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Characterization of elements at risk in the multirisk coastal context and at different spatial scales: Multi-database integration (normandy, France).

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ABSTRACT

In risk analyses, two components are taken into account: (1) hazard analysis, including susceptibility and temporal occurrence, and (2) consequence analysis, including characterization of elements at risk (EaRs) and their vulnerability. This study focused on characterization of EaRs, in which items are spatially displayed and impacted by natural events. Several methods can assess these EaRs through expert or engineering approaches. Among the expert approaches, the multicriteria method is more flexible and allows integration of a wide range of information in order to characterize and discretize different EaRs. Traditionally, the mapping and criteria accuracy of EaRs is the same at all spatial analysis scales, while the hazard accuracy changes according to the spatial scales. Therefore, we propose an approach based on the selection of different information/criteria among several private or open access multiple geographical databases to adapt the mapping and criteria accuracy of each EaR according to the hazard analysis spatial scale. After harmonizing the different databases and merging them under GIS, a single database per work scale is created through a specific procedure with interoperability of results between scales. Thus, the number of criteria used to describe these EaRs will depend on the scale of work and the spatial scale of the analysis. To develop and test the transposability of this method, three experimental coastal study sites subject to several hazards (multirisk) have been selected in Normandy (France) with error estimations ranging between 10% and 20%. Subsequently, these data can be integrated into risk and multirisk analyses.

1. Introduction

In coastal environments, the interaction between nature and societies is particularly high. For sustainable management of societies, risk and more specifically multirisk analyses are carried out and regularly updated due to global change (climate change and land use evolution). Risk analysis is a combination of hazard and consequence assessments, whereas multirisk analysis is a combination of several risks. Consequences are the result of an exposed element, called an element at risk (EaR) by the scientific community, and its vulnerability to a hazard. In this study, we focus specifically on characterization of EaRs that refer to physical injuries or structural or functional impacts that can be spatially displayed (Birkmann et al., 2013; Blaikie, Cannon, Davis, & Wisner, 2014; Cutter et al., 2008; Timmerman, 1981; UNISDR, 2017). Usually, EaRs are only considered inside hazard areas. However, potential overextension due to uncertainties in the evolution process require consideration of EaRs outside current hazards areas (Gallina et al., 2016; Papathoma-Köhle, Neuhäuser, Ratzinger, Wenzel, & Dominey-Howes, 2007).

Two main approach are commonly used to assess EaRs in a territory: engineering and expert approaches. Different engineering approaches are available, including curve vulnerability analysis, which provides precise descriptions and absolute values of the loss and potential damage depending on the hazard (Li et al., 2016; van Westen, Castellanos, & Kuriakose, 2008). However, these methods involve a huge amount of data that leads to an in-depth analysis that cannot be replicated everywhere (Petrucci & Gullà, 2010). Among the expert approaches, methods such as ranking systems are commonly used in French document planning due to their swift implementation potential and low data requirements (Malet, Thiery, Maquaire, & Puissant, 2006; MATE/

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METL, 2016). However, the subjectivity in the choice of variables induces difficult comparisons of the results (Kappes et al., 2012). Consequently, a multicriteria method has been developed to reduce the uncertainties involved in the use of ranking methods (Malet et al., 2006; Puissant, Van Den Eeckhaut, Malet, & Maquaire, 2013). This method consists of assessment using criteria and a weighting system(s) index (Carlier, Puissant, Dujarric, & Arnaud-Fassetta, 2017; Puissant et al., 2013). The main advantage of this method is its flexibility, which allows adaptation to the number of criteria and databases used to describe EaRs (Carlier et al., 2017; Puissant et al., 2013; Reghezza-Zitt & Rufat, 2016). However, the number of criteria used and their spatial accuracies must be consistent with the spatial scale analysis.

Based on this multicriteria method (expert approach), two main objectives are highlighted to enhance EaR analysis using multiple scale analysis methods and geographical databases.

The first objective is to propose consistent accuracy of EaRs in terms of mapping and criteria integration according to the spatial scale analysis. The following scales are drawn from scales used in hazard analyses (Van Westen, 2000; van Westen et al., 2008): (1) small-scale analysis (Carpignano, Golia, Di Mauro, Bouchon, & Nordvik, 2009) in the range of 1:100,000–1:250,000, which is used by regional collectives for strategic planning (MATE/METL, 2016), (2) medium-scale analysis in the range of 1:25,000–1:50,000, which is preferred for identification of critical facilities (Kappes et al., 2011; van Westen et al., 2014), (3) large-scale analysis (1:10,000–1:25,000), which is used for characterization of infrastructures, such as buildings or networks (Carlier et al., 2017; Puissant et al., 2013), and (4) local-scale analysis (1:2000–1:10,000), which provides more detailed information about the structural components of infrastructures, such as building materials and the date of construction (Chen et al., 2016; Kappes et al., 2012). In this study, we consider scales ranging from medium to local-scale analysis. Beyond the medium scale, EaRs are not considered accurate. From these different scale analyses, we used multiple geographical databases (GDBs) to characterize criteria and describe EaRs.

The second objective concerns the acquisition and harmonization of multiple databases to assess EaRs and their criteria with a coherent degree of detail. The mapping accuracy and criteria integrated to describe these EaRs depend of\n the spatial analysis scale (see above). At the global scale, the use of remote sensing is privileged; however, at the medium to large scale, the use of GDBs must prevail. Three types of GDBs are identified: (1) GDBs provided by institutions under conditions, (2) GDBs originating from volunteered geographical information (VGI), which is an open data format, and (3) archive documents available under conditions that require digitalization (Bol, Grus, & Laakso, 2016; Foody et al., 2015; Olteanu-Raimond et al., 2017). At the local scale, these databases are merged with field data acquisition or photointerpretation (Papathoma-Köhle et al., 2007; Lissak, 2012; Puissant et al., 2013; Hénaff & Philippe, 2014). Difficulties associated with these different databases are related to harmonization and verification of these data and their integration into data warehouses.

Consequently, the main challenge is defining EaRs and their criteria at different analysis scales using multiple GDBs. Multiple EaR scale descriptions and characterization are lacking in risk analyses. These terms have been defined at only one analysis scale and then zoomed in (or vice versa), and thus the accuracy of the EaRs is the same at a local or watershed scale. Furthermore, various EaRs that are incomparable are taken into account in the same analysis, such as biological areas and building functions. The development of GDBs has allowed identification of different EaRs at different scales, but different datasets must be merged to obtain adequate accuracy after verifying their reliability. The use of multiple GDBs will provide a better assessment of EaRs at the medium and large scales. At the local scale, field data acquisition is leading to identification of the intrinsic characteristics of buildings. Thus, the accuracy (spatial and attribute) varies according to the analysis scale.

In the first part of this paper, we perform a bibliographical synthesis to identify EaRs and the criteria used in different risk analysis contexts. In second part, based on this synthesis, we define a set of criteria to characterize EaRs at each spatial analysis scale. In the third part, two data integration models are calibrated for EaR assessment at medium and large scales and from the use of multiple GDBs. Then, these models are validated by field observation. In the fourth part, transposition models are performed at two other study sites in the same region. The fifth part shows the integration model results and discusses the adaptability of the models to other study sites and the possibility of updating the results obtained at different scales.

2. Methods

The proposed method consists of the following steps: (1) a review to define a different set of criteria according to different hazard and risk analyses, (2) the attribution of criteria for each of the three scale analyses according to the review, (3) an inventory of existing GDBs, which is necessary for the establishment of these criteria, and finally (4) creation of two integration models.

2.1. Towards a review to define EaRs for different hazard categories

To propose consistent criteria for a multistage EaR assessment and different types of risk, existing methods must be reviewed. In our case, three types of risks are taken into consideration: (1) flood risk analysis involving marine and continental flooding, (2) landslide risk analysis involving continental and coastal landslide hazards, and (3) multi-hazard risk analysis involving concomitance and cascade effects according to current hazards at the three study sites. In our study area, other hazards, such as collapse or seismicity, are less significant in terms of damage than hydro-gravitational hazards. At least three or more multicriteria methods were developed for single hazard analysis with corresponding analysis scales ranging from 1:50,000 (medium scale) to 1:2000 (local scale). Thirteen methods were reviewed, representing 21 authors (Table 1).

Of the five different flood analysis methods (eight authors) and fifteen identified criteria, nine involved building analyses. Among these criteria, the most important is related to the functions (Kubal, Haase, Meyer, & Scheuer, 2009; Meyer, Haase, & Scheuer, 2009a, b; Scheuer, Haase, & Meyer, 2011; Vojinovic et al., 2016) and the number of floors (Eckert, Jelinek, Zeug, & Krausmann, 2012; Hénaff & Philippe, 2014). The secondary criteria used are the type of urbanized area (*i.e.,* urban centre, residential area, etc.) and the type of natural surface (Camarasa Belmonte, López-García, & Soriano-García, 2011; Meyer et al., 2009a, b; Kubal et al., 2009; Scheuer et al., 2011).

Considering five different landslide risk analysis methods (Table 1), fifteen criteria were identified to characterize the EaRs. Among them, nine focused on building analysis to define their functions, including the number of floors, construction materials and age (Bianchini et al., 2017; Carlier et al., 2017; Lissak, 2012; Maquaire et al., 2004; Papathoma-Köhle et al., 2007; Puissant et al., 2013; Uzielli et al., 2015). Similar to flood risk analyses, other common criteria used include the urbanization type and agricultural and natural surfaces (Bianchini et al., 2017; Cascini et al., 2013).

For the multi-hazard analysis, three different methods (Table 1) considered nine criteria to characterize the EaRs. Among them, eight criteria concerned building analyses to define their functions, including the number of people, number of floors and surroundings (Chen et al., 2016; Godfrey et al., 2015; Kappes et al., 2012; van Westen et al., 2014). The EaRs and criteria for all of these methods are described in Fig. 1.

The cross-analysis of twenty-one identified criteria (floods, landslides and multi-hazards) highlights buildings as the most important component, representing 60% of the total number of criteria.

Among the 13 methods, the criteria most commonly used to characterize buildings are as follows:

Table 1
Criteria used for different risk analyses with multi-criteria methods from the 1:2000 to 1:50,000 scales.

Method	Criteria used	Attributes	Scenario	Country	Source
(1.1) Flood	Population (residential)	Low, large, high density	Working day (8–20 h)	Spain (Valencia)	Camarasa Blaikie, Cannon, Davis, and Wisner (2014)
	Urbanized area (type)	Administration, cemetery, etc.	Night time (20-8 h)		
	Agricultural (type)	Arable, citrus tree, etc.	Holidays (8–20 h)		
	Natural surface (type)	Forestry, pasture, lagoon, etc.			
(1.2) Flood (FloodCalc Urban)	Transport (function)	Streets, rails	50 Y-flood	Germany (Leipzig)	Kubal et al. (2009);
	Building (function)	Residential, commercial, etc.	100 Y-flood		Meyer et al. (2009a, b);
	Urbanized area (type)	Fairground, sport, etc.	200 Y-flood		Scheuer et al. (2011)
	Building (value)	Land value per floor space			
	Population (residential)	Pop. per building (children, etc.)			
	Population (building)	School, hospital, kindergartens, etc.			
	Natural surface (type)	Forest, contaminated sites, etc.			
(1.3) Flood	Building (floors)	1, 2, [3–4], etc.	5 m sea waves	Egypt (Alexandria)	Eckert et al. (2012)
	Building (material)	Concrete, traditional, mortar, etc.	9 m sea waves		
	Building (environment)	Shoreline distance			
(1.4) Flood	Building (environment)	Water depth, distance to refuge, etc.	None	France (Pays de la Loire)	Hénaff and Philippe (2014)
(V.I.E.)	Building (floors)	1 floor without windows or roof, etc.			
(1.5) Flood	Building (type)	Pillar house, two-story house, etc.	Activity during event	Thailand (Ayuthaya)	Vojinovic et al. (2016)
	Building (function)	Hospital, police station, etc.	Activity after event		
	Transport (material)	Asphalt roads, gravel roads, etc.			

