# A Practical Taxonomy of Methods and Literature for Managing Uncertain Spatial Data in Geographic Information Systems

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## Abstract

Perfect information is seldom available to man or machines due to uncertainties inherent in real world problems. Uncertainties in geographic information systems (GIS) stem from either vague/ambiguous or imprecise/inaccurate/incomplete information and it is necessary for GIS to develop tools and techniques to manage these uncertainties. There is a widespread agreement in the GIS community that although GIS has the potential to support a wide range of spatial data analysis problems, this potential is often hindered by the lack of consistency and uniformity. Uncertainties come in many shapes and forms, and processing uncertain spatial data requires a practical taxonomy to aid decision makers in choosing the most suitable data modeling and analysis method. In this paper, we: (1) review important developments in handling uncertainties when working with spatial data and GIS applications; (2) propose a taxonomy of models for dealing with uncertainties in GIS; and (3) identify current challenges and future research directions in spatial data analysis and GIS for managing uncertainties.



**Keywords:** Uncertainty; Spatial data; Geographic information systems; Taxonomy; Literature review.

## 1. Introduction

The modern geospatial revolution enhanced by geographic information systems (GIS) has greatly increased the understanding of our physical environment. The basic components of GIS include (Marble, 1984): (1) a data input component for collecting and processing spatial data; (2) a data storage and retrieval component for organizing spatial data; (3) a data manipulation and analysis component for changing spatial data; and (4) a data reporting component for displaying spatial data. Spatial data are not always precise and uncertainty in geographical data is widely accepted due to the way the world is perceived, measured, and represented (Zhang and Goodchild 2002). Varsi (2001a, 2001b) has observed that vagueness is a major factor in geographical information representation since concepts such a river's length or a mountain's height in a specific area are uncertain as the specification of a river or peak are vague concepts. Baofu (2015, p. 297) states "all geographical data are inherently inaccurate, and these inaccuracies will propagate through GIS operations in ways that are difficult to predict." Couclelis (2003) further describes uncertainty as an inherent property of complex geospatial knowledge that must be managed effectively. Many of the problems associated with the accurate measurement of spatial databases and GIS are also prevalent in all types of database systems. Uncertainty in many of these systems is not simply an error or flaw to be reduced or eliminated but an important component of the system that must be taken into consideration. Therefore, uncertainty plays a critical role in the analysis of spatial data and GIS which contain descriptive as well as positional data. The uncertainty can be represented by a wide range of values that may include the actual measurement of the object as only one point. Figure 1 illustrates the complexity that can be observed in a real-world example. This figure is an image of the Louisiana gulf coastal region in the area of the Atchafalaya Bay and illustrates the difficulty of specifying the characteristics of the spatial features. The boundary between the coastline and the Gulf of Mexico, the relationship of the various waterways and their characterization are difficult to specify as they exhibit both spatial and temporal uncertainty.

Insert Figure 1 Here

The remainder of this paper is organized as follows. In Section 2, we present a review of the statistical and non-statistical methods used for managing uncertain spatial data in GIS. More specifically, we review fuzzy set/possibility theory and rough set theory used for managing vague/ambiguous data and probability theory and Dempster-Shafer (D-S) theory for managing imprecise/inaccurate/incomplete spatial data. In Section 3, we discuss our study and results and

in Section 4, we draw our conclusions and outline future research directions.

## 2. Managing uncertainties in spatial data

In this section, we examine some practical approaches used to represent various aspects of geospatial data. Uncertainty can refer to vagueness, ambiguity, imprecision, inaccuracy, incompleteness, or anything that is undetermined. In this study, we refer to "vagueness" as the inability to clearly understand the meaning of a word or phrase; "ambiguity" as multiple meanings in a word or phrase; "imprecision" as the level of variation associated with a set of measurements; "inaccuracy" as a situation where the assessment fails to give the true measurement; and "incompleteness" as the lack of relevant measurement.

A wide range of statistical and non-statistical methods have been proposed in the literature to model uncertainties in spatial data. In this study, we present a practical taxonomy of these methods by grouping them into two general categories: statistical and non-statistical methods. As shown in Figure 2, statistical methods are often used to model imprecise, inaccurate, or incomplete spatial data while non-statistical methods are used to handle vague or ambiguous spatial data. Probability theory and D-S theory are the most widely used statistical methods for modeling uncertain spatial data while fuzzy set/possibility theory and rough set theory are the most commonly used non-statistical methods for managing uncertainties in spatial data modeling.

Insert Figure 2 Here

### 2.1 Statistical approaches

In this study, we identified 42 papers which applied D-S theory in a GIS environment. Malpica et al. (2007) present a survey of (D-S) theory in GIS. Here we discuss how probability and D-S theory have been used to represent geospatial data with uncertainty.

The D-S theory of evidence (also referred to as the *belief function theory* or *evidential reasoning theory*) is general framework formalized by Shafer (1976) for representing and reasoning with uncertain, imprecise, or incomplete information. Shafer's seminal book was based on Dempster's original idea (Dempster, 1967) on the modelling of uncertainty in terms of upper- and lower-probabilities induced by a multivalued mapping (Liu et al., 1992). The key concept in D-S theory is that an amount of probability mass (a value in [0, 1]) can be assigned to a subset of a set of solutions to a question (such as all the possible values of size of a particular space) rather than just a singleton set, as in the case of probability theory. When all the subsets bearing probability masses are singleton sets, D-S theory is reduced to standard Bayesian (probabilistic)

reasoning. *We should note that D-S theory is a generalization of Bayesian theory and does not compete with or replace Bayesian approaches*. D-S theory has been widely used to medical and sensor information modelling and aggregation (e.g., Lowrance et al., 1996; Strat, 1987). Yager et al. (1994) contains most of the significant works in D-S theory at the time.

There are two main interpretations of what a probability mass assigned to a subset means (Halpern & Fagin, 1992), for example, assigning 0.6 to subset {Edinburgh, Belfast} to a question: "where person A lives now?" and assigning the remaining 0.4 to the whole set of all possible cities A may live. The first interpretation views D-S theory as an extension of probability theory. With this view, when a probability distribution is propagated from one set of elements to another related set through a mapping, it is not possible to generate a probability distribution on the latter set, instead, it generates a new function which could assign probability mass values to subsets. Shafer's original work would very much follow this vine. The second interpretation views D-S theory as a new theory to model an intelligent agent's information (or knowledge), independent of probability theory. Smets' work, especially the transferable belief model (Smets, 1993), would be a typical example of such interpretation. Therefore, with the first view, assigning 0.6 to subset {Edinburgh, Belfast} can be interpreted as that from some probability evidence gathered on some relevant possible worlds, there is probability mass 0.6 supporting the hypothesis that person A lives in one of these two cities, but we do not know which one. With the second view, an agent subjectively *assumed* that person A lives in one of the two cities probably 0.6, without relating it to any probability evidence.

Largely due to the ability to assign probability masses to subsets of possible worlds, D-S theory has the ability to easily model ignorance in information. For instance, value 0.4 to the whole set of possible values to a questions suggests the agent has no knowledge as how to allocate this value to any subsets. Value 0.6 assigned to subset {Edinburgh, Belfast} also means that an agent does not have any further information as how to allocate a proportion of 0.6 to either of the two cities. If 0.3 is assigned to each of the cities, like what would have been done in probability theory, then *equal probably* assumption would have been assumed and applied, which the agent may not wish to impose upon. This is the first advantage of D-S theory.

Information or evidence may come from different sources. When this happens, a fusion process (or combination, aggregation) shall be in place to combine information from these sources to generate a consensus view of what all these pieces of evidence tell an agent. Dempster's

combination rule has the ability to combine pieces of evidence from distinct sources. Because this rule is both communicative and associative, it can be applied to combine pairs of evidence until all evidence has been considered. This rule has been widely applied (as one of the main attractions of applying D-S theory) in many real-world applications. This is the second advantage of D-S theory.

With these two advantages, the former allows an agent to describe ignorance because of lacking information, and the latter allows an agent to narrow down the possible solution space as more evidence is accumulated. D-S theory not only has a close connection with probability theory (when it is viewed as an extension of probability theory), it also takes possibility theory as its special case (described later). Essentially any possibility distribution (a basic concept to model evidence), can be transformed into a form of basic probability assignment (also called mass functions).

Even though D-S theory has been widely applied in real-world problems, it has been criticized for producing counterintuitive results in some cases when applying Dempster's combination rule (Zadeh, 1986), especially when evidence contradicts each other. Therefore, a number of alternative combination rules have been proposed to overcome the limitations of Dempster's combination rule. Nevertheless, it is proved that there does not exist a *perfect* combination rule, if a set of rational properties shall be possessed by such a rule (Dubois et al., 2013). Another issue when considering how to combine evidence is to deal with inconsistency (or conflict) among evidence. When two pieces of evidence do not agree with each other, such as one evidence assigns 0.6 to {Edinburgh, Belfast}, another assign 0.1 to the same subset, how can an agent quantify the degree of conflict? In recent years, there has been a considerable amount of research on defining conflict between evidence (Liu, 2006), and conflict within a single piece of evidence. A comprehensive survey of different measures for assessing degrees of conflict is presented by Jousselme & Maupin (2012). An additional criticism is the computational expense. As we will discuss below, D-S computations can scale exponentially. Practitioners often have to look for sparsity or approximations to reduce computational complexity.

### 2.1.1 Basic concepts in D-S theory

In our discussions below, we will use two simple running examples to illustrate key definitions in D-S theory.

Example 1 - Police suspect pursuit:

A police force is attempting to apprehend a criminal suspect. There is evidence provided to the police that the criminal may be in a geospatial area $A$ (which could be a building, a block of a city or town, a section of a forest, or etc.). The detective in charge of the case considers eyewitness reports, psychological profiles of the suspect, geographic characteristics of area $A$, etc. The detective thinks that the suspect is hiding in $A$ at least 40% of the time, and will not be in area $A$, notated as $\bar{A}$, at least 20% of the time. The detective, however, is unsure about the suspect's presence for the remaining 40% of the time.

Example 2 - Balls in an urn with incomplete information:

Consider a collection of balls in an urn that consists of three shades: white, gray or black. In a two-person experiment, Experimenter A draws balls from the urn without replacement. This person gives verbal information to Experimenter B regarding what ball was drawn. Experimenter B tallies the draw results, but does not see what is drawn. This person must rely strictly on the verbal information. Now, Experimenter A is always truthful, and will sometimes report "white," "gray" or "black"; however, Experimenter A sometimes says, "not white," which means the ball could be either gray or black. Likewise, Experimenter A also says for some of the results "not gray," "not black," or "I drew a ball." The later result means that the ball could be any of the three shades. Hence, while Experimenter A is always truthful, sometimes the information is incomplete.

With these two examples, we now review key definition as discussed in Shafer (1976). In D-S theory, a piece of information is usually described as a mass function on a frame of discernment.

**Definition 1 (Frame of Discernment).** *A set is called a frame of discernment (or simply a frame) if it contains mutually exclusive and exhaustive possible answers to a question. It is usually denoted as $\Theta$. It is required that one and only one element in the set is true at any time.*

For instance, if we assume that Emma lives in one of the cities, $city_1$, $city_2$,..., $city_6$, then, $\Theta=\{city_1, city_2, city_3, city_4, city_5, city_6\}$ is a frame of discernment for the question 'In which city does Emma live?'. For Example 1, $\Theta_{\mathbf{Ex.1}} = \{A, \bar{A}\}$. However, the frame of discernment for Example 2 is $\Theta_{\mathbf{Ex.2}} = \{W, G, B\}$, where $W, G, B$ represents "white," "gray," "black," respectively.

**Definition 2 (Mass Function).** *A function* $m$: $2^{\Theta} \rightarrow [0,1]$ *is called a mass function on frame $\Theta$ if it satisfies the following two conditions:*

*a.* $m(\varnothing) = 0$, and

*b.* $\Sigma_A m(A) = 1$,

*where ∅ is an empty set and A is a subset of Θ.*

A mass function is also called *a basic probability assignment*, denoted as *bpa*. For instance, if we know that Emma lives in the area covering the six cities, but we have no knowledge about in which city she lives, then we can only give a mass function $m(\Theta) = 1$. Alternatively, if we know that Emma lived in $city_3$ two years ago and she intended to move to other cities and tried to find a job somewhere within these six cities, but we have no definite information about where she lives now, then a mass function could be defined as $m(\{city_3\}) = p, m(\Theta) = 1 - p,$ where $p$ stands for the degree of our belief that she still lives in $city_3$.

In Example 1, the event space is binary – either the suspect is in space $A$ or not, $\bar{A}$. From the detective's assessment, $m(\varnothing) \equiv 0$, $m(\bar{A}) = 0.2$, $m(A) = 0.4$, and $m(A \cup \bar{A}) = 0.4$. Note that $m(A) + m(\bar{A}) + m(A \cup \bar{A}) = 1$.

In Example 2, the event space has the three singletons: $W, G,$ and $B$. Suppose that the person reporting the results of the draws says "white" 5% of the time, "grey" never, "black" 5% of the time, "not black" 15% of the time (note that "not black" = "white or gray"), "not gray" 10% of the time, "not white" 5% of the time, and "I drew a ball" the remaining 60% of the time. Thus, $m(\varnothing) \equiv 0$, $m(W) = 0.05$, $m(G) = 0.0$, $m(B) = 0.05$, $m(W \cup G) = 0.15$, $m(W \cup B) = 0.10$, $m(G \cup B) = 0.05$, and $m(W \cup G \cup B) = 0.60$.

