AN INTEGRATED FRAMEWORK FOR ENVIRONMENTAL MULTI-IMPACT SPATIAL RISK ANALYSIS

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ABSTRACT

Quantitative risk analysis is being extensively employed to support policy makers and provides a strong conceptual framework for evaluating decision alternatives under uncertainty. Many problems involving environmental or health risks are, however, of a spatial nature, i.e. containing spatial impacts, spatial vulnerabilities, and spatial risk-mitigation alternatives. Recent developments in multi-criteria spatial analysis have enabled the assessment and aggregation of multiple impacts, supporting policy makers in spatial evaluation problems. However, recent attempts to conduct spatial multi-criteria risk analysis have generally been weakly conceptualized, without adequate roots in quantitative risk analysis. On the other hand, assessments of spatial risk often neglect the multi-dimensional nature of spatial impacts (for example, social, economic, human) which are typically occurring in such decision problems. The aim of this paper is therefore to suggest a conceptual quantitative framework for environmental multi-criteria spatial risk analysis based on expected multi-attribute utility theory. The framework proposes: i) the formal assessment of multiple spatial impacts; ii) the aggregation of these multiple spatial impacts; iii) the assessment of spatial vulnerabilities and probabilities of occurrence of events; iv) the computation of spatial risks; v) the assessment of spatial risk mitigation alternatives; and vi) the design and comparison of spatial risk-mitigation alternatives (e.g. reductions of vulnerabilities and/or impacts). We illustrate the use of the framework in practice with a case study based on a flood-prone area in Northern Italy.

Key-words: spatial risk, spatial vulnerability, spatial impacts, spatial multi-criteria analysis.

1. INTRODUCTION

Environmental risks, such as climate change, natural hazards, human driven environmental changes, to name the most relevant, pose major challenges for policy and decision-making processes. These challenges encompass both social issues (managing participation and legitimation, ensuring accountability) and technical content, e.g. modelling multiple impacts with different spatial distributions, handling large amounts of heterogeneous data, assessing vulnerabilities, as well as dealing with multiple objectives, long time horizons, value trade-offs and uncertainties.[(1)] These risks often have important spatial impacts, such as the conversion of natural ecosystems into anthropogenic ecosystems (like farmlands, pastures, and plantations), the spread of invasive species, the impoverishment of the agricultural soil, and the increased rate of erosion of coastal land, among many others (e.g. Ager et al.[(2)]; Jongejan and Maaskant[(3)]).

Quantitative risk analysis has been extensively employed in supporting policy and decision makers (*e.g.* Morgan and Henrion[(4)]) and provides a strong conceptual framework for understanding risks and evaluating decision alternatives in decisions under uncertainty. However, the spatial nature of environmental risks creates extra challenges to risk analysts, due to three intrinsic characteristics: (i) the occurrence of multiple impacts with heterogeneous spatial distributions across the territory, (ii) the spatial heterogeneity of the land vulnerability, and (iii) the different spatial consequences of risk-mitigation alternatives. The development of sound analytical frameworks for spatial risk analysis, which may consider such characteristics, is therefore important for supporting decision-making processes when facing environmental spatial risks.

Recent developments in spatial multi-criteria analysis[(1,5)] have enabled the assessment and aggregation of multiple impacts, supporting policy makers in spatial evaluation problems.[(6)] However, despite the relevance of the approach for risk analysis modelling (*e.g.* Jongejan and Maaskant[(3)]; Rucinska[(7)]), recent attempts to conduct spatial multi-criteria risk analysis have so far been poorly conceptualized, without adequate roots in quantitative risk analysis. Despite several applications conducted in different domains (e.g. natural hazards management, health issues, etc.), the criteria they employ are often risk factors with deterministic preference modelling replacing probabilistic information. On the other hand, evaluations of spatial risks have often neglected the multi-dimensional nature of spatial impacts (for example, social, economic, human, such as infrastructure damage, lost lives, lost crops, etc.) which typically occur in such decision problems.[5] In addition, we are not aware of methods in risk analysis that can support the design of alternatives, or the allocation of resources, for spatial risk mitigation.

The aim of this paper is thus to conceptualize a quantitative framework for environmental spatial risk analysis, which considers both the evaluation of vulnerabilities and impacts in this context and the allocation of scarce resources for countermeasures. Such a theoretical framework will enable the assessment of spatial risks, following five main steps: i) the formal assessment of multiple spatial impacts; ii) the aggregation of these multiple spatial impacts; iii) the assessment of spatial vulnerabilities and probabilities of occurrence of events; iv) the aggregation of these three components for the assessment of spatial risks; v) the assessment of spatial risk mitigation alternatives; and vi) the design of spatial risk-mitigation alternatives (e.g. reduction of vulnerabilities and/or impacts) and comparison in terms of their cost per unit of risk-mitigation.

Our main contribution is providing a spatial framework which, at the same time, considers multiple impacts, drawing from the literature on multi-criteria decision analysis[8] and employs a well-established protocol for risk analysis.[4] The reminder of the paper is organized as follows: section 2 presents the findings of the literature review that we conducted on spatial risk analysis and highlights the methodological gap to be addressed; section 3 introduces the integrated framework that we propose; section 4 provides an illustrative example of the practical application of the framework and, finally, section 5 concludes the paper and suggests future developments for the research.

2. SPATIAL RISK ANALYSIS: STATE OF THE ART

There is increasing awareness in the risk and multi-criteria decision analysis communities about the importance of the spatial dimension in environmental risk assessment (*e.g.* Ager et al.[(2)]; Bengtsson and Torneman[(9)]; Jongejan and Maaskant[(3)]). This growing interest promoted the development of risk assessment models in many different areas of application, ranging from landslide susceptibility mapping (*e.g.* Akgun and Turk[(10)]), to seismic hazard evaluation (*e.g.* Anbazhagan et al.[(11)]), flood hazard zoning (*e.g.* Chen et al.[(12)]; Fernández and Lutz[(13)]), health diseases epidemics (*e.g.* Stevens and Pfeiffer[(14)]), fire and phytosanitary risk management for plant species (*e.g.* Pasqualini et al.[(15)]), risk invasion for plant species (*e.g.* Shartell et al.[(16)]), fire risk (*e.g.* Ager et al.[(2)]; Eskandari et al.[(17)]; González-Olabarria et al.[(18)]; Vadrevu et al.[(19)]), earthquake hazards (*e.g.* Armas[(20)]), erosion risk (*e.g.* Altaf et al.[(21)]), ecological risk assessment (*e.g.* Andersen et al.[(22)]; Malekmohammadi et al.[(23)]) and industrial contamination risk (*e.g.* Bengtsson and Torneman[(9)]; Yao et al.[(24)]), to name the most frequent ones.

Spatial Multicriteria Analysis is a tool that has been increasingly used to deal with environmental risk assessments across the different application domains.[(5,25)] The main rationale for integrating spatial analysis (i.e. Geographic Information Systems, GIS) and Multicriteria Decision Analysis (MCDA) in this field is that they have unique capabilities that complement each other, enhancing the effectiveness of the assessment process.[(5)] On one hand, GIS has good capabilities for storing, managing, analysing and visualizing geospatial data required to properly take into account geographical non-homogeneity in the distribution of environmental vulnerabilities and impacts. On the other hand, MCDA offers a rich collection of methodologies for structuring problems with multiple and heterogeneous impacts, enabling the design, evaluation and prioritization of decision alternatives (in this case, risk prioritization measures). However, despite several interesting applications in the environmental risk assessment domain, the field is fragmented and lacks a consistent quantitative framework for the integration of spatial analytics and risk analysis models.

Our analysis of the literature started from the reviews developed by Malczweski[5], and Ferretti[25] , where the existing applications of spatial MCDA have been classified according to the type of problem being analyzed, the context of applications, the analytical approaches being used and the spatial dimension being considered. We thus focused on those applications that have been classified as dealing with risk assessment and we expanded this set of applications with a literature search on spatial risk analysis papers.

Several weaknesses found across applications are worth discussing. Firstly, the type of criteria being used in most of the applications being analyzed are risk factors with deterministic preference modelling often replacing proper probabilistic information (*e.g*. Agostini et al.[26]; Paqualini et al.[15]). Secondly, most of the applications either do not provide information about the type of consequences associated to the event under analysis (*e.g*. Islam et al.[27]) or they take into account a single type of consequence (*e.g*. number of lives lost or damage to infrastructures, Akgun and Turk[10]; Augusto Filho[28]). Thirdly, vulnerability assessment as well as probability of occurrence assessment are rarely included in the models (*e.g*. Anbazhagan et al.[11]; Meyer et al.[29]). Finally, another shared characteristic of the applications of spatial environmental risk analysis found in the literature is the general absence of support provided for the allocation of resources for countermeasures. An interesting exception is the portfolio decision analysis framework for value-focused ecosystem management proposed by Convertino and Valverde.[30]

The findings discussed above highlight the need for a quantitative framework for environmental spatial risk analysis that is able to prescribe how to: i) formally assess multiple spatial consequences; ii) aggregate them; iii) assess spatial vulnerabilities and probabilities of occurrence of events within a proper risk analysis conceptualization and iv) prioritise spatial risk-mitigation alternatives (e.g. reductions of vulnerabilities and/or impacts) in terms of their cost per unit of risk-mitigation. This paper is an attempt to close this gap adopting an expected utility perspective, which encompasses multi-criteria assessments, risk analysis evaluations and portfolio decision analysis formulations.

3. AN INTEGRATED FRAMEWORK FOR ENVIRONMENTAL MULTI-IMPACT SPATIAL RISK ANALYSIS

In this section we suggest a framework for assessing multi-impact spatial risks, based on expected multi-attribute utility theory (MAUT, see Keeney and Raiffa[(31)]). There are many advantages of conducting such analysis employing this theory. Firstly, MAUT has a sound normative basis (see for details Keeney and Raiffa[(31)] and von Winterfeldt and Edwards[(32)]), which recently has been extended to the spatial dimension (see Simon et al.[(33)] and Keller and Simon[(34)]). Secondly, there are well-developed procedures for preference elicitation (see von Winterfeldt and Edwards[(32)]) and probability elicitation (see Keeney and von Winterfeldt[(35)]), albeit not considering a spatial dimension. Thirdly, there is extensive behavioral research on the biases that might affect judgements of experts in such elicitations and how to minimize such biases (see Montibeller and von Winterfeldt[(36)]). Fourthly, such a framework has been employed extensively in Risk Analysis, for assessing different public policies (*e.g*. Morgan and Henrion[(4)]) and risks (Keeney and von Winterfeldt[(37)]). We now detail the methodological steps needed for the development of the adapted framework that we are proposing to deal with environmental spatial risk assessments.

Let each map be discretized into (i,j) cells ($i = 1, 2, \ldots, N_i$; $j = 1, 2, \ldots, N_j$; where N_i and N_j are the number of columns and rows in the map, respectively) . Each cell thus represents a geographical area. We propose to assess three different variables for each ij-th cell: $p_{i,j}$ which measures the probability of occurrence of an adverse event (caused by a threat or hazard) on that ij-th cell; $v_{i,j}$ is an index which measures the area susceptibility to the adverse event as a function of the area's physical characteristics; and $F_{i,j}$ which evaluates the overall dis-utility of adverse impacts on the ij-th cell caused by the event, as shown in the three upper layers of Figure 1.

