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# Analysis and quantification of potential consequences in multirisk coastal context at different spatial scales (Normandy, France)

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## Abstract

Coastal environment with high interaction between nature and societies is subject to multihazard interaction such as landslides, flood or cliff retreat. These territories are characterized by numerous elements at risk located in valley bottoms, front sea or at the outlets of small dry watershed. The aim is to quantify the potential consequences of EaR by integrating multiple hazards exposure at various scale analyses. To quantify the element at risk, three steps have been required. First, an initial rank has been attributed to each class of element at risk at three different scales analysis. Second, the potential consequences are weighted according to environmental dimension. Third, the consequences are combined with a linear combination of criteria in GIS environment. At medium-scale analysis, element at risk highlighted is built-up areas, national road, railway, lifeline and urban centers. At large-scale analysis, consequences concern any kind of house, apartment and complex located on multiple exposure areas. At local scale, consequences concern buildings located on multiple exposure areas with one floor in mixed materials and built after 1980. Thus, this method proposes an approach with multiple scales analysis and by integrating multiple exposure areas to quantify potential consequences. With the environmental dimension in element at risk analysis, it is an intermediate step to traditional risk analysis and, more specifically multirisk analysis without considering in this case the spatial and temporal dimension of hazards.

Keywords Consequences · Element at risk · Spatial scale · Weighting · Multi-criteria

# 1 Introduction

In coastal environments, damages caused by climatic, marine or continental processes could be more and more significant for societies in a context of global changes (IPCC 2013; Planton et al. 2015). Due to the multiple interactions of these processes, it is necessary to identify, analyze and regularly update risk areas and their potential evolutions. In this context, the concept of risk is built around three components: (1) spatialization

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of hazard(s), (2) hazard frequency/intensity analysis and (3) the vulnerability assessment of element at risk elements (EaR) such as buildings, lifelines, agricultural surfaces and urbanized areas (Cardona 2005; Bollin and Hidajat 2006; Dilley et al. 2005; Birkmann 2007; Papathoma-Köhle et al. 2007). This definition involves an initial assessment of hazard followed by the vulnerability analysis which is defined as the potential losses/injuries of an EaR according to the intensity of hazard (Papathoma-Köhle et al. 2007; Birkmann et al. 2013; Chang et al. 2015, 2018). In a multirisk context, a hazard investigation may take some time and as part of a vulnerability assessment, EaR studies must be led independently of hazard analyses (Kappes et al. 2012b). In this context, for the first estimation of the potential losses/injuries of EaRs without considering hazard intensities or frequencies, we decided to focus on the assessment of potential consequences (Glade and Crozier 2005; Corominas et al. 2013; Puissant et al. 2013; Eidsvig et al. 2017; Carlier et al. 2018). Furthermore, potential consequences of EaRs represent the common vector of each single-hazard analysis in a multirisk assessment (Kappes et al. 2012a; van Westen et al. 2014; Godfrey et al. 2015; Chen et al. 2016).

According to scientific literature, two main approaches have been developed to assess EaRs and their potential consequences: the engineering approach, which is generally considered in an operational context, and the expert approach, which is usually used in a prevention context (Muis et al. 2015; Chen et al. 2016; Penadés-Plà et al. 2016). Among engineering approaches, methods such as damages curves or cost-benefit ratio provide an absolute value of each EaR expressed in monetary terms or degree of losses (Akbas et al. 2009; Totschnig et al. 2011; Papathoma-Köhle et al. 2017). However, the amount of data required to provide this analysis is huge and lead to considerable uncertainties in case of extrapolation to different study sites (van Westen et al. 2008; Petrucci and Gullà 2010; Kappes et al. 2012b; Li et al. 2016). Among expert approaches, methods such as ranking systems based on index value analysis or damage matrices provide a qualitative value (description in words) of EaRs based on subjective evaluation (Altenbach 1995; Léone et al. 1996; Malet et al. 2006; Papathoma-Köhle et al. 2017). Currently, used in urban French official documents such as the Natural Risk Prevention Plan (MEEM/ MLHD 2016), these methods require only few data and can be implemented quickly (Kappes et al. 2012b; Puissant et al. 2013). In order to reduce uncertainties connected to these methods, index-oriented methodologies have been developed. The aim of these methods such as Potential Damage Index (PDI) is to compute the index value of various criteria to assess one or several EaRs by integrating a variable number of criteria (Maquaire et al. 2004; Birkmann 2006; Puissant et al. 2013; van Westen et al. 2014; Chang et al. 2015; de Brito and Evers 2016; Carlier et al. 2018). However, the PDI method is mainly used for mountainous environment (Puissant et al. 2013; Carlier et al. 2018).

Given this scientific context, three significant problems have been loomed. (1) Currently, no consensus has been reached about the number and nature of criteria to integrate an index-oriented method in multirisk coastal context. (2) Moreover, the spatial accuracy of potential consequences is usually done based on a one scale analysis, contrary to hazard analyses which commonly use a multiscale analysis approach. (3) Lastly, two approaches are used to assess potential consequences, inside or outside hazard areas. However, if outside hazard areas are the most appropriate approaches such as PDI method, they do not consider the immediate environment that can affect the EaR. Consequently, in our approach, we can define potential exposed areas to integrate the environmental specificities of the study site, such as topography or hydrology. Consequently, the challenge is to quantify potential multiscale consequences of EaRs in the same way as with hazard analysis. We will then define the specific number and nature of criteria to be integrated in the consequences analysis and weight them based on their spatial location or importance.

In this way, we must adapt and improve the PDI method to a coastal context by integrating spatial location of EaR.

