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Article

Spatial Representation of Coastal Risk: A Fuzzy Approach to Deal with Uncertainty

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Abstract: Spatial information for coastal risk assessment is inherently uncertain. This uncertainty may be due to different spatial and temporal components of geospatial data and to their semantics. The spatial uncertainty can be expressed either quantitatively or qualitatively. Spatial uncertainty in coastal risk assessment itself arises from poor spatial representation of risk zones. Indeed, coastal risk is inherently a dynamic, complex, scale-dependent, and vague, phenomenon in concept. In addition, representing the associated zones with polygons having well-defined boundaries does not provide a realistic method for efficient and accurate representing of the risk. This paper proposes a conceptual framework, based on fuzzy set theory, to deal with the problems of ill-defined risk zone boundaries and the inherent uncertainty issues. To do so, the nature and level of uncertainty, as well as the way to model it are characterized. Then, a fuzzy representation method is developed where the membership functions are derived based on expert-knowledge. The proposed approach is then applied in the Perce region (Eastern Quebec, Canada) and results are presented and discussed.

Keywords: uncertainty; fuzzy set theory; coastal erosion risk assessment; spatial representation; fuzzy object

1. Introduction

Characterizing the uncertainty associated with assessed risk and representing the results together with risk value has a direct impact on decision making processes [1–4]. In fact, a large amount of spatiotemporal data, either certain or uncertain, from multiple sources with different levels of detail are used in risk assessment [5]. In this regard, realistic decisions can not be made without knowing both the value of the risk and the respective modulated uncertainty.

In risk assessment processes, spatiotemporal data are classified based on expert knowledge, through a vulnerability index [5,6]. Spatial uncertainty is correspondingly defined as the lack of knowledge regarding the true value of a parameter or an attribute of information [7,8]. This uncertainty has both a qualitative and quantitative nature, which may consist of multiple dimensions. In modeling of natural phenomena, such as coastal erosion risk assessment, uncertainty often appears as imperfect knowledge. This imperfect knowledge includes vagueness in boundary zones, ambiguities in linguistic terms, fuzziness in semantics of spatial objects, and a mix of these that pertain ontologically only to the fiat world [9,10]. This brings us to the realm of spatial data modeling by the concept of *bona fide* (spatial object models with well-defined crisp boundaries) and fiat object models (spatial object models with uncertain boundaries) [10,11]. The fiat objects refer to boundaries induced through human demarcation, qualitative differentiation, or spatial discontinuity such as river, mountain, coastline, and risk zone [9,10]. Indeed, fiat objects are conventionally approximated in the databases and represented like *bona fide* objects. Representing risk zones by polygons with well-defined boundaries is an example of such approximation. These polygons are created using aggregations of a set of spatial units defined based on either the stakeholders' interests or national census divisions [5,12]. Despite spatiotemporal variation of the multiple criteria involved at risk extent, each polygon has a unique risk value attributed homogeneously over its spatial extent [13]. In reality, risk values change gradually [13]. The transition from one zone to another is not therefore properly represented with *bona fide* (crisp) object models. Therefore, the main dimension of uncertainty in Coastal Erosion Risk Assessment (CERA) arises from this poor spatial representation of risk that is related to spatial object modeling of risk zones.

Two main approaches are widely employed to characterize spatial uncertainty associated with risk modeling and representation. These are probabilistic models based on *Probability Theory* and possibilistic models based on *Possibilitics Theory* [1,2,14–17]. Considering the nature of uncertainty, whether probabilistic or possibilistic, either approach can be employed [7]. However, the flexibility of the possibilistic approach in dealing with uncertainties related to spatial object modeling suggests that it can be an efficient solution for spatial representation of risk [2]. The possibilistic approach consists of exact models, rough models, and fuzzy models [13,18–24]. Extensive studies have been done on implementing exact and rough models, *i.e.*, an extension of crisp spatial data model, with a few references on implementing fuzzy models by means of fuzzy set theory [13,18,22]. For instance, a spatial data model based on the possibilistic approach has been developed by Schneider [19], called the vague spatial data model based on exact approach, and is extended by [18,22], called Vague Spatial Algebra (VASA). These models are simple to use and consistent with the crisp spatial data model, which is well known by geospatial communities. However, these models have inherent limitations when representing the phenomena that it is impossible to determine the sharp boundaries [25]. Moreover, if a fine-grained modeling of objects is required, the exact and rough models are not well supported [18]. In addition, continuous feature change is not completely modeled by the three-value logic of the exact and rough methods, such as the modeling of pollution zones, flood zones, erosion zones, *etc.* In other words, the extents of these spatial objects can not be bounded by precise boundaries [17,18,26]. Nevertheless in fuzzy models, the degree of uncertainty of spatial object boundary is expressed by an assigned membership value. Fuzzy models allow a continuous change of the degree of spatial uncertainty within such objects based on the multi-value logic of fuzzy set theory. This is the main motivation behind exploring fuzzy models to represent a continuous phenomenon such as coastal erosion risk.

The main objective of this paper is to develop a generic fuzzy approach for spatial representation of risk zones. First, the nature and level of spatial uncertainty in CERA is characterised. Fuzzy models based on fuzzy set theory are then explored to handle such uncertainty. To do so, a conceptual framework is proposed to deal with the problem of spatial uncertainty of risk zones using membership functions. Instead of determining the bona fide boundary between the risk zones, the proposed approach permits a smooth transition from one zone to another. Membership functions are derived from expert knowledge (e.g., from vulnerability index). The membership values of multiple indicators are then aggregated based on an elaborated risk formula and Fuzzy IF-THEN rules to represent risk zones. The proposed approach is applied to Perce region (Eastern Quebec, Canada) as a case study.

2. Background

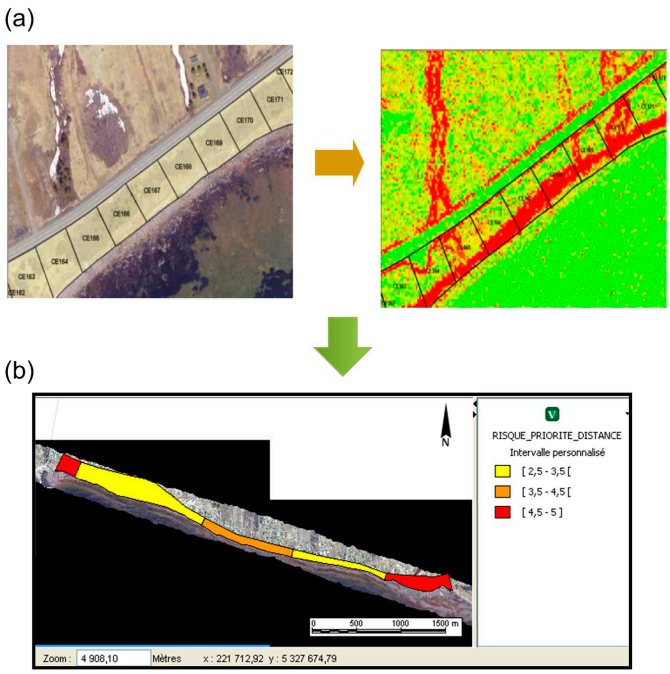
2.1. Spatial Representation of Coastal Erosion Risk

CERA includes identifying hazard, detecting elements at risk (roads, houses, and people), elaborating a vulnerability index, and characterizing the associated uncertainty [1,5]. However, this process is not as straightforward as one might imagine. The difficulties in CERA are especially due to the dynamic, complex, scale-dependent, and vague nature of erosion in coastal zones [13].

Principally, spatial phenomena are modeled and represented either as discrete-object data models (vector data structure: point, line, and polygon) or continuous-field data models (raster data structure) [27]. The extent of a spatial object is defined by its attribute and its geometry (shape and position) [27]. Spatial representation of risk requires a mathematical aggregation of vulnerability indicators (derived from elements at risk) and hazard maps in different time periods [28]. Risk is, hence, a spatial relation between hazard, elements at risk, and vulnerability [5].

