A DMDU Guidebook for Transportation Planning Under a Changing Climate

Transport Division

Climate Change Division

Authors:
Robert J. Lempert
Michelle E. Miro
Diogo Prosdocimi

Editors:
Benoit Lefevre
Ernesto Monter

TECHNICAL NOTE Nº
IDB-TN-02114

February 2021

Inter-American Development Bank

A DMDU Guidebook for Transportation Planning Under a Changing Climate

Authors:
Robert J. Lempert
Michelle E. Miro
Diogo Prosdocimi

Editors:
Benoit Lefevre
Ernesto Monter

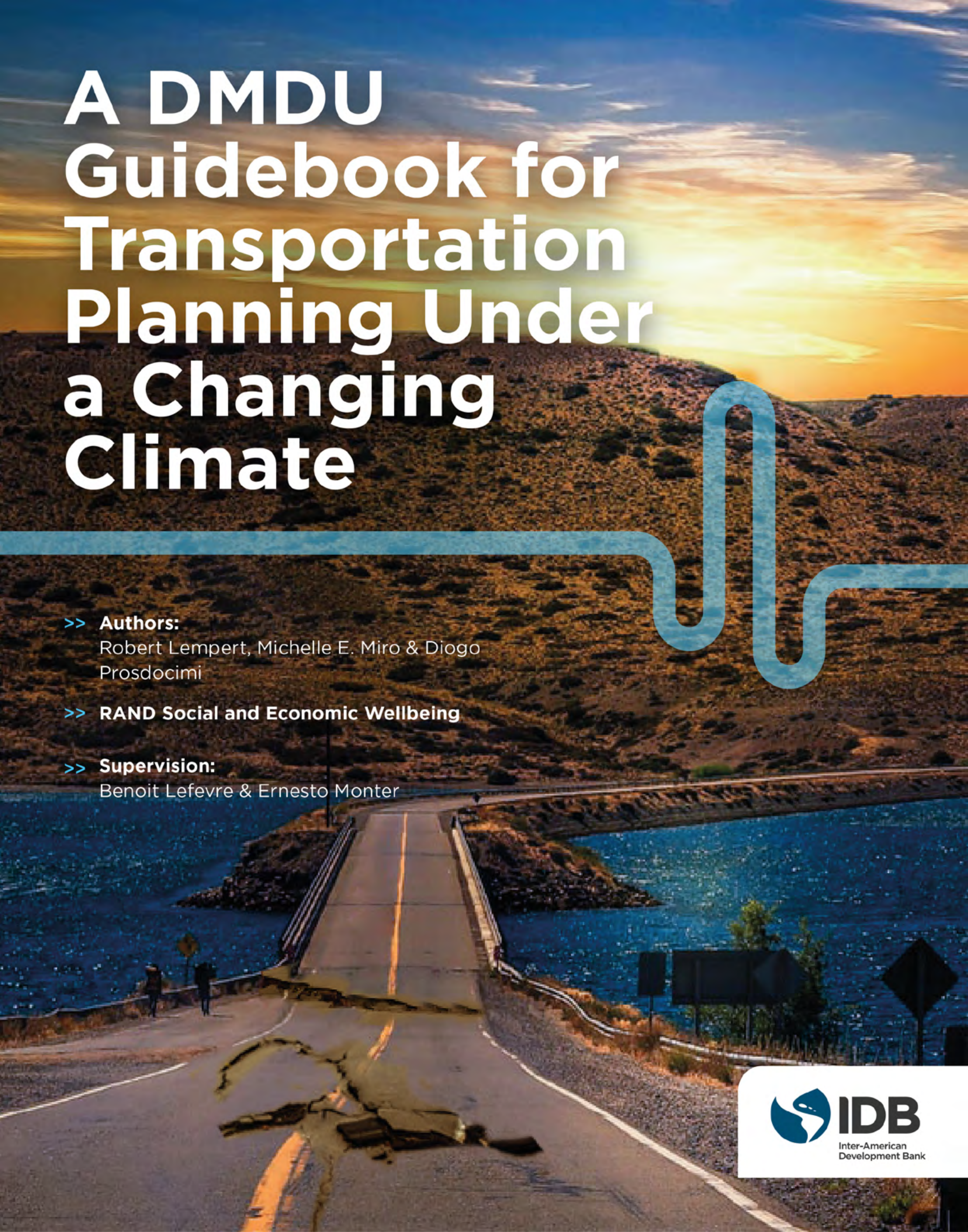
Inter-American Development Bank
Transport Division
Climate Change Division

February 2021

Cataloging-in-Publication data provided by the
Inter-American Development Bank
Felipe Herrera Library
Lempert, Robert J.
A DMDU guidebook for transportation planning under a changing climate / Robert J. Lempert, Michelle E. Miro, Diogo Prosdocim; editors, Benoit Lefevre, Ernesto Monter Flores.
p. cm. — (IDB Technical Note ; 2114)
Includes bibliographic references.
1. Transportation-Latin America-Planning. 2. Transportation-Climatic factors-Latin America. 3. Transportation-Environmental aspects-Latin America. 4. Climatic changes-Risk management-Latin America. I. Miro, Michelle E. II. Prosdocim, Diogo. III. Lefevre, Benoit, editor. IV. Monter Flores, Ernesto, editor. V. Inter-American Development Bank. Climate Change Division. VI. Inter-American Development Bank. Transport Division. VII. Title. VIII. Series.
IDB-TN-2114

JEL Codes: R42, Q54
Keywords: Climate Change, Transport, Planning, Transport network, Disaster Risk, Depp incertitude, Decision making, Adaptation, Resilience

http://www.iadb.org



A DMDU Guidebook for Transportation Planning Under a Changing Climate

>> **Authors:**
Robert Lempert, Michelle E. Miro & Diogo Prosdocimi

>> **RAND Social and Economic Wellbeing**

>> **Supervision:**
Benoit Lefevre & Ernesto Monter

IDB
Inter-American Development Bank

Preface

In 2007, the Inter-American Development Bank (IDB) formulated the *Disaster Risk Management Policy* (IDB 2007) in the context of an increase in the frequency and severity of disasters in Latin America and the Caribbean, in addition to a rising awareness of the effects of disasters on the economic and social development of the countries in the region. Likewise, the IDB's *Disaster Risk Management Policy Guidelines* (IDB 2008) established a specific procedure for the assessment of the disaster risk for IDB-funded operations. These guidelines include two main stages: i. project projection and classification, and ii. a disaster risk assessment and a disaster Risk Management plan. Furthermore, through the Bahamas Resolution in 2016 the IDB's Board of Governors formally committed the IDB to improve the assessment of climate risk and identify opportunities for resilience and Adaptation measures at the project concept stage (IDB 2016).

Subsequently, as a resource to implement both the *Disaster Risk Management Policy Guidelines* and the Bahamas Resolution in 2016, the IDB developed the *Disaster and Climate Change Risk Assessment Methodology for IDB projects* (IDB 2018). This methodology establishes a screening process and provides guidance for project teams to conduct disaster and climate change risk assessments at each stage of the project cycle. It offers a variety of methods to conduct risk assessments ranging from qualitative to quantitative and from simple to complex (for example, it includes both deterministic and probabilistic approaches). The methodology also contains methodologies for Decision Making Under Deep Uncertainty (DMDU), which is one more recent approach to evaluating and making decisions under a Risk Management context.

This guidebook is aligned with the *Disaster and Climate Change Risk Assessment Methodology for IDB projects* and introduces and provides guidance on applying methods for DMDU to transportation planning. It presents the methodological steps that are necessary for the implementation of DMDU methodologies and reviews several such methods, including scenario planning, Adaptive Pathways, and robust decision making (RDM). This review is geared towards supporting the incorporation of DMDU methods into IDB's transportation sector funding and planning processes. This guidebook was prepared for and funded by the IDB and is intended to help IDB team leaders, technical experts, planning and executing agencies, and consultants in conducting a DMDU analysis.

Table of contents

Figures

Tables

Abbreviations

Glossary

Adaptation is the process of adjustment to actual or expected climate and its effects. In human systems, Adaptation seeks to moderate or avoid harm or exploit beneficial opportunities. In some natural systems, human intervention may facilitate adjustment to expected climate and its effects (IPCC 2014).

Adaptive Pathways, also called dynamic adaptative policy pathways, is a decision-making strategy consisting of a sequence of manageable steps or decision points over time.

Decision Framing is the way that a choice or challenge is worded and structured.

Deep Uncertainty exists when experts or stakeholders do not know or cannot agree on: (1) appropriate conceptual models that describe relationships among key driving forces in a system; (2) the probability distributions used to represent uncertainty about key variables and parameters, and/or (3) how to weigh and value desirable alternative outcomes (Lempert et al. 2003).

DMDU (Decision making under Deep Uncertainty) is a set of concepts, methods, and tools for informing decisions under conditions of Deep Uncertainty.

Exploratory Modeling is a research approach that uses computational experiments to analyze complex and uncertain systems (Bankes 1993). Exploratory Modeling generally employs an ensemble of models to explore many possible futures. An Exploratory Modeling approach generally views models as tools for exploring the outcomes from alternative assumptions about the future as well as from policy choices of interest (Lempert et al. 2008).

Exposure is the presence of people; livelihoods; species or ecosystems; environmental functions; services and resources; infrastructure, or economic, social, or cultural assets in places and settings that could be adversely affected (IPCC 2014).

Flexible is used to denote a strategy that can be adjusted over time to new information.

Hazard is the potential occurrence of a natural or human-induced physical event or trend that may cause loss of life, injury, or other health impacts, as well as damage and loss to property, infrastructure, livelihoods, service provision, ecosystems and environmental resources (IPCC 2014).

Mitigation is a human intervention to reduce the sources or enhance the sinks of greenhouse gases.

RDM (Robust decision making) is an iterative decision analytic framework that helps to identify potential robust and flexible strategies, characterize the vulnerabilities of such strategies, and evaluate the tradeoffs among them.

Resilience is the capacity of social, economic, and environmental systems to cope with a hazardous event, trend or disturbance, responding or reorganizing in ways that maintain their essential function, identity, and structure, while also maintaining the capacity for Adaptation, learning, and transformation (IPCC 2014).

Risk is the potential for consequences where something of value is at stake and where the outcome is uncertain, recognizing the diversity of values (IPCC 2014).

Risk Management is the plans, actions or policies to reduce the likelihood and/or consequences of risks or to respond to consequences (IPCC 2014).

Robust is a decision criterion that seeks strategies that perform well compared to the alternatives over a wide range of plausible futures.

Scenario Planning is a planning method in which participants develop a set of scenarios that can help expand participants' understanding of the ways in which the future might unfold and help participants to develop strategies that are robust across these futures.

Vulnerability is the propensity or predisposition to be adversely affected. Vulnerability encompasses a variety of concepts and elements including sensitivity or susceptibility to harm and lack of capacity to cope and adapt (IPCC 2014).

XLRM is a framework used for Decision Framing often employed in DMDU analyses. The letters X, L, R, and M refer to four categories of important factors: metrics (M) are the performance standards used to evaluate whether or not a choice of policy levers achieves decision makers' goals; policy levers (L) are near-term actions that decision makers may want to consider in order to achieve those goals and exogenous uncertainties (X) are factors outside the decision makers' control that may affect the ability of near-term actions to achieve decision makers' goals, and relationships (R), generally represented by simulation models, describe how the policy levers perform, as measured by the metrics, under the various uncertainties.

01. Introduction

The effects of climate-related natural hazards pose a significant threat to sustainable development in Latin America and the Caribbean (LAC) region (Barandiarán, Esquivel et al. 2018) and in particular its transportation sector. Risk Management provides an appropriate framework for assessing and mitigating the impacts of climate change and other climate-related natural hazards on transportation and other systems and choosing actions to enhance their resilience (Jones, Patwardhan et al. 2014; Lempert, Arnold et al. 2018). Risk Management also forms the foundation of the Inter-American Development Bank's (IDB) *Disaster Risk Management Policy* (IDB 2007), the Bahamas commitment (IDB 2016) and the *Disaster and Climate Change Risk Assessment Methodology for IDB Projects* (Barandiarán, Esquivel et al. 2018).

However, analysts and policymakers involved in transportation planning, policy, and investment face significant challenges in managing the risks triggered by the effects of climate change. Climate change impacts the lifespan of roads, airports, and railroads as they have time horizons that surpass 40 years, thus making it harder (if not impossible) to forecast with confidence all relevant future ezvents that will affect such infrastructure. In addition, the climate has already changed, so the return frequency of storms, for example, and other extreme events may now be different than suggested by the historical record in ways that are not always currently well understood. Implementing Risk Management under conditions of such uncertainty can prove difficult (Lempert, Arnold et al. 2018).

Past climate is no longer a reliable predictor of future climate and there is a high level of uncertainty about how climate has and will change in the future. However, waiting for these uncertainties to be resolved does not offer a path forward for transportation planners, who still need to consider future climate and other conditions when developing long-term infrastructure plans. To support long-term planning, climate models, while far from perfect, can offer useful insights into future climate and are helpful when they are used appropriately. Considerations of future climate should also weigh multiple objectives (e.g., reliability, cost-effectiveness, and equity) and other socio-economic or policy conditions, as many decisions will prove effective or provide benefits under multiple future conditions.

In developing plans, weighing benefits, and considering future conditions, planners should not mistake well-characterized risk for conditions of Deep Uncertainty. Well-characterized risk exists when planners and engineers can confidently use single joint probability distributions (i.e., predictions) to describe hazard, exposure, and vulnerability that contribute to risk. In contrast, we define Deep Uncertainty (Lempert, Popper et al. 2003) as:

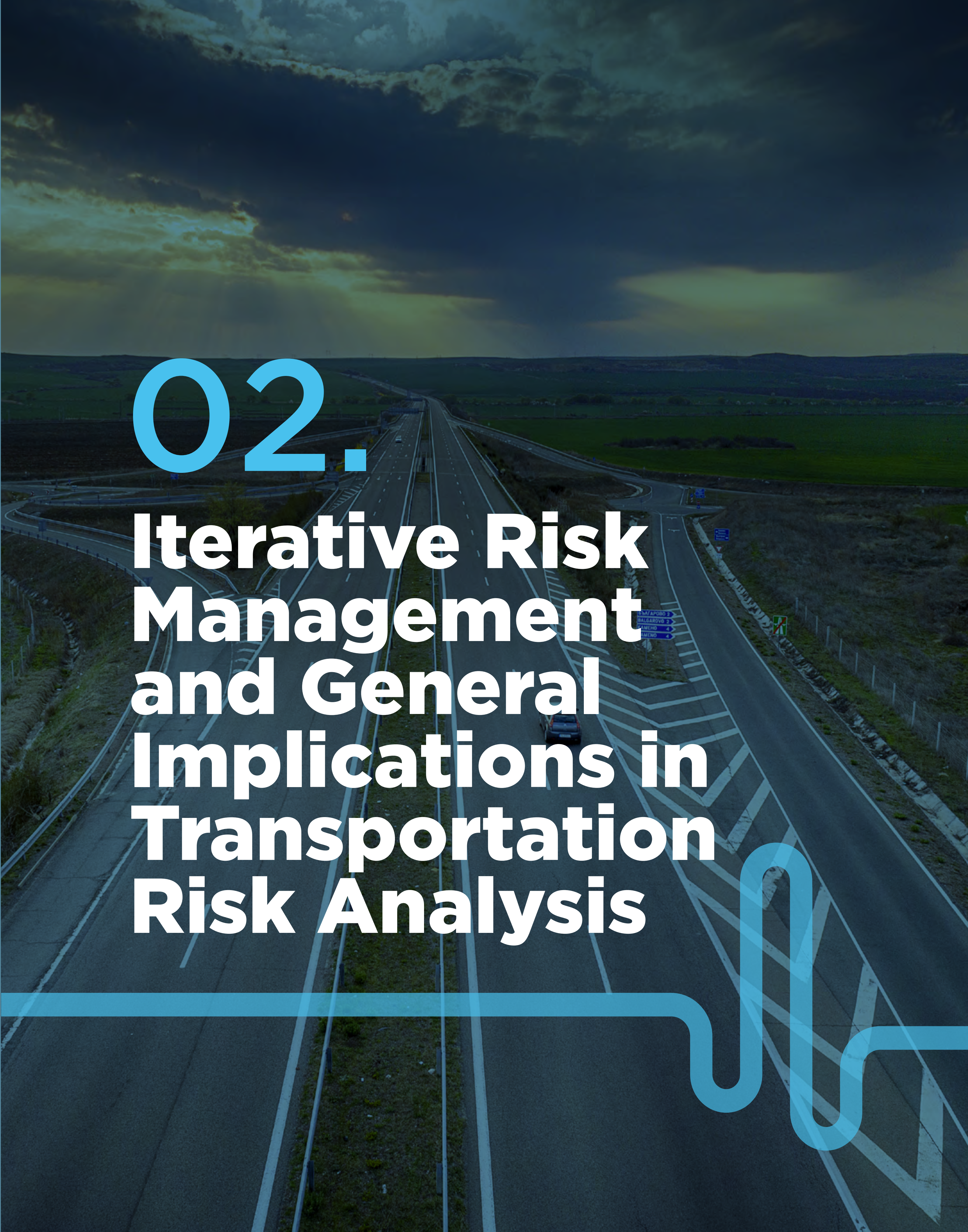
> **Deep Uncertainty** occurs when the parties to a decision do not know or do not agree on the likelihood of alternative futures or how decisions or actions are related to consequences.

As described below, Deep Uncertainty occurs when the parties to a decision do not know or do not agree on the likelihood of alternative futures or how decision or actions are related to consequences. DMDU enables Risk Management under such conditions. Decision Making Under Deep Uncertainty (DMDU) enables Risk Management under conditions of Deep Uncertainty, that is when risks cannot confidently be quantified.

This guidebook was prepared for and funded by the IDB and is intended to help IDB team leaders, technical experts, planning and executing agencies, and consultants in conducting an analysis of DMDU, which is one approach to the thinking process of evaluating and making decisions under a Risk Management context. This approach and document are therefore aligned with the *Disaster and Climate Change Risk Assessment Methodology for IDB projects* (IDB 2018) as an approach that applies to system or portfolio analyses.

Specifically, this guidebook introduces and provides guidance on applying methods for DMDU to transportation planning and reviews several such methods, including scenario planning, Adaptive Pathways, and robust decision making (RDM). This review is geared towards supporting the incorporation of DMDU methods into IDB's transportation sector funding and planning processes. In the risk calculation, instead of an "agreement on assumptions," DMDU methods pursue an "agreement on potential actions." That is, the DMDU methods refrain from making explicit predictions about which future will occur in the risk calculation, and instead focus on evaluating potential feasible actions for associated risks and benefits. The focus of such an approach addresses uncertainty not by an explicit numerical quantification, but by selecting robust actions that will maximize benefits across the likely range of potential future conditions.

Section 2 provides a brief summary of risk and iterative Risk Management, its current application to transportation, how the *Disaster and Climate Change Risk Assessment Methodology for IDB Projects* (Barandiarán, Esquivel et al. 2018) implements these ideas, and how this guidebook supports this IDB methodology for the transportation sector. Section 3 discusses the new challenges generated by climate change, and summarizes information about current and future climate change and climate impacts on transportation in the LAC region. Section 4 introduces decision making under Deep Uncertainty (DMDU) as applied to transportation and reviews several such methods, including scenario planning, Adaptive Pathways, and robust decision making (RDM). The final section offers implications and recommendations for IDB.



