A Comprehensive Methodology for Sustainable and Climate Resilient Transport Network

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ABSTRACT

Infrastructure networks, crucial for local mobility, face significant exposure to the impacts of climate change. The disruption of key links within these networks due to climate exposures has the potential to isolate entire communities, cutting off access to essential public facilities such as schools, hospitals, and markets. The use of advanced digital solutions offers a new approach to anticipate, mitigate and adapt to future constraints on the network. This article presents an innovative Climate Resilience Methodology, developed by ORIS Materials Intelligence, and an example of its application on a real case study in Asia. The methodology is based on Artificial Intelligence and advanced algorithms to evaluate the exposure of the infrastructure to the impacts of the climate change. Based on the results from this multicriteria analysis, adaptation measures are proposed to enhance the infrastructure resilience to the assessed climate exposures. Based on the Life Cycle Assessment approach, mitigation measures are also proposed based on the potential reductions of the Greenhouse Gases (GHG) emissions at various stages of the infrastructure service life. Lastly, all the proposed adaptation and mitigation measures are quantified, priced and compared on a multicriteria assessment. The example of application showed powerful results obtained from this methodology, as it provides an essential tool for policymakers and infrastructure planners to make informed decisions and better plan for climate change.

Keywords: Climate Resilience, Climate Risk Assessment, Infrastructure Network

1. INTRODUCTION

This paper introduces a novel climate resilience methodology that addresses the gap identified in the literature about climate change assessments and conceptual frameworks for evaluating infrastructure risks. Currently, there seems to be no digital tool to allow policymakers to fully understand how infrastructures can be impacted by extreme climate events, what would be the population impacted in case of disruptions, and what would this mean in terms of adaptation measures and financial investment. This new methodology is not only conceived to fill this gap, but also to couple adaptation and mitigation assessments in one single digital tool. The paper begins with a review of the background literature, introduces the novel methodology, and provides a detailed explanation of each calculation step, including an example of application in a real case study in Asia. It concludes by highlighting how the ORIS Climate Resilience Methodology empowers policymakers with a comprehensive tool for assessing and enhancing infrastructure climate resilience, while acknowledging its limitations.

2. BACKGROUND AND LITERATURE REVIEW

Climate exposure evolutions can be evaluated using climate projections, which are rigorously generated through coordinated efforts by organizations like the World Climate Research Programme (WCRP) and the Intergovernmental Panel on Climate Change (IPCC). Generating these projections involves sophisticated climate models that integrate atmospheric, oceanic, and terrestrial data to simulate the Earth's system dynamics. These climate models are developed by different research institutes around the world and their outputs depend on various input parameters that can vary from model to model. An important input parameter, for example, is the Shared Socio-economic Pathway (SSP), which represents the socio-economic scenario to be expected in the future in terms of climate policies to be implemented, greenhouse gasses emissions, and land use, for instance. The various SSP scenarios are defined in the IPCC Assessment Reports, the latest being the 6th Assessment Report. Once the inputs are well defined, those climate models generate projections for any past or future periods. Projections anomalies for future periods are often applied to historical observation data to predict future climate.

Despite substantial research efforts and advancements on conceptual frameworks to evaluate climate exposures and suitable adaptation and mitigation strategies to be proposed (ITF, 2016; OECD, 2018), a critical gap remains in the development of a digital tool that seamlessly integrates climate resilience assessment with transportation infrastructure decision-making. Zhuyu Yang highlighted that the application of the concept of critical infrastructures resilience in practical disaster management is challenged by the lack of operational tools (Yang et al, 2024). Amir Esmalian also mentioned the gap between resilience research and engineering practice and highlights the need for innovative and practical methods, processes, and information for resilience integration (Amir et al, 2022). Furthermore, several studies have also been carried out to develop individual solutions for very specific needs, but no methodology combines climate science with adaptation and mitigation proposals for no matter the infrastructure location and risk.

The Climate Resilience Methodology presented in this paper, developed by ORIS Materials Intelligence, not only fills this critical gap, but has already been successfully applied in several case studies. Notably, it was used to assess the climate resilience of more than 150 km of rural roads in Jizzakh and Syrdarya, Uzbekistan, which was critical to improve the culverts sizing and to consider more heat-resistant surface layer materials and base foundations at the design stage of the project. Another impactful application was in a network assessment for a project developed in the Republic of Karakalpakstan. In this investment prioritization project, critical roads from an entire network were prioritized in terms of climate exposures, infrastructure vulnerabilities, such as road condition and traffic, and social and economic impact, calculated by assessing the population and economy that would be affected if a network link were disrupted due to an extreme climate event.