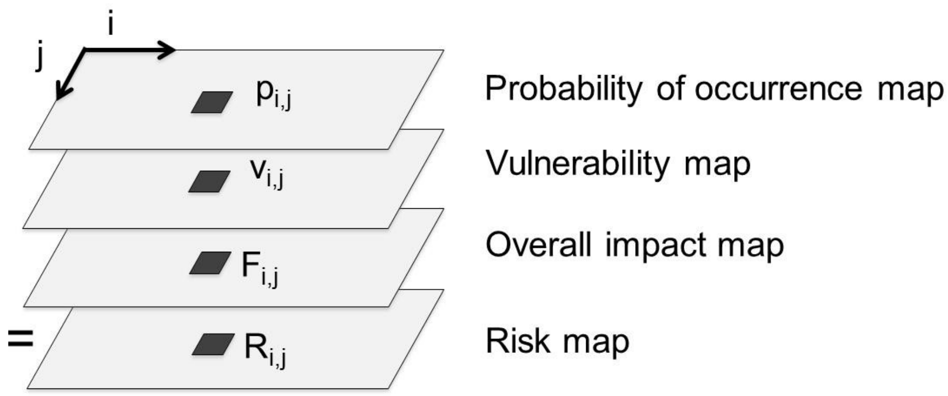

Figure 1 Spatial Risk Map.

For example, in a valley under the risk of flooding, a threat could be heavy rain (precisely defined in terms of volume and precipitation per hour), the vulnerability index would be associated with the relative altitude of the area and permeability of its soil among other physical characteristics, and the probability would be the likelihood of a flood developing in that particular area. If the flooding event hits the cell, the consequences could be for instance socio-economic (e.g. 10 houses flooded and 1,000,000 Euros lost) and environmental (e.g. loss of 0.5 square Km of ecosystem habitat) (for details about flood risks see Baecher(38) and Balica et al.(39)).

While we have tried to be as precise as possible in our definitions of the framework, we do recognize that there are multiple, and often conflicting, definitions of the key variables in risk analysis – particularly regarding vulnerabilities. This is the case both for practitioners, as the extensive review conducted by Balica et al.(39) illustrates, but also by researchers in risk analysis as, for instance, manifested in the debate by Aven(40) and Haimes(41).

3.1. Assessing Adverse Impacts

The overall adverse impact of an event on cell ij is typically multi-dimensional (for example, economic, social, and environmental). Let us consider a set of N_k maps ($k = 1, 2, \ldots, N_k$), each representing a dimension relevant to the problem. Each k-th map is discretized into $x^k_{i,j}$ cells (i =

1, 2, …, N_i ; j = 1, 2, …, N_j), where $x^k_{i,j}$ represents the impact under consideration in the ij-th cell within the range $x_*{}^k{}_{i,j} \leq x^k{}_{i,j} \leq x^{*k}{}_{i,j}$ ($x_*{}^k$ is the worst outcome for the k-th impact and x^{*k} is the best outcome for the same impact). In the flooding risk example, for instance, one impact (k = 1) could be the number of human lives lost in cell ij, e.g., $x_*{}^1{}_{i,j} = 5$ and $x^{*1}{}_{i,j} = 0$; and a second impact (k = 2) the number of square meters of valuable crops destroyed by the event in cell ij , e.g., $x_*{}^2{}_{i,j} = 1{,}000\ m^2$ and $x^{*2}{}_{i,j} = 0\ m^2$.

Each dimension is assessed by a criterion $f^k(.)$ which models the marginal dis-utility for different levels of an adverse impact on the cell ij and is normalized such as: $0 \leq f^k(.) \leq 1$, where $f^k(x^{*k}{}_{i,j}) = 0$ is the dis-utility of the best outcome for the k-th impact and $f^k(x_*{}^k{}_{i,j}) = 1$ is the dis-utility of worst outcome for the k-th impact. The dis-utility function associated with each criterion represents the preferences of policy makers or society considering the adverse impact under consideration (see von Winterfeldt and Edwards[32] for elicitation protocols of utility functions).

The k dimensions are aggregated by a multi-attribute utility function φ, so the overall dis-utility of a cell ij is given by: $F_{i,j} = \varphi\,[f^1(x^1{}_{i,j}), f^2(x^2{}_{i,j}), \ldots, f^{Nk}(x^{Nk}{}_{i,j})]$, as shown in Figure 2.

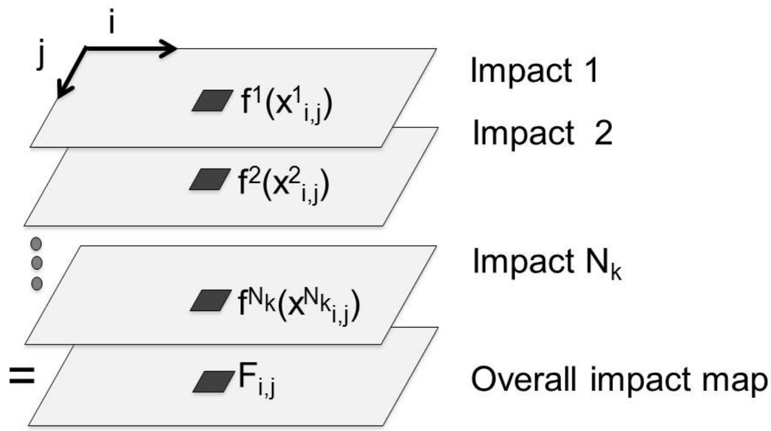

Figure 2 Assessing overall spatial impacts

If strict preference conditions hold (see Keeney and Raiffa[31]), such an aggregation function can be a simple weighted sum, which is often employed in practice in spatial multi-criteria analysis as discussed in Ferretti and Montibeller[1]. In this special case a weight $w^k{}_{ij}$ is associated with each criterion, representing the value trade-offs involved in minimizing the considered impact, given the range of their attributes (see Keeney[42]). The overall dis-utility of a cell ij is calculated then by:

$$F_{ij} = \sum_{k=1}^{N_k} w_{ij}^k \; f^k\left(x_{ij}^k\right) \qquad \text{[Equation 1]}$$

With the weights summing up to one:

$$\sum_{k=1}^{N_k} w_{ij}^k \; = 1 \qquad \text{[Equation 2]}$$

Notice that in this formulation it is possible, if required, to define different weights for different regions of the map, as recently suggested in spatial multi-criteria analysis (see Malczewski[43]).

3.2. Assessing Vulnerabilities and Probabilities of Occurrence

Next we suggest how both spatial vulnerabilities and probabilities of occurrence of an adverse event could be assessed. As in the previous section, let the probability of occurrence map be discretized into ij cells (i = 1, 2, …, N_i; j = 1, 2, …, N_j). The probability of occurrence of the averse event on each ij-th cell is assessed by function p_{ij}, with: $0 \leq p_{i,j} \leq 1$. The first layer in Figure 1 shows graphically such parameter. There are advanced frameworks in Risk Analysis on how to model and simulate the probability of occurrence of spatial threats, such as hurricanes, earthquakes and floods – please, see Michel-Kerjan et al.[44] for a detailed coverage.

In addition, let a vulnerability map be discretized into ij cells (i = 1, 2, …, N_i; j = 1, 2, …, N_j). The vulnerability of each cell ij is assessed by function $v_{i,j}$, an index which measures the area susceptibility to the adverse event as a function of the area's physical characteristics, with: $0 \leq v_{i,j} \leq 1$ (measuring from no vulnerability to maximum vulnerability, respectively). There is an extensive literature on assessing vulnerabilities for some well-known spatial risks, particularly for hurricanes, earthquakes and flooding, and this involves the development of a metric based on multiple indices that represent characteristics of the area at risk (for details see Balica et al.[39]; Michel-Kerjan et al.[44]).

Notice that in engineering practice it is often the case that p(.) and v(.) are assessed as a single parameter, which considers both the probability of the adverse event happening in a given area (e.g. annual probability of a heavy rain occurring) and the vulnerability of this area (e.g. its vulnerability to flooding), for example by calculating directly the annual probability of flooding in that area (see Baecher[(38)]). This mode provides fewer insights into the problem, particularly for designing vulnerability-reduction actions and would not encompass future events that are more severe than the historical records. However, it might be easier to elicit estimates from experts and/or use historical data sets in this way.

The integrated assessment of the spatial probability of occurrence, spatial vulnerability, and dis-utility of spatial impacts leads to the spatial risk map, assessed as:

$$R_{i,j} = p_{ij}\, v_{ij}\, F_{ij} \qquad \text{[Equation 3]}$$

The risk is measured as expected dis-utility, in a similar way as suggested by Keeney and von Winterfeldt[(37)] in the assessments of the risk of a terrorist attack. This spatial risk map is depicted by the bottom layer in Figure 1.

3.3 Evaluating Spatial Options

While the design and choice of spatial alternatives is well-developed in spatial MCDA and risk assessment (see also Malczewski[(5)]), less attention has been paid to the choice of risk mitigating alternatives. However, the comparison and support for choice of risk mitigating alternatives is often required and important in real-world risk analytic interventions.

There are several ways of comparing map profiles (*e.g.* Eastman[(45)]). In our framework we suggest three metrics that can be useful: the mean expected risk (Mean ER), the standard deviation of the expected risk (SD ER), and the overall sum of expected risk (Sum ER) – these are defined next:

$$Mean\ ER(map) = \mu = \frac{\sum_{i=1}^{N_i} \sum_{i=j}^{N_j} R_{ij}}{N_i N_j} \qquad \text{[Equation 4]}$$

$$SD\ ER(map) = \sqrt{\frac{1}{N_i N_j} \sum_{i=1}^{N_i} \sum_{i=j}^{N_j} \left[R_{ij} - \mu\right]^2}$$ [Equation 5]

$$Sum\ ER(map) = \sum_{i=1}^{N_i} \sum_{i=j}^{N_j} R_{ij}$$ [Equation 6]

There are also more advanced approaches to compare maps, for instance, by considering the contiguity of similar cells (e.g. high level risk cells), as Metchebon et al.(46) suggested.

3.4 Designing Spatial Options

There are cases in which policy makers wish to design a spatial risk mitigation alternative, instead of comparing existing proposals. An example of such a task would be flood defenses that are a composition of a layout for a dam coupled with a particular way of raising the river banks. There would be several dam layouts available and many ways of raising the banks, therefore synergies and spatial contiguities between the two components may influence their choice for the best design. Here we suggest a formulation to support such design, based on portfolio decision analysis (see Salo et al.(47)).

There are two possible types of risk mitigation. The first one is impact mitigation, for instance relocating vulnerable populations away from low land near a river to manage flooding risks. In this case, let each ij-th cell have an overall adverse impact F_{ij} and a reduced overall adverse impact F'_{ij}, both measured as dis-utility, if risk mitigation is implemented for this cell, with an associated cost m^F_{ij}. The reduction in overall consequence is defined as: $\Delta^F_{ij} = F_{ij} - F'_{ij}$.

The second type of risk mitigation is the reduction of physical vulnerabilities, whenever this is feasible in practice, for example, building up an up-stream dam to control the flow of a river in an area that is vulnerable to flooding. In this case, let each ij-th cell have a vulnerability v_{ij} and a reduced vulnerability v'_{ij}, if risk mitigation is implemented for this cell, with an associated cost m^v_{ij}. The reduction in vulnerability is defined as: $\Delta^v_{ij} = v_{ij} - v'_{ij}$.

We assume that vulnerabilities can be indeed reduced, which is not always the case as some environmental characteristics cannot be altered. If that is the case, only impact reductions are feasible. Notice that reductions in physical vulnerability might also reduce the adverse impacts in an area and these changes should be included in the analysis of consequences when considering risk mitigating alternatives (such as building an up-stream dam). However reductions in vulnerability do not have an effect on the probability of an adverse event happening, as this is an external natural phenomenon.

The optimal design can then be found with a linear programming model that maximizes the reductions in consequences and vulnerabilities, given a budget B, by minimizing the vulnerabilities while keeping the impacts constant and minimizing the impacts while keeping the vulnerabilities constant. This is represented in the linear programming formulation below with an objective function that maximizes the improvement due to mitigation:

$$Max \sum_{i=1}^{N_i} \sum_{i=j}^{N_j} p_{ij} \left\{ \Delta^v{}_{ij} \, F_{ij} \, z_{ij}^v + v_{ij} \, \Delta^F{}_{ij} \, z_{ij}^F \right\} \qquad \text{[Equation 7]}$$

Which is subject to the mitigation expenditures not exceeding the budget:

$$Max \sum_{i=1}^{N_i} \sum_{i=j}^{N_j} \left\{ m^v{}_{ij} z_{ij}^v + m^F{}_{ij} \, z_{ij}^F \right\} \leq B \qquad \text{with} \qquad z_{ij}^v , z_{ij}^F = \{0,1\}$$

Where z_{ij}^v and z_{ij}^F are binary variables indicating whether mitigation actions will be implemented (one) or not (zero) in each cell in the optimal design. In addition, it is possible to include contingency and synergy constraints, as in standard decision analytic portfolio models. Furthermore, these spatial models would also typically contain contiguity constraints, when mitigating actions for one cell affect adjacent cells.

