Modeling and Management of Spatio-temporal Uncertainty of Flood Events

Manel Chehibi*, Ahlem Ferchichi*,**
Imed Riadh Farah*

*RIADI Laboratory, National School of Computer Science, University of Manouba,
Manouba University campus, 2010 Manouba, Tunisia
webmaster@ensi.rnu.tn,
https://ensi.rnu.tn/
**University of Ha'il, Hail, Saudi Arabia
info@uoh.edu.sa
https://www.uoh.edu.sa/en

Abstract. Today, one of the most common natural hazards in the world is flooding, and over the years flooding has caused significant loss of life and property damage. Remote sensing technology and data derived from satellite imagery are useful for knowing the extent of flood, which is useful for flood risk management. An important prerequisite for flood risk management is the existence of spatial and temporal information on the extent of the flood. In general, this spatio-temporal information from remote sensing data is uncertain. The objective of our work is to model the spatial and temporal uncertainties relating to the date and extent of floods, in order to provide information and advice to the right measurements to adapt to flood problems. The estimate of the date and extent of the flood is based on the analysis of the extents of other floods that have occurred in the same area. There is always a level of spatial-temporal uncertainty inherent in such estimates.

1 Introduction

Today, one of the most common natural hazards in the world is flooding (Ha et al., 2021), and over the years flooding has caused significant loss of life and property damage (Cai et al., 2021). In 2019, 361 events occurred worldwide, of which flooding was the largest event with a total of 170 incidents, representing 47% of the total (Miau and Hung, 2020). These events affected around 3 billion people and caused 5100 deaths (Miau and Hung, 2020). These floods are caused by many factors such as climate change (Zhang et al., 2021), the socio-economic factor, geology, topography (Das, 2020), land use change (Hu et al., 2020) and spatial and temporal variabilities (Merwade et al., 2008) which become major factors of uncertainty in the management of flood risks.

Remote sensing technology and data derived from satellite imagery are useful for mapping flooded areas (Shen et al., 2019), which is useful for flood risk management (Moreira et al., 2021). Due to their wide spatial coverage and their great temporal availability, they can facilitate this type of spatio-temporal analysis. An important prerequisite for flood risk management is the existence of spatial and temporal information on the actual extent of the flood (Kurte et al., 2019). In general, this spatio-temporal information from remote sensing data is uncertain.

The main sources of uncertainty in spatio-temporal information are: cloud cover during periods of heavy flooding, mixed pixel and image quality, sub-optimal solar lighting, spatial and temporal resolution. Many of the probabilistic and non-probabilistic methods have been used for the modeling and management of uncertainties such as interval theory, fuzzy set theory (Goguen, 1973), probability theory, possibility theory (Zadeh, 1978; Dubois, 1988) and belief function theory (Dempster, 1967; Shafer, 1976).

The objective of our work is to model the spatial and temporal uncertainties using the theory of belief functions to detect the extent of flooding, in order to provide information and advice to the right measurements for adapt to flood problems.

This paper is structured as follow: Section 2 recalls the main concepts of belief functions theory, Allen's relations and the Region Connection Calculus 8 (RCC-8), Section 3 details our proposed approach for managing uncertain and imprecise spatio-temporal information, Section 4 presents an experimental study of our approach before concluding in section 5.

2 Background

In this section, we give a brief recall on the theory of belief functions (This section is mainly taken from the article (Chehibi et al., 2018)), and on the qualitative relations.

2.1 Theory of belief functions

The theory of belief functions, also called Dempster-Shafer theory, was first introduced by Dempster (Dempster, 1967) and mathematically formalized by Shafer (Shafer, 1976). This theory models imprecise, uncertain and missing data.

In the theory of belief functions, a *frame of discernment*, noted $\Theta = \{H_1, ..., H_N\}$, is a set of N exhaustive and mutually exclusive hypotheses $H_i, 1 \leq i \leq N$. only one of them is likely to be true.