**Definition 3 (Belief Function).** *A function* $bel: 2^{\Theta} \to [0,1]$ *is called a belief function if bel satisfies:*

*a.* $bel(\Theta) = 1$;

*b.* $bel(\cup_1^n A_i) \geq \sum_i bel(A_i) - \sum_{i>j} bel(A_i \cap A_j) + \ldots + (-1)^{-n} bel(\cap_i A_i)$.

It is easy to see that $bel(\varnothing) = 0$ for any belief function. A belief function is also called *a support function*. The difference between $m(A)$ and $bel(A)$ is that $m(A)$ is our belief committed to the subset $A$ excluding any of its subsets while $bel(A)$ is our degree of belief in $A$ as well as all of its subsets.

In general, if $m$ is a mass function on frame $\Theta$ then $bel$ defined in (1) is a belief function on $\Theta$:

$$bel(B) = \Sigma_{A \subseteq B} m(A) \quad (1)$$

Referring to our running examples, the power set in Example 1 is $2^{\Theta_{Ex.1}} = \{\varnothing, A, \bar{A}, (A \cup \bar{A})\}$. The mass function is $m_{Ex.1}(x): 2^{\Theta_{Ex.1}} = \{0, 0.4, 0.2, 0.4\}$. The belief function is $bel_{Ex.1}(x) = \sum_{x \subseteq A} m(x) = \{0, 0.4, 0.2, 1\}$. In Example 2, the power set is $2^{\Theta_{Ex.2}} = \{\varnothing, W, G, B, (W \cup G), (W \cup B), (G \cup B), (W \cup G \cup B)\}$. The mass function is $m_{Ex.2}(x) = \{0, 0.05, 0, 0.05, 0.15, 0.10, 0.05, 0.60\}$. The belief function is $bel_{Ex.2}(x) = \{0.00, 0.05, 0.00, 0.05, 0.20, 0.20, 0.10, 1.00\}$.

Recovering a mass function from a belief function is as follows (Shafer, 1976):

$$m(A) = \Sigma_{B \subseteq A} (-1)^{|B|} bel(B)$$

For any finite frame, it is always possible to get the corresponding mass function from a belief function and the mass function is unique.

A subset $A$ with $m(A) > 0$ is called a *focal element of this belief function*. If all focal elements of a belief function are the singletons of $\Theta$ then the corresponding mass function is exactly a probability distribution on $\Theta$. So mass functions are generalized probability distributions in this sense. In Example 2, the focal elements are all members of $2^{\Theta_{Ex.2}}$ with the exception of $\varnothing$ and $G$ as the mass of both are zero.

If there is only one focal element for a belief function and the focal element is the whole frame $\Theta$, this belief function is called a *vacuous belief function*. It represents total ignorance (because of lack of knowledge). To illustrate this concept, let us revisit Example 1. If the detective has no idea about the presence of the suspect in area $A$, then $m(x): 2^{\Theta_{Ex.1}} = \{0, 0, 0, 1\}$. Here, we have a vacuous belief function as the only non-zero mass is $m(A \cup \bar{A}) = 1$ so that $bel(x) = \{0, 0, 0, 1\}$.

**Definition 4 (Plausibility Function).** *A function pls defined below is called a plausibility function* $pls(A) = 1 - bel(\neg A)$.

where $pls(A)$ represents the degree to which the evidence fails to refute *A*. From a mass function, we can get its plausibility function as (Shafer, 1976):

$$pls(B) = \Sigma_{A \cap B6=\varnothing} m(A) \quad (2)$$

For our running examples, the plausibility for Example 1 is $pls_{Ex.1}(x) = \{0, 0.8, 0.6, 1.0\}$. In Example 2, $pls_{Ex.2}(x) = \{0, 0.90, 0.85, 0.95, 0.75, 0.95, 1.00\}$.

***Bayesian belief as a special case of the D-S belief structure***

Note that the singleton event in the frame of discernment is contained in the power set, that is $\Theta \subset 2^{\Theta}$. D-S belief reduces to Bayesian belief for the special case where the masses of all singletons add to one – all tuples have zero mass. For example, if in Example 2, the results were 40%, 20%, and 40% for the singleton events of white, gray and black, respectively, all masses for the tuples, such as $m(W \cup G)$, are zero. In this case, the mass function becomes $m_{Ex.2_{Bayesian}}(x) : 2^{\Theta_{Ex.2}} = \{0, 0.4, 0.2, 0.4, 0, 0, 0, 0\}$. The belief and plausibility functions become equal such that $bel_{Ex.2_{Bayesian}}(x) = pls_{Ex.2_{Bayesian}}(x) = \{0, 0.4, 0.2, 0.4, 0.6, 0.8, 0.6, 1\}$ because the singletons add to one for the Bayesian case.

Formally, singleton masses are *normal* for the Bayesian case and *sub-normal* in general for the D-S case. Furthermore, D-S structures have "super-additive" belief, and "sub-additive" plausibility. In Example 2 for the D-S case, $bel(W \cup G) = 0.15 > bel(W) + bel(G) = 0.05$ and $pls(W \cup G) = 0.95 < pls(W) + pls(G) = 1.7$ All three properties reduce to "additive" in the special Bayesian case.

***Multiple frames of discernment***

When more than one mass function is given on the same frame of discernment, the combined impact of these pieces of evidence is obtained using a mathematical formula called *Dempster's combination rule*.

**Definition 5.** *Let $m_1$ and $m_2$ be two bbas, and let $m_1 \oplus m_2$ be the combined bba.*

$$m_1 \oplus m_2(C) = \frac{\Sigma_{A \cap B=C}\left(m_1(A) \times m_2(B)\right)}{1 - \Sigma_{A \cap B=\varnothing}\left(m_1(A) \times m_2(B)\right)}$$

When $m_1 \oplus m_2(\varnothing) = \Sigma_{A \cap B=\varnothing}\left(m_1(A) \times m_2(B)\right) = 1$, the two pieces of evidence are totally contradict with each other and cannot be combined with the rule. The condition of using the rule

is stated as "two or more pieces of evidence are based on distinct bodies of evidence" (Shafer, 1976).

**Definition 6** (Smets, 2004)**.** *Let m be a bba on* Ω*. Its associated pignistic probability function* $BetP_m : \Omega \to [0,1]$ *is defined as*:

$$BetP_m(\omega) = \sum_{A \subseteq \Omega, \omega \in A} \frac{1}{|A|} \frac{m(A)}{1 - m(\varnothing)}, \; m(\varnothing) \neq 1 \tag{3}$$

*where* $|A|$ *is the cardinality of subset A.*

The transformation from *m* to $BetP_m$ is called the *pignistic transformation*. When an initial *bba* gives $m(\varnothing) = 0, \frac{m(A)}{1 - m(\varnothing)}$ is reduced to $m(A)$. Value $BetP_m(A)$ is referred to as the *betting commitment to A.*

The main purpose of inducing a probability distribution is for decision making such as computing expected utilities in the decision theory. That is, evidence is assumed to be modelled at the *credal level* while decisions are at the pignistic level.

On the other hand, evidence may not always be gathered over the frame (or problem space) on which a decision will be made. In many cases, decisions are made over a space that evidence will not be directly observed (whether we shall take an umbrella) but evidence can be mapped to decision choices (if it rains, then take an umbrella, otherwise, not, and whether it rains or not is observable). When this is the case, a multivalued mapping function will be required, which in fact was the original idea of Dempster's for generating a mass function.

**Definition 7.** *Given two distinct frames* Ω *and Θ, function* $\Gamma : \Omega \to 2^{\Theta}$ *defines a multivalued mapping as*:

$$\Gamma(\omega) = X, \;\; \forall \omega \in \Omega, \exists X \subseteq \Theta \tag{4}$$

From this multivalued mapping, any probability distribution observed over one frame can be propagated to another to induce a mass function. Uncertain mappings as well as evidence modelled as a mass function on the first frame (Ω) can also be propagated to the second frame using approaches proposed in (Liu et al., 1992).

***When do we use Bayesian over D-S beliefs?***

The downside to using D-S theory is the computational expense since the belief structure is based upon the power set. The BPAs scale exponentially as $2^{|\Theta|}$. Hence, the practitioner should use

Bayesian beliefs when the there is enough knowledge to model the uncertainty adequately by singleton masses alone. Indeed, one could still use D-S theory, since it is a generalization of probability theory. Such a task; however, is akin to using Einstein's general relativity instead of Newtonian mechanics to calculate the path of ball that we toss across a room. It just would not be done!

On the other hand, we may need D-S beliefs when: (1) incomplete information is a significant component of the uncertainty; and (2) use of maximum entropy as done in Bayesian beliefs is inappropriate. This latter point represents a fundamental difference for the representation of ignorance between the two approaches. For example if in Example 1, all five experts said "I don't know" as to whether or not the suspect is in $A$, the D-S belief structure would be $m(A)=0$, $m(\bar{A})=0$, and $m(A\cup\bar{A})=1$. For the Bayesian belief structure, $m(A)=m(\bar{A})=1/2$. This latter structure says implies that the suspect is in the area 50% of the time, when in reality, we have no knowledge for this assessment.

Practitioners that need to use D-S based models should look for sparsity or approximate sparseness in the belief-structure in order to reduce the computational expense should it become impractical.

### 2.1.2 Relationship with Possibility theory

Possibility theory is another popular choice for representing uncertain information. A basic function in possibility theory is a *possibility distribution* denoted as $\pi$ which assigns each possible world in the frame of discernment $\Omega$ a value in [0,1].

From a possibility distribution, two measures are derived, a possibility measure (denoted as $\Pi$) and a necessity measure (denoted as $N$). The former estimates to what extent the true event is believed to be in the subset and the latter evaluates the degree of necessity that the subset is true. The relationships between $\pi$, $\Pi$ and $N$ are as follows:

$$\Pi(A)=max(\{\pi(\omega)\,|\,\omega\in A\}) \text{ and } N(A)=1-\Pi(A^{-}) \tag{5}$$

$$\Pi(2^{\Omega})=1 \text{ and } \Pi(\varnothing)=0 \tag{6}$$

$$\Pi(A\cup B)=max(\Pi(A),\Pi(B)) \text{ and } N(A\cap B)=min(N(A),N(B)) \tag{7}$$

$\pi$ is said to be normal if there exists $\omega_0\in\Omega$ such that $\pi(\omega_0)=1$. It is not always possible to obtain a possibility distribution from a piece of evidence. Most of the time, uncertain

information is expressed as a set of weighted subsets (or a set of weighted formulas in possibilistic logic). A weighted subset $(A,\alpha)$ is interpreted as that the necessity degree of $A$ is at least to $\alpha$, that is, $N(A) \geq \alpha$.

Let $\Omega = \{\omega_1,..,\omega_n\}$, and a subset of $\Omega$ is denoted as $A_i = \{\omega_{i1},..,\omega_{ix}\}$ to make the subsequent description simpler. In this way, a set of weighted subsets constructed from a piece of uncertain information is defined as $\{(A_i,\alpha_i), i = 1,..,p\}$, where $\alpha_i$ is the lower bound on the degree of necessity $N(A_i)$. In the following, a set of weighted subsets is called a *possibilistic information base (PIB for short)* and denote such a base as *K*.

There is normally a family of possibility distributions associated with a given *K*, with each of the distributions $\pi$ satisfying the condition:

$$1 - max\{\pi(\omega) \mid \omega \in \bar{A}_i\} \geq \alpha_i$$

which guarantees that $N(A_i) \geq \alpha_i$. Let $\{\pi_j, j = 1,..,m\}$ be all the possibility distributions that are compatible with $K = \{(A_i,\alpha_i), i = 1,.., p\}$. A possibility distribution $\pi_l \in \{\pi_j, j = 1,..,m\}$ is said to be the least specific possibility distribution among $\{\pi_j, j = 1,..,m\}$ if $\nexists \pi_t \in \{\pi_j, j = 1,..,m\}, \pi_t 6 \neq \pi_l$ such that $\forall \omega, \pi_t(\omega) \geq \pi_l(\omega)$.

A common method to select one of the compatible possibility distributions is to use the *minimum specificity principle* which allocates the greatest possibility degrees in agreement with the constraints $N(A_i) \geq \alpha_i$. This possibility distribution always exists and is defined as follows:

$$\forall \omega \in \Omega, \pi(\omega) = \begin{cases} \min\{1-\alpha_i \mid \omega \notin A_i\} \\ = 1 - \max\{\alpha_i \mid \omega \notin A_i\} \text{ when } \exists A_i \text{ s.t. } \omega \notin A_i \\ 1 \qquad \text{otherwise} \end{cases} \tag{8}$$

A possibility distribution is not normal if $\forall \omega, \pi(\omega) < 1$. The value $1 - max_{\omega \in \Omega}\, \pi(\omega)$ is called *the degree of inconsistency* of *K* and is denoted as $Inc(K)$.