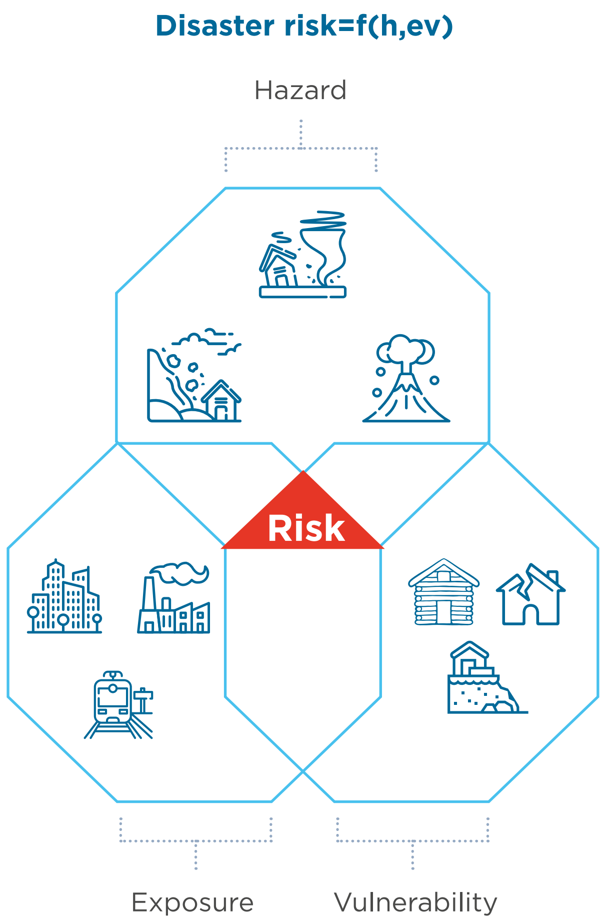
02. Iterative Risk Management and General Implications in Transportation Risk Analysis

A growing body of literature and experience suggests that when appropriately generalized, Risk Management provides an inclusive framework that enables assessment and response to the challenges and opportunities generated by climate change and other natural hazards for transportation and a wide variety of other systems (Jones, Patwardhan et al. 2014; Lempert, Arnold et al. 2018).

Iterative Risk Management

Risk is defined as the product of the probability of an event or phenomenon affecting an individual, community, population, or place and the consequence of occurrence of that event or phenomenon. A very rare event with considerable consequences may have a similar risk as a much more frequent event with moderate consequences. However, in many cases relevant to transportation resilience, it proves useful to define risk more broadly as the potential for adverse consequences when something of value is at stake and the when outcome is uncertain (Jones, Patwardhan et al. 2014). This broad definition helps include hard to quantify, but nonetheless important, factors in the assessment and management of risk.

>> **Figure 2.1** | Components of risk

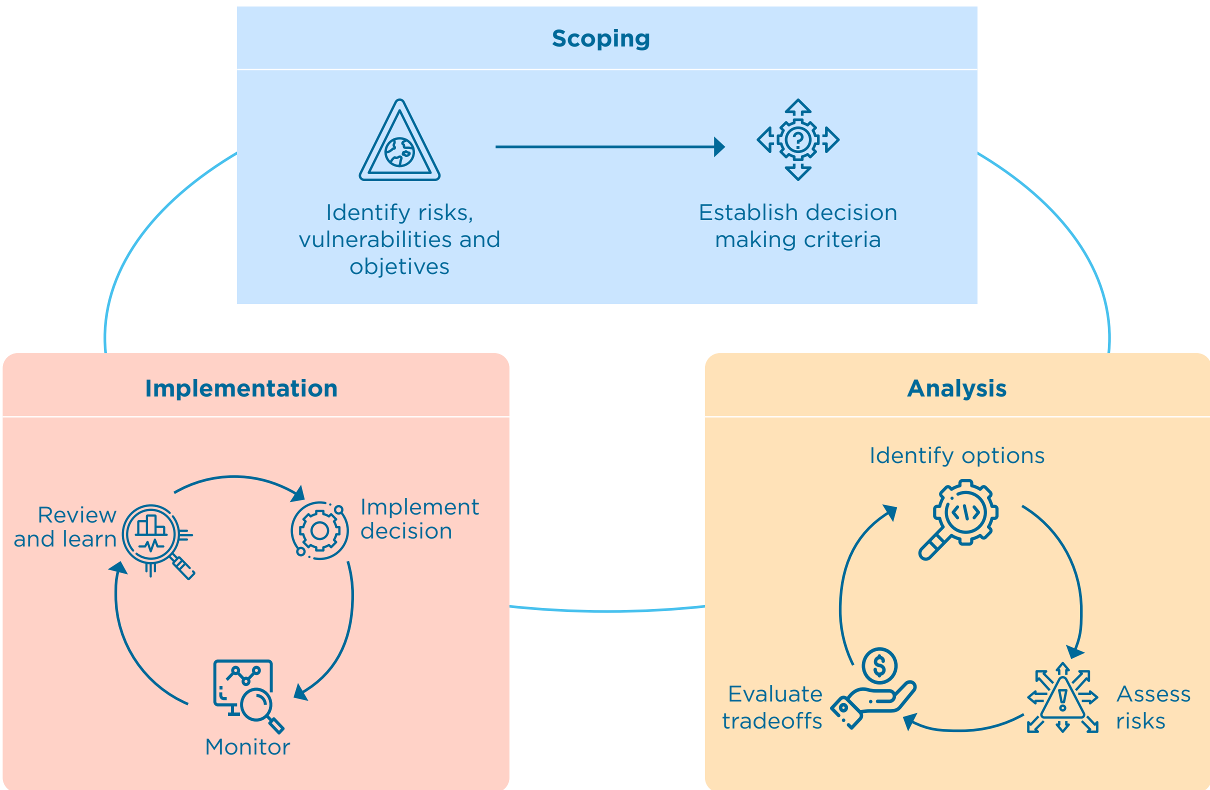


Source: (Barandiaran et al. 2018)

The literature identifies three main contributors to risk, as shown in Fig 2.1: *hazard*, which is the potential occurrence of a physical event that may cause injury or damage; *exposure*, which is the presence of people and the materials they care about in places that could be adversely affected, and vulnerability, which is the propensity to be adversely affected by the hazard. For instance, the potential for a flood would represent hazard, any transportation infrastructure in the flood plain would represent exposure, and the likelihood of damage and disruption to that infrastructure in the case of flooding would represent vulnerability.

Together, hazard, exposure, and vulnerability lead to the consequences that constitute risk. Distinguishing among these three contributors is useful because the human consequences arising from any physical hazard are strongly mediated by social factors, such as where people live and the capabilities available to them to reduce exposure and levels of vulnerability. Risk Management involves efficiently allocating resources among actions to reduce hazard, exposure, and vulnerability; thus, it offers a rich set of options for reducing risk (Knopman and Lempert2016).

>> **Figure 2.2 |** Iterative Risk Management Cycle



Source: (Jones et al. 2014)

Ideally a risk assessment and evaluation of responses should be embedded within a larger process, often called iterative Risk Management. Iterative Risk Management is an ongoing process of scoping, analysis, implementation and review, as shown in Figure 2.2. It involves (1) identifying risks, vulnerabilities, and objectives to establish a decision making criteria (scoping); (2) identifying options, assessing risks, and evaluating tradeoffs in a feedback cycle, and (3) implementing decisions, monitoring results, and learning from experience to implement better in the future.

As described below and in Section 4, the representation of risk and its components of hazard, exposure, and vulnerability varies with different decision making under uncertainty methodologies. For instance, some representations of risk include probabilities, while some do not, but the concept of risk and its components remains constant throughout.

IDB's Disaster and Climate Change Risk Assessment Methodology for IDB Projects

To assist IDB team leaders, technical experts, associated agencies, and consultants in conducting such Risk Management, IDB has developed a Disaster and Climate Change Risk Assessment Methodology (Barandiarán, Esquivel et al. 2018). Figure 2.3 summarizes the steps in this methodology.

>> **Figure 2.3** | IDB Risk Methodology

Source: (Barandiaran et al. 2018)

This methodology is an example of iterative Risk Management. The Screening section in Figure 2.3 corresponds to the Scoping in Figure 2.2 and the Qualitative and Quantitative sections in Figure 2.3 correspond to the Analysis in Figure 2.2.

Phase 1 of the IDB methodology, Screening, consists of two steps. The first step entails a risk classification based on the potential hazards that might affect the project being considered. This classification is based on answers to a questionnaire and associated with a geographic information system, allowing the identification of hazards across space. The second step consists of identifying the project's criticality and level of vulnerability. Criticality and vulnerability are classified using three main dimensions that represent the potential negative impact on physical characteristics, population and services.

Phase 2, the Qualitative Assessment, consists of constructing a risk narrative and building a risk assessment based on expert input. The risk narrative is based upon a review of data, documents and project design in order to document how and to what extent knowledge and intelligence are available about disaster and Risk Management. Building a risk assessment based on expert input requires gathering qualitative information on potential project failures and their socio-economic consequences. This could be carried out via a workshop between natural hazard experts and the project's technical team.

The final phase, the Quantitative Assessment, consists of modelling the effects of natural hazards on the project's physical system. This phase scientifically and mathematically investigates how the project under assessment would perform if exposed to a set of natural hazards.

As noted in Barandiarán, Esquivel et al. (2018), DMDU methods such as Robust Decision Making (RDM) can assist IDB in implementing their disaster risk framework, including the consideration of risk from climate change. This report explains how to do so.

Risk Management and DMDU in Transportation

Transportation engineers currently use Risk Management for planning road infrastructure and networks. Risk Management helps engineers and planners to consider uncertainties inherent in the lifecycle of the road in its design, construction, operations, and maintenance processes. The aim is to avoid the deterioration of structures, prepare for changes in cargo load demand, and protect against extreme events that may lead to infrastructure failure or disruption with local, national or larger regional economic impacts.

Within the Risk Management context, decision support tools for infrastructure include probabilistic models, rating systems, and risk screening. Traditionally these methods are implemented with the assumption that any uncertainty about the future is well-characterized, that is, that engineers and planners can confidently assign a point forecast or a single, best-estimate probability distribution to future events, such as flooding or extreme heat that would disrupt a given infrastructure asset. For instance, planners considering a new road might use a single point forecast of the future demand that the road needs to service and a single probability distribution to describe the frequency of various sized floods that might disrupt traffic on the road.

Until recently, planners would estimate the likelihood of future floods and other climate-related natural hazards by assuming that future climate would be similar to past climate. Planners and engineers would estimate the probability of future storms by looking to historic data on the past frequency of such storms' occurrence. A storm size that had occurred once in the last century would provide the best-estimate of the future one-in-hundred year storm.

In recent years, planners have increasingly used projections generated by climate models to estimate the probability of various climate-related hazards, but generally, planners and engineers continue to regard the uncertainty in such forecasts as well-characterized, either by using a single, best-estimate climate model or by employing a single, best-estimate probability distribution over an ensemble of model results. This has often led to undue focus on identifying the best climate forecasts for any particular application as the means to achieving climate resilience.

DMDU methods build on traditional Risk Management but regard uncertainty as deep, that is, regard the risks as not well-characterized. In practice, this means calculating risks for a range of forecasts and/or a range of probability distributions. As illustrated in Figure 2.4, a DMDU risk analysis may repeat a traditional analysis multiple times for each of a wide range of assumptions regarding the probability of future events. The DMDU analysis then ask questions such as: "which links in the transportation network contribute most to risk over a wide range of assumptions about the factors that might contribute to this risk?" and "which strategies could be implemented to best reduce this risk given a wide range of assumptions about the frequency of the hazard?" Section 4 describes DMDU methods in more detail.

>> **Figure 2.4** Calculating network risk in the context of DMDU

Source: (Jones et al. 2014)

03.

What Is New with Climate Change?

As noted in Section 2, transportation engineers and planners commonly practice Risk Management to assess and manage the potential consequences of natural hazards, but climate change introduces new challenges. Climate change requires new sources of information about climate conditions and climate-related natural hazards. Previously, engineers and planners assumed that current and future climate in a particular location would be similar to past climate, so they could use the historical record in designing and planning transportation projects and systems. However, overwhelming evidence now suggests that the climate will and already has changed in significant ways (Marengo, Ambrizzi et al. 2010). Designing and planning to historical conditions is no longer a reliable approach. In addition, current and future climate has and will change by amounts that are often difficult to estimate with any confidence. Thus, designers and planners need to assess and manage risk under conditions of heightened uncertainty. Finally, since climate and natural hazards may change significantly over the lifetime of transportation projects and systems, climate change makes it more important for engineers and planners to more explicitly consider multiple time scales.

Information about Current and Future Climate

What We Know about the Earth's Climate

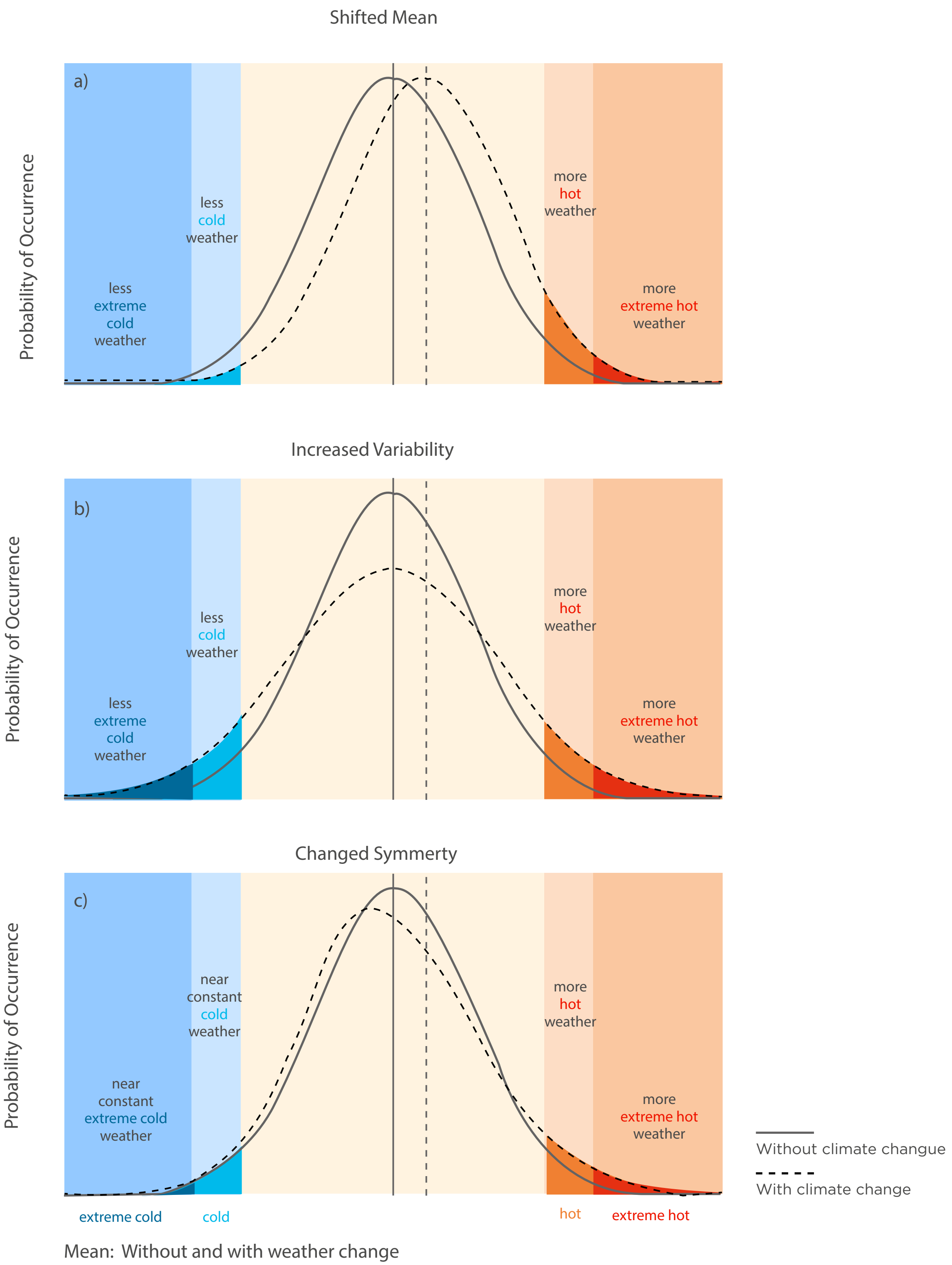
Scientists know a significant amount about current and future changes in the climate (IPCC 2014). Atmospheric carbon dioxide and other greenhouse gases (GHGs) are at their highest levels in nearly a million years because of human activities, including combustion of fossil fuels, deforestation, land use changes, livestock production, and intensification of fertilizer use among others. These heightened levels of GHGs have altered the climate, contributing to increasing numbers of extreme heat days, shifting storm and tide patterns, rising sea levels, and melting glacial and ice sheets.

Further, because GHG emissions are rising globally, such climate changes are likely to continue and increase. Therefore, it is no longer appropriate to assume that current and future climate in any particular location will be like that of the past.

What Will Change: Average and Extreme Climate Variables

Scientists expect changes in both average and extreme climate variables, as shown in Figure 3.1. Changes in average values include change in average temperature, change in precipitation patterns, and change in humidity, sea-level rise, and permafrost melting. Changes in the intensity and severity of weather phenomena include severe storms, storm surges, extreme precipitation, floods, droughts, hurricanes, and heat waves.

>> Figure 3.1 | Changes in Average and Extreme Climate Variables



Source: IPCC 2012

Scientists are confident about predicting some changes, but less so about predicting others. Scientists are confident about predictions of changes such as temperature increases, sea-level rise, earlier snowmelt, and more intense precipitation. Moreover, scientists are less confident about predictions about changes in climate variability and changes in precipitation patterns.

In summary, evidence suggests that temperatures are rising, the climate is changing, and we expect more warming in the future. However, the timing and magnitude of that change are still uncertain.

How Climate Change Will Impact Transportation

As noted above, climate changes in terms of both climate averages and extremes. The impacts of these changes will include warmer summers, warmer winters, changes in soil and air humidity, increased precipitation (average and extremes), stronger and more frequent extreme winds, sea-level rise and storm surges, changes in the frequency of winter storms, and lightening. Of these changes, scientists are confident about predicting temperature increases, sea-level rise, earlier snowmelt, and more intense precipitation, but they are less confident about predicting others such as changes in climate variability and precipitation patterns. Each of these climate changes will, in turn, have its effect on transportation in the LAC region as summarized below and in Table 3.1. However, while the direction of some changes can reasonably be predicted, the timing and magnitude are still uncertain.

Warmer Summers and Winters

In Latin America, temperature increases on the order of 1 C since the 1970s have already been observed in the region. Evidence also suggests with high confidence that warming summers is a significant trend in Central and South America. In addition to higher average temperatures, scientists have also measured increases, in number and amplitude, of extreme events such as warm days and heat waves. Observations indicate an increase in the annual maximum temperature per decade have reached up to 1.1°C per decade in Southern Chile (Vicuña, Gironás et al. 2013), 0.6°C in southern Brazil (Sansigolo and Kayano 2010), 0.8°C in Argentina and Uruguay, and 0.6°C in the Andes, among others.

Climate model predictions suggest that increases in temperatures will continue and accelerate over time. These projections show temperature increases of 0.6°C to 5.2°C in more conservative emissions scenarios and 2.2°C to 7°C in less conservative emissions scenarios. Heat waves, warmer nights and cooling degree days are forecast to increase as well. For example, cooling degree days are projected to increase by between 5 to 20 on average per year in Central America and northern South America by the end of the century (Kamiguchi, Kitoh et al. 2006; Marengo, Jones et al. 2009; Marengo, Ambrizzi et al. 2010), and warm nights are likely to increase from 12% to 24% in Brazil (Marengo, Jones et al. 2009).

With the advent of warmer summers, the following impacts on transportation could be seen:

Heat-related deterioration of materials, asphalt rutting, and rail buckling;

- Need for longer airport runway requirements;
- Loss of inland navigation capacity because of low water levels;
- Thermal expansion of bridges and joints;
- Damage to machinery and engine overheating; heat damage to intelligent transportation systems;
- Greater wildfire and smoke risk;
- Reduced construction and maintenance work hours;

- Soil subsidence because of drought;
- Accelerated melting or heaving of permafrost in soils.

