Mitig Adapt Strateg Glob Change (2024) 29:43
https://doi.org/10.1007/s11027-024-10140-6

ORIGINAL ARTICLE

Assessing climate change vulnerability of coastal roads

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Received: 6 November 2023 / Accepted: 18 April 2024

Abstract

Climate change is a global phenomenon, which affects in several ways different regions all around the world, beyond the rise in global temperature. Among the different climate change issues, the management of transport infrastructures is crucial. Particularly, their vulnerability against changes in climatic conditions should be assessed. Vulnerability indicators are based on the IPCC concept of vulnerability and can be defined as a function of Climate Exposure, Sensitivity, and Adaptive Capacity. These dimensions need to be addressed during the assessment making and can be modelled as a Multiple Criteria Decision Analysis (MCDA) problem. This study proposes an integrated approach of several MCDA methods as a possible tool for ranking the climate change vulnerability of coastal roads in Malta. The application covers six coastal roads in the islands of Malta, classified by three different MCDA methods. The results indicate that the proposed approach can produce a consistent ranking of the climate change vulnerability of coastal roads. The study provides policy and decision-makers with a definition of a coastal road, an inventory of such roads, a list of climate change impacts, and a mathematical model incorporating climate change vulnerability indicators. The model can be used to prioritize investment and plan climate change adaptation strategies for infrastructural works on coastal roads.

Keywords Road vulnerability · Malta · MCDA · VIKOR · COPRA · PROMETHEE

1 Introduction

The global threat of climate change has been highlighted very clearly in the last scientific reports published in 2021 by the Intergovernmental Panel on Climate Change (IPCC). Despite the role of natural events, such as variations in the solar cycle, since 1800 the main determinant of climate change has been the burning of fossil fuels required for human activities (IPCC 2021). Accordingly, many of the events noted so far have been

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unprecedented in thousands of years and some of them, such as the rise in sea level, will be difficult to reverse over hundreds to thousands of years in the future (IPCC 2021).

Changes are not just about rising global temperatures and have different consequences in every region of the world (UCAR 2007). As reported by Ryley and Chapman (2012), although climate change is a global problem, the burden of its consequences is borne on a local scale. Several alterations can be observed; for instance, the intensification of the water cycle brings more intense rainfall and flooding, as well as drought. In coastal areas phenomena such as the rise in sea level, increasing frequency of coastal flooding, and coastal erosion will be experienced. In some areas, changes are already taking place, such as for islands in the Pacific Ocean where sea level rise has led to land losses and the possibility of their disappearance is becoming increasingly likely. Much of Kiribati in the South Pacific, for example, is at serious risk of inundation by 2100 (Sabūnas et al. 2021; Cauchi et al. 2021). Several pieces of evidence point to the loss of Arctic sea ice (see NSIDC 2022), and the melting of glaciers and ice sheets. These phenomena, combined with permafrost reduction, may further accelerate global warming. The effect of changing temperatures on the oceans is certain: more frequent heat waves and warming oceans will lead to acidification and potentially reduced oxygen levels for marine life. Finally, cities will have the greatest effects of climate change, with hotter and longer heat waves. Heavy rainfall will also be more frequent with more frequent flooding in urban areas, especially those that lie on the coast and potentially affected by sea level rise (see for example Miralles I Garcia 2017).

Several studies have identified the importance of reliable transport infrastructure to socio-economic activity and growth (Eddington 2006; Erath et al. 2008; Calderón and Servén 2004). Road infrastructure, in particular, is one major capital asset of any country with large national budgets being dedicated to their construction and maintenance annually. This underlines the importance of investigating the vulnerability of road transport infrastructures (Jenelius et al. 2006, Miralles I Garcia 2017) especially because of climate change effects. Jaroszweski et al. (2010) identify seven impacts of climate change on transport systems including the number of hot days, decreased number of cold days, increased heavy precipitation, seasonal changes, drought, sea level change, and extreme events. It is evident that the planning, maintenance, and construction of transport infrastructures, many of which are long-term commitments, have to consider and be resilient against climatic conditions which may result from climate change in the future.

Numerous studies have examined the effects of climate change on different aspects of transportation systems and different regions of the world (see for example Koetse and Rietveld 2009; Jaroszweski et al. 2010; Ryley and Chapman 2012; Schweikert et al. 2014; Rattanachot et al. 2015; Chinowsky et al. 2015; Dawson et al. 2016; Espinet et al. 2016; Wang et al. 2020; Qiao et al. 2022). Others have extended the analysis to tourist mobility, bringing forward the important element of tourism in the discussion about climate change impact on coastal regions and the importance of tools to support decision-making (Cavallaro et al. 2019, 2021). Research on island transport systems and their vulnerability to climate change impacts however remain far and few (see for example Monioudi et al. 2018; Attard 2015; Leon et al. 2022). The 2021 EU Strategy on Adaptation to Climate Change (European Commission 2021) identified islands, alongside river basins and mountain areas as particularly vulnerable. Islands are more vulnerable to the impacts of climate change since they have large coastal zones and valuable, sometimes delicate ecosystems and environments (Veron et al. 2019). Adaptation can be challenged by geographic remoteness, low economic diversification, and the lack of economies of scale brought about by their limited economic and population agglomerations (Vrontisi et al. 2022; Weir et al. 2017). This is indeed where the motivation for this study lies. The research presented in this paper adds new data regarding an island case study, and provides an assessment framework for vulnerability using multicriteria analysis that has the potential to be generalised to different locations.

The islands of Malta, located in the Central Mediterranean will be affected by climate change through rising sea levels, rising temperatures, more frequent extreme weather events, and overall less rainfall (Malta Resources Authority 2022). The latest National Communication to the United Nations Framework Convention on Climate Change (NC8) identifies these threats and vulnerabilities but there is little in terms of adaptation for a more resilient future for the islands. Since the first high-level National Adaptation Strategy in 2012, there is still a problem related to the lack of local research in climate change forecasting, data, and information, and these gaps obstruct the identification and implementation of effective adaptation measures in various sectors (Government of Malta 2012, 2021; Malta Resources Authority 2022).

Building on the preliminary work conducted by Attard (2015), on the impact of climate change effects on transport in the islands, this study aims to assess the vulnerability of coastal roads in Malta. With increased risks from sea level rise, but also from increased intensity of precipitation, coastal roads will be inundated as most of them also act as natural water courses that deliver stormwater to the sea. The vulnerability assessment of these roads is therefore required as part of any national coastal zone management policy but also as part of a resource allocation exercise for climate change adaptation due to sea level rise, flooding and heat waves. With increased climate change impacts, there will be a need for more frequent maintenance and rehabilitation of coastal roads.

Using the Intergovernmental Panel on Climate Change (IPCC) conceptual framework for climate change vulnerability assessment (IPCC 2014), this study develops a vulnerability matrix with corresponding indicators for the three elements of Exposure, Sensitivity, and Adaptive Capacity based on the impacts of climate change namely, sea level rise, flooding and heat waves on coastal roads. The vulnerability matrix model is then used to rank six coastal roads in the islands of Malta according to their climate change vulnerability using different Multiple Criteria Decision Analysis (MCDA) methods. Multicriteria analyses are used to solve complex problems by assessing multiple set of variables, both individually and collectively, assigning specific importance to each variable (Liu 2007; Shmelev and Labajos-Rodrigues 2009). Therefore, this kind of methodology assumes a central role in the multidimensional evaluation processes, as is the vulnerability assessment (Boggia and Cortina 2010). This characteristic of the MCDA approach, along with the international reference framework which it is based on, makes the present assessment transferable to any other territorial contest.