- The first step is to identify different types of consequences for each spatial scale to define adequate accuracy of EaR for mapping. Thus, four spatial scales are commonly used in risk analyses (van Westen 2000; 2008; Birkmann 2007). The small-scale analysis [1:250,000–1:100,000] is used by national and regional agencies (Carpignano et al. 2009). The medium-scale analysis [1:50,000–1:25,000] is used to identify critical facilities in urban documents (Kappes et al. 2011; Cascini et al. 2013; van Westen et al. 2014). The large-scale analysis [1:25,000–1:10,000] provides information about infrastructural components (Maquaire et al. 2004; Malet et al. 2006; Lissak et al. 2013). And the local-scale analysis [1:10,000–1:2000] provides detailed information about structural component of buildings (Papathoma-Köhle et al. 2007; Kappes et al. 2012a; Abbas and Routray 2013; van Westen et al. 2014). In this study we have considered scales ranging from medium to local extent. Beyond the medium scale [> 1:100,000], the mapping resolution does not provide enough information on the EaRs to differentiate them. Consequently, this scale is not considered in our study.
- The second step aims to integrate the notion of potentially exposed areas (to various processes) to delineate specific zones and to characterize more accurately the potential consequences of EaRs involved (Zahran et al. 2008; Jeffers 2013; Gallina 2015; Garcia-Aristizabal et al. 2015; Muis et al. 2015; Gallina et al. 2016; Yoon et al. 2017). The interest is also to propose consistent quantification EaRs to highlight hotspots through weighting systems and make them adaptable in different scenarios (Dilley et al. 2005; Fuchs et al. 2012; Armaş et al. 2016; de Brito and Evers 2016; Zahran et al. 2017).

# 2 Study site

The study area is located in Normandy from Houlgate to Honfleur (Fig. 1). The geographical limits are considered from three components: (1) a homogenous hydrological unit (the Touques watershed), (2) an continuity between the coast and the hinterland (coastal strip of 10 km wide) and (3) a homogeneous administrative unit (Plan for Development Consistency—SCOT Cœur Côte Fleurie). Therefore, the study area is at the interface between the outlet of the Touques River (104 km of length), the English Channel, and the outlet of the Seine estuary.

A range of hazards regularly affect these territories. Concerning the hydrological hazard, it comes from both the overflowing Touques River and a muddy flow in wet and dry valleys (especially in municipalities present in the study area that are subject to legal studies on both flood risk and landslide risk assessment, eastern part of the site) (Delahaye 2008; Douvinet et al. 2015a, b). Furthermore, the territories are regularly affected by marine submergence during strong tidal conditions (Costa 1997; Laignel et al. 2008; Letortu et al. 2014; Turki et al. 2015). Strong tidal coefficient will also partially block the Touques River, thus amplifying flood hazard in coastal back. This position along the Seine estuary also amplifies the blocking effects during the Seine river flood in conjunction with a strong tidal coefficient (Fisson et al. 2014; Fisson and Lemoine 2016). However, this area is partially protected from the North Sea's current and is affected differently than the other

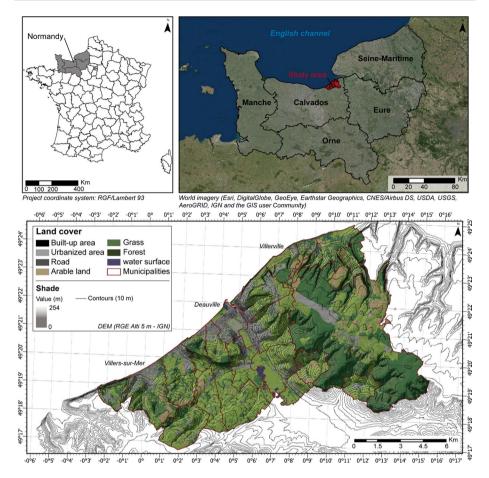


Fig. 1 Study site located in Normandy (France)

coast by severe storms. In addition, these territories are also subject to important gravity process such as slow-moving landslide (translational, rotational and complex). One can observe these processes along the coast (i.e., Vaches Noires cliffs and Cirque des Graves) (Maquaire 1990; Lissak et al. 2014) and in the hinterland (Fressard et al. 2014, 2016).

Despite the occurrence of these processes, the valley bottoms and the seafront are strongly anthropized, and these environment are particularly sensitive to global changes. Indeed, these changes may bring about effective results and lead to an increase of heavy precipitation events in both moist and dried valleys, thus increasing the risk of muddy flows (Delahaye 2008; Douvinet et al. 2015a, b). These changes are also probably reflected in the rising water level and hence increase the risk of blockage of the Touques River at its outlet in the case of spatial and temporal concomitance (Kappes et al. 2012b; Marzocchi et al. 2012; Fisson and Lemoine 2016). Municipalities of the study site are subject to legal studies on both flood risk (plan for flood risk prevention) and landslide risk (plan for landslide risk prevention) (MEEM/MLHD 2016). This method consists in performing qualitative definitions of the various components of a territory. These documents are regularly reviewed and updated.

An appreciable set of data is available in order to assess and quantify the potential consequences on this study site. These data are supplied by national, regional or local collectivities. The site also benefits from many research data and from two research observatories (OMIV-INSU et DYNALIT) producing many data on hydrology, the volume of debris, subsurface displacements, local and regional weather.

## 3 Method

We developed a three-step method (Graff et al. 2019): (1) Once all criteria had been selected to describe EaR (e.g., at a larger scale, a building is characterized by the number of floors, its type and function, etc.), an index was attributed to each one of them to describe each EaR. The number of criteria increases depending on the scale used to perform the analysis. (2) The criteria were then combined for the different spatial scales to define potential consequences, and (3) weighting systems have been proposed to readjust potential consequences at the medium, large and local scales.

#### 3.1 Definition and overview of the potential consequences at each spatial scale analysis

Three spatial scales analyses are defined to assess and quantify the potential consequences ranging from the medium- to local-scale analysis (Van Westen 2000; van Westen et al. 2008). Beyond > 1:100,000 EaRs are indistinguishable. All the data are obtained by combination of several databases available online or in the archives (Fig. 2).

The medium-scale analysis (1:100,000–1:25,000) enables the quantification of the overall potential consequences on the study site. The overall potential consequences here cover the built-up, urbanized area, transport and energy network and finally agricultural and natural surface types (Kubal et al. 2009; Scheuer et al. 2011). The built-up area type is the result of a simplification and aggregation of building footprint.

At the large-scale analysis (1:25,000–1:10,000), the potential consequences have been quantified on the basis of the infrastructures present in the study site. Infrastructures refer to the sets of human construction such as buildings, transport networks and energy networks (Cascini et al. 2013; Puissant et al. 2013; Carlier et al. 2018). Three components are considered:

- 1. the structural component is defined as the physical sheath such as type, construction materials and number or floors (Papathoma-Köhle et al. 2007; Uzielli et al. 2015);
- the functional component is defined as a disruption of human activities such as business or farming (Totschnig et al. 2011; Lissak et al. 2013);
- 3. the physical injury component is defined as possible fatalities or injuries in human beings (Akbas et al. 2009; Kappes et al. 2012b).

