From local to global scales - Quantifying climate risks and adaptation opportunities for networked infrastructure systems
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Citation: UNDRR (2022), From local to global scales - Quantifying climate risks and adaptation opportunities for networked infrastructure systems, United Nations Office for Disaster Risk Reduction (UNDRR).

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From local to global scales - Quantifying climate risks and adaptation opportunities for networked infrastructure systems

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Abstract
Investments into infrastructures of energy, transport, water, telecoms, and waste are key to meeting several sustainable development goals and targets set by the Sendai Framework for Disaster Risk Reduction. However, as these investments are being made, ever increasing climate risks threaten existing and new infrastructures, and have the potential to set back development goals by years. Infrastructure planners, investors and policy makers often struggle with the challenges of estimating climate risks at infrastructure asset locations and quantifying the costs of adaptation options to reduce the climate risks. Impacts of climate induced infrastructure failures are magnified due to network cascade effects that propagate across multiple systems, which means that failure footprints extend far beyond asset locations directly vulnerable to climate hazards. Hence, there is a need for understanding and quantifying systemic network risks to strengthen climate adaptation decision-making. There are rapid technological developments that are enabling measurement and assessment of systemic risks and adaptation options for infrastructure networks exposed to extreme climatic hazards, from local to global scales, which this paper reviews. The paper discusses the relevance of the methods and case studies in informing global, national and local policymakers and decision-makers who are involved in understanding climate risks and adaptation needs for infrastructures.

Keywords: Infrastructure networks, Vulnerability, Risk, Resilience, Adaptation
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Introduction

Infrastructures of energy, transport, water, telecoms, and waste provide essential services for people and the economy and are fundamental for achieving the 2030 Agenda for Sustainable Development (Thacker et al., 2019). However, these infrastructure systems are also vulnerable to natural hazards and the adverse impacts of climate change. Infrastructure is often disproportionately exposed to climate change: roads and railways are built across coastal areas and rivers where they are inevitably going to be vulnerable to, among others, sea level rise and river flooding (Dawson et al., 2016); thermoelectric power plants are usually located on the coast or next to large rivers for access to cooling water (Van Vliet et al., 2012) making them vulnerable to sea level rise, flooding and droughts. Since infrastructures operate collectively as networks of interconnected assets, instances of localized failures in one section of the network may propagate to others, initially non-affected, systems. Therefore, the impacts of climatic extremes can be propagated through infrastructure networks far away from the places where the extreme event hit. For example: power network failures during Hurricane Sandy in 2012 left 8.5 million people without power across 21 US states (Henry and Ramirez, 2016); the 2011 floods in Thailand inundated manufacturing sites and electricity, water and transport assets causing estimated losses of US$32 billion from disruptions to the global supply chain of automobile parts and computer hard drives (World Bank, 2012). Ultimately, disruptions and failures in infrastructure networks and the services they provide may not just undermine local and national development plans but also, they may exacerbate existing social fragilities. Different studies have shown that poor people are disproportionally affected by natural disasters (Hallegatte et al., 2020), with a survey of 200 households in Mumbai India showing that unavailability of flooded roads caused poor households to lose workdays resulting in loss of income, productivity, and sometimes jobs (Patankar, 2015).

The impacts of climatic extremes on infrastructure networks are also expected to increase in the future due to climate change. Recent analyses estimate that more than 200,000 km of roads are currently exposed to climate-related hazards worldwide (Koks et al., 2019c), which could increase to 237,000 km by 2050 due to climate change, without considering the additional highway construction that will take place in that period (Hall et al., 2019).

The need for expansion and modernization of infrastructure networks is projected at record high levels, with an estimated US$90 trillion of investments in new and existing infrastructures required worldwide from 2016-2030 (New Climate Economy, 2016). Leading private sector firms also estimate US$1 trillion potential losses due to climate impacts between 2018-2022, with 40% of these losses resulting from physical risks to assets exposed to extreme climate impacts (Bartlett and Coleman, 2019), which raises concerns for those having investments in large-scale infrastructure projects. Infrastructure investments lock in patterns 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 that climate change impacts are factored into infrastructure planning right from the outset.

All countries also have large stocks of existing infrastructure which have mostly not been designed to cope with new and changing climatic conditions, leaving a huge challenge to retrofit existing infrastructure to future risks. Similarly, many countries do not have enough infrastructure to meet growing needs, so the opportunity for resilient and adapted infrastructure is large. Repairing and replacing infrastructure after a disaster can take months or even years (Zorn and Shamseldin, 2015; Mahalingam et al., 2018), denying people of essential services...
and adding to the financial burdens on governments and communities. Recent studies suggest that infrastructure adapted to the impacts of climate change can safeguard up to 81% of the 169 targets of the Sustainable Development Goals (SDGs), and plays a critical role in the adaptation component of the Paris Agreement (including Nationally Determined Contributions and National Adaptation Plans under the UNFCCC processes) (Thacker et al., 2019; Fuldauer et al., 2022). Other studies suggest that timely investments in building climate resilient infrastructures would have an upfront cost of 3% of asset value (Hallegatte et al., 2019) but could yield average benefits of 4-5 dollars of avoided losses for every 1 dollar spent (Hallegatte et al., 2019; Hall et al., 2019).

