ADVANCED MULTI-HAZARD RISK ASSESSMENTS OF TRANSPORT NETWORKS

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ABSTRACT

Hazard risk assessments of transport systems have traditionally followed a one-dimensional approach, focusing on a single hazard at a time (e.g. river flooding, or coastal erosion) over limited geographical areas. With the emergence of high-quality national and global datasets, along with advances in computational power, multi-hazard assessments of entire national transport systems are now viable.

The Asian Development Bank initiated multi-hazard risk assessment studies for transport networks in Tajikistan, Papua New Guinea, and Pakistan. The chosen countries illustrate the methodology's applicability across diverse geographical and hazard contexts. Each project begins by leveraging Google and TomTom datasets to develop nationwide origin-destination matrices integrating points of interest from various sources, and incorporating population data from WorldPop.

Simulation of a broad spectrum of hazards, including coastal and riverine flooding (30m grid datasets and seven return periods from JBA Risk Management), earthquakes and liquefaction, landslides, cyclones, extreme heat events, and forest fires then occurs. A core feature of the modelling is its ability to test event interactions—for instance, simulating a flood that follows an earthquake or earlier flood.

Impacts on route choice are reflected in traffic detours using standard four-stage transport modelling principles, including equilibrium-based network assignment. This includes modelling the primary, secondary and tertiary road network as necessary. The approach enables the assessment of the impact of constructing new road links, or enhancing the resilience of existing links. The expected annual damage (EAD), the cost to diverted traffic—including impacts on alternate routes—and access to social services (such as the accessibility to hospitals during times of hazards) are calculated. These data-driven insights yield risk and criticality ratings for the road network, pinpointing where mitigation investment is the optimal choice versus where operational adjustments may suffice.

While commencing with a focus on motorised transport (which makes up the dominant portion of national and regional transport demand in most countries), the methodology has been expanded to enable the significant contribution that walking connectivity and resilience plays at the local level.

The findings are now influencing project prioritisation and design, and being integrated into updated design and maintenance standards, and road asset management practices including adaptation pathways.

1 INTRODUCTION

Robust transport networks form the backbone of a well-functioning society, and play a critical role in reducing poverty levels, improving access to social services, and ensuring the efficient movement of people and goods. Resilient and reliable infrastructure is therefore an essential part of the Sustainable Development Goals (SDGs) (Thacker et al., 2019). Target 9.1 of the SDGs in particular, calls for "*reliable, sustainable and resilient infrastructure, including regional and trans-border infrastructure, to support economic development and human well-being, with a focus on affordable and equitable access for all*" (Adshead et al., 2019). However, this goal is currently far from being achieved.

Transport systems in Asia and the Pacific are especially vulnerable to climate change-related hazards. The consequences of such hazards include direct damage to critical transport infrastructure, disruption to transport services, and wider social and economic impacts due to the failure of those services. Climate-induced hazards, such as the increasing occurrence of flash floods and heavy rains, are significant risks across many countries of the world – including in New Zealand as reflected by major events such as Cyclone Gabrielle (2023) and the repeated flood events in the Tasman-Nelson-Marlborough area during the winter of 2025.

Emerging economies in Asia and the Pacific face a growing transport infrastructure gap, with annual investment needs estimated at US$2.9 trillion through 2035[1]. This includes approximately US$2 trillion per year for new transport infrastructure, US$0.2 trillion for climate-proofing and US$0.7 trillion for maintenance. Climate-related hazards already account for 65%[1] of annual damage to transport infrastructure in the region, highlighting the benefits and urgency of integrating resilience into the full lifecycle of transport investments.

For these reasons, the Asian Development Bank ("ADB") is supporting its developing member countries to incorporate risk-informed approaches into all aspects of transport infrastructure. Central to this effort is the use of multi-hazard risk and criticality assessments, which provide actionable insights to prioritise transport infrastructure investments, improve design and maintenance standards, strengthen infrastructure asset management practices, and align transport infrastructure planning with climate adaptation goals.

Climate resilient projects within ADB are categorized into Type 1 and Type 2 projects. In Type 1 projects, the design of projects is incrementally adjusted or improved from a pre-defined base case to incorporate climate adaptation measures. In Type 2 projects, projects are conceived and designed to reduce vulnerability to climate change, and to build the resilience of a system. Type 2 projects are further categorised into Type 2A and Type 2B projects. Type 2A projects explicitly aim to reduce vulnerability over the long-term, and steer development in a resilient direction (e.g. including climate resilience as one of the objectives). Type 2B projects, have building climate resilience as their primary objective. The purpose of the methodology documented in this paper is to explore how a climate risk and resilience assessment can be set up to support Type 2A and Type 2B projects.

It is further noted that the impacts of transport disruptions are not always felt equally by all members of society. For instance, women often face greater challenges in mobility due to their domestic responsibilities in many societies. Road disruptions impair rural-urban commutes, increasing food and energy insecurity, and limiting access to healthcare and education (Blondin, 2022). Recognising these disparities and the role that a resilient transport infrastructure plays in overall society is essential for the long-term development of countries.

Historically owing to data and computational efforts, assessments of hazards has often been singular in nature (i.e. just assessing flood risks) or localised in geographic coverage (possibly a city or region). The increasing availability of large (often global) high quality data sets on hazards and transport systems, along with vast improvements in computing power now provide analysts with the

[1] Asian Transport Observatory

ability to address these prior shortcomings. This paper presents such a methodology that has been employed by ADB with case studies undertaken in Papua New Guinea (PNG), Pakistan (PAK) and Tajikistan (TAJ) used to demonstrate the process and the outcomes possible from such an analysis.

The PNG road network is very fragmented with significant gaps between regional road networks. Additionally, the terrain increases the risk of natural hazards from flooding, landslides, and earthquakes. The inclusion of this case study in this paper demonstrates the ability of the approach to both analyse a wide range of hazards and assess the contribution of additional road links to resilience. The PAK road network has experienced massive flooding that impacts millions of people, and provides an example of a how the method can work in such flood prone nations. The TAJ road network operates in a less challenging environment (from a transport perspective), with the range and magnitude of hazards more limited in nature. The TAJ analysis however demonstrates the ability to take the national modelling results and then zoom in to a particular route to assess the impacts of upgrades to the resilience of that route.