The aim is to have a better accuracy of these EaRs. Contrary to the building and transport networks, the energy network is only characterized by its function.

At the local scale (1:10,000–1:2000), the EaRs considered are buildings with more integrated details and criteria. What we wish to focus on here is the structural component of these buildings in order to consider the material behavior (construction materials, building conditions such as level of damage to the walls and roof, the number

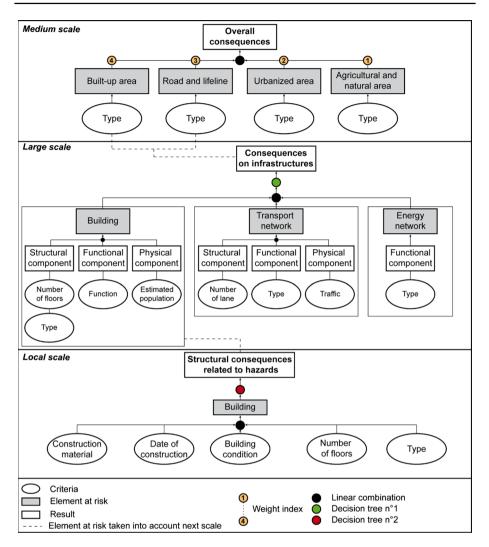


Fig. 2 General organization of the method at three different spatial scales analyses

of floors, type and construction date) in case of specific hazards (Kappes et al. 2012a; Godfrey et al. 2015; Papathoma-Köhle et al. 2017; Milanesi et al. 2018). To achieve that goal, five criteria have been chosen according to various studies carried out at this spatial scale (van Westen et al. 2014; Godfrey et al. 2015; Chen et al. 2016; Vojinovic et al. 2016; Papathoma-Köhle et al. 2017). These criteria are weighted according to two potential exposure areas present in the study site: (a) potential flood exposure areas that incorporate the overflow of rivers, marine submergence and muddy flows; (b) potential landslide exposure areas that incorporate translational, rotational and complex landslide. At this scale, the economic and social impact has been excluded due to a lack of available data such as costs at short, medium and long term of activities disposal or the visiting time of the residence (primary or secondary residence).

#### 3.2 Multiple spatial scale index assignment

There are several possibilities to assign relative weight to EaRs. For example, the relative weight can be defined from statistical distribution or through membership value assigned by fuzzy logic approach that consists in transforming initial data into a new value called fuzzify process (Nezarat et al. 2015). Another option is to use the analytic hierarchy process to attribute a weight to different EaRs from the initial hierarchy (Saaty 2006; Nezarat et al. 2015). The pairwise comparison is also used and consists of comparing elements in pairs to establish a statistical relationship between a set of value (Saaty 2006; van Westen et al. 2008; Chen et al. 2013). Finally, we have chosen a ranking system to establish a relationship within a set of elements due to the ease of transposition (Mouroux and Brun 2006; Cooke et al. 2008; Khan and Samadder 2015; Gumus et al. 2016; Van der Fels-Klerx et al. 2018). Thus, the index values defined at the medium-, large- and local-scale analysis are presented in Tables 1, 2 and 3.

The ranking system has been chosen here to determine the value to each class of criteria thanks to the swift implementation and execution of this method consisting of an association of a set of criteria by adding or multiplying them (Maquaire et al. 2004; Kappes et al. 2012a, b; Lissak et al. 2013; Puissant et al. 2013; Papathoma-Köhle et al. 2017; Carlier et al. 2018). In an operational context, it is recommended to keep a simple approach owing to the swift implementation as well as the operational simplicity to compute the potential consequences ( $P_c$ ) from different index (c) values. This linear combination consists in an addition of different criteria (1).

$$P_{\rm c} = \sum_{i=1}^{n} \left( c_i \right) \tag{1}$$

At medium scale, a weighting index (w) has been used in order to readjust potential consequences ( $P_c$ ) of EaRs depending on the degree of importance the municipality attaches to it (Maquaire et al. 2004; Puissant et al. 2013; Carlier et al. 2018). Then, this value has been standardized to obtain a final value between 0 and 1 in order to provide comparative information of consequences revealed by spatial scale analyses (Birkmann 2006, 2007). The result obtained is called the overall consequences (OCs) (2).

$$OC = \sum_{i=1}^{n} \left( P_{c} \cdot w_{i} \right)$$
(2)

At large and local scale, new weighting systems have been used in order to incorporate the EaRs exposure levels (Puissant et al. 2013). To assign the right exposure index at each EaR of the study site, weighting systems have been set in order to incorporate the two decision trees. At large scale, the first decision  $(Dt_1)$  weights the  $P_c$  to obtain the consequences on infrastructures (CI) (3).

$$CI = P_{c} \cdot Dt_{1} \tag{3}$$

At local scale, the second decision tree  $(Dt_2)$  weights the  $P_c$  related to potential exposure area (e) to obtain the structural consequences (SC) (4).

$$SC = P_c(e).Dt_2 \tag{4}$$

Basing ourselves on the results obtained, we define appropriate threshold to classify the importance of consequences. Different methods exist to classify consequences: the

Element at risk	Criteria	Class	Rank	Index
Built-up area	(a1) Type	Other	1	0.13
		Lightweight	2	0.25
		Residential	3	0.38
		Farm	4	0.5
		Industrial	5	0.63
		Commercial	6	0.75
		Monument	7	0.88
		Public	8	1.00
Road and lifeline	(a2) Type	Way	1	0.14
		Road	2	0.29
		Departmental road	3	0.43
		National road	4	0.57
		Highway	5	0.71
		Railway	6	0.86
		Power line	7	1.00
Urbanized area	(a3) Type	Area to be urbanized	1	0.09
		Leisure and tourism	2	0.18
		Farm	3	0.27
		Housing	3	0.27
		Camping	4	0.36
		Collective area	5	0.45
		Industrial area	6	0.55
		Commercial area	7	0.64
		Urban center	8	0.73
		Transport	9	0.82
		Public utilities	10	0.91
		Health and rescue	11	1.00
Agricultural and natural area	(a4) Type	Water surface	1	0.13
		Other	2	0.25
		Grassland	3	0.38
		Forest and wood	4	0.5
		Hedge	5	0.63
		Permanent crop	6	0.75
		Arable land	7	0.88
		Protected area	8	1