3. ORIS CLIMATE RESILIENCE METHODOLOGY

The ORIS Climate Resilience Methodology is designed to evaluate and enhance the resilience of transport infrastructure through a multi-step approach that combines climate screening, infrastructure vulnerability assessment, and the identification of social and economic impacts. The methodology is resumed in Figure 1.

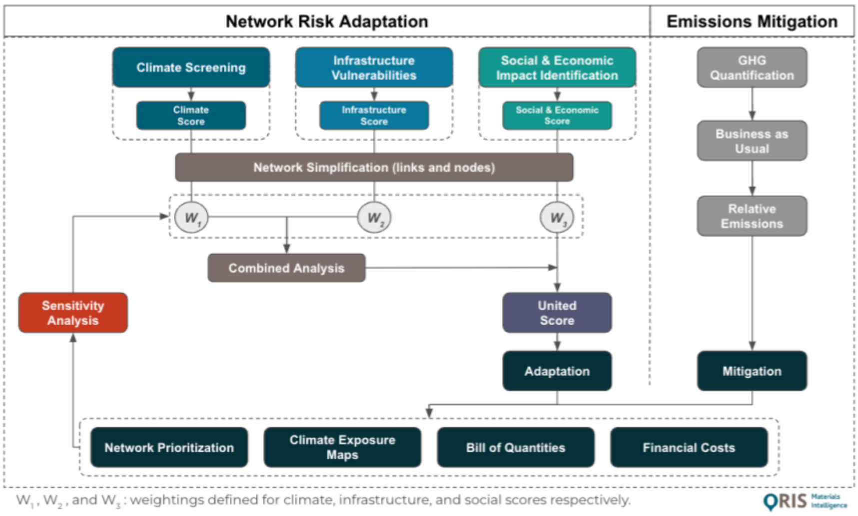

Figure 1 ORIS Climate Resilience Methodology.
(ORIS Materials Intelligence, 2024)

The foundation of the methodology is composed of three axes: the Climate Screening, the Infrastructure Vulnerabilities, and the Social and Economic Impact Identification. Each one of these axes yield a different score: climate score, infrastructure score, and social and economic score, which are then used to classify sections of a whole infrastructure network. Those scores vary in the integer values range of 1 to 5, comprising a risk classification varying among lowest (1), low (2), medium (3), high (4), or extreme (5). In this methodology, the network is a mathematical graph simplification, where roads, streets and rails are considered links and every link edge, or points of interest are considered nodes. The network is created with geometries extracted from OpenStreetMap and Here Maps. The climate score is evaluated together with the infrastructure score in order to classify the impacts of each climate exposure on each infrastructure link. This classification is done in the Combined Analysis step and it outputs an infrastructure exposure risk classification, which allows for understanding what will be the most vulnerable links of a network in case of an extreme weather or climate event. After that, social and economic impacts are identified in order to measure the impact that the critical links could have on the benefiting population and on the local freight transport. This coupling between the Combined Analysis and the Social and Economic Impact Identification leads to a United Score, which also varies in the same integer range from 1 to 5 and allows for prioritizing links out of a whole network and deciding where adaptation and mitigation plans should be foreseen. All steps of this methodology will be described in detail in the next few chapters.

3.1 Climate screening

The first step in the methodology involves defining the most relevant climate exposures for the infrastructure region. As default, these exposures include heat, freeze-thaw cycles, flash flooding, and infrastructure immersion, but, depending on local data available, can also include other indicators, such as land sliding and silting. The methodology also requires the definition of key parameters for climate projections, such as the Shared Socioeconomic Pathways (SSP) to be considered, the future period for projections, which can be a specific year or an interval between two specific dates, and the choice of the most suitable climate model. Climate models vary in their input parameters and simulation methods. For every different project, a sensitivity analysis is carried out with the goal of choosing the most suitable climate model based on the comparison of their projections with historical observations. The model providing projections with the lowest variation compared to observations is chosen as the most suitable one.