Current approaches for the representation of coastal risk are mostly based on using polygons with well-defined boundaries. The boundaries are defined according to the stakeholders' interests or census divisions along the coast (Figure 1a). The risk level is then attributed homogeneously within these units. A set of these units is aggregated to form a risk zone (Figure 1b). However, in reality, the degree of risk changes gradually, e.g., it decreases when we get farther from the coastline. If bona fide (crisp) boundaries are applied to define the risk zones, the transition from one zone to another is sudden and sharp. This is not an appropriate representation of reality in most cases. Though the representation of natural phenomena (such as erosion risk) is often taken into consideration since their definitions are fiat and vague [10,11,17].

Figure 1. An example of coastal erosion risk representation: (**a**) tessellate the region into well-defined polygons, (**b**) spatial representation of risk zones by aggregating a series of these polygons with the same level of risk [29].



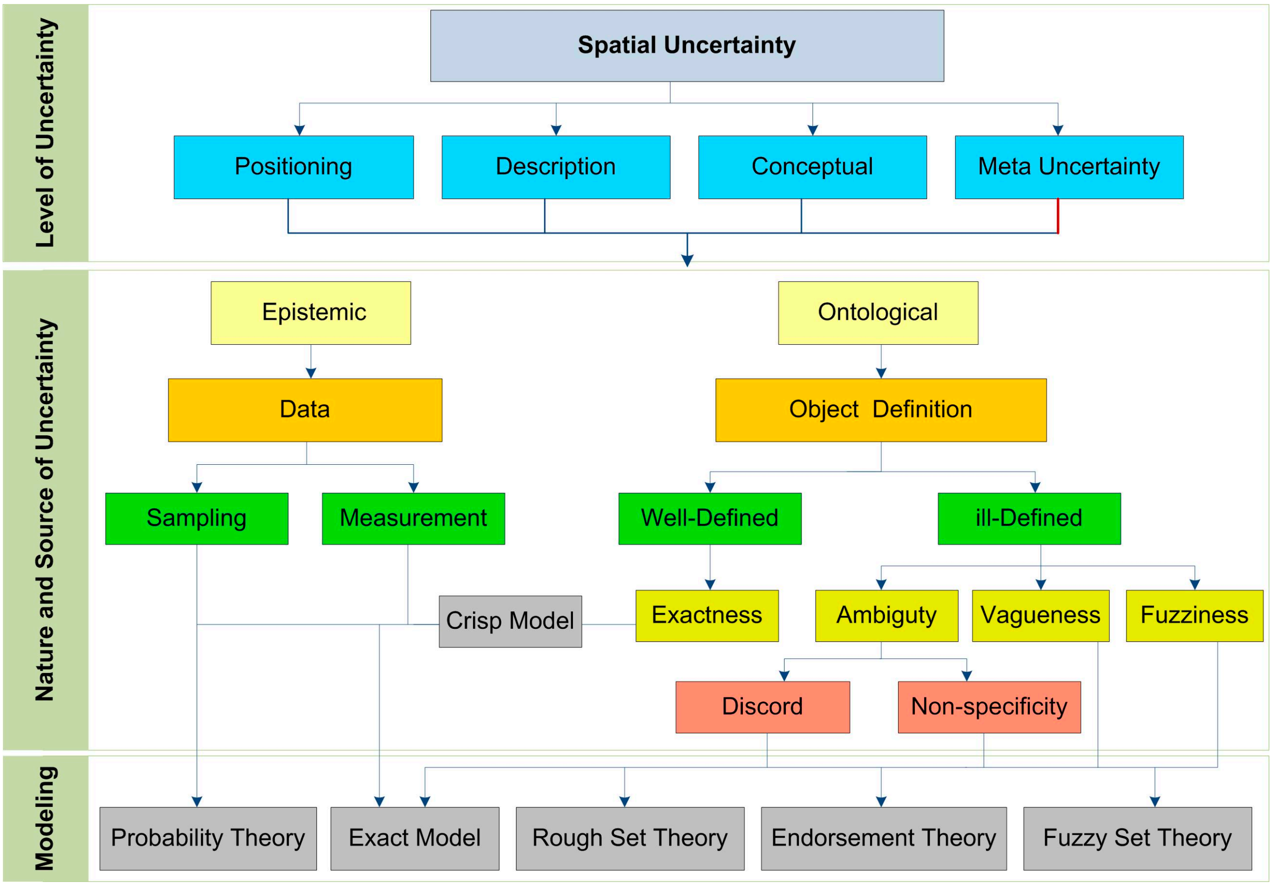
On the other hand, the technological capability of Geographical Information Systems (GIS) in integrating uncertainty in spatiotemporal modeling and representation is still a great challenge. The main limit of current GIS tools is the representation of complex fiat objects with uncertain boundaries [1,2,13,18]. Indeed, conventional GIS models geographical entities using a bona-fide concept with well-defined geometry such as points, lines, and polygons in Euclidean space whereas the spatial representation of risk zones needs to deal with fiat objects with uncertain boundaries. The following sections expose the different aspects of uncertainty in spatially representing coastal risk zones and then the approaches to handle these aspects properly.

2.2. Uncertainty Characterization

The uncertainties associated with coastal risk assessment mainly originate from data (here, to estimate risk) and object definition (here, risk zones) [7,13]. A comprehensive scheme of uncertainty in spatial data modeling and the methods to handle it is illustrated in Figure 2. Bédard, in [30], introduced uncertainty into four levels of spatial data modeling: the conceptual level (when identification of entity classification and its existence is fuzzy or imprecise), the descriptive level (when the definition of an attribute value is fuzzy or imprecise), the positioning level (when the spatiotemporal aspect of an observed reality is fuzzy or imprecise), and the meta-uncertainty level (an unknown degree of the preceding uncertainties). The nature and source of uncertainty refer to the epistemic and ontological aspects of spatial data modeling. Uncertainty from data includes sampling and measurement errors that are categorized as epistemic uncertainty [9]. This type of uncertainty is random in nature and probability theory can be applied to handle it appropriately [31]. The uncertainty from object definition is characterized as ontological uncertainty that is related to the semantics of the object and its geometry [9,13].

This refers not only to imperfect knowledge, but also to lack of knowledge about an object or a phenomenon [7,13,32].

Figure 2. A comprehensive UML class diagram of spatial uncertainty in spatial data modeling and the methods to handle it.



The spatial uncertainty associated with CERA is a combination of all these levels with a degree of vagueness, fuzziness, and ambiguity during the definition of risk zone objects. The intrinsic nature of coastal risk, *i.e.*, the continuity, heterogeneity, dynamics, and scale-dependence [13], includes both epistemic and ontological aspects of uncertainty in CERA. The vagueness, fuzziness and ambiguity that are the principal factors in semantics uncertainty [9], result from the continuity and heterogeneity of the risk zones and the scale issues in risk analysis respectively [31,33]. Vagueness and fuzziness refer to the gradual transition boundary of risk zones in space and the impossibility of determining these boundaries [9,21,31]. Ambiguity is related to the discord and non-specificity description of a classified vulnerability index to calculate risk degree within risk zones [9].

Handling spatial uncertainty related to the ontological aspect demands an integrated method, which takes into account both the semantic and the geometrical imperfections. Exact, endorsement, rough, and fuzzy models are some examples in this regard [9,17,18]. Robinson [33], Burrough [34], and Usery [35] worked on handling the descriptive, while Altman [36] and Brown [37] dealt with geometrical aspect of uncertainty. Molenaar [38] integrated both descriptive and geometrical aspects within a formal syntax model for conventional crisp objects based on the fuzzy object model. This was a revolutionary approach through a concept, which inherently takes into account uncertainty.