The *power set*, $2^\Theta = \{A/A \subseteq \Theta\} = \{\emptyset, H_1, ..., H_N, H_1 \cup H_2, ..., \Theta\}$, enumerates 2^N sub-assemblies of Θ. It includes not only hypotheses of Θ, but also, disjunctions of these hypotheses.

The true hypothesis in Θ is unknown; thus, a degree of belief is assessed to subsets of 2^Θ reflecting our degree of faith on the truth of each subset of 2^Θ.

A *basic belief assignment (bba)*, also called *mass function*, is noted m^Θ and defined such that:

$$\begin{aligned} & m^\Theta : 2^\Theta \to [0,1] \\ & m^\Theta(\emptyset) = 0 \\ & \sum_{A \subseteq \Theta} m(A) = 1 \end{aligned} \tag{1}$$

The mass $m^{\Theta}(A)$ represents the degree of belief on the truth of $A \in 2^{\Theta}$. When $m^{\Theta}(A) > 0$, A is called *focal element*.

2.2 Qualitative relations

2.2.1 Allen's interval algebra

Allen's interval algebra (Allen, 1983) is one of the most known and used formalisms in temporal reasoning. A significant part of the work on temporal representation and reasoning is concerned with time intervals. It is an algebra based on 13 primitive and mutually exclusive relations that can be applied between two time intervals $A = [a, a^{'}]$ and $B = [b, b^{'}]$. These relationships are: before (b), after (bi), meets (m), met by (mi), overlaps (o), overlapped by (oi), starts (s), started by (si), during (d), contains (di), finishes (f), finished by (fi) and equals (e). Each of these relations corresponds to a particular order of the four bounds of the two intervals. For example, the statement A overlaps B (A o B) corresponds to $(a < b) \wedge (b < a^{'}) \wedge (a^{'} < b^{'})$.

2.2.2 The Region Connection Calculus 8 (RCC-8)

Region connection calculus 8 (RCC-8) (Randell et al., 1992) is one of the most known and used formalisms in spatial representation and reasoning developed by Randell, Cui, and Cohn. A significant part of the work on qualitative spatial reasoning (QSR) is concerned with the RCC-8 model. This model describes the possible spatial relations between two spatial regions in the form of eight basic topological relations. These relationships are: DC(a,b) (a is disconnected from b), EC(a,b) (a is externally connected with b), PO(a,b) (a partially overlaps b), TPP(a,b) (a is a tangential proper part of b), NTPP(a,b) (a is a nontangential proper part of b), TPPi(a,b) (a has a tangential proper part b), NTPPi(a,b) (a has nontangential proper part b), EQ (a,b) (a is equal to b).

3 Proposed approach

Our proposed approach includes four phases: the uncertainty representation phase, the modeling of uncertain relationships between events, the measurement of similarity and the aggregation of events phase.

3.1 Representing of Uncertainty

In this section, the uncertainty of spatial, temporal and spatiotemporal events is represented and modeled using intervals. The quantification of this uncertainty is based on the theory of belief functions.

3.1.1 Spatial uncertainty

Spatial uncertainty S_U refers to the uncertainty of the extent of the flood. It is due to several possible flood extents. This uncertainty is represented using an interval-based method. This representation (fig 1) consists of a less uncertain inner interval S_{LU} of the extent of the flood and a more uncertain outer interval S_{MU}. The degrees of uncertainty of the two intervals are

modeled by a mass function m where:
$S_U = \{S_{MU} = [S_{MU1}, S_{MU2}], m(S_{MU}); S_{LU} = [S_{LU1}, S_{LU2}], m(S_{LU})\}$
with $S_{LU} \subseteq S_{MU}$ and $m(S_{MU}) = \bar{m}(S_{LU}) = 1 - m(S_{LU})$

