the national-scale road network links in Vietnam ranked by the upper bound of BCR values, evaluated for current and future extreme river flooding scenarios.**

## 5.5 Loss-probability curves

The kind of aggregated loss-probability curves we want to create at larger administrative scales in the SE Asia analytics, can be created from the Vietnam study. Figure **5-4** presents the loss-probability curves for current fluvial flooding exposures, when all the individual asset damages and losses are summed over the entire country of Vietnam. Different curves are generated for the (a) direct damages, (b) economic losses/day; and (c) total losses assuming 10-day disruptions for each asset failure everywhere. Similar curves can be created for different future hazards and climate scenarios. Also, the magnitudes of initial climate resilient investment needs for eliminating the total losses at each probability are shown in Figure **5-4**(d), without consideration of the BCR values. The purpose here is to only highlight that such an estimation can be done for informing DRFI.

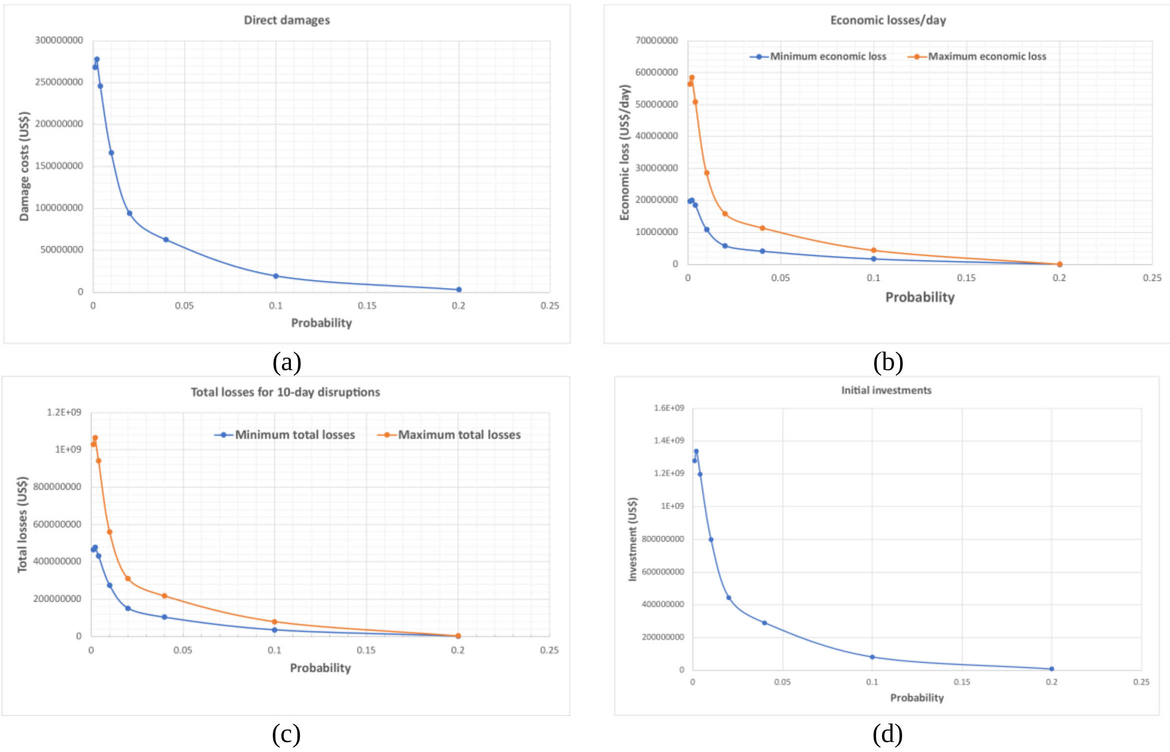


**Figure 5-4: Aggregated loss-probability curves for the national road network in Vietnam for fluvial flooding under current conditions showing the (a) Direct damages; (b) Daily economic losses; (c) Total losses for 10-day disruption events; and (d) Climate resilient investment needs.**

# Chapter 6. Gaps and recommendations for a regional and global infrastructure climate risk analysis

This study has demonstrated the feasibility of infrastructure network risk analysis of natural disasters on a very large scale. There are inevitably limitations and gaps which will need to be developed in future research and development.

## 6.1 Possible extensions to system scope: infrastructure systems and natural hazards

The study has focussed upon electricity and transport (road/rail) infrastructure. Definitions of Critical Infrastructure vary (see Figure 6-1). Electricity and transport network infrastructure fit within the scope of national infrastructure. Often also included in this category are:

- **Transport**: road, rail, ports, inland waterways and airports. So-called active travel (walking, cycling) is usually excluded.
- **Energy**: electricity supply, transmission and distribution; gas and oil pipelines. Upstream fossil fuel production is usually excluded.
- **Water** supply systems, including reservoirs, pipes and pumping stations, and unconventional water sources, including desalination and wastewater reuse.
- **Wastewater**, including sewerage systems and wastewater treatment plants.
- **Solid waste**, including incinerators, landfill and recycling facilities.
- **Flood protection systems**, including embankments, levees, dikes, walls and barriers.
- **Telecommunications**, including digital network cables and fixed and mobile telephony. Sometimes data centres are also included.

In future developments of the analysis presented in this report, we will extend the transport network to include inland water ways. We will also include water and wastewater infrastructure and will seek to include telecommunications. Flood protection is already implicitly included through the modelled flood extents in areas that are protected from flooding up to a given return period.