4. AN ILLUSTRATIVE EXAMPLE

In this section we illustrate the use of the framework in practice with a case study based on a flooding-prone area in Northern Italy[1]. We first provide a description of the decision problem and then illustrate how we could support the evaluation of spatial risk and the choice between two large risk mitigation alternatives employing the framework we explained in Section 3.

4.1 Description of the context under analysis

A severe flooding event affected the region under consideration in 2000, leading to a call for a strategic planning procedure aiming at assessing the risk of flooding in the area and proposing feasible projects for the control and limitation of possible future floods. After the development of socio-economic and environmental feasibility studies by the relevant authorities, two alternative projects have been proposed: the construction of a diversion canal which will redirect excess water to a purpose-built floodway (Alternative 1) and the construction of higher river defenses along the most critical part of the river (Alternative 2).

Drawing from the real physical characteristics of the geographical area under risk of flooding, we build in this section a simplified version of the geographical context under analysis to exemplify the spatial multi impact risk analysis methodological steps. Figures 4 and 5 highlight the key characteristics of the geographical context under analysis.

As displayed in Figure 4, the geographical area under risk of flooding includes six urban areas, most of them on the left side of the river, which have suffered severe infrastructural, social and economic consequences after recent flooding events. Most of the land on the right side of the river is instead used for agricultural purposes, with some areas used for particularly valuable local crops (the orange area in Figure 4). Moreover, two protected natural areas (i.e. one Site of

[1] Due to a confidentiality agreement and the ongoing development of the alternative projects evaluation in the geographical area under analysis, no detailed information can be provided about stakeholders or exact locations of impacts and alternatives.

Community Importance and one Special Protection Zone) are located very close to the central portion of the left side of the river.

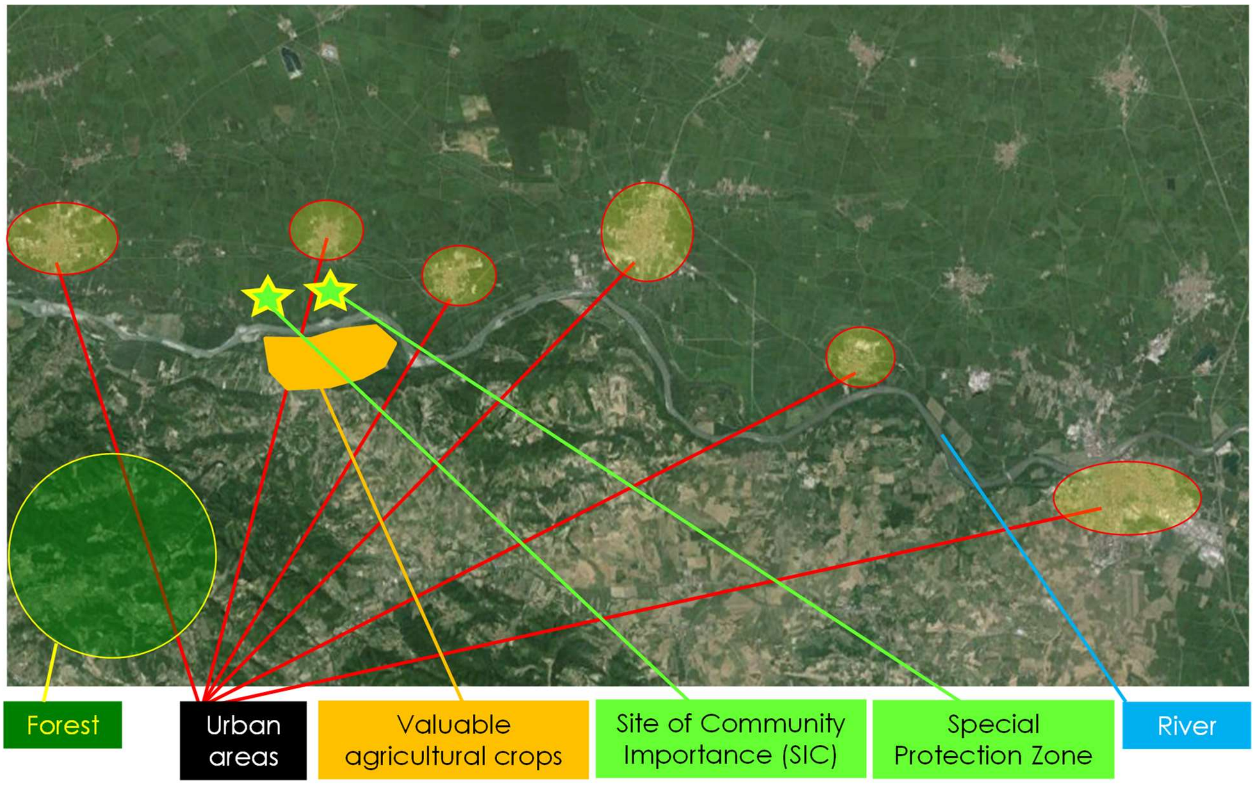

Figure 4. The area under analysis for the illustrative example.

Figure 5 Examples of sensitive elements in the area under analysis (a farm structure on the left and valuable crops on the right)

This geographical area (covering a surface of about 20 km^2) well represents the typical heterogeneity of spatial vulnerabilities and possible spatial consequences associated with a territory under risk of flooding. The area was thus selected to exemplify the framework we proposed in section 3. The map shown in Figure 4 was discretized into 20 by 20 cells, with 400 cells in total, each measuring 1 km^2.

Let us assume that the vulnerability v_{ij} has been assessed for each ij-th cell of the map and normalized as: $0 \leq v_{i,j} \leq 1$, as shown in Figure 6, which is a grid representation of the map in Figure 4. There is an extensive literature on assessing vulnerability for flooding risk (e.g. Chen et al., 2015; Fernández and Lutz, 2010; Karmakar et al., 2010), which is out of the scope of this paper.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0.17	0.16	0.23	0.19	0.20	0.21	0.22	0.23	0.23	0.24	0.24	0.16	0.20	0.19	0.16	0.15	0.23	0.17	0.23	0.25
2	0.24	0.16	0.18	0.16	0.17	0.23	0.15	0.17	0.19	0.17	0.19	0.23	0.24	0.23	0.17	0.20	0.18	0.21	0.16	0.25
3	0.20	0.17	0.15	0.21	0.23	0.17	0.25	0.20	0.21	0.22	0.17	0.23	0.17	0.24	0.17	0.16	0.24	0.19	0.20	0.21
4	0.17	0.21	0.16	0.23	0.19	0.16	0.17	0.16	0.15	0.24	0.18	0.21	0.24	0.16	0.22	0.24	0.20	0.20	0.18	0.21
5	0.46	0.51	0.20	0.53	0.50	0.21	0.55	0.18	0.17	0.20	0.20	0.19	0.19	0.17	0.20	0.22	0.21	0.24	0.50	0.50
6	1.00	0.78	0.78	0.78	0.79	0.81	0.75	0.79	0.81	1.00	0.95	0.96	0.84	0.76	0.81	0.77	0.80	0.85	0.82	0.84
7	0.99	1.00	0.84	0.76	1.00	0.97	0.81	0.81	0.80	1.00	1.00	1.00	0.84	0.78	0.80	0.76	0.77	0.84	0.78	0.80
8	1.00	0.98	0.76	0.95	1.00	1.00	1.00	0.97	0.83	0.99	0.97	0.97	0.84	0.83	0.76	0.78	0.83	0.78	0.84	0.83
9	1.00	0.99	1.00	1.00	1.00	0.96	1.00	1.00	1.00	0.95	0.96	1.00	0.76	0.84	0.83	0.76	0.75	0.81	0.78	0.82
10	1.00	1.00	0.97	0.98	0.96	1.00	0.96	1.00	0.99	0.95	0.99	0.99	0.85	1.00	0.99	0.79	0.76	0.76	0.76	0.75
11	0.98	0.97	1.00	1.00	1.00	1.00	0.99	0.97	0.81	1.00	0.98	1.00	0.97	0.97	0.99	0.78	0.78	0.77	0.78	0.84
12	0.85	0.80	1.00	0.99	1.00	0.97	0.85	0.77	0.84	0.77	1.00	0.98	0.97	0.96	0.96	1.00	0.85	0.85	0.85	0.83
13	0.78	0.84	0.76	0.77	0.78	0.75	0.81	0.78	0.84	0.77	0.98	0.95	1.00	1.00	0.99	0.96	0.96	0.96	0.99	0.99
14	0.80	0.82	0.84	0.77	0.75	0.77	0.82	0.82	0.81	0.83	0.76	1.00	1.00	0.78	0.78	0.98	1.00	1.00	0.96	1.00
15	0.81	0.77	0.76	0.84	0.81	0.81	0.80	0.75	0.50	0.48	0.48	0.85	0.85	0.84	0.49	1.00	0.97	0.95	1.00	0.99
16	0.81	0.85	0.77	0.76	0.84	0.81	0.52	0.51	0.19	0.16	0.23	0.47	0.49	0.51	0.51	0.79	0.83	1.00	1.00	1.00
17	0.54	0.52	0.84	0.80	0.85	0.82	0.55	0.22	0.16	0.18	0.15	0.16	0.15	0.19	0.46	0.50	0.82	1.00	0.96	1.00
18	0.24	0.16	0.46	0.54	0.51	0.54	0.22	0.15	0.17	0.19	0.24	0.20	0.23	0.20	0.18	0.21	0.83	0.80	0.79	0.81
19	0.16	0.21	0.21	0.20	0.21	0.17	0.16	0.20	0.18	0.24	0.20	0.23	0.15	0.24	0.25	0.19	0.17	0.76	0.77	0.80
20	0.23	0.18	0.22	0.23	0.15	0.21	0.16	0.16	0.22	0.22	0.24	0.16	0.18	0.15	0.15	0.22	0.20	0.16	0.24	0.16

vulnerability index
[0.90,1.00]
[0.65,0.90)
[0.40,0.65)
(0.10,0.40)
[0.00,0.10]

Figure 6 Map representing the vulnerability index of each ij-th cell for the illustrative example.[2]

As shown in Figure 6, low lying areas close to the river are more vulnerable to flooding, as well as areas that are heavily built where the soil cannot absorb the heavy rain.

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[2] These categories were created to reflect the policy makers' concerns: they highlight areas with high (black) and low vulnerability (white), thus their narrow ranges of size 0.10 utils; and wider ranges in the intermediate categories, with the second category from the top being wider. The same categories were employed for the other maps that follow.