Method	Criteria used	Attributes	Scenario	Country	Source
(2.1) Landslide (Potential Damage Index)	Building (type)	Housing, tourism activity, cemetery, etc.	Summer period	France (Alpes)	Maquaire, Weber, Thiery, Puissant, and Malet (2004);
	Building (function)	Education, emergency, trade, etc.	Winter period		Puissant et al. (2013);
	Building (floors)	> 6, 3–6, < 3, etc.			Lissak (2012);
	Building (state)	Good, moderate, etc.			Puissant et al. (2013);
	Building (material)	Concrete, traditional, etc.			Carlier et al. (2017)
	Building (age)	> 1900, 1970–1990, etc.			
	Population (residential)	0, < 3, [3–6], etc.			
	Transport (function)	Strategic road, servicing road, etc.			
	Lifelines (type)	Energy lines and power stations			
	Urbanized area (type)	Cemetery, camping, etc.			
	Agricultural (type)	Pasture and cropland			
	Natural surface (type)	Forest, grass, water, etc.			

(*continued on next page*)

Table 1 (*continued*)

Method	Criteria used	Attributes	Scenario	Country	Source
(2.2) Landslide	Building (function)	Education, emergency, trade, etc.	Summer period	Germany (Swabian Alb)	Papathoma-Köhle et al. (2007)
	Building (material)	Concrete, traditional, etc.	Winter period		
	Building (age)	> 1900, 1970–1990, etc.	Day time (8–20 h)		
	Building (surrounding)	Without walls, stone walls, etc.	Night time (20-8 h)		
	Building (floors)	> 6, 3–6, < 3, etc.			
	Transport (function)	Strategic road, servicing road, etc.			
	Lifelines (type)	Energy lines and power stations			
	Urbanized area (type)	Cemetery, camping, etc.			
	Agricultural (type)	Pasture and cropland			
	Natural surface (type)	Forest, grass, water, etc.			
(2.3) Landslide	Building (state)	With (or less) damage	None	Italy (Volturno)	Cascini et al. (2013)
	Road (state)	With (or less) damage			
	Urbanized area (type)	Historical centre, residential area, etc.			

Method	Criteria used	Attributes	Scenario	Country	Source
(2.4) Landslide	Building (material)	Stone masonry, concrete, etc.	None	Italy (Ancona)	Uzielli, Catani, Tofani, and Casagli (2015)
	Building (surrounding)	Without walls, stone walls, etc.			
	Building (floors)	> 6, [3–6], < 3, etc.			
	Building (age)	> 1900, 1970–1990, etc.			
	Building (foundation)	Plinths, strip footing, etc.			
(2.5) Landslide	Building (function)	Administration, industrial, etc.	None	Italy (Volterra)	Bianchini, Solari, and Casagli (2017)
	Urbanized area (type)	Campground and touristic complex			
	Agricultural (type)	Croplands, vineyards, etc.			
	Natural surface (type)	Grassland, wood, etc.			
	Transport (function)	State highway, toll road, etc.			
(3.1) Multi-hazard (Relative Vulnerability Index)	Building (material)	Stone masonry, concrete, etc.	Day (summer/winter)	France (Barcelonnette)	Kappes, Keiler, et al. (2012) and Kappes, Papathoma-Köhle, et al. (2012); van Westen et al. (2014)
	Building (floors)	> 6, [3–6], < 3, etc.	Night (summer/winter)		
	Building (surrounding)	Without walls, stone walls, etc.	Earthquake		
	Building (warning signal)	Presence (or absence) of warning signal	Landslide		
	Population (residential)	Pop. per building (children, elder, etc.)	Flood		
	Population (vulnerable)	Hospital, schools, etc.	Storm		
(3.2) Multi-hazard	Building (floors)	> 6, [3–6], < 3, etc.	River floods	Romania (Nehoiu Valley)	Godfrey, Ciurean, van Westen, Kingma, and Glade (2015)
	Building (surrounding)	Openings towards slope, slope, etc.	Flash floods		
	Building (material)	Cracks in structure, maintenance, etc.	Slow moving landslide		
	Building (foundation)	Plinths, strip footing, etc.	Debris flows		
(3.3) Multi-hazard	Building (function)	Commercial, residential, factory, etc.	River floods	Italy (Fella river valley)	Chen et al. (2016)
	Building (material)	Brick, concrete, masonry, etc.	Debris flows		
	Building (value)	[750–5.000 €], [5000–10.000 €], etc.	Flash floods		
	Population (tourism)	[1–2 people per building], etc.	Major to frequent event		
	Urbanized area (type)	Place of worship, recreational, etc.			

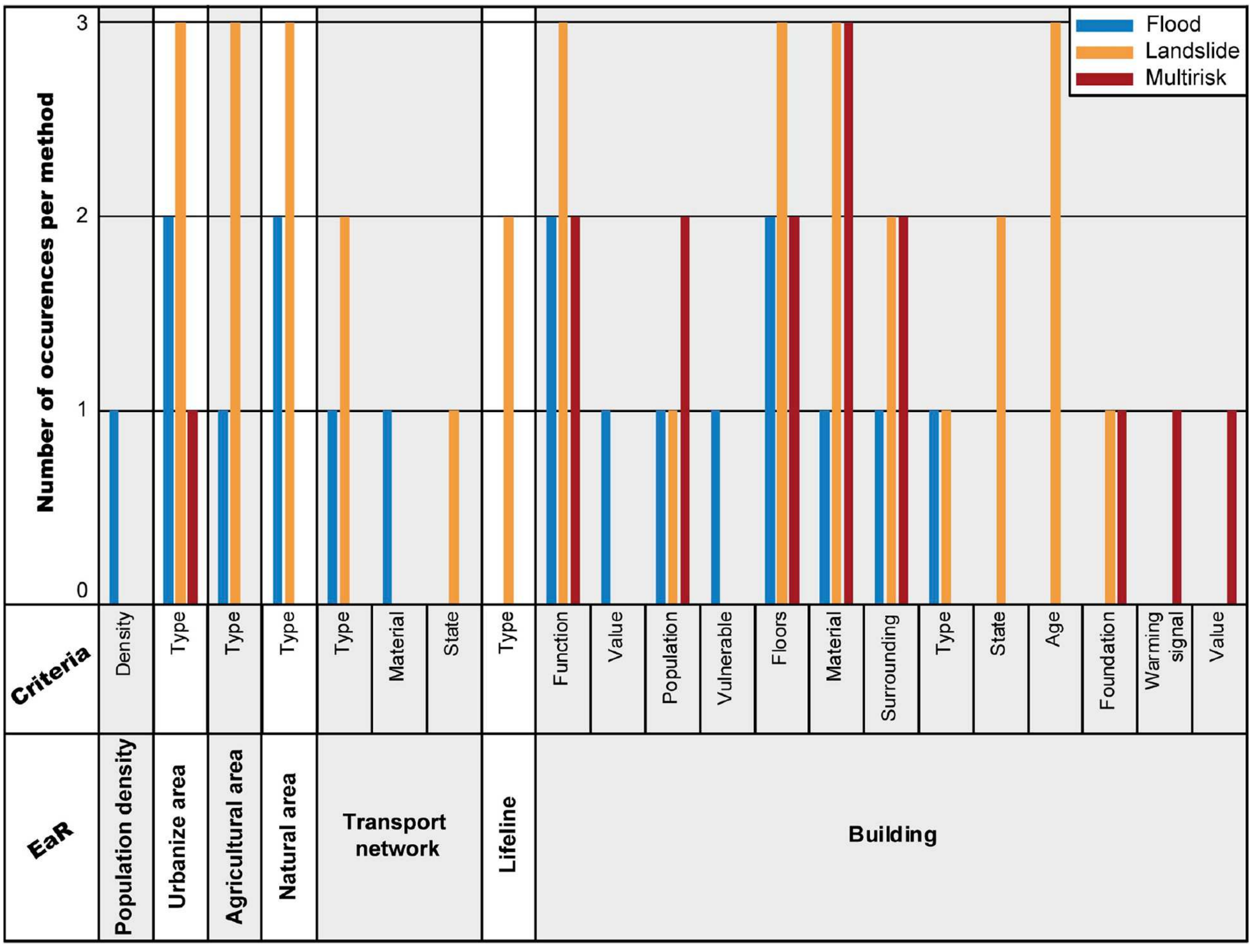

Fig. 1. Synthesis of the identified EaRs and the criteria used for the 13 multi-criteria methods (expert approach) based on three hazard types: flood, landslide and multi-hazard.

- the function within the study site (economic, administrative, cultural, etc.) (7 occurrences);
- the number of floors (7 occurrences);
- the construction materials (5 occurrences); and
- the surroundings (5 occurrences).

The secondary criteria taken into account are as follows:

- the type of urbanized areas (7 occurrences) and
- the natural surfaces (6 occurrences).

The third criteria taken into consideration are as follows:

- the type of agricultural surfaces (4 occurrences);
- the number of people by building (4 occurrences); and
- the type of transport network (3 occurrences).

Criteria with fewer than two occurrences are considered non-representative components, such as the transport network material (Vojinovic et al., 2016) or building foundation type (Godfrey et al., 2015).

For each paper analysed, two patterns are noticeable in the choice of different criteria. For the first pattern, authors take all components of the territory into consideration, including natural surfaces, network transport and buildings (Bianchini et al., 2017; Carlier et al., 2017; Puissant et al., 2013). The weighting of criteria places the EaRs considered non-significant in the background with low weights. For the second identified pattern, the authors focus on only a few elements in the territory, such as buildings with different descriptions (Chen et al., 2016; Godfrey et al., 2015; Kappes et al., 2012; van Westen et al., 2014). This approach allows analysis of different criteria with the same importance in the index weight. However, it prevents taking into account the different constraints present at the study site. The method proposed in this paper takes into account these two different approaches according to the scale analysis.

2.2. Set of criteria adapted for multi-scale analyses

Hazard analysis is well established in the literature and planning documents and operates through multiple spatial scales ranging from global to local. Thus, hazard mapping of the gain of accuracy and more details are integrated according to the spatial scale. However, in traditional EaR studies in which only one scale is considered, the spatial accuracy is the same at each scale (simply zoomed in or vice versa) (Table 1). Consequently, the EaR details are the same at each spatial scale. In this context, the aim is to provide different sets of criteria to describe EaRs according to various scale analyses with a goal of improving EaR assessment methods.

Van Westen, Van Asch, and Soeters (2006, 2008) defined a four-scale analysis for risk assessment from small (greater than 1:50,000) to local (less than 1:10,000) scales. In the small-scale analysis, the accuracy is not sufficient to define the EaRs and distinguish the various components of the territories. Consequently, this analysis scale is not considered in this paper.