The paper is organized as follows: Section 2 introduces the case study, followed by the materials and methods (Section 3) and description of results and discussion (Section 4). Conclusions are presented at the end of the paper in Section 5.

2 The case study of Malta

The islands of Malta are located in the centre of the Mediterranean Sea with an area of just 316 km^2 and are home to just over 500,000 resident population (see Fig. 1). They are visited by almost 3 million tourists every year (pre-pandemic levels), with tourism

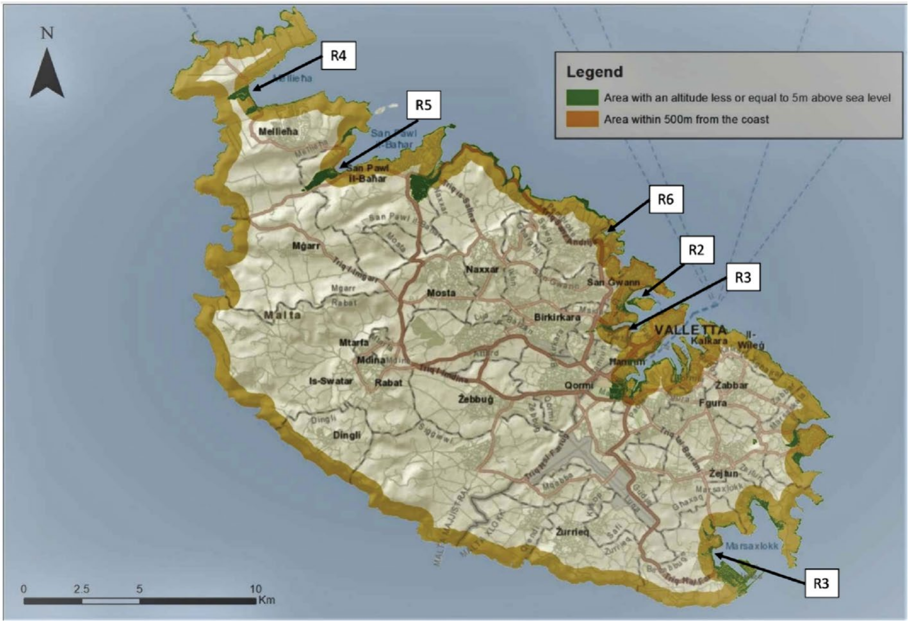


Fig. 1 The main island of Malta, its main road network and coastline classification. Adapted from Rizzo (2019)

contributing to over 20% of the GDP. The islands have continued to grow economically since joining the European Union in 2004. This high concentration of population and economic activity relies on a transport infrastructure that is heavily dependent on road transport and private vehicles. Malta's motorization rate is indeed one of the highest in Europe. This dependence has many negative effects, including that of contributing to Malta's emissions and challenging the islands' ability to reach climate change targets, but also exposes the islands' transport system to high levels of vulnerability to climate change impacts.

In an earlier study, Attard (2015) looked at the two key climate change risks that could affect the transport infrastructure in the islands. For road transport, she identified over 6% of the main road network to be potentially exposed to sea level rise with a 2 m increase in sea level, most of which reflect coastal roads. The increase in extreme weather events and flooding would affect 16% of the islands' main roads and 7% of rural roads. Coastal roads however remain the most exposed and are the focus of this current study. These cover approximately 3% of Malta's total road network and are, in terms of hierarchy a significant part of the main road network linking north to south and highly populated areas. Indeed, 8% of these are part of the critical infrastructure aligned with the Trans-European Transport Network (TEN-T) and are here defined as being more or equal to 100 m in length, having an elevation of less than or equal to 5 m above sea level and lying at 500 m or less from the coastline. These roads included in the present analysis are reported in Fig. 1, with the code R1-R6.

3 Materials and methods

3.1 Climate change vulnerability assessment

Assessing the climate change vulnerability of coastal roads is inherently complex due to the need to integrate multi-disciplinary approaches which include socio-economic, political and environmental factors (Kiker et al. 2005). Several traditions and disciplines, from economics to engineering, use the term vulnerability (see Paul 2014 for a review of definitions). Different disciplines continue to contribute to emerging approaches surrounding social-ecological systems and their inherent and dynamic vulnerability. Adger (2006) provides a review of vulnerability research and concludes on the need for a more integrated approach which includes social and physical systems. This is extended in some studies to assess specific activities such as tourism impacts in coastal areas and the inclusion of tourism and transport indicators relevant to support decision making in the methodological framework (Cavallaro et al. 2021).

The possible operational definitions of social vulnerability to natural hazards are various (Katic 2017). Dow (1992) defines it as “the differential capacity of groups and individuals to deal with hazards, based on their positions within physical and social worlds” and Bogard (1988) describes it as “the inability to take effective measures to ensure against losses”. Adger (1999) defines social vulnerability as the exposure of populations to stress as a result of the impacts of climate change and associated extreme events, where stress involves the breakdown of livelihoods of groups or individuals and forced adaptation to the changing physical environment. He argues that social vulnerability can be explained by a combination of social factors and environmental risk, where risk represents those physical aspects of climate-related hazards exogenous to the social system. In this social perspective, the concept of vulnerability is a pre-existing condition and also a "starting point" of the analysis. Consequently, exposure (to climate change) can be considered as an external element in vulnerability analysis (Gallopín, 2006). Therefore, social vulnerability is linked to the "sensitivity" and "adaptive capacity" components of the vulnerability framework.

On the other hand, physical vulnerability is a function of the frequency and severity of a given type of hazard (Brooks 2003). A hazard may cause no damage if it occurs in places where human systems are well adapted to cope or are resilient. Several authors have defined physical vulnerability in relation to the consequences or results of an impact (Quan Luna et al. 2011; Glade 2003). Vulnerability focuses on exposure to climate change and the sensitivity of the object of analysis to that exposure. Physical vulnerability is consequently perceived as the "endpoint" of the analysis, so it is conceptualized, analyzed, and based on sensitivity and exposure. Adaptive capacity is not considered in this type of analysis (Nguyen 2015).

Jenelius and Mattsson (2015) define road network vulnerability analysis as the study of potential degradations of the road transport system and their impacts on society, modelling the road infrastructure as a network with links (road segments) and nodes (intersections). Others include elements of accessibility and serviceability and robustness (Berdica 2002; Espinet et al. 2016; Snelder et al. 2008). Several measures are used in the literature to quantify vulnerability (see for example Balijepalli and Oppong 2014; Berdica 2002). Jeneluis and Mattsson (2015) conclude that a vulnerability analysis process provides the background and starting point for an evaluation of measures to reduce vulnerability. However, it is required to understand and manage vulnerability in conjunction with emergency preparedness, infrastructure development, operations, and maintenance.

The present study adopted the IPCC (2007) conceptual framework to assess the vulnerability of Malta's coastal roads. We decided to adopt this reference because the consideration of an international model, like that of the IPPC allows for its transferability and adaptability to different geographical contexts. The IPPC's periodic report provides the most comprehensive and up-to-date scientific assessment of the causes/impacts of climate change, the vulnerability of natural and human environments, and the potential for response through adaptation; it forms the standard reference for all concerned with climate change in academia, government and industry worldwide (IPPC 2007).