The two basic combination modes in possibility theory are the *conjunctive* and the *disjunctive* modes for merging possibility distributions (Benferhat et al., 97) when *n* possibility distributions are given on the same frame of discernment. For example, if we choose *min* and *max*

as the conjunctive and disjunctive operators respectively, then:

$$\forall \omega \in \Omega, \pi_{cm}(\omega) = \min_{i=1}^{n}\left(\pi_i(\omega)\right), \forall \omega \in \Omega, \pi_{dm}(\omega) = \max_{i=1}^{n}\left(\pi_i(\omega)\right) \quad (9)$$

When all the sources are believed reliable and these sources agree with each other, a conjunction operator is used. On the other hand, a disjunctive operator is applied when it is believed that some sources are reliable but it is not known which of these sources are. A conjunction operator can lead to a new possibility distribution that is not normal when some sources are not in agreement, even though all the original possibility distributions are normal. When this happens, the merged possibility distribution expresses an inconsistency among the sources.

A belief function is said to be *consonant* if its focal elements are nested Shafer (1976). That is, if $S_1, S_2, .., S_n$ are the focal elements of a mass function, then it is possible to re-arrange these focal elements in such an ascending order that for any pair of neighboring subsets, the latter is a superset of the former, e.g., $S_1 \subset S_2 \subset .. \subset S_n$ after re-subscript indexing.

Let *Bel* be a consonant function, and *Pl* be its corresponding plausibility function, *Bel* and *Pl* have the following properties:

$Bel\left(A \cap B\right) = min\left(Bel\left(A\right), Bel\left(B\right)\right)$ for all $A, B \subseteq 2^{\Omega}$

$Pl(A \cup B) = max\left(Pl\left(A\right), Pl\left(B\right)\right)$ for all $A, B \subseteq 2^{\Omega}$

These two properties correspond to exactly the requirements of necessity and possibility measures in possibility theory. Necessity and possibility measures are special cases of belief and plausibility functions.

Furthermore, a *contour function* $f :\rightarrow [0,1]$, for a consonant function is defined using equation $f\left(\omega\right) = Pl\left(\{\omega\}\right)$.

For a subset $A \subseteq \Omega$,

$$Pl\left(A\right) = max_{\omega \in A} f\left(\omega\right) \quad (10)$$

Equation (10) matches the definition of possibility measure from a possibility distribution, so a contour function is a possibility distribution.

Let $\pi$ be a possibility distribution on frame of discernment $\Omega$ and is normal. Let $B_1, B_2, .., B_p$ and $B_{p+1}$ be disjoint subsets of $\Omega$ such that:

(1) $\pi(\omega_1) = \pi(\omega_2)$ when $\omega_1, \omega_2 \in B_i$;

(2) $\pi(\omega_1) > \pi(\omega_2)$ if $\omega_i \in B_i$ and $\omega_j \in B_{i+1}$;

(3) $\pi(\omega_i) = 0$ if $\omega_i \in B_{p+1}$.

Let $m(A_i) = \pi(\omega_i) - \pi(\omega_j)$ where $\omega_i \in B_i$ and $\omega_j \in B_{i+1}$ for $i = 1,.., p$, then *m* is a mass function on focal elements $A_i$.

Example 1: *Let* $\pi$ be a possibility distribution on $\Omega = \{\omega_1,...,\omega_4\}$ where $\pi(\omega_1) = 0.7$, $\pi(\omega_2) = 1.0$, $\pi(\omega_3) = 0.8$, and $\pi(\omega_4) = 0.7$. The disjoint subsets for π are as follows: $B_1 = \{\omega_2\}$, $B_2 = \{\omega_3\}$, $B_3 = \{\omega_1, \omega_4\}$; and the corresponding focal elements as well as *bba m* are as follows: $A1 = B1$, $A2 = B1 \cup B2$, $A3 = B1 \cup B2 \cup B3$, $m(A_1) = 0.2$, $m(A_2) = 0.1$, and $m(A_3) = 0.7$.

### 2.1.3 Information fusion with D-S theory

Information fusion can be viewed as an aggregation process which aims to extract truthful knowledge from information coming from various sources. Information fusion is particularly related to the issue of uncertainty modeling and reliability measures, through identifying conflict, resolving conflict and discounting unreliable sources when producing a final result. There are many approaches and theories for modelling information, and the information fusion problem has been discussed in each of these settings almost independently. Most of the time, specialized principles or properties have been proposed in order to characterize the specific features of the fusion process in the language of each particular formal setting. We look at some of the most general properties that a fusion rule (e.g., Dempster's rule) shall comply, and use these set of rules to check some of the best known combinations rules in D-S theory as discussed in (Dubois et al., 2013).

**Property 1 (Unanimity):** when all sources agree on some results, then the latter should be preserved.

**Property 2 (Informational Monotony):** if a set of agents provides less information than another set of *non-disagreeing* agents, then fusing the former inputs should not produce a more informative result than fusing the latter.

**Property 3 (Consistency Enforcement):** this property requires that fusing individually consistent inputs should give a consistent result.

**Property 4 (Optimism):** in the absence of specific information about source reliability, one should assume as many sources as possible are reliable, in agreement with their observed mutual consistency.

**Property 5 (Fairness):** the fusion result should treat all sources on a par. Hence, the result of the fusion process should keep something from each input.

**Property 6 (Insensitivity to Vacuous Information):** sources that provide vacuous information should not affect the fusion result.

**Property 7 (Commutativity):** inputs from multiple sources are treated on a par, and the combination should be symmetric (up to their relative reliability).

The four famous rules, Dempster's combination rule, Dubois/Prade rule (Dubois & Prade, 1988), Yager's rule (Yager, 1987), and Smets' rule (Smets, 1993) satisfy most of these properties in different ways. Readers interested in details of these examinations can find full discussions presented by Dubois et al. (2013).

### 2.2 Non-statistical approaches

Here we consider how both fuzzy set and rough set theory have been used to represent geospatial data with uncertainty.

#### 2.2.1 Fuzzy set/possibility theory

The utilization of fuzzy set approaches for modeling uncertainty in spatial data has been considered frequently after the introduction of fuzzy sets by Zadeh (1965). For example, the use of fuzzy set approaches in geographical research involves areas such as geographical decision-making and behavioral geography (Gale, 1972; Fisher, 1996). However, the most consistent early approach using fuzzy set theory in applications to GIS was developed initially by Robinson and Frank (1985) where they considered several models appropriate to this situation including fuzzy database representations using simple membership values in relations, and a similarity-based approach for geospatial features. An application for which both the data as well as spatial relationships are imprecise, was modeled using imprecision intrinsic to natural language which is possibilistic (Zadeh, 1978) in nature.

A number of subsequent models using fuzzy set approaches for applications involving spatial uncertainty have been developed. These included among others: querying spatial information (Wang, 2000), representing spatial relationships (Cobb and Petry, 1998), and object-oriented modeling (De Tré and De Caluwe, 1999; Cross and Firat, 2000). Models have been

proposed as well that allow for enhancing the representation in databases for the management of uncertain geospatial data (Morris, 2006).

***Fuzzy set theory background***

Extensions to ordinary set theory, known as fuzzy set theory, provide widely recognized representations of imprecision and vagueness (Zadeh, 1965). This section overviews some basic concepts of fuzzy sets and a more complete introduction can be found in several comprehensive sources (Pedrycz and Gomide, 1996; Yen and Langari, 1999).

Ordinarily a set $S$ is specified by its characteristic function $C : S \rightarrow \{0,1\}$ If $U$ is the universal set from which values of $S$ are taken, then, we can represent $S$ as:

$$S = \{x \mid x \in U \wedge C(x) = 1\} \tag{11}$$

This is the representation for a crisp or non-fuzzy set. However, for a fuzzy set $A$, we have a membership function; $\mu_A : A \rightarrow [0,1]$.

$$A = \{x \mid x \in U \wedge \mu_A > 0\} \tag{12}$$

That is, for a fuzzy set, the characteristic function takes on all values between 0 and 1 and not just the discrete values of 0 or 1 representing the binary choice for membership in a conventional crisp set such as $S$. For a fuzzy set, the characteristic function is often called the membership function. As an example of a fuzzy set, consider a description of mountainous terrain. We want to use a linguistic terminology to represent whether an estimate of elevation is viewed as low, medium, or high. If we assume we have obtained opinions of experts knowledgeable about such terrain, we can define fuzzy sets for these terms. Clearly, it is reasonable to represent these as fuzzy sets as they represent judgmental opinions and cannot validly be given precise specification. Here we will provide a typical representation of a fuzzy set $A$ for "*HIGH*" in terms of the height in kilometers (K):

$$A_{HIGH} = \{0.0/0.1K,\ 0.125/0.5K,\ 0.5/1K,\ 0.8/2K, 0.9/3K,\ 1.0/4K\}$$

This typical representation enumerates selected elements and their respective membership values as $\mu_A(x)/x$. It is also common to more fully specify the membership function $\mu_A(x)$ in an analytic form or as a graphical depiction. The membership function for the representation shown as in $A_{HIGH}$ could be fully specified by interpolation between the consecutive elements. Also, extrapolation past the first and last elements completes the specification, i.e.,

$\mu_A(x) = 0.0 \; x \le 0.1K$ and $\mu_A(x) = 1.0 \; x \ge 4K$.

***Fuzzy set operations***

All of the basic set operations must have equivalent ones in fuzzy sets, but there are additional operations based on membership values of a fuzzy set that have no correspondence in crisp sets. We will use the membership functions $\mu_A$ and $\mu_B$ to represent the fuzzy sets *A* and *B* involved in the operations to be illustrated.

Set equality: $A = B : \mu_A(x) = \mu_B(x)$

Set containment: $A \subseteq B : \; \mu_A(x) \le \mu_B(x)$

Set complement: $\bar{A} = \{[1 - \mu_A(x)] / x\}$

For ordinary crisp sets $A \cap \bar{A} = \varnothing$; however, this is not generally true for a fuzzy set and its complement. This may seem to violate the law of the excluded middle, but this is just the essential nature of fuzzy sets. Since fuzzy sets have imprecise boundaries, we cannot place an element exclusively in a set or its complement.

Set union: $A \cup B : \mu_{A \cup B}(x) = \text{Max}\left(\mu_A(x), \mu_B(x)\right)$

Set intersection: $A \cap B : \mu_{A \cap B}(x) = \text{Min}\left(\mu_A(x), \mu_B(x)\right)$

With these definitions, the standard properties for crisp sets of commutativity, associativity, and so forth, hold as well for fuzzy sets.

Another interpretation of membership functions of fuzzy sets as possibility distributions provides the encoding for flexible constraints induced by natural language statements (Zadeh, 1978). $\Pi$ is a possibility distribution: $\Pi : X \to [0,1]$ where $\pi(x_i)$ gives the possibility that $x_i$ is the value of a variable $V$, $i = 1, \ldots, n$. Note that when we associate a fuzzy set $A$ with the variable $V$, this will specify a possibility distribution of $V$ in terms of the membership function of $A$: $\Pi_V(x) = \mu_A(x)$.

A usual requirement for a possibility distribution is the normality condition, $\underset{x}{Max}\left[\pi(x_i)\right] = 1$, $i = 1, \ldots, n$. This means that at least one element in $X$ must be fully possible.

### 2.2.2 Rough set theory

Another approach for uncertainty representation uses the rough set theory (Pawlak, 1985) concept of indiscernibility of values. The indiscernibility relation is used to partition domains into

equivalence classes, and lower- and upper-approximation regions for distinguishing between certain and possible (or partial) inclusion in a rough set. The indiscernibility relation permits grouping of items based on some definition of 'equivalence,' which basically depends on the application domain. This partitioning can be used to increase or decrease the granularity of a domain, to group items together that are considered indiscernible for a given application, or to "bin" ordered domains into range groups.

Many researchers have considered rough set approaches to modeling geospatial uncertainty. A description of spatial data using rough sets, focusing on a formal modeling framework for realm-based spatial data types can be found in (Schneider, 1995). Worboys (1998) developed a model for imprecision based on the resolution of spatial data and applied it to the integration of such data. This approach relies on the use of indiscernibility - a central concept in rough sets. Ahlqvist et al. (2000) introduced an approach for rough classification of spatial data and representation of inexact spatial locations using rough sets. Wang et al. (2004) established an approach for the field representation of a spatial entity using a rough raster space which was evaluated for remote sensing images in a classification case study. Bittner and Stell (2003) proposed the partitions' relationship to rough sets and approximated map objects with vague boundaries using *K*-labeled partitions, which can represent maps. More refined levels of details or granularity can be obtained by using stratified rough partitions for map scale transformations.

***Rough set theory background***

Here we provide an overview of the basics of rough set theory. The following is a set of common terminology and notation for rough sets:

| | |
|---|---|
| $U$ | is the universe, which cannot be empty, |
| $R$ | indiscernibility relation, or equivalence relation, |
| $A = (U,R)$ | is an ordered pair, called an approximation space, |
| $[x]R$ | denotes the equivalence class of $R$ containing $x$, for any element $x$ of $U$, elementary sets in $A$ - the equivalence classes of $R$. |

Any finite union of these elementary sets in $A$ is called a definable set. A particular rough set $X \subseteq U$, however, is defined in terms of the definable sets by specifying its lower $(\underline{R}X)$ and upper $(\bar{R}X)$ approximation regions:

$$\underline{R}X = \{x \in U \mid [x]R \subseteq X\}$$

and

$$\bar{R}X = \{x \in U \mid [x]R \cap X \neq \varnothing\}.$$

where $\underline{R}X$ is the R-positive region, $U - \bar{R}X$ is the R-negative region, and $\bar{R}X - \underline{R}X$ is the R-boundary or R-borderline region of the rough set *X*.