In the medium-scale analysis (from 1:50,000 to 1:25,000) (Fig. 2a), the aim is to provide spatial information about all components and

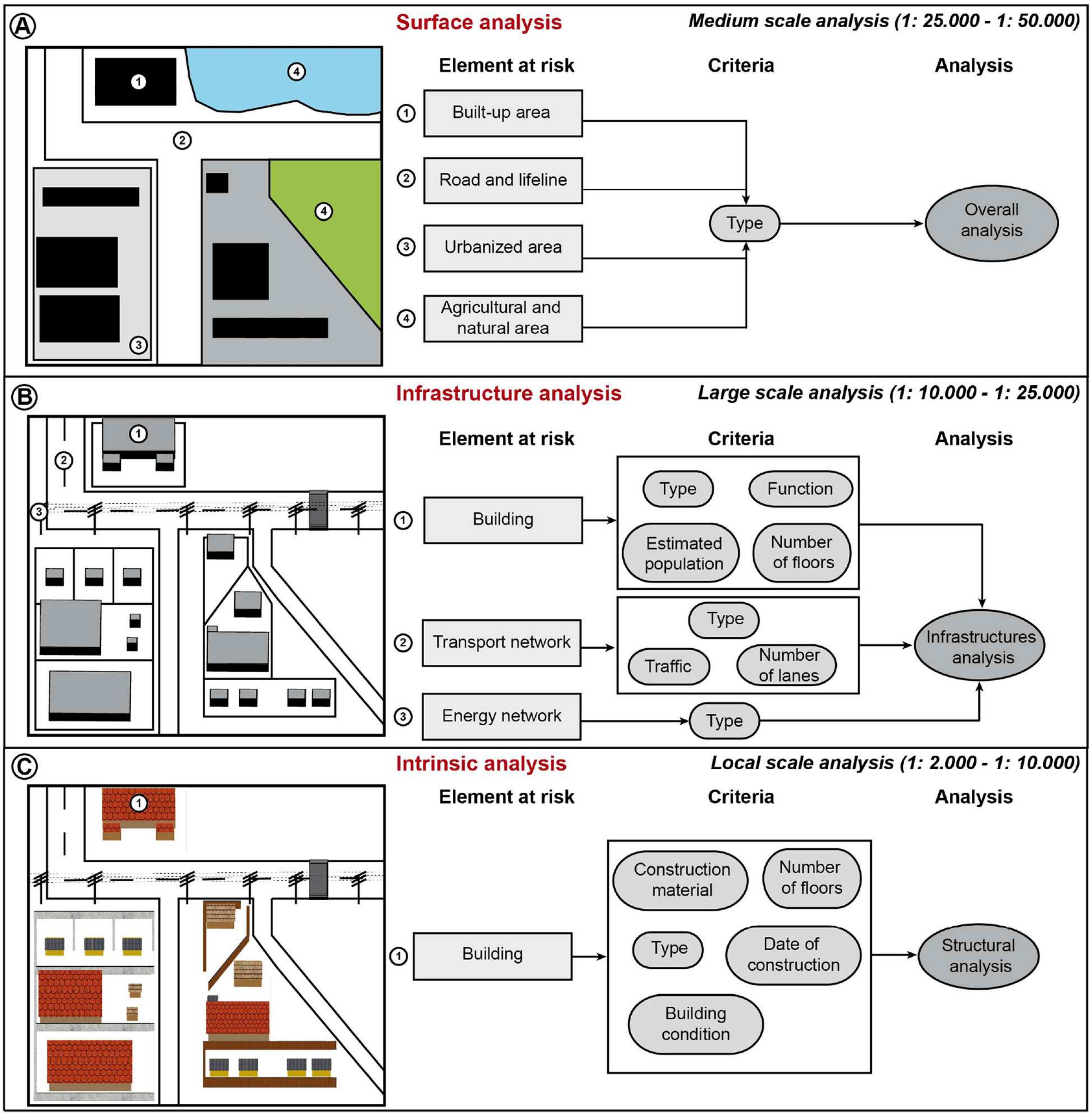

Fig. 2. Spatial and attribute accuracies of EaRs at three analysis scales with the same spatial extent.

constraints of the study sites (overall analysis), such as protected areas or agricultural surfaces. This scale analysis must provide global information about the main components of the territories, critical facilities, future development of the territory or the main resources available in the area (Armaş, Ionescu, Gavriş, & Toma-Danila, 2016; Dilley, Chen, Deichmann, Lerner-Lam, & Arnold, 2005). The use of one criterion to characterize different EaRs in the territory (1. built-up area, 2. roads and lifelines, 3. urbanized area and 4. agricultural and natural surfaces) allows all EaRs to be pooled within the same analysis.

The purpose of the large-scale analysis (from 1:25,000 to 1:10,000) (Fig. 2b) is to identify physical injury and structural and functional impacts of infrastructure components (Carlier et al., 2017; Lissak, Maquaire, Puissant, & Malet, 2013; Malet et al., 2006; Maquaire et al., 2004; Puissant et al., 2013). These infrastructures are buildings and transport-energy systems. In contrast to the medium scale, the focus of this scale is to compare similar EaRs (infrastructures such as buildings, roads, etc.) and to avoid over- or underestimation.

In this context, (1) physical injuries are defined based on the estimated population by building (Chen et al., 2016; Kappes et al., 2012; Kubal et al., 2009; Scheuer et al., 2011; van Westen et al., 2014) and road traffic, (2) functional impacts are defined based on the economic function of each building and the road and lifeline type, and (3) structural impacts are defined by both the type and number of floors of each building and by the number of lanes (road, highway, etc.). Moreover, agricultural and natural areas are not taken into account at this analysis scale, because the scale cannot consider the site specificity, such as biodiversity, economic gain or loss or productivity by plot (Ernoul et al., 2018; Ženka, Slach, Krtička, & Žufan, 2016).

In the local-scale analysis (from 1:10,000 to 1:2000) (Fig. 2c), the aim is to obtain a better assessment of the structural elements related to building. The focus of this analysis scale is to provide better information about different forms of vulnerability (Kappes et al., 2012; Papathoma-Köhle, Gems, Sturm, & Fuchs, 2017). Thus, for each building, five criteria can be used to characterize the structure: (1) the construction

Table 2
Sources and data used for characterization of the EaRs in the medium-scale (M), large-scale (L) and local-scale (l) analyses.

Range	Source	Data provided	Updated	M	L	l
Global	Open Street Map (OSM)	1. Building (surface, function, type, name)	2018	●	●	●
		2. Land use (surface, type, name)	2018	●	●	●
		3. Natural area (surface, type, name)	2018	●		
		4. Place (surface, type, name)	2018	●	●	●
		5. Network (type, name)	2018	●	●	
National (France)	IGN[a] (BD TOPO®)	1. Traffic network (surface, type, name, state, etc.)	2017	●	●	
		2. Lifeline (type, tension, operating)	2017	●	●	
		3. Natural area (surface, type)	2017	●		
		4. Building (surface, height, function, type)	2017	●	●	●
		5. Land use (surface, function)	2017	●	●	
	CdL[b]	1. Protected area (surface, name)	2011	●		
		2. Land cover (type)	2011	●		
	RPG[c]	1. Agricultural plot (surface, type)	[2007–2016]	●		
	INSEE[d]	1. Tiles_200 × 200 (population)	2010		●	
	INPN[e]	1. Protected area (surface, type, name)	2017	●		
	Notary/INSEE	1. Land price (value)	2018			●
Regional	CETE[f]	1. Building (surface, date)	2011			●
	MOS Normandy[g]	1. Land use (surface, type, function)	2009	●	●	
Local	PLU/PLUi[h]	1. Land use (surface, function)	[2007–2018]	●	●	
	Field data and photointerpretation	Building (Material construction, condition)	2018			●

[a] IGN (National Geographic Institute).
[b] CdL (Coastal conservatory).
[c] RPG (Graphical Parcel Register).
[d] INSEE (French National Institute for Statistic and Economic Research).
[e] INPN (National Inventories for Cultural and Natural Heritage).
[f] CETE (Public Works Regional Engineering Centres).
[g] MOS Normandy (Normandy Land Cover).
[h] PLU/PLUi (urban planning documents).

material, (2) the number of floors, (3) the construction type, (4) the date of construction and (5) the building condition. These criteria, which are complementary to the large-scale analysis, require the acquisition of field data and should be limited to a few buildings (Lissak, 2012).

2.3. Geographical databases used in integration models

The use of multiple GDBs to identify EaRs at different scales is a recent addition to risk analyses due to the development of multiple data platforms and sources (Campelo, Bertolotto & Corcoran, 2017; Johansson, Olofsson, & Mangold, 2017; Jokar Arsanjani, Mooney, Zipf, & Schauss, 2015). These different platforms and sources represent an alternative to traditional data collection from the field or photointerpretation (Ambrosi, Strozzi, Scapozza, & Wegmüller, 2018; Defossez, Vinet, & Leone, 2017). In this paper, multiple GDBs were integrated for the medium- and large-scale analyses, and local-scale field data were promoted.

Three types of GDBs are available for open access or under conditions (Table 2). The GDBs produced by national institutes are regularly updated and controlled. Consequently, confidence in these GDBs is particularly high.

The second type of GDB comes from (2) VGI (Bol et al., 2016; Foody et al., 2015; Olteanu-Raimond et al., 2017), which is an open data format, such as *Open Street Map* (OSM). Multiple associations or users supply the GDBs produced by this institution. These GDBs are updated in near real-time but require an audit before integration with other GDB types.

The third type of GDB comes from archive documents available in municipalities, such as the *Local Urbanism Plan* (PLU) or the *Intercommunal Local Urbanism Plan* (PLUi). New platforms, such as *Geoportail Urbanism*, are increasingly being developed. This platform provides digitalized urban documents with geo-referencing and harmonized data. The confidence in these data is high, but verification is required when the data update is long-standing.

At the medium scale (1:50,000–1:25,000), (1) built-up areas and (2) road and lifeline types are defined through the BD TOPO® (provided by IGN) and OSM databases (Table 2). For (3) urbanized areas, we assign a higher importance to official urban documents (PLU/PLUi), which are regularly updated but are not available for all municipalities. Municipalities without official urban planning are subject to National Urban Planning Regulations. The *MOS Normandy* substitutes for urban documents when the municipalities are subject to the National Planning Regulation. This database is available for Upper Normandy and is provided by the Normandy region (last updated in 2009) to obtain information about land cover and land use. The (4) agricultural and natural areas are defined based on four data sources. The agricultural areas are defined with RPG, which provides information about the crop type, and official urban documents define the boundaries of agricultural surfaces. Natural and protected surfaces are defined with BD TOPO® and the INPN and CdL databases.

At the large scale (1:25,000–1:10,000), most information concerning buildings, roads and lifelines is collected from BD TOPO® because of the spatial accuracy of the database. The OSM database is also used to complete the information obtained from BD TOPO®. In the results, the function and type of buildings are defined using this combination of data sources. To define physical injury, the function of the building and the number of floors must be known. In addition to these datasets, a third database (INSEE) can be exploited to obtain information about the number of people living in specific areas (200 × 200 tiles). Then, a weighting system can be used to estimate the population per building (physical injury).

At the local scale (1:10,000–1:2000), data about the building condition and construction material are gathered by photointerpretation or field data acquisition. The spatial footprint of the building comes from databases defined at the large scale. The construction date is available in the CETE databases and is provided under conditions. A complementary database is available concerning land prices at the communal scale (notarial database) to estimate the costs or benefits of buildings on the study sites.