While global infrastructure investors and policy makers recognize the need for integrating climate resilience with long-term planning in mind, quantifying and developing climate resilience of existing and new infrastructure networks is currently inadequate. This gap is recognized in the Sendai Framework for Disaster Risk Reduction (SFDRR), which emphasizes “the need for improved understanding of disaster risk in all its dimensions of exposure, vulnerability and hazard characteristics” (UNISDR, 2015). In existing research and practice there is a limited understanding of systemic vulnerabilities and risks and the performance of adaptation options for infrastructures, in addition to a lack of models and tools that capture uncertainties to future climate risks due to the dynamic nature of changing hazards, infrastructures and socio-economic systems. Some questions relevant to informing climate resilience decision-making include (Hall et al., 2019; Pant, 2020):

1) How do we identify network locations and assets vulnerable to climatic hazards in the present and future?
2) How do vulnerabilities and risks cascade across infrastructure networks?
3) What are the indirect socio-economic consequences of infrastructure failures?
4) How are infrastructure network assets prioritized for climate adaptation measures to reduce systemic network risks?
5) How do we engage local stakeholders to actively participate in mainstreaming quantitative climate risk and adaptation methods into their long-term planning objectives?
6) What are some novel geospatial infrastructure tools to quantify and inform resilience decision-making?

This paper discusses how the above questions are being answered with generalized methodologies supported by quantitative case studies in different countries and at the global scale. These methodologies and case studies, mostly from the Infrastructure Transition Research Consortium (ITRC, 2021), rely on quantitative models for the identification of spatial network vulnerabilities, risks and resilience to support decision-making.

The remainder of the paper is organized as following. Section 2 sets up the background principles for formalizing infrastructure and hazard models and provides definitions and concepts relevant to vulnerability, risk and adaptation assessments of infrastructures. Section 3 presents an overarching framework for infrastructure vulnerability, risk and adaptation assessment and demonstrates different outcomes and metrics through several national and global case studies. Section 4 highlights the relevance of our work in informing policy, supported by examples of stakeholder uptake in some countries. Section 5 looks at some ongoing developments on data and tools that are necessary for the creation of detailed quantitative infrastructure spatial analysis. Finally, Section 6 highlights the conclusions of the paper and discusses areas of further development of such work.
Understanding infrastructure failures: Concepts and definitions

In this paper, through different case studies, we look at energy (electricity, gas, liquid fuels), transport (road, rail, waterway ports, airports), water (supply and sanitation), waste (solid waste), and telecommunications (fiber-optics, digital communications and data storage or processing) sectors. While an agreeable definition for such infrastructures is challenging (Torrisi, 2009), we define them as *the collection and interconnection of all physical assets and human systems that are operated in a coordinated way to provide a particular infrastructure service* (Hall et al., 2016). This definition emphasizes the importance of the services that infrastructures provide, such as energy, water, mobility or data connectivity, upon which societies and economies depend.

Infrastructures have evolved into large spatially distributed networks that generally exhibit *multi-scale hierarchical structures* (Thacker et al., 2017b). We observe such hierarchies, for example: in electricity networks where larger high-voltage transmission systems provide power to smaller low-voltage distribution systems; in communications systems where information is exchanged between high-capacity long distance core networks, local internet exchange networks and smaller network clusters of cellular towers; and in road networks where short-distance rural or local roads merge towards national roads for long-distance mobility. Infrastructure networks are also typically *interdependent*, which implies that they affect each other through the exchange of physical resources, geographic proximity, information exchange, and socio-economic factors (Rinaldi et al., 2001). For example, telecommunications networks cannot function without electricity supply, and in turn most operations of the electricity networks require information exchange through a telecommunications network. We conceptualize the collective representation of the interdependent hierarchical infrastructure networks as a *system-of-systems* that provides goods and services to individual members of the population, households, business and industrial installations (Thacker et al., 2017b). Figure 1 shows a conceptual representation of the system-of-systems, with an example of the hierarchy seen in the real-world network representation of the electricity infrastructure of England and Wales (*Ibid*).
Figure 1. Systems-of-system model representation of interdependent infrastructure networks providing services to customers. Also shown is the real-world hierarchy present in the electricity network providing service to customers in England and Wales (Figure adapted from Thacker et al. 2017b).

The system-of-systems representation of the infrastructure networks has been key in understanding how interdependencies, while desirable for improving infrastructure performance and increasing systems efficiencies, create cascading effects, where small initial failures manifest into larger events (Watts, 2002). As captured in the following real-world system-of-systems failure example:

‘On September 9, 2011, high temperatures tripped a transmission line near Yuma, Arizona … that shut down the San Onofre nuclear power plant, caused the release of untreated sewage … The blackout, which lasted 12 hours, disrupted emergency communications, which made it difficult to notify people that sewage had infiltrated San Diego’s drinking water. Altogether, more than 7 million gallons of sewage was released from plants in Southern California and Mexico, and 7 million people lost power’ (Lehmann, 2014).

The failures of infrastructure networks are frequently triggered by extreme weather events, spread over large spatial areas, resulting in adverse impacts that are a function of the severity of extreme weather hazards, infrastructure assets exposed and the vulnerability of assets and networks. Hazards refer to the possible, future occurrence of natural or human-induced physical events that may have adverse effects on vulnerable and exposed elements (IPCC, 2014). In our analyses, hazards are denoted in two ways: (1) as spatially coherent extreme weather event sets, e.g., an ensemble of flood event maps showing the spatial dependence between different flood depths and areas; and (2) as exceedance probability maps, e.g., a map showing flood depths and areas based on a given 1 in 10-year return period flow occurring simultaneously at all locations. Exposure refers to the inventory of elements in an area in which hazard events may occur (Ibid). Infrastructure exposure is quantified in terms of numbers and dimensions (lengths, areas) of assets that lie within the spatial extent of hazards. Vulnerability is defined as the propensity or predisposition of exposed elements such as
infrastructures assets, human beings and economies to suffer adverse effects when impacted by hazard events (Cardona et al., 2012). We measure vulnerability of infrastructures terms of the negative impacts or consequences suffered due to failures induced by external hazard shocks (Pant et al., 2016).