Warmer winters could have the following transportation effects, some of which counteract the impacts from warmer summers:

- Reduced ice and snow removal costs;
- More opportunities for winter-time maintenance and construction;
- Potential increase in fogginess;
- Asset deterioration because of more frequent freeze-thaw cycling;
- More accessible inland waterways;
- Loss of the use of snow and ice roads and an increase in permafrost heave;
- Increased flood risk because of an increase in wet winter precipitation.

Changes in Precipitation

The last sixty years of observations reveal that rainfall has become irregular in space and time, particularly later in the summer. Changes in precipitation, the timing of rainfall onset, and the intensity and magnitude of rainfall extremes have already been noted in all of Central and South America. Increases in precipitation of about 0.94 mm/day have been observed in Central

America (Englehart and Douglas 2006) and of 1.5 mm/day in Brazil (Dai, Qian et al. 2009). Decreases in precipitation were observed in the Andes region (44 mm less per decade) (SENAMHI 2009) and Northeastern Brazil (a 0.3 mm/day decrease over 50 years) (Dai, Qian et al. 2009; Dai 2011).

The number and intensity of heavy precipitation events is a prominent change in the LAC region. Rainfall extremes increased in number by 1.3% per decade in the last 50 years (Cavazos, Turrent et al. 2008). São Paulo saw 5 to 8 additional days of extreme rainfall per year (Silva Dias, Dias et al. 2012), as well as experienced increases in the magnitude of precipitation of between 50 to 75 mm over 40 years (Dufek and Ambrizzi 2008). While rainfall is increasing in some regions, it is reducing in others. Northern and Central Chile faced a reduction of rainfall between 45 to 105 mm over 31 years (Dufek, Ambrizzi et al. 2008).

Changes in the timing of seasonal heavy rainfall and the duration of the dry season has been occurring in many places in Latin America. The onset of this period has become steadily earlier in the Amazon over the last 60 years, with a total shift of about 170 days earlier (Carvalho, Jones et al. 2011). The number of dry months, with low precipitation, in Southern Brazil, Uruguay and Argentina increased by 1-2 months between 1980 to 2000 (Barrucand, Vargas et al. 2007).

Climate projections indicate that departures from historical average rainfall (both positive and negative) will be larger in the region in the future. Projections also suggest that spatial variability in precipitation will increase. According to one study (Kitoh, Endo et al. 2013), Central America, Colombia and Venezuela will face a shift in historical precipitation averages by about -10%/+10%, and in other studies, using other models and variables, researchers project significant changes ranging from -20% to +50%. Heavy precipitation is likely to change as well with a reduction of up to five days of heavy precipitation per year in some regions of LAC and an increase of 105 days in other regions (Marengo, Jones et al. 2009).

Increased precipitation will also affect transportation:

- Increase in weather-related crashes, traffic disruptions, and delays;
- Flooding of land transport infrastructure, hydraulic damage to bridge abutments and footings, prolonged standing water damage to geotechnical substrata, culvert failures and road and rail washouts, the collapse of embankments, and mudslides, landslides, and slope failures;
- Flooding of subways and public transport facilities (e.g., bus depots);
- Inability for transport workers to get to their work, and
- Increased incidence of slush flow avalanches.

Changes in soil moisture and air humidity

Changes in temperature and precipitation have direct effects on soil moisture and air humidity. The number of wet days has increased by 0.37% in Chile since the 1970s (Quintana and Aceituno 2012). Many places in Central and South America have faced increased dryness such as Chile and Ecuador (Dai 2011) and the Pampas region (Barrucand, Vargas et al. 2007).
Climate model projections suggest that changes in soil moisture and air humidity will continue in coming decades. In Central and South America, the combination of decreasing precipitation and increasing evaporation will produce significant decreases in soil moisture (Nakaegawa, Kitoh et al. 2013). Researchers note that:

- Decreased soil moisture can lead to subsidence of geotechnical substrata.
- Increases in soil moisture can lead to

increased runoff due to saturation, loss of cohesion resulting in structural instability for bridges, sub-bases, slope cuts and embankments, or increased landslide risk.

- Increases in air humidity, in conjunction with heat, can reduce working hours available for construction, operations and maintenance.

Stronger and More Frequent Extreme Winds

Changes in wind intensity and the frequency of extreme wind has already been observed in Latin America in many regions, such as coastal Chile (Garreaud and Falvey 2009). Climate models predict that future surface winds on the west coast of South America will increase on average by 1.5 m/s over the next century (Garreaud and Falvey 2009). Stronger and more frequent extreme winds will lead to the following effects on transportation systems:

- Damage to the technical superstructure of roads, railroads, ports, and airports;
- Damage to lighting, power, and communications networks;
- Traffic disruption and closures from felled trees;
- Temporary closures of ports and airports and subsequent backlogged operations;
- Storm debris clearance.

Sea Level Rise and Storm Surge

Sea level rise has already been observed in the LAC region, varying from increases of 2-7 mm/year since 1950, but the rate is accelerating over time. Such a rate of sea level rise contributes to an increased occurrence and magnitude of coastal flooding and erosion. The effects on transportation systems from sea level rise and storm surge include the following:

- Erosion of coastal roads and railroad infrastructure; disruption of transport networks and activities situated in low-lying areas;
- Higher tides for port facilities and potential disruption or road/rail access to ports;
- Potential for flooding, exacerbated by inadequately dimensioned drainage facilities;
- Exposure of low-lying coastal airports to storm surge damage and flooding;
- More frequent and/or permanent inundation of transport facilities in low-lying areas;
- Corrosion of steel and concrete materials, and
- Increased scour on defensive structures and bridges.

Other Changes

Changes in the frequency of winter storms will affect the timing and magnitude of snowfall and shift its effects on transportation system. Projections suggest increases in intensity of storms, and subsequently lightening, which could lead to the disruption of the power supply, affecting overhead catenaries, lights, ICT, and related infrastructure.

>> **Table 3.1** Climate Change in Latin America

Climate Changes	Observed Changes	Predicted Changes	Impacts on Transportation
Warmer Summers and Winters (high confidence)	***Increased average temperature*** » Temperature increased by 1°C since the 1970s in Central and South America. ***Increased annual maximum temperature*** » Annual maximum temperature increased up to 1.1°C per decade in Southern Chile, 0. 6°C in southern Brazil, 0.8°C in Argentina and Uruguay, and 0.6°C in the Andes. ***More extreme heat events*** » The number and magnitude of extreme heat events, such as warm days and heat waves, increased.	***Increases in average temperature*** » Temperatures are projected to increase 0.6°C to 5.2°C in more conservative emissions scenarios and 2.2°C to 7°C in less conservative emissions scenarios. ***Increases in heat waves, warmer nights and cooling degree days*** » Cooling degree days are forecast to increase from 5 to 20 days per year on average in Central America and north South America by the end of the century » Warm nights are likely to increase from 12% to 24% of days each year in Brazil.	***Warmer Summers*** » Heat-related deterioration of materials, asphalt rutting, and rail buckling; » The need for longer airport runway requirements; » The loss of inland navigation capacity because of low water levels; » Thermal expansion of bridges and joints; » Damage to machinery and engine overheating, as well as heat damage to intelligent transportation systems; » Greater wildfire and smoke risk; » Reduced construction and maintenance work hours; » Soil subsidence because of drought; » Accelerated heave and/or loss of cohesion of permafrost soils. *Warmer Winters* » Reduced ice and snow removal costs; » More opportunities for winter-time maintenance and construction; » A potential increase in fogginess; » Asset deterioration because of more frequent freeze-thaw cycling; » More accessible inland waterways; » Loss of the use of snow and ice roads and an increase in permafrost heave, and » Increased flood risk because of an increase in wet winter precipitation.

Climate Changes	Observed Changes	Predicted Changes	Impacts on Transportation
Changes in Precipitation	***Increased average precipitation*** » Increased precipitation of about 0.94 mm/day has been observed in Central America and 1.5mm/day in Brazil. ***Decreased average precipitation*** » Increased precipitation of about 0.94 mm/day has been observed in Central America and 1.5mm/day in Brazil. » Decreased precipitation was observed in the Andes region (44 mm less per decade) and Northeastern Brazil (0.3 mm/day less precipitation over 50 years). » Northern & Central Chile faced a reduction in rainfall between 45-105 mm over 31 years. ***Increased extreme precipitation*** » Increased precipitation of about 0.94 mm/day has been observed in Central America and 1.5 mm/day in Brazil. » Extreme precipitation events increased in number by 1.3% per decade in the last 50 years. » São Paulo saw an additional 5 to 8 more days of extreme rainfall per year as well as increases in the magnitude of precipitation by 50 to 75 mm over 40 years. ***Earlier Rainy Season*** » The onset of the rainy season has become steadily earlier in the Amazon over the last 60 years, with a total shift of about 170 days earlier. ***Longer Dry Season*** » The number of dry months, with low precipitation, in Southern Brazil, Uruguay and Argentina increased by 1-2 months between 1980 to 2000.	***Increases in extreme precipitation*** » Heavy precipitation is likely to change with a reduction of up to five days of heavy precipitation in some regions of LAC and an increase of 105 days in other regions. ***Increases in variability of rainfall*** » Central America and Venezuela will face a shift in historical precipitation averages by about -10%/+10% or -20% to +50%, depending on the study.	» Increase in weather-related crashes, traffic disruptions, and delays; » » Flooding of land transport infrastructure, hydraulic damage to bridge abutments and footings, prolonged standing water damage to geotechnical substrata, culvert failures and road and rail washouts, the collapse of embankments, and mudslides, landslides, and slope failures; » Flooding of subways and public transport facilities (e.g., bus depots); » Inability for transport workers to get to their work, and » Increased incidence of slush flow avalanches.

Climate Changes	Observed Changes	Predicted Changes	Impacts on Transportation
Changes in soil moisture and air humidity	*Increased number of wet days* » The number of wet days has increased by 0.37% in Chile since the 1970's. *Increased dryness* » Increased dryness has occurred in Chile and Ecuador and the Pampas region.	*Decreases in soil moisture* » In Central and South America, the combination of decreasing precipitation and increasing evaporation will produce dramatic decreases in soil moisture.	» Decreased soil moisture can lead to subsidence of geotechnical substrata. » Increases in soil moisture can lead to increased runoff due to saturation, loss of cohesion resulting in structural instability for bridges, sub-bases, slope cuts and embankments or increased landslide risk. » Increases in air humidity, in conjunction with heat, can reduce working hours available for construction, operations and maintenance.
Extreme Winds *Sea-Level Rise and Storm Surge*	*Stronger and more frequent extreme winds* » Changes in wind intensity and frequency of extreme winds is already observed in Latin America in many regions such as coastal Chile. » *Sea level rise* » Sea level rise has been observed varying from 2 to 7mm/year since 1950, but the rate is accelerating over time.	*Increased wind speeds* » Climate models predict that surface winds in the west coast of South America will increase by 1.5m/s in the next century. *Increased wind speeds* » Climate models predict that surface winds in the west coast of South America will increase by 1.5m/s in the next century.	» Damage to the technical superstructure of roads, railroads, ports, and airports; » Damage to lighting, power, and communications networks; » Traffic disruption and closures from felled trees; » Temporary closures of port and airports and subsequent backlogged operations; » Storm debris clearance. » Erosion of coastal roads and railroad infrastructure; disruption for transport networks and activities situated in low-lying areas; » Higher tides for port facilities and potential disruption or road/rail access to ports; » Potential for flooding, exacerbated by inadequately dimensioned drainage facilities; » Exposure of low-lying coastal airports to storm-surge damage and flooding; » More frequent and/or permanent inundation of transport facilities in low-lying areas; » Corrosion of steel and concrete materials; » Increased scour for defensive structures and bridges.

Sources of Information on Current and Future Climate

In carrying out climate resilient transportation planning, planners and policy makers will need to rely on information derived from climate models. While such models are the best source of information on future climate, they have many important limitations. Climate models can project potential changes in climate, but they cannot predict them. There are many sources of uncertainty, including uncertainty about future emissions and exact climate changes. Some of these sources of uncertainty will not lessen with time. This section provides an overview of climate models to help readers understand their strengths and limitations and of the information they provide.

Climate Change Projections and Predictions

What is a "projection?" A projection is a plausible future condition that may be conditional on predetermined events (i.e., projections based on a specific Representative Concentration Pathway, RCP). Individual model estimates of future climate conditions are considered projections. Projections do not have occurrence probabilities assigned to them.

What is a “prediction” or “forecast?” A prediction or forecast is a “most likely” outcome. It is a precise statement about the future, such as “there is a 70 percent chance of rain tomorrow” or “global mean temperatures will rise 4 to 11ºF by 2100 over 1990.”

The Importance of Climate Models

Climate models are an important source of information on current and future climate and are the only way to project changes in climate due to human activities. There are three reasons for this. First, climate is a very complex system, and climate models represent the best current understanding of the system. Second, there is no analog for human-induced warming. Third, it is impossible to carry out deliberate controlled experiments.

However, models are not crystal balls; they are simplifications of reality. They can be wrong, even if all or most scientists agree with them. Nevertheless, they are still the best source of information available on climate change and are continuously improving in terms of resolution and the processes they simulate. When comparing models, some comparisons are based on how well a given model simulates climate processes, on its vintage (newer tends to be better), and on how well it simulates historical observed climate. Any of these suggest that one model could represent the future better than other models.

Climate models simulate many processes on globe-spanning grids. Such models include General Circulation Models (GCMs) and earth system models. These models are mathematical simulations of many parts of the earth system, such as atmospheric dynamics, ocean and land surface processes (including vegetation), and the cryosphere (those portions of the Earth’s surface where water is in solid form). Global models generally divide these systems into grid boxes. Typical grid boxes in GCMs are about two by three degrees of latitude and longitude (~140 miles by ~200 miles or 28,000 square miles). The size of grid boxes determines the spatial resolution, so the larger the grid boxes, the lower the resolution.

Resolution matters, but how models handle climate and biophysical processes is more important. Resolution is important because all projections used for climate change are represented, in part, by the model’s spatial resolution. Further, all projections are uniform within a given grid box and may not fully account for sub-grid scale processes (e.g., convective thunderstorms). The resolution of climate model grids is particularly problematic along coasts and in mountains where earth system dynamics vary widely across small regions.

Another set of climate projections is available at higher spatial resolutions. To achieve higher resolutions, these projections are spatially downscaled using a variety of statistical and dynamic methods. Researchers create downscaled climate model data because some climate information is more useful at higher resolution. However, downscaling to a higher resolution does not mean the GCMs are more accurate.

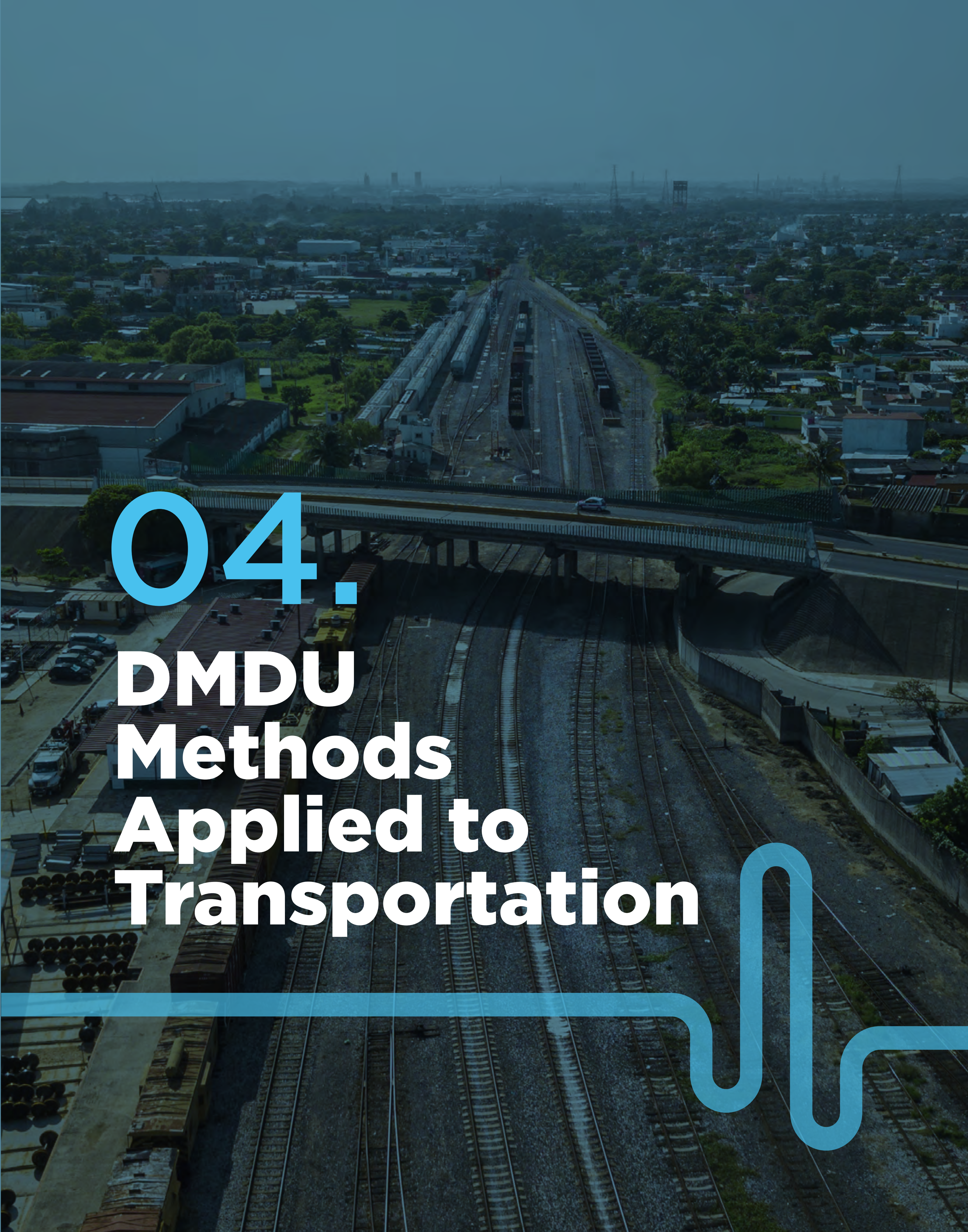
The key question is whether downscaling improves the results. Downscaling raises many questions, such as:

- Do the results make physical sense?
- Is there a better understanding of the direction of change at high resolution?
- Do the models project how change varies within the GCM grid box?
- Does downscaling provide more accuracy or just more precision?
- Does downscaling provide insight into sub-grid scale processes?

Key Takeaways

The key takeaways from this section are the following:

- Temperatures are rising; the climate is changing.
- More warming is to be expected in the future, but the timing and magnitude of that warming are uncertain.
- Planners can project potential changes in climate, but they cannot predict them.
- There are many sources of uncertainty, including uncertainty about future emissions and exactly how the climate will change.
- Some sources of uncertainty are not expected to end.
- Climate models are the best source of information on future climate, but they have important limitations and their outputs are projections, not predictions.



04.

DMDU Methods Applied to Transportation

The preceding chapters have shown that past climate is no longer a reliable predictor of future climate, and that there is a high level of uncertainty about how climate has and will change in the future. However, waiting for these uncertainties to resolve does not offer transportation planners a path forward as they still need to consider future climate and other conditions when developing long-term infrastructure plans. To support long-term planning, climate models, while far from perfect, can offer useful insights into future climate, and are helpful when they are used appropriately. Considerations of future climate should also weigh multiple objectives (e.g., reliability, cost-effectiveness and equity) and other socio-economic or policy conditions, as many decisions will prove effective or provide benefits under multiple future conditions.