This allows for the distinction between certain and possible inclusion in a rough set. The set approximation regions provide a mechanism for determining whether something certainly belongs to the rough set, may belong to the rough set, or certainly does not belong to the rough set. *X* is called R-definable if and only if $\underline{R}X = \bar{R}X$. Otherwise, $\underline{R}X \neq \bar{R}X$ and *X* is rough with respect to *R*. In Figure 3, the universe *U* is partitioned into equivalence classes denoted by the rectangles. Those elements in the lower approximation of *X*, $\underline{R}X$, are denoted by the letter "*p*" and elements in the *R*-negative region by the letter "*n*". All other classes belong to the boundary region of the upper approximation.

Insert Figure 3 Here

To obtain possible results, in addition to the obvious, when querying an ordinary spatial information system, we may employ the use of the boundary region information in addition to that of the lower approximation region. The results in the lower-approximation region are certain, corresponding to exact matches. The boundary region of the upper-approximation contains those results that are possible, but not certain.

The approximation regions of rough sets are useful when information related to spatial data regions is queried (Beaubouef et al., 2000). Consider a region such as a woodland. One can reasonably conclude that any grid point labeled as "woods" which on all sides is surrounded by grid points also classified as "woods" is, indeed a point characterized by the feature "woods." But we may also be interested in grid points labeled as "woods" that adjoin points identified as "field." It is possible that such points represent field areas as well as forest areas but were identified as "woods" during the classification. Likewise, points identified as "field" but adjacent to "woods" points may represent areas that contain part of the forest.

If we force a finer granulation of the partitioning, a smaller boundary region results. This occurs when the resolution is increased. As the partitioning becomes finer and finer, a point is finally reached where the boundary region is non-existent. The upper- and lower-approximation regions are then the same and there is no uncertainty in the spatial data as can be determined by

the representation of the model.

## 3. Literature review of GIS applications

In this study, we conducted a comprehensive and methodic survey of papers where probability theory, (D-S) theory, fuzzy/set/possibility theory, and rough set theory were used in GIS applications to model uncertain spatial data. We found 421 relevant papers listed in our bibliographical list of GIS papers with uncertain spatial data (Appendix A). Appendix B provides a complete listing of the methods, applications, and locations for the papers reviewed in this study. Looking at the year of the publications in Figure 4, the majority of the papers are published during the past five years where the average number of such papers has doubled in those years.

Insert Figure 4 Here

We then considered the methods used in these papers to model uncertain spatial data in GIS applications. As shown in Figure 5, 214 (51%) papers used fuzzy set/possibility theory, 145 (34%) papers used probability theory, 42 (10%) papers used (D-S) theory, and 20 (5%) papers used rough set theory. In general, statistical methods are the preferred methods for handling uncertain spatial data in GIS when prior knowledge is available and non-statistical methods are used when vagueness and ambiguities result from the imprecision of the meaning of a concept in geospatial data.

Insert Figure 5 Here

We then further studied different methods used in the 214 fuzzy set/possibility theory and probability theory papers. As shown in Table 1, fuzzy membership, fuzzy Analytic Hierarchy Process (AHP), fuzzy multi-criteria analysis, fuzzy rules, and neuro fuzzy methods are the most commonly used techniques in GIS. The analysis shows that the pervasive use of fuzzy membership indicates the power of this concept and the fact that it is extremely useful in capturing the vagueness and ambiguity associated with the natural environment. Multi-criteria decision making refers to a general collection of methods widely used for making decision in the presence of multiple and often conflicting criteria. The AHP is a multi-criteria decision making approach and was introduced by Saaty (1977, 1994). Spatial decision problems typically involve a large set of feasible alternatives and multiple and often conflicting evaluation criteria. The combination of multi-criteria decision making and GIS benefit from the rich collection of the multi-criteria tools and procedures for structuring decision problems and evaluating decision alternatives and the capabilities of GIS as a problem solving tool for spatially referenced data. Malczewski (2006)

presents a comprehensive a survey of the GIS-based multi-criteria decision analysis literature.

Insert Table 1 Here

Next, we analyzed different methods used in the 145 application using probability theory. As shown in Table 2, general probability theory, Bayesian probability, and probability map are most commonly used in GIS. Our review showed that while general probability theory and frequency distribution is naturally the most widely used statistical method, Bayesian probabilities are also very popular among the GIS researchers. Bayesian probabilities are used not only to proceed from causes to consequences, but also to deduce the probabilities of different causes given the consequences. Uusitalo (2007) presents advantages and challenges of Bayesian probabilities in environmental modelling and Ellison (2004) provides a comprehensive review of the differences of Bayesian and frequentist probabilities.

Insert Table 2 Here

Next, we studied different applications where one of the statistical and non-statistical methods is used in GIS. As shown in Table 3, landslide susceptibility modeling, land suitability modeling, natural hazard modeling, groundwater resource modeling, land use modeling, soil suitability modeling, urban planning and modeling, mineral potential modeling, and marine environmental modeling were among the most common uncertain spatial data applications in GIS. As broad characterization we see that hazard/disaster prediction and general planning encompass the majority of these applications. It is not surprising to see landslide susceptibility modeling as one of the most widely used application of GIS since over the last two decades a wider range of methods have been proposed to improve the prediction and mapping of landslide susceptibility. Binaghi et al. (1998) discussed the limitations of GIS in addressing different layers of data for landslide modelling and recommended using soft computing approaches (such as fuzzy set theory, neural networks, probabilistic, and evidential approaches) for handling uncertain spatial data in landslide research. Chacón et al. (2006) provide an excellent review of the landslide susceptibility research and Malczewski (2006) presents a critical overview of the GIS-based land-use suitability analysis.

Insert Table 3 Here

We then examined the locations (country/region) where the 421 studies were conducted. As shown in Table 4, most studies are conducted in China, Iran, United States, India, Korea, Australia, Turkey, Canada, Greece, Spain, Malaysia, Italy, Taiwan, and Germany. It is

understandable that China has the most of such publications based on its rapid growth and development in last decade. For Iran, it is possible that the common occurrences of earthquakes and such natural disasters have influenced such publications. Overall, the data shows that the applications of uncertain spatial data in GIS is more common in countries with very diverse geophysical landscape and climatic conditions.

Insert Table 4 Here

Finally, we considered the journals where these 421 papers appeared. As shown in Table 5, Natural Hazards, Environmental Earth Sciences, Computers and Geosciences, Arabian Journal of Geosciences, Environmental Geology, and International Journal of Geographical Information Science were the journals that had the most published papers on managing uncertain spatial data in GIS.

Insert Table 5 Here

## 4. Conclusion and future research directions

GIS have become critical components of the global cyberinfrastructure and converging technological trends such as global positioning tools and geo-enabled devices have provided many opportunities for GIS applications. Our literature survey highlights the importance of representing and managing uncertainty in GIS applications. We note that in recent years, an increasing number of publications have used both statistical and non-statistical methods to solve such problems. Statistical methods are better suited for handling uncertain spatial data in GIS when prior knowledge is available in one form or another. The availability of prior knowledge eliminates the need for time-consuming and expensive data acquisition. In addition, Bayesian methods have been widely used to process environmental data with an uncertain mixture of objective and subjective data. Dempster-Shafer uncertainty representations, which are generalizations of Bayesian approaches, are suitable for situations where there are incomplete or missing geospatial information. For spatial data, we are often faced with situations in which it is not possible to completely specify or survey certain areas. For example, sonar bathymetry surveys of the ocean floor use sonar swaths that leave gaps causing less 10% of the ocean floor to be mapped (Becker et al., 2009). Therefore, a seafloor area which has only partial swath coverage is suitable for a Dempster-Shafer representation of such incomplete information.

In contrast to the statistical methods that predominantly model positional and measurement uncertainty, non-statistical methods are useful in situations where uncertainty cannot be measured

using precise quantitative or statistical methods, but can be viewed in terms of the vagueness/ambiguities resulting from the imprecision of meaning. For these kinds of situations, we should use fuzzy set/possibility theory to model fuzziness or rough sets which work with lower- and upper-approximations of spatial data.

Many basic geographical concepts and categories do not have exact definitions and are often open to interpretation by an expert for a particular application (Varsi, 2001b). In such situations, representing spatial information with a precise quantification would be misleading and could lead to faulty conclusions (Couclelis 2003). Instead, fuzzy sets can be a more realistic approach for representing this kind of geographical information. Another practical alternative is the use of rough set approaches which are based on an indiscernibility relation. This type of representation can produce a clustering using a definition of 'equivalence,' which depends on the application domain. The clustering process creates a partitioning which can increase or decrease the granularity of a spatial domain, groups geospatial items that are considered indiscernible in the application, or bin-orders spatial domains into range groups. For example, when considering the problem of map conflation in a GIS, different information sources often use distinct terms for the same spatial location or item (Rahimi et.al 2002). A rough set based indiscernibility relation can be helpful in this kind of situation by indicating that different terms may actually be equivalent.

The key challenges for future research directions in GIS with uncertain spatial data are:

a. Communicating the importance of considering uncertainty in geospatial information and taking into account the cost of ignoring uncertainty in GIS applications which could lead to suboptimal conclusions and decisions.
b. Developing scientific methods for assessing data quality and assisting GIS users with evaluating error and the implications of uncertainty in geospatial data.
c. Measuring the relative sensitivity of the statistical methods with respect to the quality of the dependent variables, sampling strategy, size and type of the probability map, and the validation process used to evaluate the predictive capability of the models.
d. Developing hybrid methods for handling uncertainty by integrating the qualitative and quantitative spatial data in seamless and user-friendly frameworks.
e. Implementing spatially-explicit reliability tools and technologies for spatial sensitivity and uncertainty analysis associated with hybrid qualitative-quantitative methods.
f. Developing analytical and statistical methods for validating and measuring the effectiveness

of GIS with uncertain spatial data.

An enormous amount of progress has been achieved in GIS research in recent years. Much of the published GIS applications in the past decade concern natural disasters (i.e., landslides, floods, hurricanes, tsunamis, tornadoes, earthquakes, volcanoes, wild fires, etc.) as well as man-made disasters (war, epidemics, social unrest, toxic spills, explosions, fires, etc.). On the other hand, very few studies have been published in areas such as search and rescue, intelligence, and terrorism among others. Today's GIS applications involve multiple data sets with varying levels of confidence, some precise or objective and some uncertain or subjective. New methods are needed to integrate these data sets efficiently and effectively into dynamic models.

## Appendix A

## Bibliographical list of GIS papers with uncertain spatial data


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Zhang, J, Su, Y., Wu, J., & Liang, H. (2015). GIS based land suitability assessment for tobacco production using AHP and fuzzy set in Shandong province of China, Computers and Electronics in Agriculture, 114, 202-211.
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# Appendix A