It is recognised that while this paper focusses on the resilience of the transport system, community resilience – especially at the local level – can often be better served through the placement of key facilities within a community. For instance the placement of medical facilities within a community may mitigate the need for travel outside the community during and after natural disasters. The concept of community resilience is explored further in papers such as that by Thornley et al (2014). While the methodology described in this paper can be used to test the impact of manually defined alternative placement of key facilities (such as medical facilities), it does not currently optimise such approaches.

2 MODEL FRAMEWORK

There are four main phases of the overall modelling process, with these being:

- The establishment of an origin-destination matrix for travel demand as well as network-wide roadway link flows;
- Analysis of the hazards and their impact on the transport network;
- Economic assessment of the impacts – both direct damage to the assets, and disruption to transport routes;
- The development of adaptation pathways to mitigate the risks and hazards.

The methodology employed by ADB draws extensively on the following prior work of the authors:

- The work to establish the origin-destination matrix and network flows is based upon that of Waller et al. (2021), Waller et al. (2023) and Bäck & Schwefel (1993).
- The hazard modelling work is built upon that of Koks et al. (2019).
- The economic assessment is based upon that of the Highway Development and Management version 4 (HDM-4) models for which two of the authors – namely, Greenwood and Odoki – were heavily involved in the production of.

The remainder of this paper explores these different phases of the modelling process, using the case studies of PNG, PAK and TAJ to demonstrate the method employed.

2.1 Traffic Origin-Destination Matrix Development

The Rapid Planning modelling process uses machine learning/Applied AI techniques in conjunction with traditional transport planning methodologies to rapidly construct a regional or national network planning model capable of hypothetical scenario evaluation. The technical details of the methodology are documented in Waller et al. (2021), Waller et al. (2023) and Lalwani et al. (2024). This approach substantially improves the efficiency with which traffic network planning models can be established while maintaining their core attributes, such as the ability to identify equilibrium travel demands on the road network under hypothetical “alternative” scenarios.

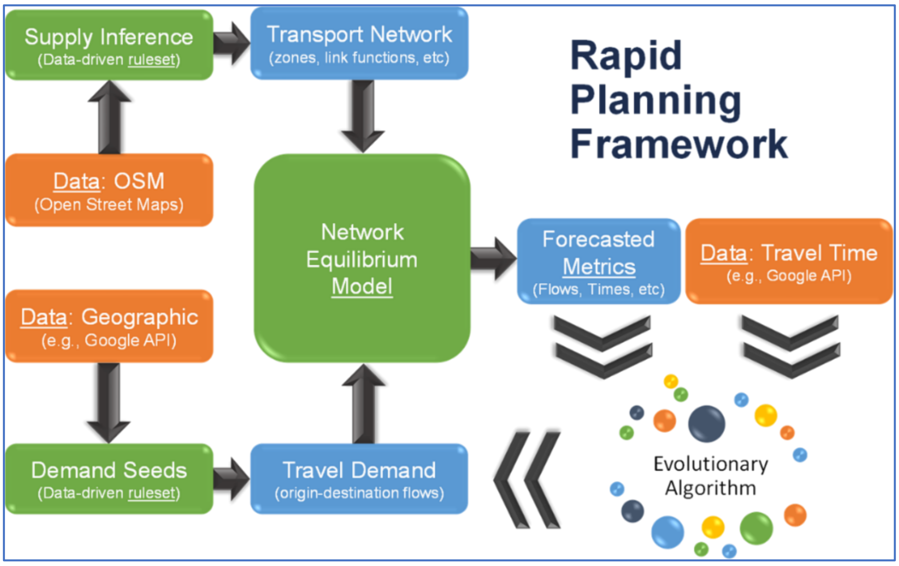

Figure 1: Rapid Planning Framework Presented in Waller et al. (2021)

Figure 1 shows the overall framework. Several core features are stressed within the framework (1) the capability of emerging data is leveraged by the inclusion of OpenStreetMap and Google (or other sources such as TomTom, Baidu, etc.) (2) Machine Learning/AI techniques are used to automate model development via Evolutionary Algorithm techniques to search for an appropriate travel OD matrix and (3) critical principles of traditional transport planning are retained via the inclusion of network equilibrium within the core functioning of the approach. Together, these features enable aspects of model development to be automated while retaining the models relevance.

To determine the needed model parameters, the framework relies on a tailored problem-specific Evolution Algorithm (EA). As shown in Figure 2, the specific EA approach utilised for this project represents all network-wide travel origin-destination demand variables as a chromosome to be optimised over many generations of potential solutions. In each generation, hundreds to thousands of chromosomes are maintained with numerous chromosome alterations including reproduction, mutation and recombination employed to develop new generations of potential solutions. As in the general case for EA approaches, the value of any specific chromosome is determined via a fitness function. The specific fitness function formulation can vary by problem with numerous options existing even for a given single context.