Table 1 Index defined on each class of criterion at the medium-scale analysis

automatic method (e.g., natural breaks, quantile classification) or the empiric one such as relative cumulative frequency (RCF) methods (de Tsuzuki and Shimada 2003; Dimakos and Aas 2004; Wei and Chen 2009; Gaspar-Escribano and Iturrioz 2011; Puissant et al. 2013; Lai et al. 2015). Initially used in the PDI method, the RCF method has been applied to define thresholds as a consequence of frequency distribution (Puissant et al. 2013; Lissak et al. 2013; Fressard et al. 2014; Franci et al. 2016). This approach is based on the analysis of frequency distribution to determine the number of EaRs located above or below

Element at risk			Rank	Index	
Building	(b1) Type	Shed/hut	1	0.09	
		Warehouse	2	0.18	
		House	3	0.27	
		Farm	4	0.36	
		Apartment	5	0.45	
		Mixed used	6	0.55	
		Industry	6	0.55	
		Office	7	0.64	
		Castle	8	0.73	
		Church	8	0.73	
		Monument	8	0.73	
		Tower	8	0.73	
		Commercial center	9	0.82	
		Station	10	0.91	
		Complex	11	1.00	
	(b2) Function	Abandoned/none	0	0.00	
		Garage, shed, etc.	1	0.09	
		Religion	2	0.18	
		Storage	2	0.18	
		Residential	3	0.27	
		Farm	4	0.36	
		Commercial	5	0.45	
		Industrial	5	0.45	
		Mixed residential commercial	6	0.55	
		Administrative	6	0.55	
		Tourism	7	0.64	
		Leisure	7	0.64	
		Transport	8	0.73	
		Education	9	0.82	
		Energy	10	0.91	
		Health and rescue	10	1.00	
	(b3) Estimated population	0	0	0.00	
	(00) Estimated population	[1-2]	1	0.17	
		[3-4]	2	0.33	
		[5-6]	3	0.50	
		[7–8]	4	0.67	
		[9–10]	5	0.83	
		>10	6	1.00	
	(b4) Number of floors	1	1	0.14	
			2	0.14	
		2			
		3	3	0.43	
		4	4	0.57	
		5	5	0.71	
		6	6	0.86	

 Table 2
 Index defined on each class of criterion at the large-scale analysis

Element at risk	Criteria	Class	Rank	Index
		>6	7	1.00
Transport and energy	(b5) Type	Way	1	0.11
network		Road	2	0.22
		Departmental	3	0.33
		National	4	0.44
	Highway	5	0.56	
		Power line	6	0.67
		Railway	7	0.78
		Pylon	8	0.89
		Other energy structure	9	1.00
(b6) Traffic (b7) Number of lar	(b6) Traffic	Very low (5)	1	0.20
		Low (4)	2	0.40
		Standard (3)	3	0.60
		High (2)	4	0.80
		Very high (1)	5	1.00
	(b7) Number of lane	1 lane	1	0.17
		2 lanes with same direction	2	0.33
		2 lanes with opposite direction	3	0.50
		3 lanes with same direction	4	0.67
		3 lanes with opposite direction	5	0.83
		4 lanes or more	6	1.00

Table 2 (continued)

a specific threshold value. The threshold values can be adjusted in order to highlight a specific number of elements or determine a specific value that translates a type of consequences (low, medium, etc.) and reflects an expert vision.

#### 3.3 Weighting systems (exposure)

On the basis of combination systems, we must reflect the exposure of EaRs by weighting the initial index value. There are two possibilities: (1) The initial index value is weighted with a specific value to readjust it (Fig. 2), or (2) the index value is readjusted according to the spatial location.

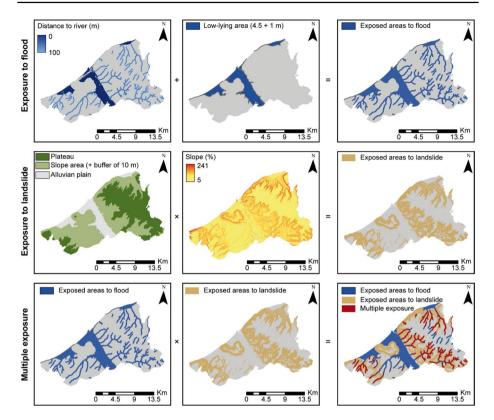
At the medium scale, the possibility (1) has been selected, in the same way as with the PDI method (Puissant et al. 2013; Lissak et al. 2013; Carlier et al. 2018). At this scale, the interest is to take account of all components of the territory in order to identify the main EaRs.

The large and local scales gave us the opportunity to highlight the potentially exposed EaRs. Two weighting systems are defined to readjust the  $P_c$ . It depends on the spatial location of EaRs (Marzocchi et al. 2012; Liu et al. 2015). Potential exposure areas are determined relative to the three points (Fig. 3):

• The first spatial location is defined by the potential exposure to flood-prone areas. This area is based on the distance from rivers to low-lying areas;

Element at risk	Criteria	Class	Index (flood)	Index (landside)
Building	(c1) Construction material	Pillar	0.20	0.20
		Concrete	0.40	0.30
		Metal	0.30	1.00
		Mixed	0.50	0.60
		Traditional	0.50	0.40
		Brick wall	0.50	0.40
		Wood	1.00	0.90
	(c2) Number of floors	1	1.00	0.40
		2	0.50	0.60
		3	0.30	0.60
		4	0.30	0.80
		5	0.30	0.80
		6	0.30	0.80
		>6	0.30	1.00
	(c3) Construction date	<1900	1.00	1.00
		[1900-1950]	0.90	0.90
		[1950–1970]	0.70	0.70
		[1970–1990]	0.50	0.50
		> 1990	0.30	0.30
	(c4) Building condition	Good	0.30	0.20
	•	Medium	0.50	0.50
		Bad	0.70	0.80
		Ruin	1.00	1.00
	(c5) Type	Other	0.00	0.00
		Shed/hut	0.09	0.09
		Warehouse	0.18	0.18
		House	0.27	0.27
		Farm	0.36	0.36
		Apartment	0.45	0.45
		Mixed used	0.55	0.55
		Industry	0.55	0.55
		Office	0.64	0.64
		Castle	0.73	0.73
		Church	0.73	0.73
		Monument	0.73	0.73
		Tower	0.73	0.73
		Commercial center/sale outlet	0.82	0.82
		Station	0.91	0.91
		Complex	1.00	1.00