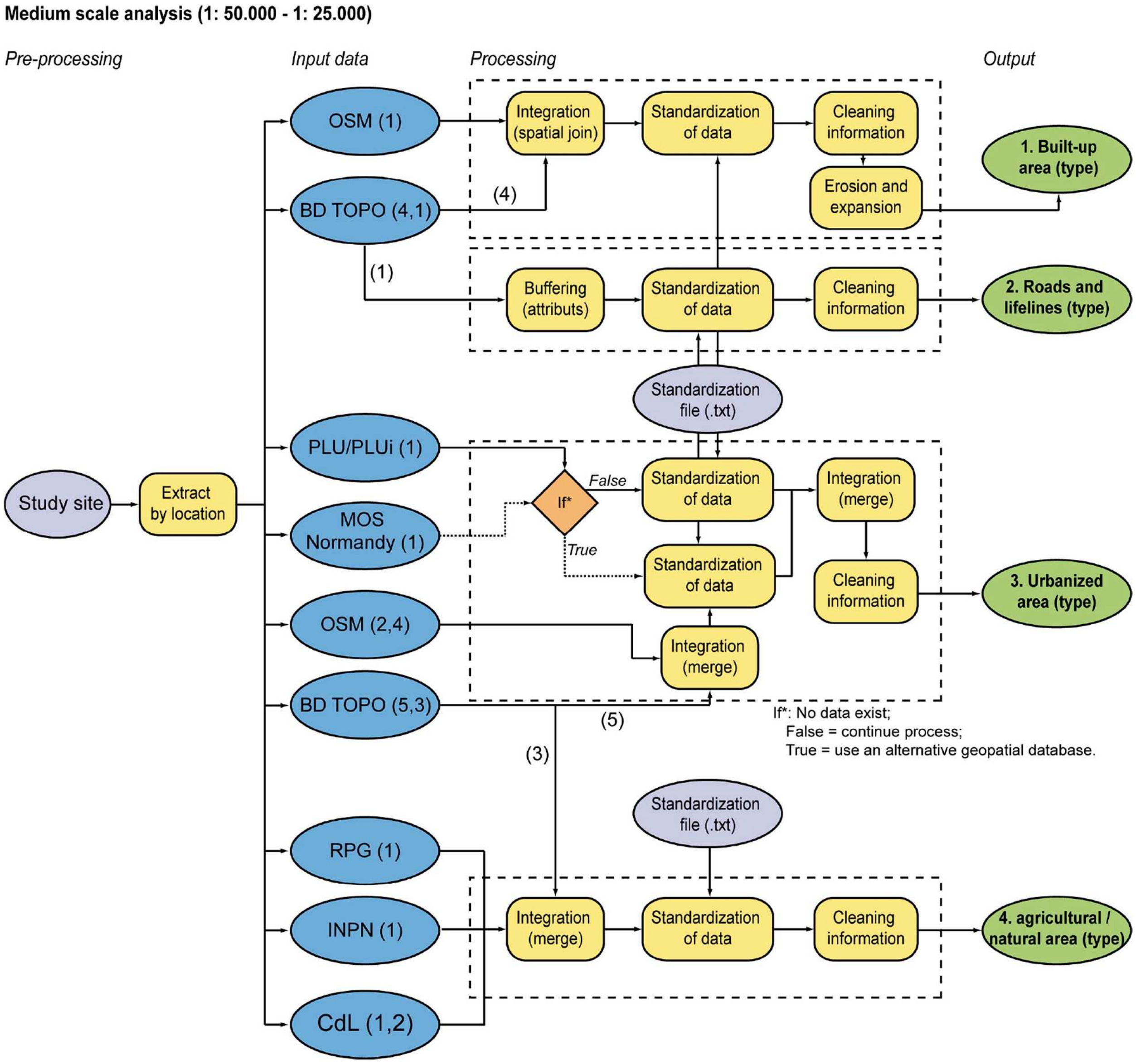

Fig. 3. Integration model for the medium-scale analysis with primitive visual scripting tools (model builder under the GIS environment).

2.4. Integration models

Once all criteria are defined (2.2) and the dataset is identified (2.3) for all analysis scales, the next step is the extraction, transformation and loading of GDBs into a final data warehouse (Biljecki, Heuvelink, Ledoux, & Stoter, 2018; Hanus, Pęska-Siwik, & Szewczyk, 2018; Yılmaz & Canıberk, 2018). This step, which is called the 'integration process' (pre-processing, input data, processing, and output Figs. 3 and 4), concerns only the medium- and large-scale analyses. Therefore, two integration models are produced to obtain adapted data corresponding to each scale. The first step (pre-processing) consists of delineation of the study area and extraction of the associated database. Concerning the input data shown in Fig. 3, the number following the source name corresponds to the data provided in Table 2. Third, to initiate the processing step and to automate data standardization, an extra pre-treated file is added. Therefore, these models two models extract data from database identify, transform (new classification) geometric primitives and/or attribute tables and load them in a final data warehouse.

For the integration model in the medium-scale analysis, thirteen databases from seven sources are used (Fig. 3). The aim is to obtain (1) built-up areas by simplification of attribute data and erosion-dilatation of the spatial extent of buildings. For (2) roads and lifelines, the road width information allows the spatial extent determined by the buffering process to be defined. At this scale, only the type is used to characterize the EaRs. The main difficulties concern (3) urbanized areas and (4) agricultural and natural areas because of the importance of the information provided by each GDB. For each criterion, the cleaning process consists of a visual check (photo-interpretation and field survey) to identify possible inconsistencies between different attribute fields in case of conflict between two information sources.

For the second integration model in the large-scale analysis (Fig. 4), the native resolution has been kept for the spatial extent of buildings to determine the four criteria (type, function, number of floors and estimated population). The number of floors and estimated population require complementary calculations. The type and function of buildings are defined from five data sources. BD TOPO® provides some of this information and can be completed by the OSM database, urban documents or regional databases. For network characterization, the spatial extent is the same as that of the medium scale, but more criteria are integrated in the analysis. Thus, we focused on the types of roads and lifeline, the number of lanes in each road and the traffic density. BD TOPO® provides all of this information.

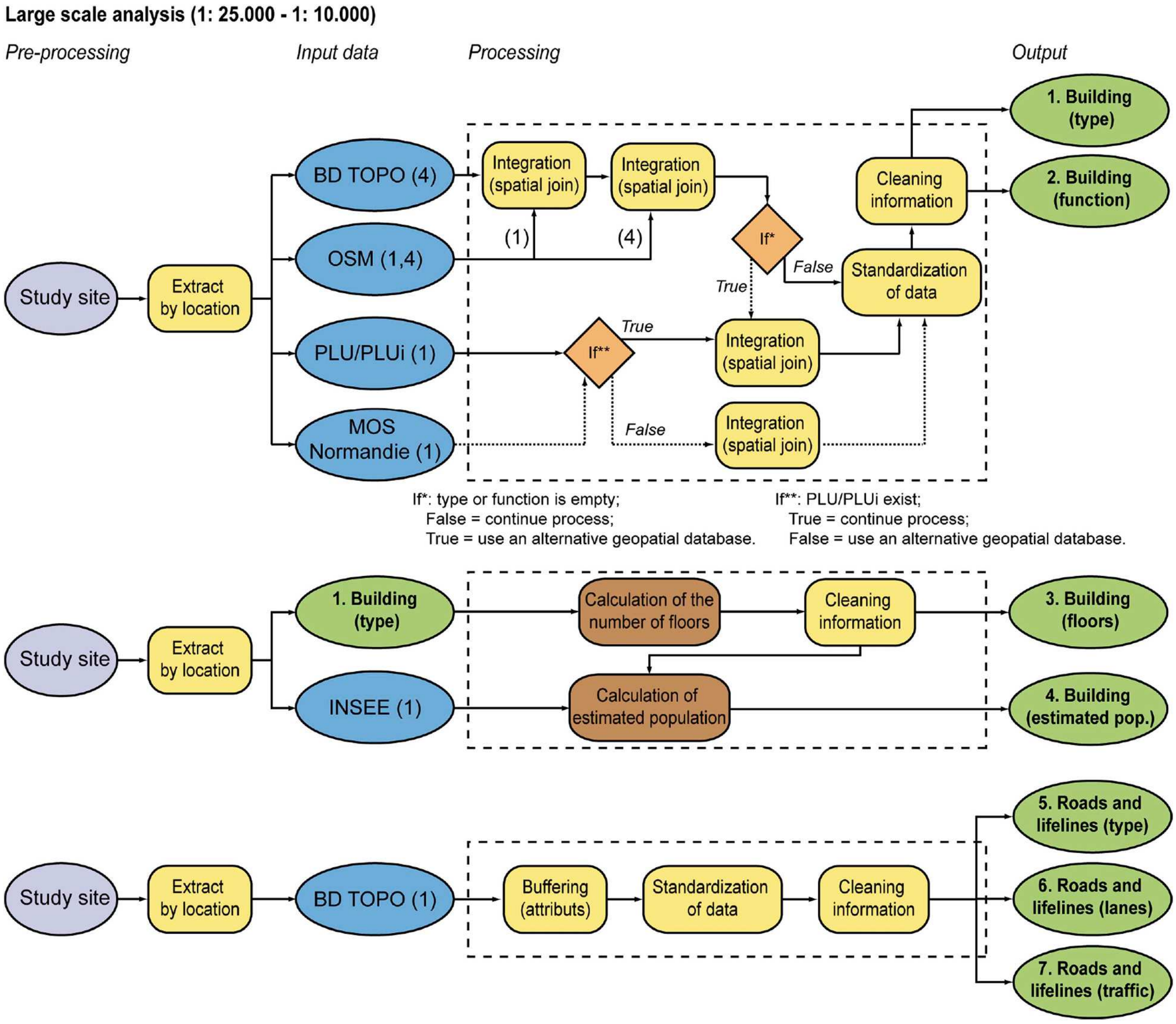

Fig. 4. Integration model for the large-scale analysis with primitive visual scripting tools (model builder under the GIS environment).

Table 3
Average floor elevation (f) based on European standards for different building types.

European standards	*f* (m)
House	3.0
Apartment	3.1
Office	3.9
Mixed use	3.5
Other	3.1

CTBUH. 2015. Height Calculator. http://www.ctbuh.org/.

To estimate the population of each building (for physical injuries), we must define (1) the living space (m^2), (2) number of floors, and (3) building footprint. Some authors use a unique average floor height value to identify the number of floors for all buildings (Martani, Cattarinussi, & Adey, 2018; Zhao, Myint, Wentz, & Fan, 2015). BD TOPO® provides information about the minimal and maximum heights of each building in the territory from photogrammetry ($<$ 1 m accuracy). However, at our study sites, the height of the floors significantly varies according to the building type. Therefore, we have used the European standards defined by the *Council on Tall Buildings and Urban Habitat* (CTBUH) to define the average floor height for different building types (Table 3). For the maximum height based on the building type and European standard, we have defined the number of floors by dividing the maximum height by the average elevation of floors for each building type.

For the criterion 'estimated population by building' (Logan, Stults, & Xu, 2016), the INSEE database was associated with the total living space of each residential house, apartment and mixed-use building (Fig. 5). To obtain the living space, we have multiplied the number of floors by the surface area for residential buildings (Azad, Morinaga, & Kobayashi, 2018). Based on the population census, INSEE provides GDBs based on the number of people living in a 200 m × 200 m mesh size over all of the French territory. The population by mesh (*i*) has been reassigned for each residential building according to the total living space (*Ls*) of each building by mesh.

For the local-scale analysis, the CETE database has been used to obtain the date of building construction at the three study sites. The building condition and material construction have been acquired by photointerpretation or field campaign for a few buildings in selected areas according to their hazard proximity (Fressard, 2013; Letortu, 2013; Lissak, 2012). The spatial accuracy of the buildings and their types are obtained from large-scale databases in the data warehouse.