We further characterize infrastructure impacts in terms of direct and indirect effects. Direct impacts or direct damages measure the fragility or sensitivity of assets to be damaged by varying severities of hazards, which is quantified terms of the monetary value of physical stock damaged - a function of an asset' reconstruction costs, and the probability (or percentage) of the asset reaching a failure limit state when exposed to a hazard of given magnitude and extent (Koks et al., 2019b). Indirect impact measures include socio-economic losses resulting from disruptions of infrastructure network services (e.g., Giga Watts of electricity, vehicles/day or freight tons/day on roads, Mega-liters of water) leading towards losses in terms of numbers and monetary values attached to affected populations (Hu et al., 2015; Thacker et al., 2017a; Zorn et al., 2020) and business customers (Koks et al., 2019a) or metrics associated with the targets of the SDGs (Fuldauer et al., 2021). Further indirect impacts include macroeconomic losses due to production and labor disruptions affecting outputs of macroeconomic sectors that contribute to regional economic flows (Koks et al., 2019a; Oh et al., 2019). Network interdependencies play a crucial role in cascading failures from the directly damaged assets towards other assets either physically or through the flow of resources (goods, information, etc.) resulting in the indirect impacts.

In the context of climate change, understanding the nature of the hazards and the scale of vulnerabilities and impacts to infrastructures from these hazards is key. Sudden climatic shocks and hazards such as extreme precipitation (inducing floods and landslides), windstorms, snowstorms and heatwaves may suddenly shock infrastructures, making them vulnerable in a short timespan (within hours or days). Slow on-set events and hazards such as droughts make infrastructure vulnerable gradually (over several weeks, months or years), for example, by depleting or drying out the water levels and flows in rivers that affect the hydropower potential of power plants or diminish the use of the river for transport of passengers and goods.

Table 1 presents a summary of key climatic hazards, including: (1) their direct threats (ranked-colored as: low-green, medium-orange, high-red) to different types of physical infrastructure assets; (2) their potential to result in further cascading/multiplier effects (ranked-colored as: low-green, medium-orange, high-red); and (3) the largest spatial scale of potential cascading failure impacts (ranked-colored as: green-local/subnational, orange-national, red-international). Some observed real-world examples of the kinds of failure and impacts are also shown in the table. Arguably, direct damages to infrastructures such as energy, transport and telecommunications systems can produce cascading impacts at global scales, because communications (both digital and physical) are globalized, whilst most countries are dependent on transboundary energy interconnections that transfer electricity or fossil fuels. Water supply infrastructure failures generally have national scale impacts, while solid waste and sanitation systems are typically more localized. The possibility that any of these immediate cascades magnify to larger scales always exists.

Due to climate change, there is an increasing chance of occurrence of compound events two or more hazards shown in Table 1, potentially creating larger cascading effects (Zscheischler et al., 2018). In recent years the electricity networks in the United States have suffered repeated failures under multi-hazard (tornadoes and flooding, hailstorms and severe weather,
hurricanes and flooding) affecting millions of households and contributing to billion-dollar economic losses (Preston et al., 2016; Mukherjee et al., 2018).

In our studies, climate risks are measured as the product of the probabilities of hazards, exposures and vulnerabilities summed over all possible hazard and network failure and disruption scenarios (Pant, 2020). Climate risk evaluations rely on the use of climate projections, derived from Global (or Regional) Climate Models (GCMs and RCMs), which introduce large uncertainties associated decision making at the infrastructure-level (Deser et al., 2012; Hartmann et al., 2013; Stainforth et al., 2007). Uncertainties may come from the type of physical or system model, which is then used to translate climatology to surface or sectorial-relevant variables. For example, uncertainties in changes in precipitation create uncertainties to changes in river flow, which adds to the uncertainties in estimating the risks to energy generated from a hydropower plant or to inundation levels in a road network. Furthermore, uncertainties also arise due to the dynamic nature of infrastructure and socio-economic systems. For example, the fragilities of assets might change over time due to aging and future socio-economic conditions might change under different populations and GDP scenarios. In our studies we have accounted for uncertainties by simulating large ensembles of climate hazards and infrastructure failure scenarios and testing the sensitivity of different parameters that influence the risk outcomes (Hu et al., 2019; Koks et al. 2019; Oh et al., 2019).

The aim of risk quantification is to inform resilience planning, which involves actions that help infrastructures to anticipate, resist, absorb, recover, adapt and transform in response to external shocks (NIC, 2020). Quantifiable options for building resilience (to climate or any shock event) of individual assets and the networks include, but are not limited to, upgrading existing design standards of assets to withstand more extreme shocks, incorporating backup options to substitute for disruptions of services provided from one network to another (e.g. electricity backup generators at railway stations), increasing network redundancy and rerouting options to maintain resource flows, or speeding up the recovery of damaged assets to bring back the networks to normal levels of service.

In the context of climate change, the resilience options are part of a climate adaptation assessment, which is the process of anticipating the adverse effects of climate change and evaluating the relative success of specific actions aimed at reducing climate vulnerabilities (Möhner, 2018; Berrang-Ford et al., 2019). Climate adaptation involves comparing the costs of the specific options with the benefits of avoided risks, realized over a time horizon and climate scenario. Here again there are uncertainties linked to the type of climate scenario or time horizon chosen to evaluate climate risks. If the most conservative scenario is chosen and adaptation strategies are drawn accordingly, an infrastructure system may be under designed making it more vulnerable to other to other climatic, meteorological, or geological hazards. Conversely, if a more extreme scenario is chosen, strategies may overestimate the actual risk leading to important opportunity costs. To overcome such gaps in our studies, we have evaluated the efficacy of adaptations options over different time horizons, climate scenarios and changes in infrastructure networks and socio-economic conditions by testing the sensitivities of avoided risks to different factors that can be influenced by putting in adaptation measures – such as reducing durations of disruptions, influencing future network usage and economic growth (Oh et al. 2019; Pant et al., 2019).

The next section presents a methodological framework for quantifying infrastructure exposures, vulnerability, risk, resilience, climate adaptation and demonstrates its implementation through several case-studies.
Table 1. Description of direct climate hazard threats to physical critical infrastructures and their cascading effects. Note this presents a non-exhaustive generic perspective that recognizes that vulnerabilities are contingent of localized geographic and infrastructure conditions.