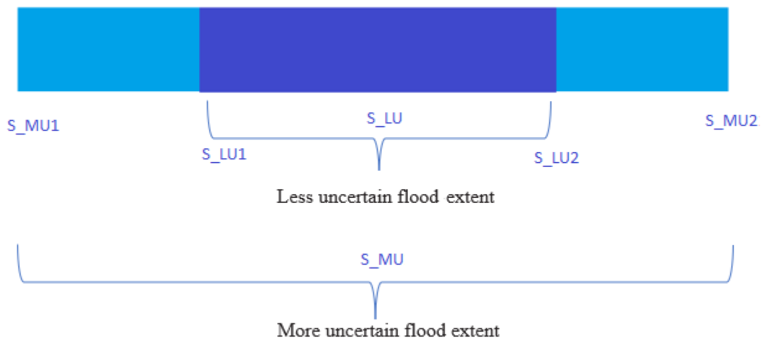

FIG. 1 – *Spatial uncertainty*

3.1.2 Temporal uncertainty

Temporal uncertainty T_U refers to the uncertainty of the date of the flood. This is due to several possible dates of the flood. This uncertainty is represented using an interval-based method. This representation (fig 2) consists of a less uncertain inner interval T_{LU} of the date of the flood and a more uncertain outer interval T_{MU}. The degrees of uncertainty of the two intervals are modeled by a mass function m where:
$T_U = \{T_{MU} = [T_{MU1}, T_{MU2}], m(T_{MU}); T_{LU} = [T_{LU1}, T_{LU2}], m(T_{LU})\}$
with $T_{LU} \subseteq T_{MU}$ and $m(T_{MU}) = \bar{m}(T_{LU}) = 1 - m(T_{LU})$

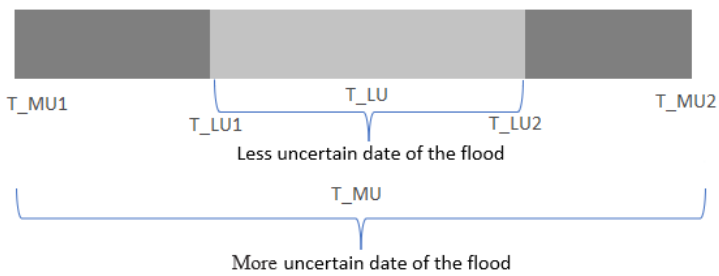

FIG. 2 – *Temporal uncertainty*

3.1.3 Spatio-temporal uncertainty

Spatio-temporal uncertainty ST_U refers to the uncertainty of the date and extent of the flood. This is due to several possible dates and extents of the flood. This uncertainty is represented using an interval-based method. This representation (fig 3) consists of a less uncertain inner interval ST_{LU} of the date and extent of the flood and a more uncertain outer interval ST_{MU}. The degrees of uncertainty of intervals are modeled by a mass function m where:
$ST_U = S_U \otimes T_U = \{ST_{LU}; ST_{MU}; ST_{LMU}; ST_{MLU}\}$