The probability of occurrence of flooding p_{ij} for a given planning horizon, normalized between 0 and 1, also must be estimated for every ij-th cell, either via historical records and/or expert judgment[4]. For the map in Figure 4, let us assume that the probabilities are given by Figure 7 which provides for each cell the probability that the entire cell is covered by at least 0.2 meters of flood water for at least 1 hour.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0.18	0.15	0.23	0.24	0.22	0.16	0.20	0.25	0.23	0.21	0.16	0.18	0.24	0.16	0.23	0.21	0.20	0.23	0.25	0.16
2	0.23	0.20	0.23	0.24	0.18	0.16	0.21	0.19	0.21	0.19	0.25	0.22	0.16	0.24	0.24	0.23	0.19	0.22	0.21	0.16
3	0.23	0.22	0.19	0.19	0.20	0.16	0.20	0.19	0.22	0.25	0.15	0.19	0.19	0.16	0.20	0.15	0.24	0.19	0.18	0.17
4	0.20	0.20	0.16	0.18	0.17	0.82	0.19	0.17	0.16	0.20	0.18	0.21	0.22	0.18	0.22	0.19	0.21	0.21	0.18	0.24
5	0.76	0.24	0.17	0.76	0.81	0.78	0.19	0.16	0.77	0.82	0.83	0.16	0.25	0.16	0.22	0.24	0.22	0.17	0.19	0.16
6	0.76	0.77	0.76	0.78	0.80	1.00	0.76	0.82	0.78	0.84	0.84	0.19	0.19	0.16	0.24	0.19	0.21	0.21	0.24	0.20
7	0.96	0.78	0.80	1.00	0.97	0.98	0.80	0.83	1.00	0.99	1.00	0.21	0.20	0.83	0.78	0.23	0.21	0.19	0.24	0.21
8	1.00	0.98	1.00	1.00	0.99	0.95	0.95	1.00	1.00	1.00	1.00	0.84	0.79	0.79	0.84	0.83	0.19	0.19	0.16	0.20
9	1.00	0.99	0.99	1.00	0.99	1.00	1.00	0.99	0.99	1.00	1.00	0.84	0.84	0.98	0.97	0.75	0.80	0.81	0.77	0.78
10	0.99	0.98	1.00	1.00	0.97	0.97	0.95	1.00	1.00	1.00	1.00	1.00	0.76	1.00	0.97	0.98	0.78	0.79	0.78	0.83
11	0.95	0.96	1.00	0.95	1.00	1.00	1.00	1.00	0.98	0.96	0.95	0.97	1.00	1.00	0.98	1.00	1.00	1.00	1.00	0.98
12	0.99	1.00	1.00	1.00	0.98	0.95	0.97	1.00	1.00	1.00	0.99	1.00	1.00	0.97	1.00	0.98	0.99	1.00	0.99	0.96
13	0.80	1.00	0.96	0.98	0.83	0.78	0.95	0.97	0.81	0.76	1.00	1.00	1.00	1.00	0.98	1.00	1.00	1.00	0.98	1.00
14	0.82	0.79	0.77	0.83	0.80	0.79	0.83	0.82	0.78	0.85	0.96	0.96	0.96	1.00	1.00	1.00	1.00	0.97	0.98	0.99
15	0.00	0.82	0.76	0.78	0.79	0.84	0.83	0.81	0.46	0.49	0.78	1.00	1.00	0.96	1.00	0.98	1.00	1.00	1.00	1.00
16	0.03	0.05	0.01	0.04	0.03	0.01	0.50	0.53	0.15	0.24	0.75	1.00	1.00	0.75	0.84	0.98	0.98	1.00	0.97	0.99
17	0.04	0.04	0.04	0.01	0.03	0.03	0.53	0.22	0.19	0.22	0.23	0.84	0.78	0.79	0.77	0.84	0.97	1.00	0.83	0.77
18	0.02	0.04	0.02	0.01	0.00	0.05	0.17	0.17	0.17	0.19	0.17	0.76	0.77	0.22	0.20	0.76	0.75	0.82	0.82	0.78
19	0.03	0.01	0.04	0.04	0.02	0.04	0.20	0.20	0.18	0.16	0.24	0.21	0.21	0.17	0.24	0.19	0.83	0.77	0.21	0.18
20	0.02	0.01	0.01	0.02	0.02	0.01	0.18	0.24	0.25	0.15	0.21	0.19	0.24	0.17	0.17	0.19	0.23	0.24	0.21	0.22

probability
[0.90,1.00]
[0.65,0.90)
[0.40,0.65)
(0.10,0.40)
[0.00,0.10]

Figure 7 Map representing the probability of flooding occurrence for the illustrative example.

Although flooding risk may generate multiple impacts, in this example we assume the presence of only two types of impacts, which are assessed for each cell, i.e. socio-economic impact x^{SE}_{ij} and environmental impacts x^{EN}_{ij}. For each impact a utility function assesses the preferences of decision makers, $f^{SE}(x^{SE}_{ij})$ and $f^{EN}(x^{EN}_{ij})$, respectively, and is normalized between 1 (maximum dis-utility) and 0 (minimum dis-utility). Figure 8 shows the two impacts if flooding occurs and no mitigation measures are implemented in the area.

We assume that the preference conditions for a simple weighted aggregation are fulfilled (see Keeney and Raiffa[31]), including the ones for spatial dimensions (see Simon et al.[33] and Keller and Simon[34]), so the overall impact is calculated by Eq.1 : $F_{ij} = w_{SE}\, f^{SE}(x^{SE}_{ij}) + w_{EN}\, f^{EN}(x^{EN}_{ij})$.

The parameters w_{SE} and w_{EN} are the criteria weights (with $w_{SE} + w_{EN} = 1$ from Eq. 2) and represent value trade-offs (see Keeney[42] for details). We assume that the same weights are used to assess impacts for all cells in the map.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0.05	0.01	0.03	0.04	0.01	0.01	0.01	0.02	0.03	0.04	0.01	0.02	0.02	0.03	0.03	0.01	0.03	0.02	0.02	0.02
2	0.03	0.05	0.01	0.02	0.05	0.03	0.03	0.02	0.01	0.02	0.04	0.04	0.02	0.00	0.02	0.02	0.02	0.05	0.04	0.00
3	0.22	0.18	0.25	0.24	0.23	0.24	0.20	0.20	0.21	0.17	0.19	0.18	0.16	0.25	0.21	0.21	0.19	0.17	0.22	0.25
4	0.18	0.19	0.22	0.17	0.21	0.22	0.18	0.22	0.24	0.22	0.16	0.23	0.18	0.24	0.16	0.20	0.23	0.20	0.21	0.19
5	0.79	0.77	0.83	0.23	0.22	0.19	0.22	0.22	0.82	0.83	0.84	0.78	0.78	0.16	0.22	0.20	0.19	0.21	0.24	0.21
6	1.00	1.00	0.80	0.84	0.82	0.80	0.82	0.22	0.76	0.97	0.99	0.99	0.77	0.21	0.22	0.15	0.22	0.15	0.23	0.17
7	1.00	1.00	0.78	0.81	0.98	0.95	0.83	0.84	0.83	1.00	1.00	0.99	0.80	0.24	0.21	0.20	0.16	0.16	0.23	0.17
8	0.95	0.98	0.83	0.83	0.96	1.00	0.97	1.00	0.80	1.00	1.00	1.00	0.82	0.21	0.15	0.20	0.17	0.21	0.15	0.21
9	1.00	1.00	0.83	0.78	0.82	0.83	0.97	1.00	0.79	0.78	0.81	0.81	0.84	0.78	0.80	0.84	0.25	0.23	0.19	0.21
10	0.83	0.77	0.81	0.76	0.83	0.80	0.82	0.76	0.84	0.52	0.53	0.50	0.75	0.95	1.00	0.81	0.24	0.19	0.17	0.22
11	0.24	0.18	0.16	0.83	0.77	0.85	0.81	0.53	0.47	0.55	0.53	0.51	0.76	1.00	0.99	0.82	0.16	0.18	0.23	0.16
12	0.18	0.19	0.21	0.79	0.78	0.77	0.84	0.50	0.55	0.51	0.47	0.49	0.81	0.97	1.00	0.76	0.22	0.22	0.16	0.20
13	0.17	0.20	0.24	0.78	0.82	0.78	0.79	0.46	0.52	0.52	0.46	0.49	0.77	0.81	0.83	0.84	0.78	0.77	0.75	0.79
14	0.18	0.22	0.17	0.52	0.52	0.51	0.51	0.46	0.53	0.53	0.45	0.53	0.49	0.45	0.47	0.51	0.80	0.97	1.00	0.99
15	0.20	0.16	0.18	0.53	0.47	0.48	0.46	0.49	0.52	0.52	0.50	0.50	0.49	0.49	0.53	0.49	0.77	1.00	0.97	1.00
16	0.17	0.16	0.21	0.51	0.46	0.54	0.49	0.47	0.50	0.48	0.49	0.50	0.47	0.50	0.52	0.47	0.77	1.00	0.98	1.00
17	0.23	0.24	0.24	0.50	0.48	0.54	0.53	0.52	0.45	0.51	0.54	0.48	0.47	0.49	0.52	0.53	0.81	1.00	0.95	0.99
18	0.17	0.18	0.17	0.21	0.24	0.20	0.22	0.17	0.18	0.21	0.18	0.24	0.55	0.50	0.54	0.54	0.75	0.77	0.78	0.80
19	0.02	0.02	0.03	0.00	0.02	0.02	0.03	0.01	0.03	0.02	0.04	0.04	0.46	0.51	0.54	0.53	0.52	0.53	0.52	0.50
20	0.03	0.00	0.03	0.04	0.03	0.02	0.04	0.04	0.04	0.03	0.03	0.03	0.45	0.52	0.52	0.45	0.52	0.51	0.55	0.46

a) Socio-economic impact index [dis-utility]

	[0.90,1.00]
	[0.65,0.90)
	[0.40,0.65)
	(0.10,0.40)
	[0.00,0.10]

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0.83	0.84	0.82	0.79	0.84	0.83	0.78	0.79	0.77	0.85	0.77	0.80	0.75	0.78	0.77	0.85	0.81	0.83	0.78	0.83
2	0.83	0.77	0.79	0.76	0.76	0.84	0.79	0.83	0.81	0.80	0.83	0.81	0.80	0.85	0.81	0.78	0.81	0.81	0.79	0.80
3	0.79	0.78	0.77	0.84	0.77	0.80	0.80	0.79	0.84	0.81	0.80	0.79	0.79	0.85	0.82	0.84	0.83	0.75	0.80	0.84
4	0.83	0.82	0.84	0.85	0.81	0.79	0.81	0.78	0.76	0.84	0.82	0.84	0.78	0.81	0.79	0.76	0.84	0.77	0.83	0.78
5	0.85	0.78	0.84	0.81	0.77	0.77	0.82	0.79	0.84	0.84	0.84	0.77	0.83	0.75	0.81	0.83	0.77	0.77	0.83	0.85
6	0.78	0.84	0.84	0.84	0.83	0.80	0.79	0.81	0.77	0.76	0.01	0.76	0.81	0.78	0.82	0.84	0.80	0.82	0.80	0.81
7	0.02	0.80	0.76	0.84	0.02	0.04	0.83	0.81	0.84	0.78	0.05	0.78	0.80	0.80	0.82	0.79	0.83	0.77	0.78	0.76
8	0.02	0.82	0.97	0.97	0.96	0.97	0.04	0.01	0.84	0.78	0.05	0.81	0.80	0.75	0.82	0.80	0.76	0.79	0.77	0.84
9	1.00	1.00	1.00	0.97	1.00	1.00	0.03	0.01	0.98	0.96	1.00	0.76	0.83	0.76	0.83	0.83	0.83	0.75	0.85	0.77
10	0.95	1.00	1.00	0.99	0.97	1.00	0.99	1.00	1.00	0.98	0.96	0.83	0.75	0.04	0.02	0.77	0.83	0.82	0.80	0.81
11	1.00	0.97	0.97	0.96	0.97	0.98	1.00	1.00	0.77	1.00	1.00	1.00	0.97	1.00	0.97	0.83	0.76	0.82	0.79	0.76
12	0.80	0.82	1.00	0.98	1.00	1.00	0.79	0.81	0.78	0.75	1.00	0.96	0.95	1.00	0.97	1.00	0.80	0.85	0.76	0.84
13	0.76	0.81	0.76	0.81	0.84	0.79	0.76	0.79	0.81	0.75	0.97	0.99	1.00	1.00	1.00	0.97	0.99	1.00	0.98	1.00
14	0.78	0.78	1.00	0.97	0.96	0.80	0.77	0.80	0.81	0.84	0.80	1.00	0.99	0.81	0.81	1.00	1.00	1.00	0.98	0.97
15	0.97	0.95	1.00	1.00	0.97	0.83	0.83	0.84	0.83	0.75	0.83	0.85	0.80	0.83	0.75	0.99	0.99	0.97	0.05	0.00
16	1.00	0.96	0.95	0.99	0.99	1.00	0.84	0.81	0.80	0.83	0.80	0.81	0.79	0.83	0.80	0.82	0.78	0.77	0.04	0.01
17	1.00	0.96	1.00	0.95	1.00	0.97	0.77	0.79	0.84	0.85	0.78	0.77	0.83	0.81	0.81	0.76	0.81	0.82	0.85	0.77
18	0.99	0.99	1.00	0.98	1.00	1.00	0.80	0.82	1.00	1.00	0.81	0.85	0.84	0.82	0.78	0.82	0.85	0.80	0.83	0.77
19	0.97	1.00	1.00	1.00	1.00	0.96	0.82	0.81	0.98	1.00	0.96	0.81	0.83	0.83	0.78	0.82	0.82	0.79	0.81	0.83
20	1.00	0.98	0.99	0.99	0.98	1.00	0.80	1.00	1.00	1.00	0.99	0.98	0.77	0.78	0.79	0.84	0.85	0.80	0.76	0.79

b) Environmental impact index [dis-utility]

	[0.90,1.00]
	[0.65,0.90)
	[0.40,0.65)
	(0.10,0.40)
	[0.00,0.10]

Figure 8 Socio-economic and environmental impacts for the case without mitigation measures in the illustrative example

As shown in Figure 8a, the main socio-economic impacts happen in the cities and their surroundings as well as in the valuable farmland. On the other hand (Figure 8b), the main environmental impacts affect the forest area and the lowlands by the river.