Many papers and research results demonstrate the flexibility of fuzzy set theory to treat the ontological spatial uncertainty [13,17,19,21,22,25,26,32,39–46]. In this regard, the following section describes how to use fuzzy set theory to model a spatial object.

3. Spatial Fuzzy Object

The concept of fuzzy set theory is originally proposed by Zadeh [47] to model ill-defined concepts such as the distinction between a "tall person" or a "short person". A fuzzy set is a set of objects whose membership to the set takes a value between zero and one. Each fuzzy object can have partial or multiple memberships [33]. A fuzzy set A in X is mathematically characterized by a membership function $\mu_A(x)$ which associates with each x in X a real number in the interval [0,1], with the membership value at x representing the "degree of membership" of x in A [47]:

$$A = \left\{ \left(x, \mu_A(x) \middle| x \in X \quad \wedge \quad \mu_A : X \to [0,1] \right) \right\} \tag{1}$$

Cheng [41] distinguished four approaches to model fuzzy spatial objects. These include Fuzzy-Fuzzy (FF) objects, objects with α-cut boundaries (αF), Fuzzy-Crisp (FC) objects, and Crisp-Fuzzy (CF) objects. FF-object model or smooth fuzzy object results from fuzzy classification where the spatial extent of an object and its attributes are uncertain [19]. This uncertain part is then described by a membership function. α-cut boundaries is another way to represent a fuzzy object by assuming a threshold value α for each cell of each layer [48]. The main advantage of this method is that it can be applied to known geometric data structures such as a Triangular Irregular Network (TIN). FC objects are similar to the "Egg-Yolk" model upon conditional boundaries [24]. The inner region, the "yolk", gives the certain part of the object. The outer region, the "white", is the indeterminate boundary that delineates limits on the range of vagueness. The white and yolk together form the egg that is the full extent of the fuzzy object [49]. An object with fuzzy spatial extent (transition zones) and a certain core is called a CF-object [19]. The main advantage of this model lies in the implementation phase, since efficient representation algorithms from crisp models can be adopted and reused [18,22]. However, the insufficiency of knowledge to characterize the uncertain part of the object is the main drawback.

All these methods suggest another type of data model that is often called the vague or fuzzy spatial data model. The difference between the terms vague and fuzzy refers to the approach used to define the data model as an exact model and approach based on mathematical theories (rough set theory and fuzzy set theory), as illustrated in Figure 2. The authors of [18,20–23,50] used exact and rough approaches to define the vague spatial data model. In contrast, [19,25,26,51,52] used fuzzy set theory to define the fuzzy spatial data model. Regardless the term vague or fuzzy, this type of spatial data model consists of vague or fuzzy points, vague or fuzzy lines, vague or fuzzy polygons, and vague or fuzzy partitions/grids [18,19,21,22,25,26,40,51,52]. Our focus in this study is fuzzy set theory due to its flexibility in modeling continuous and heterogeneous phenomena, such as coastal erosion risk. Hereafter, we will use the term fuzzy spatial data model. Extending the idea of [19,32], a fuzzy object is defined by its position, geometry, and attributes where each of these components can be uncertain and considered by a degree of membership with respect to their vulnerability index classification.

Fuzzy Membership Function (MF) is a subjective study in nature that is defined by adapting crisp classification of the region by extending these boundaries into a transition zone. However, defining the shape of a MF is a challenge. Two active and passive approaches are used to find the shape of a MF [53]. In the active approach, MF is defined based on expert knowledge, which is the case for CERA in this paper. Examples are Semantic Import Model (SIM) or Fuzzy IF-THEN rules [35,54]. In the passive approach, numerical taxonomy methods such as Fuzzy C-Mean approach [55], Self-Organized Map [56], fuzzy supervised classification [57], or neural network methods [58] are employed. In fact, all input variables (qualitative or quantitative) are initially converted into fuzzy variables using membership functions; a process known as fuzzification. The shape of the membership function is then optimized through successive observations [33]. The most difficult step in fuzzy modeling is defining MF. Here, we use the active approach based on expert classification of vulnerability index. The details are provided later in this manuscript.

4. Fuzzy Representation of Coastal Erosion Risk: A Conceptual Framework

The proposed conceptual framework for fuzzy representation of risk zones is illustrated in Figure 3. This framework consists of two main steps: (1) Tessellation and (2) Fuzzy representation including (a) Fuzzification and (b) Fuzzy aggregation sub-steps. The applied algorithm is presented in Table 1.

Figure 3. UML activity diagram of conceptual framework for spatial fuzzy representation of coastal risk zones.

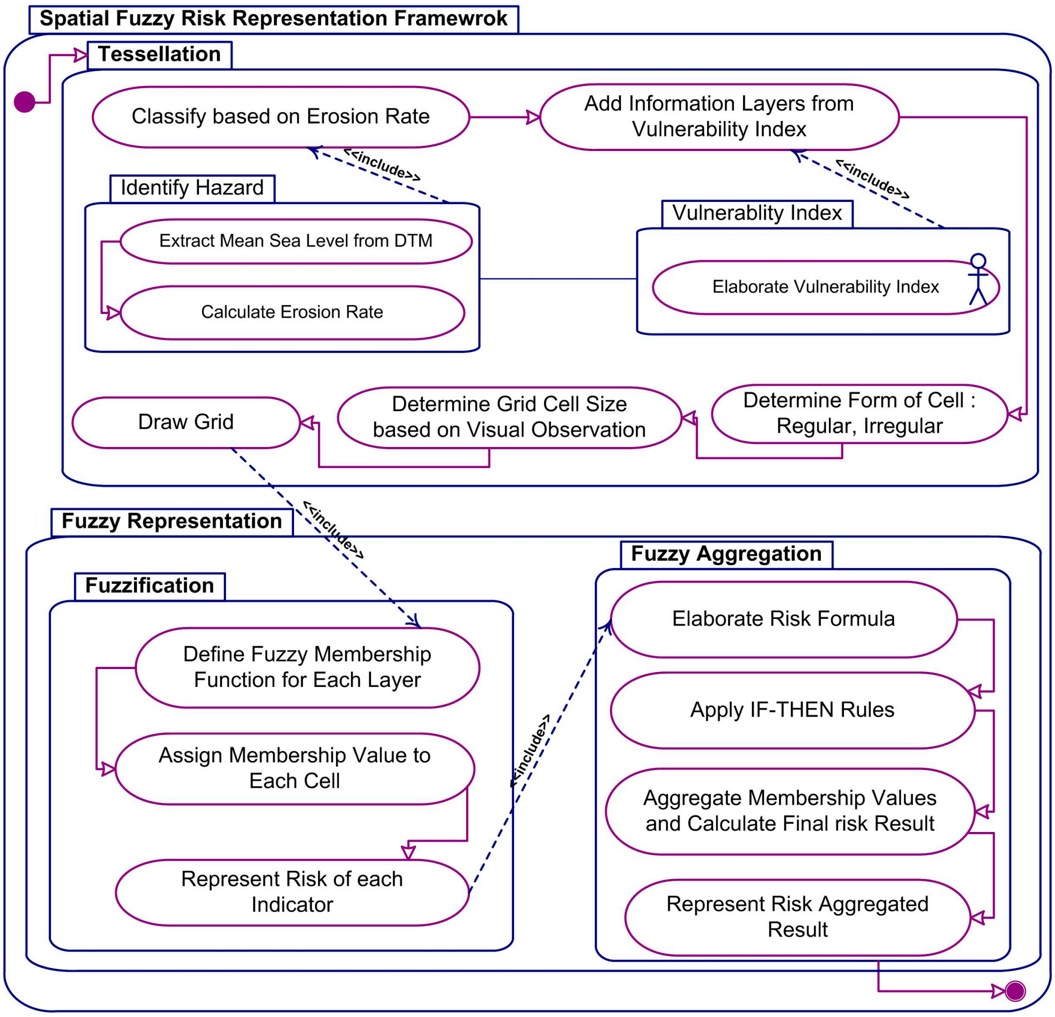


Table 1. Applied algorithm for spatial fuzzy representation of coastal risk zones.