## Methods, applications, and location for GIS papers with uncertain spatial data

| Text Reference | Method | Application | Location |
|---|---|---|---|
| Abbaspour et al. (2011) | Fuzzy AHP | Land suitability modeling | Iran |
| Abd Manap et al. (2014) | Frequency ratio | Groundwater resource modeling | Malaysia |
| Abdalla et al. (2014) | Fuzzy membership | Natural hazard modeling | Canada |
| Abdul Rahaman et al. (2015) | Fuzzy AHP | Groundwater resource modeling | India |
| Abdullahi & Pradhan (In Press) | General probability theory | Land use Modeling | Malaysia |
| Adab et al. (2013) | General probability theory | Natural hazard modeling | Iran |
| Ahadnejad et al. (2009) | General probability theory | Land use Modeling | Iran |
| Ahilan et al. (2012) | General probability theory | Natural hazard modeling | Ireland |
| Akgün & Bulut (2007) | General probability theory | Landslide susceptibility modeling | Turkey |
| Akgün & Türk (2011) | Fuzzy membership | Natural hazard modeling | Turkey |
| Akgun et al. (2012) | General probability theory | Landslide susceptibility modeling | Turkey |
| Akgün et al. (2012) | Mamdani's fuzzy inference modeling | Landslide susceptibility modeling | Turkey |
| Akumu et al. (2015) | Fuzzy membership | Soil suitability modeling | Canada |
| Al-Abadi (2015) | General probability theory | Groundwater resource modeling | Iraq |
| Al-Ahmadi et al. (2009) | Fuzzy rules | Urban planning and modeling | Saudi Arabia |
| Al-Ahmadi et al. (2014) | General probability theory | Natural hazard modeling | Red Sea |
| Alesheikh et al. (2008) | Fuzzy membership | Natural hazard modeling | Iran |
| Alexakis & Sarris (2014) | Fuzzy membership | Land suitability modeling | Greece |
| Alexakis et al. (2014) | General probability theory | Landslide susceptibility modeling | Cyprus |
| Al-garni (1995) | General probability theory | Urban planning and modeling | Saudi Arabia |
| Aliniai et al. (In Press) | FUZZY ordered weighted average | Land suitability modeling | Iran |
| Allen et al. (2007) | Fuzzy membership | Groundwater resource modeling | Canada |
| Al-Rafadain (2013) | General probability theory | Rain water harvesting modeling | Iraq |
| Al-sharif & Pradhan (2014) | Transition probability | Land use Modeling | Libya |
| Althuwaynee et al. (2012) | Dempster-Shafer | Landslide susceptibility modeling | Malaysia |
| Althuwaynee et al. (2014) | Dempster-Shafer | Landslide susceptibility modeling | Korea |
| Amici et al. (2010) | Fuzzy classification | Habitat suitability modeling | Italy |
| Anane et al. (2012) | Fuzzy AHP | Land suitability modeling | Tunisia |
| Anbalagan et al. (In Press) | Fuzzy membership | Landslide susceptibility modeling | India |
| Antonakos et al. (2014) | Fuzzy multi-criteria analysis | Groundwater resource modeling | Greece |
| Ardeshir et al. (2014) | Fuzzy AHP | Bridge location modeling | Iran |
| Arnous et al. (2011) | General probability theory | Landslide susceptibility modeling | Egypt |
| Assimakopoulos et al. (2003) | Fuzzy membership | Soil suitability modeling | Greece |
| Ayala-Carcedo et al. (2003) | Probability map | Rock-fall susceptibility modeling | Spain |
| Ayalew et al. (2011) | General probability theory | Landslide susceptibility modeling | Japan |
| Aydi et al. (2013) | Fuzzy AHP | Land suitability modeling | Tunisia |
| Aydin et al. (2010) | Fuzzy multi-criteria analysis | Land suitability modeling | Turkey |
| Baalousha (2010) | Probability map | Underground vulnerability modeling | Palestine |
| Badia et al. (2011) | General probability theory | Wilderness land modeling | Mediterranean |
| Bai et al. (2011) | Probability map | Landslide susceptibility modeling | China |
| Baja et al. (2002) | Fuzzy membership | Land suitability modeling | Australia |
| Baja et al. (2007) | Fuzzy multi-criteria analysis | Land use Modeling | Australia |
| Balla et al. (2013) | Fuzzy membership | Geo-historical modeling | Greece |
| Batty et al. (1999) | General probability theory | Urban planning and modeling | Not available |
| Bekkby et al. (2008) | Probability map | Marine environmental modeling | Norway |
| Benomar et al. (2009) | General probability theory | Mineral resources modeling | China |
| Beucher et al. (2014) | Fuzzy membership | Soil suitability modeling | Finland |
| Biass & Bonadonna (2013) | Bayesian probability | Natural hazard modeling | Ecuador |
| Biass et al. (2012) | Probability map | Natural hazard modeling | Ecuador |
| Biass et al. (2013) | Probability map | Natural hazard modeling | Ecuador |
| Binaghi et al. (1998) | Dempster-Shafer | Landslide susceptibility modeling | Italy |
| Biswas (2009) | Transition probability | Groundwater resource modeling | India |

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|---|---|---|---|
| Bojórquez-Tapia et al. (2013) | Fuzzy membership | Land degradation modeling | Mexico |
| Bone et al. (2005) | Fuzzy membership | Natural hazard modeling | Canada |
| Bone et al. (2006) | Fuzzy membership | Insect infestation modeling | Not available |
| Bone et al. (2007) | Fuzzy membership | Forest management modeling | Canada |
| Boroushaki and Malczewski (2010) | Fuzzy majority procedure | Land suitability modeling | Not available |
| Brown et al. (2003) | Fuzzy membership | Mineral potential modeling | Australia |
| Bruce et al. (2014) | General probability theory | Whale migration modeling | Australia |
| Bui et al. (2012a) | Adaptive neuro-fuzzy inference system (ANFIS) | Landslide susceptibility modeling | Vietnam |
| Bui et al. (2012b) | Fuzzy membership | Landslide susceptibility modeling | Vietnam |
| Burrough et al. (2001) | Fuzzy k-means | Forest management modeling | USA |
| Busch (2012) | Fuzzy rules | Environmental modeling | Germany |
| Canning (2005) | Dempster-Shafer | Archaeological predictive modelling | Australia |
| Cao et al. (2015) | Rough set | Urban planning and modeling | China |
| Capolongo et al. (2002) | General probability theory | Landslide susceptibility modeling | Italy |
| Carranza et al. (2005) | Dempster-Shafer | Mineral potential modeling | Zambia |
| Carrasco et al. (2003) | Probability map | Landslide susceptibility modeling | Spain |
| Carver et al. (2012) | Fuzzy multi-criteria analysis | Wilderness land modeling | Scotland |
| Cassel-Gintz, & Petschel-Held (2000) | Fuzzy membership | Environmental modeling | Germany |
| Ceballos-Silva & López-Blanco (2003) | Fuzzy multi-criteria analysis | Land use Modeling | Mexico |
| Chacón et al. (2006) | Dempster-Shafer | Landslide susceptibility modeling | Spain |
| Chang & Shiuan (In Press) | Rough set | Landslide susceptibility modeling | Taiwan |
| Chang et al. (2008) | Fuzzy multi-criteria analysis | Land suitability modeling | USA |
| Chang et al. (2009) | Fuzzy AHP | Land suitability modeling | Taiwan |
| Charabi & Gastli (2011) | Fuzzy multi-criteria analysis | Site suitability modeling | Oman |
| Charnpratheep et al. (1997) | Fuzzy AHP | Land suitability modeling | Thailand |
| Chen et al. (2005) | Probability map | Mineral resources modeling | China |
| Chen et al. (2015) | General probability theory | Landslide susceptibility modeling | China |
| Cheng et al. (2011) | Fuzzy membership | Mineral potential modeling | China |
| Choi et al. (2010) | Fuzzy membership | Mineral potential modeling | Korea |
| Choi et al. (2011a) | General probability theory | Marine environmental modeling | Korea |
| Choi et al. (2011b) | General probability theory | Urban planning and modeling | Korea |
| Chubey & Hathout (2004) | Transition probability | Natural hazard modeling | Canada |
| Coelho et al. (2012) | Fuzzy multi-criteria analysis | Water resource management | Brazil |
| Cowell & Zeng (2003) | Fuzzy membership | Marine environmental modeling | Australia |
| Crider et al. (2014) | General probability theory | Health risk modeling | USA |
| Dahal et al. (2014) | General probability theory | Landslide susceptibility modeling | Nepal |
| Daniel & Lauffenburger (2012) | Dempster-Shafer | Speed limit modeling | Not available |
| Dasgupta et al. (2013) | Fuzzy membership | Land use Modeling | India |
| Davidson et al. (1994) | Fuzzy membership | Land suitability modeling | Greece |
| Davis & Keller (1997) | Fuzzy membership | Land suitability modeling | Canada |
| De Runz et al. (2014) | Fuzzy membership | Geo-historical modeling | France |
| Di Martino & Sessa (2011) | Fuzzy C-means | Hotspot modeling | USA |
| Diodato & Ceccarelli (2004) | Probability map | Soil suitability modeling | Italy |
| Diodato & Ceccarelli (2006) | Probability map | Groundwater resource modeling | Italy |
| Dixon (2005a) | Neuro fuzzy | Groundwater resource modeling | USA |
| Dixon (2005b) | Fuzzy rules | Groundwater resource modeling | USA |
| Djamaluddin et al. (2011) | Fuzzy membership | Land movement modeling | China |
| Dlamini (2011) | Bayesian Probability | Natural hazard modeling | Swaziland |
| Donevska et al. (2012) | Fuzzy AHP | Land suitability modeling | Macedonia |
| Donglin et al. (2012) | Bayesian Probability | Mineral potential modeling | China |
| Dragićević et al. (2015) | Fuzzy multi-criteria analysis | Landslide susceptibility modeling | Canada |
| Du et al. (2012) | Rough set | Land suitability modeling | China |
| Edwards et al. (2015) | General probability theory | Recreational modeling | Australia |

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|---|---|---|---|
| Eikaas et al. (2005) | General probability theory | Fish habitat modeling | New Zealand |
| El-Haddad (In Press) | Dempster-Shafer | Landslide susceptibility modeling | Saudi Arabia |
| Elheishy et al. (2013) | Rough set | Shelter suitability modeling | Egypt |
| Eskandari & Emilio Chuvieco (2015) | General probability theory | Fire propagation modeling | Iran |
| Feizizadeh & Blaschke (2013) | Dempster-Shafer | Landslide susceptibility modeling | Iran |
| Feizizadeh & Blaschke (2014) | Dempster-Shafer | Landslide susceptibility modeling | Iran |
| Feizizadeh et al. (2013) | Fuzzy AHP | Landslide susceptibility modeling | Iran |
| Feizizadeh et al. (2014a) | Dempster-Shafer | Landslide susceptibility modeling | Iran |
| Feizizadeh et al. (2014b) | Dempster-Shafer | Landslide susceptibility modeling | Iran |
| Feizizadeh et al. (2014c) | Fuzzy AHP | Landslide susceptibility modeling | Iran |
| Feng et al. (2006) | General probability theory | Landslide susceptibility modeling | China |
| Feoli et al. (2002) | Fuzzy membership | Environmental modeling | Ethiopia |
| Feoli et al. (2009) | Fuzzy membership | Land suitability modeling | Ethiopia |
| Ferrier & Wadge (1997) | Dempster-Shafer | Sedimentary basins modeling | England |
| Filippini-Alba & de Souza Filho (2010) | Fuzzy membership | Environmental modeling | Brazil |
| Flantua et al. (2007) | General probability theory | Geo-historical modeling | Colombia |
| Fleming et al. (2007) | Fuzzy membership | Health risk modeling | Southern Africa |
| Foody & Boyd (1999) | Neuro fuzzy | Land suitability modeling | Ghana |
| Friedrich et al. (2002) | Fuzzy membership | Soil suitability modeling | Germany |
| Fustes et al. (2014) | Fuzzy classification | Marine environmental modeling | Spain |
| Gahegan & Flack (1999) | Dempster-Shafer | Land use Modeling | Not available |
| Ge et al. (2011) | Rough set | Urban planning and modeling | China |
| Gemitzi et al. (2007) | Fuzzy AHP | Land suitability modeling | Greece |
| Ghayoumian et al. (2007) | Fuzzy membership | Groundwater resource modeling | Iran |
| Ghinoi & Chung (2005) | Fuzzy membership | Snowpack instability modeling | Italy |
| Ghosh & Carranza (2010) | Dempster-Shafer | Landslide susceptibility modeling | India |
| Gimpel et al. (2015) | Fuzzy membership | Marine environmental modeling | Germany |
| Giordano & Liersch (2012) | Fuzzy rules | Soil salinization modeling | Uzbekistan |
| Giuffrida et al. (2014) | Rough set | Land use Modeling | Itlay |
| Gong et al. (2011) | General probability theory | Health risk modeling | USA |
| González-Álvarez et al. (2010) | Fuzzy membership | Mineral potential modeling | Australia |
| Gorsevski & Jankowski (2010) | Fuzzy membership | Landslide susceptibility modeling | USA |
| Gorsevski et al. (2005) | Dempster-Shafer | Landslide susceptibility modeling | USA |
| Gorsevski et al. (2012) | Fuzzy multi-criteria analysis | Land suitability modeling | Macedonia |
| Gorsevski et al. (2013) | Fuzzy membership | Wind farm suitability modeling | USA |
| Grekousis et al. (2013) | Fuzzy classification | Urban planning and modeling | Greece |
| Guo et al. (2007) | Fuzzy membership | Air pollution modeling | USA |
| Guo et al. (2014) | Fuzzy membership | Natural hazard modeling | China |
| Guoxin et al. (2004) | General probability theory | Land use Modeling | Worldwide |
| Gupta et al. (2008) | Neuro fuzzy | Landslide susceptibility modeling | India |
| Hajehforooshnia et al. (2011) | Fuzzy AHP | Wilderness land modeling | Iran |
| Hao et al. (2014) | Probability map | Biological hazard modeling | China |
| Harris et al. (2001) | Probability map | Mineral potential modeling | Canada |
| Hashemi et al. (2013) | General probability theory | Natural hazard modeling | Iran |
| He et al. (2007) | Bayesian Probability | Geo-historical modeling | USA |
| He et al. (2010) | Probability map | Mineral potential modeling | China |
| Hennecke (2004) | General probability theory | Coastal modeling | Australia |
| Houshyar et al. (2014) | Fuzzy AHP | Land suitability modeling | Iran |
| Hu et al. (2011) | Bayesian Probability | Health risk modeling | China |
| Huang & Cai (2007) | Transition probability | Land use Modeling | China |
| Huang et al. (2007) | General probability theory | Land use Modeling | China |
| Huang et al. (2011) | Fuzzy classification | Marine environmental modeling | Australia |
| Ilanloo (2011) | Fuzzy membership | Landslide susceptibility modeling | Iran |
| Jalayer et al. (2014) | Bayesian Probability | Natural hazard modeling | Africa |