 Table 3
 Index defined on each class of criterion at the local-scale analysis

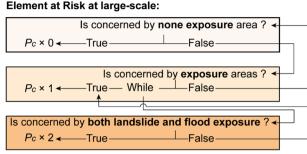


**Fig.3** Calculation of the three exposure levels. The flood-prone area is the merge of the distance to the river (0-100 m) and low-lying areas (4.5 m+1 m of sea level for 100-year event), slope areas + buffer of 10 m from the top and the bottom of the slope to consider the ablation and propagation areas of landslides-prone areas with a slope threshold > 5%. Multiple exposure areas are the interaction between flood-prone and landslide-prone areas

- The second spatial location is defined by the exposure to landslide-prone areas computed from landform (slope areas + buffer of 10 m from the top and the bottom of the slope to take into account ablation and propagation areas of landslides) and a slope threshold > 5%;
- The third spatial location is defined by the multiple exposure computed from the interaction between flood-prone and landslide-prone areas.

Two decision trees have been developed in order to integrate the spatial location of EaRs on  $P_c$  at large- and local-scale analyses (3, 4). These decision trees iterate on EaRs from three operators: *true*, *false* and *while*. If an EaR is not concerned by an exposed area, the  $P_c$  value does not change. The operator *true* assigns the weight index related to the stage in progress. The operator *while* is a verification step that submits the EaRs to the next stage. The operator *false* returns to the previous value. At large scale, the interest is the first sorting step between what is potentially exposed (regardless of the type of area exposed) and what is not. In this first sorting, we differentiate single and multiple exposure areas (Fig. 4).

At the local scale, the identification of exposure areas aims to define different consequences according to the type of potential exposure areas. Thus, more criteria (structural



Pc is the Potential consequence

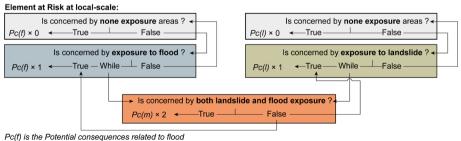
**Fig. 4** Decision tree n°1 ( $Dt_1$ ) applied to element at risk on a large scale in order to readjust potential consequences ( $P_c$ ) according to the level of exposure

components) have been integrated to describe the potential consequences of EaRs. Consequently, three types of potential consequences have been defined related to flood exposure  $(P_c(f))$ , landslide exposure  $(P_c(l))$  and multiple exposure  $(P_c(m))$  computed from maximum values between  $P_c(f)$  and  $P_c(l)$  (Fig. 5).

A synthetic value of structural consequences regarding multiple exposure areas at local scale is computed from the sum of  $P_c(f)$ ,  $P_c(l)$  and  $P_c(m)$ .

# 4 Results

From the different indexes defined in a three-scale analysis, the linear combination and three weighting systems (including two decision trees at large and local scale) were able to define three types of consequences: (1) overall consequences (OCs) at medium scale, (2) consequences on infrastructure (CI) at large scale and (3) structural consequences (SC) at local scale. For all scales analyses considered, we classified different types of consequences (OC, CI and SC) in four classes (low, medium, high and very high) by using RCF similarly to the initial PDI method.



*Pc(I)* is the Potential consequences related to hood *Pc(I)* is the Potential consequences related to landslide

Pc(m) is the maximum Potential consequences value between flood and landslide consequences

Fig. 5 Decision tree  $n^{\circ}2$  ( $Dt_2$ ) applied to element at risk on a local scale in order to readjust potential consequences according to their different spatial location inside different types of potential exposure areas ( $P_c(f, l \text{ or } m)$ )

#### 4.1 Overall consequences at medium-scale analysis (1:100,000–1:25,000)

At medium-scale analysis, overall consequences (OCs) are computed from the sum of four criteria: (a1) built-up type, (a2) road and lifeline type, (a3) urbanized area type and (a4) agricultural and natural surface type. Feature scaling method has been used to standardize the OC index in the range of [0, 1] (Fig. 6).

In very high consequences (3% of the total surface area), five elements are highlighted: built-up areas (all types), national roads, railways, lifelines (all types) and urban centers. In high consequences (9% of the total surface area), four elements are highlighted: activity areas (industrial and commercial), collective residential areas, arable lands and departmental roads. In average consequences (48% of the total surface area), four elements are highlighted: residential (individual) areas, protected areas (zone of floristic, faunal and ecological value and hedge as ecological corridor), touristic areas (garden, park, equipped beach, golf, etc.) and communal roads. Finally, areas to be urbanized, grasslands, scrubs, woods, water surfaces and other natural elements result in low consequences (40% of the total surface area).

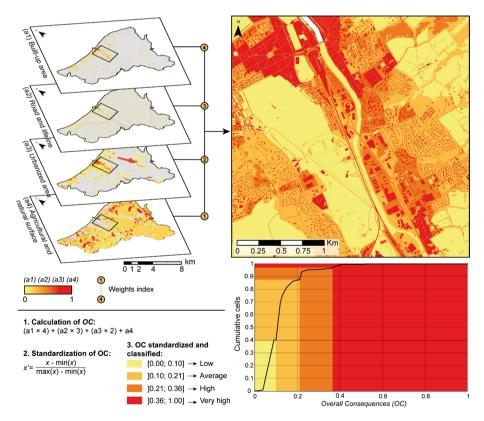


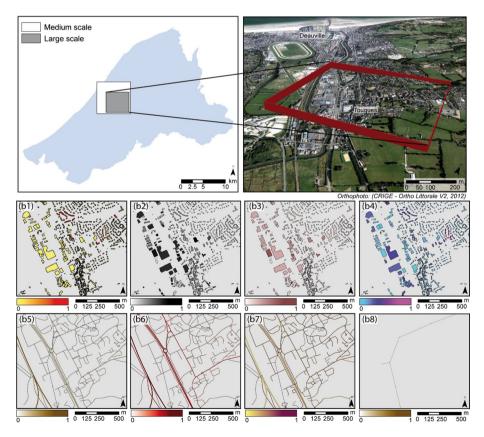
Fig. 6 Quantification of overall consequences at medium-scale analysis