Both global and regional climate models, GCMs and RCMs respectively, are evaluated for their performance against historical data. The methodology incorporates the latest phase of the Coupled Model Intercomparison Project (CMIP), specifically CMIP6, to ensure accurate climate exposure evolution maps. With the projections generated from climate models, the climate exposures can be evaluated. The next few chapters are dedicated to give more detail on how each variable is calculated and taken into account in the context of the methodology being presented.

In the climate axis of this methodology, three data sources are used in order to carry out sufficiently precise analyses:

- Historical data: data source from the climatologies at high resolution for the earth's land surface areas (Karger et al., 2017).
- High resolution rainfall data: the major source used is the ECMWF Reanalysis v5 (ERA5) data (Hersbach et al., 2023). The consideration of ERA5 data is paramount when evaluating flood risks due to its detailed and high-resolution historical weather records.
- Projection data: the sources considered come from the more than 100 climate models that are part of the Coupled Model Intercomparison Project Phase 6 (Eyring et al., 2016).

Those data are automatically treated before generating climate exposures that help identify if an infrastructure could be exposed to climate events. The data processing included in the methodology is the subject of the next section.

Data processing: statistical downscaling and clustering

When assessing the evolution of a particular climate exposure (e.g. heat, freeze-thaw cycles, and flooding), historical observations are computed together with climate projections obtained from CMIP6 climate models. This computation is done using a technique of statistical downscaling. Figure 2 shows a schematic representation of this process from its input data until its output risk classification.

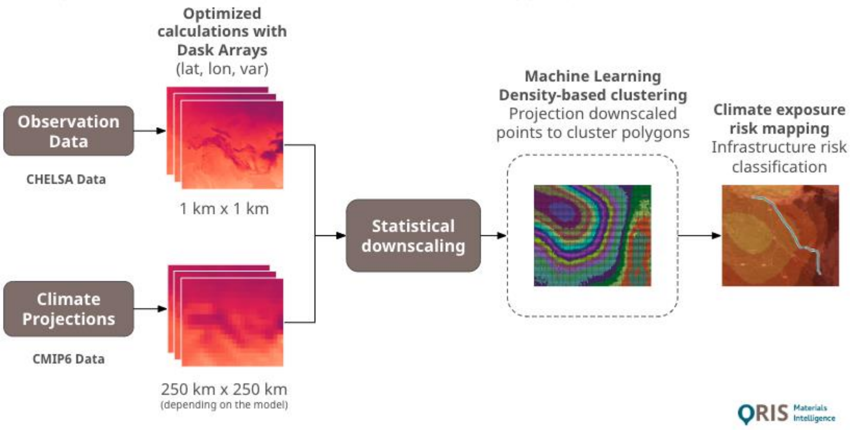

Figure 2 Statistical downscaling and clustering of climate data.
(ORIS Materials Intelligence, 2024)

Further in the climate exposure subsections, climate exposure maps are shown to demonstrate how the results of this data processing are displayed on the ORIS digital platform using the climate exposures heat, freeze-thaw cycles, and flooding as examples. The figures to be shown as examples are based on a successful project developed in Uzbekistan, where a whole network assessment was conducted in order to prioritize roads to be adapted. It is important to note that the methodology is in constant development with the goal of increasing the number of climate exposures to be assessed from the climate screening until the proposition of tailor-made adaptation measures.

Climate Exposures: Heat

The heat exposure is by computing the maximum 2-m air temperatures historical data from CHELSA together with maximum 2-m air temperature projections from the most suitable CMIP6 climate model. The data is passed through a statistical downscale and clustering before being available on the ORIS digital platform.

Freeze-thaw cycles

The freeze-thaw cycles indicator is calculated using the same historical datasets and climate projections used for heat exposure. The higher spatial resolution from observation data is used to improve the projection resolution through statistical downscaling. Analogously, the higher temporal resolution from historical data is used to fill gaps in time from climate projections through time-series regression. This regression is used for developing the freeze-thaw cycles indicator and the procedure follows the same calculation methods presented in CHELSA (Karger D.N. et al, 2017).

Flooding

The flooding assessment is split into two different but complementary evaluations:

- Assessment of runoff risk: associated with flash floods.
- Assessment of infrastructure immersion risk: associated with long-term floods.