The risk map $R_{ij} = p_{ij}\, v_{ij}\, F_{ij}$ [Eq. 3] is shown in Figure 9 for $w_{SE} = w_{EN} = 0.5$. The figure also shows the Mean Expected Risk (Mean ER) [Eq. 4], Standard Deviation of the Expected Risk (SE ER) [Eq. 5] and the Sum of Expected Risks (Sum ER) [Eq. 6].

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0.01	0.01	0.02	0.02	0.02	0.01	0.02	0.02	0.02	0.02	0.01	0.01	0.02	0.01	0.01	0.01	0.02	0.02	0.02	0.02
2	0.02	0.01	0.02	0.02	0.01	0.02	0.01	0.01	0.02	0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.01	0.02	0.01	0.02
3	0.02	0.02	0.01	0.02	0.02	0.01	0.03	0.02	0.02	0.03	0.01	0.02	0.02	0.02	0.02	0.01	0.03	0.02	0.02	0.02
4	0.02	0.02	0.01	0.02	0.02	0.07	0.02	0.01	0.01	0.03	0.02	0.02	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.02
5	0.29	0.09	0.03	0.21	0.20	0.08	0.05	0.01	0.11	0.14	0.14	0.02	0.04	0.01	0.02	0.03	0.02	0.02	0.05	0.04
6	0.68	0.55	0.49	0.51	0.52	0.65	0.46	0.34	0.48	0.73	0.40	0.16	0.12	0.06	0.10	0.07	0.08	0.09	0.10	0.08
7	0.48	0.70	0.52	0.63	0.48	0.47	0.54	0.56	0.67	0.88	0.52	0.19	0.13	0.33	0.32	0.09	0.08	0.07	0.10	0.08
8	0.49	0.87	0.68	0.86	0.95	0.94	0.48	0.49	0.68	0.88	0.50	0.74	0.53	0.32	0.31	0.32	0.07	0.07	0.06	0.09
9	1.00	0.98	0.91	0.88	0.90	0.88	0.50	0.50	0.87	0.82	0.87	0.66	0.53	0.64	0.65	0.48	0.32	0.32	0.31	0.31
10	0.88	0.87	0.88	0.86	0.84	0.88	0.83	0.88	0.91	0.71	0.74	0.66	0.48	0.49	0.49	0.61	0.31	0.30	0.29	0.32
11	0.58	0.54	0.56	0.85	0.87	0.91	0.90	0.74	0.50	0.75	0.71	0.73	0.84	0.97	0.96	0.65	0.36	0.38	0.40	0.38
12	0.41	0.40	0.61	0.88	0.87	0.82	0.67	0.50	0.56	0.48	0.73	0.71	0.85	0.92	0.95	0.86	0.43	0.46	0.39	0.42
13	0.29	0.43	0.37	0.60	0.54	0.46	0.60	0.47	0.45	0.37	0.70	0.70	0.89	0.90	0.89	0.87	0.85	0.85	0.85	0.88
14	0.32	0.33	0.38	0.48	0.44	0.40	0.43	0.42	0.43	0.48	0.46	0.73	0.71	0.49	0.50	0.74	0.90	0.95	0.93	0.97
15	0.00	0.35	0.34	0.50	0.46	0.45	0.43	0.41	0.16	0.15	0.25	0.57	0.54	0.53	0.31	0.73	0.85	0.94	0.51	0.50
16	0.01	0.02	0.00	0.03	0.02	0.01	0.17	0.17	0.02	0.03	0.11	0.31	0.31	0.26	0.28	0.50	0.63	0.88	0.50	0.50
17	0.01	0.01	0.02	0.01	0.02	0.02	0.19	0.03	0.02	0.03	0.02	0.08	0.08	0.10	0.24	0.27	0.65	0.91	0.71	0.68
18	0.00	0.00	0.00	0.00	0.00	0.02	0.02	0.01	0.02	0.02	0.02	0.08	0.12	0.03	0.02	0.11	0.50	0.52	0.52	0.50
19	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.03	0.04	0.02	0.09	0.39	0.11	0.10
20	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.03	0.02	0.03	0.02	0.03	0.02	0.02	0.03	0.03	0.03	0.03	0.02

Criteria Weights

Socio-Econ =	50%
Environm =	50%

Statistics

Mean ER =	0.318
SD ER =	0.321
Sum ER =	127.074

Risk Index

	[0.90,1.00]
	[0.65,0.90)
	[0.40,0.65)
	(0.10,0.40)
	[0.00,0.10]

Figure 9 Spatial risk map for the case without mitigation measures in the illustrative example.

4.2 Comparing Alternatives for Risk Mitigation

As anticipated in the description of the decision context, two alternatives are under consideration for the mitigation of the risk of flooding in the area: a diversion canal and higher river defenses (Figure 10). The first project consists of the creation of a diversion canal which will redirect excess water to a purpose-built floodway (this is represented by the transparent grey shape on both sides of the river in Figure 10). The estimated cost of this alternative was 21 million Euros.

The second project under consideration for the control of possible future flooding events in the area consists in the construction of higher river defenses along the most critical part of the river (colored in white in Figure 10). The estimated cost of this second alternative was 32 million Euros.

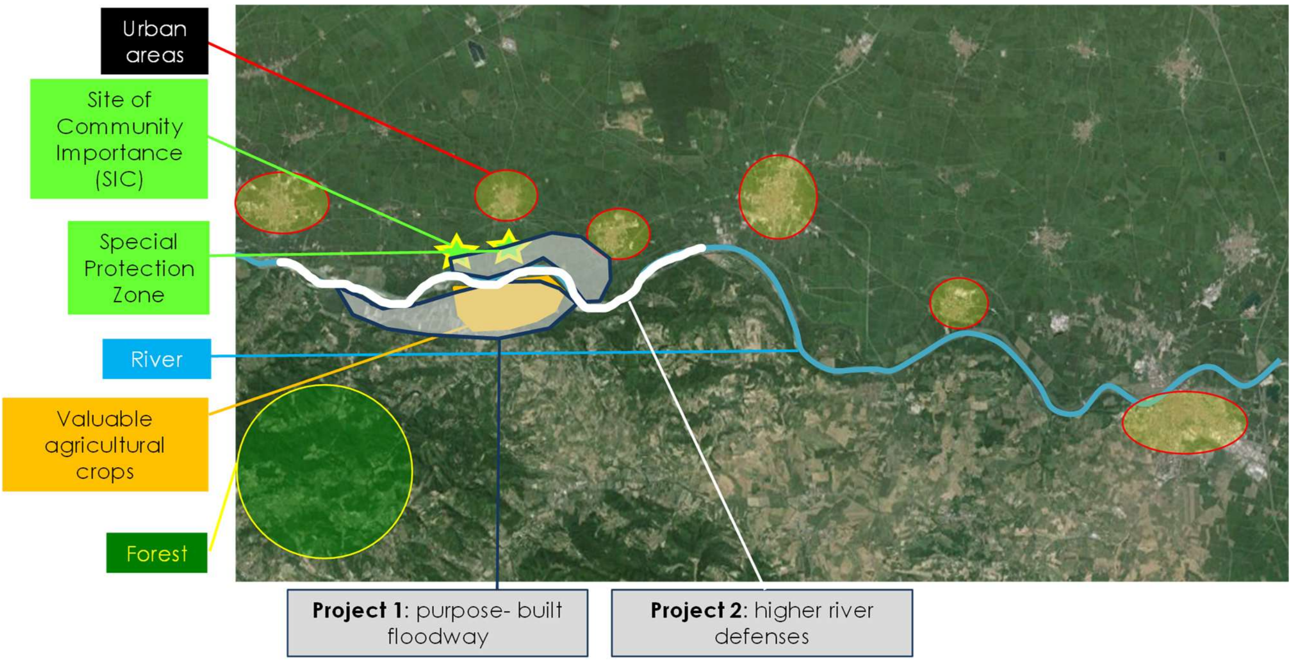


Figure 10 Locations of projects 1 and 2 within the geographical area under analysis.

The impact maps for Alternative 1 are shown in Figure 11. As Figure 11a shows, alternative 1 allows a significant reduction of the socio-economic impacts from the diversion canal downwards, because all excess water will be collected in the purpose-built floodway. However, the environmental impacts increase upstream up to the end of the diversion canal (Figure 11b) because the excavation works needed to create the purpose-built floodway will destroy the natural habitat of the local flora and fauna.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0.00	0.01	0.04	0.02	0.01	0.02	0.02	0.00	0.05	0.05	0.01	0.01	0.04	0.03	0.03	0.01	0.04	0.02	0.00	0.01
2	0.04	0.04	0.02	0.01	0.00	0.01	0.03	0.04	0.05	0.04	0.01	0.03	0.01	0.03	0.02	0.04	0.02	0.00	0.02	0.01
3	0.01	0.02	0.00	0.03	0.04	0.03	0.05	0.03	0.03	0.02	0.02	0.02	0.04	0.01	0.05	0.01	0.01	0.01	0.03	0.00
4	0.01	0.00	0.00	0.01	0.01	0.02	0.01	0.05	0.03	0.04	0.05	0.02	0.01	0.04	0.01	0.05	0.01	0.02	0.03	0.02
5	0.76	0.84	0.80	0.15	0.17	0.20	0.15	0.20	0.24	0.24	0.15	0.16	0.17	0.22	0.17	0.24	0.18	0.17	0.22	0.16
6	0.97	1.00	0.80	0.19	0.23	0.20	0.21	0.23	0.17	0.51	0.46	0.50	0.18	0.22	0.15	0.20	0.20	0.20	0.22	0.20
7	0.98	1.00	0.81	0.81	0.79	0.79	0.55	0.45	0.54	0.47	0.46	0.54	0.21	0.23	0.21	0.18	0.16	0.16	0.18	0.19
8	0.99	0.99	0.79	0.85	0.77	0.80	0.83	0.83	0.55	0.49	0.51	0.54	0.23	0.22	0.17	0.15	0.22	0.18	0.20	0.22
9	1.00	0.96	0.80	0.83	0.46	0.50	0.80	0.76	0.48	0.52	0.45	0.46	0.16	0.23	0.25	0.24	0.20	0.19	0.19	0.18
10	0.84	0.79	0.77	0.78	0.51	0.55	0.47	0.78	0.54	0.48	0.52	0.47	0.15	0.55	0.49	0.20	0.18	0.21	0.18	0.19
11	0.23	0.19	0.19	0.51	0.47	0.49	0.50	0.46	0.53	0.47	0.47	0.54	0.16	0.52	0.48	0.20	0.18	0.21	0.20	0.17
12	0.20	0.25	0.18	0.48	0.52	0.50	0.48	0.24	0.16	0.17	0.50	0.46	0.20	0.48	0.54	0.24	0.17	0.17	0.17	0.19
13	0.17	0.17	0.22	0.23	0.16	0.16	0.23	0.24	0.21	0.23	0.24	0.19	0.15	0.20	0.24	0.19	0.20	0.22	0.23	0.20
14	0.24	0.18	0.18	0.21	0.24	0.16	0.21	0.20	0.16	0.22	0.18	0.18	0.23	0.21	0.22	0.17	0.22	0.54	0.49	0.52
15	0.18	0.22	0.24	0.23	0.20	0.21	0.16	0.15	0.23	0.23	0.17	0.22	0.18	0.17	0.20	0.16	0.20	0.48	0.54	0.53
16	0.15	0.15	0.15	0.19	0.20	0.23	0.18	0.17	0.21	0.16	0.20	0.23	0.18	0.19	0.25	0.23	0.17	0.50	0.53	0.53
17	0.15	0.20	0.18	0.18	0.18	0.24	0.17	0.19	0.24	0.15	0.19	0.18	0.19	0.21	0.25	0.17	0.24	0.48	0.53	0.54
18	0.18	0.16	0.18	0.19	0.23	0.23	0.20	0.23	0.23	0.19	0.16	0.25	0.20	0.15	0.20	0.23	0.16	0.19	0.17	0.21
19	0.04	0.04	0.00	0.02	0.04	0.04	0.04	0.03	0.02	0.04	0.01	0.03	0.02	0.04	0.01	0.03	0.03	0.00	0.01	0.01
20	0.04	0.00	0.04	0.03	0.02	0.04	0.01	0.00	0.04	0.05	0.00	0.02	0.04	0.04	0.00	0.02	0.01	0.05	0.00	0.04