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|---|---|---|---|
| Jasiewicz (2011) | Mamdani's fuzzy inference modeling | Natural hazard modeling | USA |
| Jebur et al. (2015) | Dempster-Shafer | Natural hazard modeling | Malaysia |
| Jeong et al. (2013) | Fuzzy AHP | Land suitability modeling | Spain |
| Jiao et al. (2012) | Fuzzy membership | Land suitability modeling | China |
| Jie et al. (2012) | General probability theory | Natural hazard modeling | China |
| Joerin & Musy (2000) | Rough set | Land suitability modeling | Switzerland |
| Jordan et al. (2007) | General probability theory | Soil suitability modeling | Ireland |
| Jung & Merwade (2012) | Fuzzy membership | Natural hazard modeling | USA |
| Kalantari et al. (2014) | General probability theory | Natural hazard modeling | Sweden |
| Kanungo et al. (2006) | Neuro fuzzy | Landslide susceptibility modeling | India |
| Kanungo et al. (2009) | Fuzzy membership | Landslide susceptibility modeling | India |
| Kayastha (2012) | Fuzzy membership | Landslide susceptibility modeling | Nepal |
| Khamespanah et al. (2013) | Dempster-Shafer | Seismic vulnerability modeling | Iran |
| Khan et al. (2014) | Rough set | Groundwater resource modeling | India |
| Khoi & Murayama (2010) | Fuzzy AHP | Land suitability modeling | Vietnam |
| Kiavarz Moghaddam et al. (2014) | Fuzzy multi-criteria analysis | Geothermal modeling | Japan |
| Kim et al. (2006) | General probability theory | Ground subsidence modeling | Korea |
| Kirschbaum et al. (In Press) | Fuzzy membership | Landslide susceptibility modeling | Central America and Caribbean Islands |
| Klingseisen et al. (2008) | Fuzzy membership | Land suitability modeling | Australia |
| Ko et al. (2006) | General probability theory | Marine environmental modeling | North-Eastern Pacific |
| Kocabas & Dragicevic (2013) | Bayesian Probability | Land use Modeling | Canada |
| Kollias & Kalivas (1998) | Fuzzy membership | Soil suitability modeling | Greece |
| Kollias et al. (1999) | Fuzzy membership | Soil suitability modeling | Greece |
| Kontoes et al. (1993) | Dempster-Shafer | Land use Modeling | Not available |
| Kordi & Anders Brandt (2012) | Fuzzy AHP | Dam location modeling | Costa Rica |
| Kritikos & Davies (In Press) | Fuzzy membership | Landslide susceptibility modeling | New Zealand |
| Kühmaier et al. (2014) | Fuzzy multi-criteria analysis | Energy wood terminal location modeling | Austria |
| Kumar & Anbalagan (2015) | Fuzzy membership | Landslide susceptibility modeling | India |
| Kundu et al. (2013) | General probability theory | Landslide susceptibility modeling | India |
| Lagacherie at al. (2000) | Possibility Theory | Soil suitability modeling | France |
| Lai et al. (2015) | Fuzzy multi-criteria analysis | Natural hazard modeling | China |
| Lamelas et al. (2008) | Probability map | Landslide susceptibility modeling | Spain |
| Lark & Bolam (1997) | Fuzzy membership | Soil suitability modeling | United Kingdom |
| Lee & Choi (2003) | General probability theory | Landslide susceptibility modeling | Korea |
| Lee (2004) | Bayesian Probability | Landslide susceptibility modeling | Korea |
| Lee et al. (2002) | Bayesian Probability | Landslide susceptibility modeling | Korea |
| Lee et al. (2013a) | Dempster-Shafer | Landslide susceptibility modeling | Korea |
| Lee et al. (2013b) | Bayesian Probability | Urban planning and modeling | Taiwan |
| Lee et al. (2014) | Frequency ratio | Landslide susceptibility modeling | Korea |
| Lee et al. (2015) | Adaptive neuro-fuzzy inference system (ANFIS) | Landslide susceptibility modeling | Korea |
| Lei et al. (2008) | Rough set | Agricultural image classification | Taiwan |
| Leung et al. (2007) | Rough set | Land suitability modeling | Hong Kong |
| Lewis et al. (2014) | Fuzzy membership | Land suitability modeling | USA |
| Li et al. (2001) | General probability theory | Natural hazard modeling | China |
| Li et al. (2010) | General probability theory | Landslide susceptibility modeling | China |
| Li et al. (2011) | General probability theory | Mineral potential modeling | China |
| Li et al. (2012) | Fuzzy AHP | Landslide susceptibility modeling | China |
| Li et al. (2015) | Dempster-Shafer | Landslide susceptibility modeling | Iran |
| Likkason et al. (1997) | Dempster-Shafer | Geo-physical modeling | Nigeria |
| Lin & Lin (2013) | Fuzzy AHP | Urban planning and modeling | Taiwan |
| Lisitsin et al. (2014) | Fuzzy membership | Mineral potential modeling | Australia |
| Lister et al. (2014) | General probability theory | Land use Modeling | USA |

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| Liu & Phinn (2003) | Fuzzy membership | Urban planning and modeling | Australia |
| Liu (2012) | Fuzzy constrained method | Urban planning and modeling | Australia |
| Liu et al. (2009) | General probability theory | Vegetation coverage modeling | China |
| Liu et al. (2011) | General probability theory | Land use Modeling | China |
| Liu et al. (2012) | Fuzzy AHP | Natural hazard modeling | China |
| Liu et al. (2013) | Rough set | Land suitability modeling | China |
| Liu et al. (2015) | Dempster-Shafer | Tungsten polymetallic mineralization modeling | China |
| Lorz et al. (2010) | General probability theory | Natural hazard modeling | South-Eastern European countries |
| Lu et al. (2012) | Fuzzy membership | Habitat suitability modeling | China |
| Lu et al. (2014) | Fuzzy risk modeling | Marine environmental modeling | China |
| Lucas et al. (2012) | Possibility Theory | Disaster management modeling | Germany |
| Ludwig et al. (2003) | Fuzzy membership | Environmental modeling | Germany |
| Ma et al. (2006) | Fuzzy membership | Economic modelling | China |
| Magesh et al. (2015) | Fuzzy membership | Mineral potential modeling | India |
| Magliulo et al. (2008) | General probability theory | Landslide susceptibility modeling | Italy |
| Maina et al. (2008) | Fuzzy AHP | Marine environmental modeling | Western Indian Ocean |
| Malczewski & Rinner (2005) | Fuzzy multi-criteria analysis | Urban planning and modeling | Canada |
| Malczewski (2006) | Fuzzy membership | Land suitability modeling | Mexico |
| Malekmohammadi et al. (2012) | Fuzzy rules | Water quality modeling | Iran |
| Malinowska (2011) | Fuzzy membership | Land suitability modeling | Poland |
| Malins & Metternicht (2006) | Fuzzy membership | Soil salinization modeling | Australia |
| March,et al. (2013) | Bayesian Probability | Marine environmental modeling | Mediterranean Sea |
| Marquínez et al. (2003) | General probability theory | Rock-fall susceptibility modeling | Spain |
| Martin-Clouaire et al. (2000) | Possibility Theory | Soil suitability modeling | France |
| Massei et al. (2014) | Rough set | Soil suitability modeling | Italy |
| Meinhardt et al. (2015) | General probability theory | Landslide susceptibility modeling | Vietnam |
| Metternicht & Gonzalez (2005) | Fuzzy rules | Natural hazard modeling | Bolivia |
| Metternicht (2001) | Fuzzy rules | Soil salinization modeling | Bolivia |
| Mihai et al. (2010) | Dempster-Shafer | Landslide susceptibility modeling | Romania |
| Mitra et al. (1998) | Fuzzy membership | Land suitability modeling | USA |
| Mogaji et al. (2015) | Dempster-Shafer | Groundwater resource modeling | Malaysia |
| Mohammadi et al. (2009) | Fuzzy classification | Groundwater resource modeling | Iran |
| Mohammadi et al. (2014) | General probability theory | Natural hazard modeling | Iran |
| Mohammady et al. (2012) | Dempster-Shafer | Landslide susceptibility modeling | Iran |
| Mosadeghi et al. (2015) | Fuzzy AHP | Urban planning and modeling | Australia |
| Mousavi et al. (2011) | General probability theory | Landslide susceptibility modeling | Iran |
| Mousavi et al. (2014) | General probability theory | Natural hazard modeling | Iran |
| Münch & Conrad (2007) | Probability map | Groundwater resource modeling | South Africa |
| Nachbaur & Rohmer (2011) | Fuzzy membership | Underground vulnerability modeling | France |
| Nampak et al. (2014) | Dempster-Shafer | Groundwater resource modeling | Malaysia |
| Nasserabadi et al. (2013) | Fuzzy membership | Land suitability modeling | Iran |
| Nath (2004) | General probability theory | Seismic hazard modeling | India |
| Navas et al. (2011) | Neuro fuzzy | Marine environmental modeling | Ireland |
| Navas et al. (2012) | Neuro fuzzy | Coastal modeling | Not available |
| Nelson et al. (2007) | Fuzzy membership | Landslide susceptibility modeling | Chile |
| Neshat & Pradhan (In Press) | Dempster-Shafer | Groundwater resource modeling | Iran |
| Neshat et al. (2015) | General probability theory | Groundwater resource modeling | Iran |
| Neuhäuser et al. (2012) | General probability theory | Landslide susceptibility modeling | Austria |
| Nguyen et al. (2015) | Fuzzy membership | Land suitability modeling | Vietnam |
| Ning & Chang (2004) | Fuzzy multi-criteria analysis | Water quality modeling | Taiwan |
| Nisar Ahamed et al. (2000a) | Fuzzy membership | Land suitability modeling | India |
| Nisar Ahamed et al. (2000b) | Fuzzy membership | Soil suitability modeling | India |

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|---|---|---|---|
| Nobre et al. (2007) | Fuzzy membership | Groundwater resource modeling | Brazil |
| Nourqolipour et al. (2015) | Fuzzy membership | Land use Modeling | Malaysia |
| Nurmiaty (2014) | Fuzzy membership | Land suitability modeling | Indonesia |
| Ocalir et al. (2010) | Fuzzy membership | Site suitability modeling | Turkey |
| Ogburn (2006) | Fuzzy membership | Geo-historical modeling | Ecuador |
| Oh & Jeong (2002) | Fuzzy membership | Urban planning and modeling | Korea |
| Oh & Lee (2011) | General probability theory | Landslide susceptibility modeling | Korea |
| Oh & Pradhan (2011) | Adaptive neuro-fuzzy inference system (ANFIS) | Landslide susceptibility modeling | Malaysia |
| Oh et al. (2011) | Frequency ratio | Ground subsidence modeling | Korea |
| Osna et al. (2014) | Mamdani's fuzzy inference modeling | Landslide susceptibility modeling | Turkey |
| Ozdemir (2009) | Bayesian probability | Landslide susceptibility modeling | Turkey |
| Park (2011) | Dempster-Shafer | Landslide susceptibility modeling | Korea |
| Park et al. (2012) | Adaptive neuro-fuzzy inference system (ANFIS) | Ground subsidence modeling | Korea |
| Park et al. (2013) | General probability theory | Landslide susceptibility modeling | Korea |
| Park et al. (2014) | Neuro fuzzy | Ground subsidence modeling | Korea |
| Parry et al. (2013) | General probability theory | Marine environmental modeling | Australia |
| Pászto et al. (2015) | Fuzzy membership | Urban planning and modeling | Czech Republic |
| Pathak & Hiratsuka (2011) | Fuzzy pattern recognition | Groundwater resource modeling | Nepal |
| Pawlin Vasanthi et al. (2015) | Probability map | Health risk modeling | India |
| Peled & Gilichinsky (2013) | General probability theory | Land use Modeling | Israel |
| Peng (1998) | Bayesian probability | Soil salinization modeling | China |
| Peng et al. (2014) | Rough set | Landslide susceptibility modeling | China |
| Perakis & Moysiadis | Dempster-Shafer | Geo-historical modeling | Greece |
| Pezeshki et al. (2012) | Fuzzy classification | Health risk modeling | Iran |
| Plewe (2003) | Dempster-Shafer | Geo-historical modeling | Not available |
| Pollak (2014) | Bayesian probability | Urban planning and modeling | Israel |
| Pourghasemi et al. (2012) | Bayesian probability | Landslide susceptibility modeling | Iran |
| Pourghasemi et al. (2013a) | Dempster-Shafer | Landslide susceptibility modeling | Iran |
| Pourghasemi et al. (2013b) | General probability theory | Landslide susceptibility modeling | Iran |
| Pourghasemi et al. (2014a) | Dempster-Shafer | Landslide susceptibility modeling | Iran |
| Pourghasemi et al. (2014b) | General probability theory | Landslide susceptibility modeling | Iran |
| Pourtaghi & Pourghasemi (2014) | Bayesian Probability | Groundwater resource modeling | Iran |
| Pradhan (2010) | Fuzzy membership | Landslide susceptibility modeling | Malaysia |
| Pradhan (2013) | Adaptive neuro-fuzzy inference system (ANFIS) | Landslide susceptibility modeling | Malaysia |
| Pradhan et al. (2009) | Fuzzy membership | Landslide susceptibility modeling | Malaysia |
| Pradhan et al. (2014) | Probability map | Ground subsidence modeling | Malaysia |
| Prasannakumar & Vijith (2012) | Probability map | Landslide susceptibility modeling | India |
| Qi et al. (2006) | Fuzzy membership | Soil suitability modeling | USA |
| Qi et al. (2013) | General probability theory | Flood management modeling | USA |
| Qiu et al. (2014) | Fuzzy membership | Land suitability modeling | USA |
| Rahman et al. (2014) | Fuzzy AHP | Environmental modeling | China |
| Rahman et al. (In Press) | General probability theory | Soil erosion modeling | China |
| Ramani et al. (2011) | General probability theory | Landslide susceptibility modeling | India |
| Ramnarine et al. (2015) | General probability theory | Soil suitability modeling | USA |
| Razandi et al. (In Press) | General probability theory | Earth Science Informatics | Iran |
| Refice & Capolongo (2002) | General probability theory | Landslide susceptibility modeling | Italy |
| Regmi et al. (2014) | Bayesian probability | Landslide susceptibility modeling | Nepal |
| Remondo et al. (2003) | Fuzzy membership | Landslide susceptibility modeling | Spain |
| Reshmidevi et al. (2009) | Fuzzy rules | Land suitability modeling | India |
| Robinson et al. (2004) | General probability theory | Mineral potential modeling | USA |
| Romanelli et al. (2012) | General probability theory | Landslide susceptibility modeling | Argentina |
| Romero-Calcerrada et al. (2008) | Bayesian Probability | Human-caused wildfire modeling | Spain |
| Rüger et al. (2005) | Fuzzy membership | Habitat suitability modeling | Uzbekistan |