Assessing runoff risk is a complex task. One significant challenge in modeling flash floods is the accurate representation of hydrological and hydraulic processes at fine spatial and temporal scales. Flash floods involve quick runoff generation and rapid changes in water levels, requiring detailed modeling of both surface and subsurface flows. The complexity is further increased by the need to incorporate diverse environmental factors, such as soil moisture, land cover, topography, and urban infrastructure, which all influence flood dynamics. Great research work has been developed in order to improve predictability of flash floods, e.g. in (Sayama T. et al, 2020). The current state of the ORIS methodology adopts an adaptation-driven approach to evaluate the risk of flash floods: use of the hydrological rational method (Equation 1) in order to calculate the peak runoff flow along the infrastructure. Furthermore, the use of this method requires the collection of important data on:

Table 1 Data needed for carrying out a runoff risk assessment.

Rational method parameter	Data description	Data source implemented
Maximum rainfall [i, in mm/h]	The maximum rainfall is computed by fitting a Gumbel distribution into the historical daily rainfall data from ERA5.	ERA5 (Hersbach et al., 2023) and CMIP6 (Eyring et al., 2016)
Catchment area [A, in m2]	The catchment area is computed using the topographic wetness index (TWI) as an algorithm to identify watersheds. Object segmentation algorithms from satellite imagery are also used to validate results.	SRTM data (Farr et al., 2007)
Runoff coefficient	The runoff coefficient estimate necessitates data	SRTM data (Farr et

[C – dimensionless]	on soil type and vegetation index in the region of interest. Data for this can come from object segmentation using satellite imagery or land cover estimations already done by the Copernicus institute.	al., 2007) and Copernicus Climate Data Store

With all these parameters, the runoff flow (Q, in m3/s) can be calculated using the rational method, Equation 1.

$$Q = C \cdot i \cdot A \tag{1}$$

The results of this runoff calculation are used to design or resize the hydraulic structures of the infrastructure links prioritized as adaptation proposed in the end of the ORIS climate resilience methodology. The infrastructure immersion risk is evaluated using a very comprehensive dataset provided by a powerful tool called Aqueduct, (Philip J. et al, 2020). This data source contains vast amounts of data on the observed coastal and riverine floods, as well as estimation of flood-prone areas evolution considering projections from selected climate models. The data helps understand if an infrastructure is located in a flood area and what is the estimated water depth of flood expected on each pixel of the data grid.

3.2 Infrastructure vulnerabilities

Evaluating infrastructure vulnerabilities is essential to understand how climate exposures could impact infrastructure links. The infrastructure score is determined by considering indicators that highlight vulnerabilities: infrastructure surface layer condition, General User Delay (GUD), and traffic.

Surface layer condition

Evaluating the condition of infrastructure layers is a critical component of ensuring the resilience and sustainability of transport networks. This evaluation typically involves assessing various factors such as surface distress, structural integrity, and functional performance. The study carried out by (Bennett C.R. et al, 2006) is still of interest nowadays, as it highlights the issues related to data availability and the implications for road management practices. These methods provide valuable insights, but one of the most significant challenges in this evaluation process is the availability and accessibility of reliable data. Accurate and up-to-date data on surface layer conditions are essential. Unfortunately, such data are often scarce or inconsistent, particularly in regions with limited resources or less developed data collection infrastructure. In the case of the ORIS climate resilience methodology, the surface layer state of a whole network is considered using interpolation and merge methods of different regional and reliable data sources. Those data sources are a mix of open source, closed source data, and data enrichment through machine learning techniques, such as density-based clustering algorithms.

Traffic

The traffic score that is calculated in this step comes from a standard traffic assignment usually carried out in transportation planning projects. Because of the lack of precise data on the Origin-Destination matrices for every administrative region of the world, the methodology used is a simplification of the Four-Step Model (Manheim, 1979; Florian et al., 1988). As not all steps of this model (trip generation, trip distribution, mode choice, and traffic assignment) can be followed in a global coverage, here is the major approach of the trip distribution step: the trip distribution phase aims at distributing the trips generated by the previous step. For this project, a gravitational model (Suzanne P. Evans, 1973) has been used to estimate the attractiveness of each centroid (city/town) when it comes to traffic demand. The gravitational formula used as an estimator for this project is described in Equation 2 (Sheffi, Yossi, 1984). Equations 3 and 4 are necessary to deal with the limitation of not having Origin-Destination (O-D) surveys available in order to estimate traffic production and demand.

$$T_{ij} = K\frac{O_i \cdot D_j}{d^2} \tag{2}$$

Where: T_{ij} is the number of trips from the origin zone i to the destination zone j; K is a factor to be calibrated; O_i is the population from the origin zone i; D_j is the population from the destination zone j; d is the distance between the origin i and the destination zone j.