In the IPPC framework, the vulnerability of any system, for each possible scale, reflects the level of exposure and sensitivity of that system to hazardous conditions, and its ability to adapt to or recover from the effects of those conditions (Fig. 2). These are defined as:

1. Climate exposure (E) refers to the range of climate-related stimuli, such as sea level rise, changes in temperature or precipitation, heat waves, severe storms, and drought.
2. Sensitivity (S) is the degree to which a system is modified or affected by disturbances.
3. Adaptive capacity (AC) is the capability of a system to adapt to environmental hazards or policy changes and to expand the range of variability with which it can cope (Adger 2006).

Mathematically, vulnerability (V) is defined as:

$$V = \alpha X E + \beta X S + \gamma X A C$$

where α, β, γ are the weights for E, S, and AC, respectively.

3.2 Indicators

Considering the theoretical background for Vulnerability as described in 3.1, an indicators framework has been constructed to allow the assessment. The construction of the framework must be simple and transparent to allow the transferability of the approach in other contexts. The selection of the criteria is based on the following rules:

- Each criterion should be representative of one of the dimensions identified;
- Scientific foundation, according to the current scientific and technical literature;
- Data availability or ease of collecting data;
- Avoid the presence of redundant or overlapping indicators.

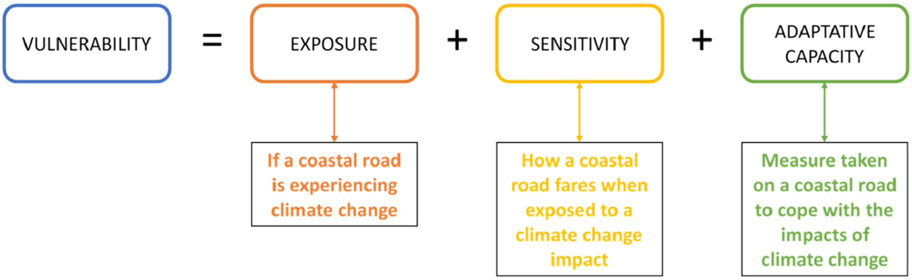


Fig. 2 Framework for vulnerability assessment. Adapted from IPCC (2007)

In the selection of data for the case study, the technical literature containing expert reports, studies, and vulnerability assessment tools were particularly analysed. Each set of indicators is described below.

3.2.1 Exposure indicators

The elevation of the coastal road above sea level is an important indicator for exposure to sea level rise, storm surges and heavy precipitation. It serves as a natural protection with higher coastal roads being less exposed. This is also relevant for the proximity of the road to the coastline. The closer the road is to the coast, the higher the exposure to impact. Lastly, the area of the watercourse present near the coastal road was taken as an indicator of exposure to heavy precipitation. Table 1 describes the indicator, data source, measurement unit, and related literature.

3.2.2 Sensitivity indicators

Coastal roads that experienced flooding in the past are more likely to be impacted by sea level rise, flooding and storm surges. A count of such reports was used as a measure for each coastal road. Another sensitivity indicator is the presence of any infrastructure to protect against impact, such as sea walls. A measure of whether the relevant infrastructure was present or not was used. Coastal roads experience greater stress from high bus traffic especially during hot weather and heat waves and are more sensitive to temperature-related damage. Therefore, the sensitivity indicator for heat waves was the weekly number of buses using the coastal road. Another measure for heat sensitivity is related to shading provided by trees. Trees that line a coastal road can create cool areas by providing shade. The length of the road lined with trees providing shade as a percentage of the total length of the coastal road was used as a measure of this indicator. Table 2 provides more information about these indicators.

3.2.3 Adaptive capacity indicators

The annual average daily traffic (AADT) is a measure of the volume of traffic on the coastal road, with disruption and impact being higher where traffic volumes are larger. Similarly, there is greater impact if there is a higher presence of businesses served by the coastal road. The number of businesses present along the coastal road was observed on site. The replacement cost, which is directly proportional to the area of the road to be replaced, directly affects the adaptive capacity of the coastal road. The area covered by the coastal road was used as a proxy in this case. Lastly, the detour length as an indication of redundancy, was identified as an indicator for adaptive capacity. Longer detour lengths are assumed to provide for more adaptive capacity. Table 3 provides the information about these indicators.

3.3 Multicriteria methods

The term multicriteria decision analysis (MCDA) is used to describe a wide number of decision support system methods. They differ mainly in the solution proposed (choosing, ranking, classifying), the algorithm used (each method supports a specific one), and the weighting approach. This generates a great number of methods available, although it should be noted that there is no one-size-fits-all method to solve every decision-making

Table 1 Exposure indicators

Ref	Indicator	Rationale	Data Source	Units	References
E1	Elevation	Elevation can serve as a natural protection from Sea Level rise, heavy precipitation and Storm surges. The higher the asset, the less exposed it may be to sea level rise, flooding and storm surges	GIS STREETs Data and 3D terrestrial (LiDAR) data (ICCSD)	Height in meters	Kleinosky et al. 2007; Wu et al. 2002; Abuodha and Woodroffe 2006; Kumar et al. 2010
E2	Proximity to coastline	Roads closer to the coast may be more likely to be exposed to sea level rise, flooding and storm surges	GIS STREETs Data (ICCSD)	Distance in meters (distance from street centre line to the coast)	Özyurt and Ergin 2009; Özyurt 2007; Brody et al. 2008; Rajesh et al. 2016
E3	Location in watercourse	Roads located in watercourses are more likely to be exposed to flooding from changes in precipitation	Fieldwork	Area of road located in watercourse	U.S. DOT Vulnerability Assessment Scoring Tool (VAST) (n. d.)

Table 2 Sensitivity indicators

Ref	Indicator	Rationale	Data Source	Units	References
S1	Past experience with flooding from heavy precipitation, extreme weather and storm surges	Roads that have experienced flooding during heavy precipitation, surge storms and extreme events in the past are likely to be some of the roads affected by climate change	Times of Malta Digital Archive	Number of reports	Dawson et al. 2016; Keller and Atzl 2014
S2	Protection against sea level rise, flooding and storm surges	Roads protected by a sea wall or other infrastructure are less likely to be affected by climate change	Fieldwork	Yes = 1 No = 5	Azevedo de Almeida and Mostafavi 2016
S3	Number of buses	Coastal roads experience greater stress from heavy vehicle traffic. Road ways with high bus traffic may therefore be more sensitive to temperature-related damage	MPT Bus Route Map, Good Earth (Version 7.3.2, 2018)	Number of buses per week	U.S. DOT Vulnerability Assessment Scoring Tool (VAST) (n. d.)
S4	Tree shading	Tress that line a coastal road can have multiple benefits, including controlling storm water and cooling areas off by providing shade	Fieldwork	% length of road lined with trees	Akbari et al. 1997

Table 3 Adaptive capacity indicators

Ref	Indicator	Rationale	Data Source	Units	References
AC1	Annual Average Daily Traffic (AADT)	AADT is the volume of traffic for a road daily. Roads with higher traffic volumes would affect more drivers and cause greater disruptions. The higher the AADT the more adaptive capacity	Transport Malta	Number of vehicles per day	Jun-Qiang et al. 2017; Jenelius 2009; McLaughlin et al. 2002; Jenelius and Mattsson 2015; Attard 2015
AC2	Number of affected businesses	Number of businesses in road. The higher the number, the greater the impact, the more adaptive capacity	Fieldwork	Number of businesses	Lu and Peng 2018;
AC3	Replacement cost	The replacement cost is directly proportional to the area of the road. The higher the cost, the less adaptive capacity	Fieldwork	Area in sq. m	U.S. DOT Vulnerability Assessment Scoring Tool (VAST) (n.d.); Adger et al. 2005; Fakhruddin et al. 2015; Havko et al. 2017
AC4	Detour length	Detour length can be considered as a proxy for road network redundancy. Roads with longer detours are assumed to have higher adaptive capacity than those with shorter detours	Google Earth (Version 7.3.2, 2018)	Length in km	Taylor et al. 2006; Erath et al. 2008

problem (Guitouni and Martel 1998; Watróbski et al. 2019; Sałabun et al. 2020); at the same time, answering the question of which method is the most suitable to solve a specific type of problem is a difficult task (Roy and Słowinski 2013; Watróbski et al. 2019; Cinelli et al. 2022).