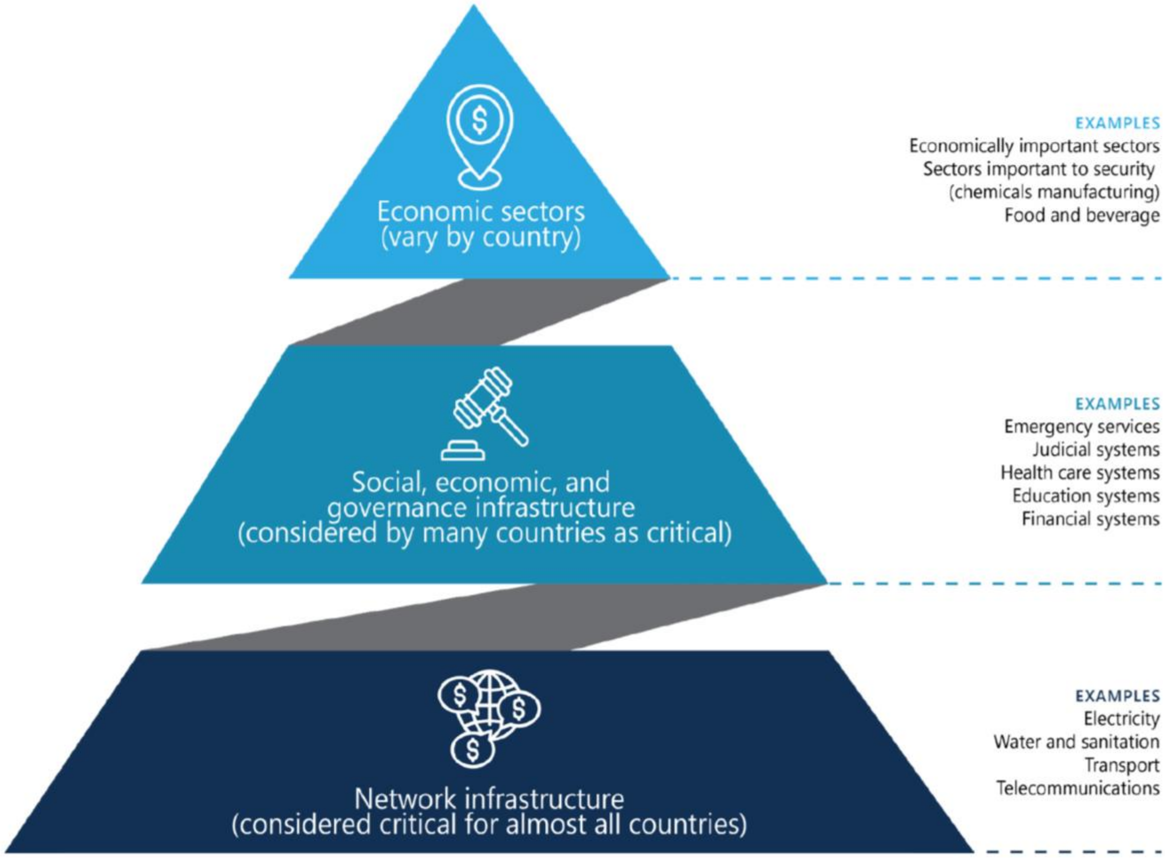


**Figure 6-1: Varying definitions of Critical Infrastructure (World Bank, 2021)**

This study has focussed upon three hazards:
- Fluvial (river) flooding
- Coastal flooding, including subsidence
- Cyclones

Additional climate-related hazards to infrastructure that could be incorporated include:
- Pluvial (surface water / storm water) flooding
- Droughts
- Extreme heat
- Wildfires
- Lanslides
- Bridge scour
- Coastal erosion

In addition, the framework could include geophysical hazards, including:
- Earthquakes and liquefaction
- Tsunamis
- Volcanic eruptions
- Space weather

Aspects of the framework could be used to assess man-made hazards, both accidental and malicious. However, quantification of malicious hazards is usually considered to be impossible, so different frameworks are adopted, based primarily on network vulnerability assessment, but also sometime including game-theoretic representation of the strategies of an adversary.

## 6.2 Improvements to the representation of relevant processes

Any model is a simplified representation of the real world. There is little merit in developing excessively complex models, in particular for broad scale studies such as this one, because they are difficult to interpret and validate and computationally costly to execute. Nonetheless, there are several areas where we believe that improved process representation would make a significant improvement to our models.

### 6.2.1 Hazards

Our study has been limited by the availability of hazard data, as we are using publicly available sources. Some further hazard data (notably high-resolution flood maps) are available under licence to private sector providers. At smaller scales there is a proliferation of available hazard modelling methods, but the application of these methods at regional and global scales is much more limited. As explained in Chapter 2 and Chapter 3, the hazard maps that we have used represent the extent and severity of a hazard at a given return period, which is not the ideal way of representing hazards for large-scale risk analysis. Ideally, we would make use of large-scale spatial *event sets* which are sample simulations of synthetic extreme weather events. Cat modelling is usually driven by a large ensemble of event sets. This approach was used in the 2017 Global Assessment Report on Disaster Risk Reduction[64] and new global event set is under development under the auspices of the Coalition for Disaster Resilient Infrastructure.

As we are considering multiple hazards to infrastructure systems, it is important to consider the cross-correlation between different hazard variables, for example between cyclones and coastal storm surges. A multi-hazard event set would implicitly capture these dependencies between hazard variables, though a multi-hazard event set covering a large spatial domain (like SE Asia or all of the inhabited continents) would have to have a very large set of simulations if the statistics of extremes are to be adequately sampled to create accurate risk estimates.

Hydrometeorological hazards (floods, droughts, hurricanes, storm surges etc.) are subject to the impacts of climate change. In this study we have used projections of the impacts of climate change, based on models available from the Coupled Model Intercomparison Program (CMIP) for the World Climate Research Programme. There are inevitable limitations to these model outputs, in particular due to the spatial resolutions at which these models are executed which means that they are not ideal for simulating extreme events. The limited number of realisations in CMIP ensembles also limits their suitability for exploration of extreme events. Future CMIP exercised should yield higher resolution outputs and larger ensembles.

### 6.2.2 Infrastructure asset exposure

Our analysis has been enabled by rapid advances in geolocated infrastructure asset data, notably OpenStreetMap and globally available power plant datasets. Methods for synthesising power grids (i.e. GridFinder) have also assisted. There are still significant gaps in infrastructure asset location datasets, notably in electricity substations, water treatment plants, pumping stations, waste water treatment plants, solid waste facilities, ICT infrastructure and flood defences. High resolution satellite datasets are filling some of these gaps, and we are using computer vision techniques for asset recognition. However, there are still assets that are difficult or impossible to recognise in satellite images, notably electricity sub-stations and mobile phone base stations, which can be rather small, and telephone exchanges which are located in regular-looking buildings.

[64] https://www.preventionweb.net/english/hyogo/gar/atlas/

### 6.2.3 Infrastructure asset fragility

Going from exposure analysis of infrastructure assets to quantified risk analysis critically depends upon information on the fragility of the assets i.e., a probabilistic description of the decay in infrastructure performance given increasing severity of hazard. The simplest version of a fragility curve (used in this study) describes the assumed deterioration in system performance given increasing flood depth, which may be a binary function. There are also generic fragility functions for earthquake-induced ground accelerations and cyclone wind speeds (Koks et al, 2019)[6]. More generally however, an infrastructure asset's resistance to hazards will depend upon its design standard, lifetime since construction and rate of deterioration, which will in turn depend upon the intensity of its use, the quality of maintenance and the severity and frequency of hazards to which it has been exposed. Information on asset design standards is time-consuming to obtain, and information on maintenance regimes and asset condition is even harder to obtain. A global survey to obtain some of this information is currently under way, under the auspices of the Coalition on Disaster Resilient Infrastructure.

In general, we could consider many degrees of asset damage, which would result in corresponding deterioration in performance, leading ultimately to total loss of performance. In practice we only consider this final state of total loss of performance. The cost of direct damage and repair (see below) would ideally reflect the degree of impact on assets' state. Intermediate conditions of partial performance deterioration could be considered in principle but would require a lot more data and would add another dimension of computational complexity.

### 6.2.4 Costs of direct damage to infrastructure assets

Estimates of the direct damage to infrastructure from natural hazards depends upon data on the costs of repairing or replacing physically damaged infrastructure. Previous studies have demonstrated how widely these costs can vary. We know that the costs of newly built infrastructure can vary enormously[65], and given the fraught conditions under which post-disaster repair and recovery take place, we can expect these costs to vary even more – quite possibly by factors of 10s.

### 6.2.5 Infrastructure usage and disruption

The amount of disruption caused by infrastructure asset failures depends on what economic and social purposes the infrastructure is used for. We have characterised infrastructure network usage in this and other studies by using quantified metrics of infrastructure use e.g. the number of households and businesses that rely upon a power plant and the number of vehicles travelling along a road. We are well equipped to approximate these metrics via a variety of methods, but empirical measurements would help to validate these approximations.