As the origin-destination survey is often missing, the variables K , O_i, and D_j are estimated, as follows in the set of Equations 3, 4, and 5, in order to obtain a rough estimation of the number of vehicles that are used in the trip movement in the most recent year of data availability. The data sources used for this estimation is a mix of the World Bank Data catalog and regional statistical data from local authorities of different countries, such as the Statistics Agency of Uzbekistan (https://stat.uz/ru/) and the Australian Bureau of Statistics (https://www.abs.gov.au/).

$$K = \sum_{pf=1}^{t} \sum^{n} w_{pf} \tag{3}$$

$$O_i = v_i \cdot t_i \cdot P_i \tag{4}$$

$$D_j = v_j \cdot t_j \cdot P_j \tag{5}$$

Where: v is the vehicle factor, expressed by the number of vehicle registration per inhabitant in the region of interest; t is the trip percentage and it should be calibrated using regional data. Local statistical bureaux are often a very good data source; P_i is the population from the origin i. This allows for generating coherent trips from i to j.

As an hypothesis taken for this methodology, the K factor, defined in Equation 3, is considered as a public facilities attractiveness score, which helps fill the gap created by the lack of precise O-D surveys using public facilities as attractivity factors for distributing trips. The factor K depends on the following parameters: pf, which is the public facility type and t is the total number of public facilities types in the destination zone; $\sum^{n}$, which is the count of the total number (n) of public facilities of type pf in the destination zone; w_{pf}, which is the weight used for each public facility. Double weight has been used for hospitals and schools.

The traffic assignment was carried out using an all-or-nothing assignment (Sheffi, Yossi, 1984). It assumes that there are no congestion effects and that all drivers perceive route choice the same way. The result of the traffic assignment is the traffic passing on each link of the network.

General user delay

The process of General User Delay (GUD) evaluation is based on a detailed modeling and simulation of the transport network to predict traffic flow patterns under normal and disrupted conditions. The results of the traffic estimation are used to estimate the increase in travel time on every network link when they are disrupted. As of the publication date of this paper, the zones considered for this evaluation are the cities and towns of a region of interest pre-set before the resilience assessment. This indicator is calculated by computing the distance skim matrix (DSM). In this evaluation, the average nominal speeds are considered constant and traffic jams and lights are not taken into account, i.e. a free flow is assumed for the whole network.

The sequence used for calculating the GUD criticality map is as follows considering a network with n links: compute the original DSM for the full network for all zones of interests; for each link l: create a new network graph while excluding l - Θ_{i-l} - then compute the resulting DSM, Θ_i; compute the difference between the average sum on all dimensions of the two DSM matrices; convert it into a time unit based on hypotheses on the uniformity of speed v and trip distribution. The final time GUD score of each link could be then formulated by Equation 6.

$$GUD(l) = \frac{1}{v}\sum_{i=0}^{n}\frac{\Theta_{i-l} - \Theta_i}{m} \tag{6}$$

The results of this evaluation are appealing for infrastructure planners. By classifying network links according to their disruption risk, it becomes possible to prioritize investments and interventions aimed at enhancing network resilience. For instance, links with high disruption risks can be targeted for structural reinforcements, improved drainage systems, or better alternative route planning.

3.3 Combined analysis

The Combined Analysis step involves coupling the assessed infrastructure vulnerabilities with climate exposures. This analysis is critical as it identifies which infrastructure links could be impacted or disrupted by climate events based on the vulnerabilities studied. The output of this analysis is called infrastructure exposure risk and is used together with the social and economic score to compose a comprehensive final scoring for the network links.