In this work three different MCDA methods have been applied, namely VIKOR, COPRAS, and PROMETHEE, to (i) validate the feasibility of each method in the context of the climate change vulnerability; and (ii) assess the stability of the results, independently of the method applied. All the methods chosen in the study are based on the guidelines of Guitouni and Martel (1998) and the following criteria:

1. Commonly used method – used by several researchers in the environment, engineering business management.
2. Simple and transparent – simple to use and each step is calculated using basic and or advanced mathematics.
3. Classified as partial and or total ranking methods – using the decision tree proposed by Wątróbski et al. (2019).

The use of the guidelines proposed by Guitouni and Martel (1998) guarantees the methodological replicability of the approach used, along with the indicator framework construction.

The choice of VIKOR and COPRAS is justified, as they form a coherent group of methods of the American MCDA school and are based on the same principles (i.e. reference points), and unlike other methods of the same school, they are not merely elaborations of the simple additional or multiplicative weighted aggregation (Sałabun et al. 2020). On the other hand, PROMETHEE is a method that belongs to the European school and implements the properties of other European school-based MCDA methods (outranking relations, thresholds, and different preference functions); moreover, unlike other methods of this school, the method provides a full, quantitative final ranking of decision-making options (Sałabun et al. 2020).

3.3.1 The complex proportional assessment (copras) method

Complex Proportional Evaluation (COPRAS) postulates a direct proportional relationship of the degree of importance of alternatives on a system of criteria that adequately describe the decision variants and, on the values, and weights of the criteria (Zavadskas et al. 2008). This approach ranks alternatives according to their relative importance (weights): the final ranking is created using the positive and negative ideal solutions.

Assuming a decision matrix with m alternatives and n criteria $(A = (a_{ij})_{mXn}$, the COPRAS method is defined in five steps:

Step 1. Calculate the normalized decision matrix to make the criteria comparable

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}, \text{where } i = 1,\ 2, \dots, m; \text{ and } j = 1,\ 2, \dots, n; \tag{1}$$

r_{ij} is the normalized value assumed by the j^{th} indicator for the i^{th} alternative.

Step 2. Calculate the weighted decision matrix $V = (v_{ij})_{mxn}$

$$v_{ij} = w_j \bullet r_{ji}, \tag{2}$$

where w_j is the relative weight of the j^{th} indicator, while v_{ij} is the normalised value of j^{th} alternative according t i^{th} criterion.

Step 3. Determine the sums of weighted normalized values, for beneficial and non-beneficial criteria, which are in our case study the criteria that contribute towards vulnerability and the ones that reduce or do not contribute towards the vulnerability of the coastal roads, respectively

$$S_{+i} = \sum_{j=1}^{n} v_{+ij} \tag{3}$$

$$S_{-i} = \sum_{j=1}^{n} v_{-ij} \tag{4}$$

where v_{+ij} and v_{-ij} are respectively the weighted normalized values for the beneficial (to be maximized) and non-beneficial (to be minimized) criteria. Therefore, the S_{+i} and S_{-i} values show the level of the goal achievement for alternatives. The higher value of S_{+i} the more vulnerable the coastal road and the lower value of S_{-i} the less vulnerable the coastal road.

Step 4. Calculate the relative significance of alternatives Q_i, which represents the degree of satisfaction provided by the individual alternative

$$Q_i = S_{+i} + \frac{S_{-min} \bullet \sum_{i=1}^{m} S_{-1}}{S_{-min} \bullet \sum_{i=1}^{m} \left(\frac{S_{-min}}{S_{-i}}\right)} \tag{5}$$

where S_{-min} is the minimum value of S_{-i}.

Step 5. Final ranking is performed according U_i values, the quantitative utility, which can be calculated by comparing the relative significance of alternatives.

$$U_i = \frac{Q_i}{Q^{max}} \bullet 100\% \tag{6}$$

where Q^{max} is the maximum relative significance value. The utility value ranges from 0 to 100%: COPRAS allows the evaluation of direct and proportional significance and utility degrees of weight and performance values according to all criteria.*VIKOR*

VIKOR (Vlse Kriterijumska Optimizacija I Kompromisno Resenje) establishes the compromise ranking list, the compromise solution, and the weight stability intervals for the preference stability of the compromise solution obtained with the given weights. The basis of the method is distance measurements, as is done in TOPSIS, seeking a compromise solution. The preferred alternative will be the one that minimizes the distance from the ideal solution, and solutions are evaluated according to all criteria considered (Opricovic 1998). Assuming the same decision matrix with m alternatives and n criteria $A = (a_{ij})_{mXn}$, the five steps of the method are:

Step 1. Determine the best x_i^+ and the worst x_i^- values for each criterion where $i = 1, 2, \ldots, n$. If the $i.^{th}$ criterion measure increasing vulnerability then $x_j^+ = max_i(A)$ and $x_j^- = min_i(A)$

Step 2. Calculate the S_i and R_i values, $i = 1, 2, \ldots, m$ using the following equations:

$$S_i = \sum_{j=1}^{n} \frac{w_j\left(x_j^+ - x_{ij}\right)}{(x_j^+ - x_j^-)} \tag{7}$$

$$R_i = \max[\sum_{j=1}^{n} \frac{w_j\left(x_j^+ - x_{ij}\right)}{\left(x_j^+ - x_j^-\right)}] \tag{8}$$

where w_j is the weight of the j^{th} criterion and expresses the relative importance of the criterion itself.

Step 3. Compute the Q_i values using the equation:

$$Q_i = v\frac{(S_i - S^*)}{(S^- - S^*)} + (1 - v)\frac{\left(R_i - R^*\right)}{(R^- - R^*)} \tag{9}$$

where $S^* = min_i S_i$; $S^- = max_i S_i$; $R^* = min_i R_i$; $R^- = max_i R_i$; v is the strategic weight of satisfying the majority of criteria, considered in this application equal to 0.5.

Step 4. Rank the alternatives, sorting by the $S, R, andQ$ values from the minimum value. The results are three ranking lists.

Step 5. In order to have a compromise solution or a set of compromise solutions it is possible to use the three ranking lists. However, it is possible also to rank the alternatives according to the minimum value of Q, as a compromise solution (Sałabun et al. 2020). In particular, we considered the following two conditions for considering a rank valid:

C1: "Acceptable advantage": $Q\left(A''\right) - Q(A\prime) \geq DQ$ where $A\prime$ is the first ranked alternatives (ie the coastal road in our study), while A'' is the second one in the list by min Q, $DQ = 1/(m - 1)$ and m is the number of alternatives (R_m).