In developing plans, weighing benefits and considering future conditions, planners should not mistake well-characterized risk for conditions of Deep Uncertainty. Well-characterized risk exists when planners and engineers can confidently use single joint probability distributions (i.e., predictions) to describe hazard, exposure, and vulnerability that contribute to risk. In contrast, Deep Uncertainty is defined (Lempert, Popper et al. 2003) as:

Deep Uncertainty occurs when the parties to a decision do not know or do not agree on the likelihood of alternative futures, or how decisions or actions are related to consequences.

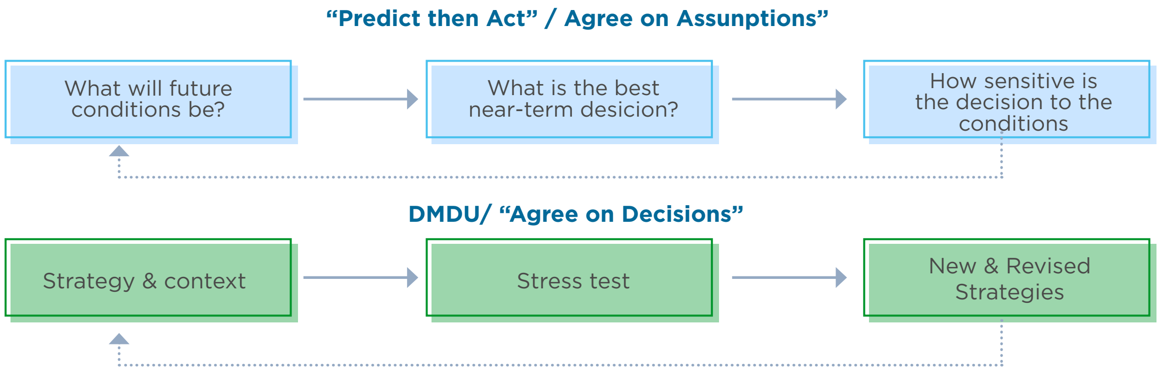
Decision Making Under Deep Uncertainty (DMDU) enables Risk Management under conditions of Deep Uncertainty, that is when risks cannot be confidently quantified. This section provides an overview of DMDU methods and tools, beginning with DMDU's basic principles.

"Predict-then-Act" and DMDU

Assessing climate change presents a Risk Management challenge. Risk Management is an ongoing process of assessment, action, reassessment, learning, and response. As discussed in Section 2, it is often useful to take a broader view of risk in assessing climate change and planning for appropriate responses. To illustrate this broader view, traditional "predict-then-act" approaches to Risk Management are described here and an alternative "agree on decisions" framework that characterizes DMDU methods is presented (Walker, Robert J. Lempert et al. 2013; Marchau, Walker et al. 2019).

Transportation planners often assume risks are well-characterized. As a result, planners frequently use historical precipitation records, such as a 100-year design storm, to assess the reliability of assets in their network against such events. Similarly, in projecting the traffic flowing through the network, planners often use best-estimate demand forecasts.

>> **Figure 4.1** | "Predict-then-Act" Compared to DMDU Approaches



The upper panel of Figure 4.1 suggests how such traditional Risk Management can be characterized by a "predict then act" process. "Predict-then-act" begins with a well-characterized, consensus understanding of the future and the uncertainty surrounding it. This understanding is most formally represented as joint probability distributions over fully enumerated future states of the world, though in practice it is often represented as a best-estimate forecast which is then used to rank the desirability of near-term decisions. Finally, sensitivity analysis can suggest how sensitive the ranking of options is to various assumptions.

Consider, for example, the design and siting of a new bridge. In "predict-then-act," a transportation engineer might use a demand forecast as one input to determine the size and location of a new bridge. The engineer might also use a 50-year storm, estimated based on historical precipitation, as a design criterion. The bridge would then be designed to accommodate the future predicted demand, and to provide reliability against the design storm. A safety factor may also be added to account for a small amount of future uncertainty.

Predict-then-act processes are usefully termed "agree on decisions" because they require the parties to the decision to agree on the best-estimate characterization of the future states of the world before they can proceed with the subsequent stages of the analysis and have confidence in its policy recommendations.

Predict-then-act works well when uncertainly is well-characterized but can break down when uncertainties are deep. Under such conditions, uncertainties are often underestimated, competing analyses and

predictions of future conditions can contribute to gridlock, and misplaced certainty in future conditions can blind decision makers to surprise (Lempert 2019).

Under these deeply uncertain conditions, it is often useful to employ a DMDU analysis. As shown in the lower panel of Figure 4.1, such analysis inverts the "predict-then-act" process. The analysis begins with one of more proposed strategies or engineering designs. Models and data are then used to stress test these strategies over many futures, seeking to understand the conditions in which the strategies will and will not meet their goals. Using this information, the analyst can then identify new and revised strategies that are more robust, that is, those that perform well over a wide range of plausible futures.

Such DMDU process can be usefully termed "agree on decisions" in contrast to "agree on assumptions" approaches. The latter type of analysis can prove contentious in situations in which the parties to a decision have different expectations regarding the future, for instance regarding the seriousness of climate change in their region. Parties to a decision often have self-consistent clusters of policy preferences and expectations about the future. They understand that accepting certain assumptions might steer an analysis towards policy recommendations counter to their preferences, and will thus contest those assumptions. Under conditions of Deep Uncertainty, planners who agree on assumptions methods may have difficulty marshalling evidence sufficient to generate the necessary consensus characterization of the future. In contrast, the DMDU process enables parties to a decision who disagree on expectations to nonetheless agree on the nature (though perhaps not the magnitude) of the risks they face, and on appropriate strategies for reducing those risks (Kalra et al. 2014).

Alternative DMDU Approaches

Many DMDU approaches exist (Marchau, Walker et al. 2019). This section will focus on three such DMDU methods most relevant for developing robust transportation strategies. These are:

1. **Scenario Planning,** which develops robust strategies from scenarios that people create;
2. **Adaptive Pathways and flexible design,** which provides a framework for developing strategies that adjust over time; and
3. **Robust Decision Making (RDM)**, which runs simulation models over many futures to stress-test proposed strategies, identify future scenarios that illuminate vulnerabilities of strategies, and develop new strategies that mitigate those vulnerabilities.

Basic DMDU Principles

While these methods differ in their implementation, are appropriate in different cases, and require different levels of effort and data, they all share common principles and purpose. The basic principles underlying DMDU are the following (Lempert, Popper et al. 2003; Lempert 2019):

- Consider multiple futures, not one single future, in planning. Choose these futures to stress test the organization's plans;
- Seek robust plans that perform well over many futures, not optimal plans designed for a single, best-estimate future, and that perform well over a comprehensive set of metrics that is multi-objective;

- Make flexible and adaptable plans that will be more robust;
- Use analytics to explore many futures and options, not tell what to do.

Examples of these principals in practice include:

- Consideration of a plausible range of future population growth, rather than a single estimate, in sizing, designing and investing in public transportation projects.
- Development of a city-wide transportation plan with investments that improve transportation conditions, walkability, and system flexibility, as well as livability, equity, health and safety across a range of future population growth, temperature changes and precipitation levels.
- Identification of key climatic, population or ridership thresholds that, if surpassed, would suggest the need to refocus investment plans, resize infrastructure projects, or adjust operations.

DMDU approaches can help planners focus on important questions about decision making under Deep Uncertainty and considering multiple futures. These questions may be useful:

- Can a robust and flexible strategy perform well over a wide range of futures?
- What uncertainties are most important in determining the success or failure of plans?
- What actions needed to be taken now to keep future options open?
- What actions can be postponed?

Decision Framing—First Step of All DMDU Analysis

The first step in the "agree on decisions approach" involve Decision Framing, as shown in Table 4.1. Decision Framing is a key component of Scenario Planning (Tasks 1-3) and RDM-supported "deliberation." It is used to untangle a problem, build a shared understanding, make choices about the analysis explicit, and make decisions transparent. Decision Framing produces the information needed to build the scenarios in scenario planning, and organize the modeling and analysis for Adaptive Pathways and RDM exercises.

>> **Figure 2.4 |** XLRM Matrix Used to Organize Decision Framing

XLRM Matrix Organizes Key factors

X: Uncertainties	**L:** Management Strategies (levers)
Uncertain factors that may affect ability to reach goals	Uncertain strategies (levers) considerer to pursue goals
R: Relationships (models)	**M:** Performance Metrics
Relationships among metrics, levers, and uncertainties **X, L** —**R**→ **M**	Metrics that reflect desicion makers´goals

Source: (Lempert et al. 2003)

This component of DMDU methods is often accomplished by working with stakeholders in a workshop. It often proves useful to organize the discussions at such workshops into four key sets of factors, labelled "XLRM." As shown in Table 4.1 the "Ms," performance metrics, ask "What are we trying to achieve?" The "Ls," policy levers, ask "What actions might we take to pursue these goals?" The "Xs" are the uncertain factors outside the decisionmakers' control that affect their ability to pursue their goals. The "Rs" are models that connect the other factors in the matrix.

To illustrate the output and content of Decision Framing, we detail the example of Ruta Nacional 5, a highway in Argentina connecting the provinces of La Pampa and Buenos Aires. Ruta Nacional 5 is an important route for Mercosur, because the highway connects Paraguay, Argentina, Bolivia, and Brazil. The highway has been recurrently closed because of floods; thus, key segments have been forced to close requiring a 165-kilometer (km) detour of over 4,000 vehicles a day.

Table 4.2 shows XLRM factors for the Ruta Nacional 5. These factors were chosen using the focal question, "How can the Dirección Nacional de Vialidad (DNV), Argentina's National Highway Department best prepare the Ruta Nacional 5 to foster resilience of the traffic flow over the next 75 years?" The contents of this matrix are utilized in DMDU methodologies detailed in this section.

>> **Table 4.2 |** Example Complete XLRM Matrix for Ruta Nacional 5

Uncertainty Factors (x)	Policy Levers (L)
» Temperature and rain variability » Number of intensity of storms » Economic growth and traffic demand » Environmental regulation » Construction and maintenance costs » Funding (local, state, private, economic conditions) » Political climate (provincial disputes) » Policy environment (provincial, national)	» Bridge design » Redundancy (increasing road network to reduce detour in eventual flooding)
Relationships (R)	**Performance Metrics (M)**
» Change in logistic costs -> change in traffic and in socio-economic variables (GCD, labor, poverty, inequality) » Change in the reliability of the network -> change in socio-economic variables (GCD, labor, poverty, inequality) » Change in highway supply -> change in the highway demand	» Average operational costs (logistics) » Operational cost (logistics) » Average speed » Number of days without traffic interruption » Provincial and Mercosur connection » Jobs created for the public work » Long-term jobs created » Reduction of regional inequality » International competitivity of the provinces » GDP growth

Once an XLRM matrix is developed, it can then be used across DMDU methods in a number of ways: i) to build future scenarios either qualitatively or quantitatively, using the factors identified as “Xs”; ii) test how various policy levers “Ls” perform across these scenarios; iii) measure the performance of “Ls” with the list of relevant metrics “Ms,” and iv) qualitatively or quantitatively model (using “Rs”) the transportation system, asset or network being considered under the future scenarios, based on the “Xs”, and with or without the various policy levers “Ls”.

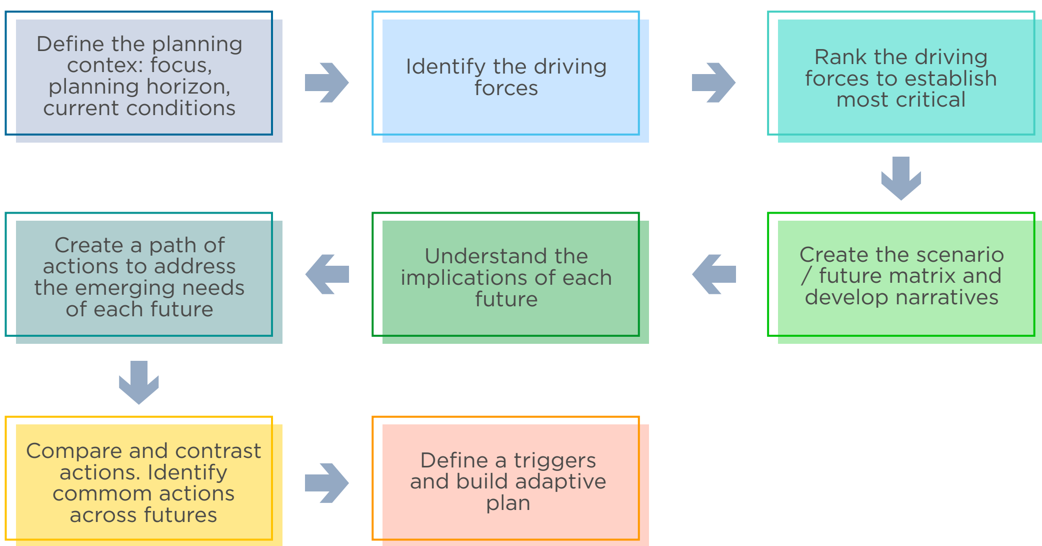
Method 1 | Scenario Planning

Humans are avid scenario builders. They tell stories, imagine each other’s experiences, contemplate potential explanations, and reflect on moral dilemmas. Such scenarios benefit humans, and help them to reduce overconfidence in planning. Scenario Planning as a planning method concerns being prepared for whatever happens in the future. However, scenario planning is not about envisioning what people want to happen in the future or predicting what will happen in the future.

There exist many scenario planning processes (Schwartz 1996). Transportation planners can usefully employ the eight-step scenario planning process, as shown in Figure 4.2 (Lyons, Davidson et al. 2014).

Scenario Planning begins with a framing process. The analyst first determines the planning context, particularly the focus, planning horizon, and current conditions. Second, the analyst identifies the driving forces and the decision challenges. The scenario process continues with the third, in which the analyst ranks the driving forces to establish which are the most critical. The fourth step is to use these drivers to create a matrix of future scenarios and develop narratives that describe those scenarios.

>> **Figure 4.2 |** Scenario Planning Process



Source: (Lyons et al. 2014)

The scenarios can now be used to expand and enrich understanding of the future (Wack 1985), and to stress test proposed plans. The fifth step shown in Figure 4.2 is to understand the implications of each future, where quantitative analysis was used to enrich each scenario. The last steps in the scenario planning process develop a path of actions to address the emerging needs of each future, compare and contrast actions, identify common actions across futures, and define triggers and build an adaptive plan.

To illustrate the scenario planning process, New Zealand's scenario planning that was undertaken to explore future travel demand, as shown in Figure 4.3 (Lyons, Davidson et al. 2014) was used. Their planning was focused on the slow growth of automobile usage in developed countries, particularly among the young, partially due to the fast growth of alternative technologies that are generating many new mobility options. Nevertheless, for over a century, private automobiles have provided increasing mobility. As a result of these changing dynamics, planners in New Zealand asked: what are the implications on the demand for mobility and the means for supplying it in the mid-21st century?

Through these stages of the New Zealand scenario planning process, participants in a series of workshops suggested 16 drivers of change. Then, they grouped and ranked these drivers based on importance and uncertainty. For example, urbanization, ageing population, decentralization of shopping, digitally-connected society, responding to environmental change, and the rise of Asia were characterized as known changes occurring in their region. In contrast, values, community and identity, fundamentalism, smart infrastructure and nanotechnology, personal and state security and ownership of the internet were characterized by workshop participants as uncertain dynamics potentially affecting the transportation system. A third grouping of drivers also emerged from this process, which represented those with more mixed views on their likelihood and outcome. This group included: resilience to climate change, pressures on raw materials and resource management, technologies driving new industries and business models, wealth and access to employment, and governance, regulation and politics.

The fourth step is to use these drivers to create a matrix of future scenarios and develop narratives that describe those scenarios. In the New Zealand example, different costs of energy (low and high) and accessibility preference (physical or virtual) were used to construct four scenarios with corresponding narratives: cooperative and close, global locals, travelers' paradise, and digital decadence (Figure 4.3, which also shows descriptions of each scenario). These scenarios were built upon the drivers identified and ranked in steps one through three (e.g., urbanization, digitally-connected society). The relative cost of energy was a key future driver used to organize the four scenarios. That is, relative to other costs of living, the affordability of energy influences what people will be able to do. The second dimension of the future scenario matrix—accessibility preference—frames what members of society will want to do. That is, while it is technologically possible to connect physically (transport) or virtually (telecommunications), a critical uncertainty is how people will want to access other people, goods, services and opportunities in the future.

Within the four scenarios that defined plausible futures for New Zealand, planners could have also incorporated variables related to climate change. For example, planners could have added a very wet and hot future as a part of "Cooperative and Close", which could exacerbate demands on high-cost and complicate preferences by society to maintain transportation (rather than virtual) access. Planners could also consider the effects of decarbonization on transportation technologies across the scenarios.

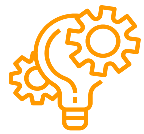
The New Zealand scenario analysis did not focus on the final steps shown in Figure 4.2. We will address those in the next section on Adaptive Pathways.

>> **Figure 4.3 |** New Zealand Scenario/Future Matrix with Narratives

high

Cooperative and close

While people value face-to-face contact, high energy costs have forced them to adapt. New Zealanders persevered througt challenges by simplifying their lifestyles. They value strong communities, resourcefulness and simplicity.



Global Locals

In response to rising energy costs, society invested in energy-efficient technologies and virtual interfaces. Society has moved from car dependency to virtual confidence. People value adaptability, efficiency and ingenuity.

Relative cost of energy

physical — Accessibility preference — virtual

Travelers' Paradise

New Zeland is awash with cheap energy, which powers rapid growth. Citizens prefer to connect with one another face-to-face as digital life feels less authentic. People support network pircing to ensure they have the transport systems they need. They value individual liberties, privacy and self-reliance.

Digital Decadence

People enjoy a vast array of experiences and services anywhere, anytime, via their digital interfaces. Many people now feel more comfortable in digital worlds than in their own skins. They value openness, collaboration and innovation.

low

high

Relative cost of energy

low

physical — Accessibility preference — virtual

Cooperative and close

Digital connectivity effect	
Change in total VKT by 2042	
Work - main/other job	0%
work - employers´ business	0%
Education	0%
Shopping / personal business	0%
Social visits	0%
Recreation	0%

Urbanisation effect

Urban population share by 2042

90%

Energy price change effect

Change in fuel price in 2042 compared to the baseline

500%

Fuel efficiency effect

Petrol vehicle efficiency (km per litre) **14.00**

Global Locals

Urbanisation effect

Urban population share by 2042

85%

Energy price change effect

Change in fuel price in 2042 compared to the baseline

300%

Digital connectivity effect	
Change in total VKT by 2042	
Work - main/other job	0%
work - employers´ business	0%
Education	0%
Shopping / personal business	0%
Social visits	0%
Recreation	0%

Fuel efficiency effect

Petrol vehicle efficiency (km per litre) **12.00**

Travelers' Paradise

Digital connectivity effect	
Change in total VKT by 2042	
Work - main/other job	15%
work - employers' business	15%
Education	15%
Shopping / personal business	15%
Social visits	15%
Recreation	15%

Urbanisation effect

Urban population share by 2042

80%

Energy price change effect

Change in fuel price in 2042 compared to the baseline

-50%

Fuel efficiency effect

Petrol vehicle efficiency (km per litre) **11.00**

Digital Decadence

Urbanisation effect

Urban population share by 2042

85%

Energy price change effect

Change in fuel price in 2042 compared to the baseline

300%

Digital connectivity effect	
Change in total VKT by 2042	
Work - main/other job	-50%
work - employers´ business	-25%
Education	-50%
Shopping / personal business	-50%
Social visits	-50%
Recreation	10%

Fuel efficiency effect

Petrol vehicle efficiency (km per litre) **11.00**

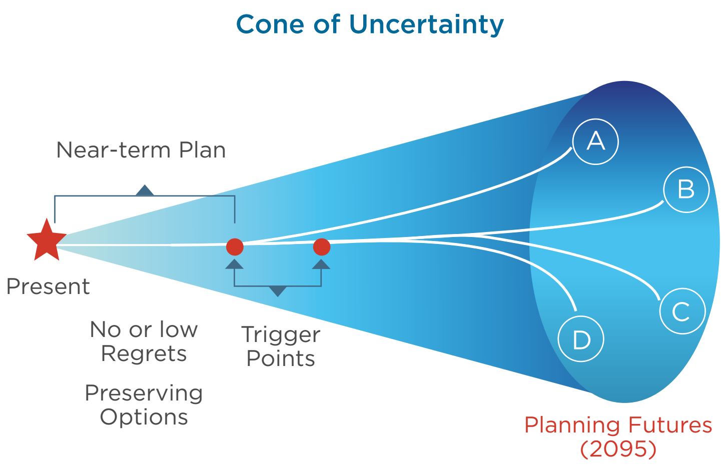
Source: (Lyons et al. 2014)

Method 2 | Adaptive Pathways

Scenarios have long been used to help identify robust strategies that can perform well over a wide range of futures (van der Heijden 1996). After developing a set of scenarios, analysts and decision makers can stress test proposed strategies against them. A robust strategy will perform relatively well in all the scenarios.