#### 4.2 Consequences on infrastructures at large-scale analysis (1:25,000–1:10,000)

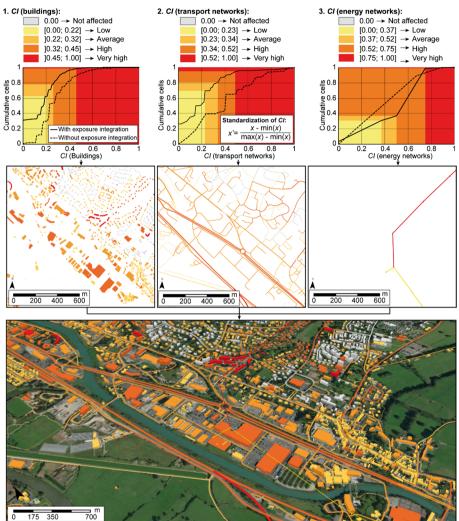
At large-scale analysis, the consequences on infrastructure are computed from buildings, transport networks and energy networks. For buildings and transport networks, the physical, functional and structural components are taken into account. For energy networks, the functional component is considered. The sum of type, number of floors, function and estimated population by building index have been realized on 31,251 buildings. The sum of traffic, number of lanes and type of roads index have been realized on 1201.3 km transport networks. Finally, 35.2 km energy networks have been identified (Fig. 7).

Once the set of criteria is identified and merged, we have used the first decision tree  $(Dt_1)$  to sort EaRs depending on their spatial location and target high infrastructural potential consequences (Fig. 8).

On 31,251 buildings, 9967 (32%) are located outside the potential exposure areas. Low consequences represent 12,140 buildings (39%) and concern mainly any type of hut or residential houses with one floor and no estimated population inside and located in an exposure area. Average consequences represent 6080 buildings (19%) and concern



**Fig. 7** Set of criteria used to quantify consequences on infrastructure (CI) at large-scale analysis. (b1) Index of the estimated population by building; (b2) index of the type of building; (b3) index of the function of building; (b4) index of the number of floors; (b5) index of the type of transport networks; (b6) index of the traffic; (b7) index of the number of lanes (transport network); (b8) index of the type of energy networks



World imagery (Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AeroGRID, IGN and the GIS user Community)

Fig. 8 Consequences on infrastructure (CI) at large-scale analysis. The CI presented are weighted according to the exposure level of element at risk through a decision tree in GIS environment

mainly residential apartment with at least three floors and an estimated population index under 0.5 located in exposure area. High consequences represent 2458 buildings (8%) and concern mainly commercial, industrial or administrative complexes, generally composed of three or more floors and located in exposed area. Very high consequences represent 605 buildings (2%) and concern any kind of house, apartment and complex located on multiple exposure areas. It equally concerns health or rescue institutes located in a zone of a low exposure.

Among the 1201.3 km of transport networks, 324.4 km (27%) are situated outside the potential flood or landslide exposure areas. Low consequences represent 516.6 km of networks (43%) and concern mainly any kind of way or road with two lanes (double

direction) and traffic index value of 0.2 or less located in exposure area. Average consequences represent networks of 120.1 km (10%) and concern mainly roads with two lanes (double direction) and a traffic index value equal to or greater than 0.5 located in an exposure area. High consequences represent networks of 192.2 km (16%) and concern departmental roads and roads located in multiple exposure areas or highways located in an exposure area. Very high consequences represent networks of 108.1 km (9%) and concern railways and national roads with a traffic index value equal to or greater than 0.8 located in multiple exposure areas.

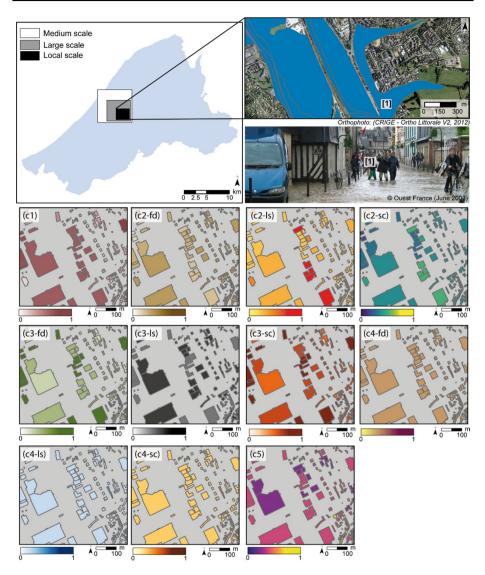
Among the 35.2 km energy networks identified, 0.7 km (2%) are outside the potential flood-prone or landslide-prone areas. Low consequences represent 9.9 km (28%) and concern power lines in exposed areas. Average consequences represent 2.1 km (6%) and concern pylons in exposed areas. High consequences represent 22.2 km (63%) and concern power lines in multiple exposure areas. Very high consequences represent 0.4 km (1%) and concern pylons in multiple exposure areas.

#### 4.3 Structural consequences related to hazard at local-scale analysis (1:10,000– 1:2000)

At the local scale, the aim is to quantify more precisely the structural consequences (SC) of buildings related to different potential exposure areas. We have chosen five criteria currently used in multirisk literature to precise this component (against two at large scale): (1) the type of building, (2) the construction materials, (3) the building condition, (4) the number of floors and (5) the construction date (Kappes et al. 2012a; van Westen et al. 2014; God-frey et al. 2015; Chen et al. 2016). An index has been defined according to the relationship between each criterion of each building, and the various hazards have been taken into consideration. Therefore, flood and landslide exposure have been taken into consideration in order to attribute an index to each criterion, and the maximum of both values have been chosen in case of multiple exposure. At this scale, 861 buildings have been analyzed (from multiple geographical databases and data field acquisition). They are located between Touques and the southern part of Deauville (Fig. 9). This site is partially affected by both landslide and flood exposure (Delahaye 2003; Douvinet 2006; Douvinet et al. 2009, 2015a, b).