C2: "Acceptable stability in decision making": alternative $A\prime$ must also be the best ranked by $Sand/orR$

If one of the conditions is not satisfied, then a set of compromise solutions is proposed (Huang et al. 2009), which consists of:

(i) Alternatives $A\prime$ and A'' if only condition C2 is not satisfied, or.

(ii) Alternative $A\prime, A'' \ldots A^m$ if condition C1 is not satisfied; and A^m is determined by the relation $Q(A^m) - Q(A\prime) \geq DQ$ for maximum M (the positions of these alternatives are in closeness).

3.3.2 PROMETHEE

The preference ranking organization method for enrichment evaluations (PROMETHEE) is an outranking method and it includes itself several different approaches. The PROMETHEE family of methods was originally developed by Brans (1982), including PROMETHEE I (partial ranking) and PROMETHEE II (Complete ranking). Then, several versions were developed to make the method more feasible in complex scenarios (Brans et al. 1986; Brans and Mareschal 1992; Macharis et al. 1998; Figueira et al. 2004), In this paper, PROMETHEE I and II were applied and thus described according to the procedure proposed in Behzadian et al. (2010), assuming the same decision matrix used for the other methods.

Step 1. Determination of the deviation based on the pairwise comparisons, as follow:

$$d_j(a,b) = g_j(a) - g_j(b) \forall a,b \in A \tag{10}$$

$d_j(a,b)$ denotes the difference between the evaluations of alternatives a and b on each criterion.

Step 2. A preference function has to be applied to each criterion,

$$P_j(a,b) = F_j[d_j(a,b)] \tag{11}$$

where $P_j(a,b)$ is the function of the difference between the evaluations of alternative a regarding alternative b on each criterion into a degree ranging from 0 to 1. The smaller the value, the greater the decision maker's level of indifference between the two alternatives, the closer to 1 the greater the preference. PROMETHEE admits several preference functions: a linear preference function was applied to all the criteria.

Step 3. Calculation of the overall global preference index according to the formula:

$$\pi(a,b) = \sum_{j=1}^{k} P_j(a,b) w_j \tag{12}$$

where $\pi(a,b)$ represents the preference of a over b for all the criteria: if its value is close to 0 that implies a weak preference of a over b, the contrary if the value is close to 1; w_j is the weight associated with the j^{th} criteria.

Step 4. Calculation of the outranking flows, positive and negative, using the equations (PROMETHEE I Partial ranking):

$$\Phi^+(a) = \frac{1}{n-1} \sum_{x \in A} \pi(a,x) \tag{13}$$

$$\Phi^-(a) = \frac{1}{n-1} \sum_{x \in A} \pi(x,a) \tag{14}$$

where $\Phi^+(a)$ and $\Phi(a)$ are respectively the positive and negative outranking flows for each of the alternatives. In partial ranking the alternative with a higher value of $\Phi^+(a)$ and the lower value of $\Phi^-(a)$ is the best alternative.

Step 5. Calculation of the net outranking flow, (PROMETHEE II complete ranking), denoted by $\Phi(a)$:

$$\Phi(a) = \Phi^{+}(a) - \Phi^{-}(a) \tag{15}$$

The alternatives can be compared using the values of $\Phi(a)$: the highest value of it denotes the most preferred alternative.

3.4 Weighting

Weighting is an essential phase of the MCDA approach. Weights can be established by involving decision-makers or experts and using an elicitation technique to identify a user-defined subjective set, or by applying an objective weighting process. Although the first strategy is usually recommended, in a complex scenario it can be too difficult to adopt, leading to unsatisfactory results. In some contexts, decision makers may fail to provide consistent numerical judgments about the relative importance or criteria. In other cases, while able, they may be unwilling to do so (Boroushaki 2017). In these scenarios, objective weights can be a solution. In this study, the following widely applied objective weighting methods were used: Information Entropy Weighting (IEW) (Deng et al. 2000; Boroushaki 2017), Coefficient of Variation (COV) (El-Santawy and Ahmed 2012), Mean Weight (MW) (Diakoulaki et al. 1995; Deng et al. 2000), Criteria Importance Through Inter-criteria Correlation (CRITIC) (Diakoulaki et al. 1995; Yilmaz and Harmancioglu 2010), Standard Deviation Method (SDW) (Diakoulaki et al. 1995; Deng et al. 2000) and Statistical Variance Procedure (SVP) (Mohanty and Mahapatra 2014). Moreover, the chosen methods can be divided in two categories. The first category includes the methods that require normalisation of the Vulnerability Matrix (IEW, COV and CRITIC). Notwithstanding the need to normalise the Vulnerability Matrix, the normalization process involves different mathematical approaches and is followed by the application of different mathematical formulae. The second category of methods, on the other hand, do not require the normalisation of the Vulnerability Matrix and use different mathematical approaches to identify the weightings (MW, SDW and SVP). Details about the singular methods computation are provide in the 5..

It was decided to use multiple methods following Zardari et al. (2015), who emphasize that there is no one technique that is inherently superior to the others and therefore it is desirable not to rely on a single method. Following that, the Coefficients of Correlations method (Aldian and Taylor 2005) was used to combine the weightings derived from the various techniques.

The aggregated indicator weights can be derived using the following equations:

$$c_d = \left(\sum\nolimits_{l=1}^{t} e^{r_{dl}}\right) - e^{r_{dl}} \tag{16}$$

And

$$w_d = \frac{c_d}{\sum_{l=1}^{t} c_l} \tag{17}$$

where w_d represent the weight derived from the d technique, t is the number of indicators and r_{dl} is the Coefficient of Correlation between the technique d and l. The exponential value is used to convert all coefficients of correlation into a positive sign, and therefore c_d represents an aggregate measure of the correlation.

The aggregated weights (w_j) are determined by:

$$w_j = \sum_{d=1}^{t} w_d w_{jd} \tag{18}$$

where w_j is the weight of indicator j according to the method d. The aggregated weights w_{jc} have been used in formulas (2), (7), (8), and (12).

4 Results and discussion

4.1 Vulnerability matrix and weights

The vulnerability matrix used for all the methods is reported in Table 4. The codification for the alternatives (Roads 1–6) and criteria is the same as reported in Section 3.1.

Figure 3 provides a graphical representation of weights distribution according to the six methods used, while Table 5 reports the numerical values.