1. Draw the grid on the region with respect to the identified hazard and elaborated vulnerability index,
2. For I = 1:number of vulnerable indicators,
a. For j = 1:length of the grid,
i. Determine the fuzzy membership value for each cell of the grid using defined fuzzy membership function of each indicator,
ii. Assign membership value to center of each cell for each indicator,
iii. Represent the risk value for each indicator,
b. End
3. End
4. Aggregate the risk value of different indicators based on assign operator,
i. Elaborate risk formula,
ii. Apply IF-THEN rules,
iii. Calculate the risk value,
5. Represent the aggregated result,
6. End.

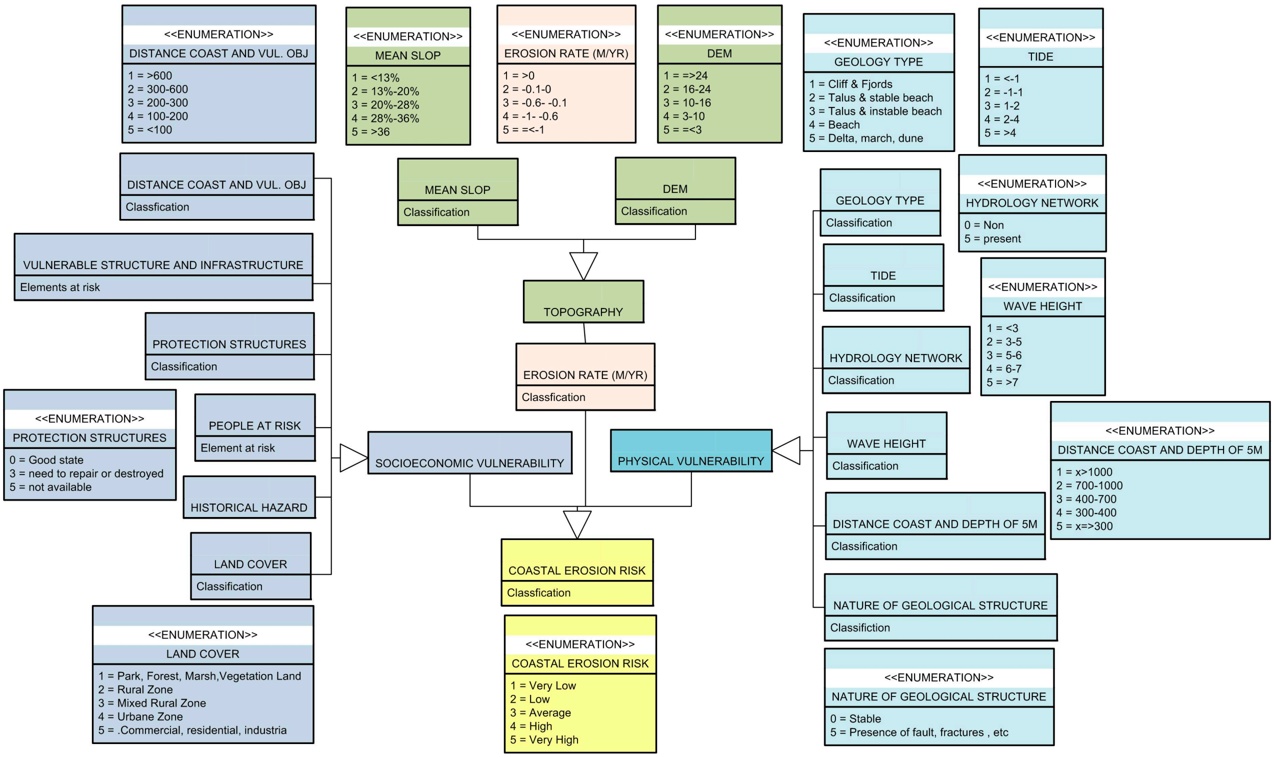
4.1. Tessellation

The tessellation step is performed with respect to identified hazard and elaborated vulnerability index. Hence, the identification of hazard and the elaboration of vulnerability index are indispensable actions in this step. Indeed, the proposed method is a generic framework to represent risk zones based on the fuzzy approach (Figure 3). This framework can be adapted to any other application and phenomena for risk assessment. Here, in this paper, coastal erosion risk representation is chosen as a special case study and, hence, erosion rates and coastal vulnerability index are included in the diagram.

The common way of identifying coastal erosion in coastline change is by calculating the erosion rate in different epochs [59]. Mean Sea Level (MSL) extracted from Digital Terrain Models (DTM) is commonly used to estimate erosion rates. The coastal erosion rates are then calculated by transecting a perpendicular profile line along these MSL lines with respect to different time periods.

The elaboration of vulnerability index is commonly based on expert-knowledge and the interests of stakeholders and decision makers through multiple indicators [5,60]. Since the scope of this paper is confined to investigating a fuzzy approach for spatial representation of risk zones, the vulnerability index is used from Jadidi *et al.* [5]. In fact, vulnerability index consists of multiple indicators. These vulnerability indicators are presented in Figure 4 within a generic schema of coastal erosion risk assessment. These indicators are classified based on expert knowledge to characterize the susceptibility of exposed elements at risk by a degree of risk from 1 to 5 and their importance. These classifications are always performed based on experimental studies and the specific needs of stakeholders. The reason to define the scores from 1 to 5 is associated with human feeling perception from low sensitive to high sensitive situations, *i.e.*, very low, low, average, high, and very high [6].

Figure 4. UML class diagram of a generic schema of coastal erosion risk assessment adapted from [5].



Henceforth, with respect to the estimated erosion rate, the region is classified into five categories. A risk level is assigned to each class of erosion rate from very low, low, average, high and very high as presented in Figure 4, "Erosion Rate" class. The information about vulnerability indicators, e.g., road network, houses, people density, *etc.*, are then integrated to provide a clear perception of the distribution of elements at risk and the variation of erosion. This step can be performed using any available GIS tools, such as ArcGIS. However, choosing the size and shape of the grid cells is always a challenging issue in this step and it is totally experimental. A regular tessellation is chosen in this study because of its simplicity to perform in many GIS tools and in the fuzzification step. The size of the cell depends on required scales and available information. Indeed, if a fine-grain risk representation is needed and high dense data (e.g., LiDAR) is available, the cell size can vary from the same resolution of derived DTM from LiDAR data to census units (hundreds square meters).

4.2. Fuzzy Representation

The fuzzy representation step consists of two sub-sections (a) Fuzzification and (b) Fuzzy Representation explained hereafter.

4.2.1. Fuzzification

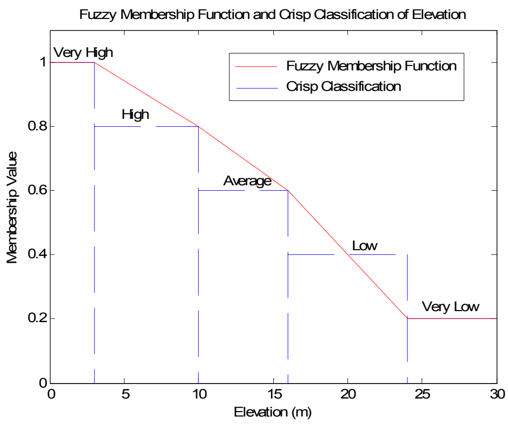
Fuzzification consists of determining the membership functions and the respective membership value for each cell of a grid within each vulnerability indicator. As stated previously, the fuzzy set theory is employed in this study to handle uncertainty related to spatial fiat objects. Regarding the intrinsic nature of coastal erosion risk, the FF-object model is used in this paper to represent risk zones.