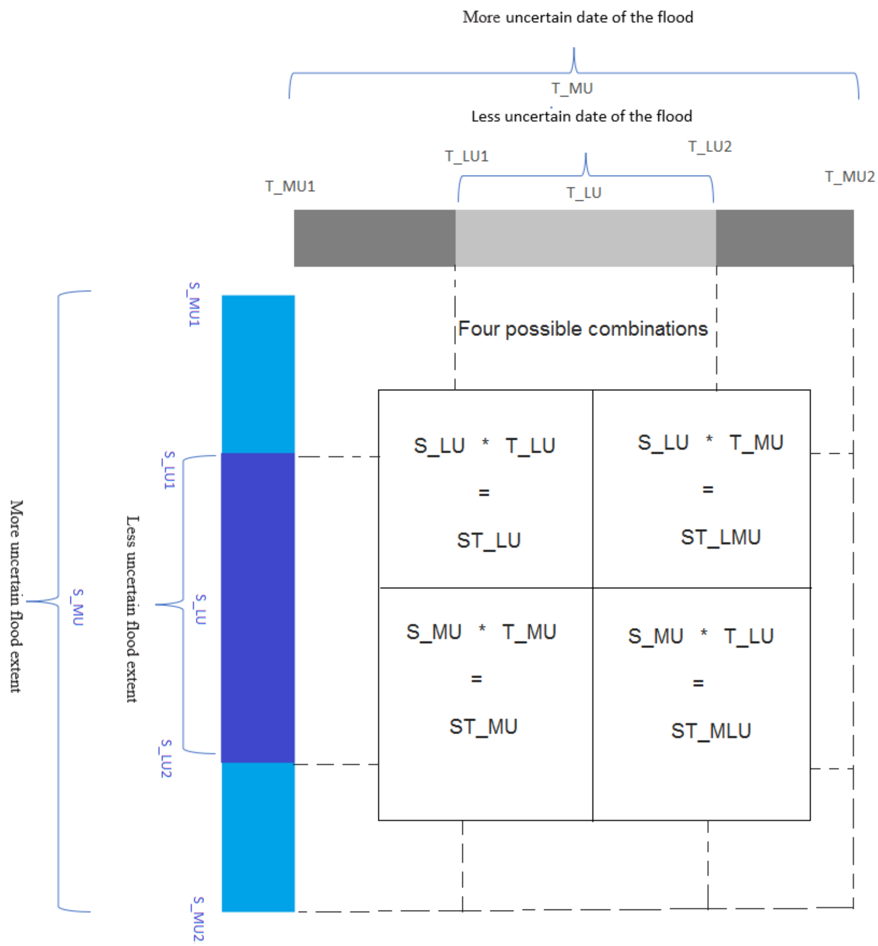

FIG. 3 – *Spatio-temporal uncertainty*

with $ST_{LU} = \{(S_{LU} \otimes T_{LU}); m(ST_{LU}) = m(S_{LU}) * m(T_{LU})\}$
$ST_{MU} = \{S_{MU} \otimes T_{MU};\ m(ST_{MU}) = m(S_{MU}) * m(T_{MU})\}$

TAB. 1 – *Spatio-temporal relations*

Temporal relation	**Spatial relation**	**Spatio-temporal relation**
before (b), after (bi)	Disconnected (DC)	Disconnected (DC)
meets (m), met by (mi)	Externally connected (EC)	Externally connected (EC)
overlaps (o), overlapped by (oi)	Partially overlaps (PO)	Partially overlaps (PO)
starts (s), finishes (f)	is a tangential proper part (TPP)	is a tangential proper part (TPP)
started by (si), finished by (fi)	has a tangential proper part (TPPi)	has a tangential proper part (TPPi)
during (d)	is a nontangential proper part (NTPP)	is a nontangential proper part (NTPP)
contains (di)	has a nontangential proper part (NTPPi)	has a nontangential proper part (NTPPi)
equal(e)	equal (EQ)	equal (EQ)

$ST_{LMU} = \{S_{LU} \otimes T_{MU},\ m(ST_{LMU}) = m(S_{LU}) * m(T_{MU})\}$
$ST_{MLU} = \{S_{MU} \otimes T_{LU},\ m(ST_{MLU}) = m(S_{MU}) * m(T_{LU})\}$

3.2 Modeling the uncertain relationships of flood events

The nature of the relationship between two flood events depends on the nature of their spatial and temporal relationships. Uncertain relationships between spatial intervals representing flood extent are modeled using the RCC-8 model and uncertain relationships between temporal intervals representing date/time of flooding are modeled using Allen's interval algebra. The possible relations between intervals are deduced from their structure and the corresponding mass values. Table 1 presents some possible spatio-temporal relationships that may exist between two flood events and which may be useful for the analysis and evaluation of flood events. These spatio-temporal relationships are represented using RCC-8 model.