Such robust strategies are often adaptive, that is, they are designed to adjust over time in response to new information. Figure 4.4 shows the basic concept (Kaatz 2015). A strategy or design begins with a near-term component. These are actions that will be taken in the present and, depending on the context, over the next few months or years. The strategy will also monitor key trends that might suggest the need to modify or update these near-term actions. The plan also includes contingency actions that might be taken if specific trends are observed. These are often called tipping points, trigger points, or thresholds.

>> **Figure 4.4 |** Scenarios Can Support Development of Robust and Flexible Strategies



Source: IPCC 2012

In recent years, dynamic Adaptive Pathways has emerged as a powerful approach for developing and visualizing such robust and adaptive plans (Haasnoot, Kwakkel et al. 2013; Haasnoot, Warren et al. 2019). Adaptive Pathways provide a framework for developing contingency plans. The Adaptive Pathways approach has several key steps. The Decision Framing step identifies important performance measu-

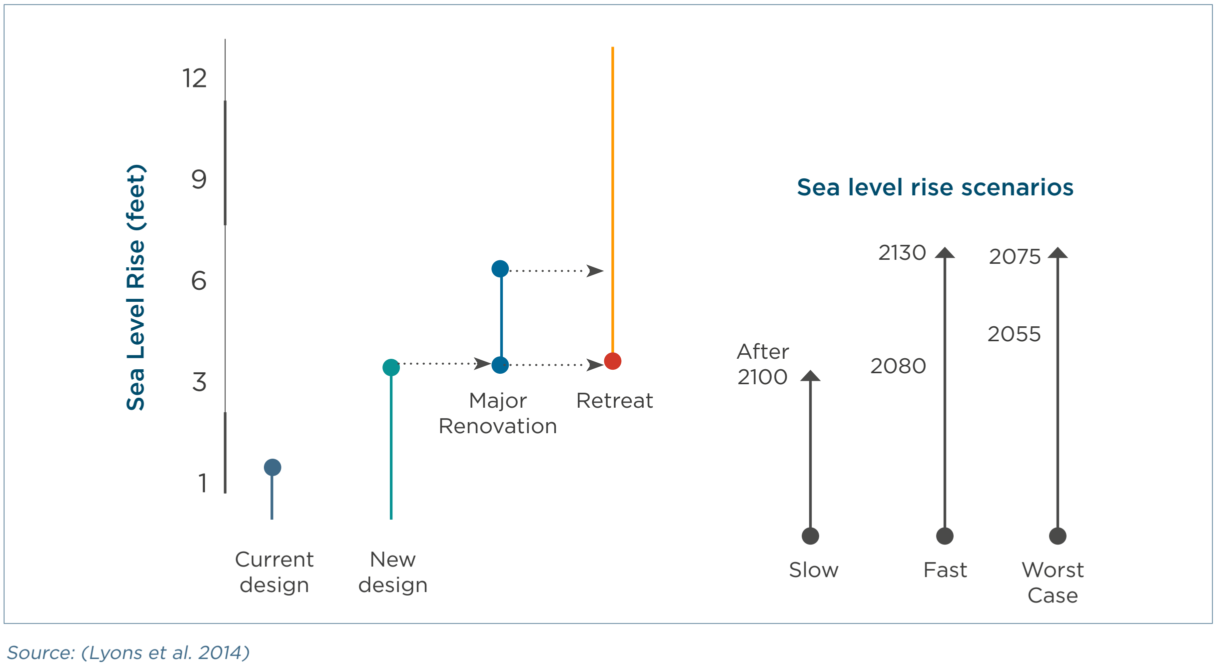
res for the project or system in question, scenarios that may impede the ability to achieve desired performance levels, and alternative decision options that might be used to increase resilience. The stress test and new strategies steps organize the options into pathways consisting of initial actions, and subsequent contingency actions that can meet the performance measures with increasing levels of hazard. The steps of the Adaptive Pathways approach are as follows:

- Identify the level of hazard for each alternative decision option at which the option would no longer provide adequate performance according to the measures. These are called the Adaptation tipping points.
- Identify a range of scenarios for the hazard and note the date at which the Adaptation tipping points might be reached in each scenario.
- Trace how one would step through the sequence of options in each scenario.
- Identify signposts that would indicate which scenario is occurring.

Adaptive Pathways help ask which options to deploy first, what options to deploy next, and how to make choices less vulnerable to uncertainties in the scenario. Figure 4.5 summarizes the approach with a notional example.

Imagine a road near a shoreline. The road is intended to meet a certain level of reliability, for instance allowing traffic to pass along it 99 percent of the time. Engineers determine that the road can maintain such reliability with up to one foot of sea level rise. Since sea level rise might exceed this level, the road's operators consider a new design. As shown by the purple line on the left-hand side of Figure 4.5, they might consider a design that can maintain reliability with up to three feet of sea level rise. The design is such that with a major renovation sometime in the future, the road could retain reliability with up to six feet of sea level rise.

>> **Figure 4.5 |** Adaptation Pathways



Source: (Lyons et al. 2014)

Adaptive Pathways is becoming increasingly popular. Recently, New Zealand's *Coastal Hazards and Climate Change: Guidance* for Local Government and the State of California Sea-Level Rise Guidance recommended the approach, and it was recently used to examine urban flooding in Miami (California Ocean Protection Council 2018, Bouwer et al. 2018; Ministry for the Environment 2017).

Method 3 | Robust Decision Making (RDM)

RDM is an iterative analytic DMDU analysis designed to inform decisions under Deep Uncertainty (Lempert, Popper et al. 2003; Lempert, Groves et al. 2006; Groves and Lempert 2007; Groves, Molina Perez et al. 2019; Lempert 2019). RDM uses models and data to stress-test strategies over many plausible paths into the future, use the resulting database to identify conditions where strategies fail, and use this information to identify more strategies that perform better under more plausible futures.

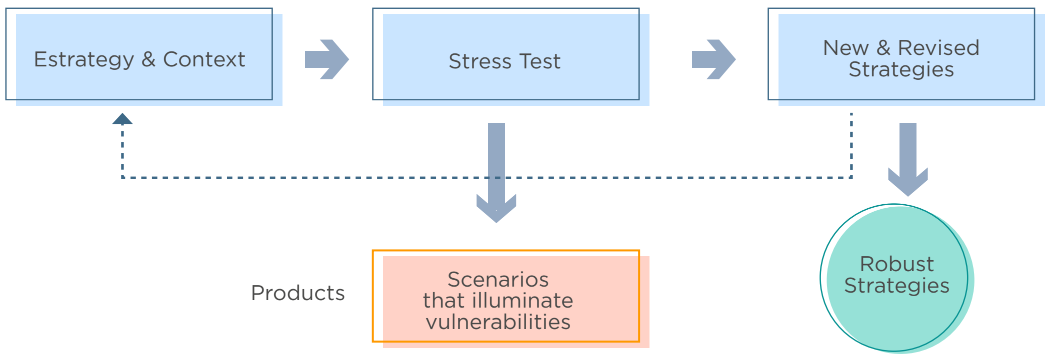
As shown in Figure 4.6, RDM follows the DMDU process and produces two key products: scenarios that illuminate vulnerabilities of proposed strategies, and 2) more robust strategies that reduce these vulnerabilities.

RDM begins with the Decision Framing exercise, as described earlier in this section. In this exercise, stakeholders define the key factors in the analysis: the decisionmaker's objectives and criteria; the actions they can take to pursue those objectives; the uncertainties that may affect the connection between actions and consequences, and the relationships, often instantiated in computer simulation models, between actions, uncertainties, and objectives. One important product of this Decision Framing is often one of more proposed strategies to consider.

RDM next uses simulation models to evaluate the proposed strategies in each of many plausible paths into the future. These calculations generate a large database of simulation model results. Each record in the database shows the performance of one strategy in one future.

This database can be used to stress-test each proposed strategy. Analysts and decisionmakers use visualization and data analytics to explore and characterize the future conditions that best distinguish when a proposed strategy meets and misses its goals. Understanding these conditions illuminates the vulnerabilities of each proposed strategy and tradeoffs among the strategies.

>> **Figure 4.6 |** The RDM Process



Next, analysts and decisionmakers use this information to identify and evaluate potentially more robust strategies that provide better tradeoffs than the existing options. These new options generally incorporate additional policy levers and often include the key components of adaptive planning: a set of near-term actions, defined signposts that signal when and under what conditions additional strategies may be needed, and contingent actions to be taken if the pre-designated signpost signals are observed. This process is described in detail in the example that follows.

At each of the RDM steps, information produced may suggest a reframing of the decision challenge. The process produces key deliverables including (1) the scenarios that illuminate the vulnerabilities of the strategies and (2) potential robust strategies and the tradeoffs among them. As discussed in the text surrounding Figure 4.1, DMDU follow an "agree on decision" process designed to enable parties to a decision who disagree on expectations of the future to nonetheless agree on actions to reduce risk. Accordingly, both these RDM products represent high confidence information in a world of Deep Uncertainty. Parties to a decision can agree on the conditions under which a proposed strategy would meet or miss its goals without agreeing on the likelihood of those conditions. Parties to a decision can also agree that some strategies are more robust than others, that is, better able to succeed over a wide range of futures.

Box 4.1

RDM and Monte Carlo Analysis

Traditional risk analysis often employs Monte Carlo methods. RDM and Monte Carlo share similarities and important differences. It can prove important to make these clear.

A Monte Carlo analysis involves running a simulation model many times with different values of the inputs. These input values are generally chosen by sampling from a best-estimate probability distribution over those inputs. The resulting model outputs are then interpreted as a probability distribution and summarized with that distribution's mean and moments (i.e., standard deviation).

Monte Carlo analysis and RDM both involve running a model many times with different assumptions regarding the model input values, but RDM and Monte Carlo analysis differ in two important ways. First, RDM regards Monte Carlo analysis as conflating two distinct concepts: a) choosing a set of different model input parameters in order to efficiently sample, and then understand the behavior of the model over those inputs, and b) choosing a probability distribution over model inputs that reflects an understanding of the likelihood of alternative futures in the real world. Second, RDM regards the means and moments of probability distributions as only one of several ways analysts can usefully summarize the information in a large database of model runs.

Thus, RDM separates the two distinct concepts conflated by Monte Carlo. RDM will often use a Monte Carlo or similarly type of stochastic experimental design over the model inputs to efficiently sample the model behavior. RDM then uses methods such as interactive computer visualization and statistical classification to extract policy relevant information from the resulting database of model runs, without assuming that the distribution used to generate the sample of model runs is the same as the probability distribution of futures in the real world. In situations with both well-characterized and Deep Uncertainty, RDM analyses will often run a risk model using standard Monte Carlo analysis over the well-characterized uncertainties, while exploring the deep uncertainties.

RDM also shares similarities and differences with standard sensitivity analysis, such as that mentioned in the upper panel of Figure 4.1. Simiarly to sensitivity analysis, RDM seeks to understand how a model's outputs vary with respect to its inputs, but RDM inverts the standard questions of sensitivity analysis. Rather than ask "how sensitive are our results to uncertainties in our assumptions?" RDM asks "What actions can we undertake whose success is insensitive to those aspects of the future that remain deeply uncertain?"

Example 1: RDM Analysis: Diagnosing Vulnerability and Economic Resilience of Transport Systems, Infrastructure, and Operations in the Western Balkans (DIVERSION)

We will now present these RDM steps in more detail, using as an example the World Bank's *Diagnosing Vulnerability and Economic Resilience of Transport Systems, Infrastructure and Operations in the Western Balkans* (DIVERSION) project. This effort aims to: i) use spatial analysis to determine potentially high-risk priority roads along vital transportation corridors, ii) assess the economic and social impacts of disruptions to these priority roads, and iii) identify priority interventions to most cost-effectively reduce risk and increase resilience of the transportation network. Because deep uncertainties surround the hazards, the project employs RDM to both conduct a risk assessment, and to identify a robust portfolio of responses to those risks. To engage with the priorities of local stakeholders, the project also built two decision support tools, one that displays the hazard and transportation network data, and the other that helps decision makers identify high-risk priority roads according to their own criteria.

This RDM analysis shows that:

- The Western Balkans is exposed to wide range of natural hazards.
- The region's road network is relatively resilient because it has lots of connectivity.
- Most of the natural-hazard related risk to the network is due to a few high-impact links.
- Relatively small investments, properly targeted, can significantly reduce this risk.

We now describe the analysis that generates these high-level results.

RDM Checklist

Figure 4.6 suggests a useful checklist of steps for any RDM analysis. These steps are:

1. Frame the decision challenge
2. Stress test proposed strategies over a wide range of futures
3. Identify new or revised strategies that meet planning goals over a wider range of futures

The Balkans transportation network example implements each of these steps.

Step 1: Decision Framing

The strategic road network of the Western Balkans—Albania; Bosnia and Herzegovina; Kosovo; North Macedonia; Montenegro; and Serbia—includes the Mediterranean corridor (MED) and the Orient/East-Mediterranean (OEM) corridors as shown in Figure 4.7. This network is vital to the economy and social welfare of the region, but it threatened by natural hazards including earthquakes, landslides, flooding, extreme precipitation and temperature, blizzards, and extreme winds. All these hazards, except for earthquakes, are affected by climate change.

The World Bank and the six national governments along both corridors have current and proposed investments in this Balkans Road network. The DIVERSION project analysis aims to improve the resilience of such investments to climate change and other natural hazards by asking the questions, "Which links in the network generate the most natural hazard-related risk to network as a whole?" and "What interventions would most cost-effectively reduce those risks?" The first question focuses on identifying vulnerabilities, and the second focuses on identifying responses to those vulnerabilities.

RDM was useful for answering these questions because they involve many deep uncertainties, in particular the frequency and magnitude of natural hazards affected by climate change.

>> **Figure 4.7 |** Western Balkans Mediterranean (MED) and Orient/East-Mediterranean (OEM) corridors

Source: DIVERSION Report

The project team conducted the Decision Framing in close consultation with the World Bank project manager. The discussions also included several sessions with transportation decision makers in the Western Balkans. As is typical in RDM analyses, the results of these discussions were organized using the 'XLRM' framework, as shown in Table 4.3.

Decision makers' goals are represented by three types of performance measures: risk, as measured by potential increases in travel time and travel distance for passenger cars and for freight; economic impacts as measured by value of losses, costs of repair and recovery, and costs of disruptions, and the cost of policy interventions. All these outcomes are evaluated in the year 2030.

For the stress test, the analysis considers the existing road network in the Western Balkans. For the options analysis of robust strategies, the analysis considers a wide variety of potential interventions including construction, monitoring and maintenance, and operation incident report, as shown in Table 4.3. These interventions affect the susceptibility of links to disruptions and, to a certain extent, the impact from disruption.

>> Table 4.3 | XLRM Factors for the Balkans Transportation Resilience Analysis

Uncertain Factors (X)	Policy Levers (L)
Natural hazards: Frequency and magnitude of: » Earthquakes » Landslides » Flooding » Wildfires » Wind » Extreme heat and cold » Extreme precipitation	**Construction** » Bridges and crossings » Drainage » Erosion and stabilization » Flood protection » Landscaping » Planning, design and construction » Road surface and structure **Other** » Monitoring and maintenance » Operation incident reporting
Relationships (R)	**Performance Measures (M)**
• Risk calculated from: » Hazard » Exposure » Vulnerability • GIS overlays to calculate exposure • REBIS VISUM model for impacts of disruption » Economic analysis of costs of delay and loss of accessibility	In the year 2030: • Risk, as measured by potential increase in: » Travel time for cars and freight » Travel distance for cars and freight **Economic impacts** » Value of losses » Costs of repair, recovery » Cost of disruptions • Cost of policy interventions

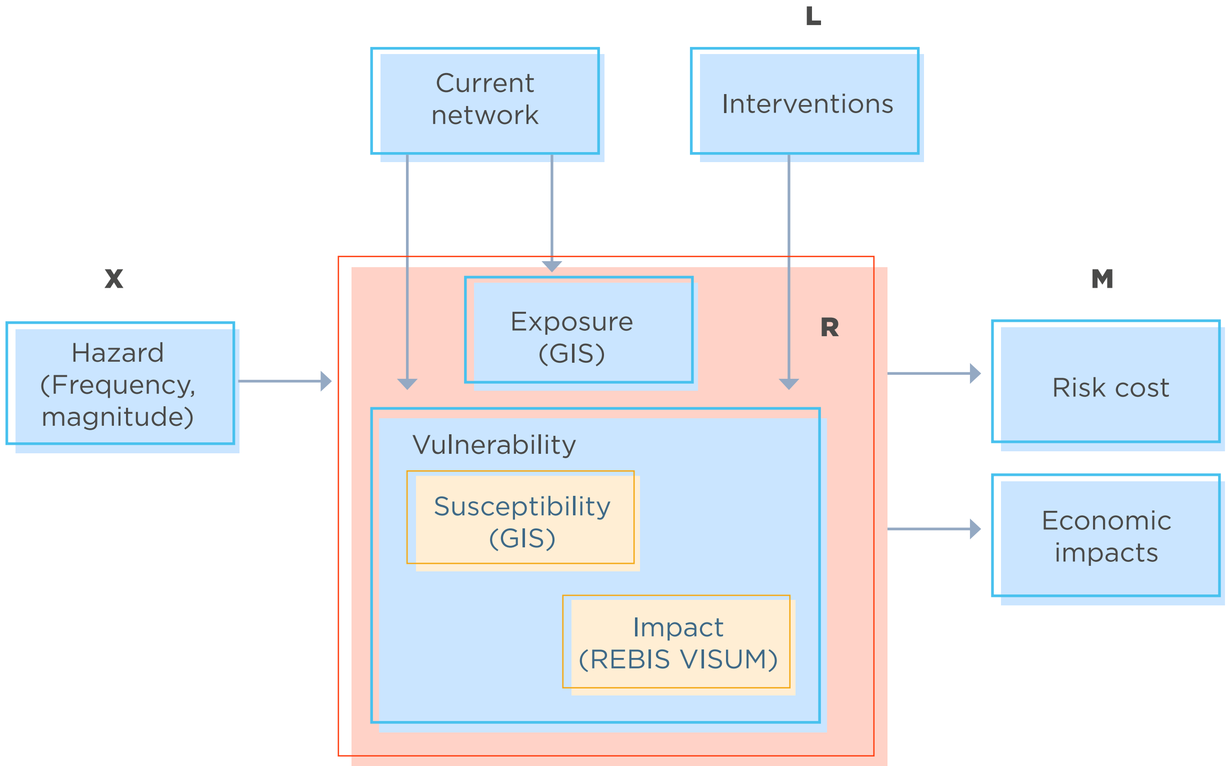
Source: DIVERSION REPORT Table 2.1

This study focuses on Deep Uncertainty in the natural hazards, in particular on the magnitude and return period. Based on consultations with the World Bank and country representations, and drawing on the databases discussed below, the study considers eight hazards that can affect links in the transportation network: earthquakes, landslides, wildfires, flooding, wind, extreme heat, extreme cold, and precipitation. Earthquakes, landslides, and flooding can reduce road capacity and damage the road. Wildfires and precipitation can reduce capacity. Extreme cold and heat can damage the road. As described in more detail below, the study represents Deep Uncertainty by considering a range of return periods for each of the hazards.