The scale of disruption depends crucially upon the duration of disruption and the amount of redundancy there is in the system e.g., are there alternative routes or back-up supplies. The possibility of rerouting is considered in our Vietnam analysis, though this is based just on network connectivity, whereas a more complete analysis would consider the capacity of alternative links and the potential for network congestion even if rerouting is in theory feasible.

The time it takes to repair and reinstate infrastructure assets is a crucial variable in this analysis, but there is limited empirical data with which to estimate recovery time. There have been some studies based on ex-post analysis of disasters, notably in New Zealand and Japan, but the duration of recovery relates to very particular circumstances and it is doubtful whether these insights are directly transferrable to other situations. The speed of recovery will depend upon the capacity organisation to mobilise resources for repair and recovery, and the extent, severity

[65] Flyvbjerg, B., Holm, M.S. and Buhl, S., 2002. Underestimating costs in public works projects: Error or lie?. *Journal of the American planning association*, *68*(3), pp.279-295.

and complexity of damaged infrastructure that they have to reinstate. In the absence of better data, we recommend sensitivity analysis around the assumed duration of disruption, which is a critical and highly uncertain variable in the analysis.

### 6.2.6 Economic impacts

The micro-scale disruptions to homes, businesses, travel and supply chains that we compute from the bottom up in the infrastructure risk analysis aggregates up into wider macro-economic impacts. There is a variety of approaches to modelling these impacts[66], which make use of variants, and hybrids, of economic input-output (IO) and Computational General Equilibrium (CGE) models. These models have not been applied in this study, though we have done so previously, including for Vietnam[12]. There is a major mismatch between the spatial/temporal scales of these models and the spatial characteristics that we model from the 'bottom-up', which are represented at quite precise point/vector resolutions. Some previous studies have been able to obtain georeferenced firm-level data[30] which has enabled more spatially resolved economic modelling. Nonetheless, we see significant gaps in the spatial modelling of the economic impacts of disasters which our work will be addressing in the future.

## 6.3 Validation, uncertainty and sensitivity analysis

Quantified risk analyses are inherently difficult to validate, because they analyse a wide range of conditions, very few of which (if any) have actually been observed. Validation therefore relies upon several different strategies:

- **Validation of model components:** Though a risk analysis is difficult to validate in its entirety, the datasets and component calculations can be verified and validated, which if done systematically can provide evidence of validity.
- **Comparison with observed events:** Any observed extreme event is by definition a rare sample from a multitude of possible events, so does not provide a validation of a risk estimate. Observations of specific extremes does however provide evidence to validate that the processes enacted in a model represent the real world.
- **Comparison with long-run average damages:** In circumstances when damage is relatively frequent, it may be possible to compare a few observed damaging events with risk estimates.

This study has not carried out any of these validation techniques. Systematic validation should be planned for future developments. As part of this, uncertainty and sensitivity analysis should be conducted to illustrate the range of possible model predictions and the sources of variability,

## 6.4 Linking infrastructure disaster risk analytics with DRFI

The purposes that disaster risk analysis plays in DRFI was introduced in Chapter 1. Here we review the extent to which the analysis presented in this study can fulfil these purposes.

- **National economic losses:** We have estimated the potential economic losses from infrastructure failures as a percentage of GDP. However, we have not in this study conducted macro-economic modelling to estimate wider economic losses. Our estimates of economic loss should therefore be considered to be a lower bound on national economic losses in disasters. Multi-regional economic models for SE Asia do

[66] Okuyama, Y. and Rose, A. eds., 2019. *Advances in Spatial and Economic Modeling of Disaster Impacts*. Berlin, Germany: Springer.

exist, so it would be possible to use one of these models to better estimate wider economic losses.

- **Government's financial liabilities:** We have estimated the risks from direct damage to road, rail and energy infrastructure. We do not have information on asset ownership, so we have not been able to distinguish public assets. Nonetheless, it is recognised that governments may have implicit liability for all critical infrastructure, so these direct damage estimates are a reasonable approximate of government liabilities at different exceedance probabilities. The estimates are sensitive to all of the issues and data gaps listed in Section 6.2. Using these estimates of losses at different return periods provides a basis for quantifying different layers of DRFI (see Figure 1-5).
- **Financial liabilities for private actors and IFIs**: We do not have information on the asset exposure of private investors or IFIs in the countries under consideration, so the study does not provide an estimate of the risks to which they are exposed. This would be straightforward given a georeferenced asset portfolio.

## 6.5 Linking infrastructure disaster risk analytics with wider risk management practices

This study, and the preceding discussion, has focussed upon estimating risks to infrastructure from natural hazards. However, in the introduction we identified how risk information can provide the starting point cost-benefit analysis of a range of decisions including:

- Optimal maintenance
- Upgrades to improve the strength and resistance of infrastructure assets
- Setting design standards

To make these decisions not only requires 'base line' information on the risk if not decision is taken (e.g., to maintain or upgrade and asset), but it also requires information on the cost of the intervention and a new risk analysis of the residual risk once the intervention has been implemented, in order to calculate the beneficial risk reduction.

## 6.6 Further improvements in the infrastructure risk analysis platform

The interface that has been presented in Chapter 4 is a rapid prototype that has been developed for this study. This provides a means of navigating all of the spatial data and also graphical visualisation of aggregate risk metrics. We are planning continued development of this platform in the following directions:

- Continuous improvement to the underlying datasets and models, as described above.
- Inclusion of a wider range of hazards and infrastructure categories
- Extension of the geographical scope to global scale
- Incorporation of macro-economic modelling to provide estimates of wider economic impacts.
- Extensive sensitivity analysis to key uncertainties, including hazard probabilities, asset fragilities, damage costs, damage durations and economic impacts.
- A customised interface to inform specific risk analysis tasks including:
    - Parametric insurance pricing
    - Estimating budget contingencies
    - Estimating the quantum and trigger criteria for pre-arranged loans
    - Prioritising infrastructure adaptation investments

# Appendix A – List of abbreviations

| | |
|---|---|
| AAL | Average Annual Loss |
| CAT | Catastrophe |
| CDRI | Coalition on Disaster Resilient Infrastructure |
| CGE | Computable General Equilibrium (model) |
| CI | Critical Infrastructure |
| CMIP | Coupled Model Intercomparison Program |
| CRFD | Climate-Related Financial Disclosure |
| DRFI | Disaster Risk Finance and Insurance |
| DRFIP | Disaster Risk Finance and Insurance Program |
| EDGAR | Emissions Database for Global Atmospheric Research |
| GDP | Gross Domestic Product |
| GFDRR | Global Facility for Disaster Reduction and Recovery |
| ICT | Information and Communications Technology |
| IFIs | International Financial Institutions |
| IMF | International Monetary Fund |
| IO | Input-Output (model) |
| IPCC | Intergovernmental Panel on Climate Change |
| MDB | Multilateral Development Bank |
| OD | Origin-Destination |
| O&M | Operations and Management |
| QRA | Quantified risk analysis |
| RCP | Representative. Concentration Pathways |
| ROCKS | Road Costs Knowledge System |
| SEA | South-East Asia |
| SEADRIF | South-East Asia Disaster Risk Insurance Facility |
| UK | United Kingdom |

# Appendix B – Review of existing platforms and data needs

In the implementation of our methodology, we will leverage upon our previous experiences and incorporate new methods to integrate financial instruments with the risk assessment approach. The following subsections provide the steps in the implementation of this project.