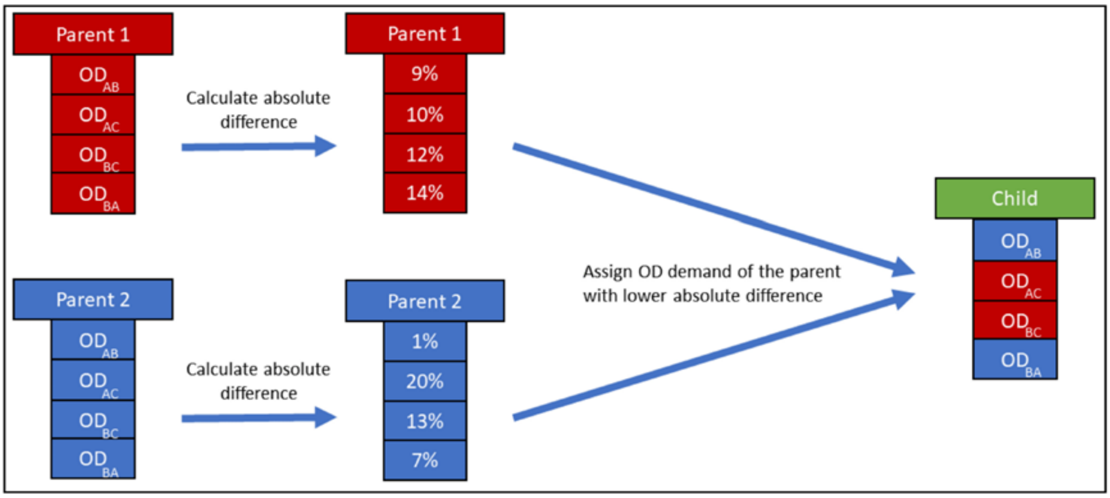

Figure 2: Chromosome Definition Within the Evolutionary Algorithm (EA) Machine Learning (ML) implementation (Waller et al., 2021)

An additional overview on specific procedural steps within the framework is discussed next:

1. **Network Data Extraction and Zoning**:
The process begins by extracting road network data and classifying roads, followed by zoning the network. The size of the zones is adjusted based on the parameters of the obtained network and the required level of detail. This step utilises OpenStreetMap (OSM) data and the OSMnx tool to create a detailed road network, including attributes such as road length, number of lanes, and speed limits. In addition, world population and other demographic data informs the exact sizing and spatial orientation of the zonal structure.

2. **Travel Time Data Collection**:
Travel time data for each network link is fetched using pervasive data aggregators including Google, TomTom or Baidu. These platforms provide both real-time and typical travel times. The default approach is to extract typical travel times, as they represent average conditions and are less prone to fluctuations. However, when specific timeframes are useful for a given application, real-time values are fetched.

3. **Origin-Destination (OD) Matrix Estimation**:
An Evolutionary Algorithm (EA) machine learning approach is used to estimate the Origin-Destination (OD) travel demand matrix. Critical to the EA process though are the initial chromosome solutions. The initial OD chromosome values are generated using a range of strategies. One key methodology incorporates geographic Point of Interest (POI) data such as businesses and population data from WorldPop as the basis. From these initial chromosome solutions, the bi-level optimisation approach involves an upper level that estimates the OD matrix by minimising errors between observed and predicted values, and a lower level that applies user-equilibrium traffic assignment to model the interaction of travellers with the network.

Acronym	Method Name	Governing Equation	Notation
TFM	Travel time—free flow travel time model.	$d_{rs} = \frac{\frac{TT_{rs}^{obs}}{TT_{rs}^{f}}}{\sum_{rs} \frac{TT_{rs}^{obs}}{TT_{rs}^{f}}} \cdot D$	TT_{rs}^{obs}—Observed (from any pervasive platform) travel time between OD pair r and s. $TT^{f}{}_{rs}$—Observed free-flow travel time between OD pair r and s. k_{rs}—Average shortest distance between the OD pair r and s when the network is empty. G_r—user-defined proportion value of zone r, where $\sum G_r = 1$. A_s—user-defined proportion value of zone s, *where* $\sum A_s = 1$.
FDM	Free flow travel time—distance model.	$d_{rs} = \frac{\frac{TT_{rs}^{f}}{k_{rs}^{2}}}{\sum_{rs} \frac{TT_{rs}^{f}}{k_{rs}^{2}}} \cdot D$	
TDM	Travel time distance model.	$d_{rs} = \frac{\frac{TT_{rs}^{obs}}{k_{rs}^{2}}}{\sum_{rs} \frac{TT_{rs}^{obs}}{k_{rs}^{2}}} \cdot D$	
CGM	Custom gravity model.	$d_{rs} = \frac{\frac{G_r A_s}{k_{rs}^{2}}}{\sum_{rs} \frac{G_r A_s}{k_{rs}^{2}}} \cdot D$	

Figure 3: Examples of initial solutions used in the EA machine learning implementation (Waller et al., 2021)

4. **Model Optimisation**:
The estimated model is compared with the fetched travel time data as well as any additional data which can be optionally obtained such as target OD matrices, traffic counts, travel time survey, etc. The outputs of the modelling process include link travel times and volumes, estimated OD matrices, and estimated OD travel times. Any of these can serve as points of comparison for model optimisation. Given the points of data comparison, a broad range of potential fitness functions can be examined to help direct the model search.

The analysis uses an existing codebase which is managed by Mobility Thinking Pty Ltd (MOTH). In collaboration with TU Dresden, this has resulted in a Python package called RAPIDPy, which provides tools to automate network extraction, missing data imputation, and ensure network connectivity. RAPIDPy leverages travel time APIs to extract the required travel time data for the network and interfaces to optimisation methods for demand estimation using a range of open data sources. In addition, numerous open source solutions for model visualisation, analysis and extraction are under continual development including an ongoing collaboration with NVIDIA.

The Rapid Planning methodology as applied to the nation-wide traffic model in Tajikistan is presented in the figures and table below. The comprehensive network ensures that even the most remote areas are integrated into the national transport system, supporting economic development and social inclusion.