For simplicity, we assume as example that $ST1_U$ is a fully uncertain flood event (uncertain spatio-temporal event) and $ST2$ is a definite flood event.
$ST1_U = \{S1_U \otimes T1_U\}$
where $S1_U = \{S1_{MU} = [E3, E6],\ m(S1_{MU}),\ S1_{LU} = [E4, E5];\ m(S1_{LU})\}$;
and $T1_U = \{T1_{MU} = [D3, D6];\ m(T1_{MU});\ T1_{LU} = [D4, D5];\ m(T1_{LU})\}$.

$ST2 = \{S2\ \otimes\ T2\}$
where $S2 = [E1, E2];\ m(S2) = 1$;
and $T2 = [D1, D2];\ m(T2) = 1$.

With: $D2 > D3$ / $D2 < D4$ and $E2 > E3$ / $E2 < E4$

Thus, the uncertain spatio-temporal relationship between the two flood events is:

$PO(ST1_U, ST2),\ m(ST1_{MU})$
$DC(ST1_U, ST2),\ m(ST1_{LU})\}$

3.3 Similarity of flood events

In many applications especially for flood risk management, comparing the similarity of spatio-temporal events can help in making a judgment or decision. Also, if two events are similar, it will be very useful to merge them and then have more reliable information. We propose here our method of measuring the similarity of flood events. This method is based on their spatio-temporal relationships and the masses of beliefs of the intervals corresponding to these events. Let $I1$ and $I2$ be two intervals, and any intersection between them is the interval INT. We base the similarity measure on the relationship between the length of INT and the length of $I1$ and $I2$. We therefore have for $Sim(I1, I2)$
$Sim(I1, I2) = (|INT|/|I1| + |INT|/|I2|)/2$
Here, we are interested in the evaluation of the similarity between two uncertain Flood events, $ST1_U$ and $ST2_U$. Since the inner intervals of events are more certain, we can rely on their intersection to determine the degree of similarity between events using the following rule:
$\{Sim(ST1_{LU}, ST2_{LU}) = (Sim(S1_{LU}, S2_{LU}) + Sim(T1_{LU}, T2_{LU}))/2\}$
The outer intervals can also be taken into account to determine the similarity of events, but as a secondary factor since they are less certain. It should be noted that if we have a strong belief in inner intervals, we can overlook the external intervals' similarity and say that E1 and E2 are thought to be quite comparable events.
For some types of relationships between flood events, the similarity value can be calculated without measuring the length of the intersection between the intervals, for example:
1) $TPP(S1_{LU}, S2_{LU})$ or $NTPP(S1_{LU}, S2_{LU})$:
$|INT| = |S1_{LU}|\ and\ Sim(S1_{LU}, S2_{LU}) = (|S1_{LU}|/|S1_{LU}| + |S1_{LU}|/|S2_{LU}|)/2 = (1 + |S1_{LU}|/|S2_{LU}|)/2$
2) $TPPi(S1_{LU}, S2_{LU})$ or $NTPPi(S1_{LU}, S2_{LU})$:
$|INT| = |S2_{LU}|\ and\ Sim(S1_{LU}, S2_{LU}) = (|S2_{LU}|/|S1_{LU}| + |S2_{LU}|/|S2_{LU}|)/2 = (1 + |S2_{LU}|/|S1_{LU}|)/2$
Also, depending on the nature of the relationship between two events, the similarity value can be inferred directly:
1)$DC(S1_{LU}, S2_{LU})$ So $Sim(S1_{LU}, S2_{LU}) = 0$
2)$EQ(S1_{LU}, S2_{LU})$ So $Sim(S1_{LU}, S2_{LU}) = 1$