## B.1 Review of existing platforms

Most of the existing risk platforms that are available rely on the information described in the section. In the academic community, several open-source platforms are available for doing risk analysis for different hazards. Examples are an open-source high resolution wind damage model for Europe, which can be easily adapted to other geographies[67], and the open-source probabilistic tropical cyclone risk model CLIMADA[68]. Moreover, several open-source risk platforms exist. The most relevant ones are discussed in Table B-1.

In short, a number of platforms exist to (1) perform loss calculations to assets using data input from the user (RISKSCAPE, HAZUS, RiskChanges, OASIS), (2) visualize and extract results from processed risk analysis (Global Earthquake Model, WRI Aqueduct, GRID Global Risk Platform), and (3) interactively perform risk analysis and cost-benefit analysis for countries for a particular hazard (WRI Aqueduct Floods). However, several limitations/restrictions should be noted. First, most analysis focus on physical damages only and do not consider indirect losses due to infrastructure interdependencies or second-order losses due to infrastructure service disruptions. Second, the interactive platform of WRI Aqueduct is the only platform to perform cost-benefit analysis without users having to process data themselves but is only restricted to floods. Third, most tools use return period maps as hazard data, which does not allow for an event-based loss analysis (which is more relevant for governments). Such hazard data is commonly provided by commercial providers, such as various insurance companies and risk modelling companies (e.g., SwissRe, Intensel, Ambiental).

*Existing risk platforms used for World Bank projects*

A number of World Bank risk analysis are discussed in Table B-2 with a focus on the hazard, exposure and vulnerability data sources used, including a discussion on the risk metrics adopted. This is followed by a brief reflection on the ability to reproduce such an analysis using publicly global data sources.

## B.2 Review of data needs

As noted above, data is one of the greatest challenges in high resolution geospatial analysis. We are accustomed to dealing with incomplete data, though that always has implications for the validity of results. Our goal for the SEA platform is that it should as far as possible be based on globally or regionally available datasets, at least at the default level of analysis. This will include:

1. OSM data on transport (roads, railways and possibly ports/airports);
2. GridFinder map of the electricity network;
3. GLOFRIS map of fluvial and coastal flooding; and
4. World Pop population exposure layer.

We will systematically review them for this study. We will identify gaps and explain how they could be filled, using examples from Vietnam as appropriate.

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67 E. E. Koks, T. Haer, A high-resolution wind damage model for Europe. *Sci. Rep.***10**, 1–11 (2020).
68 G. Aznar-Siguan, D. N. Bresch, CLIMADA v1: A global weather and climate risk assessment platform. *Geosci. Model Dev.***12**, 3085–3097 (2019).

An overview is provided with suitable data sources that can inform large-scale risk analysis. The data sources are separated into land use/landcover, hazard data, exposure data, vulnerability data, and socioeconomic data. We focus on global data products, whereas more detailed country-specific data products could be available (such as a high-resolution land cover map for Vietnam from the Japanese Aerospace Agency).

**Table B-1: Existing risk platforms of relevance to this project.**

| Name | Link | Description |
|---|---|---|
| GRID Global risk data platform | https://preview.grid.unep.ch | The global risk data platform, hosted by UNEP/GRID-Geneva, is an online platform that offers information on global risks from multiple hazards. It incorporates a wide range of data sources on hazard data, exposure (both human and economic) and risk, covering tropical cyclones, earthquakes, floods, storm surges and landslides. Moreover, it includes the data sources that were used for the 2015 Global Assessment Report on Disaster Risk Reduction (GAR). The risk metrics included are average annual losses (in US$) and mortality risk. Some of the risk data is now outdated, as many alternative (and improved) data sources are available. |
| RISKSCAPE | https://www.riskscape.org.nz | Riskscape is a New Zealand based organisation that provide a software for risk modelling of multiple natural hazards. The focus of the risk model is to evaluate risk to assets in New Zealand, although a user can upload their own hazard and asset data. The model provides a range of risk layers, including hazard maps for New Zealand, a building inventory, and various vulnerability curves. Both asset and human losses can be evaluated. |
| HAZUS | https://www.fema.gov/flood-maps/products-tools/hazus | HAZUS is FEMA's disaster risk modelling platform to estimate the losses from natural hazards in the United States. The loss modules included are; (1) physical damages to buildings and critical infrastructure, (2) economic losses to business interruptions, job loss and repair costs, and (3) social impacts such as displaced households and exposed population. A multi-hazard framework is incorporated, including detailed documentation on the earthquake, hurricane, and flood models. The intended users are states and communities in the United Stated, and although HAZUS can be applied to regions outside the United States, the flexibility of the modelling framework is restricted[69]. |
| RiskChanges | https://github.com/ashokdahal/RiskChanges | RiskChanges is an open-source tool (still under development) for performing multi-hazard risk assessments developed by the ITC (University of Twente). It allows users to perform risk analysis of various elements-at-risk (such as buildings, populations, infrastructure) and a tool for performing cost-benefit analysis of risk reduction measures. Users need to provide all data sources (e.g., hazard maps, exposure data, vulnerability curves, risk reduction measures), whereas the system can perform risk analysis under a variety of different settings. The system is flexible in working with both raster and vector data files for exposure data. Only risks to physical asset losses and population can be evaluated using the platform. |
| WRI Aqueduct | https://www.wri.org/aqueduct | The Aqueduct platform hosted by the World Resources Institute provides a tool for global analysis of current and future water risks. The water risk platform includes indicators of water stress, drought risk and flood risk (both coastal and riverine) on a river basin scale.<br>For the water stress analysis, the user can import a database with locations (lat/lon) in the platform, resulting in current and future (2030-2040) water stress indicator for each location.<br>The Aqueduct Floods is the most comprehensive open data platform for analysing the impacts of flooding, as well as providing a tool for analysing the cost-benefit ratio of improved flood protection under a range of conditions (infrastructure lifetime, unit costs, discount rate, operation and maintenance cost). It is based on previous work on estimating global river and coastal flood risk using GLOFRIS for river flooding[70] and the Global Surge and Tide Model (GSTM) for coastal flooding[71]. One can easily calculate flood risk for every country, including defining the existing flood protection standards in place. |

69 G. Kaveckis, G. Paulus, K. J. Mickey, "HAZ-I – A New Framework for International Applications of the Hazus-MH Flood Risk Assessment" (2012).
70 H. C. Winsemius, J. C. J. H. Aerts, L. P. H. Van Beek, M. F. P. Bierkens, A. Bouwman, B. Jongman, J. C. J. Kwadijk, W. Ligtvoet, P. L. Lucas, D. P. Van Vuuren, P. J. Ward, Global drivers of future river flood risk. *Nat. Clim. Chang.***6**, 381–385 (2016).
71 S. Muis, M. Verlaan, H. C. Winsemius, J. C. J. H. Aerts, P. J. Ward, A global reanalysis of storm surges and extreme sea levels. *Nat. Commun.***7**, 1–11 (2016).