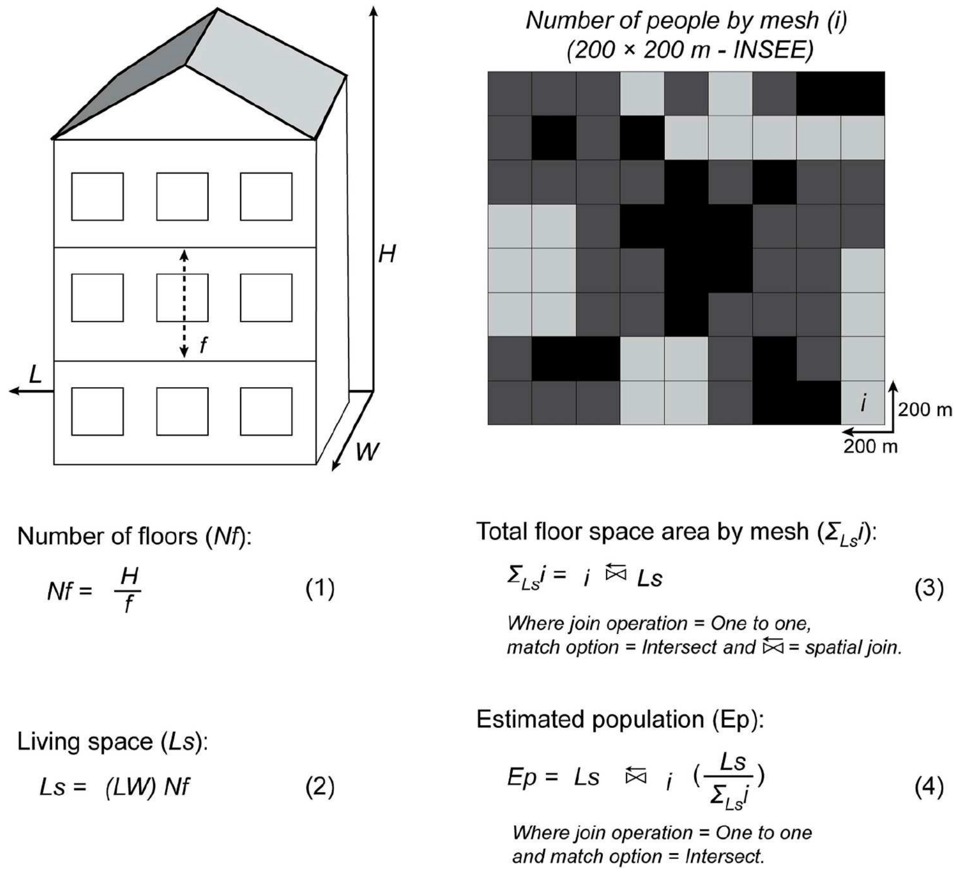

Fig. 5. Calculation model for the number of floors and estimated population by residential building (house, apartment and mixed use).

3. Study sites

Three study sites have been selected in French coastal environments (in the Normandy region) with distinctive characteristics to test the reliability and transposability of this method. These experimental study sites are affected by a range of hazards and issues and are located on the hedge (north-west) of the Parisian sedimentary basin. The first territory extends from Houlgate to Honfleur and covers 149 km^2 (Fig. 6). This site is the interface between the Touques River and the sea in the cuesta context. The average elevation is between 130 and 200 m with formation of a thick clavey-marly layer. The major problems of the first study site are linked to flash flood issues (Delahaye, 2008; Douvinet, Mallet, Escudier, Delahaye, & Christol, 2015) at the valley bottom, coastal and continental landslides (Maquaire, 1990; Fressard, 2013; Lissak et al., 2013) and marine submersions (Maanan & Robin, 2015; Letortu, 2013).

The second territory is east of Le Havre and extend from Quiberville to Puys (161 km^2). Three stream valleys (La Saâne Valley, La Scie Valley and L'Arques Valley from west to east) are arranged in alternating sequences with a chalky plateau (150 m altitude). Problems related to the second site are due to cliff retreat and rockfall (Maanan & Robin, 2015; 2002; Dewez, Rohmer, Regard, & Cnudde, 2013; Letortu, Costa, Bensaid, Cador, & Quénol, 2014), followed by the overflowed river in the valley bottom coupled with storm submersion and the relationship between the atmospheric pressure and climate indications (Delmas, Cerdan, Cheviron, Mouchel, & Eyrolle, 2012; Laignel et al., 2008; Turki, Laignel, Chevalier, Costa, & Massei, 2015). Lastly, runoff at the river basin head regularly leads to flash floods (Douvinet et al., 2015).

The third territory is east of Dieppe and extends from Criel-sur-Mer to Ault (174 km^2). This study site is similar to the second site and contains the Yères Valley and La Bresle Valley from west to east. The average altitude is between 100 and 120 m. This site has been the subject of resettlement of people from an integrated risk management perspective (Meur-Ferec, 2007). This type of management actually leads to strong societal constraints with risk prevention plans at this site (MATE/METL, 2016). In this third study site, the identified risks are similar to those of study site n°2 (cliff retreat, flash flood, and continental and marine floods).

All three territories benefit from a large number of GDBs from national or regional public organizations (*i.e.,* the BD TOPO® databases), research observatories and academic databases but have a lack of visibility concerning the spatial evolution of different hazards related to climate change and the evolution of concomitant areas (Delmonaco, Margottini, & Spizzichino, 2006; Marzocchi, Garcia-Aristizabal, Gasparini, Mastellone, & Di Ruocco, 2012; van Westen et al., 2014).

4. Results

The results and margins of error of the two integration models will be presented successively based on the analysis scale. The two models are first developed at study site n°1. Then, they are validated by random sampling with a 5% margin of error at the same site. Once the models are validated, they are transposed to study sites n°2 and 3. The different data warehouses produced from the two models can be used for multifunctional applications in terms of mapping, statistical analysis or land use and cover analyses.

4.1. Integration processes in the medium-scale analysis: land use and cover mapping

For the medium-scale analysis, thirteen databases are required to cover the 484 km^2 of the three studied territories. To provide simplified EaR information, the built-up area has been classified into eight categories and represents 1.7% (site n°1) to 2.7% (site n°2) of the total land

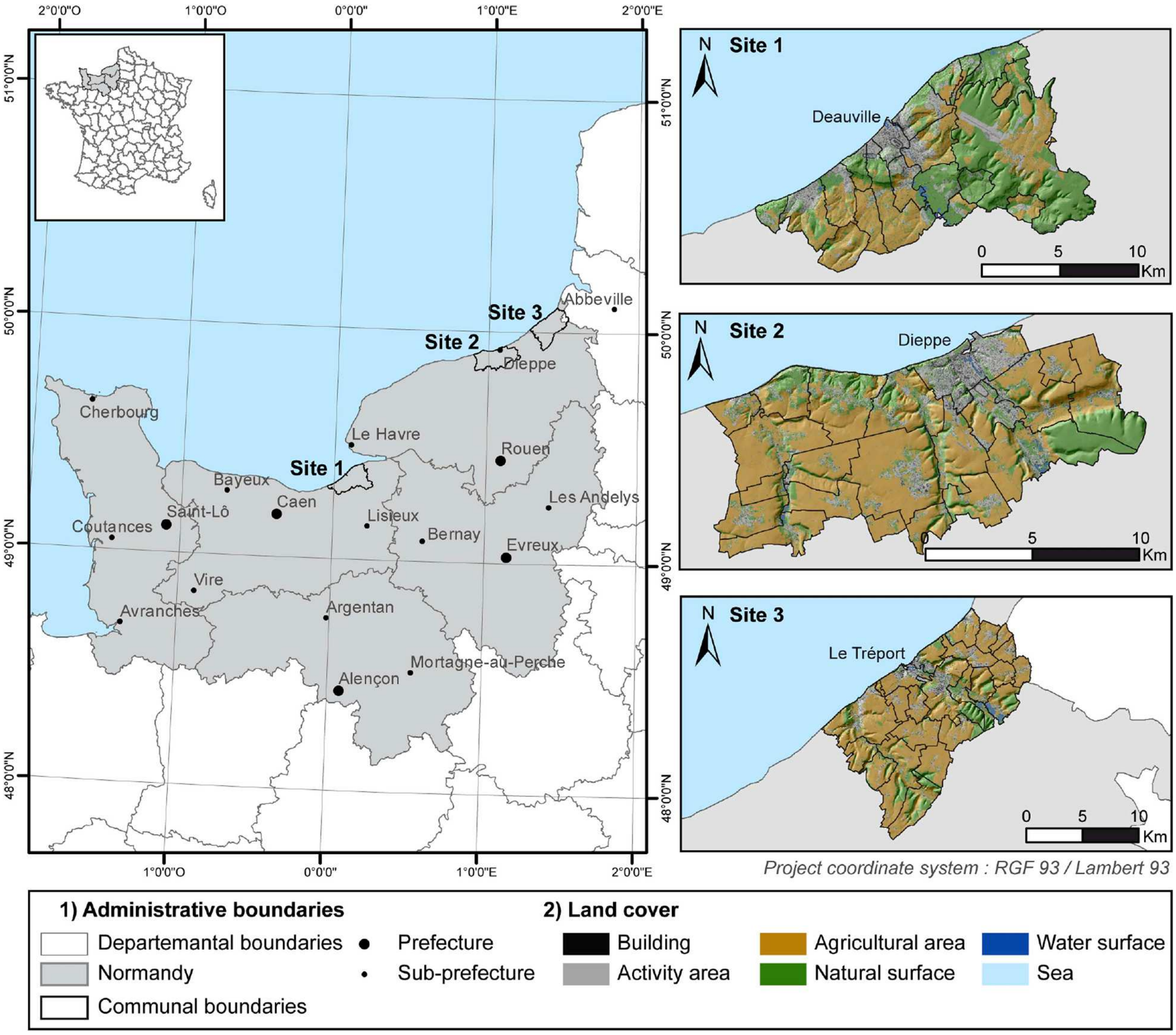

Fig. 6. Locations of the study areas. These three study sites are prone to multiple hazards in urbanized areas located in the valley bottoms.

area. Seven categories have been defined for roads and lifelines that represent between 1.8% and 2.3% of the total area. The average proportion of urbanized area varies from 12% (site n°3) to 20% (site n°1) and is defined in twelve categories. Natural and agricultural surfaces represent proportions between 76% (site n°1) and 82% (site n°2) and are divided into eight categories (Fig. 7).

The use of a unique GDB has proven insufficient to characterize all of the EaRs. In the case of urbanized areas, urban documents (urban plans) provide accurate information for residential areas (collective or housing), urban centres or areas to be urbanized. All of these urbanized areas represent 36% of the final adequate information (Fig. 7). To add information for farms, administrative areas, industrial areas, commercial areas, health centres and camps sites, BD TOPO® has been essential and has been associated with OSM databases to provide 64% of the global information.

OSM databases are particularly accurate (type and function) in highly urbanized areas, such as urban centres, and allow detection and rectification of some erroneous data (cleaning process). For natural and agricultural surfaces, urban documents provide information on boundaries but are insufficient to define the crop type. Consequently, the combination of the RPG and IGN databases provides information about crop, forest, and hedge types and about protected areas with the INPN and CdL databases (Fig. 8).

The temporal accuracy of the GDBs at the medium scale is directly linked to database updates. Updates of urban documents depend on municipalities. The IGN databases are upgraded every year, and the OSM databases are updated every day. Consequently, medium-scale databases must be easily and regularly updated. Prospectively, urban documents integrate land reserves (areas to be urbanized) at 15-year and 30-year terms, which enables predictions of future land use/cover changes (Johnson & Iizuka, 2016; Stehman, Fonte, Foody, & See, 2018) using non-random patterns. To ensure spatial accuracy, footprint data from public institutions have been prioritized for the VGI and digitalized data.

The data validation is based on the attribute accuracy. To validate EaR attributes, four EaRs have been identified (build-up, roads and lifelines, urbanized areas, and agricultural areas), and several items have been randomly selected. The number of chosen items is computed according to Cochran's formula (2007) (5). Then, each sample is checked by a field audit and photointerpretation with World Imagery (ESRI) or using Google Street View (Google).

$$\mathit{Sample\ size} = \frac{Z^2pq}{e^2} \tag{5}$$

where e is the number of items, Z is the Z-score with a 95% confidence level, e is the desired level of precision at 5%, p is the estimated proportion of an attribute that is present in the population and q is 1-p.