| | | | |
|---|---|---|---|
| Sadeghi & Khalajmasoumi (2015) | Fuzzy membership | Geothermal modeling | Azarbayejan |
| Saeidi (2014) | Dempster-Shafer | Land extraction modeling | Malaysia |
| Sahoo et al. (2015) | General probability theory | Groundwater resource modeling | India |
| Sakamoto & Fukui (2004) | Fuzzy AHP | Habitat suitability modeling | Japan |
| Samranpong et al. (2009) | Fuzzy membership | Land suitability modeling | Thailand |
| Schindler et al. (2012) | General probability theory | Natural hazard modeling | Germany |
| Schmidt & Hewitt (2004) | Fuzzy classification | Land suitability modeling | New Zealand |
| Schotten et al. (2001) | General probability theory | Land use Modeling | Netherlands |
| Semple et al. (2013) | General probability theory | Health risk modeling | USA |
| Şener & Şener (2015) | Fuzzy AHP | Groundwater resource modeling | Turkey |
| Shad et al. (2009) | Fuzzy membership | Air pollution modeling | Iran |
| Shadman Roodposhti et al. (2014) | Fuzzy AHP | Landslide susceptibility modeling | Iran |
| Shahabi et al. (2015) | Fuzzy membership | Landslide susceptibility modeling | Iran |
| Shahid et al. (2002) | Fuzzy membership | Groundwater resource modeling | India |
| Sharma et al. (2013) | Fuzzy membership | Landslide susceptibility modeling | India |
| Sheng et al. (2012) | Rough set | Land use Modeling | China |
| Shengyuan et al. (2008) | Fuzzy membership | Land suitability modeling | China |
| Shi et al. (2009) | Fuzzy C-means | Wind erosion modeling | Mongolia |
| Shi et al. (2013) | Fuzzy membership | Groundwater resource modeling | China |
| Shi et al. (2014) | Fuzzy membership | Natural hazard modeling | China |
| Shirzadi et al. (2012) | Probability map | Rock-fall susceptibility modeling | Iran |
| Sicat et al. (2005) | Fuzzy multi-criteria analysis | Land suitability modeling | India |
| Simav et al. (2013) | General probability theory | Coastal modeling | Turkey |
| Široký et al. (2011) | Probability map | Health risk modeling | Czech Republic |
| Skov & Svenning (2003) | Fuzzy cognitive modeling | Soil suitability modeling | Denmark |
| Solaimani et al. (2013) | Dempster-Shafer | Landslide susceptibility modeling | Iran |
| Soltani et al. (2013) | Dempster-Shafer | Land use Modeling | Iran |
| Soto et al. (2012) | Fuzzy membership | Natural hazard modeling | Chile |
| Steinhardt (1998) | Fuzzy membership | Land use Modeling | Germany |
| Stoms et al. (2002) | Fuzzy membership | Land suitability modeling | USA |
| Subburayalu et al. (2014) | Possibility Theory | Soil suitability modeling | USA |
| Sujatha & Rajamanickam (2011) | Fuzzy membership | Landslide susceptibility modeling | India |
| Sun et al. (2014) | Fuzzy membership | Natural hazard modeling | China |
| Sutcu et al. (2012) | General probability theory | Mineral resources modeling | Turkey |
| Svoray et al. (2004) | Fuzzy rules | Land suitability modeling | Israel |
| Taboada et al. (2008) | Fuzzy AHP | Mineral potential modeling | Spain |
| Talaei (2014) | General probability theory | Landslide susceptibility modeling | Iran |
| Tang & Zhu (2006) | General probability theory | Torrent risk modeling | China |
| Tang et al. (2012) | Fuzzy membership | Environmental modeling | USA |
| Tang et al. (2013) | Bayesian Probability | Fishing grounds modeling | North Pacific |
| Tangestani & Moore (2002) | Dempster-Shafer | Mineral potential modeling | Iran |
| Tangestani & Moore (2003) | Fuzzy membership | Mineral potential modeling | Iran |
| Tangestani (2009) | Dempster-Shafer | Landslide susceptibility modeling | Iran |
| Thiam (2005) | Dempster-Shafer | Land degradation modeling | Mauritania |
| Tripathi et al. (2015) | Fuzzy C-means | Soil suitability modeling | India |
| Tsutsumida et al. (2015) | General probability theory | Urban planning and modeling | Mongolia |
| Tucker et al. (1997) | Bayesian Probability | Bird Distribution Modeling | United Kingdom |
| Uddameri & Honnungar (2007) | Rough set | Groundwater resource modeling | USA |
| Urbański & Szymelfenig (2003) | Fuzzy membership | Benthic habitat modeling | Poland |
| Vadrevu et al. (2010) | Fuzzy membership | Natural hazard modeling | India |
| Vafai et al. (2013) | Fuzzy multi-criteria analysis | Marine environmental modeling | Iran |
| Vahidnia et al. (2009) | Fuzzy AHP | Land suitability modeling | Iran |
| Vakalis et al. (2004) | Neuro fuzzy | Natural hazard modeling | Greece |
| Venkataraman et al. (2000) | Fuzzy membership | Mineral potential modeling | India |
| Venkatramanan et al. (In Press) | Fuzzy AHP | Groundwater resource modeling | Korea |
| Verbeeck et al. (2011) | Transition probability | Urban planning and modeling | France |

| | | | |
|---|---|---|---|
| Vijith & Madhu (2008) | Frequency ratio | Landslide susceptibility modeling | India |
| Vijith et al. (2012) | General probability theory | Landslide susceptibility modeling | India |
| Wan et al. (2008) | Rough set | Debris flows moldeing | Taiwan |
| Wan et al. (2010) | Rough set | Landslide susceptibility modeling | Taiwan |
| Wan et al. (2012) | Rough set | Landslide susceptibility modeling | Taiwan |
| Wang et al. (2009) | Fuzzy membership | Landslide susceptibility modeling | China |
| Wang et al. (2012) | Fuzzy cellular automata | Urban planning and modeling | China |
| Wang et al. (2013) | Neuro fuzzy | Reservoir characterization | Canada |
| Weissteiner et al. (2011) | Fuzzy membership | Land suitability modeling | Mediterranean |
| Wikramanayake et al. (2004) | General probability theory | Wilderness land modeling | India and Nepal |
| Wiley et al. (2011) | General probability theory | Marine environmental modeling | USA |
| Wood & Dragicevic (2007) | Fuzzy membership | Marine environmental modeling | Canada |
| Wu et al. (1998) | Fuzzy membership | Land use Modeling | China |
| Wu et al. (2012) | Transition probability | Land use Modeling | China |
| Wu et al. (2013) | Rough set | Landslide susceptibility modeling | China |
| Xia & Chen (2015) | Fuzzy membership | Water quality modeling | China |
| Xie et al. (2004) | Probability map | Landslide susceptibility modeling | Japan |
| Xu (2001) | General probability theory | Landslide susceptibility modeling | Hong Kong |
| Yalcin et al. (2011) | Frequency ratio | Landslide susceptibility modeling | Turkey |
| Yang & Yang (2005) | Dempster-Shafer | Soil salinization modeling | China |
| Yang et al. (2005) | Dempster-Shafer | Soil salinization modeling | China |
| Yang et al. (2008) | Grey relational analysis | Land suitability modeling | China |
| Yang et al. (2014a) | Fuzzy membership | Nature conservation modeling | China |
| Yang et al. (2014b) | Fuzzy AHP | Soil suitability modeling | China |
| Yi et al. (2010) | General probability theory | Natural hazard modeling | Korea |
| Yigit (2012) | General probability theory | Mineral potential modeling | Turkey |
| Yilmaz et al. (2013) | Bayesian probability | Natural hazard modeling | Turkey |
| Youssef et al. (In Press-a) | Dempster-Shafer | Landslide susceptibility modeling | Saudi Arabia |
| Youssef et al. (In Press-b) | General probability theory | Landslide susceptibility modeling | Saudi Arabia |
| Zahiri et al. (2006) | General probability theory | Mineral potential modeling | Australia |
| Zamorano et al. (2008) | General probability theory | Land suitability modeling | Spain |
| Zeller at al. (2011) | General probability theory | Wilderness land modeling | Nicaragua |
| Zeng & Zhou (2001) | Fuzzy rules | Urban planning and modeling | Australia |
| Zhang & Guilbert (2013) | Fuzzy membership | Groundwater resource modeling | Russia |
| Zhang et al. (2004) | Fuzzy AHP | Soil suitability modeling | China |
| Zhang et al. (2009) | Fuzzy AHP | Land suitability modeling | China |
| Zhang et al. (2010) | General probability theory | Natural hazard modeling | China |
| Zhang et al. (2013a) | Fuzzy AHP | Land suitability modeling | China |
| Zhang et al. (2013b) | Fuzzy membership | Urban planning and modeling | China |
| Zhang et al. (2014) | Fuzzy multi-criteria analysis | Urban planning and modeling | Finland |
| Zhang et al. (2015) | Fuzzy AHP | Land suitability modeling | China |
| Zhijun et al. (2009) | General probability theory | Natural hazard modeling | China |
| Zhou et al. (1997) | Fuzzy AHP | Land suitability modeling | Thailand |
| Zhou et al. (2003) | General probability theory | Landslide susceptibility modeling | Japan |
| Zhu & Mackay (2001) | Fuzzy membership | Hydro-ecological modeling | USA |
| Zhu et al. (1996) | Fuzzy membership | Soil suitability modeling | USA |
| Zhu et al. (2006) | Rough set | Soil suitability modeling | Chaina |
| Zhu et al. (2014) | Fuzzy membership | Landslide susceptibility modeling | China |
| Zou et al. (2013) | Fuzzy AHP | Natural hazard modeling | China |

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**Figure 1. Gulf of Mexico coastal region: Atchafalaya Bay area**