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| | | All hazard scenarios, both current and future, for several return periods are freely available from the website, and allow a quick quantification of flood risk, given any type of exposure input (e.g., asset database). For coastal flooding, it also includes subsidence scenarios, which is a major driver of future coastal flood risk in several regions globally[72]. |
| Global Earthquake Model foundation | https://www.globalquakemodel.org | The Global Earthquake Model foundation provides a set of freely available seismic global hazard, exposure and risk maps, and several open access regional models for earthquake risk analysis. Regional models are available for Arabia, Caribbean and Central America, Indonesia, South Africa, Southeast Asia (Myanmar, Thailand, Vietnam, Laos, Cambodia, Singapore, and West Malaysia).<br>Globally available products include a global hazard database for PGA and spectral acceleration, and a global risk map. The global exposure model (to calculate risk) consists of a density grid of population and buildings and is based on data of commercial, industrial, and residential buildings, and population at administrative level 1 (province level). The vulnerability module includes a database of building-specific fragility curves (~600 curves) that are used for the risk calculation. The resulting global risk layers quantify the average annual losses to buildings (at 0.2/0.4 degrees, ~22-44km at equator) and average annual mortality to people (at 0.2/0.4 degrees, ~22-44km at equator). |
| OASIS loss modelling framework | https://oasislmf.org | The OASIS loss modelling framework aims to provide an open source, free to use, catastrophe modelling platform. It includes, among others, a platform for running catastrophe models, a toolkit with hazard and vulnerability data, and a toolkit for developing and testing catastrophe models. 90 models from 19 different providers are included in the platform for different hazards (called perils in the insurance industry) and geographies (see https://oasislmf.org/community/model-providers). For instance, it includes the following models for South-East Asian countries: (1) AXA XL flood model for Thailand and Malaysia, (2) Impact Forecasting flood models for Malaysia, Vietnam and Thailand, (3) JBA Risk Management flood and surface water model for Malaysia, Vietnam and Thailand. All models are intended to calculate total losses, direct/insured and reinsured losses. |

72 P. J. Ward, H. C. Winsemius, S. Kuzma, M. F. P. Bierkens, A. Bouwman, H. DE Moel, A. D. Loaiza, D. Eilander, J. Englhardt, E. Gilles, E. Gebremedhin, C. Iceland, H. Kooi, W. Ligtvoet, S. Muis, P. Scussolini, E. H. Sutanudjaja, R. Van Beek, B. Bemmel, J. Van Huijstee, F. Van Rijn, B. Van Wesenbeeck, D. Vatvani, M. Verlaan, T. Tiggeloven, T. Luo, "Aqueduct Floods Methodology" (2020), (available at www.wri.org/publication/aqueduct-floods-methodology).

**Table B-2: Existing risk platforms used for World Bank projects.**

| Name | Category | Description |
|---|---|---|
| Vulnerability of Bangladesh to Cyclones in a Changing Climate<br>S. Dasgupta, M. Huq, Z. H. Khan, M. M. Z. Ahmed, N. Mukherjee, M. F. Khan, K. Pandey, Vulnerability of Bangladesh to Cyclones in a Changing Climate Potential Damages and Adaptation Cost. Policy Res. Work. Pap. 5280. 16, 54 (2010). | Overview | Methodology to perform a risk analysis of the coastal regions of Bangladesh to storm surges (from tropical cyclones) and sea-level rise by 2050 and the potential adaptation options. |
| | Hazard | The method identifies the exposed coastal zones under different projections of sea-level rise + storm surge. A two-dimensional hydrodynamic model is used for this study, given that global storm surge models are not able to adequately simulate storm surges in estuary regions and regions with complex geomorphologies (like the coastal zone of Bangladesh). The hydrodynamic model has a Tropical Cyclone module that can simulate storm surges based on the path and wind speed/pressure of past cyclones. |
| | Exposure | A database of critical elements at risk was built for the coastal zone of Bangladesh, including data on buildings (housing), educational institutes, factories, roads, railways, bridges, power plants, electricity network, tube wells, religious places. Moreover, gridded data on land-use, population, poverty, and agricultural land were collected. |
| | Risk and adaptation | The risk analysis performed includes an estimation of potential human casualty and injury, and damages to housing, education, (road, rail, energy) infrastructure, agriculture, and coastal production works. Several adaptation options were considered: height enhancement of coastal polders, afforestation, multi-purpose cyclone shelters, cyclone-resistant housing, strengthening early warning. Both damages and loss (referring to disruption to services) are included, although loss-estimates are mainly based on past cyclone experiences in Bangladesh instead of any quantitative analysis. |
| | Reflection | Most of the analysis can be performed using publicly available global data sources, although with a few words of caution. The available global storm surge output is not well suited for TC-induced storm surges, given that the resolution (at this moment) is not sufficient to reproduce the physical processes of cyclone dynamics and higher-resolution model are required to include the estuary inlets and rivers. Most of the infrastructure data would be available in OpenStreetMap, except assets like tub wells, religious places, and cyclone shelters. Moreover, the location of coastal protective infrastructure (e.g., the embanked polder areas) are not publicly available. The focus of this study is on the physical asset/land use damages and a first indicator of the wider economic losses (although derived from previous post-disaster reports instead of actual modelling). The latter relies on detailed context specific data that are hard to obtain on a larger scale. |
| Vietnam Catastrophe Risk Assessment<br>World Bank, "Vietnam Catastrophe Risk Assessment: Summary Report" (Washington, D.C., 2017). | Overview | Project to develop state-of-the-art risk information and decision-support tools for Vietnam. Catastrophe risk models for tropical cyclones, precipitation and earthquakes were developed and combined with a database of buildings (both public and private), infrastructure (roads, bridges, airport, seaports, utility assets) and population. |
| | Hazard | A parametric typhoon model based on synthetic events was used to estimate the path, wind speed, precipitation, and storm surge for the country. For flood risk analysis (both pluvial and fluvial), a stochastic event dataset has been created using multi-variate statistical methods. Moreover, a stochastic earthquake model covering 10,000 realizations was developed including PGA and Vs30 as indicators. All hazard modelling was performed by Aon (Impact Forecasting cat models). |
| | Exposure | For population data, the 2014 Census data was distributed to the Worldpop data (100m resolution). A detailed set of buildings data (both private and public) was collected based on Vietnam's Establishment Census data and World Bank data. Data on infrastructure was collected from publicly available data sources (Vietnam official website, global data sources and OSM data). A range of damage functions for building were considered that vary by building construction, year built, height, and its association with different land-use classes (e.g., residential, commercial, public). |
| | Risk and adaptation | The physical losses are calculated for residential, commercial, industrial, and public buildings, and public infrastructure. Moreover, the government contingent liability (e.g., losses to low-income households and public buildings), emergency losses, and affected population |