3.4 Aggregation of events

If the events' similarity is assessed and they appear to be considerably similar, then a merger or combination of events could be considered. As a result, we obtain the aggregated event $ST12_U$. The merge operation is performed by applying the operator max on the upper limits of the inner and outer intervals of the two events and min on the lower limits. The mass of a combined interval is equal to the mass of the first interval multiplied by the mass of the second interval. To satisfy the condition of sum of belief masses, it is necessary to normalize them to be equal to 1.
For example, let:
$ST1_U = \{S1_{MU} = [170, 300],\ m(S1_{MU});\ S1_{LU} = [200, 280],\ m(S1_{LU});$

$T1_{MU} = [10, 20],\ m(T1_{MU});\ T1_{LU} = [13, 19],\ m(T1_{LU})\}$ and
$ST2_U = \{S2_{MU} = [190, 350],\ m(S2_{MU});\ S2_{LU} = [220, 330],\ m(S2_{LU});$
$T2_{MU} = [14, 25],\ m(T2_{MU});\ T2_{LU} = [17, 22],\ m(T2_{LU})\}$
therefore:
$S12_{MU} = [min[170, 190],\ max[300, 350]];\ m(S12_{MU}) = m(S1_{MU}) * m(S2_{MU})$
$S12_{LU} = [min[200, 220],\ max[280, 300]];\ m(S12_{LU}) = m(S1_{LU}) * m(S2_{MU})$
$T12_{MU} = [min[10, 24],\ max[20, 25]];\ m(T12_{MU}) = m(T1_{MU}) * m(T2_{MU})$
$T12_{LU} = [min[13, 17],\ max[19, 22]];\ m(T12_{LU}) = m(T1_{LU}) * m(T2_{MU})$
Then:
$S12_{MU} = [170, 350];\ m(S12_{MU})$
$S12_{LU} = [200, 330];\ m(S12_{LU})$
$T12_{MU} = [10, 25];\ m(T12_{MU})$
$T12_{LU} = [13, 22];\ m(T12_{LU})$
Then:
$ST1_U = S12_{MU} = [170, 350];\ m_{norm}(S12_{MU}), S12_{LU} = [200, 330];\ m_{norm}(S12_{LU});$
$T12_{MU} = [10, 25];\ m_{norm}(T12_{MU}), T12_{LU} = [13, 22];\ m_{norm}(T12_{LU})$

4 Experiments

Our area of interest is Chad. In fact, this country suffers from frequent floods. These floods cause displacement of residents and loss of life and material damage in several areas, especially those located on the shores of Lake Chad Or those crossed by the Logone or Chari rivers.

Floods are uncertain spatio-temporal events. Estimating when the flood occurred and the area affected by the flood (the extent of the flood) is not obvious enough. This is why we use Remote sensing technology and data derived from satellite imagery.

The extent of the flood is created by detecting changes in Sentinel-1 (SAR) data. To do this, we use different satellite images. These images are obtained by determining time intervals and not time points before and after the flood. In fact, this allows selecting a sufficient number of tiles to cover the area of interest. These intervals are of the form:
$< Before\_start,\ Before\_end;\ After\_start,\ After\_end >$.

In this work we are only interested in the area of the flood extent. At this point, our goal is to estimate the area of flood extent in 2015 based on the information extracted from these images (those from 2016 to 2021). This means that these images will be our source of information.

These information indicated that:
1) The most flood events occurred during the month of August with a mass equal to $0, 57$, and the remaining events occurred during the months of June, July and September with a mass equal to $0, 43$. Thus, August is the most certain time interval for a flood event to occured in 2015, with $m([01/08/2015 - 31/08/2015]) = 0, 57$ and $m([01/06/2015 - 31/09/2015]) = 0, 43$.

2) Most of the floods events affected between 150000 hectares and 450000 hectares with a mass equal to $0, 71$, and the remaining events affected either less than 150000 hectares or more than 450000 hectares with a mass equal to $0, 29$. Thus, We can estimate the extent of the flood that occurred in 2015 with $m([150000 - 450000]) = 0.71$ and $m([100000 - 700000]) = 0, 29$.