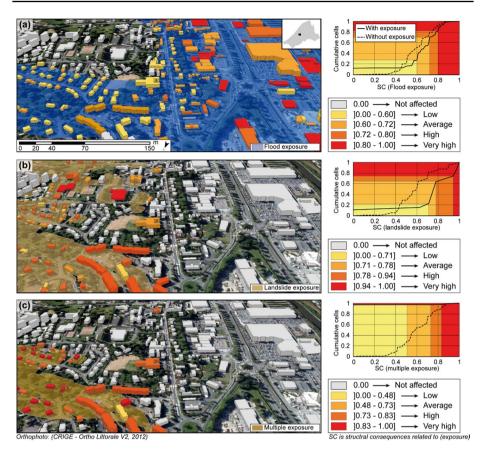
For each type of potential exposure area (flood, landslide and multiple), we have combined different types of criteria such as c1+c2-fd+c3-fd+c4-fd+c5, then c1+c2-ls+c3-ls+, etc. Then, they are weighted with the second decision tree ( $Dt_2$ ) and standardized with a feature scaling method. The linear combination of different structural index values is readjusted according to their spatial location and presented below (Fig. 10).

For SC (flood), about 861 buildings were identified, of which 122 (14%) are outside the potential flood exposure area. Low consequences represent 301 buildings (35%) and mainly concern houses in traditional materials built after 1990 in good state with two floors (Fig. 11). Average consequences represent 186 buildings (22%) and concern mainly houses or flats with two or three floors built in traditional or concrete materials between 1950 and 1970. High consequences represent 99 buildings (11%) and concern complexes, warehouses, commercial centers and industry in mixed materials with two floors or more. Also, it concerns houses with one floor built before 1970 in traditional materials. Very high consequences represent 88 buildings (10%) and concern building in bad conditions, gas stations, complexes commercial centers and industries with one floor built in mixed materials.



**Fig. 9** Set of criteria used to quantify structural consequences (SC) at local-scale analysis. The picture represents the flash flood of June 1, 2003, that generated 5.3 million euros of damages and on death. (c1) is the index value of the type of building; (c2-fd) is the index value of construction material related to flood; (c2-ls) is the index value of construction material related to spatial concomitance. (c3-fd) is the index value of the number of floors related to flood; (c3-ls) is the index value of the number of floors related to flood; (c3-ls) is the index value of the number of floors related to flood; (c3-ls) is the index value of the number of floors related to flood; (c3-ls) is the index value of the number of floors related to spatial concomitance. (c4-fd) is the index value of the building condition related to flood; (c4-ls) is the index value of the building condition related to spatial concomitance. (c5) is the index value of the construction date of building condition related to spatial concomitance. (c5) is the index value of the construction date of building condition related to spatial concomitance. (c5) is the index value of the construction date of building condition related to spatial concomitance. (c5) is the index value of the construction date of building condition related to spatial concomitance. (c5) is the index value of the construction date of building condition related to spatial concomitance. (c5) is the index value of the construction date of building condition related to spatial concomitance. (c5) is the index value of the construction date of building condition related to floors related to spatial concomitance. (c5) is the index value of the construction date of building condition related to floors related to

For SC (landslide), about 861 buildings were identified, of which 759 (88%) are outside the potential landslide exposure areas. Low consequences represent 13 buildings (1.5%), such as houses with one or two floors, in traditional materials (good state), and built after



**Fig. 10** Structural consequences (SC) readjusted according to weighting system ( $Dt_2$ ) at local-scale analysis. **a** Structural consequences related to potential flood exposure; **b** structural consequences related to potential landslides exposure; **c** structural consequences related to potential multiple exposure

1990. It concerns equally sheds and huts. Average consequences represent 6 buildings (0.7%) and concern flats with two or three floors in traditional or concrete materials (good state) built after 1990. High consequences represent 18 buildings (2%) and concern flats and houses with three or more floors, in traditional or concrete materials (good state) and built before 1980. Very high consequences represent 30 buildings (3%) and concern monuments, complexes and flats with more three floors in traditional materials (good state) and built before 1980.

For SC (multiple exposure), about 861 buildings were identified, of which 110 (13%) are outside the potential multiple exposure areas. Low consequences represent 151 buildings (18%) and concern sheds and houses built after 1990 in traditional materials (good state), with two floors. Average consequences represent 338 buildings (39%) and concern houses with two floors, built in traditional materials (good state) before 1990. High consequences represent 172 buildings (20%) and concern houses with two or three floors built before 1980 in traditional materials. Very high consequences represent 90 buildings (10%) and concern flats or houses with three or more floors built between 1980 and 1990 in traditional or concrete materials (good state).

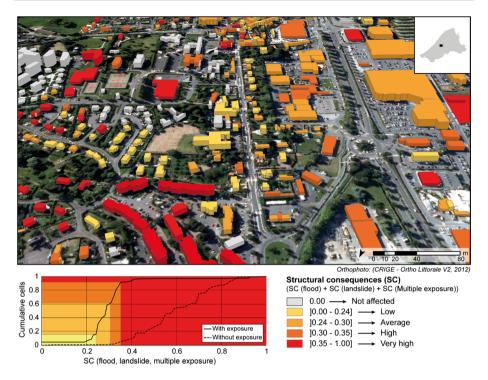


Fig. 11 Sum of structural consequences (SC) at local-scale analysis by using feature scaling method to discretized index values

Among the 861 buildings identified, 51 (5.9%) are located outside the potential exposure areas. Low consequences represent 98 buildings (11.4%) and concern houses with two floors built between 1970 and 1990 in traditional materials (good state) and located in exposed area. Average consequences represent 371 buildings (43%) and concern complexes, commercial centers and industries with two or more floors built in mixed materials (good state) after 1970. It concerns equally sheds and houses with one or two floors built in traditional or brick materials (good state) before 1970. High consequences represent 269 buildings (31%) and concern complexes, commercial centers and industries with one floor (good state) and built after 1980 in mixed materials. It concerns equally warehouses with one floor and flats with two floors built in concrete materials (good state) before 1970. Very high consequences concern any kind of buildings located on multiple exposure areas.

#### 5 Discussion

The aim of this last section is to compare the advantages and limits of the developed method in relation to other index-oriented methodologies. Moreover, the discussion focuses on the interest to use multiple spatial scales analysis in relation to two different weighting systems (use weights index or the spatial location of EaRs to readjust the initial value). Finally, we developed the transposition keys of this method to other study sites.