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| | | were included. This all resulted in detailed risk profiles (loss-exceedance curves) of average annual losses for the separate districts of Vietnam and the country as a whole. |
| | Reflection | The study relies on detailed risk modelling and asset locations and information. The stochastic event hazard datasets used are not yet publicly available. Hence, publicly available data sources are not yet capable in replicating such detailed risk analysis. |
| Resilient Shores: Vietnam's Coastal Development Between Opportunity and Disaster Risk<br><br>J. Rentschler, S. de Vries Robbé, J. Braese, D. H. Nguyen, M. Van Ledden, B. P. Mayo, "Resilient Shores: Vietnam's Coastal Development Between Opportunity and Disaster Risk" (Washington, DC, 2020). | Overview | A multi-hazard risks analysis of people, towns, key economic sectors, infrastructure systems and public services for the coastal zone of Vietnam. The different components can be summarized as: (1) People (people exposed in built up areas), (2) Sectors: risk to agriculture, aquaculture, tourism and industry, (3) Public services: hazard exposure to schools and hospitals, (4) hazard exposure to lifeline infrastructure (transport, electricity, power plants). |
| | Hazard | Multiple hazards are analysed, including flooding (riverine, pluvial, and coastal flooding), typhoons, coastal erosion and drought and saline intrusion. Riverine and pluvial flood extents are taken from Fathom (90 x 90 m). New coastal flood maps have been developed based on detailed storm surge modelling of possible typhoons and a high-resolution digital elevation model. Typhoon wind speed are derived from a global typhoon model with a 30 x 30 km resolution (which can be extracted from the Global Assessment Report in Disaster Risk Reduction). Coastal erosion estimates are taken from satellite-derived shoreline data[73]. For saline intrusion, a raster file for the saline intrusion in 2016 (considered the worst event) was used. Moreover, sea-level rise data was analysed, and its impacts assessed, in particular for the Mekong Delta. |
| | Exposure | To characterise agriculture and urban areas, a high-resolution land-use dataset was used, which is publicly available from the Japanese Aerospace Agency (10m resolution). A number of additional data sources were collected specifically for Vietnam including aquaculture ponds, nightlight data, the location of industrial zones, hotels (based on OSM data), health care facilities and schools (health care from the Government sources, schools from OSM data), energy (power plants from Global Power Plant database, electricity network from publicly available data provided by the World Bank) and aggregate statistics on sector data (output, employment, production area, yield). |
| | Risk and adaptation | An exposure analysis was performed of the assets by overlaying flood maps with location of assets and population (using the build-up area). For typhoons, the risk of trees falling on electricity lines is assessed by incorporating land use data (density of forest). For coastal erosion, the location of hotels is overlayed with the stretches of coasts that experience coastal retreat, whereas for saline intrusion the high-resolution agriculture datasets are overlayed with the saline intrusion map. The economic damages to agriculture, aquaculture, industry, and tourism is evaluated using the proxies of output per asset in terms of economic impacts and jobs affected. The damages to the road and rail network are derived from a previous study[74] |
| | Reflection | The analysis combines both global datasets and Vietnam-specific data sources. The river/pluvial flooding data (although commercially), coastal erosion and typhoons are publicly available, while the aquaculture, land use, coastal flooding and saline intrusion data are country-specific. Most of the asset data come from global datasets or can be easily replaced by globally-available datasets (although at a lower resolution, e.g., land use). The risk analysis to asset is focused on direct damages and macro-economic losses (due to job and output losses), but indirect impacts and service disruptions are not included. |
| Addressing Climate Change in Transport: | Overview | The study applied a system-of-systems methodology for the transport system of Vietnam and its resilience to natural disasters. It includes a criticality assessment of infrastructure assets, a vulnerability analysis to understand the negative economic consequences of disruptions, a risk analysis, and an adaptation planning exercise. |

73 A. Luijendijk, G. Hagenaars, R. Ranasinghe, F. Baart, G. Donchyts, S. Aarninkhof, The State of the World's Beaches. *Sci. Rep.***8**, 6641 (2018).
74 J. E. Oh, X. E. Alegre, R. Pant, E. E. Koks, T. Russell, R. Schoenmaker, J. W. Hall, "Addressing Climate Change in Transport Volume 2: Pathway to Resilient Transport" (2019).

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| Pathway to Resilience Transport J. E. Oh, X. E. Alegre, R. Pant, E. E. Koks, T. Russell, R. Schoenmaker, J. W. Hall, "Addressing Climate Change in Transport Volume 2: Pathway to Resilient Transport" (2019) | Hazard | The hazards included were landslides, flash floods, typhoon induced storm surges (and flooding) and fluvial flood maps. Moreover, some future (2030) flood maps (based on GLOFRIS, see WRI Aquaduct Floods) and future (2025-2050) flash flood and landslide susceptibility maps were accessed. Apart from the future flood maps, all hazard maps (except the future flood maps) came from internal sources. |
| | Exposure | A detailed national-scale transport network model was set-up that includes roads, railways, inland waterways, maritime ports, and airports. All data sources came from internal sources, including different transport network attributes. This data was linked to origin-destination matrices provided by the government, an input-output table, traffic count data, crop production data, and other socio-economic data (all internally provided). A freight flow model was set up that assigns commodity freight flows to different transport modes between the origin and destination locations. |
| | Risk and adaptation | Different risk metrics were adopted in this study. Apart from the direct exposed infrastructure assets and the potential direct physical damages, the wider macro-economic impacts of transport disruptions are calculated including the average annual daily freight disrupted, total macroeconomic loss and freight redistribution costs (due to edge failures). Climate proofing of roads is considered as the main adaptation option (pavement strengthening, improved pavement drainage, earthwork protection, slope protection, improved cross drainage). The benefits of climate proof roads were evaluated by comparing the costs (upfront and maintenance) against the benefits of reduced rehabilitation costs and reduced annual economic losses. |
| | Reflection | Most of the analysis relies on internally provided data by the Vietnam government. Some of the datasets could be replaced by publicly available data sources, such as OSM road and railway networks and the location of ports and airports. Moreover, input-output tables are publicly available for most countries from places like the EORA platform. However, many of the attributes and detailed OD matrices are not publicly available and should therefore be approximated. The same holds for some of the calibration/validation data. The hazard data could be replaced by global model output, although this would be much less accurate than the detailed country-specific hazard maps that were provided. |
| Strengthening financial preparedness of Myanmar power networks | Overview | The objective of this study is the perform a vulnerability and risk analysis of the power infrastructure to natural disasters from a system-wide perspective. |
| | Hazard | Hazards include earthquakes, floods and tropical cyclones and hazard maps are provided by a modelling firm. |
| | Exposure | A network-based model of the powerplants (nodes) and distribution and transmission network (edges) has been constructed. The data sources are not known. |
| | Risk and adaptation | An analysis of the exposure of assets, and the population affected, and the economic damages was performed, identifying the critical and most at-risk elements in the network (from a system-wide perspective). |
| | Reflection | The modelling framework relies on a state-of-the-art system modelling framework of interdependent infrastructure networks. The electricity network data, however, could be replaced by globally available network data, although it likely lacks the asset attributes that might be necessary. The hazard data could, in theory, be replaced by global datasets. However, data on asset fragility, damages, and recovery costs are very context specific. |