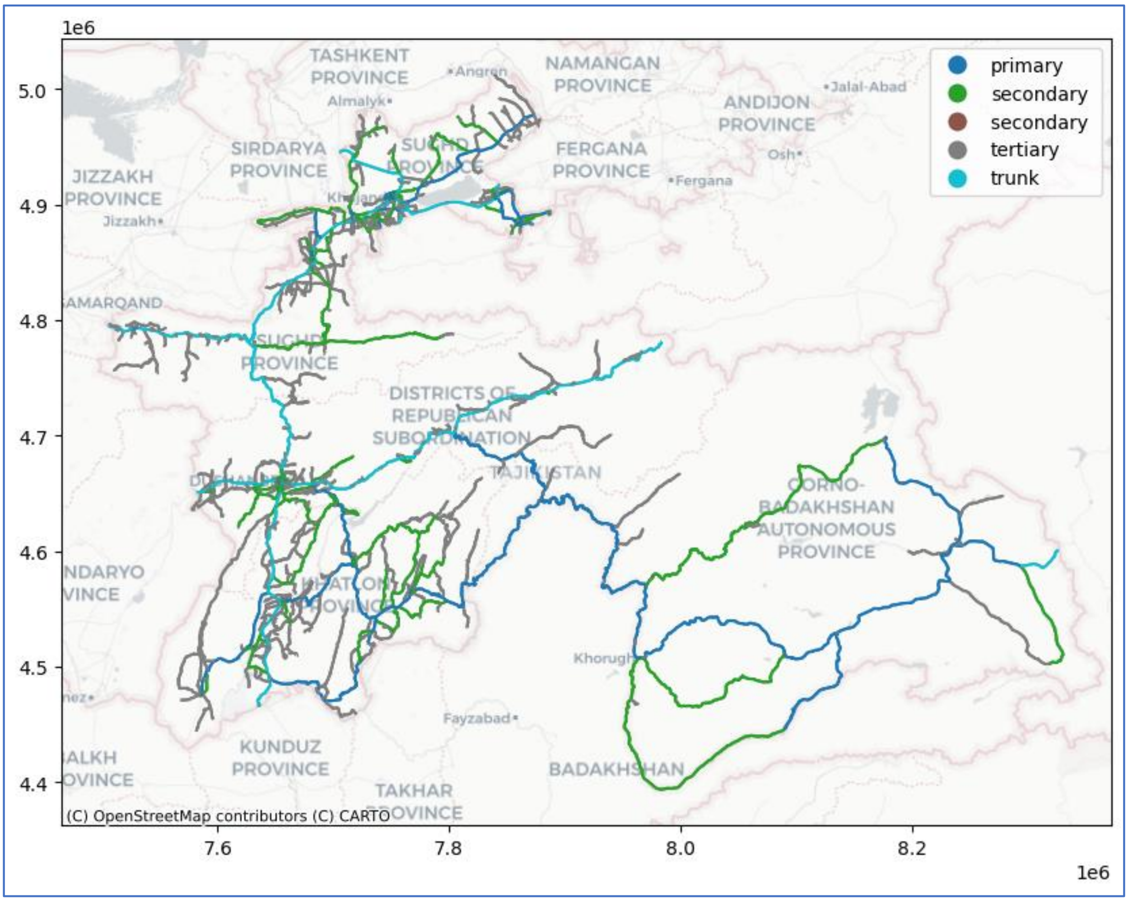

Figure 4: Major Road Network of Tajikistan

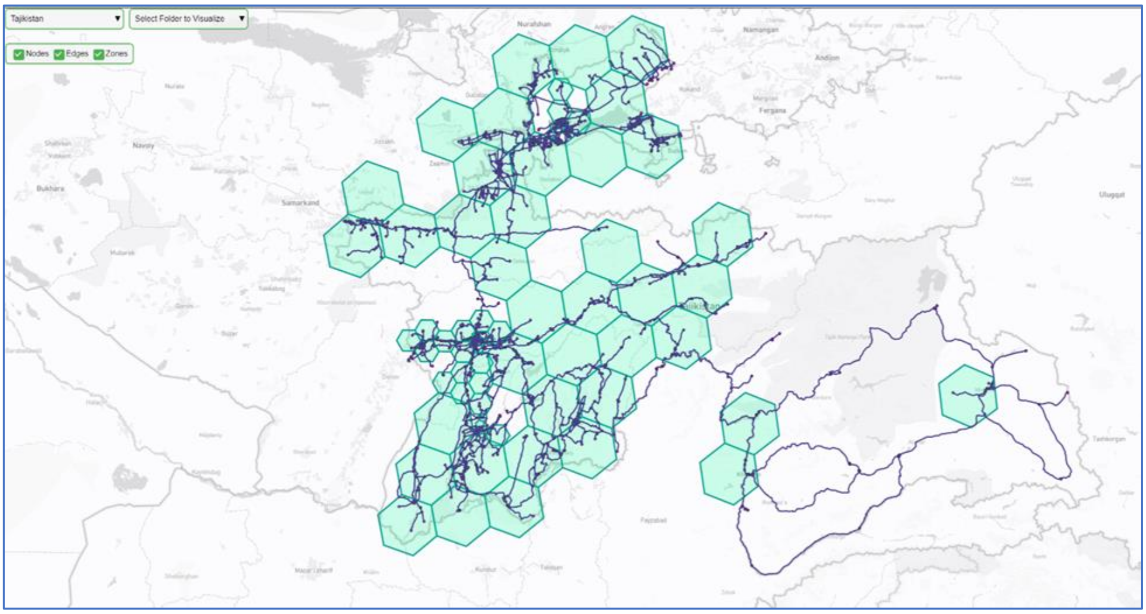

Figure 5: TAJ Rapid Model Network and Zonal Structure

The developed Tajikistan model includes roads classified as trunk, primary, secondary, and tertiary. Tajikistan's modelled road network consists of 7,660 edges, covering a total of 20,566 km. This includes 2,368 km of trunk roads, 3,787 km of primary roads, 4,814 km of secondary roads, and 9,566 km of tertiary roads. Additionally, 30 km of uncategorised roads are included to ensure network connectedness. The network is divided into 70 zones, with zone sizes based on the Uber H3 spatial indexing system. The average zone sizes are approximately 1,770 km² at resolution 4, 253 km² at resolution 5, and 36 km² at resolution 6. The total Vehicles-Kilometres Travelled (VKT) in the modelled network is 56,593,963 km per day. The total Vehicle Travel Time (VT) in the modelled network is 1,856,842 veh-hr per day, which implies an average speed of 30.5 km/hr.