This kind of representation comes intuitively from fuzzy classification results (here, from vulnerability index classification). Risk zones are extracted from these classifications consisting of continuous sets of grid cells belonging to one class. The objects of one class are then represented as a layer of the grid, so that N layers of objects will be formed, each consisting of fuzzy regions. A membership value is assigned to each element (cell) of the grid. It is worth stating that, based upon Schneider [19]'s definition, fuzzy objects are finite collections of elements from a regular tessellation, forming a partition of bounded subspace of $\Re^2$.

In the present paper, the membership functions are derived from vulnerability index classification, where a degree of risk is attributed to each indicator based on experimental studies [5]. The membership values are determined by associating the vulnerability index with the independent variable of each indicator (horizontal axis, Figure 5) and dependent variable of the membership value (vertical axis, Figure 5). In Figure 5a,b the membership functions of elevation and erosion rate are presented as graphical examples to compare with their respective crisp classifications.

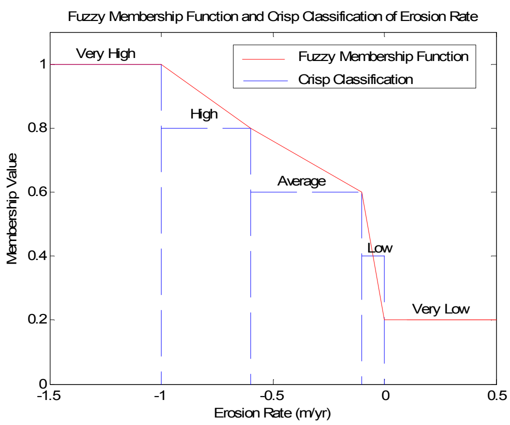
Figure 5. A graphical example of membership functions of some indicators and their crisp classifications: (**a**) Elevation and (**b**) Erosion Rate.

$$\mu = \begin{cases} 1 & x \le 3 \\ \dfrac{0.8-1}{10-3}x+1 & 3 < x \le 10 \\ \dfrac{0.6-0.8}{16-10}x+0.8 & 10 < x \le 16 \\ \dfrac{0.4-0.6}{24-16}x+0.6 & 16 < x \le 24 \\ 0.2 & x > 24 \end{cases}$$



(**a**)

$$\mu = \begin{cases} 1 & x \le -1 \\ \dfrac{0.8-1}{-0.6-(-1)}x+1 & -1 < x \le -0.6 \\ \dfrac{0.6-0.8}{-0.1-(-0.6)}x+0.8 & -0.6 < x \le -0.1 \\ \dfrac{0.4-0.6}{0-(-0.1)}x+0.6 & -0.1 < x \le 0 \\ 0.2 & x > 0 \end{cases}$$



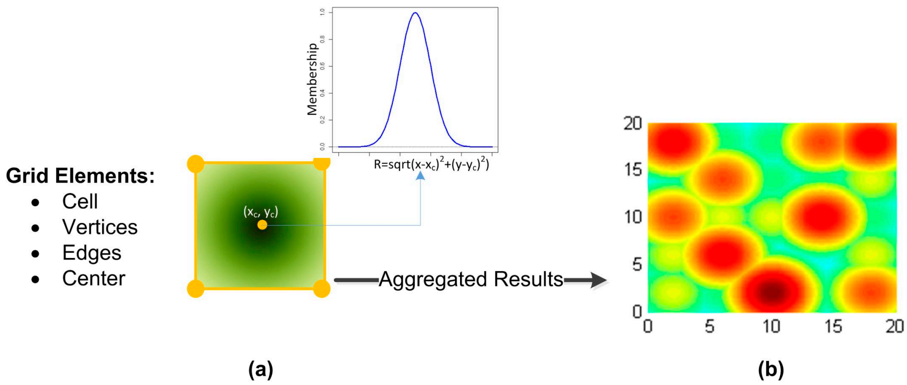
(**b**)

The risk zones are represented by a grid based data structure. Each grid cell is identified by its center, vertices, and edges (see Figure 6a). The membership value is assigned to the center of each cell and scattered as a Gaussian function toward the outside [2]. For any other point (X,Y), the membership value is calculated from Equation (2):

$$F(X,Y) = mv \times e^{(-\sqrt{(X-X_c)^2+(Y-Y_c)^2})} \tag{2}$$

where *mv* is the amplitude at the cell's center (X_c,Y_c). Indeed, the Gaussian function is used to feed the cell neighbors with respect to the inverse of weighted distance from the cell's center (see Figure 6a). MAX (union) operator is applied to choose the membership value of neighboring cells. A risk zone in this case is generated by aggregating a set of cells with the same values (see Figure 6b). In Figure 6b, the color hue represents the risk value. Dark red represents higher risk with a membership value close to 1 and light blue represents lower risk with membership values closer to 0.

Figure 6. (**a**) Proposed approach based on fuzzy model. (**b**) Fuzzy representation of risk level.