Table 4 Vulnerability matrix

Coastal Roads	Vulnerability Indicators										
	E1	E2	E3	S1	S2	S3	S4	AC1	AC2	AC3	AC4
R1	2	112	4	8	2	1984	27	4913	28	3240	1
R2	1	23	3	9	1	5279	41	16469	107	24721	2
R3	2	20	2	0	4	9786	48	26541	55	8580	1
R4	3	64	1	1	2	1892	53	11634	6	9419	5
R5	2	10	8	6	2	2558	23	24216	6	5647	7
R6	2	9	18	0	2	325	3	3029	16	3405	2

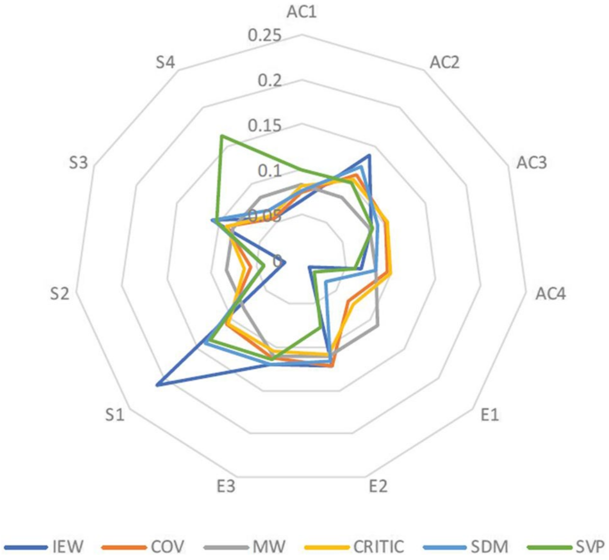


Fig. 3 Radar representation of the weights obtained using the different methods

Table 5 Vulnerability indicator weights calculated using the different methods

		WEIGHTING METHODS					
		IEW	COV	MW	CRITIC	SDM	SVP
Vulnerability Indicator weights	E1	0.01	0.07	0.11	0.07	0.04	0.02
	E2	0.12	0.12	0.11	0.11	0.12	0.08
	E3	0.12	0.11	0.11	0.11	0.12	0.11
	S1	0.21	0.11	0.08	0.11	0.14	0.13
	S2	0.02	0.06	0.08	0.06	0.04	0.04
	S3	0.11	0.09	0.08	0.08	0.11	0.10
	S4	0.06	0.06	0.08	0.06	0.07	0.16
	AC1	0.07	0.07	0.08	0.08	0.08	0.10
	AC2	0.14	0.11	0.08	0.11	0.12	0.10
	AC3	0.08	0.10	0.08	0.10	0.09	0.09
	AC4	0.07	0.10	0.08	0.10	0.08	0.06

Comparing the weights obtained, SVP and SDM produced similar results. Considering them altogether, the criteria belonging to the Adaptive Capacity dimension obtained higher weights than the Sensitivity and Exposure indicator categoriesfor all the methods except for the Information Entropy Method; the same can be said for the Sensitivity indicators weighting in comparison to the Exposure indicator ones. Note the above observations excludes the mean weight method due to the fact that method allocates equal weighting for the Adaptive Capacity, Sensitivity and Exposure dimensions (i.e. 0.333333 for each one).

The combination of the different weights using the Coefficients of Correlation method is reported in Table 6.

The distribution of the weights is not equal across the three vulnerability indicators, and therefore we analysed the results, using the Spearman's Correlation Coefficient to study the level of correlation between the weights produced by the different methods, including the combination of them but excluding the Mean Weight method as it is the only one which does not produce weights which are normally distributed. Analyzing

Table 6 Combined weights for vulnerability indicators

	Vulnerability Indicators		Weights %	
Vulnerability Indicator weights	Exposure	E1	4.93	28.2
		E2	11.69	
		E3	11.53	
	Sensitivity	S1	13.90	34.1
		S2	4.51	
		S3	9.76	
		S4	5.87	
	Adaptive capacity	AC1	8.51	37.8
		AC2	11.76	
		AC3	9.21	
		AC4	8.31	

Table 7 Spearman's Ranking Correlation Coefficient for the objective weighting method

	IEW	COV	CRITIC	SDM	SVP
IEW	1	0.8727	0.9091	0.9909	0.5273
COV		1	0.9727	0.8545	0.1727
CRITIC			1	0.8818	0.2000
SDM				1	0.5727
SVP					1

Table 8 A qualitative summary of the Spearman's Ranking Correlation Coefficient for the objective weighting methods

	IEQ	COV	CRITIC	SDW	SVP
Combined Weightings	0.9818 Very High +	0.8636 High +	0.9000 Very High +	0.9727 Very High +	0.5455 Moderate +

the Spearman's Ranking Correlation Coefficient (Table 7), the weights produced by the different methods have high correlation, except for the SVP method. The same can be said for the correlation between the weights produced by each method and the combined weights (Table 8). According to the results, the combined weight vector reflects more the results produced by IEW, CRITIC and SDM.

4.2 VIKOR results

To provide a full ranking of the vulnerability of the coastal roads using the VIKOR method, first the best and worst values for all criteria were determined. The utility and regret measures were determined for each of the selected coastal roads and finally the three lists of VIKOR ranking were determined (Table 9).

The alternative to choose is the one that minimize Q_i if it meets the conditions C1 and C2, i.e. R2 in this case study. However, condition C1 (Acceptable advantage) was not respected considering the R5 (second best rank according to Q_i). Only condition C2 (Acceptable stability) was satisfied and therefore the set of compromise solutions were used to verify the obtained ranking. Condition C2 was used and the valid ranking was derived (Table 10).

Table 9 Ranking of the climate change vulnerability of coastal roads using VIKOR method

Selected Coastal Roads	S_i	R_i	Q_i	Ranking
R1 Triq il-Bajja is-Sabiħa—Birżebbuġa	0.5934	0.5934	0.5934	5
R2 Triq ix- Xatt—Sliema	0.3808	0.1126	0.1126	1
R3 Triq Marina—Pieta'	0.5520	0.1363	0.7866	4
R4 Triq il-Marfa -Mellieħa	0.6795	0.1211	0.8592	6
R5 Xatt il-Pwales—St Paul's Bay	0.4993	0.0825	0.1984	3
R6 Xatt ta' San Ġorġ—St Julian's	0.4171	0.1363	0.5608	2

Table 10 Valid ranking—Ranking of the climate change vulnerability of coastal roads using VIKOR method

Selected Coastal Roads	S_i	R_i	Q_i	Ranking
R2 Triq ix- Xatt – Sliema	0.3808	0.1126	0.1126	2
R5 Xatt il-Pwales—St Paul's Bay	0.4993	0.0825	0.1984	1

The obtained compromise solution could be accepted because it provides a maximum utility of the majority (represented by min S), and a minimum individual regret of the opponent (represented by min R). This means that the measures S and R are integrated into Q for the compromise solution. In conclusion, R5 (Xatt il-Pwales—St Paul's Bay) was found to be the most vulnerable road, followed by R2 (Triq ix- Xatt – Sliema).

4.3 COPRAS results

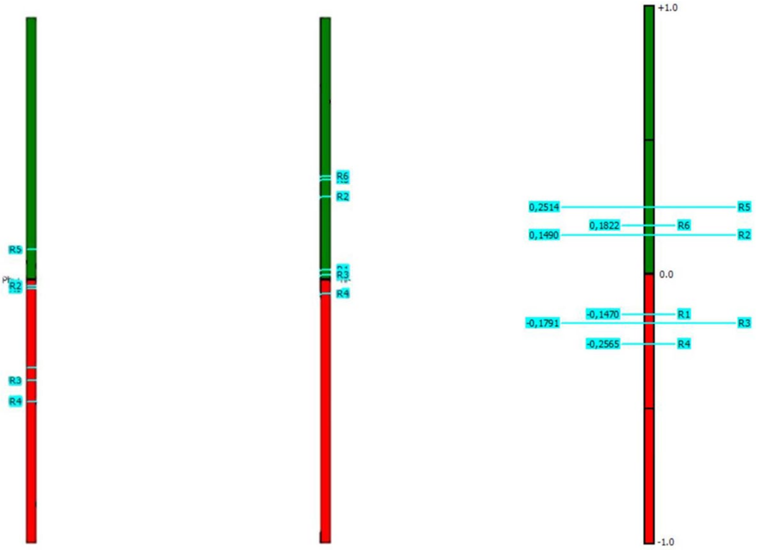
After normalising the Vulnerability Matrix, the weighted normalised matrix was formed, and subsequently the value of every criterion was calculated separately according to the effect it has on the climate change vulnerability on a coastal road. The degree of vulnerability was calculated for each coastal road. Then, the final ranking of the coastal road was derived. The coastal roads with the higher value of $\boldsymbol{U_i}$ are ranked higher, i.e. are more vulnerable. The results are shown in Table 11. In this case the most vulnerable alternative was R6 (Xatt ta' San Ġorġ—St Julian's), which was not included in the VIKOR partial ranking, followed by R2 and R5, which on the contrary were included.