3.4 Social and economic impact identification

Rural connectivity

The Rural Connectivity indicator is calculated based on the existing Rural Access Index (RAI) (World Bank Group, 2016) and on possibilities of scaling this indicator to allow link prioritization. Rural Connectivity is expressed by the rural population density living around a link. This new indicator allows for having a more granular view on how the link is important in terms of rural population connected living under 20-25 min walking distance. The steps taken to generate the score for this indicator are: selection of commonly used tags from OpenStreetMap (Trunk, Primary, Secondary, Tertiary) that serve as an approximation for all-season roads; creation of a mask based on 2.5 km buffer on these roads; mapping only the rural areas by subtracting the urban areas as defined by the Global Rural-Urban Mapping Project (Center for International Earth Science Information Network, 2021); calculating the amount of rural population that are up until 2.5 km far away from a road in, at least, good condition.

Accessibility to public facilities

The accessibility to public facilities is evaluated through a disruption simulation analysis. In this analysis, every link of the infrastructure network is disrupted one by one in order to understand if some links are crucial for connecting population to hospitals, schools, and markets, for example. If a link disruption leads to an isolated population that could not access public facilities without that link, this link is associated with an extreme accessibility risk. This indicator is very important to understand which links could impact the population the most when an extreme weather or climate event happens. The result of this analysis also helps prioritization of maintenance investments to keep a well-connected population. This indicator is calculated by carrying out an iterative graph analysis of the infrastructure network. In each iteration a link is deleted from the network and its impact on the creation of isolated islands are evaluated using programming algorithms in Python.

3.5 United score and network prioritization

The united score is one of the most important outputs of the ORIS climate resilience methodology. It is the computation of the final risk score of each link after evaluating climate, infrastructure vulnerabilities, and social and economic impacts. It is the weighted average of each one of the climate, infrastructure, and social and economic scores. As the results of each score are intrinsically related to each other - a link can cause social and economic impact if it is disrupted due its vulnerabilities to the climate exposures assessed - the weights to be considered are issued from a sensitivity analysis. This analysis is necessary to correctly account for all scores of the methodology. This analysis avoids considering wrong hypotheses that could culminate in neglecting some scores that are classified as high (4) or extreme (5).

The weights indicated by W_i, where i indicates each score calculated, can vary between 0 and 1. The composition of the united score is shown in Equation 7.

$$United\ score(l) = W_0\ Climate(l)\ + W_1 Infrastructure(l) + W_2 Social(l) \tag{7}$$

In Equation 7, the parameter l is used to indicate that the calculation of such an equation is carried out for every link of the infrastructure network. This allows for a comparison between every link of a whole network and ultimately the prioritization of the most critical infrastructures. From this prioritization, efforts and investments can also be prioritized according to adaptation and mitigation strategies proposed for the most critical links.

3.6 Adaptation and mitigation strategies

After the prioritization phase, when the result of the united score is used to identify the most critical infrastructure, adaptation and mitigation strategies are automatically proposed and displayed on the ORIS digital platform. The adaptation proposals are designed to enhance infrastructure resilience to the assessed climate exposures. Examples of such adaptations are employing rigid pavement as the surface layer, using stabilized bases and foundations, dimensioning or resizing culverts and ditches for extreme rainfall events, and reinforcing foundations or embankments to prevent water immersion.

The mitigation proposals are based on the Life Cycle Assessment approach, taking into account: the quantification of the Greenhouse Gases (GHG) emissions at various stages of the infrastructure service life, the quantification of possible emissions of a Business-as-Usual scenario, and the calculation of the relative emission between these two first quantifications. Possible measures to be proposed include strategies like the use of low-carbon materials to reduce carbon emissions, optimized long-term maintenance programs, as well as compensation measures, e.g. reforestation, which supports absorbing carbon dioxide from the atmosphere.

4. EXAMPLE OF APPLICATION OF ORIS CLIMATE RESILIENCE METHODOLOGY

This section offers examples, extracted from a case study in Uzbekistan, of the outputs generated by the ORIS Climate Resilience Methodology. These outputs are seamlessly integrated with the ORIS digital platform, enabling users to visualize, analyze, and interact with the results. The selected screenshots show outputs for different climate exposures used to prioritize roads from a whole network in the Republic of Karakalpakstan, Uzbekistan.

Figure 3 displays an example result of the heat exposure risk classification for each network road.