These factors are connected by the relationships sketched in Figure 4.8. As described in the next section this allows us to estimate exposure and susceptibility for each link in the network. We use the REBIS VISUM model to calculate the impacts of a disruption to any link in the network. As discussed in the next section, we use this information in an RDM analysis to identify sets of single and pairs of links whose potential disruption generates the most risk to the network.

We then estimate the economic impacts that would result from disruption of these high-risk links.

>> **Figure 4.8 |** Connections among factors in Balkans analysis



Step 1: Stress Test

The stress aims to identify the links that generate the most natural hazard risk to the network as a whole. In particular, to help simplify and focus the subsequent options analysis, we aim to identify a small number of links that generate the most risk to the network. The project employs a risk framework to organize this calculation and RDM to identify the links the generate the most risk in the face of Deep Uncertainty about the hazards.

Risk framing: The project defines risk as:

$R_{hs} = H_h \times E_{hs} \times V_{hs}$

where H is the hazard h, E is the exposure of link s to that hazard, and V is the vulnerability of link s to that hazard.

The hazard, exposure, and vulnerability are all estimated by overlaying various datasets, including those on:

» Administrative units—including European Union NUTS admin and country specific boundaries;

» Strategic routes—OEM and MED road corridors;

» OSM Strategic road network—Detailed road network data covering the six countries covered by the study;

» ERI Population data—Population and demographics data for 2017 downloaded from ESRI ArcGIS Online;

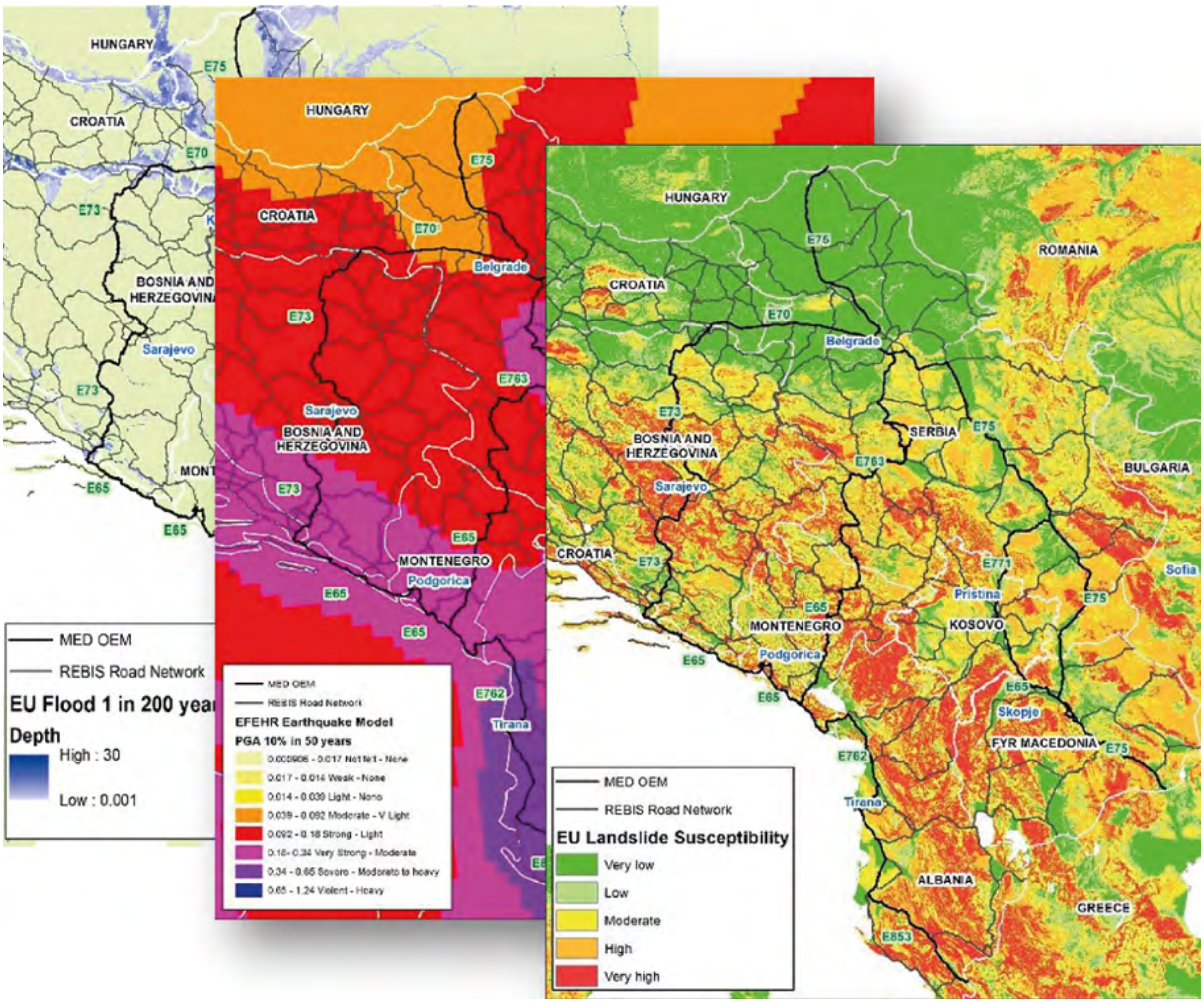
» EU Flood Hazard maps—Flood hazard maps for 1 in 10 to 1 in 500-year return periods. Hazard as flood depth in meters;

» EU hydro drainage—Drainage and river system layers developed by the EU Corpernicus program;

- EU Landslide Susceptibility map—Detailed landslide susceptibility map covering the study area;
- EFEHR Earthquake Hazard map—Earthquake potential map for peak ground acceleration of 10% in 50 years;
- EU Corine Land Use 2012—Land cover mapping covering Europe developed by the EU Copernicus program, and
- EU DEM Elevation Model—Detailed elevation model covering Europe developed by the EU Copernicus program.

Users can then view and overlay these GIS datasets. Figure 4.8 shows an example of the data, in particular maps for flooding, earthquake, and landslide hazard data.

>> Figure 4.8 | Project maps showing flooding, earthquake, and landslide hazard data



Source: DIVERSION REPORT Table 2.1

Each *hazard* has three levels of magnitude: low, medium, and high, which can cause increasing levels of damage and capacity reduction. Infrequent and frequent hazards are differentiated. Infrequent hazards, such as earthquakes, landslides, wildfires, and floods occur less often but can cause significant disruption to the road network. Frequent hazards, such as wind, extreme temperatures, and heavy precipitation occur more often, but the disruption dissipates after a relatively short period of time (e.g., hours to days).

Each hazard at each magnitude has a deeply uncertain return period, characterized by a wide range of potential values. Exposure and vulnerability are treated as if they were well-known.

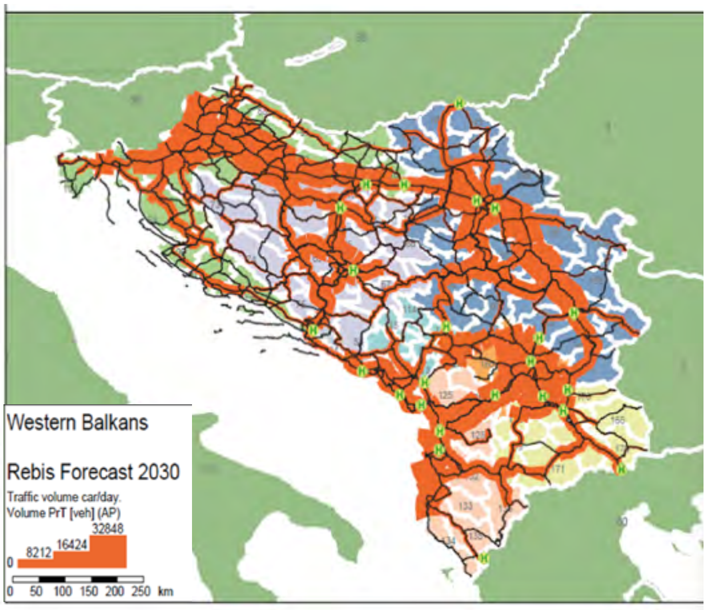
Each link in the network is exposed to a greater or lesser degree to each hazard. This exposure is characterized by a number between 0 and 1, which was determined by overlaying the road network with a GIS map of each hazard.

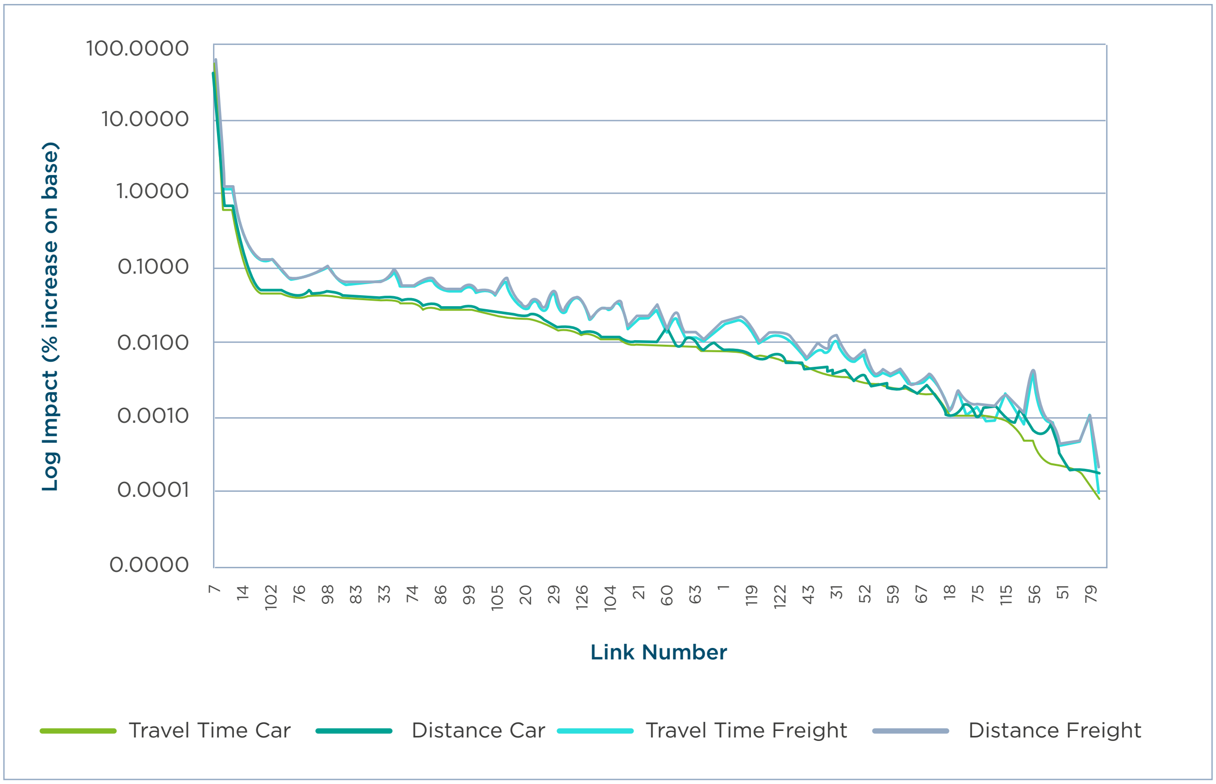
The *vulnerability* of each link in this study is given by the susceptibility of disruption from exposure to a hazard multiplied by the impact to the network of that link being disrupted. The susceptibility is measured on a scale of 0 to 1. For some links, a survey team derived susceptibility values based on direct observation of the links, but for many links, the study assumes a susceptibility of 1, reflecting the poor condition of many of the roads within the Western Balkans region.

Overall, the RDM stress test is conducted by calculating the natural hazard risk to the network, given by Eq 3.1, multiple times, each time using an alternative set of assumptions about the return period of each of the eight hazards.

Transportation modeling: The impact of disruption of each link was given by runs of the REMIS VISUM model. VISUM is a travel optimization model. The model is given as inputs of a network of road links, and the capacity of each link, along with data describing the volume of passenger car and freight traffic that needs to move from each origin to each destination. The model then calculates the flow of traffic along each link that minimizes either travel time or travel length. To calculate the impacts of a disruption, analysts then reduce or eliminate capacity on a single or a pair of links, reflecting the effects of a natural hazard event. The model then reroutes the traffic finding the new minimum for travel time or length given the links' reduced capacity. The impact of the disruption is given by the resulting increase in overall traffic time or length, calculated independently for passenger cars and freight, as shown in Figure 4.9.

>> **Figure 4.9 |** Transportation model impacts results





RDM risk ranking: The project employs this risk framework and RDM to identify the links that cause the largest risk to the road network. The project considered both single link disruptions and disruptions that affect pairs of links. For simplicity, this discussion focuses on the former.

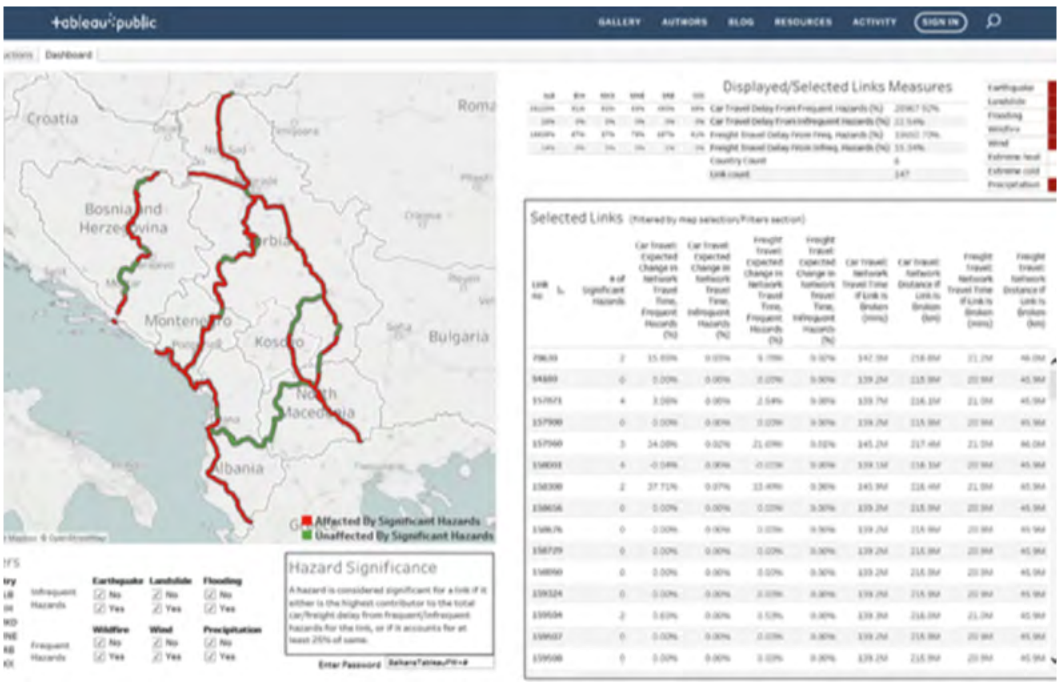
For the single link disruptions, the project seeks to identify the 15 links that generate the most risk. These links are then the focus of more detailed analysis of the economic impacts of disruption and of potential risk mitigation measures. Since decision makers may have differing criteria for making this selection, we treat this risk ranking as a multi-objective RDM challenge. We consider three criteria for the risk ranking: risk from infrequent hazards, risk from frequent hazards, and the extent to which every country in the region is represented with at least one high-risk link. Decision makers in the region suggested they might find this an important criterion.

A sorting algorithm ranks the links from highest to lowest according to the risk they generate the network. The ranking depends on the criteria used and the specific assumptions about the return frequency of each of the hazards. The algorithm is used to generate many thousands of lists, one for each of a wide range of combinations of these three criteria and a wide range of assumptions about the frequency of the hazards.

The algorithm then tallies how many times each link appears in the list of top fifteen. Some links appear in this top fifteen list no matter what criteria or assumptions are used. Some links never appear in this list. A small number of links appear in the top fifteen for some combinations of criteria and assumptions, but not for others. The insensitivity of the risk ranking to the criteria and assumptions for most links owes to the dominance of the impact of disruption calculations on the risk ranking.

Figure 4.10, which is explained in more detail below, displays a resulting risk ranking.

>> **Table 4.10 |** Example Link Selection Tool Showing Results of Risk Ranking



Economic impacts: Once the links that generate the most risk have been identified, the analysis can estimate in more detail the economic consequences of their disruption. The analysis focuses on quantifying the daily impacts of potential natural disaster events on the transportation system, and on providing information about potential resilience investment prioritization. Results showed considerable variability across scenarios, depending largely on the pattern of network usage that results from the disruption, including increases in travel distance and travel time due to rerouting and congestion. This result, coupled with information on hazard probabilities, suggests that the benefits from resilience investments will vary across space, and that a targeted investment strategy focused on high-impact, vulnerable areas would provide the largest return on investment.

Economic losses from transportation system disruptions generally fall into three categories: user costs, spillover costs (broader economic damage induced by changes in network structure), and physical damage costs. Metrics for the first two categories were developed and analyzed both as a prioritized list of daily single-link and multiple-link disruptions. User costs were estimated monetarily, while spillover costs were proxied by changes in accessibility, which should be related to overall economic damage. Physical damage costs were not calculated as they depend on the physical consequences of specific disruptions.

Results based on transportation model runs showed the variability of potential economic impacts across scenarios. Within the single-link scenarios, changes in user costs varied from about one percent (about 0.14 million per day disrupted, in 2019) to 2.302 percent (about 339 million per day disrupted) of baseline user costs, with the largest scenario a clear outlier. Changes in average accessibility by traffic zone for these scenarios ranged from decreases between 0.6% and 7.1%, though within-zone variation was considerable. For example, in some cases, results showed accessibility declines on the order of 90% for some zones, while others showed limited, local impacts on accessibility.

Box 4.2

Combining deep and well-characterized uncertainties

"Agree on assumptions" approaches work best when uncertainties are well-characterized. "Agree on decisions" DMDU approaches work best when uncertainties are deep. DMDU approaches can also be used for situations with a mix of deep and well-characterized uncertainties.

In such situations, an RDM analysis would divide the uncertainties into these two categories: deep and well-characterized. The analysis would then conduct the stress test only over the deep uncertainties, but each future examined in the stress test would be analyzed stochastically using the probabilistic well-characterized uncertainties. The measures (Ms) used in such an RDM analysis would typically become means and moments of stochastic model outputs.
For example, the Balkans transportation DIVERSION analysis considers only deep uncertainties. In particular, it considers Deep Uncertainty in the frequency of the natural hazards as shown in Table 4.3. Figure 4.10 shows the results of the stress test. In each future considered in the figure, the risk contributed by each link (as calculated by Equation 3.1) is deterministic, that is, a single number. This single number can vary over the futures, along with the values of the deep uncertainties.

Imagine that the DIVERSION analysis also considered well-characterized uncertainties, perhaps representing the susceptibility of each link to disruption from each hazard as normal distribution. In such an analysis the risk contributed by each link would also be a normal distribution. This distribution would in general vary over the futures. Figure 4.10 might then show one or two numbers summarizing the distribution in each future, perhaps its mean and the 95th percentile value. The choice of which mean and moments to use to summarize the distributions would be part of the Decision Framing process.

Decision Support Tools: The project employs two decision support tools to facilitate the analysis and to make it readily available to decision makers. The first decision support tool allows users to view and overlay the GIS hazard, exposure, and transportation network datasets. Figure 4.8 shows images from this tool.