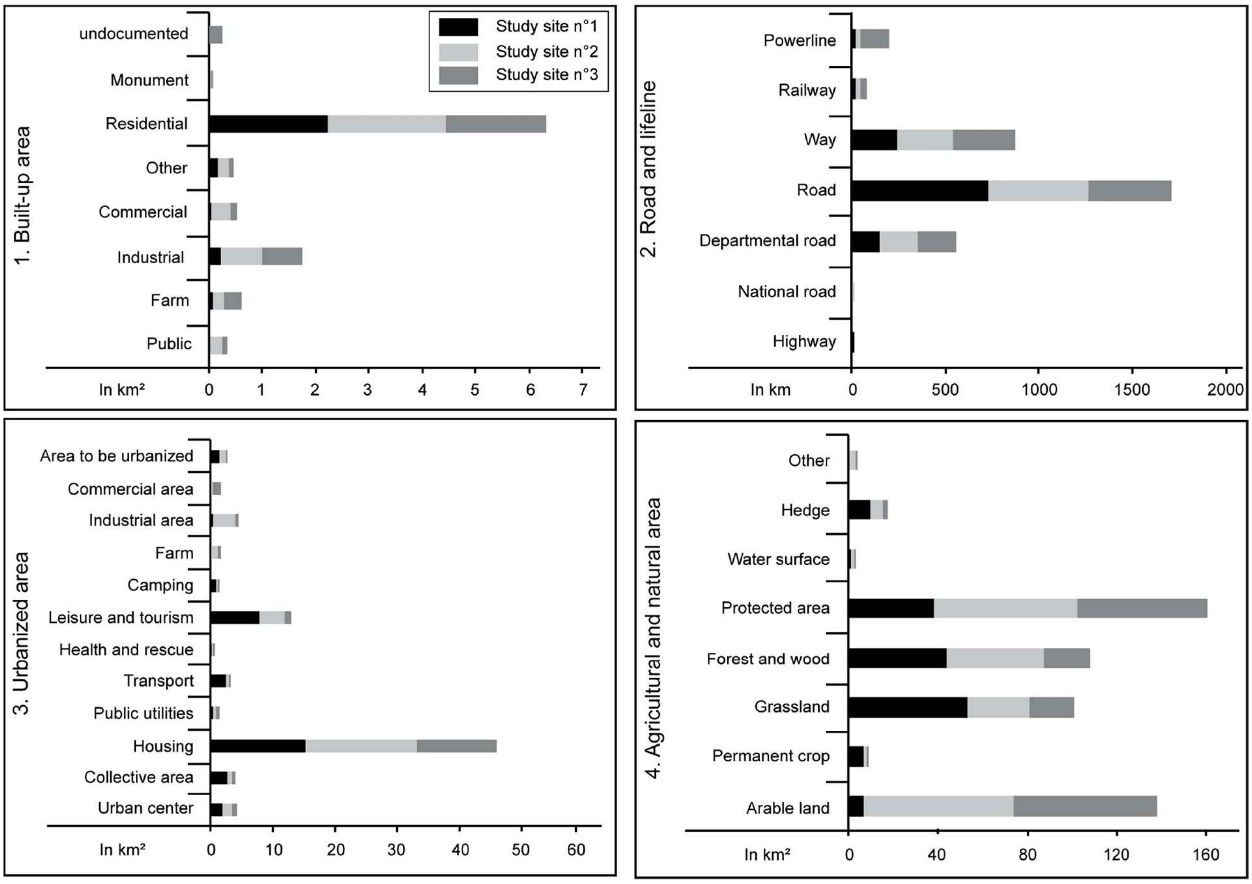

Fig. 7. Cumulated surface or linear areas for the four EaR types identified at the three study sites in coastal environments from thirteen GDBs.

Regarding our results, the built-up area accuracy varies between 85% and 90%. Roads and lifelines have the best accuracy, with 100% of the sample validated. Urbanized areas and agricultural and natural surfaces have an accuracy greater than 90%. Consequently, the margin of error of the data warehouse for the medium-scale analysis is below 10%, and the confidence degree is defined as sufficiently important for use in multifunctional applications.

4.2. Mapping, integration process and assessment of the calculation model for the large-scale analysis

At the large scale, the analysis is carried out for buildings, roads and lifelines. Four criteria have been defined: the type, function, number of floors and estimated population. The population is estimated for each building type (2.4). Thus, particular attention is given to the building type and function assessments to provide more accurate information. The model was run and validated at study site n°1 before being transposed to study sites n°2 and n°3.

To define the building types and functions, three GDBs have been used at study site n°1 (BD TOPO®, OSM databases and urban plans). Due to the spatial accuracy of the BD TOPO® database, it is used as a basis for the final database (especially for the location and building function items). BD TOPO® provides type and function information for 5% of the 31,251 buildings identified at site n°1 (Table 4). By integrating the OSM databases, the degree of information increases by 30%. A first cleaning phase is performed at this point in cases with conflicting information. For example, a building can be specified as an industrial building in BD TOPO® and as a commercial centre in the OSM databases. Consequently, field validation is performed to correct the final database (cleaning phase of the model in Fig. 4). Urban documents (PLU/PLUi) can complete missing information by defining residential buildings and specifying their types (housing or apartments).

It.1 is the first iteration with integration of the IGN databases, It.2 is the second iteration with integration of the OSM and IGN databases, and It.3 is the third iteration with integration of PLU/PLUi, OSM and BD TOPO®.

For study site n°1, the height is missing for 5426 building (17% of the global data). The margin of error (root mean square error (RMSE) 6) of the estimated population calculation (2.4) has been defined by comparison between the observed and predicted numbers of floors for 381 buildings.

$$RMSE = \frac{\sqrt{\sum (Fo - Fp)^2}}{n} \tag{6}$$

where *Fo* is the number of floors observed, *Fp* is the number of floors predicted and *n* is the total amount of sample.

With this calculation model, 80% of the supplied information is accurate (Table 6), and the number of floors of one building tends to be overestimated with an RMSE at 0.78 (Fig. 9). Hence, the calculation model can be improved but is considered reliable enough for use at this analysis scale.

Once these criteria have been defined, the number of people in a 200 × 200 m mesh from INSEE are distributed in residential buildings according to their living space (Fig. 10). Roads and lifelines are extracted from BD TOPO® and are incorporated precisely in the medium-scale database.

Similar to the medium-scale analysis, data from the large-scale analysis are validated with randomly picked items, and the sample size has been defined with Cochran's formula (5). At this scale, the audit covers the criteria linked to buildings. The confidence degree of BD TOPO® concerning roads and lifelines is considered sufficiently important (Table 5) but has not been double checked. Furthermore, no

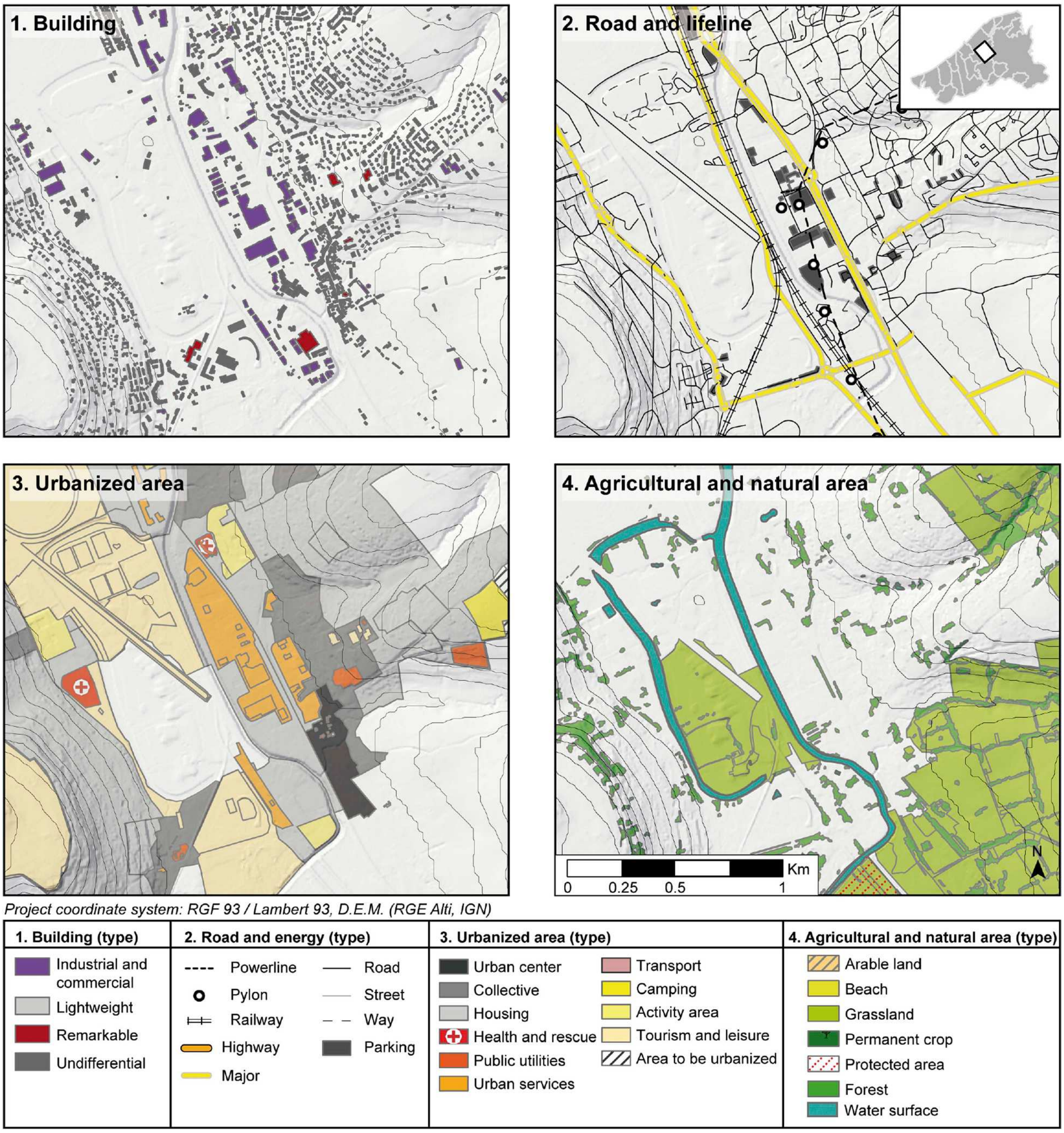

Fig. 8. Spatial representation of the databases for the medium-scale analysis at study site n°1.

Table 4
Attribute validation of the data warehouse for the medium-scale analysis with a margin of error of 5%.

Element at risk	Built-up	Roads and lifelines	Urbanized areas	Agricultural and natural areas	Total
Number of items	23,978	9117	1129	7441	41,665
Sample size	379	369	287	367	1402
Validation	336	369	260	339	1304
Non-identifiable*	25	0	12	0	37
Error	43	0	27	28	98
Validity	88.7%	100.0%	90.6%	92.4%	92.9%

data are available for the estimated population, and verification of this information is particularly complex because of the impossibility of determining the exact number of people per building in the field. This information is recorded in city halls but is not disseminated. Therefore, this criterion cannot be verified.

In view of the obtained results, the type of building has an accuracy between 85% and 90%. The economic function has better accuracy at greater than 90%. The number of floors is the least accurate with 80% of the sample validated. Consequently, the margin of error of the data warehouse for the large-scale analysis is approximately 13% and is considered sufficiently accurate.

Table 5
Number of buildings by type and function at study site n°1 at different integration phases.