<table>
<thead>
<tr>
<th>Sector and assets</th>
<th>Inundation (floods and sea-level rise)</th>
<th>Windstorms</th>
<th>Subsidence and landslides due to extreme precipitation</th>
<th>Extreme Temperatures</th>
<th>Droughts</th>
<th>Examples</th>
</tr>
</thead>
<tbody>
<tr>
<td>Energy Generation</td>
<td>Threat – High</td>
<td>Multiplier effect – High</td>
<td>Scale of impacts – International</td>
<td>Threat – Low</td>
<td></td>
<td>Droughts in California from 2012-2014 reduced hydroelectricity production, which costed customers about $1.4 billion in increased electricity usage from other sources (Gleick, 2015).</td>
</tr>
<tr>
<td>Water Supply</td>
<td>Threat – High</td>
<td>Multiplier effect – High</td>
<td>Scale of impacts – National</td>
<td></td>
<td></td>
<td>Floods and landslides of treatment plants and canals in 2017 in Lima, Peru, limited water supply for up to five days and various treatment plants remained inactive for 6 months (Collyns, 2017).</td>
</tr>
<tr>
<td>Waste Landfills</td>
<td>Threat – High</td>
<td>Multiplier effect – Moderate to Low</td>
<td>Scale of impacts – Sub-national or local</td>
<td></td>
<td></td>
<td>30% of 1064 Austrian landfills are in areas where flooding is a major risk. A 25,000 m$^3$ old landfill was completely eroded during a 2005 flood of Alfenz River in Austria leading to water pollution (Laner et al., 2009).</td>
</tr>
</tbody>
</table>

Legend:
- High/International
- Moderate/National
- Low/Sub-national
<table>
<thead>
<tr>
<th>Sector and assets</th>
<th>Inundation (floods and sea-level rise)</th>
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<th>Extreme Temperatures</th>
<th>Droughts</th>
<th>Examples</th>
</tr>
</thead>
<tbody>
<tr>
<td>Roads</td>
<td>Threat – High</td>
<td></td>
<td>Multiplier effect – High</td>
<td>Scale of impacts – International</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Railways</td>
<td>Threat – High</td>
<td></td>
<td>Multiplier effect – Moderate to High</td>
<td>Scale of impacts – National</td>
<td></td>
<td></td>
</tr>
<tr>
<td>River and Sea Ports</td>
<td>Threat – High</td>
<td></td>
<td>Multiplier effect – High</td>
<td>Scale of impacts – International</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Airports</td>
<td>Threat – High</td>
<td></td>
<td>Multiplier effect – High</td>
<td>Scale of impacts – International</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ICT</td>
<td>Threat – High</td>
<td></td>
<td>Multiplier effect – High</td>
<td>Scale of impacts – International</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Flooding in Somalia in 2019 damaged about 320 km of roads and 23 bridges, with losses to the transport sector estimated to surpass $US 100 million (Parvez et al., 2020).

Flooding in Thailand in 2011 caused damages and losses of over $US 100 million due to inundations in embankments, signaling systems, and station structures (World Bank, 2012).

In Puerto Rico following Hurricanes Irma and Maria, port closures resulted in an estimated loss of 1.2 million barrels per day of petroleum, over the course of 11 days, and directly affected the major generation stations which relied exclusively on imported fuel types (U.S. Department of Energy, 2018).

Research suggests that more than 100 major airports around the world would be below mean sea level in 2100 and at risk to flooding even under modest sea level rise (Yesudian and Dawson, 2021).

Following Hurricane Maria in 2017, about 95% of cell towers in Puerto Rico were taken out. This led the country with almost no signal and internet connection. Also, several countries in South America, that rely on submarine cables that land in the country, experienced disruptions (Internet Health Report, 2019).
Methodology and implementation for quantifying systemic vulnerabilities, risks and resilience and adaptation outcomes

Figure 2 presents a generalized methodology for quantifying climate vulnerabilities, risks, resilience and adaptation outcomes for networked infrastructure systems. These are applicable across multiple scales and the approaches used depend on the specific outcomes or questions being asked of the investigator in the context of the regions being studied. However, there are overarching similarities between the definitions and methods that creates a process of learning that carries across different scales and contexts. The following sections will highlight each of the components of Figure 2 showing and linking examples across multiple countries and scales.

Stress testing infrastructure networks to highlight failure cascades

Stress testing is carried out by simulating the removal of assets from the networks one-by-one or in combinations to sample exhaustive sets of failure scenarios. For example, in a network of $n$ electricity substations an exhaustive stress testing covers the possible set of $2^n-1$ failure combinations of one of more substations failing at the same time. Generally, $2^n-1$ might be very large number, so a smaller sample of different combinations of asset failures are tested based of first testing failure of assets in isolation and then sampling more combinations of those assets with highest individual failure impacts (Pant et al., 2016; Lamb et al., 2019). Such a hazard agnostic approach, called a criticality assessment, is a very effective way to highlight systemic failures that might not be captured otherwise when failures are tested over fixed hazards over limited locations and scenarios while also accounting for climatic uncertainty (Pant et al., 2016).
The effectiveness of such approaches is entirely dependent on the accuracy and completeness of input data, which is translated to spatial network models. This includes the spatial locations of assets and the interconnectivity both within an infrastructure network and between infrastructures (i.e., interdependencies, as defined in Section 2). An example of this is given in Figure 3 where infrastructure data from various open- and private data sources across Great Britain were collected and (inter)dependencies between layers were mapped as shown by the directions of the flows of resources in the figure (Pant et al., 2020).

**Figure 3.** Representation of real-world asset and interdependent network layered data created for Great Britain to conduct criticality analysis (for details see Pant et al., 2020).