a) Socio-economic impact index [dis-utility]

	[0.90,1.00]
	[0.65,0.90)
	[0.40,0.65)
	(0.10,0.40)
	[0.00,0.10]

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0.79	0.81	0.82	0.82	0.82	0.79	0.83	0.02	0.02	0.03	0.05	0.00	0.05	0.01	0.03	0.03	0.04	0.01	0.03	0.04
2	0.80	0.84	0.80	0.83	0.79	0.77	0.84	0.01	0.02	0.02	0.05	0.02	0.03	0.04	0.02	0.02	0.01	0.05	0.03	0.03
3	0.76	0.80	0.84	0.85	0.79	0.16	0.24	0.03	0.04	0.05	0.05	0.04	0.04	0.01	0.04	0.04	0.02	0.05	0.03	0.00
4	0.79	0.81	0.81	0.82	0.48	0.22	0.02	0.00	0.00	0.04	0.04	0.04	0.05	0.01	0.04	0.03	0.00	0.03	0.04	0.01
5	0.79	0.80	0.76	0.78	0.52	0.24	0.01	0.03	0.00	0.04	0.03	0.02	0.01	0.00	0.01	0.03	0.04	0.02	0.04	0.01
6	0.84	0.78	0.83	0.52	0.46	0.15	0.19	0.22	0.18	0.18	0.18	0.20	0.19	0.02	0.03	0.01	0.02	0.03	0.04	0.04
7	0.00	0.83	0.83	0.50	0.05	0.05	0.19	0.18	0.20	0.23	0.16	0.21	0.17	0.04	0.00	0.04	0.01	0.00	0.01	0.04
8	0.03	0.84	0.76	0.95	1.00	0.98	0.00	0.04	0.24	0.23	0.20	0.18	0.21	0.25	0.17	0.20	0.19	0.23	0.22	0.24
9	1.00	0.99	0.96	1.00	1.00	0.98	0.01	0.03	0.47	0.46	0.45	0.17	0.22	0.19	0.15	0.16	0.19	0.24	0.24	0.16
10	1.00	1.00	1.00	1.00	0.98	1.00	1.00	0.49	0.49	0.51	0.48	0.22	0.16	0.03	0.04	0.20	0.20	0.21	0.19	0.20
11	1.00	1.00	1.00	0.96	0.99	0.99	1.00	0.48	0.17	0.50	0.46	0.49	0.53	0.51	0.52	0.23	0.18	0.19	0.17	0.20
12	0.75	0.81	0.98	1.00	1.00	1.00	0.21	0.23	0.25	0.16	0.53	0.48	0.48	0.47	0.52	0.46	0.16	0.15	0.17	0.22
13	0.82	0.83	0.81	0.80	0.82	0.76	0.17	0.21	0.20	0.25	0.54	0.53	0.52	0.46	0.45	0.55	0.46	0.52	0.49	0.46
14	0.81	0.78	0.77	0.83	0.77	0.80	0.20	0.19	0.18	0.23	0.22	0.51	0.52	0.23	0.19	0.46	0.49	0.49	0.49	0.46
15	0.78	0.85	0.81	0.78	0.85	0.76	0.20	0.23	0.19	0.24	0.16	0.25	0.24	0.25	0.19	0.49	0.53	0.53	0.01	0.00
16	0.85	0.76	0.83	0.78	0.76	0.76	0.20	0.17	0.19	0.21	0.22	0.22	0.15	0.18	0.17	0.18	0.16	0.15	0.03	0.01
17	0.82	0.75	0.78	0.84	0.80	0.79	0.18	0.02	0.00	0.04	0.01	0.03	0.01	0.03	0.04	0.03	0.04	0.00	0.00	0.04
18	0.77	0.84	0.76	0.75	0.82	0.84	0.22	0.02	0.03	0.02	0.00	0.02	0.01	0.04	0.02	0.02	0.02	0.03	0.03	0.00
19	0.84	0.76	0.84	0.81	0.82	0.79	0.20	0.01	0.02	0.01	0.05	0.03	0.02	0.04	0.05	0.05	0.03	0.02	0.04	0.01
20	0.77	0.79	0.76	0.81	0.85	0.83	0.23	0.03	0.00	0.04	0.04	0.01	0.03	0.01	0.03	0.03	0.02	0.01	0.02	0.05

b) Environmental impact index [dis-utility]

	[0.90,1.00]
	[0.65,0.90)
	[0.40,0.65)
	(0.10,0.40)
	[0.00,0.10]

Figure 11 Socio-economic and environmental impacts of Alternative 1 for the illustrative example.

The risk map for Alternative 1 is shown in Figure 12. The Sum ER is reduced to 70.697 utils, from the original 127.074 utils of the case without mitigation measures. The mean ER and SD ER also were reduced to 0.177 utils [SD = 0.231 utils] from 0.321 utils [SD = 0.321], therefore leading to a significant reduction in spatial risks.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0.01	0.01	0.02	0.02	0.02	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.02	0.01	0.02	0.02	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3	0.02	0.01	0.01	0.02	0.02	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4	0.01	0.02	0.01	0.02	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
5	0.27	0.10	0.03	0.19	0.14	0.04	0.01	0.00	0.02	0.02	0.02	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.01	0.01
6	0.69	0.54	0.48	0.22	0.22	0.14	0.12	0.14	0.11	0.29	0.25	0.06	0.03	0.01	0.02	0.02	0.02	0.02	0.03	0.02
7	0.47	0.71	0.55	0.49	0.41	0.40	0.24	0.22	0.30	0.35	0.31	0.08	0.03	0.09	0.07	0.02	0.01	0.01	0.02	0.02
8	0.51	0.88	0.59	0.85	0.87	0.85	0.39	0.42	0.33	0.36	0.34	0.29	0.14	0.15	0.11	0.11	0.03	0.03	0.03	0.04
9	1.00	0.95	0.87	0.91	0.73	0.71	0.40	0.39	0.47	0.47	0.43	0.27	0.12	0.18	0.16	0.11	0.12	0.14	0.13	0.11
10	0.91	0.88	0.86	0.87	0.69	0.75	0.67	0.64	0.51	0.47	0.50	0.34	0.10	0.29	0.25	0.15	0.11	0.13	0.11	0.12
11	0.57	0.55	0.59	0.70	0.73	0.74	0.74	0.46	0.28	0.47	0.43	0.50	0.34	0.50	0.49	0.17	0.14	0.15	0.14	0.15
12	0.40	0.42	0.58	0.74	0.75	0.70	0.28	0.18	0.17	0.13	0.51	0.46	0.33	0.44	0.51	0.34	0.14	0.14	0.14	0.16
13	0.31	0.42	0.37	0.39	0.32	0.27	0.16	0.17	0.14	0.14	0.38	0.34	0.34	0.33	0.34	0.35	0.32	0.36	0.35	0.33
14	0.34	0.31	0.31	0.33	0.30	0.30	0.14	0.13	0.11	0.16	0.14	0.33	0.36	0.17	0.16	0.30	0.35	0.50	0.46	0.48
15	0.00	0.33	0.31	0.33	0.34	0.33	0.12	0.12	0.05	0.05	0.06	0.20	0.18	0.17	0.10	0.32	0.36	0.48	0.28	0.26
16	0.01	0.02	0.00	0.02	0.01	0.00	0.05	0.05	0.01	0.01	0.04	0.11	0.08	0.07	0.09	0.16	0.13	0.32	0.27	0.26
17	0.01	0.01	0.02	0.00	0.01	0.01	0.05	0.01	0.00	0.00	0.00	0.01	0.01	0.02	0.05	0.04	0.11	0.24	0.21	0.22
18	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.02	0.02	0.00	0.00	0.02	0.05	0.07	0.07	0.07
19	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Criteria Weights

Socio-Econ =	50%
Environm =	50%

Statistics

Cost Inv [million] =	€21.00
Mean ER =	0.177
SD ER =	0.231
Sum ER =	70.697
Risk/Inv [util/million] =	€3.37

Risk Index

[1.00,0.90]
(0.90,0.65]
(0.65,0.40]
(0.40,0.10)
[0.10,0.00]

Figure 12 Spatial risk map for Alternative 1 in the illustrative example.

The impact maps for Alternative 2 are shown in Figure 13. While the socio-economic impacts (Figure 13a) are similar to the previous alternative (Figure 11a), the spread of environmental impacts is more concentrated along the river banks (Figure 13b).