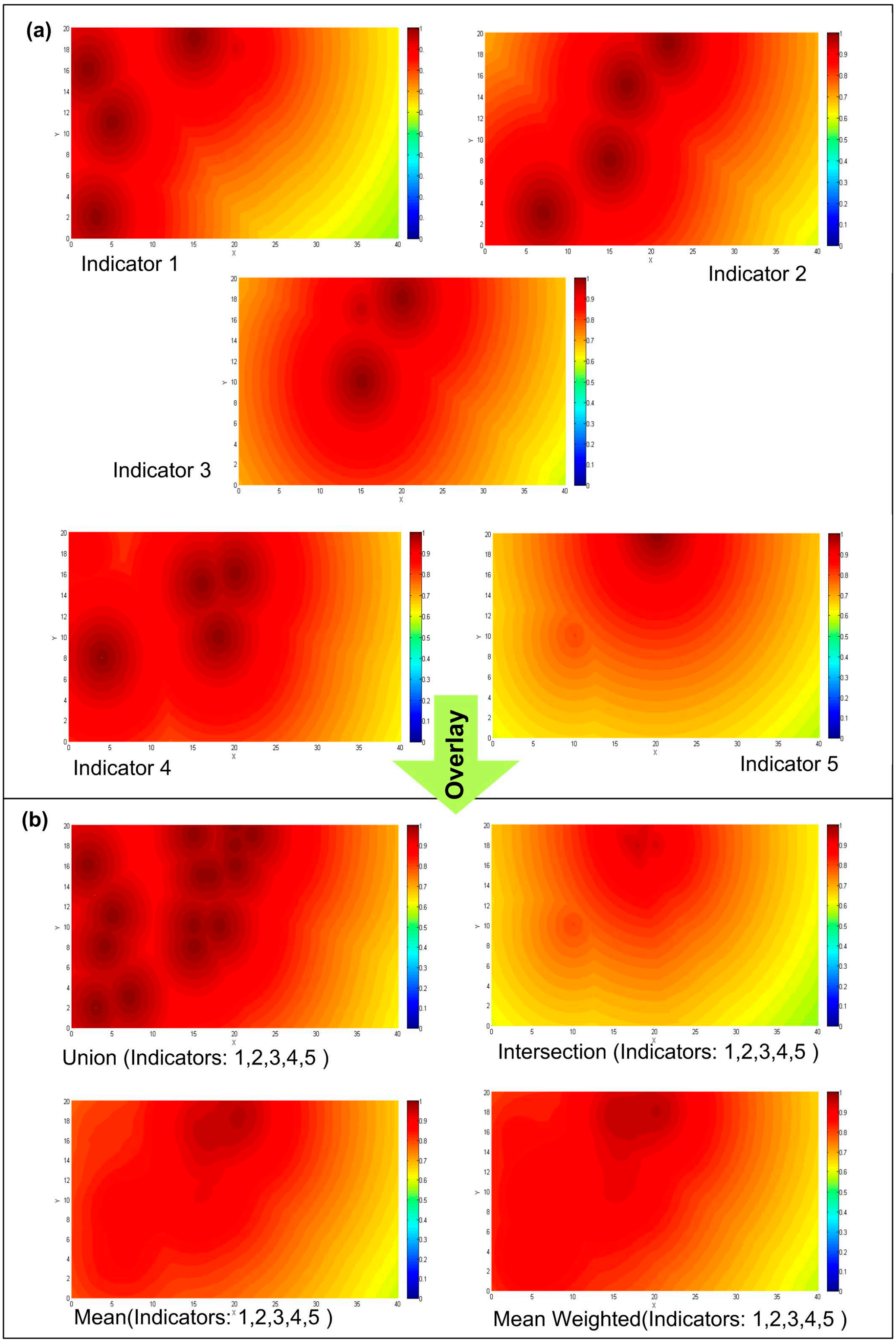
4.2.2. Fuzzy Aggregation

To calculate the overall risk value for a given region, the aggregation of multiple layers of information is required. A risk formula is thus elaborated in this step consisting of hazard, element at risk, and vulnerability indicators (see Jadidi *et al.* [5] for more details) to perform a vertical integration of information [61]. IF-THEN rules are defined based on the risk formula and the priority of stakeholders and authorities of the region under study. An example of a fuzzy rule is shown in Table 2. Fuzzy operators translate IF-THEN rules and combine the individual output of membership values. In fact, IF-THEN rules link computationally multiple outputs with multiple inputs. To aggregate multiple layers, the "Overlay" operation is performed using "Union", "Intersection", "Mean", or "Mean Weighted". The "Union" operator returns the maximum membership value of compared layers. This operator is also called the "MAX" or "OR" operator. The "Intersection" operator returns the minimum membership value of compared layers. It is also referred to as the "MIN" or "AND" operator. "Mean" and "Mean Weighted" operators calculate the average and weighted average membership values of compared layers, respectively.

Table 2. An example of fuzzy IF-THEN rules.

IF *(HydroNetwork is VH) and (ProtectStructure is VH) and (DistObjVul is VH) and (ErosionRate is H)*
THEN *(Use "MAX" operation for "Erosion Risk" calculation)*
VH: very high, H: high, A: Average, L: low, VL: very Low

Figure 7. (**a**) Representation of five different indicators. (**b**) Fuzzy aggregation of these indicators: an overlay operation (union, intersection, mean, and weighted mean).



The choice of fuzzy operators reflects the specific needs to lay out by CERA that require knowing the maximum, minimum, average, or weighted average of the erosion risk associated in the given region. The results from the risk assessment can then be represented either using a risk map (see Figure 7) or using tables and charts after the defuzzification of fuzzy risk values. Figure 7 illustrates the fuzzy representation of a region with respect to five arbitrary varied indicators (Figure 7a) and their overlaid results using fuzzy operators (Figure 7b). If there are cells without data, the membership values for these cells are calculated using their neighbours' membership values using the MAX operator. This operation is likewise based on one of the following fuzzy operators: "Union", "Intersection", "Mean", or "Mean Weighted".

Defuzzification is the process of translating fuzzy result values into crisp values or linguistic expressions [2]. In fact, defuzzification is the reverse process of fuzzification. This step is essential in CERA because some decision makers prefer using the traditional method with crisp values of linguistic expressions. The common defuzzification methods are centroid, maximum, and mean methods [2]. The centroid method is employed in this study for its reputed performance on extremely large amounts of uncertain data. The centroid method determines the centre of the area of the combined membership values. Accordingly, the relation between risk degree for each fuzzy value, crisp value, and linguistic expression is established. The defuzzification relationships used and proposed in this paper are provided in Table 3. This classification also matches with linguistic variables in the fuzzy membership values of vulnerability index. It should be noted that defuzzification generally causes information loss embedded in fuzzy values.

Table 3. Defuzzification results for final erosion risk classification.

Linguistic Expression	Crisp Value	Fuzzy Risk Value
Very Low Risk of Erosion	Risk(Erosion) = 1	$0 \leq$ Risk(Erosion) ≤ 0.175
Low Risk of Erosion	Risk(Erosion) = 2	$0.175 <$ Risk(Erosion) ≤ 0.375
Average Risk of Erosion	Risk(Erosion) = 3	$0.375 <$ Risk(Erosion) ≤ 0.575
High Risk of Erosion	Risk(Erosion) = 4	$0.575 <$ Risk(Erosion) ≤ 0.775
Very High Risk of Erosion	Risk(Erosion) = 5	$0.775 <$ Risk(Erosion) ≤ 1

5. Results: A Case Study

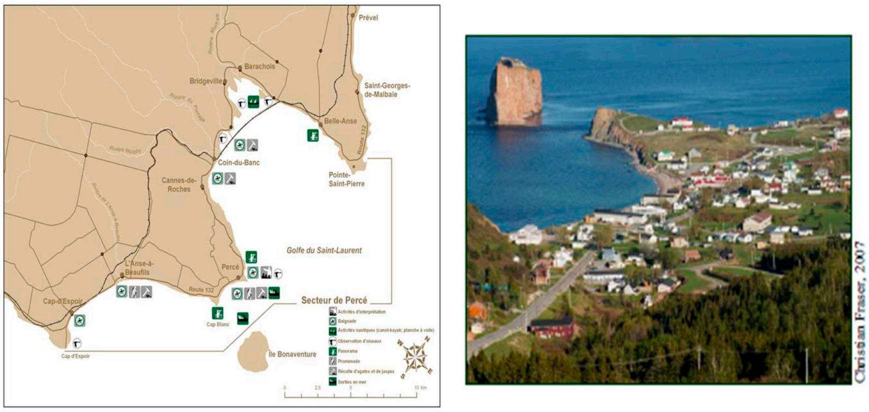
To validate the proposed framework, a case study was carried out by executing multiple steps mentioned in Section 4.

5.1. Study Site

The region along the coast of the St-Laurence River in Perce, near the tip of the Gaspe Peninsula in Eastern Quebec, Canada (see Figure 8) was chosen as the study site to implement and validate the proposed framework. This region is one of the most attractive touristic locations in Quebec because of the well-known Perce Rock and Bonaventure Island. It has 52 km of coastline, 432.39 km^2 surface, a population density equal to 7.7 people per km^2, and a total population of 3312 [62].

Perce is principally characterized by rocky cliffs consisting of sedimentary rock, sandstone, and Gaspe limestone covering 76% of the surface area of the region. The region also contains 17 smaller segments, rocky inlets, and beach terraces for 12% and a spit of beach and tidal marsh cover 11%. 80% of Perce coasts experience severe coastal erosion with an average rate of −0.20 m/year (1994–2001) [63]. Sea Level Rise (SLR) also has a particular impact on coastal erosion by reducing the width of beaches, according to study results from 1934 to 2001 [64]. Heavy rain is another factor that accelerates the erosion process at cliff bottoms and may even provoke sudden and discrete damaging events, such as rock falls and landslides along or far from the coasts. An average erosion rate of −0.49m/yr is predicted until 2050 in the region [64].

Figure 8. Geographical view of Perce, Eastern Quebec, Canada.