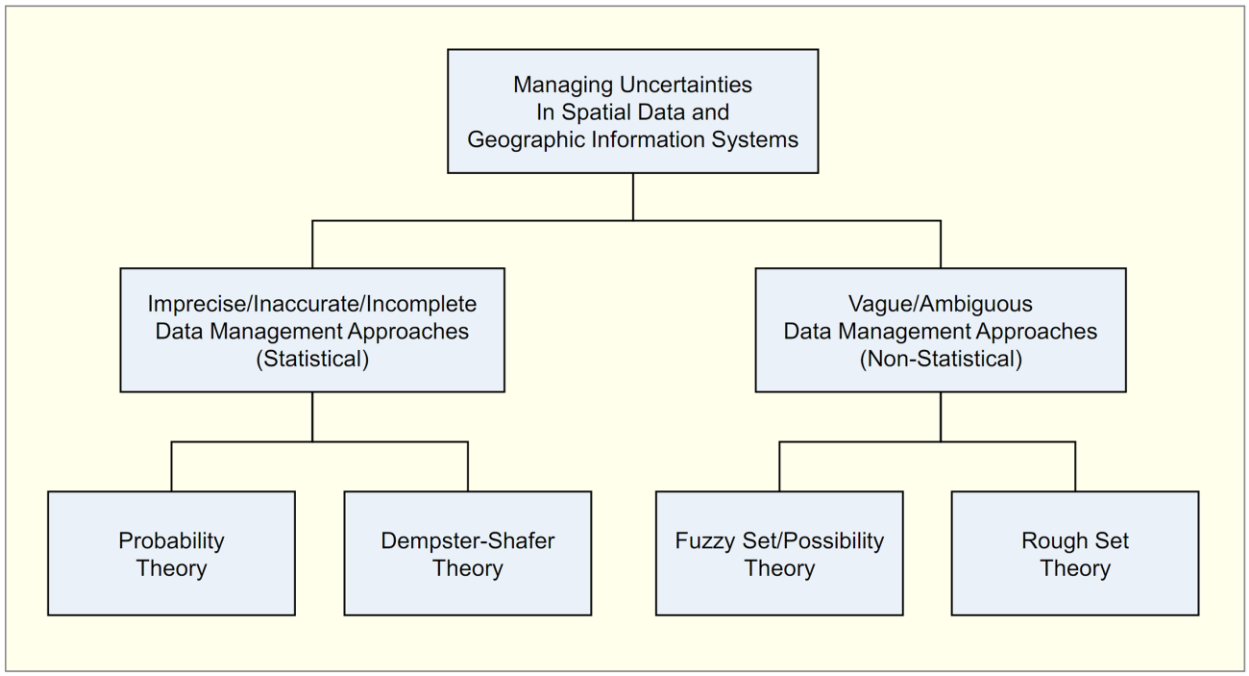


**Figure 2. A practical taxonomy of methods used for managing uncertainties in GIS**

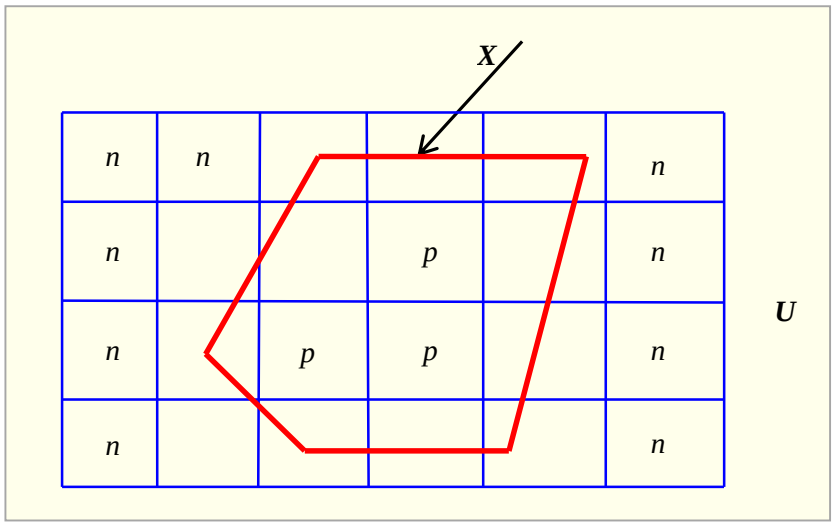


**Figure 3. Illustration of the concept of a rough set *X***

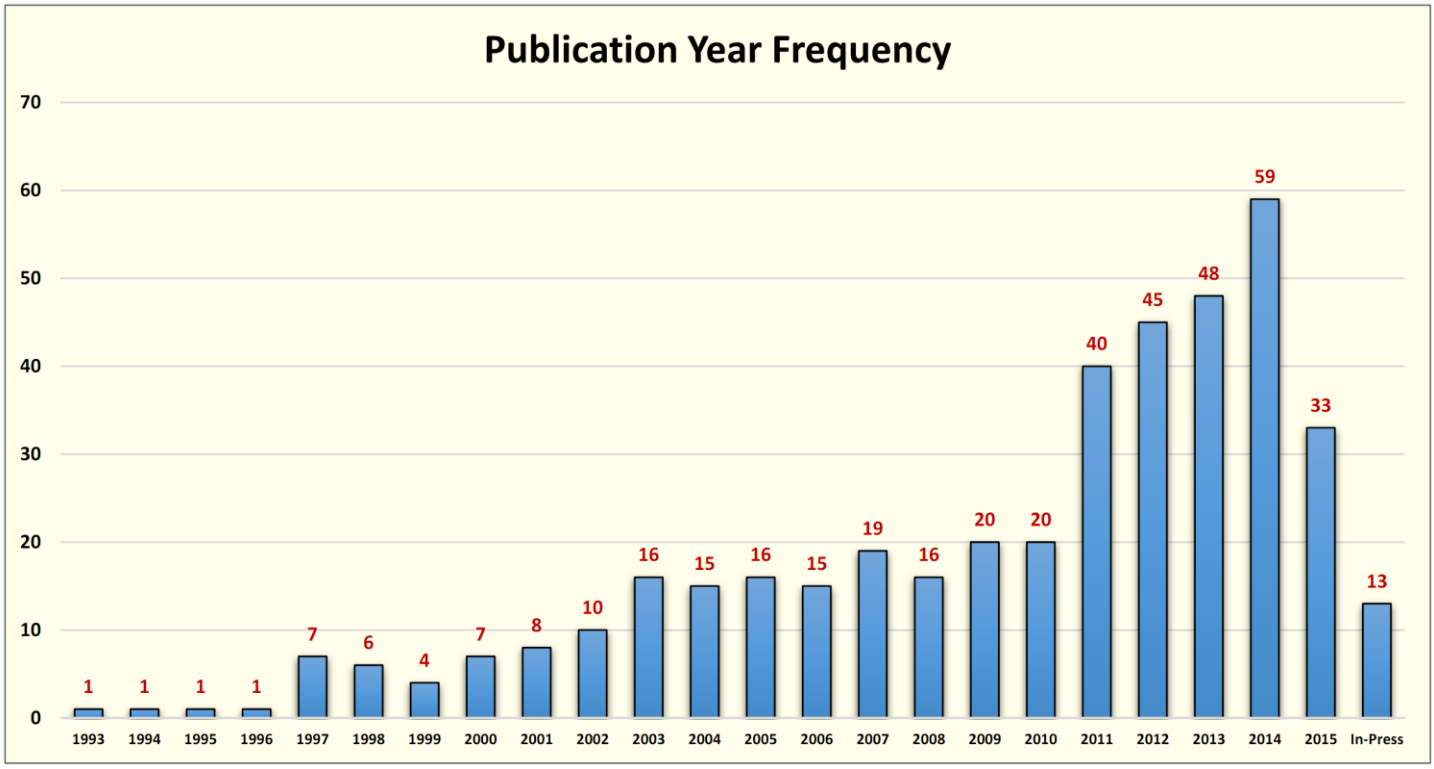


**Figure 4: Frequency of the publication year**

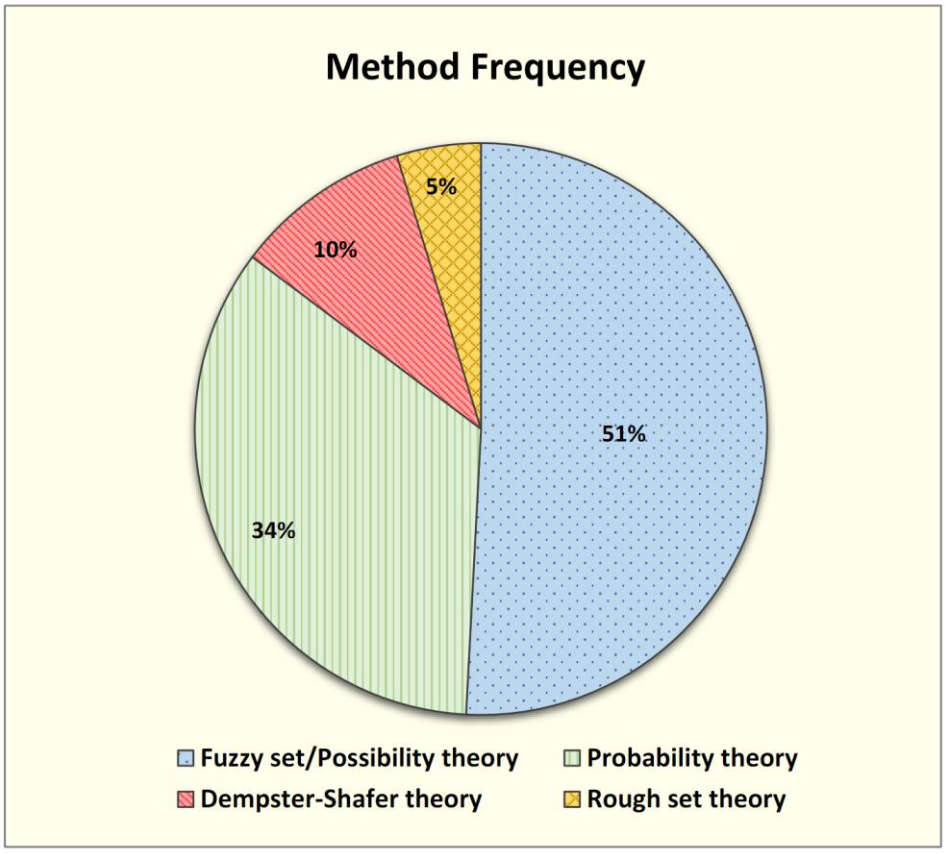


**Figure 5: Frequency of the uncertain spatial data modeling method used in GIS**

**Table 1: Frequency of fuzzy set/possibility theory methods**

| Fuzzy set/possibility theory method | Frequency |
|---|---|
| Fuzzy membership | 111 |
| Fuzzy AHP | 35 |
| Fuzzy multi-criteria analysis | 18 |
| Fuzzy rules | 10 |
| Neuro fuzzy | 9 |
| Fuzzy classification | 7 |
| Adaptive neuro-fuzzy inference system (ANFIS) | 5 |
| Possibility Theory | 4 |
| Fuzzy C-means | 3 |
| Mamdani's fuzzy inference modeling | 3 |
| Fuzzy cellular automata | 1 |
| Fuzzy cognitive modeling | 1 |
| Fuzzy constrained method | 1 |
| Fuzzy k-means | 1 |
| Fuzzy majority procedure | 1 |
| FUZZY ordered weighted average | 1 |
| Fuzzy pattern recognition | 1 |
| Fuzzy risk modeling | 1 |
| Grey relational analysis | 1 |
| Total | 214 |

**Table 2: Frequency of probability theory methods**

| Probability theory method | Frequency |
|---|---|
| General probability theory | 92 |
| Bayesian probability | 21 |
| Probability map | 21 |
| Transition probability | 6 |
| Frequency ratio | 5 |
| Total | 145 |

**Table 3: Frequency of applications**

| Application | Frequency |
|---|---|
| Landslide susceptibility modeling | 98 |
| Land suitability modeling | 51 |
| Natural hazard modeling | 38 |
| Groundwater resource modeling | 27 |
| Land use modeling | 23 |
| Soil suitability modeling | 22 |
| Urban planning and modeling | 22 |
| Mineral potential modeling | 18 |
| Marine environmental modeling | 15 |
| Health risk modeling | 8 |
| Environmental modeling | 7 |
| Geo-historical modeling | 7 |
| Soil salinization modeling | 6 |
| Ground subsidence modeling | 5 |
| Wilderness land modeling | 5 |
| Habitat suitability modeling | 4 |
| Coastal modeling | 3 |
| Mineral resources modeling | 3 |
| Rock-fall susceptibility modeling | 3 |
| Water quality modeling | 3 |
| Air pollution modeling | 2 |
| Forest management modeling | 2 |
| Geothermal modeling | 2 |
| Land degradation modeling | 2 |
| Site suitability modeling | 2 |
| Underground vulnerability modeling | 2 |
| Others | 41 |
| Total | 421 |

**Table 4: Country data**

| Country/Region | Frequency |
|---|---|
| China | 62 |
| Iran | 49 |
| USA | 30 |
| India | 29 |
| Korea | 20 |
| Australia | 18 |
| Turkey | 14 |
| Canada | 13 |
| Greece | 11 |
| Spain | 11 |
| Malaysia | 10 |
| Italy | 9 |
| Taiwan | 9 |
| Germany | 8 |
| France | 5 |
| Japan | 5 |
| Vietnam | 5 |
| Ecuador | 4 |
| Nepal | 4 |
| Saudi Arabia | 4 |
| Brazil | 3 |
| Ireland | 3 |
| Israel | 3 |
| Malaysia | 3 |
| Mexico | 3 |
| New Zealand | 3 |
| Thailand | 3 |
| Others | 72 |
| Not Available | 8 |
| Total | 421 |

## Table 5: Journal data

| Journal | Frequency |
|---|---|
| Natural Hazards | 29 |
| Environmental Earth Sciences | 22 |
| Computers and Geosciences | 17 |
| Arabian Journal of Geosciences | 10 |
| Environmental Geology | 10 |
| International Journal of Geographical Information Science | 10 |
| Ecological Modelling | 8 |
| Geoderma | 8 |
| Environmental Management | 7 |
| Journal of Environmental Management | 7 |
| Natural Resources Research | 7 |
| CATENA | 6 |
| Computers, Environment and Urban Systems | 6 |
| Engineering Geology | 6 |
| Environmental Modelling and Software | 6 |
| Applied Geography | 5 |
| Environmental Monitoring and Assessment | 5 |
| Geomorphology | 5 |
| Hydrogeology Journal | 5 |
| Journal of the Indian Society of Remote Sensing | 5 |
| Landscape and Urban Planning | 5 |
| Agricultural Systems | 4 |
| Agriculture, Ecosystems and Environment | 4 |
| Computers and Electronics in Agriculture | 4 |
| Environmental Modeling and Assessment | 4 |
| International Journal of Applied Earth Observation and Geoinformation | 4 |
| Journal of Earth System Science | 4 |
| Journal of Geographical Systems | 4 |
| Journal of Mountain Science | 4 |
| Landslides | 4 |
| Applied Geomatics | 3 |
| Applied Mechanics and Materials | 3 |
| Bulletin of Engineering Geology and the Environment | 3 |
| Ecological Informatics | 3 |
| GeoJournal | 3 |
| Journal for Nature Conservation | 3 |
| Journal of Asian Earth Sciences | 3 |
| Journal of Geographical Sciences | 3 |
| Journal of Hydrology | 3 |
| Landscape Ecology | 3 |
| Stochastic Environmental Research and Risk Assessment | 3 |
| Transactions in GIS | 3 |
| Others | 160 |
| Total | 421 |