In this work and in order to have more relevant information on the extent and date of the flooding in 2015, a second source of information will be used. This second source is a database of floods that occurred in Chad between 2012 and 2015.

The information in this database indicated that:
1) The most flood events occurred during the month of August with a mass equal to $0, 68$, and the remaining events occurred during the months of July, September and October with a mass equal to $0, 32$. Thus, August is the most certain time interval for a flood event to occur, with $m([01/08/2015 - 31/08/2015]) = 0.68$ and $m([01/07/2015 - 31/10/2015]) = 0.32$.
2) Most of the floods affected between 100000 and 500000 hectares, and the remaining events affected either less than 100000 hectares or more than 500000 hectares. Thus, We can estimate the extent of the flood that occurred in 2015 with $m([100000 - 500000]) = 0.53$ and $m([5000 - 800000]) = 0.47$.

So, we now have two spatio-temporal information about the uncertain flood event, provided by two different sources of information. According to the first source of information:
$ST1_U = \{S1_{MU} = [100000 - 700000],\ m(S1_{MU}) = 0, 29;$
$S1_{LU} = [150000 - 450000],\ m(S1_{LU}) = 0.71;$
$T1_{MU} = [01/06/2015 - 31/09/2015],\ m(T1_{MU}) = 0, 43;$
$T1_{LU} = [01/08/2015 - 31/08/2015],\ m(T1_{LU}) = 0, 57\}$
According to the second source of information:
$ST2_U = \{S2_{MU} = [5000 - 800000],\ m(S2_{MU}) = 0.47;$
$S2_{LU} = [100000 - 500000],\ m(S2_{LU}) = 0.53;$
$T2_{MU} = [01/07/2015 - 31/10/2015],\ m(T2_{MU}) = 0.32;$
$T2_{LU} = [01/08/2015 - 31/08/2015],\ m(T2_{LU}) = 0.68\}$

The relationship between the two outer spatial uncertain information is: $NTTP(S1_{MU}, S2_{MU})$
The relationship between the two inner spatial information is: $NTTP(S1_{LU}, S2_{LU})$
Then the relationship between the two spatial information is: $NTTP(S1_U, S2_U)$.
The relationship between the two outer temporal uncertain information is: $T1_{MU}\ O\ T2_{MU}$
The relationship between the two inner temporal uncertain information is: $T1_{LU}\ E\ T2_{LU}$
Then The relationship between the two temporal uncertain information is: $T1_{MU}\ O\ T2_{MU}$ with $m(O(T1_{MU}, T2_{MU})) = 0, 43$ or $T1_{LU}\ E\ T2_{LU}$ with $m(O(T1_{MU}, T2_{MU})) = 0, 57$

Since, the relationship between the two inner spatial information is: $NTTP(S1_{LU}, S2_{LU})$, then the similarity value can be calculated without measuring the length of the intersection between the intervals:
$Sim(S1_{LU}, S2_{LU}) = (1 + |S1_{LU}|/|S2_{LU}|)/2 = (1 + (450000 - 150000)/(500000 - 100000))/2 = 0.875$
Since, the relationship between the two inner temporal information is: $T1_{LU}\ E\ T2_{LU}$, then the similarity value can be inferred directly:

$Sim(S1_{LU}, S2_{LU}) = 1$
We note that we have a strong belief in inner intervals, so, we can overlook the external intervals' similarity and say that $ST1_U$ and $ST2_U$ are thought to be quite comparable events.