Figure 6: Example Network Connectivity in TAJ Capital, Dushanbe

The developed rapid traffic planning model results are compared with (1) travel times across all links between modelled travel times and collected travel times (via pervasive sources, specifically Google) and (2) Annual Average Daily Traffic (AADT) flow values for specific trunk and primary links as collected by local agency activity. Figure 7 notes the comparison of Vehicle Kilometres Travelled (VKT) ***on the specific observed AADT flow links***. A high degree of match was achieved for VKT with only 0.22% difference for the observed links. In terms of travel time, the overall percentage difference was 6.65%. Critically, when weighted by distance (emphasising the modelling impact of longer road segments), the average weighted travel time comparison difference was only 0.32%. Figure 8 notes the comparison of estimated/modelled and observed AADT values by road classification. At the aggregate level, a high degree of match is achieved for a national strategic-level traffic model.

VKT_Estimated (for observed links)	4,499,025 km
VKT_Observed (for observed links)	4,489,053 km
Percentage .Diff	0.22 %
Percentage .Diff for Total Travel Time	6.65 %
Percentage .Diff for Total (Travel Time * distance)	0.32 %

Figure 7: TAJ Aggregate Network Flow Comparison (only for observed links)

Classification	Estimated_AADT	Observed_AADT	AADT_Percent_diff
trunk	8478	7894	7.4%
primary	4526	4591	-1.42 %
secondary	2759	3181	-13.27%

Figure 8: TAJ Table 7 | Modeled and Observed AADTs

Within PNG, a further level to the modelling of traffic has been added through the examination of walking routes. This then enables the assessment of the creation of additional resilience by adding pedestrian bridges over barriers such as rivers, to be compared against the upgrading of road infrastructure. While walking plays a significant role in local transport choices, the origins of this paper in assessing major corridors where the focus was on regional or national level resilience meant that walking was not included from the outset. Where public transport routes are known, these can be tested within the system also – although the method of generating the OD matrices does not automatically enable the separation of vehicles by type (car, bus, truck etc.).

2.2 Climate Risk Modelling

The second major stage of the process is that of identifying the potential natural hazards risks to each individual asset within the transport system. As per Figure 9, the model applies a hazard event (often in the form a return-period hazard footprint map), and this in turn is assessed for direct impacts on the transport system (i.e. damage to the infrastructure asset). For each hazard it is necessary to develop vulnerability curves that reflect the direct damage that would occur to the asset in the event of different size events. Finally the model generates the output metrics related to the impact on the asset, as well as feeding into the economic model that assesses the impact of diverted traffic.

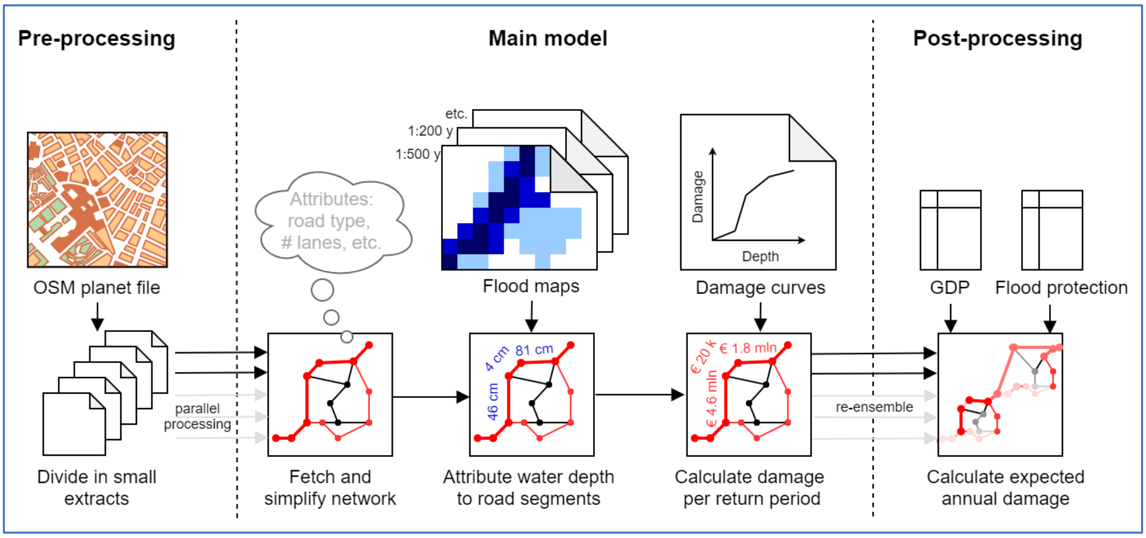

Figure 9: Climate Risk Modelling Overview (Van Ginkel et al. 2021)

Hazard data were obtained for floods (courtesy of JBA risk modelling at 30m grids and for a range of return periods and flooding types), earthquakes and landslides as these were considered the primary risks for each of PNG and/or TAJ. The model is equally able to handle other risks such as forest fires should these be of significance in the area under study.

Having identified the range of hazards to be modelled, it is then necessary to develop road damage factors (vulnerability curves) for a range of scenarios as per Figure 10. A road is more severely damaged if the quality of the road is poor (either in poor state of maintenance or lower quality of construction overall), and the model automatically accounts for this impact. We assume that a good road would correspond with the least steep vulnerability curve (F7.6 for flooding), whereas a road in poor condition would relate to the steepest vulnerability curve (F7.12 for flooding).

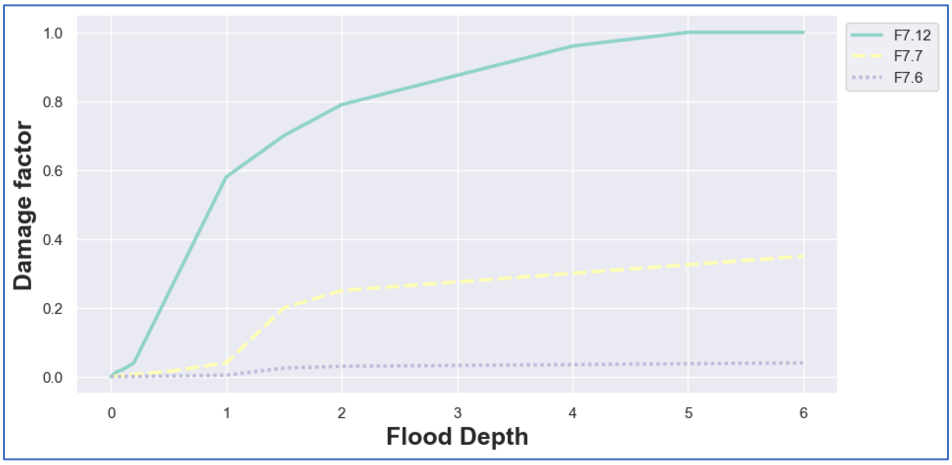

Figure 10: Overview of Vulnerability Curves Used to Assess Damage Due to Floods

The resulting outputs from the model in terms of the direct impacts on the infrastructure are then readily estimated for the range of hazards, with Figure 11 indicating the annual risk costs to the PNG transport system from earthquakes.