4.4 PROMETHEE results

Figure 4 reports the results of both PROMETHEE I (left) and II (right). In both the graphs the red area indicates lower values (which in this case means less vulnerable roads), while the green area indicates higher ones (more vulnerable roads). Figure 4(a) which represents the partial ranking, is composed of two different lines. The left line represents the positive flow (Φ^+): here R5 is the first option, the only one in the green area, and it outdistances the others options which are grouped in two groups (R6-R2; R1-R3-R4). The right line represents the negative flow (Φ^-): in this flow there are a leading and a trailing group. Roads R6-R5-R2 are the "leading" group (more vulnerable), with very close results in particular between R5 and R6; R1-R3-R4 are the "trailing" group (less vulnerable), with very close performances between R1 and R3 while R4 is the only alternative in the red area.

Table 11 Ranking of the climate change vulnerability of coastal roads using COPRAS method

Selected Coastal Roads	S_i	R_i	Q_i	U_i	Ranking
R1 Triq il-Bajja is-Sabiħa – Birżebbuġa	0.0411	0.1027	0.1179	50.6	5
R2 Triq ix- Xatt – Sliema	0.1373	0.1115	0.2080	89.2	2
R3 Triq Marina—Pieta'	0.0760	0.1060	0.1505	64.6	4
R4 Triq il-Marfa -Mellieħa	0.0334	0.1074	0.1069	45.9	6
R5 Xatt il-Pwales—St Paul's Bay	0.0898	0.0843	0.1835	78.7	3
R6 Xatt ta' San Ġorġ—St Julian's	0.0639	0.0467	0.2331	100.0	1



(a) (b)

Fig. 4 Ranking of (**a**) PROMETHEE I and (**b**) PROMETHEE II results

Figure 4(b) shows the complete ranking produced by the PROMETHEE II. The three first alternatives (R5-R6-R2) are in the green area and the others in the red one. Alternatives R5 and R4, the highest and the lowest, are distant from the other alternatives in each group. Therefore, the PROMETHEE II results show that the three most vulnerable alternatives are the same produced by COPRAS, although not in the same order. Table 12 reports the numerical results for both PROMETHEE I and II.

Looking at the general results, the ranking produced by the three methods applied is not identical. However, the two more vulnerable roads are always the same (R2-R5), which means that there is a certain degree of consensus between the different methods. Moreover, for COPRAS and PROMETHEE there is consensus over three most vulnerable roads (R2-R5-R6), although the ranking is not the same. The similarity in the results obtained despite the diversity of the methods used is a strong point, allowing us to consider the results obtained as reliable. In two out of three ranking R6 is in the second position and R5 in the third one; R2 never duplicates its position. According to both PROMETHEE and

Table 12 PROMETHEE I and II results

	PROMETHEE I		PROMETHEE II
	Φ^+	Φ^-	Φ
R5 Xatt il-Pwales—St Paul's Bay	0.5596	0.3081	0.2514
R6 Xatt ta' San Ġorġ—St Julian's	0.4840	0.3018	0.1822
R2 Triq ix- Xatt—Sliema	0.4887	0.3397	0.1490
R1 Triq il-Bajja is-Sabiħa—Birżebbuġa	0.3334	0.4804	-0.1470
R3 Triq Marina—Pieta'	0.3100	0.4891	-0.1791
R4 Triq il-Marfa -Mellieħa	0.2690	0.5255	-0.2565

COPRAS the three less vulnerable roads are always the same and in the same order (R4—R1- R3 from the less to the most vulnerable), while is not possible to make any consideration with VIKOR because of the incomplete ranking.

Looking back to the different criteria from which the rankings derived, bad and good values in the Exposure dimension seem to affect more the final results than the other dimensions, although it is the dimension with the lower weight, which means that the exposure to climate change is particularly relevant in vulnerability assessment. In particular, all of the three most vulnerable alternatives are simultaneously those that have increasing exposure values to climate change. The performances in the other two dimensions are not so clearly in disfavour of the three most vulnerable alternatives. For instance, alternative R3 shows a higher Sensitivity than R2, however R2 is ranked in the three most vulnerable while R3 is not. The same happens with the Adaptative Capacity, where R2, R5 and R6 have both good and bad performances, without a clear prevalence.

5 Conclusions

With the worsening of climate change consequences, there is an urgency to assess how they can specifically hit different areas. This is particularly true in case of islands which are more vulnerable to the effects of climate changes. Literature has highlighted the great impact of climate change effects on transport in the island context, requiring tools for a better understanding and increased knowledge about the infrastructure vulnerability.

Understanding this vulnerability against climatic conditions is a prerequisite for efficient management. In this paper, we developed an evaluation framework based on the international IPCC vulnerability concept and defined it as a function of Climate Exposure, Sensitivity, and Adaptive Capacity. These dimensions allowed us to model the problem as a MCDA issue, applying three different methods. The application of the model to Malta provided a ranking for the vulnerability of its coastal roads. The results indicated a hierarchy as two of the three methods used in this study pointed to the same three road sections (R2-R5-R6) as being the most vulnerable, even if not always in the same order. Similarly, according to these two methods, the same three roads resulted to be the least vulnerable (R4-R1-R3). Moreover, even for the third method (VIKOR) which produces a partial ranking, the two most vulnerable are R2 and R5. Ultimately, the Exposure dimension seemed to be the one having a significant impact on the results within the Vulnerability framework of this study.

The proposed approach can be applied in any other territorial context to assess the vulnerability of the roads to climate change. The use of a structured framework, built on existing scientific literature and practices, allows for the transferability of the approach. Moreover, MCDA methods are usually applied to decision support issues for their flexibility and capacity to deal with multidimensional problems as has been demonstrated in this case.

There are several ways in which this study could be extended to increase its value for policy and decision makers in Malta, but not only. Extending the study area, including a larger sample of coastal road sections and testing the methods to other islands while incorporating the modelled impacts of climate change could be one area of further development. While this research adopted the IPCC vulnerability framework, other indicators could also be tested, based on a broader engagement with experts and stakeholders.

This study confirmed the usefulness of decisions support systems to direct prevention, protection and recovery policies at the territorial level. The need for prevention, mitigation and adaptation actions in the territory are continuously increasing and most probably will increase even faster, due to the dynamics of the ongoing global climatic crisis. Political, regulatory and operational decisions must be faster, and will necessarily have to take into account the priorities in terms of places where to intervene. Decision support systems such as MCDA will therefore be increasingly useful for decision makers.