Using similar data collection and spatially connected network modelling approaches in different countries, different studies have demonstrated the systemic nature of the cascading failures across interdependent network through exhaustive stress testing (Pant et al., 2020; Zorn et al., 2020). Figure 4, where every single electricity node asset (from the system-of-systems model of Figure 3) was individually stress tested to fail, shows ∼40% of failure instances originating in electricity networks created a sequence of cascading failures that could be traced towards other networks and back to electricity via telecoms networks. Similar analysis for interdependent energy, water, waste, telecommunications, and transportation network failures in New Zealand showed that nearly half (46%) of the total disruptions could be attributed to network propagation effects instead of disruptions attributed to the directly failed assets (Zorn et al., 2020). These studies have proved effective in informing stakeholders, such as the UK National Infrastructure Commission’s resilience study (NIC, 2020) and infrastructure owners/operators in New Zealand, about ways in which...
interdependencies influence failure cascades, especially creating feedbacks that lead to further disruptions in the networks where the failures originate.

**Figure 4.** Quantifiable evidence of the systemic nature of failure propagation from electricity towards telecoms, water, rail and road networks in Great Britain. The results show ~18,000 instances of individual electricity assets that were stress tested to fail and the cascading effects of such failures at the systems level were understood by tracing the proportion (%) of failures that lead to higher order failures in other networks (Pant et al., 2020).

As the stress-testing of infrastructure networks referred to above is hazard-agnostic, this does not incorporate realistic scenarios of a particular asset to be vulnerable. Hence, this is just one version of stress testing, the other being based on selected hazard events. To do this hazard maps are adopted which is discussed in the next section.

**Hazard exposures**

The intersection of geospatial databases of infrastructure assets and extreme hazard maps provides an indication of the likelihood a particular asset will be affected compared to others.

In Curacao, Adshead et al. (2018) studied potential exposure effects of a future 1-metre sea-level rise (forecasted for 2100) and a 4-metre storm-surge event on the island, which are presented in Figure 5. Their study highlighted that flooding exposure of all economic infrastructure assets (roads, ports, water oil refinery) was concentrated in the capital city (zoomed in region in Figure 5), with potential interdependent consequences for the social infrastructures concentrated in that area (access to healthcare, finance, education, tourism facilities).
Figure 5. Potential areas and assets exposed to a future 1-metre sea-level rise (forecasted for 2100) and a 4m storm-surge event in Curacao (Adshead et al., 2018).

Hu et al. (2019a) examined the exposure of wastewater treatment plants (WWTP) in China, to current and future flooding at return periods varying from 1 in 5 to 1 in 1000 years under different climate emission scenarios (RCP4.5 and RCP8.5). Their study found that net increases in future asset exposures where almost always higher for a lower return period flooding event than a higher return period event, implying that future extremes would become more frequent due to climate change. Furthermore, analysis of the changes in spatial variations of flood exposures for 1 in 50-year flooding, which is close to the flood protection design standards of such assets in China, highlighted that a large number of WWTP’s in the economically important Southern and Eastern parts of the country would be increasingly exposed and potentially at risk to flooding in the future (see Figure 6).
Exposure analysis has been very useful in informing stakeholders that the location-sensitivity of hazards can significantly impact climate resilient infrastructure planning. The exposure of an infrastructure asset to a climatic hazard is just one part of the picture. In reality, assets are designed and constructed using different engineering standards, which vary considerably across geographies and year of construction. Ultimately, this means for a hazard of a given intensity, the expected damage to an asset can vary significantly. This approach is further detailed in the following section.

Direct damage assessments

To quantify the direct vulnerabilities as expected damages to infrastructure physical assets hazard exposure analyses can further integrate fragility or vulnerability functions. Such functions are commonly used to relate the intensity of a hazard to the probability of damage or reduced level of service. By combining the uncertainties of vulnerability functions with the uncertainties associated with the location-sensitivity of the hazards (discussed in the previous section), a sensitivity analysis-based stress testing approach is very useful in quantifying a robust range of direct damages to assets exposed to multi-hazards.

Koks et al. (2019c) adopted this approach in the first estimate of global exposure of road and railway assets to a range of probabilistic climatic and geohazards (tropical cyclones, surface flooding, river flooding, coastal flooding, and earthquakes) to quantify the exposures and expected annual direct damage costs (EADs) to linear road and rail assets at national and sub-national scales. Figure 7a shows their results of the spatial disaggregation of relative expected annual exposed lengths of road and rail assets globally, where the classification from very low to very high was based on the 20th percentile values. The results highlighted that low income and lower to middle income countries had the highest multi-hazard exposures, and ~27% of all road and railway assets globally were exposed to at least one hazard with a 1 in 250 return period and ~7.5% of the road and railway assets are exposed to a 1 in 100-year flood event.

The direct damage costs from asset vulnerability to different hazard types showed (Figure 7b) 73% of the global EADs were caused by surface and river flooding, followed by coastal floods (15.5%), earthquakes (7.3%), and tropical cyclones (3.8%). These direct risks per kilometer rose steeply from low-income countries to lower middle-income countries and declined as...
country incomes grew. For example, high losses in lower middle-income countries in Central Asian and Africa countries were due to high surface flooding exposure. This is directly correlated to the level of investment made in existing infrastructure design standards, which improves as country incomes increases. Such insights can have major implications in terms of how the funding of resilience building initiatives can be best targeted globally for the greatest relative impact.

Figure 7. (a) Global multi-hazard exposure map of road and rail linear infrastructure assets showing the relative exposures based on 20th percentiles (b) Estimated EAD for different hazard types classified by income groups of countries (Koks et al. 2019a).

Indirect Impacts: Societal

While direct damages help understand the extent of physical stock of assets that are at risk, they provide an incomplete picture about the wider societal consequences of infrastructure outages that are many times more important in planning recovery from major disasters. By incorporating the effects of disruptions of infrastructure services on the dependent population on each individual infrastructure asset across a network, a much more human-centric and consistent metric can be achieved across infrastructures.