Infrastructures such as the road network (Highway 132) and the railway along the spit of Barachois include 34.6% of the socio-economic features at risk in this region; 79% of these features have already been affected by erosion with a total cost of $15.5 million [63]. Businesses related to the tourism industry, together with the majority of jobs associated with this industry, are at a high risk. In addition, the residential areas (23.4%) and villages (5.8%) located around the ports and along the coast are also affected significantly by erosion. It is reported that a total of 13 residential houses, three rural houses, seven commercial buildings, and two industry buildings are in danger with regard to coastal erosion [64]. 30.7% of the coastlines are natural and wild areas. Any change along the beach caused by erosion may considerably reduce the tourist attraction of the region. The landscapes and natural areas such as lagoons and beaches can then be considered as vulnerable elements that should be taken into account in any sustainable planning for the region. Fishing ports, harbors, and docks are also vulnerable indicators in this regard.

5.2. Implementing Proposed Framework on Study Site

Multiple sources of data are used to accomplish the coastal risk assessment of the study site. Table 4 presents a list of datasets and the related parameters that are used for CERA in this case study. Most of the information is extracted from technical reports and is then projected to geographical positions. ArcGIS 10 is used to produce DTM from LiDAR data and Digital Shoreline Analysis System [65] is employed to obtain the erosion rate in this study. The information about vulnerability index is extracted from technical and research reports and formally investigated in ArcGIS 10 yielding a regular tessellation. A grid of 40 m × 40 m is produced along the coast with a width of 1.4 km to 2.8 km (dependent upon data availability). The 40 m × 40 m grid was selected based on the resolution of produced DTM from available LiDAR data on the region under study. This size can vary depending upon needed specifications and the objective of performing CERA.

Table 4. The list of data sets used for erosion risk assessment.

Source	Extracted Information
LiDAR Data	Slop, DEM, erosion rate
Technical and Research Reports	Protection structure, Infrastructure situation, type of coastline, state of coastline, land use information, distance coast and 5 m depth, distance coast element at risk
Geobase	Hydrology network and drainage, land use
Quebec Prov. Transport Dept.	Road network

Matlab code is developed to perform a fuzzy representation of the risk zones. A fuzzy membership value is assigned to each cell based on the defined membership function of each parameter as presented in Table 5. The risk with respect to a specific priority *i.e.*, element at risk is then calculated using the following formula [5]:

$$CoastalErosionRisk(ElementAtRisk, time) = ErosionRate(ElementAtRisk, time) \times \sum_{i=1}^{n} v_i \times w_i(ElementAtRisk, time) \quad (3)$$

The element at risk in this case study is the road network. v_i is the vulnerability indicator and w_i is the weight value. Table 5 presents the list of risk parameters, associated weights, and defined membership functions derived from technical reports from the Quebec Provincial Transport Department that are used in our case study [66]. In this case study, we do not apply any Fuzzy IF-THEN rules, because there were no stakeholder concerns to take into account. The calculated fuzzy risk values are then aggregated using the "Mean Weighted" operator as it is the best fit for the risk formula (Equation (3)). A fuzzy representation of the risk zones is shown in Figure 9. It is worth stating that the list of vulnerability indicators provided in Figure 5 is a complete list of coastal vulnerability index. Nevertheless, not all of them are available in the case studies.

Table 5. Risk parameters, their weight and membership functions used in the case study (adapted from [66]).

Risk Parameters	Weight (w_i)	Membership Function
Protection Structure	34%	$\mu = \begin{cases} 1 & x = \text{"Fault" OR "Fracture" OR "Subsidence"} \\ 0 & x = \text{non} \end{cases}$
Distance coast and element at risk	17%	$\mu = \begin{cases} 1 & x \le 100 \\ \frac{0.8\text{-}1}{200\text{-}100} x + 1 & 100 < x \le 200 \\ \frac{0.6\text{-}0.8}{300\text{-}200} x + 0.8 & 200 < x \le 300 \\ \frac{0.4\text{-}0.6}{600\text{-}300} x + 0.6 & 300 < x \le 600 \\ 0.2 & x > 600 \end{cases}$

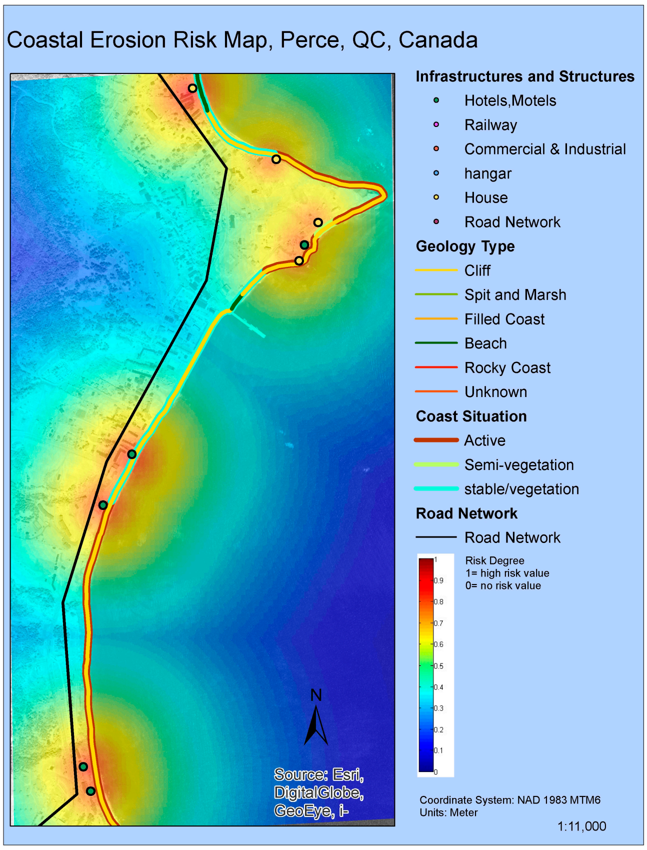
Table 5. *Cont.*

Risk Parameters	Weight (w_i)	Membership Function
Mean Slop	13%	$\mu = \begin{cases} 1 & x \geq 35 \\ \frac{1\text{-}0.8}{35\text{-}28}\mathrm{x}+0.8 & 28 \leq \mathrm{x} < 35 \\ \frac{0.8\text{-}0.6}{28\text{-}20}\mathrm{x}+0.6 & 20 \leq x < 28 \\ \frac{0.6\text{-}0.4}{20\text{-}13}\mathrm{x}+0.4 & 13 \leq x < 20 \\ 0.2 & x < 13 \end{cases}$
DEM	10%	$\mu = \begin{cases} 1 & x \leq 3 \\ \frac{0.8\text{-}1}{10\text{-}3}\mathrm{x}+1 & 3 < x \leq 10 \\ \frac{0.6\text{-}0.8}{16\text{-}10}\mathrm{x}+0.8 & 10 < x \leq 16 \\ \frac{0.4\text{-}0.6}{24\text{-}16}\mathrm{x}+0.6 & 16 < x \leq 24 \\ 0.2 & \mathrm{x} > 24 \end{cases}$
Geology Type	8%	$\mu = \begin{cases} 1 & x = \text{"Delta"or"Dune"} \\ 0.8 & x = \text{"Beach"} \\ 0.6 & x = \text{"Talus with no vegetation"} \\ 0.4 & x = \text{"Talus with vegetation"} \\ 0.2 & x = \text{"Cliff" or "Fjords"} \end{cases}$
Land Cover	7%	$\mu = \begin{cases} 1 & x = \text{"Park"or"Marsh"or"Vegetation Land"} \\ 0.8 & x = \text{"Rural Zone"} \\ 0.6 & x = \text{"Mixed Rural Zone"} \\ 0.4 & x = \text{"Urban Zone"} \\ 0.2 & x = \text{"Commercial" or "Residential"or "Industial"} \end{cases}$
Hydrology Network	6%	$\mu = \begin{cases} 1 & x = Yes \\ 0.6 & 28 = \text{small} \\ 0 & x = \text{non} \end{cases}$
Distance coast to 5 m depth	5%	$\mu = \begin{cases} 1 & x \leq 300 \\ \frac{0.8\text{-}1}{400\text{-}300}\mathrm{x}+1 & 300 < \mathrm{x} \leq 400 \\ \frac{0.6\text{-}0.8}{700\text{-}400}\mathrm{x}+0.8 & 400 < \mathrm{x} \leq 700 \\ \frac{0.4\text{-}0.6}{1000\text{-}700}\mathrm{x}+0.6 & 700 < \mathrm{x} \leq 1000 \\ 0.2 & x > 1000 \end{cases}$