**Table B-3: Land-use/Land-cover data sources that can inform large-scale risk analysis.**

| Name | Link | Description | Meta |
|---|---|---|---|
| Copernicus global land cover 100m | https://zenodo.org/record/3939050#.X7uObi-cZp8 | Global land cover map with 23 discrete classes based on UN-FAO's land cover classification system. High resolution maps (100m) are available for 2015-2019, whereas coarser (300m) resolution maps are available for 1992-2019. | Resolution: 100m/300m. Spatial extent: global. Accessibility: free |
| JRC Global Human Settlement Layer | https://ghsl.jrc.ec.europa.eu/download.php | Global layer of build-up area derived from Landsat image collection. Multiple products are available including a 30m product, a 250m product and a 1km product. Classification includes water surface areas and build-up at different epochs (1975, 1975-1990, 1990-2000, 2000-2014). | Resolution: 30m/250m/1km. Spatial extent: global. Accessibility: free |
| Global present and future (2010-2100) urban fractions | J. Gao, B. C. O'Neill, Mapping global urban land for the 21st century with data-driven simulations and Shared Socioeconomic Pathways. *Nat. Commun.* 11, 1–12 (2020). | The present (2010) global urban extent represented as the fraction of urban area per land area within a grid cell (1/8 degree). Moreover, a spatial urban development model has been constructed to predict the future urban extent under different Shared Socioeconomic Pathways (SSP) scenarios (also 1/8 degree). | Resolution: 1/8 degree. Spatial extent: global. Accessibility: free |
| WorldPop global gridded population density | https://www.worldpop.org | A top-down approach is utilised to distribute population data (derived from administrative unit-based census data) to the geospatial location of satellite-derived building footprints. The highest resolution product is a 100x100m gridded population density map which is consistent with population census and the UN national population estimates. Data can be downloaded for every individual country. | Resolution: 100m. Spatial extent: global. Accessibility: free |
| A harmonized global night-time light dataset 1992-2018 | X. Li et al. harmonized global night-time light dataset 1992–2018. *Sci. Data*. **7**, 1–9 (2020). | A global night-time light dataset that has harmonized data from the DMSP satellites (1992-2013) and the VIIRS satellites (2012-2018). The newly derived product is an extension of both individual sources and can hence be used as for temporal analysis. The data product is available on a 30arc-seconds resolution (~1km at equator). | Resolution: 30 arc-seconds. Spatial extent: global. Accessibility: free |
| SPAM: global gridded agriculture production maps | L. You et al., Generating global crop distribution maps: From census to grid. *Agric. Syst.* **127**, 53–60 (2014). | Global spatially explicit datasets on agricultural production for the year 2010, including crop area, yield, and production for 42 major crops under four farming systems (e.g., irrigated). All maps are available at a 5 arc-minute resolution (~10km at equator). | Resolution: 300 arc-seconds. Spatial extent: global. Accessibility: free |
| Global livestock distribution maps | M. Gilbert et al., Global distribution data for cattle, buffaloes, horses, sheep, goats, pigs, chickens, and ducks in 2010. *Sci. Data*. **5**, 1–11 (2018). | Global gridded datasets of the presence of livestock, including cattle, horses, pigs, ducks, sheep, goats, buffaloes, and chickens. The data is based on census data and a statistical downscaling model. All data is provided in a 0.08333 degrees resolution (~10km at equator). | Resolution: 0.083333 degrees. Spatial extent: global. Accessibility: free |
| Global mining areas dataset | V. Maus et al., A global-scale data set of mining areas. *Sci. Data*. **7**, 1–13 (2020). | A dataset of global mining areas (polygons), consisting of around 21,000 mining locations derived from manually mapping mining areas from satellite images. | Resolution: polygons. Spatial extent: global. Accessibility: free |

**Table B-4: Hazard data sources that can inform large-scale risk analysis.**

| Name | Link | Description | Meta |
|---|---|---|---|
| Global river and coastal flood maps WRI Aquaduct Floods. | http://wri-projects.s3.amazonaws.com/AqueductFloodTool/download/v2/index.html | Historical and future (2030, 2050, 2080) hazard maps (2, 5, 10, 25, 50, 100, 250, 500, 1000 years) for both coastal and river flooding. For the future, both data for RCP4.5 and RCP8.5 are available. All data is available at a 30 arc-seconds resolution (~1km at equator), although this is regridded from a 5 arc-minutes resolution (~10km at equator). See the WRI Aquaduct Floods data platform for details about the hazard data. | Resolution: 30 arc-seconds. Spatial extent: global. Accessibility: free |
| Fathom global river and pluvial flood model | C. C. Sampson et al., A high-resolution global flood hazard model. *Water Resour. Res.* **51**, 7358–7381 (2015). | Fathom has developed a global pluvial and fluvial flood model at a high resolution (90m) which are considered the best available flood hazard products. Maps for 10 different return periods are available. | Resolution: 90m. Spatial extent: global. Accessibility: commercial |
| Global synthetic tropical cyclones paths and wind speeds | N. Bloemendaal et al., Estimation of global tropical cyclone wind speed probabilities using the STORM dataset. *Sci. Data*. **7**, 1–11 (2020). | A dataset of 10,000 synthetic tropical cyclones paths with cyclone characteristics (e.g., wind speed, pressure) on a global scale. Moreover, global wind speed probabilities were derived globally (10 meter 10 minutes sustained speed) for different return periods (10 to 10,000 years) at 10km resolution. | Resolution: 10km. Spatial extent: global. Accessibility: free |
| Global Earthquake hazard maps | https://www.globalquakemodel.org | See Data Platforms. The global hazard database for PGA and spectral acceleration is available on a 0.2/0.4 degrees (~22-44km at equator) resolution. | Resolution: 0.2/0.4 degrees. Spatial extent: global. Accessibility: free |
| Global current and future coastal flood maps | M. I. Vousdoukas et al., Global probabilistic projections of extreme sea levels show intensification of coastal flood hazard. *Nat. Commun.* **9**, 2360 (2018). | Global extreme sea-level rise projections for the years 2010-2100 under different climate scenarios. Considered the best available coastal flood hazard maps. The 1/100-year total water component along the global coastline for the present and future (RCP4.5 and 8.5, 2015-2100) are available for free, whereas the coastal hazard maps need to be requested from the author. | Resolution: global coastline. Spatial extent: global. Accessibility: request author |
| Global Assessment Report 2015 data on tropical cyclones and earthquakes | https://preview.grid.unep.ch/index.php | Global hazard maps for earthquakes and tropical cyclone wind speed can be downloaded for different return periods (50, 100, 250, 500, 1000 years for cyclones and 250, 475, 975, 1500, 2475 years for earthquakes, both PGA and spectral acceleration). Data is available at 0.072 degrees (~8km at equator). | Resolution: 0.072 degrees. Spatial extent: global. Accessibility: free |
| Global liquefaction susceptibility map | https://zenodo.org/record/2583746 | A liquefaction potential map that combines ground-motion intensities with a range of geospatial characteristics to predict the liquefaction susceptibility. Data is available on a 1.2km global grid. | Resolution: 1.2km. Spatial extent: global. Accessibility: free |
| JRC global flood maps | F. Dottori et al., Development and evaluation of a framework for global flood hazard mapping. *Adv. Water Res.* **94**, 87–102 (2016).<br>https://data.jrc.ec.europa.eu/collection/floods | Global flood hazard maps for several return periods (10, 20, 50, 100, 200, 500 years) available at a 30 arc-seconds resolution (~1km at equator). | Resolution: 0.2/0.4 degrees. Spatial extent: global. Accessibility: free |

**Table B-5: Raster data sources that can inform large-scale risk analysis.**

| Name | Link | Description | Meta |
|---|---|---|---|
| Global gridded GDP and human development index 1990-2015 | M. Kummu, M. Taka, J. H. A. Guillaume, Gridded global datasets for Gross Domestic Product and Human Development Index over 1990-2015. *Sci. Data*. **5**, 1–15 (2018). | National and Subnational data on GDP, GDP per capita and Human Development Indicators were disaggregated using the Global Human Settlement layer and the high-resolution population dataset (HYDE3.2). Time series data (1990-2015) are available for the low-resolution data products (5 arc-minutes, ~10km at equator), whereas time stamps (1990, 2000, 2015) are available for the higher resolution data products (30 arc-seconds, ~1km at equator). | Resolution: 30 arc-seconds/300 arc-seconds.<br>Spatial extent: global.<br>Accessibility: free |
| Global asset exposure dataset | S. Eberenz, et al., Asset exposure data for global physical risk assessment. *Earth Syst. Sci. Data*. **12**, 817–833 (2020). | A global asset exposure dataset, using total asset value as indicator of exposure, was derived based on high resolution population and night-time light data. The same is done for GDP, which was used to validate the accuracy of the disaggregation method. The resolution is equal to 30 arc-seconds (~1km at equator). | Resolution: 30 arc-seconds.<br>Spatial extent: global.<br>Accessibility: fre |