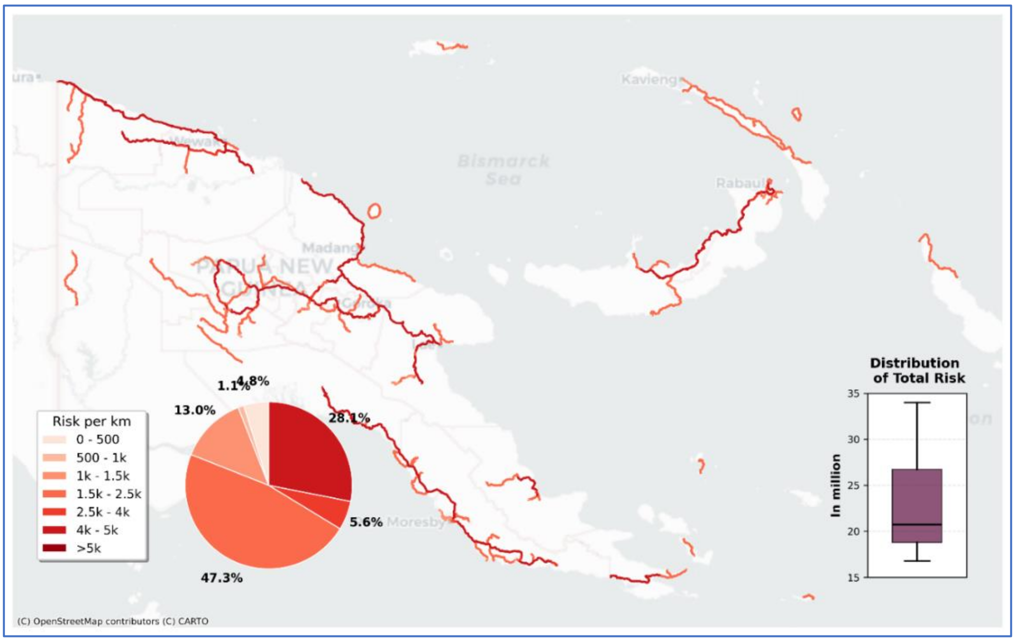

Figure 11: PNG Earthquake Risks

The impact of climate change is able to be assessed through the model as illustrated in Figure 12, where changes in rainfall intensity is reflected by an increase in the impact on the transport system.

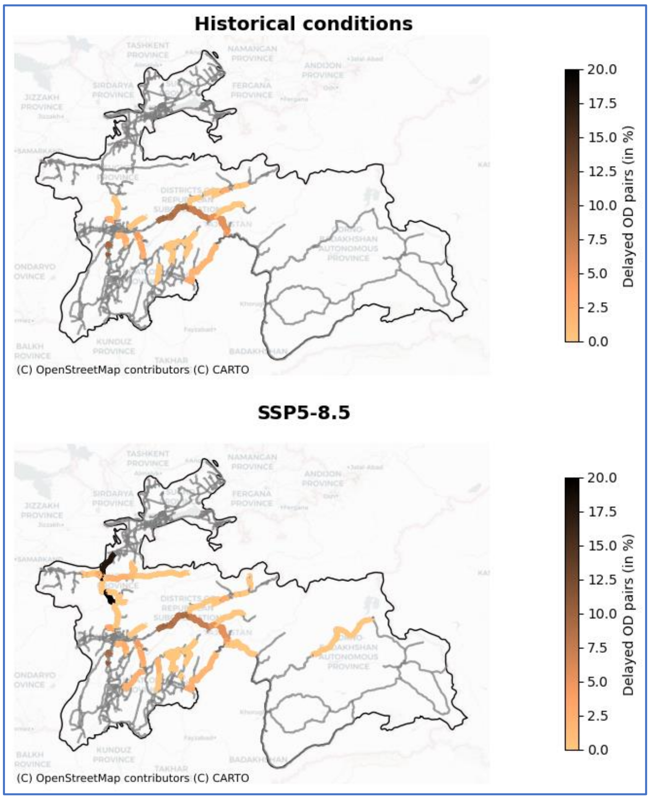

Figure 12: Percentage of delayed OD pairs due to a 1/10 landslide event triggered by a 1/200 rainfall event under historical conditions, and under SSP5-8.5.

The methodology also enables for the assessment of non-independent hazard events – i.e. a second flood occurring before the infrastructure is fully restored from a prior flood, or a major storm striking after a prolonged drought period. In this case, the impacts of the second event will typically be more significant in terms of both the damage done and the time to regain full network operation.

2.3 Economic and Social Impacts

The third step in the process is that of assessing the economic and social impacts of the hazard events. The economic impacts are assessed using standard modelling practices reflecting changes to travel paths, and in turn travel times and speeds. HDM-4 was calibrated and used to assess the impacts of the rerouting on road user costs as well as the impact on the secondary routes that the traffic would divert to.

The economic analysis includes for the increased vehicle operating costs due to the use of detours/alternative routes when the network flows are disrupted by natural hazards, along with the impact of delays on the movement of goods. These additional costs are computed for each disruption scenario.