The spatial effects of infrastructure failures on populations at the national scale have been represented in different studies through spatial hotspot maps, where hotspots show the geographical influence of the infrastructure failures within an area, measured according to relative numbers of customers directly or indirectly disrupted across the whole nation by such failures. These hotspots may be quantified through nonparametric Kernel Density Estimation (KDE) techniques that create continuous gridded surfaces, by integrating a number of
observations (infrastructure assets and their customer disruptions) within a certain distance, to represent geographic interdependencies between clusters of infrastructures that could be exposed to the same hazard surface (Thacker et al., 2017a).

Figure 8 (see caption) shows three case-studies that quantified customer disruption-based infrastructure hotspots at national scale. Thacker et al. (2017a) analyzed the hotspots from disruptions to customers and users of connected networks of electricity, gas, wastewater, solid waste, telecoms, roads and railways in England and Wales. They revealed that while most disruption hotspots were concentrated around urban conurbations there were several assets in locations of low population densities that had significant impacts due to network effects (Figure 8a). Hu et al (2016) applied a similar approach in China, integrating a 1 in 100-year river flood hazard with infrastructure clusters. They showed that the average number of infrastructure users who could be disrupted by the impacts of flooding on energy, water and waste sectors in China were 103 million, many of whom were concentrated in areas of economic importance (Figure 8b). Zorn et al. (2020) highlighted the spatial reach, disruption frequency, and consequences to infrastructure users/customers across ten interdependent infrastructures disrupted by spatially constrained hazards in New Zealand. They demonstrated that cascading disruptions between infrastructures from electricity, road, and water supply networks had a much more widespread reach of indirect infrastructure outages – often far removed from the initiating disruption (Figure 8c).

Such results confirm that while infrastructure owner/operators may invest in resilience building measures across networks, there is still significant potential for widespread disruptions resulting from indirectly initiated failures if supporting networks do not concurrently introduce network redundancies or upgrade system robustness to disruptions.
Figure 8. National-scale hotspot maps showing the relative importance of concentrations of infrastructure clusters in terms of the direct and indirect customers disrupted by their failures. (a) In England and Wales where the higher composite z-scores in 1-km² gridded areas show the locations where disruptions are the highest through connected networks of energy, transport, waste, water and telecoms. (b) In China where the hotspots, ranked from 1-8, show the locations where failures of clusters of electricity, rail, port, airport and wastewater assets produce the highest disruptions when exposed to 1 in 100-year flood hazards at 5-km² gridded resolutions. (c) In New Zealand where the increasing sizes and darker colors of the 5-km edge hexagonal surfaces correlate with the increase disruptive impact and spatial reach of the failures of interdependent clusters of energy, transport, water, waste and telecoms network assets within the hexagons.

The indirect socio-economic impacts of infrastructure failures can also affect a country’s ambitions towards meeting the SDG targets, especially in Small Island Developing States (and low-income countries) where very few assets might be responsible for a significant proportion of economic activity. Fuldauer et al. (2021) highlighted this in their study of potential storm surges at the two most important ports (Castries and Vigie Cargo Port) in Saint Lucia (see Figure 9). Their analysis showed that storm surges could cause the largest percentage of potential freight capacity loss, leading to the disruption of up to 577 thousand tons of freight/year, worth US$446 million, and further impacting the import of goods and services to the value of EC$ 1.77 billion (US$650 million) yearly, as well as the export of numerous industries that employ more than 25 percent of the labor force. These imports included vital goods, including wheat, medicaments and food, but also fuel for cooking and electricity, which are essential inputs for most of Saint Lucia’s other industries and therefore numerous dimensions of development. They concluded that exposed freight capacity can thus indirectly harm numerous development areas, including food (SDG 2), healthcare (SDG 3), electricity (SDG 7), and economic growth (SDG 8). The study highlighted that, given their importance, risk-reduction investments in the Castries and Vigie Port can help ensure the country’s resilience in the face of disasters.
Indirect impacts: Business to macroeconomic effects

A more complete economic case for enhancing infrastructure resilience is made by estimating the monetary losses to businesses and the wider economic supply chains affected by infrastructure failures and disruptions. Most research and policy documents related to disaster risk financing and insurance have only focused on the economic values associated with direct damage assessments to infrastructure, property and building assets exposed to hazards (World Bank 2013; Wing et al., 2020), very often ignoring the wider economic impacts of infrastructure failures. However, macroeconomic Input-Output (IO) based impact assessment models (Koks et al., 2019a) are increasingly being integrated with spatial infrastructure network models to quantify indirect economic losses associated with infrastructure failures. The case studies below demonstrate how this is being done, with increasing focus on improving spatial granularity of business, supply-chain and macroeconomic data to provide more realistic understanding of economic losses.

Verschuur et al. (2021) performed a criticality analysis of port and maritime transport networks globally with respect to their interdependency with global supply-chains, concluding that several low-income countries and island states were often more dependent on maritime transport through one or two key ports (also shown by the Fuldauer et al. (2021) example of Figure 9). They found more examples, such as Congo, Malta, Mauritius and Tanzania, where 20.3-43.5% of economic activity was dependent on trade flows flowing through a single port. Their study also showed on a global scale, 9.3% of the total industry output depends upon trade flowing through only the top 10 ports, with the port of Shanghai alone embedding 1.7% of global output. Therefore, large macro-economic impacts, both on a national and global scale, could be expected when ports are affected by climatic extremes.