The second decision support tool, the Tableau Link Selection Tool, enables users to view the high-risk links as ranked by the algorithm. The tool also allows users to adjust the criteria used by the algorithm, as well as substitute links of their own choosing for those selected by the algorithm.

Figure 4.10 shows a typical output of this Tableau Link Selection Tool. The map in the upper left-hand corner shows selected high-risk links as chosen by the user and/or the algorithm. The panel on the lower left allows the user to adjust the criteria used by the algorithm to select links. The panel on the upper right summarizes the overall risk to the road network generated by the links shown on the map using each of the multi-objective criteria. The panel on the lower right allows the user to select links to be shown on the map.

As one important purpose, this Tableau Link Selection Tool allows users to engage with the RDM analysis, both by viewing the results of the analysis and exploring the implications of using different criteria and of substituting links into the high risk set based on criteria not considered in the analysis.

Step 3: Options Analysis

The options analysis uses RDM to identify the best combination of interventions to reduce natural hazard risk to the Balkans road network. The analysis focuses on the high-risk generating links identified by the stress test.

The options analysis first identifies and categorizes engineering interventions that can reduce the vulnerability of various links to natural hazards. The analysis then estimates the incurred costs of each intervention and the extent to which they reduce sensitivity to each natural hazard. Onsite engineering-based assessments of the condition of some high risk links was available. In most cases, however, a systematic literature review helped to identify the set of appropriate interventions and to estimate their cost and effectiveness. Each option could affect the risk calculations by reducing the sensitivity of the link to one or more hazards. For instance, removing vegetation around a road would reduce its sensitivity to wildfire, that is, the ability of a wildfire to disrupt traffic on that link. Interventions that would affect exposure, for instance by re-routing roads along routes less exposed to natural hazards were not considered.

This survey identified 70 discrete interventions which we organized into nine sets of options. These sets and their corresponding costs and the effectiveness by which they reduce sensitivity are:

1. **Bridges and crossings** interventions has a weighted average cost of 127,380 EUR/km and 51.96% effectiveness

2. **Drainage** interventions has a weighted average cost of 64,078 EUR/km and effectiveness of 58.16%.

3. **Erosion and stabilization** interventions has a weighted average cost of 119,42 EUR /km and effectiveness of 66.69%.

4. **Flood protection** has a weighted average cost of 395,836 EUR/km and effectiveness of 87.87%.

5. **Landscaping** has a weighted average cost of 204, 256 EUR/km and effectiveness of 25.32%.

6. **Monitoring and maintenance** has a weighted average cost of 18.421 EUR/km and effectiveness of 30.73%.

7. **Operation incident reporting** has a weighted average cost of 65,090 EUR/km

8. **Planning, design and construction** has a weighted average cost of 85,988 EUR/km and effectiveness of 35.52%.

9. **Road surface and structure** has a weighted average cos of 39,886 EUR/km and effectiveness of 31.73%.

The project then employs RDM to help inform decisions about how to best allocate these interventions among the high-risk links, given Deep Uncertainty regarding the return frequency of the hazards.

This RDM options analysis considers seven alternative budget constraints; $15 million; $30 million; $40 million; $50 million; $80 million; $120 million, and $160 million. For each budget, the analysis considers 100 alternative sets of assumptions regarding the return frequency of the hazards as used in the stress test. For each budget allocation, the RDM analysis repeatedly applies a “knapsack” algorithm, one commonly used in the field of operations research. Each application of the knapsack algorithms determines the most cost-effective set of interventions for reducing risk, contingent on the budget constraint, and a set of assumptions about the hazard return frequencies. For each budget allocation, the analysis then identifies the interventions that always appear in the set of most cost-effective interventions, which never appear in the most cost-effective set, and those which sometimes appear.

Table 4.4 shows results of the options analysis for 14 links critical links for three budgets: $15 million, $50 million, and $160 million. The numbers in the cells indicate the number of futures in which a particular option for a particular link appears in the set of most cost-effective risk-reducing interventions.

>> **Table 4.4 |** Robust allocations over 14 high risk generating links

a)

	$15Mil		Bridge and Crossings	Drainage	Erosion and stabilization	Food and protection	Landscaping and vegetatoin	Monitoring and maintenance	Operation and incident response	Planing, design and construction	Road surface and structure
2	788210	Serbia	0	0	0	0	0	0	0	0	0
3	788211	Serbia	0	0	0	0	0	0	0	0	0
4	1663042	Albania	0	100	0	0	0	2	0	0	0
5	158308	Albania	0	100	100	0	0	100	0	0	100
6	788159	Serbia	0	0	0	0	0	0	0	0	0
7	788160	Serbia	0	0	0	0	0	0	0	0	0
8	1661229	Serbia	0	100	100	0	0	100	100	98	100
9	788200	Serbia	0	0	0	0	0	0	0	0	0
10	420742	Serbia	0	0	0	0	0	98	0	0	0
11	352838	Kosovo	0	100	100	0	0	100	0	0	100
12	784983	Serbia	0	0	0	0	0	0	0	0	0
13	256855	Macedonia	0	98	0	0	0	0	0	0	0
14	11661597	Montenegro	0	0	0	0	0	0	0	0	0
15	11661486	Kosovo	0	0	0	0	0	0	0	0	0

b)

	$50Mil		Bridge and Crossings	Drainage	Erosion and stabilization	Food and protection	Landscaping and vegetatoin	Monitoring and maintenance	Operation and incident response	Planing, design and construction	Road surface and structure
2	788210	Serbia	0	100	0	0	0	3	0	0	0
3	788211	Serbia	0	100	100	0	0	97	0	0	100
4	1663042	Albania	0	100	100	0	0	100	0	0	100
5	158308	Albania	100	100	100	0	0	100	100	86	100
6	788159	Serbia	0	0	0	0	0	0	0	0	0
7	788160	Serbia	0	0	0	0	0	0	0	0	0
8	1661229	Serbia	100	100	100	100	0	100	100	100	100
9	788200	Serbia	0	0	0	0	0	0	0	0	0
10	420742	Serbia	0	100	100	0	0	100	0	0	100
11	352838	Kosovo	100	100	100	0	0	100	100	86	100
12	784983	Serbia	0	0	0	0	0	0	0	0	0
13	256855	Macedonia	0	100	14	0	0	17	0	0	86
14	11661597	Montenegro	0	0	0	0	0	0	0	0	0
15	11661486		0	97	0	0	0	14	0	0	0

c)

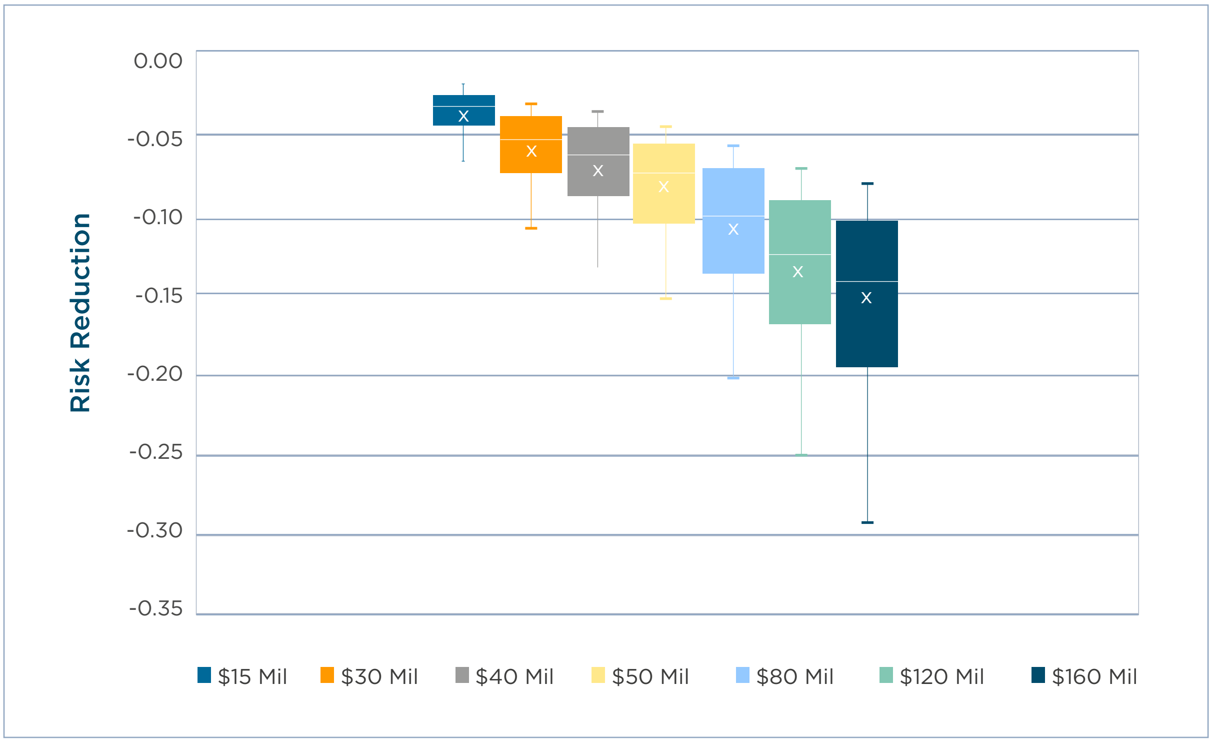
	$160Mil		Bridge and Crossings	Drainage	Erosion and stabilization	Food and protection	Landscaping and vegetatoin	Monitoring and maintenance	Operation and incident response	Planing, design and construction	Road surface and structure
2	788210	Serbia	100	100	100	0	0	100	100	95	100
3	788211	Serbia	100	100	100	9	0	100	100	100	100
4	1663042	Albania	100	100	100	100	0	100	100	5	100
5	158308	Albania	100	100	100	100	0	100	100	100	100
6	788159	Serbia	0	100	6	0	0	100	0	0	100
7	788160	Serbia	0	100	0	0	0	78	0	0	7
8	1661229	Serbia	100	100	100	100	0	100	100	100	100
9	788200	Serbia	0	100	0	0	0	65	0	0	0
10	420742	Serbia	100	100	100	84	0	100	100	36	100
11	352838	Kosovo	100	100	100	100	0	100	100	100	100
12	784983	Serbia	0	100	0	0	0	90	0	0	79
13	256855	Macedonia	100	100	100	8	0	100	100	100	100
14	11661597	Montenegro	0	0	0	0	0	0	0	0	0
15	11661486		100	100	100	0	0	100	1	1	100

As shown in Table 4.4, the robust allocation of a limited investment of $15 million occurs in seven categories of options spread across four links: two in Albania, and one each in Serbia and Kosovo. These choices are in the most cost-effective set independent of assumptions about the return period for the natural hazards. In addition, in almost all the futures (98 out of 100), the optimal investment also includes investing in planning, design, and construction for a link in Serbia, in monitoring and maintenance for a link in Serbia, and in drainage for a link in Macedonia. However, in two futures it is preferable to invest in monitoring and maintenance for a fifth link in Albania.

If the available budget is $160 million, Table 4.4 shows that the robust allocation includes options in eight categories spread across 13 links. All the options are employed on at least one link except for Landscaping and vegetation. The robust allocations of investments for budgets between $15 million and $160 million almost always lie between these two cases.

Figure 4.11 shows the risk reduction achieved as a function of budget by each of the robust investment allocations. The bar and whisker plots show the variation over the 100 alternative futures representing different assumptions regarding the return frequencies of the hazards. While the range of risk reduction is large, as noted above this large range has only a small effect on the ranking of best risk-reducing options. Overall, the $15 million budget for the 14 links shown in Table 4.4 achieves about 25% of the risk reduction achieved by the $160 million budget. This $160 million budget over the 14 links achieves 1.5% more risk reduction than the $80 million budget.

>> **Figure 4.11 |** Risk reduction achieved by robust allocations of interventions as a function of budget.



As noted above, for all budget levels the options analysis suggests many robust options independent of the value of the uncertainties. However, in some cases the best option depends on the value of the uncertainties. For instance, for the $15 million budget, the options analysis suggests investing in the Monitoring and maintenance options for a particular link in Albania if the return periods for low intensity earthquakes and landslides are at the high end of their range. Otherwise, the options analysis suggests investing in Planning, design, and construction, as well as Monitoring and maintenance in Serbia, and in Drainage for a link in Macedonia.

Decision makers can use these options analysis results to inform decisions on the investments that best improve the resilience of the Balkans road network to natural hazards. With some exceptions, the ranking of high priority options is robust over the uncertainties, that is, are recommended by the options analysis for all 100 alternative futures. The ranking is also monotonic with budget in almost all cases; that is, decision makers can choose a set of options for one budget, and these options remain appropriate even if the budget subsequently increases. In those cases where an option is not ranked highly in all 100 futures, decision makers can: 1) skip that option in favor of an option further down the list that is ranked highly in all 100 futures, 2) chose any option that is highly ranked in 50 or more futures, or 3) delve into the database of results to determine which combinations of uncertainties determine whether or not the option is highly ranked.

Example 2 RDM Analysis: Africa Transportation Resilience

These RDM methods have also been applied to the resilience of transportation infrastructure in Africa.

Roads are a key asset for African countries and necessary for development. The Program for Infrastructure Development in Africa (PIDA) was thus launched to provide a common framework for African stakeholders to build the necessary roads and other infrastructure. However, the initial PIDA analyses did not include the potential impacts of climate change, so the World Bank conducted the Enhancing the Climate Resilience of Africa's Infrastructure (ECRAI): The Roads and Bridges Sector (Cervigni, Losos et al. 2017) study to determine how climate change might affect the proposed PIDA investments. Because climate change and other factors affecting these investments are deeply uncertain, the World Bank used Robust Decision Making (RDM) to help guide investments to improve the climate resilience of transport networks in Africa.

Decision Framing

The ECRAI transportation resilience study asked how climate change might affect the proposed PIDA investments. These effects include changes in maintenance costs depending on the stress caused by climate change and the impacts of disruptions in transport networks. The ECRAI report used more than 100 projections of global climatic models re-scaled to the region to reflect the range of plausible climatic conditions that paved and unpaved roads in throughout Africa. The study used the Infrastructure Planning Support System (IPSS) (http://clicslab. org/ipss. html) to estimate: (1) the increase in maintenance costs caused by increases in temperature, precipitation patterns, and flood events, and (2) the number of interruption days due to climate change in the entire road network of Africa.

Stress test

The ECRAI study demonstrated a wide and diverse range of implications around the set of climate projections considered. The study considered the direct costs of climate change on the roads. It also considered the economic costs of disruption of travel along the road network. Because these disruptions costs are uncertain, and because

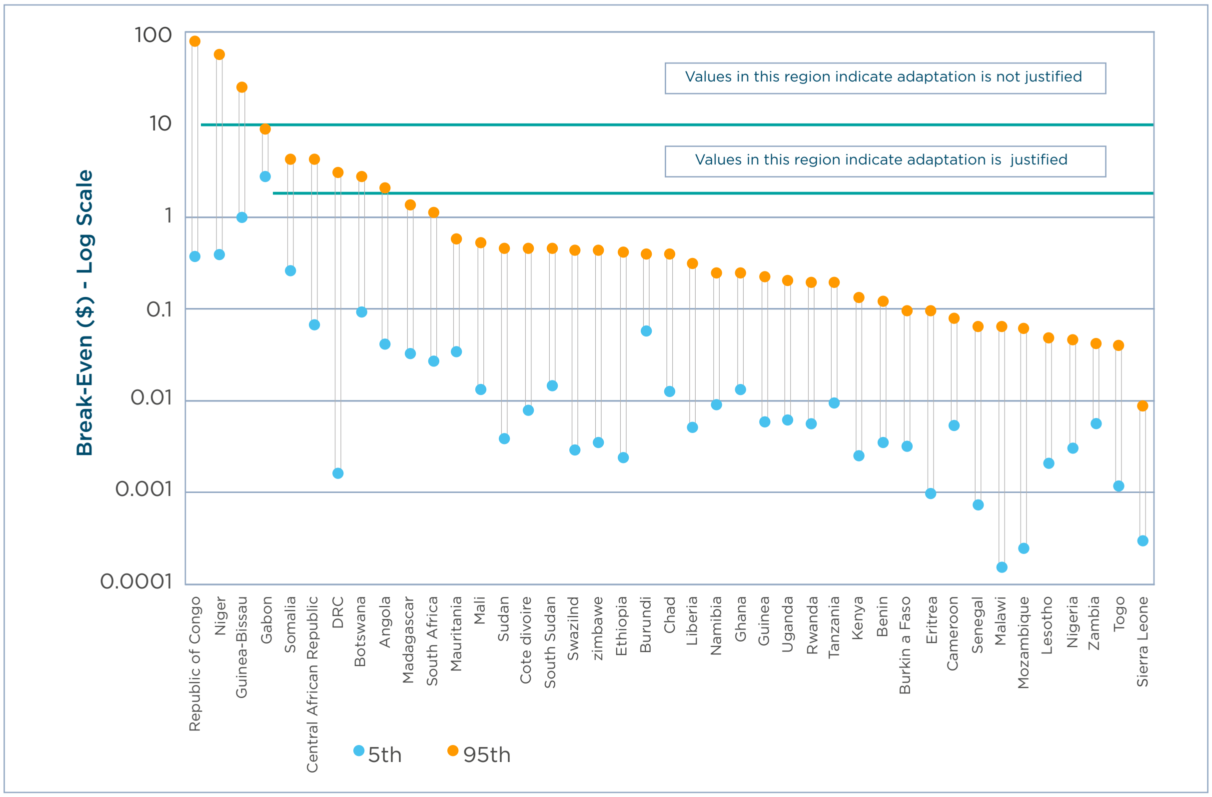
the study lacked the data to even estimate these costs across various countries, it was instead decided to treat disruption costs as deeply uncertain. The analysis explored over a wide range of potential disruption costs.

Identify new and revised strategies

The proposed PIDA investments considered in this study were recommended by analyses that did not consider climate change. That is, the underlying analysis assumed the design of the PIDA projects was based on historic climate conditions in each project location in each country. The ECRAI study compared these proposed base case options with proactive strategies, in which PIDA projects would be built according to projected climate conditions in each location in each country. These proactive strategies were then compared to the base case strategies. These base case strategies were called reactive because the study assumed that they would be adjusted in the future if and when the climate had changed sufficiently.

The study compared the benefit-cost ratio of the proactive vs. reactive strategies over a wide range of assumptions regarding future climate and the future cost of disruption due to climate change. As shown in Figure 4.12, in all but a small number of countries in a relatively small number of futures, the proactive strategies for investments in road surfaces (e.g., type of pavement) had higher benefit-cost ratios than the reactive strategies over a wide range of such uncertainties. The proactive strategies were even more favored for investments in bridges and other longer-lived infrastructure.

>> **Figure 4.12 |** Distribution of break-even costs



Source: (Cervigni et al. 2017)

05.

Implications and Recommendations

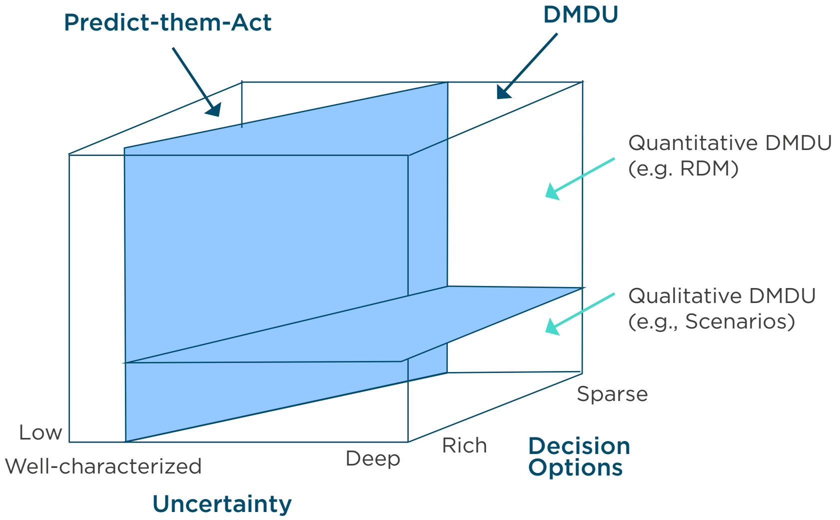
This section offers some practical advice for using DMDU to support iterative Risk Management for transportation projects and systems.