A full range of indicators are readily extracted from the model including time to reach key destinations such as hospitals, ports and the like. It is also possible to zoom in to parts of the model and assess the impact of a particular event, such as is illustrated in Figure 13 which presents the scenario that causes the largest amount of population affected, and is located in the district of Kulob within TAJ. This is a combination of both people experiencing delays (~70%) and people experiencing a lost connection (~30%).

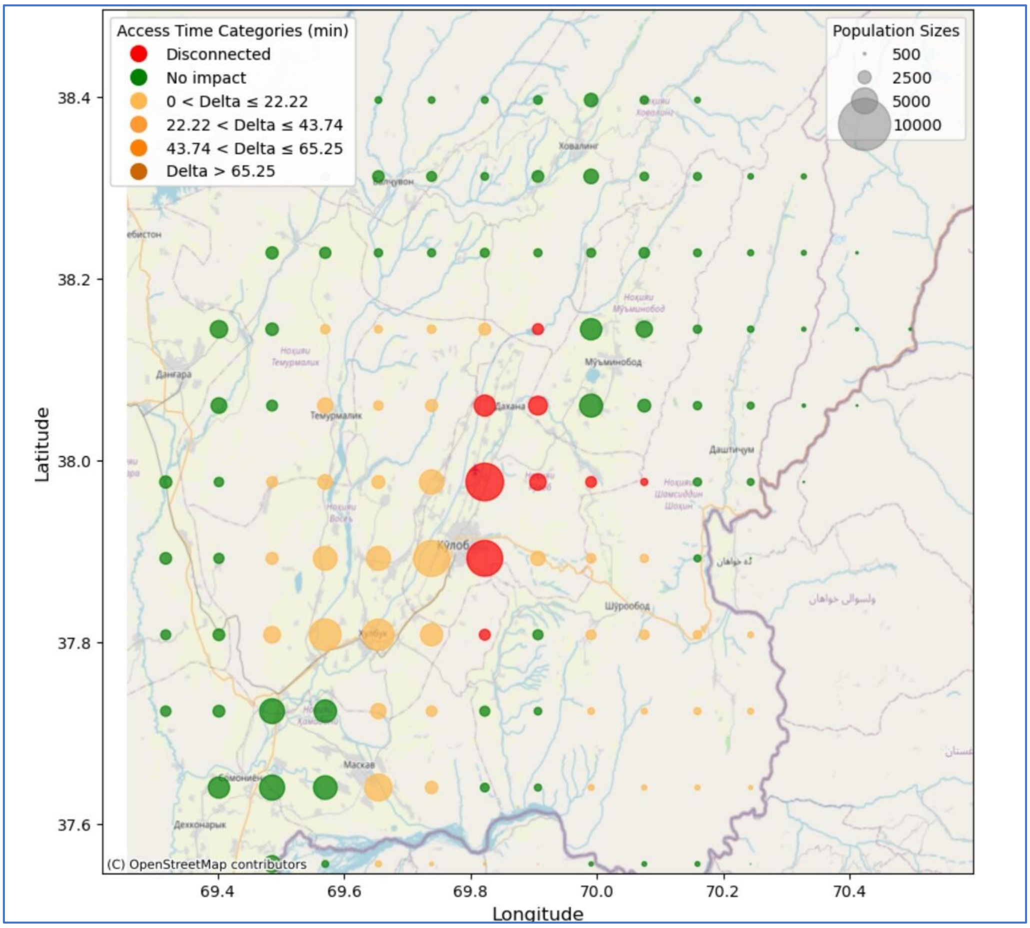

Figure 13: Zoomed View of Single Flood Event in TAJ

The PNG road network has limited alternative routes for much of its length (outside of the major urban settlements) and therefore the impact of a singular event can readily result in substantial increases to the average travel times as per Figure 14.

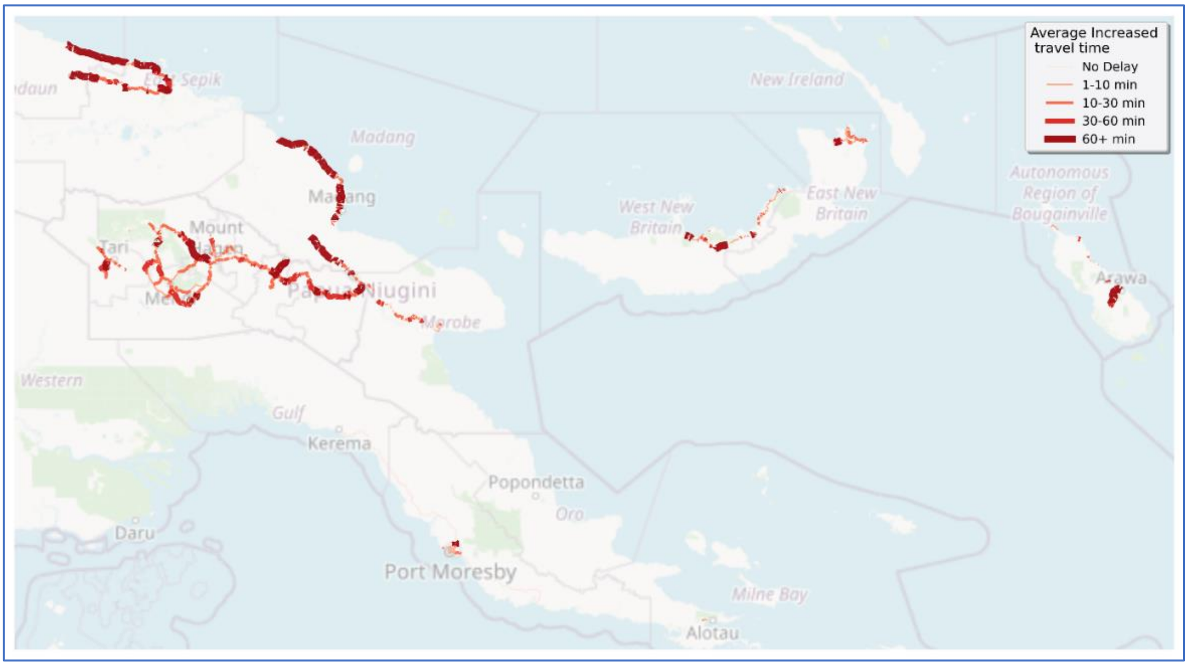

Figure 14: PNG Travel Time Impacts of Hazard Events

2.4 Adaptation Pathways

The final step in the process is that of developing adaptation pathways for each country that mitigate the risks and contributes to more resilient transport networks. Within the page constraint of this paper these cannot be explored in detail here, but are broadly indicated as per Figure 15.