Criterion 1 (type)	It.1	It.2	It.3	Criterion 2 (function)	It.1	It.2	It.3
House	0	0	13,101	Residential	0	0	19,630
Apartment	0	0	6525	Commercial	57	250	250
Office	0	126	126	Industrial	985	1009	1009
Farm	169	215	215	Farm	169	215	215
Industry	985	1009	1009	Administrative	26	72	72
Mall	57	125	125	Education	68	68	68
Castle	31	40	40	Health	0	37	37
Church	37	66	66	Tourism	0	219	219
Monument	27	27	27	Energy	188	188	188
Station	2	2	2	Leisure	0	164	164
Warehouse	0	3315	3315	Transport	2	2	2
Tower	7	7	7	Garage, shed, etc.	0	9331	9331
Complex	23	164	164	Religion	37	66	66
Shed/hut	12	6530	6529	Unknown	29,719	19,630	0
Unknown	29,901	19,625	0				

4.3. 3D mapping of structural components in the local-scale analysis for EaRs located in hazard-prone areas

The third scale concerns the analysis of EaRs at a local scale and focuses on structural aspects of the buildings. This analysis must be carried on few elements that are highly sensitive to various processes (flood, landslide, etc.) and consequently occur in hazard-prone areas. At study site n°1, plans for natural risk prevention have been used to identify the number of sensitive EaRs. Of the 31,251 buildings, 13,142 (42%) are located in hazard-prone areas. Among them, 8685 (28%) are affected by landslides, 4197 (13%) are located in flood zone areas (Fig. 11) and 260 (1%) may be affected by both flood and landslide hazards.

The model was applied to study sites n°2 (Fig. 12) and n°3. In fact, all municipalities in study site n°1 have harmonized urban documents (PLU/PLUi). Only 4 out of 21 PLU/PLUi at study site n°2 and 2 out of 23 are found at study site n°3. An alternative solution has been found to replace missing PLU/PLUi with other GDBs. The MOS Normandy database produced in 2009 at the regional scale provides the data sources for the two other study sites. The transposition of this model and these tools can be considered for other coastal or continental sites but requires adaptation of local GDBs.

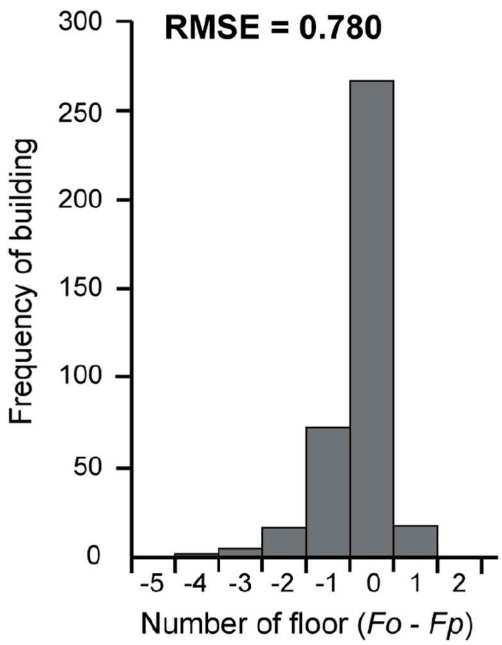

Fig. 9. Differences between observed and predicted floors for 381 buildings.

5. Discussion

The results from the data models at the medium (1:50,000–1:25,000) and large scales (1:25,000–1:10,000) depend largely on the spatial resolution and accuracy of the input databases. At each of three study sites, the level of accuracy of the input dataset is considered according to the geometry delineation and data attribute precision, database completeness, importance of the provided information, and semantic and temporal accuracy (Girres & Touya, 2010; Kresse & Fadaie, 2004). In the case of volunteered geographical information (VGI), such as the Open Street Map (OSM) databases (Haklay, 2010), there are offsets in the spatial footprint (Brovelli, Minghini, Molinari, & Zamboni, 2016) but good attributes and temporal accuracy due to regular updating by users. To resolve this issue, the geometry accuracy of BD TOPO® has been used as a reference, because it provides highly accurate building, network and natural surface locations (Betaille, Peyret, Ortiz, Miquel, & Godan, 2016). Then, spatial information from other databases has been integrated into BD TOPO®.

The results of our medium-scale analysis model are satisfactory (> 90%) due to harmonized intercommunal urban documents (last updated in 2012) for the whole of study site n°1. This accuracy will tend to decrease according to the availability and time validity of these documents at other study sites. The results concerning built-up areas (15% uncertainty) are mainly linked to erosion followed by expansion, which are partially generalized and can generate mistakes in attributed

Table 6
Determination of the confidence level of GDBs for the large-scale analysis (building) with a margin of error of 5%.

Element at risk	Building (type)	Building (function)	Building (number of floor)	Building (estimated population)	Total
Number of items	31,319	31,319	31,319	ND	31,319
Sample size	381	381	381	ND	1143
Validation	339	349	307	ND	995
Error	42	32	74	ND	148
Validity	88.9%	91.6%	80.6%	ND	87.1%

ND is non-documented.

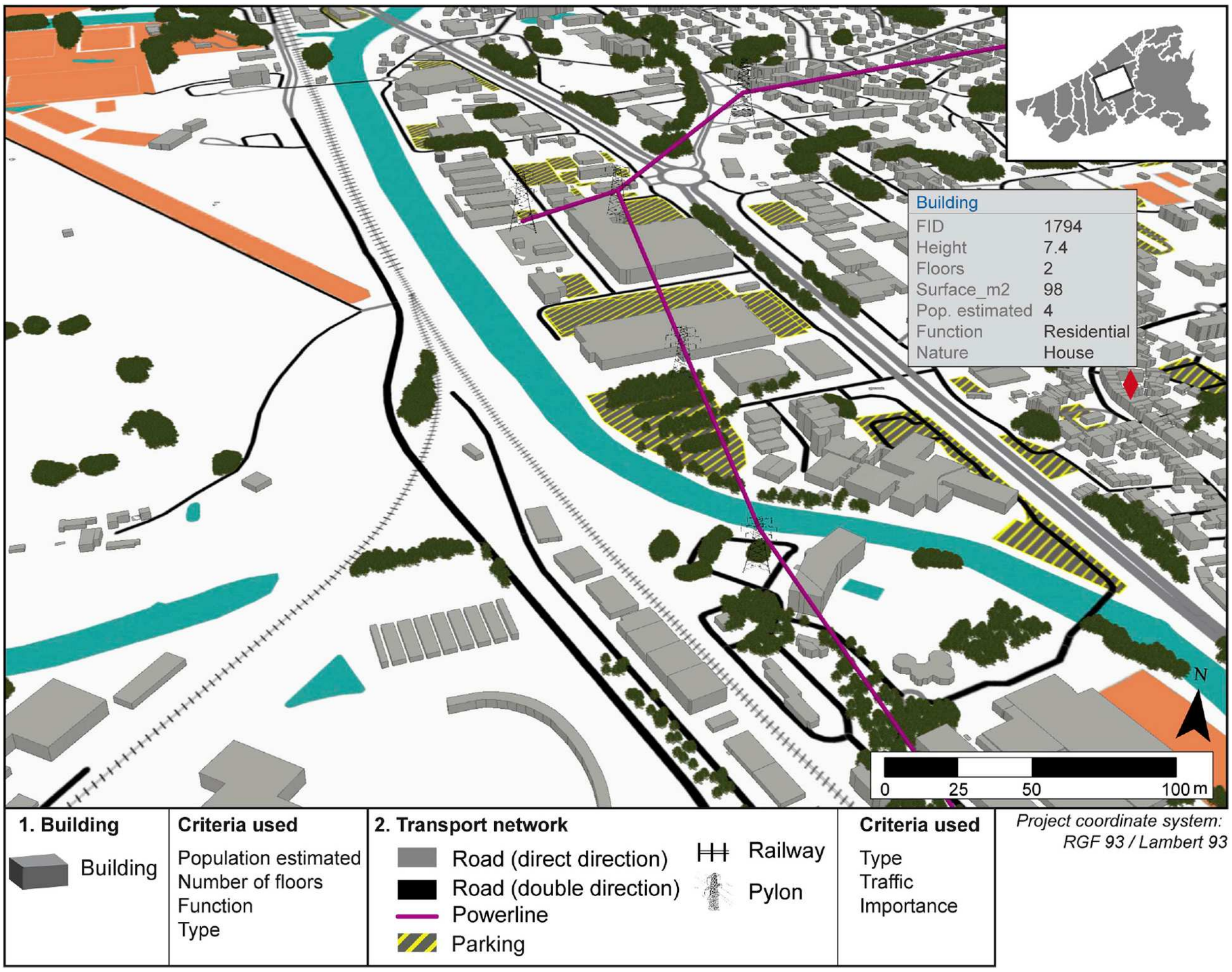

Fig. 10. 3D mapping for the large-scale analysis with different criteria for a portion of study site n°1.

data (particularly in highly urbanized areas). In the large-scale analysis, uncertainties mainly concern computation of the number of floors (20% uncertainty). In addition, this uncertainty increases if cellars are considered (actually, none of the data provide this information, because the method used to compute the number of floors concerns exclusively aboveground elements). The criteria concerning the building type and function and the roads and lifelines are high ($\geq 90\%$) due to merging of the OSM and BD TOPO® databases. Concerning building characterization, the highest density of urban areas increases the accuracy of this attribute thanks to the VGI databases. In the local-scale (1:10,000–1:2000) analysis, data are collected in the field, through photointerpretation or using software (such as *Google Street Map*), and thus the confidence degree is highest.

The main challenge of our study is the standardization phase of the various databases. This step is crucial for the models. For the medium-scale model, thirteen databases are needed to extract, transform and load the final data warehouse (Johansson et al., 2017), and seven databases are needed for the large-scale model. Generally, this standardization phase is based on Urban Atlas, Corine Land Cover, OSM or GMESUA standardization (Campelo et al., 2017; Jokar Arsanjani et al., 2015). However, these terminologies are adapted to define land use or land cover in the small-scale analysis, and adaptation is necessary to describe EaRs at the medium, large and local scales. Furthermore, one EaR has one or more criteria, and an increased number of criteria for the same element enhances the complexity of the integration phase.

Checking whether the information provided for specific criteria is sufficiently precise or requires an upgrade with another database represents a difficulty. To check the correct connection between the input and upgraded data, defining the order of the execution model is fundamental. This step includes knowing the degree of information and importance provided by each database. For example, urban documents (PLU/PLUi) provide the first information for agricultural areas, but no information is given about the agriculture type. The RPG database provides information on the use of individual agricultural plots (Cantelaube & Carles, 2014) through volunteered geographical information. The combination of these two databases provides information about the official limit of the agricultural area, limit of the plots and type of agricultural plots.