Hu et al. (2019) combined a detailed firm-level econometric analysis, from compiled statistics on flood exposures of 399,356 firms over the period 2003–2010, with a macroeconomic IO model to estimate flood impacts on China’s manufacturing sector. They found that large flooding events on average reduced firm outputs (measured by labor productivity) by about 28.3% per year, which resulted in macroeconomic impact to be a 12.3% annual loss in total...
output amounting to 15,416 RMB billion in the year of flooding, and further lagged flood effects over the following two years reduced firm level outputs by 5.4% and caused 2.3% loss in total output or 2,486 RMB billion at the macro-level. These results indicated that the scale of economic impacts from flooding is much larger than microanalyses of direct damage indicate, thus justifying greater action, at a policy level and by individual firms, to manage flood risk.

Using a more nuanced IO impact assessment model, Koks et al. (2019b) combined geospatial locations of electricity infrastructure assets in the south-east of England supplying to local industrial areas, with a multiregional supply-use IO model of the UK economy that traced the impacts of electricity flooding casing supply-side disruptions to businesses in South-East England which led to macroeconomic losses across 37 subnational economic regions of the UK. This study, involving the stress testing of every combination of failures of five substations exposed to more than 1-meter of flooding, demonstrated that for a 1 in 1000-year flood event business disruptions at a local level were magnified by a factor of 23 when incorporating electricity failure in the loss assessment. When looking at the macroeconomic impacts at a national level (see Figure 10), the results showed that daily direct output flow losses could increase up to a factor 33 and total output flow losses up to a factor 3, when including electricity failure in the loss assessment.

Figure 10: Total daily macroeconomic output losses for the United Kingdom for business activity affected by different failure combinations (s1-s31) of 5 substations found to the exposed to greater than 1m depth of flooding in 1 in 1000-year return period flood event. The left panel shows the impacts that do not account for electricity failures of flooded businesses, while the right panel shows the impacts due to a flood and failure of the electricity substation at the same time. The details of industry sectors A-H are explained in Koks et al. (2019a).
Understanding adaptation options and their effectiveness

Using methods highlighted across Section 3.1-3.5 to estimate the direct and indirect impacts to probabilistic hazards leads to the estimation of network risks associated with individual asset failures, which can then inform climate adaptation planning. Climate risk assessment should be able to account for the uncertainties and sensitivities associated with different climate models, scenarios, timelines along with the uncertainties associated with infrastructure vulnerability impacts. The effectiveness of climate resilience options is then evaluated by comparing their costs with the benefits (of avoided risks) over the life cycle of asset and network management. The costs included: (1) initial investment or one-time costs of a resilience option when they were implemented; and (2) costs of routine maintenance (assumed to apply every year) and periodic maintenance (assumed to apply every few years) over the life cycle of the asset. Network asset and location specific benefit-cost ratios (BCR), discounted over time, can help identify options for which the avoided asset risks would be worth implementing (BCR ≥ 1) and which options would not be worth investing in (BCR <1). Case studies on national-scale transport risks analysis in Vietnam (Oh et al., 2019) and Argentina (Pant et al., 2019) have been able to incorporate such principles in an effective way.

Figure 11a shows results for Vietnam (Oh et al. 2019) where direct and indirect risks (Figure 11a – left panel) of road networks damages and freight disruptions due to multiple climate hazards (floods, cyclones, landslides) were quantified and compared with costs (Figure 11a – center panel) for options of upgrading roads and bridges to higher climate resilience designs. This helped identify the locations where climate investment should be prioritized based on highest BCRs, as shown in Figure 11a – right panel. Estimates suggested that costs of upgrading the 20 worst-climate-impacted national roads in Vietnam to become climate resilient would be high, but the cumulative benefits over 35 years of such investments were substantial, where for every 1 US$ invested in enhancing climate resilience the benefits of avoiding risks would be equivalent to safeguarding US$7-23 of economic value associated with freight supply chains. 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 11b, 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. Furthermore, the case for investing in climate resilience became stronger as the durations of disruptive impacts increased, which in turn meant that investing in reducing the duration of disruption should be a priority of adaptation planners in Vietnam. Such analysis proved useful in providing scientific evidence to the transport ministries to develop a national strategy for climate resilient transport and plans, as part of the transport sector’s contribution to the Nationally Determined Contributions, to meet the Paris Climate Agreement targets.
Policy relevance and use of models in practice

The broad range of case studies presented in this paper have demonstrated various useful map outputs and metrics useful for policy makers who want to make better informed decisions on infrastructure risk and climate adaptation. There has been a growing interest and support for several of these case studies from different national governments and stakeholders involved in national-scale infrastructure planning, as highlighted throughout Section 3.1-3.6. Here we highlight some examples showing how the methodologies and case studies have been relevant to policymakers and used in practice.

As mentioned previously, interdependent network analysis for UK (National Infrastructure Commission) and New Zealand have provided stakeholders with opportunities to pilot systems...
thinking and modelling infrastructure interdependencies (NIC, 2020; Pant et al., 2020; Zorn et al., 2020). The English Environmental Agency’s (EA) Long-Term Investment Scenarios (LTIS) 2019 policy report also included similar national infrastructure modelling tools to quantify the potential wider impacts that flooding could have on infrastructure systems and their users, which led to a revision of the estimated annual damage from flooding upwards from a long-term annual average of £860 million to £933 million, increasing risk reduction from 12% to about 15% and resulting in the overall benefit to cost ratio for investment in flood protection increasing from about 5 to 1 to about 9 to 1 (Environment Agency, 2019).

In the Saint Lucia study (Adshead et al., 2020), the modelling was performed in close collaboration with engineers and policy advisors in the Ministry of Finance, who were trained on using the model to underpin evidence-based decision-making and further updating it with improved datasets. A wider workshop was conducted on the modelling tool in country, hosted by Saint Lucia’s National Integrated Planning and Programme Unit (NIPP), which has been streamlined on TV (https://youtu.be/-VbzkWgjpDA). Practically, the tool can support application for the Green Climate Fund to adapt to the impacts of climate change. Results from the modelling were further endorsed by the Prime Minister, who highlighted the importance of the modelling in providing granularity of where to prioritize adaptation under commitments under the Paris Agreement and aligned with the SDGs. A similar training workshop was conducted in Curacao (Adshead et al., 2018), and attended by stakeholders across government ministries, infrastructure stakeholders and academia. The local university’ engineering department is committed to further updating the tool.