There are some limitations of the study which need to be taken into consideration. The number of road sections investigated in this study is limited even though they are indeed roads which represent typical coastal roads in the islands, and the methods applied can be used to handle larger samples. The availability of data for such assessments might also need further development as this might differ from one island to another and is dependent on time and resources to collect and compile. Despite these limitations, the study provides policy and decision-makers with key indications to incorporate in their strategic actions for climate change adaptation, as well as for prioritizing investment according to the vulnerability of the roads.

Appendix I: Weights methods

Information entropy weighting (IEW)

The Information Entropy Weighting method is a measure of uncertainty in the information formulated using probability theory. It indicates that a broad distribution represents more uncertainty than the sharply peaked one (Deng et al. 2000). To calculate the weightings by IEW first the information matrix is normalised then the following equations are used:

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}, i = 1, 2 \ldots m, j = 1, 2 \ldots n \tag{19}$$

$$E_{ij} = -(\frac{\sum_{i=1}^{m} p_{ij} \ln\left(p_{ij}\right)}{\ln(m)}, j = 1, 2 \ldots n \tag{20}$$

$$p_{ij} = \frac{1 - E_j}{\sum_{i=1}^{n} \left(1 - E_j\right)}, j = 1, 2 \ldots n \tag{21}$$

where, x_{ij}= original measured data, E_j= Information Entropy Method and w_j = Entropy method weight.

Coefficient of variation (COV) method

The COV method to allocate the weights to different indicators was first used by El-Santawy and Ahmed (2012). Using the Vulnerability Matrix model indicated above, the COV Method can be summarised as follows:

Step 1. Normalise the Criteria Matrix $\mathrm{V} = \left(\mathrm{x_{ij}}\right)_{\mathrm{mxn}}$ using the Eq. (22):

$$R_{ij} = \frac{x_{ij} - Min\left(x_{ij}\right)}{Max\left(x_{ij}\right) - Min\left(x_{ij}\right)}, i = 1, 2, \ldots, m; j = 1, 2, \ldots n, \tag{22}$$

$D = (r)_{mxn}$ is the matrix after range standardisation; $Max(x_{ij})$ and $Min(x_{ij})$ are the maximum and the minimum values of the criterion (j) respectively; all values in D are $0 \leq r_{ij} \leq 1$.
Step 2. Calculate the Standard Deviation (σ_j) of the normalised matrix $D = (r)_{mxn}$. The Standard Deviation (σ_j) is calculated for every indicator as shown in equation below:

$$\sigma_j = \sqrt{\frac{1}{m}\sum\nolimits_{i=1}^{m}\left(r_{ij} - r_j\right)^2} \tag{23}$$

where r_j is the mean of the values of the j^{th} indicator after the normalization and $j = 1, 2, \ldots n$
Step 3. After calculating the Standard Deviation (σ_j) for all the indicators the COV of indicator j will be calculated as follows

$$CV_j = \frac{\sigma_j}{r_j} \tag{24}$$

Step 4. The weight W_j for each indicator is then calculated using the equation:

$$w_j = \frac{CV_j}{\sum_j^n CV_j} andj = 1, 2, \ldots n, \tag{25}$$

The criteria importance

Through Intercriteria Correlation (CRITIC) Method This CRITIC method was proposed by Diakoulaki et al. (1995) and uses correlation analysis to detect contrasts between indicators. Using the Vulnerability Matrix (1) model the CRITIC Method (Yilmaz and Harmancioglu 2010) can be summarised as follow:

Step 1. Normalise the Vulnerability Matrix $V = \left(xnx_{ij}\right)_m$ using the equation below.

$$r_j = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij,}}, \mathrm{i} = 1, 2 \ldots \mathrm{m}; \mathrm{j} = 1, 2, \ldots \mathrm{n} \tag{26}$$

Step 2. By examining the j^{th} criterion in isolation, we generate a vector rj denoting the scores of all n coastal roads:

$$r_j = (r_{1j,}, r_{2j,\ldots,} r_{nj}) \tag{27}$$

Each vector r_j is characterised by the standard deviation σ_j, which quantifies the contrast intensity of the corresponding indicator. So, the standard deviation of r_j is a measure of the value of that indicator to be considered in the ranking process. Next, a symmetric matrix is constructed, with dimensions mxm and a generic element 1_{jk}, which is the linear correlation coefficient between the vectors r_j and r_k. The more discordant the scores of each coastal road indicator j and k are, the lower is the value 1_{jk}. In this sense, a measure of the conflict created by indicator j with respect to the decision situation defined by the rest of the indicators:

$$\sum\nolimits_{k=1}^{m}\left(1 - l_{jk}\right) \tag{28}$$

The amount of information C_j conveyed by the j^{th} indicator can be determined by composing the measures which quantify the above 2 notions through the multiplicative aggregation formula:

$$C_j = \sigma_j \sum\nolimits_{k=1}^{m} \left(1 - l_{jk}\right) \tag{29}$$

According to the previous analysis, the higher the value C_j is, the larger is the amount of information transmitted by the corresponding indicator and the higher is its relative importance for the ranking process. Objective weights are derived by normalising these values to unity as shown in the equation below:

$$w_j = C_j \left[\sum\nolimits_{k=1}^{m} C_k\right]^{-1} \tag{30}$$

Mean weight (MW) method

The MW method was proposed by Diakoulaki et al. (1995) and Deng et al. (2000). In the MW the weights were derived objectively using the following equation:

$$w_j = \frac{1}{(nc * c)} \tag{31}$$

where nc is the number of indicator categories and c is the number of indicators within the category. This method assumes that indicator categories are of equal importance. The MW is normally used when no expert opinion on the weighting of indicators is sought.

Standard deviation weight (SDW) method

The SDW method was also proposed and used by Diakoulaki et al., (1995) and Deng et al. (2000). The SDW is similar to the IEW method which assigns weights to an indicator if it has similar values across all the coastal roads. The SDW method determines the weights of the 137 indicators in terms of their Standard Deviation through the following equation (Jahan et al. 2012):

$$w_j = \frac{\sigma_j}{\sum_j^n \sigma_j}, andj = 1, 2, \ldots n, \tag{32}$$

$$\sigma_j = \sqrt{\frac{1}{m} \sum\nolimits_{i=1}^{m} \left(x_{ij} - x\prime_j\right)^2} \tag{33}$$

where w_j= weight of indicator and σ_j= standard deviation.

Statistical variance procedure (SVP) method

The SVP method is another method in which objective indicator weightings are derived. The method was used by Mohanty and Mahapatra (2014). Using the Vulnerability Matrix (1) model indicated above SVP method can be summarised as follows:

Step 1. Calculate the statistical variance of information using:

$$SV_j = \left(\frac{1}{n}\right)\sum_{I=1}^{N}\left(x_{ij} - \left(x_{ij}\right)_{mean}\right)^2 \tag{34}$$

SV_j= Statistical Variance.

Step 2. Calculate the objective weight obtained through the following equation:

$$w_j = SV_j\left[\sum_{i=1}^{m} SV_j\right]^{-1} \tag{35}$$

Funding Open access funding provided by Università degli Studi di Perugia within the CRUI-CARE Agreement.

Data availability The author confirms that all data generated or analyzed during this study are included in this published article. Furthermore, primary and secondary sources and data supporting the findings of this study were all publicly available at the time of submission.

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