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0.01	0.05	0.00	0.03	0.01	0.03	0.05	0.03	0.04	0.01	0.02	0.05	0.01	0.04	0.04	0.04	0.02	0.01	0.01	0.02
2	0.02	0.02	0.04	0.03	0.01	0.00	0.03	0.05	0.04	0.00	0.02	0.03	0.05	0.02	0.04	0.03	0.02	0.02	0.05	0.02
3	0.24	0.16	0.16	0.15	0.22	0.23	0.17	0.17	0.04	0.02	0.02	0.03	0.04	0.03	0.02	0.05	0.04	0.02	0.04	0.03
4	0.21	0.24	0.17	0.21	0.22	0.20	0.24	0.24	0.20	0.04	0.05	0.01	0.01	0.01	0.05	0.03	0.02	0.05	0.02	0.03
5	0.83	0.79	0.46	0.24	0.19	0.24	0.22	0.20	0.18	0.19	0.16	0.15	0.20	0.04	0.03	0.03	0.02	0.00	0.03	0.04
6	1.00	0.96	0.84	0.51	0.16	0.20	0.24	0.17	0.15	0.21	0.24	0.23	0.20	0.04	0.03	0.02	0.04	0.00	0.04	0.01
7	0.96	1.00	0.78	0.45	0.45	0.51	0.51	0.51	0.47	0.24	0.16	0.16	0.16	0.05	0.03	0.00	0.01	0.03	0.02	0.01
8	1.00	0.99	0.79	0.80	0.81	0.47	0.49	0.55	0.50	0.22	0.24	0.20	0.22	0.05	0.04	0.00	0.05	0.01	0.01	0.02
9	0.99	0.99	0.84	0.84	0.76	0.83	0.83	0.55	0.53	0.23	0.24	0.22	0.23	0.20	0.21	0.21	0.03	0.04	0.04	0.02
10	0.77	0.84	0.79	0.80	0.80	0.83	0.80	0.77	0.76	0.51	0.51	0.46	0.17	0.20	0.22	0.25	0.02	0.00	0.05	0.05
11	0.22	0.21	0.21	0.76	0.79	0.78	0.75	0.55	0.55	0.50	0.47	0.48	0.21	0.22	0.17	0.19	0.03	0.03	0.00	0.02
12	0.24	0.23	0.16	0.48	0.48	0.53	0.50	0.46	0.49	0.48	0.45	0.47	0.17	0.19	0.23	0.24	0.00	0.01	0.02	0.00
13	0.23	0.19	0.22	0.22	0.18	0.19	0.15	0.46	0.45	0.48	0.49	0.50	0.21	0.22	0.19	0.19	0.16	0.17	0.24	0.23
14	0.20	0.17	0.24	0.16	0.21	0.21	0.15	0.18	0.25	0.15	0.17	0.25	0.20	0.23	0.23	0.20	0.24	0.15	0.18	0.20
15	0.23	0.18	0.21	0.21	0.24	0.22	0.24	0.20	0.23	0.25	0.20	0.20	0.22	0.18	0.23	0.18	0.17	0.22	0.15	0.18
16	0.17	0.17	0.15	0.20	0.19	0.15	0.21	0.16	0.22	0.16	0.20	0.23	0.21	0.20	0.18	0.22	0.20	0.20	0.18	0.25
17	0.18	0.16	0.16	0.21	0.15	0.24	0.22	0.21	0.18	0.19	0.17	0.17	0.19	0.24	0.24	0.24	0.17	0.15	0.23	0.23
18	0.19	0.22	0.17	0.01	0.02	0.03	0.03	0.04	0.03	0.04	0.04	0.03	0.03	0.00	0.03	0.00	0.24	0.19	0.25	0.22
19	0.03	0.02	0.03	0.03	0.04	0.05	0.03	0.03	0.02	0.01	0.04	0.01	0.04	0.03	0.04	0.05	0.03	0.03	0.03	0.04
20	0.00	0.01	0.01	0.01	0.02	0.01	0.04	0.04	0.03	0.01	0.00	0.05	0.03	0.03	0.02	0.02	0.03	0.05	0.01	0.03

a) Socio-economic impact index [dis-utility]

	[0.90,1.00]
	[0.65,0.90)
	[0.40,0.65)
	(0.10,0.40)
	[0.00,0.10]

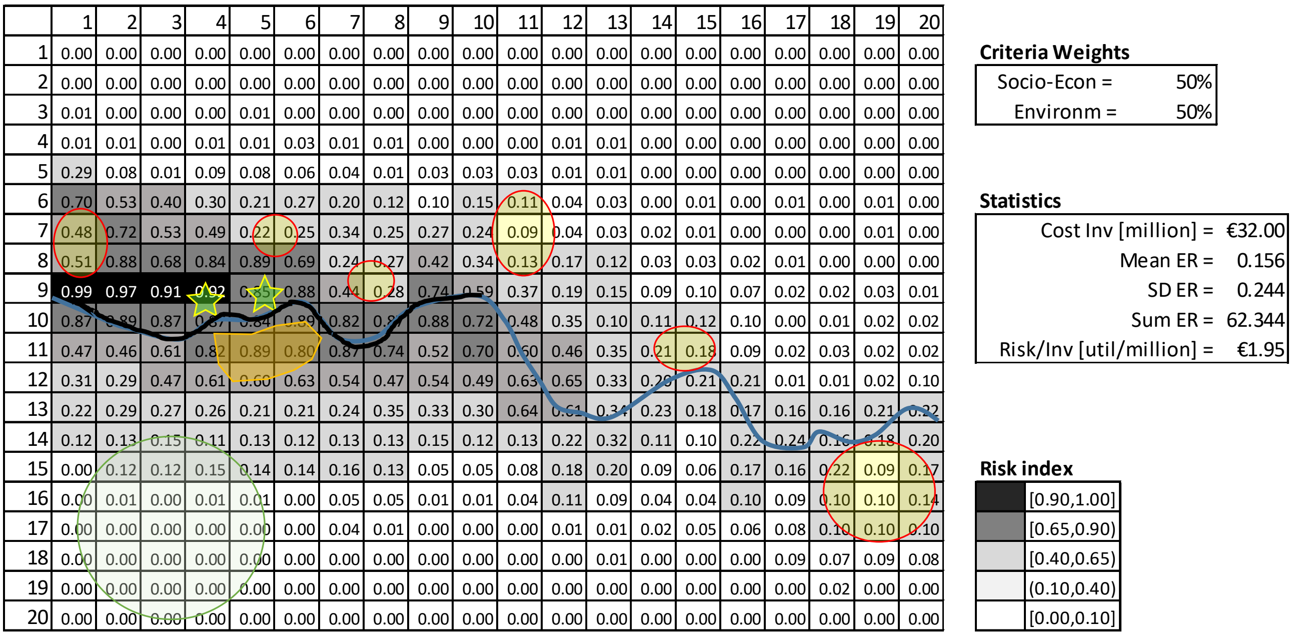
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0.03	0.04	0.05	0.00	0.02	0.02	0.02	0.03	0.04	0.04	0.00	0.04	0.03	0.03	0.03	0.03	0.03	0.03	0.01	0.04
2	0.03	0.02	0.03	0.04	0.01	0.04	0.01	0.01	0.05	0.05	0.00	0.04	0.04	0.04	0.02	0.02	0.03	0.03	0.01	0.04
3	0.23	0.03	0.03	0.03	0.00	0.02	0.00	0.03	0.05	0.05	0.03	0.01	0.02	0.03	0.02	0.04	0.05	0.04	0.00	0.03
4	0.45	0.24	0.17	0.19	0.21	0.25	0.18	0.17	0.21	0.16	0.21	0.25	0.23	0.03	0.01	0.05	0.02	0.03	0.03	0.05
5	0.79	0.53	0.17	0.20	0.19	0.49	0.52	0.17	0.23	0.15	0.19	0.18	0.16	0.01	0.03	0.05	0.02	0.04	0.02	0.04
6	0.84	0.80	0.52	0.47	0.49	0.47	0.46	0.19	0.16	0.16	0.03	0.20	0.20	0.03	0.03	0.02	0.03	0.02	0.03	0.03
7	0.05	0.84	0.80	0.84	0.01	0.01	0.53	0.21	0.21	0.25	0.02	0.18	0.18	0.02	0.01	0.03	0.03	0.00	0.05	0.02
8	0.02	0.84	1.00	0.97	1.00	0.97	0.00	0.01	0.51	0.47	0.03	0.22	0.15	0.04	0.05	0.05	0.02	0.04	0.03	0.03
9	1.00	1.00	1.00	1.00	0.96	1.00	0.05	0.02	0.97	1.00	0.54	0.22	0.24	0.01	0.03	0.05	0.03	0.01	0.04	0.01
10	1.00	0.98	1.00	0.99	1.00	1.00	1.00	0.97	1.00	1.00	0.46	0.25	0.16	0.03	0.02	0.00	0.00	0.02	0.04	0.03
11	0.78	0.77	1.00	0.97	1.00	0.82	1.00	0.98	0.76	0.96	0.81	0.47	0.51	0.21	0.20	0.04	0.02	0.04	0.04	0.04
12	0.51	0.50	0.78	0.75	0.75	0.83	0.83	0.77	0.78	0.80	0.83	0.85	0.50	0.23	0.21	0.19	0.03	0.01	0.03	0.25
13	0.48	0.50	0.53	0.46	0.48	0.52	0.48	0.48	0.53	0.54	0.83	0.79	0.49	0.24	0.17	0.17	0.17	0.16	0.18	0.22
14	0.17	0.23	0.24	0.19	0.21	0.18	0.25	0.22	0.24	0.18	0.18	0.21	0.47	0.04	0.02	0.25	0.24	0.18	0.21	0.20
15	0.20	0.22	0.20	0.24	0.19	0.19	0.24	0.22	0.16	0.18	0.24	0.22	0.25	0.05	0.03	0.16	0.17	0.24	0.02	0.16
16	0.19	0.19	0.18	0.24	0.20	0.20	0.17	0.25	0.20	0.15	0.22	0.22	0.17	0.02	0.02	0.04	0.01	0.00	0.02	0.04
17	0.03	0.05	0.00	0.03	0.02	0.03	0.03	0.05	0.04	0.02	0.03	0.05	0.02	0.05	0.04	0.02	0.03	0.05	0.02	0.03
18	0.03	0.01	0.02	0.03	0.02	0.03	0.02	0.01	0.04	0.03	0.01	0.02	0.05	0.03	0.05	0.00	0.03	0.03	0.05	0.04
19	0.03	0.01	0.01	0.02	0.01	0.03	0.02	0.01	0.04	0.01	0.03	0.01	0.01	0.00	0.03	0.02	0.03	0.02	0.02	0.02
20	0.04	0.03	0.00	0.03	0.02	0.03	0.04	0.02	0.01	0.00	0.04	0.02	0.01	0.05	0.01	0.05	0.04	0.03	0.05	0.01

b) Environmental impact index [dis-utility]

	[0.90,1.00]
	[0.65,0.90)
	[0.40,0.65)
	(0.10,0.40)
	[0.00,0.10]

Figure 13. Socio-economic and environmental impacts of the Alternative 2 for the illustrative example.

The risk map for Alternative 2 is shown in Figure 14. The Sum ER was reduced to 62.344 utils, from the original 127.074 utils of the case without mitigation measures and more than for Alternative 1. The mean ER was also reduced to 0.156 utils, again more than for Alternative 1 (but the ER SD slightly increased to SD = 0.244 utils). Therefore Alternative 2 provides a larger reduction in spatial risks but is more expensive than Alternative 1. Alternative 1 provides better value for money, with a Risk/Investment ratio of 3.37 utils/million euros, against Alternative 2 that has a ratio of 1.95.



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4	0.01	0.01	0.00	0.01	0.01	0.03	0.01	0.01	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
5	0.29	0.08	0.01	0.09	0.08	0.06	0.04	0.01	0.03	0.03	0.03	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
6	0.70	0.53	0.40	0.30	0.21	0.27	0.20	0.12	0.10	0.15	0.11	0.04	0.03	0.00	0.01	0.00	0.01	0.00	0.01	0.00
7	0.48	0.72	0.53	0.49	0.22	0.25	0.34	0.25	0.27	0.24	0.09	0.04	0.03	0.02	0.01	0.00	0.00	0.00	0.01	0.00
8	0.51	0.88	0.68	0.84	0.89	0.69	0.24	0.27	0.42	0.34	0.13	0.17	0.12	0.03	0.03	0.02	0.01	0.00	0.00	0.00
9	0.99	0.97	0.91	0.92	0.85	0.88	0.44	0.28	0.74	0.59	0.37	0.19	0.15	0.09	0.10	0.07	0.02	0.02	0.03	0.01
10	0.87	0.89	0.87	0.87	0.84	0.89	0.82	0.87	0.88	0.72	0.48	0.35	0.10	0.11	0.12	0.10	0.00	0.01	0.02	0.02
11	0.47	0.46	0.61	0.82	0.89	0.80	0.87	0.74	0.52	0.70	0.60	0.46	0.35	0.21	0.18	0.09	0.02	0.03	0.02	0.02
12	0.31	0.29	0.47	0.61	0.60	0.63	0.54	0.47	0.54	0.49	0.63	0.65	0.33	0.20	0.21	0.21	0.01	0.01	0.02	0.10
13	0.22	0.29	0.27	0.26	0.21	0.21	0.24	0.35	0.33	0.30	0.64	0.61	0.34	0.23	0.18	0.17	0.16	0.16	0.21	0.22
14	0.12	0.13	0.15	0.11	0.13	0.12	0.13	0.13	0.15	0.12	0.13	0.22	0.32	0.11	0.10	0.22	0.24	0.16	0.18	0.20
15	0.00	0.12	0.12	0.15	0.14	0.14	0.16	0.13	0.05	0.05	0.08	0.18	0.20	0.09	0.06	0.17	0.16	0.22	0.09	0.17
16	0.00	0.01	0.00	0.01	0.01	0.00	0.05	0.05	0.01	0.01	0.04	0.11	0.09	0.04	0.04	0.10	0.09	0.10	0.10	0.14
17	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.01	0.00	0.00	0.00	0.01	0.01	0.02	0.05	0.06	0.08	0.10	0.10	0.10
18	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.09	0.07	0.09	0.08
19	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00
20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Criteria Weights

Socio-Econ =	50%
Environm =	50%

Statistics

Cost Inv [million] =	€32.00
Mean ER =	0.156
SD ER =	0.244
Sum ER =	62.344
Risk/Inv [util/million] =	€1.95

Risk index

	[0.90,1.00]
	[0.65,0.90)
	[0.40,0.65)
	(0.10,0.40)
	[0.00,0.10]

Figure 14 Spatial risk map for Alternative 2 in the illustrative example.