The global transport multi-hazard damage assessment (Koks et al., 2019) and the China WWTP hazard exposure and impact (Hu et al., 2019) studies featured prominently in high level global policy reports including the World Bank’s Lifelines report on infrastructure resilience (Hallegatte et al., 2019) and the Global Commission of Adaptation’s report on climate adaptation (Hall et al., 2019).

The transport risks analysis studies, in Vietnam (Oh et al., 2019) and Argentina (Pant et al., 2019), resulted in coordinated stakeholder engagements and data collection with different agencies in central and province level government agencies with Ministries of Transport of these countries. In addition to informing them about the scale of climate risks and adaptation costs needs for building climate resilient transport network, the studies created unique computational tools (see Section 5) that were made available to the government agencies to enhance their capability to undertake similar analysis in the future. The recently created Resilience Rating System (RRS) by the World Bank’s Action Plan on Climate Change and Resilience gave an A+ rating to the Vietnam study (Oh et al., 2019) in satisfaction of the criteria: “As well as increasing the resilience of beneficiaries, the project uses at least one climate indicator to monitor the progress of those resilience-building activities and/or outcomes. Climate indicators that reflect resilience measures are thoroughly embedded in the project’s overall theory of change or road map for achieving long-term goals, as part of its monitoring and evaluation strategy” (World Bank Group, 2021).
Generalizing compiling datasets and developing computational tools

The methodologies and case studies presented here all take a quantitative computational modelling and simulation approach towards building and stress testing infrastructure networks. Historically, the acquisition of geospatially accurate databases of infrastructure asset inventories was largely limited to developed or higher income countries. More recently, projects such as OpenStreetMap has greatly democratized access to geospatial data (Hacklay and Weber, 2008). This is in addition to more infrastructure owners/operators providing open access to datasets and novel applications in data collection such as the use of satellite nighttime imagery to create global power transmission network datasets (Arderne et al., 2020) and Google Street View (Dick et al., 2019) to recognize the presence of infrastructure. Harnessing such resource and complimenting them the country specific richer datasets gathered through stakeholder engagements, various novel geospatial datasets were created in the different case studies covered in this paper.

For the benefit of wider usage of these approaches, geospatial computational models have been developed in Python programming language and shared as open-source code repositories and tools. A few relevant repositories include:

1) Argentina Transport Risk Analysis - https://github.com/oi-analytics/argentina-transport
2) Vietnam Transport Risk Analysis - https://github.com/oi-analytics/vietnam-transport

The Argentina analysis was also translated into a web-based risk visualization platform (https://github.com/oi-analytics/oi-risk-vis), to enable stakeholders identify and zoom in on the locations of the most vulnerable transport network assets in the country, identify locations of the roads and bridges where adaptation investments should be prioritized based on their BCRs, as shown in Figure 12. The tool has been embedded within the Ministry of Transport’s data systems and analytics capabilities in Argentina.
Figure 12. Risk Visualization tool outputs at asset level for Argentina transport analysis study showing:
(a) Characteristics and level of flood exposures of a road; and (b) Road asset highlighted and identified by the BCRs of investing in climate adaptation.
Discussion and Conclusions

Investing in infrastructure resilience to meet climate adaptation and SDG targets relies upon dependable risk analytics, which is demonstrated through different case studies in this paper. These case studies provide useful insights and tools that can potentially inform decisions made towards meeting the targets set by the SFDRR which include (UNISDR, 2015): (a) reducing disaster damages to critical infrastructures and basic services; (b) reducing the number of affected people by 2030; and (3) reducing disaster economic losses with relation of global GDP by 2030. 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 as well as the uncertain characteristics of climate risk modelling. 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 and uncertain 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.

The diversity of studies presented here highlight how various climate-risk quantification techniques and tools can inform policy decisions from the local to the systems (global) scale. While policymakers and investors make infrastructure planning decisions at the asset scale, they lack knowledge on spatial network vulnerabilities and risks, resulting in investments being often not prioritized with the aim of building systemic resilience. But this gap is being filled as such network analyses are becoming more prevalent and achievable because more data on spatial hazards, spatial assets and network topology, customer and economic usage are becoming available. Improving these methodologies and their uptake worldwide has been highlighted as one of the greatest adaptation opportunities.

Through insights from a number of quantitative infrastructure network analysis case studies around the world we show that the indirect impacts of network disruptions are a can significantly magnify economic losses. In existing research and practice, there is a lot of focus on only quantifying direct damage losses while indirect loss estimations are not very well understood.

The studies presented in this paper aim to highlight existing research and further opportunities, for national governments and climate adaptation planners across multiple sectors, to improve and enrich bottom-up infrastructure risk analyses with top-down climate assessment tools. Apart from quantifying very complex and interesting results, its value goes beyond a purely academic/technical exercise which influences decision making and engages different stakeholders. Key opportunities, amongst others, lie in: (1) better data creation and sharing of asset locations, network connectivity, structural design standards and conditions of assets, operational rules; (2) improving upon the lack of empirical evidence of cascading mechanisms seen during network failures, and their resulting disruptive impacts; (3) data on indirect socio-economic losses which are less understood and validated in practice, as most risk assessments and investment decisions are being made based on direct damage losses; (4)
creating more empirical evidence on the timelines and patterns of infrastructure asset, network and socio-economic recovery for disruptions; (5) integrating local knowledge on adaptation options and their costs; and (6) engaging local and national decision makers and key stakeholders throughout the various scales of this process.

It is critical these focus areas continue to be addressed and developed to for future climatic risks to infrastructures. Realizing opportunities to continue to adapt and protect infrastructures in the face of climate change will be critical to build the much-needed resilience for a sustainable.
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