Table 5. *Cont.*

Risk Parameters	Weight (w_i)	Membership Function
Erosion Rate		$\mu = \begin{cases} 1 & x \le -1 \\ \frac{0.8\text{-}1}{\text{-}0.6\text{-}(\text{-}1)} x + 1 & -1 < x \le -0.6 \\ \frac{0.6\text{-}0.8}{\text{-}0.1\text{-}(\text{-}0.6)} x + 0.8 & -0.6 < x \le -0.1 \\ \frac{0.4\text{-}0.6}{0\text{-}(\text{-}0.1)} x + 0.6 & -0.1 < x \le 0 \\ 0.2 & x > 0 \end{cases}$

Figure 9. Fuzzy representation of coastal erosion risk zones on the study site.



5.3. Results Interpretation

As illustrated in Figure 9, regions at higher risk are along the coast. About 800 m of Highway 132 are severely at risk (north, center, and southwest). The residential area (a total of 4 houses in the yellow circles) and two motels (green circles) on the nose of Perce rocks are also at very high risk. From the nose of Perce rocks toward the southwest, four motels are also at high risk. Additionally, having the high risk region (red zone) along Highway 132 confirms the results of previous studies in the region [29,66]. This region is reported as an active cliff coastline with an erosion rate of 0 m/year. However, due to its geology type, the erosion may happen all of sudden as a land-slide. The main difference between our method and other studies is how spatial uncertainty related to risk modeling is handled through the fuzzy approach.

The high risk areas are well recognized with respect to existing infrastructures, buildings, people, and their properties. Indeed, the obtained results in this study are more consistent with human reasoning and perception, conveying the level of risk in a continuous and smooth manner. The continuity is not only handled by raster format but is also conducted by the fuzzy representation.

6. Discussion and Remarks

In addition to spatial uncertainty, defined as the lack of knowledge [7], the imperfection of very large amounts of data and information should also be considered in CERA. CERA is traditionally an expert-based process. Flexibility and the capability of integrating expert knowledge (structured as linguistic expression) as well as characterizing and handling data uncertainty have always been stated as important issues in improving the quality of results in CERA. The proposed approach in this study was to employ knowledge-based solutions such as fuzzy set theory with the following advantages:

- Spatial uncertainty associated with object definition is explicitly dealt with through the fuzzy approach. It is also possible to attach a probability density to the values of position and measurement uncertainty. If this is the case, before using this data in CERA, cleaning the data using probability approaches with an accepted confidence level is recommended.
- Membership function definition issues are resolved by converting the crisp classification of vulnerability index to a fuzzy classification. Accordingly, the integration of multiple criteria is performed by aggregating their respective membership values using fuzzy aggregation operators. If the vulnerability index classification is not available, methods such as Fuzzy C-Mean and Fuzzy K-Mean are recommended to define the required membership functions based on available data.
- The grid-based structure of the proposed approach avoids the difficulties of combining different membership values to compute the fuzziness inside of objects where various criteria lead to fuzziness. Further, several studies confirm that the fuzzy approach works well with grid-based format [18,61].
- Elaborating risk formula and then constructing IF-THEN rules of associated indicators allows direct control over the entire CERA process. In addition, this provides more flexibility if one or more indicators or their classifications are changed. In this case, updating the desired information by re-running the fuzzification step or modifying the IF-THEN rules by re-executing the fuzzy aggregation step will be sufficient.
- The proposed approach allows performing multiple fuzzy aggregation operators (union, intersection, mean, mean weighted) that is required in any CERA process. The result in Figure 7b shows how significantly the choice of fuzzy operators can affect the end result. Therefore, with regards to the needs of decision makers and the emergence of protection actions, the choice of these operators is also varied.
- The flexibility of fuzzy set theory to characterize and handle inherent spatial uncertainty through the entire assessment process widely increases the confidence levels of adapted strategies for protection regions under study. It also accelerates the implementation of response plans in case

of a disaster through the interpretation of the results and the prioritization of planning actions based on expert perception. From another point of view, traditional risk assessment methods lead to crisp decisions, *i.e.*, "Yes" or "No" while the fuzzy approach leads to smooth transitions between these two extremes.

- Fuzzy risk representation is a relatively new concept for decision makers. In this new context, decision-making processes need to be adapted and meaningful criteria need to be established to accept and manipulate fuzzy risk values. Changing the decision making culture to use fuzzy results requires finding evidence to convince the decision makers of the benefits of this new approach. The defuzzification step explained briefly in this paper is an alternative in this regard to translate fuzzy values to measurable values, making them understandable for decision makers. Kentel and Aral [2] propose a risk-tolerance measure method based on a crisp compliance guideline, which is already available in some domains, such as the health system.

On the other hand, the main limitations of the proposed approach in this paper are as follows:

- The proposed fuzzy representation is tested only on regular tessellation. The neighborhood relation is implicit, based on the ID of a cell. If an irregular tessellation is needed, more effort in neighborhood concepts and topological predicates are required.
- The temporal aspect of the fuzzy object is not taken into account in this approach. This paper only discusses the spatial extent of fuzzy objects and the situations in which the fuzzy classification is due to the multi-criteria nature of CERA and spatial uncertainty associated with object definition. This means that the risk zones are represented spatially as a snapshot of a given time period. How to handle fuzzy objects that change in different time periods needs more investigation.
- The proposed approach is employed only on a small region with a given level of detail (scale). When the analysis of extremely large amounts of data within a hierarchical system is required, the proposed approach needs to be adjusted with respect to selected technology. In this regard, efforts are mainly needed on fuzzy aggregation operators such as "Fusion" where the multi-scale representation is required.

7. Conclusions

Characterizing spatial uncertainty is important in coastal risk assessment for effective decision-making. Additionally, accurate spatial representation of coastal risk is essential in providing the necessary knowledge of the potential impact of risk and to help decision makers take the necessary actions to better protect people, infrastructures, and other installations along the coast. This paper has focused on the improvement of spatial representation of coastal erosion risk by taking into account the inherent uncertainty related to spatial objects and risk zone representation. The associated uncertainties were characterized as vagueness and fuzziness of objects and then handled by fuzzy set theory. A conceptual framework was proposed to represent risk zones based on a fuzzy model. Vulnerability index classifications were used to determine membership functions for each indicator as a separate layer. A regular tessellation of the region was generated for each indicator by assigning an appropriate membership value to each cell indicating the degree of risk. IF-THEN rules were defined to aggregate multiple layers of indicators by using aggregation operators such as Union, Intersection, Mean, and

Mean Weighted. Finally, a spatial fuzzy representation of CERA was presented. The proposed approach was applied to a study site in Perce, Quebec, Canada to demonstrate the validity and advantages of the proposed method. This method provides a better tool for decision-making, as the risk values were better adapted to the reality of the region. Since the ultimate objective of any risk assessment is to assist in efficient decision making, so confronting very large amounts of data is unavoidable. Nowadays, geospatial intelligence systems are extensively used in this regard. Implementing the proposed method can lead to new insights on how to deal with spatial uncertainty in such databases. Manipulating fuzzy models in a hierarchical system requires fuzzy aggregation operators. The expansion and redefinition of these concepts in the context of spatial multidimensional systems are of concern for future work.

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Author Contributions

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Conflicts of Interest

The authors declare no conflict of interest.

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