Once integration and transformation are completed, a verification and cleaning process is performed to avoid inconsistencies or missing information. This phase is more complex for the large-scale model than for the medium-scale model due to the number of criteria that need to be checked. In certain cases, conflict exists between information provided from two different databases. For example, BD TOPO may have identified the function of a building as an industrial building, while the OSM database indicates that this industrial building is actually a shopping centre. Therefore, the verification requires further analysis by field observation, photointerpretation or use of software, such as *Google Maps* or *Google Earth*. After this phase, the degree of confidence for all data produced must be assessed according to verification of the margin of error. The random sampling process (Cochran, 2007) has shown than the margin of error is below 10% at the medium scale and is approximately 15% at the large scale. Consequently, the confidence degree of the produced data is defined as sufficiently important for use in

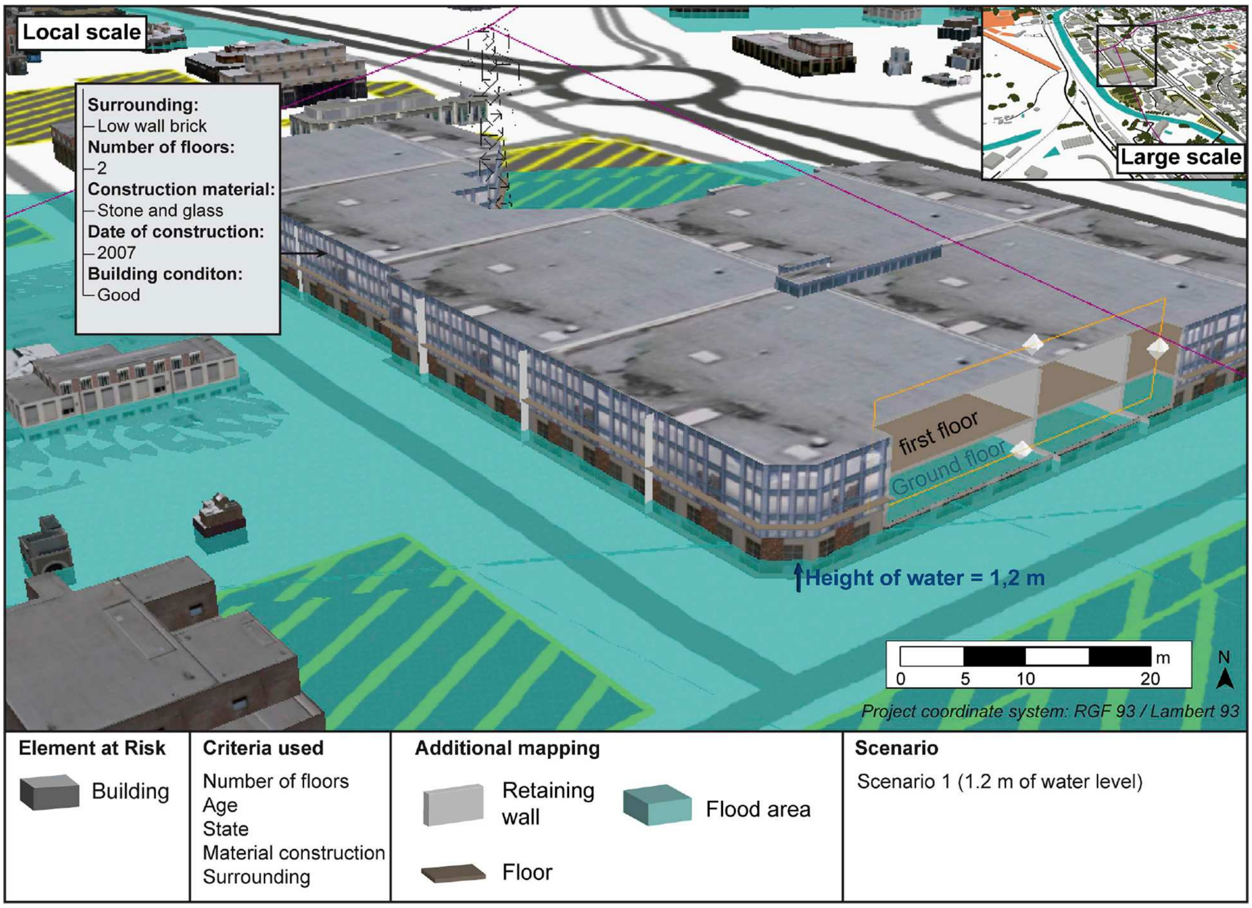

Fig. 11. EaRs identified in flood zone areas for a 1.2 m water level at the local scale.

multifunctional applications and by multiple users.

The time validity of GDBs is a recurring issue in the literature (Devillers & Jeansoulin, 2006; Zhang et al., 2018). This question highlights the problem of upgrading and managing spatial data (Fonte et al., 2017). Near real-time systems have begun to be developed (Yılmaz & Canıberk, 2018) but require significant resources and will depend on the type of data integrated. At the three study sites, the OSM databases are updated every hour and are the closest source of near real-time data. BD TOPO® is updated every year (Girres & Touya, 2010), and the other databases are updated every two years, five years and more for urban documents. This question of updates will directly impact risk assessment and management. As shown in Fig. 12**,** buildings destroyed during the summer of 2013 (Michoud et al., 2015) appear on orthophotographs from 2012 but are missing from the 2017 version of the GDBs. The two models presented at the medium and large scales have been planned for relatively fast and easy upgrades. The main constraint and time spent updating will be linked to the standardization or transformation phase in the case of a new element to be incorporated. These models are optimized for annual updates.

The replicability of models at study sites n°2 and n°3 have be applied quickly. The main difficulties are related to integration of new databases at the medium and large scales that do not exist at study site n°1. Furthermore, unlike those of study site n°1, urban documents are not harmonized at study sites n°2 and n°3. Only four of twenty-one urban documents at study site n°2 and two of twenty-three at study site n°3 were available. Other communes were found in the National Urban Planning Regulation. Therefore, the MOS Normandy database has been used to make up for the absence of these urban documents. For study site n°3, eleven of twenty-three communes are located in other departments and have no urban documents. Therefore, the CdL database, which provides information about land cover, has been used to fill the data gaps, and then the type of urban area has been identified by photointerpretation. Similar to the data updates, the main difficulty in transposing the models is the standardization and transformation of the input data. A complete inventory of datasets available for the study sites and their quality is required before executing the models.

In other countries, the replicability of the methods will depend on the amount of data available. In Europe and Greenland, forty-one national agencies have been identified (Olteanu-Raimond et al., 2017) that acquire topographic data, such as the National Geographic Institute of Belgium or National Land Survey of Finland. The combined use of national and VGI databases (Bol et al., 2016) will significantly increase the accuracy of the data even more if the countries have data in administrative units with urban documents.

6. Conclusion

The geographical database produced from institutional, volunteered geographic information and archive sources allowed elements at risk analysis at three scales. Analysis at the medium scale shifted the emphasis to surface analysis, which compared different elements present at the same site on the same basis. Large-scale analysis adds additional information about infrastructure to the analysis based on integrated physical injury of people in each building and the functional and structural aspects. Finally, the local-scale analysis takes into account intrinsic parts of the infrastructure by integrating material construction, surroundings, date of construction, etc. Therefore, these GDBs are set for multifunctional usage through a series of spatial or attribute requests for extraction of 2D or 3D maps or statistical elements.

In the medium-scale analysis, the elements at risk are characterized

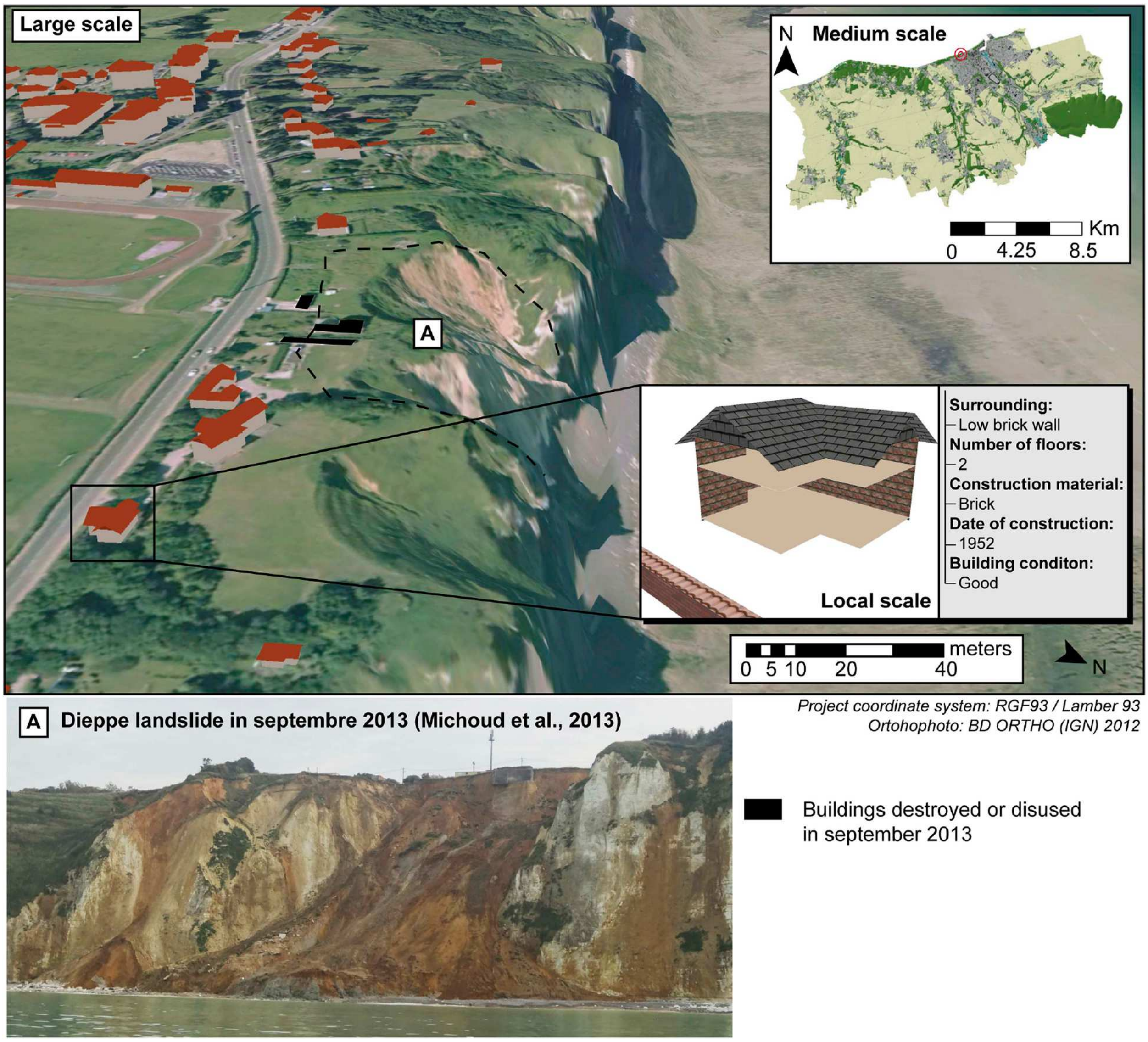

Fig. 12. Replicability of the integration models with updated data from 2017 for study site n°2.

using four criteria (type) with uncertainties of less than 10%. In the large-scale analysis, the uncertainties are approximately 15%. In the local-scale analysis, no uncertainties exist, because the data are collected from field observations, photointerpretation or using software (such as *Google Street View*). Consequently, determining the confidence degree of each data warehouse for different analysis scales is sufficiently important prior to their use in potential consequence analyses.

From these GDBs, the objective will be to set up an index from criteria obtained using a weighting system, such as the Potential Damage Index (Maquaire et al., 2004; Malet et al., 2006; Puissant et al., 2013; Carlier et al., 2017), Relative Vulnerability Index (Kappes et al., 2012; van Westen et al., 2014) or fuzzy logic method (Thiery, 2007; Castillo Soto, 2012; Grekousis & Thomas, 2012; Fressard, 2013; Potter, Doran, & Mathews, 2016). This quantification will serve to assess potential consequences at the three study sites a priori of hazard-prone areas. Finally, these potential consequences will be coupled with vulnerability analysis for each type of hazard in a multi-risk analysis approach (Chen et al., 2016; Godfrey et al., 2015).

Finally, this method can be transferred to technical services for risk analyses to increase the assessment of elements at risk in the *Risk Prevention Plan* (PPR in France). The quick installation of this method at different study sites supports the integration of physical, infrastructural and functional components.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apgeog.2019.102076.

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