Figure 3 Heat climate exposure displayed on the ORIS digital platform.
(ORIS Materials Intelligence, 2024)

Analogously, the flooding (runoff and road immersion) risk classification results are also automatically integrated with the ORIS digital platform (Figure 4).

Figure 4 Flooding climate exposure displayed on the ORIS digital platform.
(ORIS Materials Intelligence, 2024)

For already prioritized infrastructures, the ORIS Climate Resilience Methodology provides a comprehensive list of adaptation and mitigation measures to be considered to make the project more resilient to climate change. Figure 5 depicts how this list is displayed directly on the digital platform.

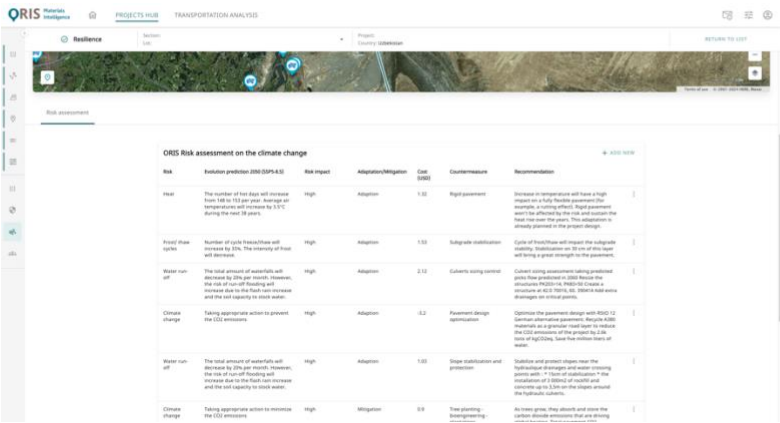

Figure 5 List of adaptation and mitigation measures proposed on the ORIS digital platform.
(ORIS Materials Intelligence, 2024)

5. CONCLUSIONS

The ORIS Climate Resilience Methodology represents a significant advancement in the field of infrastructure resilience and climate risk assessment. This paper provided an in-depth exploration of the methodology, detailing each calculation step and showcasing its practical application through several examples extracted from case study in Asia. The analysis underscored the methodology's potential to significantly enhance infrastructure planning and decision-making. The following conclusions were drawn:

- The ORIS Climate Resilience Methodology effectively bridges the gap between climate science and infrastructure planning. By integrating climate projections, infrastructure vulnerability assessments, and social-economic impacts into a digital platform, it provides a robust tool for policymakers and infrastructure planners to make informed decisions to make transport infrastructures more climate-resilient.

- The methodology's reliance on a wide range of data sources ensures that the assessments are both comprehensive and replicable across different geographical locations. This adaptability is a key strength, allowing the methodology to be applied to various infrastructure projects globally.

- The application of the methodology in a road network prioritization project in the Republic of Karakalpakstan highlighted its power and utility. The study revealed that 25% of the roads were exposed to high to extreme climate risk, affecting 30% of the local population. The assessment underscored the significant challenges posed by rising temperatures and frequent freeze-thaw cycles, showcasing how digitalization can facilitate and accelerate decision-making processes.

6. LIMITATIONS AND FUTURE CONSIDERATIONS

Some limitations have been identified in the current version of the methodology, deserving special attention. Methods to calculate surface pavement temperature from 2-m air temperature vary in their hypotheses and results; the traffic parameter from the infrastructure score is created based on simplifications made from the four-step model (FSM). Usually, this method requires at least a phase of Origin-Destination survey to correctly estimate demands and attractions of traffic from each O-D pair. Nevertheless, these surveys are usually time-consuming and not carried out in all countries. The major hypothesis taken to estimate traffic in no matter the region of the world generated good results, but, as it is an estimation, those results are only good when used for comparison purposes. The results should not be taken by their absolute values, but only comparatively. Moreover, further research needs to be done to better understand the best materials to be implemented as adaptation measures for various climate events, and further work is required to enhance multi-risk assessments.

Despite the abovementioned limitations, the most important objective has been achieved, which is the development of a digital tool that supports network infrastructure decision-making. The methodology is in constant development and is improving considering the state-of-the art research on climate science, artificial intelligence, and infrastructure risk evaluation. Hence, new versions that address those limitations will be published in the future.

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