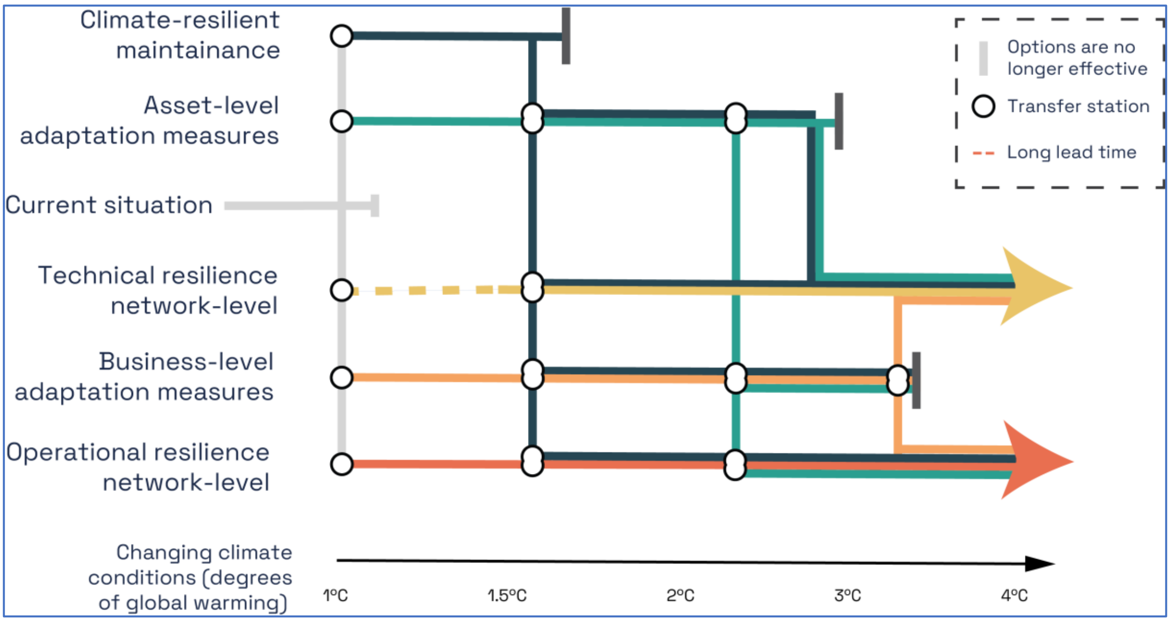

Figure 15: Concept of Adaptation Pathways

The use of adaptation pathways provides a means to identify both infrastructure and non-infrastructure solutions to improve the long-term resilience of the transport network. Solutions in the infrastructure space can include options for the existing road network such as the raising of roads out of flood plains or the construction of retaining walls, through to options involving the construction of new transport routes – whether that be roads for all users or select users (such as walking routes).

In PNG a parallel project being funded by ADB is linking the outputs of this study to an update for the national road design and maintenance guidelines. Conceptually where a section of road is identified as being of high criticality and is subject to a high risk (say of flooding) then the design standards will require a higher level of flood mitigation measures and protection to be applied to that section of road, and then the maintenance standards will further require that the same section's drainage system has to be maintained at a high level also. This ensures that limited funds are best allocated to the road network throughout the life of the road.

This broad range of options to mitigate the hazards, when considered at a national level, enables for the best possible value from any resilience investment to be had.

3 CONCLUSIONS AND RECOMMENDATIONS

This paper has demonstrated methods for undertaking large scale assessments of multi-hazard risk impacts for transport networks, with case studies based on PNG, PAK and TAJ. The ability to analyse a full range of hazards, including interlinking of hazards, along with the assessment of transport and economic impacts at the national, regional or single link level provides a seamless and consistent approach to assessing existing risks and the potential benefits of interventions.

The methodology employs leading edge modelling of both traffic systems and hazards, and can support the development of adaptation pathways to mitigate those risks. Further development is ongoing and involves the inclusion of local pedestrian linkages, as these can play a major part in maintaining accessibility of communities in many countries across the Asia-Pacific region.

The outputs of this work are now being used in the three case study nations to assist in the identification and prioritisation of investment projects – ensuring that they meet the definition of Type 2 projects. In the case of PNG this includes the ability to assess the impact of the many thousands of kms of roads proposed to be constructed under the Government of PNG ConnectPNG programme.

The outputs of this work is currently been incorporated into new road design and maintenance manuals for PNG, wherein the route criticality and outputs from the risk assessment process are being used to provide site specific guidance into the way roads should be designed and maintained. For instance, a highly critical route that is in a flood prone area will require application of advanced approaches to managing flood protection (including being out of the flood zone for more significant sized flood events), as well as having a requirement to maintain those drainage systems to a very high level. Conversely low criticality roads with little risk of flooding will be subject to less stringent requirements for both the design and maintenance.

Collectively we now have an end-to-end analysis framework that can assess transport systems at the national, regional or local level; can model impacts of motorised and non-motorised transport; can determine the impact of new transport links being added to the network; and on through to ensuring that design and maintenance details all explicitly account for resilience.

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6 AUTHOR CONTRIBUTION STATEMENT

The authors worked collaboratively in the preparation of this paper and the underlying analyses. As noted within the paper, the methodologies employed were built upon that previously developed by several of the authors – in particular the traffic modelling by T. Waller, and the hazard modelling by E. Koks. The primary analysis was undertaken by T. Waller, E. Koks and J. Odoki, with M. Anyala and I. Greenwood being the ADBs project leads.