When to use which method

When should transportation engineers and planners use DMDU methods and when should they use traditional predict-then-act methods?

DMDU methods provide many benefits, but also impose costs. Figure 5.1 summarizes the main factors that determine when the benefits of scenario planning and more quantitative DMDU methods are likely to exceed the costs. Most clearly, DMDU is more useful the more uncertainties are deep, rather than well-characterized. In addition, RDM can prove more useful when the set of decision options has more, rather than fewer degrees of freedom. When uncertainties are well-characterized and/or few degrees of decision freedom exist, DMDU yields fewer benefits over traditional predict-then-act approaches, but DMDU can prove valuable when high confidence probabilistic forecasts are not available and when opportunities exist for constructing strategies robust against such uncertainty.

>> **Figure 5.1 |** When to Use DMDU Approaches



Source: (Marchau et al. 2019 display a variant of this figure in their Box 1.1.

In transportation planning and management applications, Figure 5.1 can be used to guide how and when DMDU, scenario planning or predict-then-act may be relevant to strategic services planning, capital improvement plans or project-level planning, design, and operations. Using the dimensions in Figure 5.1, planners and managers will need to consider the complexity, decision space and magnitude of uncertainty of a given application. The Balkans and Africa road network studies both used DMDU methods because of Deep Uncertainty in the climate hazard. The Balkans example also considered a rich array of decision options, creating opportunities for robust strategies. The Africa transportation resilience study considered a narrower range of decision options, proactive vs. reactive Adaptation to climate change, but examined the conditions that would favor one option over the other. DMDU is useful in this latter case because proactive Adaptation strategies dominate in most cases.

Table 5.1 below highlights a few example applications and which method is likely relevant in each case. Deep Uncertainty is the most important attribute, but in some cases the richness of the decision options is also important.

>> **Table 5.1 |** Example Transportation Planning and Management Applications

		Example	Attributes	Method
Planning	Capital improvement (infrastructure)	A long-term capital improvement plan for a regional rail system exposed to flooding; in a region with stable population and economic growth	Medium to long-term time horizon Some deep uncertainties Rich set of decision options	DMDU
	Services	A strategic urban transportation services plan considering multiple modes in a rapidly-growing area prone to various climate hazards	Medium to long-term time horizon Many deep uncertainties Rich set of decision options	DMDU
Project	Planning and Design	A road planning and design project with limited vulnerability to climate change and limited options on size, material and route	Short-term time horizon Uncertainty well-characterized Sparse set of decision options	Predict-then-Act
		A bridge planning and design project, vulnerable to climate change and with many decision options and potential for flexible design	Long-term time horizon Many deep uncertainties Rich set of decision options	DMDU
	Operations	Operational adjustments to a city-wide metro bus line over the next month based upon well-known demand	Short-term time horizon Uncertainty well-characterized Rich set of decision options	Predict-then-Act
	Operations	Change in bus fare	Short-term time horizon Some deep uncertainties Spare set of decision options	Predict-then-Act

When a DMDU method seems appropriate, which method should transportation engineers and planners use? In addressing this question, it is first important to note that DMDU methods are not distinct, but rather represent variations on the same theme. Scenario Planning, Adaptive Pathways, and RDM all embody the basic principles discussed in Section 4:

» Consider multiple futures, not one single future, in planning. Choose these futures to stress test the organization's plans;

» Seek robust plans that perform well over many futures, not optimal plans designed for a single, best-estimate future, and that perform well over comprehensive set of metrics (that is, are multi-objective);

» Make plans flexible and adaptive, which often makes them more robust;

» Use available analytics to explore many futures and options, not tell what to do.

Figure 5.1 also uses a third condition, complexity, to distinguish between situations when qualitative DMDU methods, such as scenarios, and quantitative DMDU methods, such as RDM, prove more useful. Complexity is used here as heuristic for how well appropriate experts can intuit an appropriate set of scenarios are robust responses. When expert intuition is sufficiently good that they can identify the most important combinations of uncertainties affecting a decision, and link potential actions to all the relevant consequents, then qualitative scenario planning may suffice. However, when simulation models have the potential to surprise, then a quantitative RDM analysis may prove valuable.

Table 5.2 provides a richer comparison of the conditions under which engineers and planners may find the various DMDU methods more useful. Scenario Planning can handle situations in which vulnerabilities arise from multiple uncertainties, and does not require a simulation model that links actions to consequences. However, scenario planning is less valuable for evaluating alternative strategies, and is more reliant on expert intuition and judgement than the other methods. Adaptive Pathways excel at helping engineers and planners develop plans that are robust over many scenarios by adapting over time in response to new information. While many Adaptive Pathways analysis use simulation models, the approach can also be usefully combined with qualitative scenario planning. It is worth noting that Adaptive Pathways becomes difficult to implement if the vulnerabilities arise from more than a few uncertainties. RDM is the most general of the three methods, incorporating concepts from scenario planning and Adaptive Pathways. RDM is particularly useful when vulnerability can arise from combinations of more than a few uncertainties and/or when engineers and planners want to supplement expert judgment with analytic evidence in determining which uncertainties are most important and which strategies are most robust. Furthermore, RDM generally requires a simulation model that relates actions to consequences.

>> **Figure 5.1 |** When to Use DMDU Approaches

	Expect vulnerabilities to arise from multiple uncertainties	Need to evaluate robust strategies	Require a simulation model
Scenario Planning	Yes	No	No
Adaptive Pathways	No	Yes	No
RDM	Yes	Yes	Yes

List of consultants and tools

An increasing number of consultants, researchers, governments, and non-governmental organizations are using DMDU methods and tools. The Society for Decision Making Under Deep Uncertainty provides one of the best sources of information on these groups, as well as a number of open source software tools. The Society's website is www.deepuncertainty.org. Here is a brief overview of these resources.
RAND Corporation in the United States and TU Delft in The Netherlands are among the leaders in applying DMDU methods to transportation.

Available software tools for conducting DMDU analyses include:

- Exploratory Modeling and analysis (EMA) workbench, an open source platform that has been developed at TU Delft to support a wide range of DMDU functions: https://emaworkbench.readthedocs.io/en/latest/index.html
- Rhodium, an open-source platform that has been developed at Penn State, Cornell, and RAND to support RDM and a wide range of DMDU functions: https://github.com/RANDCorporation/Rhodium
- Scenario discovery toolkit, an R-based package developed by RAND to support scenario discovery: https://cran.r-project.org/web/packages/sdtoolkit/index.html
- TMIP-EMAT, an Exploratory Modeling package developed by the US Transportation Modeling Improvement Program (TMIP) at the US Federal Highway Administration, https://tmip.org/content/tmip-exploratory-modeling-and-analysis-tool-tmip-emat
- Tableau, a commercial visualization package widely used to support DMDU analysis: https://www.tableau.com

The best survey of DMDU methods can be found in the recent book, *Decision Making Under Deep Uncertainty: From Theory to Practice,* edited by Marchau, Walker, Bloemen and Popper (2019). The DMDU Society, RAND, TU Delft, and other organizations also provide training in the use of DMDU methods.

References

Barandiarán, M., M. Esquivel, S. Lacambra Ayuso, G. Suarez and D. Zuloaga (2018). *Executive Summary of the Disaster and Climate Risk Assessment Methodology for IDB Projects: A Technical Reference for IDB Project Teams,* IDB.

Barrucand, M., W. Vargas and M. Rusticucci (2007). "Dry conditions over Argentina and the related monthly circulation patterns." *Meteorology and Atmospheric Physics* **98**(1-2): 99–114.

Berg, N. and A. Hall (2015). "Increased Interannual Precipitation Extremes over California under Climate Change." *Journal of Climate* **28**: 6324-6334.

Bouwer, L., Haasnoot, M., Obeysekara, J., Konyha, K., Hagemann, K., Vazquez, A., ... & Jeuken, C. (2018, April). Dynamic adaptive planning for urban coastal flooding in the city of Miami, Florida. In *EGU General Assembly Conference Abstracts* (Vol. 20, p. 7942).

Bryant, B. P. and R. J. Lempert (2010). "Thinking inside the box: A Participatory, computer-assisted approach to scenario discovery." *Technological Forecasting and Social Change* **77**: 34-49.

California Ocean Protection Council (2018). "State of California Sea-Level Rise Guidance". California Natural Resources Agency. http://www.opc.ca.gov/webmaster/ftp/pdf/agenda_items/20180314/Item3_Exhibit-A_OPC_SLR_Guidance-rd3.pdf

Carvalho, L. M. V., C. Jones, A. E. Silva, B. Liebmann and P. L. Silva Dias (2011). "The South American Monsoon System and the 1970s climate transition." **31**(8): 1248-1256.

Cavazos, T., C. Turrent and D. P. Lettenmaier (2008). "Extreme precipitation trends associated with tropical cyclones in the core of the North American monsoon." *Geophysical Research* Letters **35**(21).

Cervigni, R., A. Losos, P. Chinowsky and J. E. Neumann (2017). "Enhancing the Climate Resilience of Africa's Infrastructure: The Roads and Bridges Sector." 136 pp.

Dai, A. (2011). "Drought under global warming: a review." **2**(1): 45-65.

Dai, A., T. Qian, K. E. Trenberth and J. D. Milliman (2009). "Changes in Continental Freshwater Discharge from 1948 to 2004." **22**(10): 2773-2792.

Dufek, A. and T. Ambrizzi (2008). *Precipitation variability in São Paulo State, Brazil*.

Dufek, A. S., T. Ambrizzi and R. P. da Rocha (2008). "Are reanalysis data useful for calculating climate indices over South America?" *Ann N Y Acad Sci* **1146**: 87-104.

Englehart, P. J. and A. V. Douglas (2006). "Defining Intraseasonal Rainfall Variability within the North American Monsoon." **19**(17): 4243-4253.

Garreaud, R. and M. Falvey (2009). *The coastal winds off western subtropical South America in future climate scenarios.*

Groves, D. G. and R. J. Lempert (2007). "A New Analytic Method for Finding Policy-Relevant Scenarios." *Global Environmental Change* **17**: 73-85.

Groves, D. G., E. Molina Perez, E. Bloom and J. R. Fischbach (2019). Robust Decision Making (RDM): Application to Water Planning and Climate Policy. *Decision Making under Deep Uncertainty: From Theory to Practice*. V. A. W. J. Marchau, W. E. Walker, P. J. T. M. Bloemen and S. W. E. Popper, Springer**:** 329.

Haasnoot, M., J. H. Kwakkel, W. E. Walker and J. ter Maat (2013). "Dynamic Adaptive Policy Pathways: A New Method for Crafting Robust Decisions for a Deeply Uncertain World." *Global Environmental Change* **23**(2): 485-498.

Haasnoot, M., A. Warren and J. H. Kwakkel (2019). Dynamic Adaptive Policy Pathways (DAPP). *Decision Making under Deep Uncertainty: From Theory to Practice*. V. A. W. J. Marchau, W. E. Walker, P. J. T. M. Bloemen and S. W. E. Popper, Springer.

Inter-American Development Bank (2008). Disaster Risk Management Policy Guidelines. Retreieved from. http://idbdocs.iadb.org/wsdocs/getdocument.aspx?docnum=360026.

Inter-American Development Bank (2007). Disaster Risk Management Policy. Retrieved from http://idbdocs.iadb.org/wsdocs/getDocument. aspx?DOCNUM=35004515

Inter-American Development Bank. (2016). Resolution AG-6/16 AND CII/AG-2/16. Retrieved from: http://www.iadb.org/document.cfm?id=EZSHARE-1983553961-1676

IPCC (2014). Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, R. K. Pachauri and L. A. Meyer (eds.)]. IPCC, Geneva, Switzerland, 151 pp.

IPCC (2012). Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change [Field, C.B., V. Barros, T.F. Stocker, D. Qin, D.J. Dokken, K.L. Ebi, M.D. Mastrandrea, K.J. Mach, G.-K. Plattner, S.K. Allen, M. Tignor, and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, UK, and New York, NY, USA, 582 pp.

Jones, R. N., A. Patwardhan, S. Cohen, S. Dessai, A. Lammel, R. Lempert, M. M. Qader Mirza and H. von Storch (2014). Foundations for Decision Making. *Climate Change 2014: Impacts, Adaptation, and Vulnerability*. Intergovernmental Panel on Climate Change (IPCC).

Kaatz, L. (2015). "Embracing Uncertainty: A Case Study Examination of How Climate Change is Shifting Water Utility Planning." *Prepared for the Water Utility Climate Alliance (WUCA), American Water Works Association (AWWA), Water Research Foundation (WRF) and Association of Metropolitan Water Agencies (AMWA)*: 92 pp.

Kalra, N., S. Hallegatte, R. Lempert, C. Brown, A. Fozzard, S. Gill and A. Shah (2014). Agreeing on Robust Decisions: A New Process fo Decision Making Under Deep Uncertainty. *Policy Research Working Paper*. W. Bank, World Bank.

Kamiguchi, K., A. Kitoh, T. Uchiyama, R. Mizuta and A. Noda (2006). *Changes in Precipitation-based Extremes Indices Due to Global Warming Projected by a Global 20-km-mesh Atmospheric Model.*

Kitoh, A., H. Endo, K. Krishna Kumar, I. Cavalcanti, P. Goswami and T. Zhou (2013). *Monsoons in a changing world: A regional perspective in a global context.*

Knopman, D. and R. Lempert (2016). Urban Responses to Climate Change: Framework for Decisionmaking and Supporting Indicators., RAND**:** 156.

Lempert, R. (2013). "Scenarios that illuminate vulnerabilities and robust responses." *Climatic Change* **117**: 627-646.

Lempert, R. (2019). Robust Decision Making (RDM). *Decision Making under Deep Uncertainty: From Theory to Practice*. V. A. W. J. Marchau, W. E. Walker, P. J. T. M. Bloemen and S. W. E. Popper, Springer**:** 329.

Lempert, R., J. G. Arnold, R. Pulwarty, K. Gordon, C. Greig, C. Hawkins Hoofman, D. Sands and C. Werrell (2018). Reducing Risks Through Adaptation Actions. *Impacts, Risks, and Adaptation in the United States: Fourth National Climate Assessment*, Vol II. D. R. Reidmiller, C. W. Avery, K. E. Easterling et al. Washington, DC, U.S. Global Change Research Program.

Lempert, R. J., Bryant, B. P., & Bankes, S. C. (2008). Comparing algorithms for scenario discovery. *RAND, Santa Monica, CA*.

Lempert, R. J., D. G. Groves, S. W. Popper and S. C. Bankes (2006). "A General, Analytic Method for Generating Robust Strategies and Narrative Scenarios." *Management Science* **52**(4): 514-528.

Lempert, R. J., S. W. Popper and S. C. Bankes (2003). *Shaping the Next One Hundred Years : New Methods for Quantitative, Long-term Policy Analysis.* Santa Monica, CA, RAND Corporation.

Lyons, G., C. Davidson, T. Forster, I. Sage, J. McSaveney, E. MacDonald, A. Morgan and A. Kole (2014). Futuredemand: How could or should our transport system evolve in order to support mobility in the future? Wellington, New Zealand, Ministry of Transport.

Marchau, V. A. W. J., W. E. Walker, P. J. T. M. Bloemen and S. W. E. Popper (2019). *Decision Making under Deep Uncertainty: From Theory to Practice*, Springer.

Marengo, J., T. Ambrizzi, R. P. Rocha, L. Alves, S. Cuadra, V. Ramírez, S. Ferraz, R. Rodrigues Torres and D. Santos (2010). *Future change of climate in South America in the late XXI century: intercomparison of scenarios from three regional climate models*, Climate Dynamics.

Marengo, J. A., R. Jones, L. M. Alves and M. C. Valverde (2009). "Future change of temperature and precipitation extremes in South America as derived from the PRECIS regional climate modeling system." *International Journal of Climatology* **29**(15): 2241-2255.

Ministry for the Environment (2017.) Coastal Hazards and Climate Change: Guidance for Local Government. Ministry for the Environment Publication ME-1341. Ministry for the Environment, Wellington. https://www.mfe.govt.nz/sites/default/files/media/Climate%20Change/coastal-hazards-summary.pdf

Nakaegawa, T., A. Kitoh, H. Murakami and S. Kusunoki (2013). *Annual maximum 5-day rainfall total and maximum number of consecutive dry days over Central America and the Caribbean in the late twenty-first century projected by an atmospheric general circulation model with three different horizontal resolutions*.

OECD (2015). Adapting to the Impacts of Climate Change - Policy Perspectives. http://www.oecd.org/env/cc/Adapting-to-the-impacts-of-climate-change-2015-Policy-Perspectives-27.10.15%20WEB.pdf

Parker, A. M., S. Srinivasan, R. J. Lempert and S. Berry (2015). “Evaluating Simulation-Derived Scenarios for Effective Decision Support.” Technological Forecasting & Social Change **91**: 64-77.

Quintana, J. and P. Aceituno (2012). Changes in the rainfall regime along the extratropical west coast of South America (Chile): 30-43° S.

Sansigolo, C. A. and M. T. Kayano (2010). “Trends of seasonal maximum and minimum temperatures and precipitation in southern Brazil for the 1913-2006 period.” *Theoretical and Applied Climatology* **101**((1-2)): 209-216.

Schwartz, P. (1996). *The Art of the Long View - Planning for the Future in an Uncertain World.* New York, NY, Currency-Doubleday.

SENAMHI (2009). “Escenarios de Cambio Climático en la Cuenca del Río Mantaro para 2100: Resumen Técnico [Climate Change Scenarios in the Mantaro river Basin by 2100: Technical Summary][Avalos, G., A. Díaz, C. Oria, L. Metzger, and D. Acuña (eds.)]. Parte de la fase de preparación del Proyecto de Adaptación al Impacto del Retroceso Acelerado de Glaciares en los Andes Tropicales (PRAA), el cual es implementado en Bolivia, Ecuador y Perú con financiamiento el Fondo Mundial del Medio Ambiente (GEF) a través del Banco Mundial, coordinado por la Secretaría General de la Comunidad Andina e implementado en el Perú por el Ministerio del Ambiente (MINAM), Centro de Predicción Numérica (CPN), Servicio Nacional de Meteorología e Hidrología (SENAMHI), Lima, Peru.” 56.

Silva Dias, M. A. F., J. Dias, L. Carvalho, E. Freitas and P. L. Silva Dias (2012). “Changes in extreme daily rainfall for São Paulo, Brazil.” *Climatic Change* **116**((3-4)): 705-722.

Suddendorf, T. (2013). *The Gap: The Science of What Separates Us from Other Animals,* Basic Books.

Tariq, A., R. J. Lempert, J. Riverson, M. Schwartz and N. Berg (2017). “A climate stress test of Los Angeles’ water quality plans.” *Climatic Change* **144**(4): 625-639.

van der Heijden, K. (1996). “Scenarios: The Art of Strategic Conversation.”

Vicuña, S., J. Gironás, F. J. Meza, M. L. Cruzat, M. Jelinek, E. Bustos, D. Poblete and N. Bambach (2013). “Exploring possible connections between hydrological extreme events and climate change in central south Chile.” *Hydrological Sciences Journal* **58**(8): 1598-1619.

Wack, P. (1985). “Scenarios: Uncharted Waters Ahead.” *Harvard Business Review* No. 85516.

Walker, W. E., Robert J. Lempert and J. H. Kwakkel (2013). Deep Uncertainty. *Encyclopedia of Operations Research and Management Science*, Springer US.**:** 395-402.


IDB
Inter-American
Development Bank