**Table B-6: Asset data sources that can inform large-scale risk analysis.**

| Name | Link | Description | Meta |
|---|---|---|---|
| Global electricity network data | C. Arderne, C. Zorn, C. Nicolas, E. E. Koks, Predictive mapping of the global power system using open data. *Sci. Data*. **7**, 1–12 (2020). | A predictive map of the global high-voltage, medium-voltage, and low-voltage electricity networks. The map relies on data from OpenStreetMap and a variety of high-resolution geospatial datasets. Data is available as vector format with the lines representing the electricity network. The location of substations is not available on a global scale. | Format: Vector (lines).<br>Spatial extent: global.<br>Accessibility: free |
| Global dataset of health facilities | https://healthsites.io | The geospatial location of ~870000 health facilities (clinic, hospital, pharmacy, dentist, doctors). Health facility data is extracted from OpenStreetMap and validated by a global community of users. Some facilities are included as points while others are polygons. | Format: Vector (point and polygon).<br>Spatial extent: global.<br>Accessibility: free |
| Global road and rail network | J. R. Meijer, et al. Global patterns of current and future road infrastructure. *Environ. Res. Lett.* **13** (2018), doi:10.1088/1748-9326/aabd42. | Global road and rail network map have been developed based on OpenStreetMap data that nowadays contains an almost complete set of roads globally. Meijer et al. (2018) developed the Global Roads Inventory Project (GRIP), which merges national road data with OSM data. | Format: Vector (lines).<br>Spatial extent: global.<br>Accessibility: free |
| Global port dataset | World Port Index: https://msi.nga.mil/Publications/WPI<br>Verschuur et al. (2020), in preparation. | The World Port Index contains the location and characteristics of all major ports and terminals globally (~3700 ports). It is by far the most comprehensive dataset of ports globally, although the location of many ports is misplaced. Moreover, ports are represented as points in this data. Verschuur et al. (2020) manually mapped the ~1300 largest ports including the exact location of ports, and the outlines of main port | Format: Vector (points and polygons).<br>Spatial extent: global.<br>Accessibility: free |

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| | | facilities (e.g., container, breakbulk, raw materials terminals). This dataset is still under development. | |
| Global passenger and cargo airport dataset | L. Mao, X. Wu, Z. Huang, A. J. Tatem, Modeling monthly flows of global air travel passengers: An open-access data resource. *J. Transp. Geogr*. **48**, 52–60 (2015).<br>A. Bombelli, B. F. Santos, L. Tavasszy, Analysis of the air cargo transport network using a complex network theory perspective. *Transp. Res. Part E Logist. Transp. Rev.* **138**, 101959 (2020).<br>OurAirports: https://ourairports.com/data/ | The passenger air network dataset developed by Mao et al. contains the 3416 largest airports taken from the 2010 FlightStats database. A monthly flight passenger network was build based on a validated predictive model. Airports are geolocated based on the latitude/longitude of the airport.<br>This data could be supplemented by other airport databases such as OSM or the OurAirports database (~47000 entries), although this does not contain information about airport connectivity.<br><br>Bombelli et al. (2020) developed a global cargo network of the major 335 airports. An estimated yearly Available Freight Tonnes (AFT) per origin-destination airport pair is estimated based on a variety of data sources. The AFT should be interpreted as the maximum capacity, and not the actual freight flow. | Format: Vector (point) and network.<br>Spatial extent: global. Accessibility: free |
| Global reservoirs and dams | B. Lehner et al., High-resolution mapping of the world's reservoirs and dams for sustainable river-flow management. *Front. Ecol. Environ.* **9**, 494–502 (2011).<br>M. Mulligan, A. van Soesbergen, L. Sáenz, GOODD, a global dataset of more than 38,000 georeferenced dams. *Sci. Data*. **7**, 1–8 (2020). | The Global Reservoir and Dam (GRanD) database (Lehner et al., 2011) collates information on around 7300 dams and their reservoirs globally include a range of attributes. The database includes the location of the dams and the outline of the reservoir areas. The GlObal geOreferenced Database of Dams (GGOOD) covers 38,000 manually mapped dams globally (point data of dam walls). | GRanD:<br>Format: Vector (points and polygons). Spatial extent: global. Accessibility: free<br>GGOOD:<br>Format: Vector (points). Spatial extent: global. Accessibility: **request author** |
| WRI Global Power Plants database | https://datasets.wri.org/dataset/globalpowerplantdatabase | The global power plant database includes the geolocation of 28,700 power plants covering around 80% of the globally installed capacity. A large variety of fuel types are included, including Nuclear, Geothermal, Coal, Hydro, Natural Gas/Oil, Biomass, Wind and Solar plants. The dataset includes attributes such as the capacity, generation, status, technology, and owner (if available). | Format: Vector (points). Spatial extent: global. Accessibility: free |
| OpenStreetMap | https://www.openstreetmap.org | OpenStreetMap contains a user-defined asset map of the world. A lot of useful asset-level data can be extracted from here, such as the location of industrial facilities, infrastructure data or educational facilities. The coverage and accuracy of data, however, varies from country to country. | Format: Vector (points, line, polygon).<br>Spatial extent: global. Accessibility: free |
| Industry facilities | Variety of data sources | A variety of data sources exist that map the geospatial location of various key/heavy industry facilities, such as oil refineries, car manufacturing plants, heavy industry, and textile manufacturing plants. | // |

**Table B-7: Vulnerability data sources that can inform large-scale risk analysis.**

| **Name** | **Link** | **Description** |
|---|---|---|
| JRC Global Flood Depth Damage Functions | J. Huizinga, H. De Moel, W. Szewczyk, "Global flood depth-damage functions. Methodology and the database with guidelines." (2017), doi:10.2760/16510. | A set of flood depth damage functions per continent and asset type. |
| Miyamoto International Engineering Options for Increasing Infrastructure Resilience | Miyamoto International, "Overview of Engineering Options for Increasing Infrastructure Resilience" (2019), (available at http://documents1.worldbank.org/curated/en/474111560527161937/pdf/Final-Report.pdf). | A comprehensive overview of the vulnerability of infrastructure assets to a variety of natural disasters and a list of engineering options to improve resilience. |

**Table B-8: Socio-economic data sources that can inform large-scale risk analysis.**

| **Name** | **Link** | **Description** |
|---|---|---|
| EORA MRIO | https://worldmrio.com | National input-output (IO) tables or supply and use (SUT) tables for individual countries as well as a multi-regional input-output tables covering most countries globally. |
| IPUMS socio-economic database | https://ipums.org | An online resource for census and survey data around the world. For instance, IPUMS international has harmonized census data (on a subnational level) for 102 countries globally. This includes for instance information on income and employment. |