4.3 Sensitivity Analysis

There are several possible ways of conducting sensitivity analysis in these spatial risk maps, for example using Monte-Carlo simulations if the impacts are estimated as ranges, or distributions, instead of deterministic values as we assumed here. This type of simulation analysis can also be performed for probabilities of occurrence and vulnerabilities.

Here we illustrate instead an analysis on the sensitivity of solutions to criteria weights which is frequently employed in non-spatial multi-criteria analysis.[48] Ideally, this should be done interactively with policy makers in facilitated workshops (see Ferretti and Degiovanni[49] and Franco and Montibeller[50]), so they can "play with the model", find the best solution given their preferences and get confidence on the way forward.[51] When this type of interaction is not feasible, a diagram such as the one shown in Figure 15 can be presented.

The first row of figure 15 shows risk maps for the case without mitigation measures (NM), its second row for Alternative 1 (ALT1), and its third row for Alternative 2 (ALT2). The central column shows the maps when criteria have the same weight (as detailed in Figures 9, 12, 14, respectively), the left column for a weight of 25% on Socio-Economic impact and 75% on Environmental impact, and the right column for a weight of 75% on Socio-Economic impact and 25% on Environmental impact.

We can notice in this same figure that the overall risk (Sum ER) [Eq. 6] reduces for the three alternatives when the weight on Socio-Economic Impact increases. When the weight is w_{SE} = 25%, we have Sum ER(NM) = 133.75, Sum ER(ALT1) = 72.59 and Sum ER(ALT2) = 63.99. When, instead, the weight is increased to w_{SE} = 75%, we have Sum ER(NM) = 120.40, Sum ER(ALT1) = 68.80 and Sum ER(ALT2) = 60.69.

Between Alternative 1 and 2, the overall risk is consistently lower for the latter but the Risk/Investment ratio is always higher for the former, in those three scenarios. Alternative 1 would thus be a better solution in terms of value for money, if we consider this rule for the choice.

If the risk analyst wants to consider multiple scenarios of an adverse event happening (for instance, in case of flooding risk, a minimal, a moderate and an enormous flood), she could use the proposed framework to analyze each scenario and its expected consequences in a similar way as we exemplified for the weights. For example, a first scenario could be a minimal flood with a probability of occurrence of 0.001 and 100 deaths in total, a second scenario a moderate flood with a probability of 0.0002 and 200 deaths in total and a third scenario an enormous flood with a probability of 0.00003 and 300 deaths in total. The framework would enable one to calculate the risk index associated with each scenario.

5. CONCLUSIONS AND DIRECTIONS FOR FUTURE RESEARCH

In this paper we suggested an integrated framework for conducting multi-impact spatial risk analysis in environmental decision-making. The framework suggests the assessment of spatial vulnerabilities and probability of occurrence of events, coupled with the assessment of multiple impacts, the latter drawing from the literature on spatial multi-criteria decision analysis. We suggested that the framework may be employed to assess spatial risks, to compare spatial alternatives for risk management and to support the design of new spatial alternatives for risk mitigation.

We hope that this framework can help policy makers and risk analysts involved in those problems, given how relevant the environment is for long term sustainability of the species, how many environment-related risks are occurring, and the relevance of the spatial dimension in many environmental risk assessments.

As with any new conceptual development, there are some limitations to our framework. Firstly, it is an open question to what extent the information required on spatial vulnerabilities and probabilities of occurrence can be accurately identified as assumed by the framework in practice and how to consider contiguity aspects in such assessments. Secondly, while we formally defined the framework, we have not provided a full axiomatization of the conditions required for such an assessment, which is beyond the scope of the paper. In particular, we assumed a linear model for preferences and also for the design of optimal risk mitigating alternatives. While these assumptions are often made in practical applications of multi-criteria analysis and portfolio decision analysis (*e*.g. Huang et al.[52]) we recognize that they are simplistic. Furthermore, spatial impacts and vulnerabilities might have complex relationships that are not properly represented by linear models as we had assumed. Thirdly, our coverage of metrics to compare spatial alternatives and design new alternatives was rather concise. Fourthly, we considered in the paper only the case of adverse impacts, as these represent the most common situation in risk analysis.

However, some events may also generate improvements, i.e. positive impacts such as when a flood deposits fine silt (alluvium) onto the floodplain, making it very fertile and excellent for agriculture.

These limitations open several opportunities for research in this emerging field in Risk Analysis. Firstly, there is a need to identify practical and reliable ways of assessing spatial physical vulnerabilities and spatial probabilities of occurrence of adverse events within the context of the proposed framework. When reliable data is not available, risk analysts often rely on expert judgement [(35)] so there is a need to extend these elicitation protocols for spatial problems (see also Keller and Simon[(34)]) and minimization of cognitive biases in such judgments (see Montibeller and von Winterfeldt[(36)] as well as Gotham et al.[(53)]). Secondly, a full axiomatization of this model is important, as it may inform both elicitation procedures and aggregation rules. In addition, more sophisticated, non-linear, models for preference modeling and risk aggregation should be explored. One possible solution for the estimations of vulnerabilities and estimations of impacts is to employ spatial statistical models to represent complex relationships and correlation structures among the variables (*e.g.* von Ruette et al.[(54)]). Thirdly, more sophisticated way of modelling spatial preferences, which take into account contiguities among cells and different patterns of risk spread, such as the ones suggested by Metchebon et al.[(46)] are also welcome. Fourthly, future extensions may consider how to adapt the framework when the adverse event also causes positive impacts. One solution would be evaluating dis-utilities on negative scales (from 0 to -1) and utilities on positive scales (from 0 to +1), thus allowing for compensation between positive and negative impacts. Fifthly, there is a need for testing the framework in real-world risk assessments, to assess both its feasibility and usefulness in practice. Sixthly, the literatures on choice of spatial alternatives and resource allocation for spatial risk mitigation are very limited, as far as we are aware. Spatial alternatives are harder to compare and design, when compared with non-spatial ones. Thus conceptual developments on this front are welcome.

Concluding, recent advances in spatial multi-criteria analysis, as well as in risk analysis for policy making, make the time ripe for exploring synergies between these two fields of research. This research thus lies in the interface between these two disciplines and may benefit risk analysts and policy makers. On one hand, risk analysis can benefit from a deeper understanding of the spatial dimension inherent in many environmental problems, in which spatial impacts can be aggregated taking into account societal concerns and priorities. On the other hand, environmental policy and decision-making can benefit from an in depth understanding of the assumptions underpinning risk analysis, when these are extended to the spatial dimension. We see this paper as just the beginning of an exciting journey for spatial risk analysis.

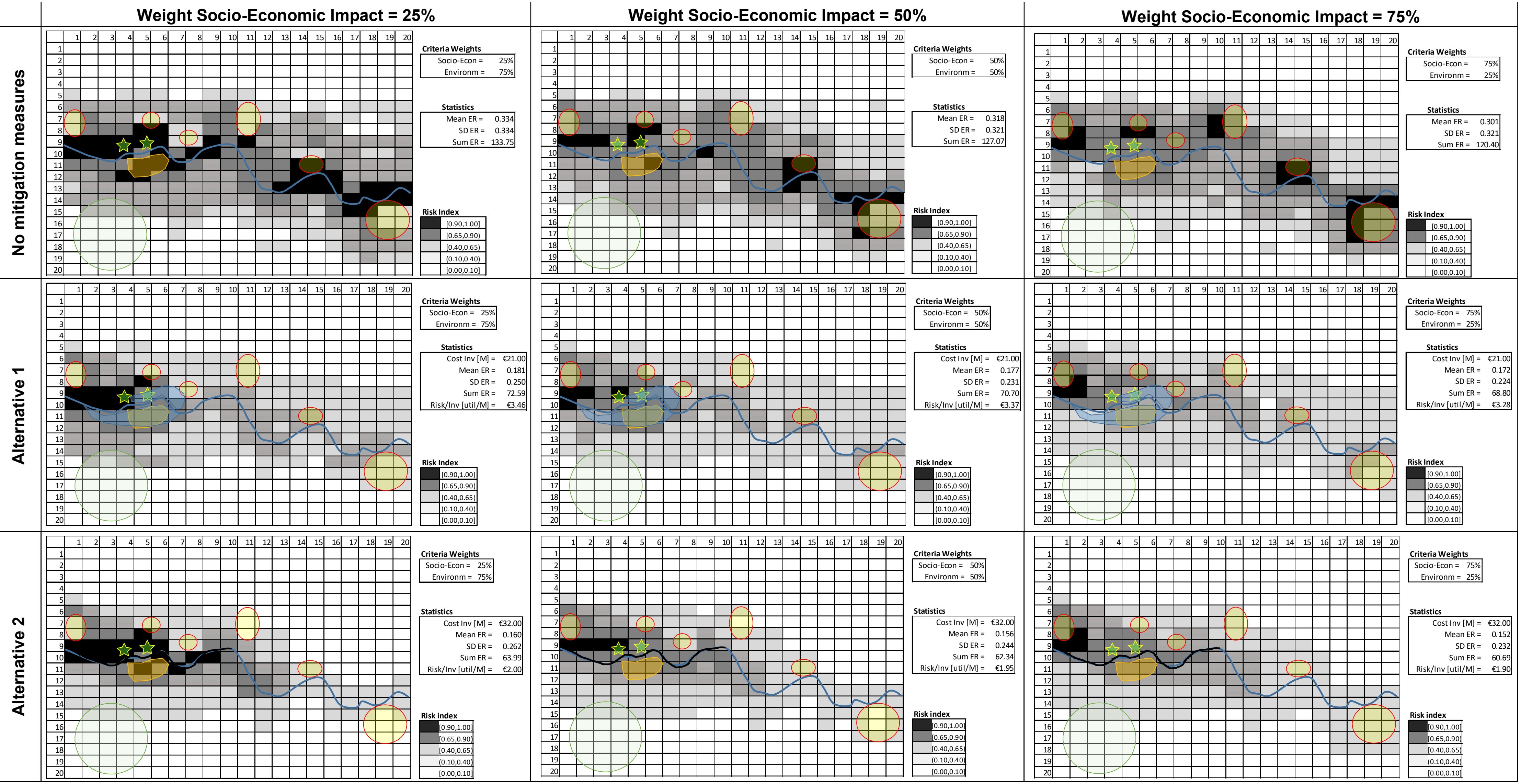


Figure 15 Spatial Sensitivity Analysis on the Criteria Weights for the Illustrative Example.

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