#### 5.1 Elements at risk, spatial scale analyses and weighting systems

Unlike consequences analysis, risk analysis requires a deep knowledge of hazards in terms of spatial extent, intensity and temporal occurrence (Léone et al. 1996; Muis et al. 2015; Yin et al. 2016; Van der Fels-Klerx et al. 2018). This step can be long, and an analysis of EaRs must be done in parallel. Conversely, the common potential consequences analysis can highlight the most significant EaRs but tend to disconnect the EaRs from their environment. For example, PDI method considers all EaRs that can be potentially affected by landslide exposure even in flat areas (alluvial fan or plain, etc.) without a real possible exposure (Maquaire et al. 2004; Malet et al. 2006; Puissant et al. 2013; Carlier et al. 2018).

The weighting systems and the use of multiple spatial scales allow the integration of environmental conditions in EaR analysis. The social dimension has been excluded from EaRs analysis because of the lack of data. Information was only available at the municipal level, requiring field interviews on communities to collect it (Carlier et al. 2018). Apart from the medium scale, the EaRs taken into consideration are close to relative vulnerability index method (Papathoma-Köhle et al. 2007; Kappes et al. 2012a; van Westen et al. 2014) and PDI method (Maquaire et al. 2004; Malet et al. 2006; Lissak et al. 2013; Puissant et al. 2013; Carlier et al. 2018) which focus on buildings and lifelines.

At medium-scale analysis, the whole elements are taken into consideration without considering potential exposure and first information is provided about potential hotspots considered from type of land used or land cover (Kappes et al. 2011; Cascini et al. 2013; van Westen et al. 2014). However, the information available at this scale is not sufficient to estimate precisely the type and the amount of the potential impact (physical, functional or structural) on EaRs.

This is the aim of the large-scale analysis to provide this information by focusing on buildings, transports and energy networks (Lissak et al. 2013; Puissant et al. 2013; Carlier et al. 2018) according to the potential exposure of EaRs. The large scale provides the first selection about what is harmful but requires an additional analysis to estimate how the EaRs (buildings) could be affected inside the potential exposure areas.

The local scale provides this information but requires field data acquisition and, therefore, cannot be implemented on large areas due to the complexity to collect this type of data (Papathoma-Köhle et al. 2007; Kappes et al. 2012b; Abbas and Routray 2013). That is why data should be filtered using specific parameters, such as exposure areas.

#### 5.2 Ranking system, combination method and classification

The index attribution by ranking system represents the part of subjectivity in this method (Mouroux and Brun 2006; Cooke et al. 2008; Khan and Samadder 2015; Gumus et al. 2016; Van der Fels-Klerx et al. 2018). To partially overcome this part of subjectivity, a statistical distribution of EaRs has been taken into consideration (Zahran et al. 2017; Sahoo and Bhaskaran 2018). There is a need to merge statistical and expert vision in order to reflect the reality. The advantage of the ranking system is that replicability is very quick and easy and allows the comparison of EaRs on any geographical context. The main disadvantage is that ranking allocation may be controversial and cause conflicts between scientists and stakeholders (Maquaire et al. 2004; Malet et al. 2006; Papathoma-Köhle et al. 2007; Kappes et al. 2012a, b; Lissak et al. 2013; Puissant et al. 2013).

The methods combination strongly influences the results achieved. This method is foreseen for multiple contexts (scientist, operational, etc.), and consequently, the execution of the combination of various criteria must be easy to do. This is the reason why the fuzzy logic and artificial intelligence methods (neuronal networks) have been excluded since they require a long coding stage (Tayyebi et al. 2011; Lai et al. 2015) and a long process of defuzzification. Therefore, a linear combination method has been chosen because it is very easy and quick to apply.

After the combination and the weighting steps, the objective is to standardize the results to obtain a global index value between 0 and 1. Then, value thresholds must be defined to classify each type of consequences. For this purpose, the relative cumulative frequency method has been used (Saha et al. 2005; Çetinkaya et al. 2015). With this method, it is possible to adapt manually the threshold value of each class of consequences to reflect expert judgment and integrate different vision (such as end users) of the territory. Thus, the operator can define threshold value for each type of consequences.

#### 5.3 Replicability of the method

The time-consuming part of this method is the adaptation and the updating of the various geographical databases on the study site and their combination in a final data warehouse (Ponniah 2001; Saint-Martin et al. 2018). Consequently, it is easier to apply this method for a study site which is well supplied in geographical databases. The growing development of collaborative and free geographical databases such as *Open Street Map*<sup>®</sup> allows the application of this method in various parts of the world, knowing quality of information will vary according to parts of the world (Haklay 2010; Jokar Arsanjani et al. 2015; Fonte et al. 2017).

The attribution of index value to each class of criteria also depends on the specificities of the studied area. Consequently, the method must be updated according to the presence/ absence of specific EaRs. This value attribution must be done from review of the literature, field knowledge and if it is possible according to advices of local stakeholders in order to avoid controversies (Puissant et al. 2013; Carlier et al. 2018).

Finally, the adaptation of the method must consider different types of exposure related to the environmental specificities of the study site such as snow avalanche, earthquakes, lahar, etc., to adjust the index values of each class of criteria in order to describe EaRs at large and local spatial scale.

## 6 Conclusion

In conclusion, the use of multiple spatial scales provides a complete analysis of EaRs on a study site and highlights the type of consequences through integration of one or multiple criteria in an EaR. To quantify potential consequences, it is reasonable to consider the EaRs from a medium scale (1:50,000–1:25,000) to a local scale (1:10,000–1:2000). In terms of local criteria (> 1:2000), the analysis remains an operational approach (local contingency plan, insurance, etc.). Beyond medium scale (> 1:50,000), the method could be envisaged but requires harmonized databases on the whole region and the process of verification is harder and longer. The integration of environmental dimension, with exposure areas, in a weighting system provides the first solution in the process of risk and multirisk assessment. Indeed, in all cases, hazard is included in the delineated potential exposure areas.

Although the multi-criterion approach has a part of subjectivity, it remains quick and easier to apply than engineering approaches and remains more accurate than the expert approach. However, it can be controversial due to the choice of ranking assignment. That is why an important work of bibliographical is required to integrate end-user considerations in the process. The method developed in this paper could be easily transposed to other coastal study sites. This transposition must considerate new EaRs (such as nuclear plant, smokestacks, etc.) and needs to adapt the rank assigned to each class of criteria. Finally, this adaption must consider potential exposure areas with their uncertainties and consider an adaptation of databases integration.

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