Since, the events' similarity is assessed and they appear to be considerably similar, then a merger or combination of events could be considered.
$ST1_U = \{S1_{MU} = [100000-700000],\ m(S1_{MU}) = 0,29;\ S1_{LU} = [150000-450000],\ m(S1_{LU}) = 0.71;$
$T1_{MU} = [01/06/2015 - 31/09/2015],\ m(T1_{MU}) = 0,43;\ T1_{LU} = [01/08/2015 - 31/08/2015],\ m(T1_{LU}) = 0,57\}$
and
$ST2_U = \{S2_{MU} = [5000-800000],\ m(S2_{MU}) = 0.47;\ S2_{LU} = [100000-500000],\ m(S2_{LU}) = 0.53;$
$T2_{MU} = [01/07/2015 - 31/10/2015],\ m(T2_{MU}) = 0.32;\ T2_{LU} = [01/08/2015 - 31/08/2015],\ m(T2_{LU}) = 0.68)\}$
therefore:
$S12_{MU} = [min[100000, 5000],\ max[700000, 800000]];\ m(S12_{MU}) = m(S1_{MU}) * m(S2_{MU}) = 0.29 * 0.47$
$S12_{LU} = [min[150000, 100000],\ max[450000, 500000]];\ m(S12_{LU}) = m(S1_{LU}) * m(S2_{MU}) = 0.71 * 0.53$
$T12_{MU} = [min[01/06/2015, 01/07/2015],\ max[31/09/2015, 31/10/2015]];\ m(T12_{MU}) = m(T1_{MU}) * m(T2_{MU}) = 0.43 * 0.32$
$T12_{LU} = [min[01/08/2015, 01/08/2015],\ max[31/08/2015, 31/08/2015]];\ m(T12_{LU}) = m(T1_{LU}) * m(T2_{MU}) = 0.57 * 0.68$
Then:
$S12_{MU} = [5000, 800000];\ m(S12_{MU}) = 0,1363$
$S12_{LU} = [100000, 500000];\ m(S12_{LU}) = 0,3763$
$T12_{MU} = [01/06/2015, 31/10/2015];\ m(T12_{MU}) = 0,1376$
$T12_{LU} = [01/08/2015, 31/08/2015];\ m(T12_{LU}) = 0,3876$
Then:
$ST1_U = \{S12_{MU} = [5000, 800000];\ m_{norm}(S12_{MU}) = 0.38,$
$S12_{LU} = [100000, 500000];\ m_{norm}(S12_{LU}) = 0.62;$
$T12_{MU} = [01/06/2015, 31/10/2015];\ m_{norm}(T12_{MU}) = 0.375,$
$T12_{LU} = [01/08/2015, 31/08/2015];\ m_{norm}(T12_{LU}) = 0,625\}$

The combined spatio-temporal information estimates that the date of the uncertain flood event is during the month of August 2015 with a degree of certainty equal to 0.62 and that the extent of the flood is between 100000 and 500000 hectares with a certainty equal to 0.625. Which is really true, in fact, according to the database, a flood event happened on 30/08/2015 and the extent of this flood is evaluated at 118000 hectares.

5 Conclusions

Since the flood is an event with spatial and temporal uncertainties, we propose in this paper a novel approach based on belief function theory to represent and manage the combined

spatio-temporal uncertainty of a flood. Belief function theory is chosen because it is an ideal solution for modeling and quantifying non-specific uncertainty and because of the combining rules that allow merging information from multiple sources.
In our approach, spatial, temporal and spatio-temporal information are represented with intervals. Each interval consists of a more certain inner part and a more uncertain outer part. In fact, this interval structure provides considerable flexibility for the representation of subjective uncertainty. The degree of the belief on each part is expressed by means of a mass function.
In this work, the relationships between uncertain flood events are deduced based the relationships between spatial and temporal information and their corresponding mass. These relationships are useful for the analysis and evaluation of flood events.
Our proposed approach also provides some similarity measurement rules that allow to compare the similarity of flood events and then help to make a judgment or decision.
If the events' similarity is assessed and information from multiple sources appear to be considerably similar, then a combination of flood events could be considered. The purpose of the combination operation is to obtain more reliable information about the uncertain flood event.
The proposed approach for modeling and managing uncertain floods were conducted at the Chad site. Chad was chosen as our area of interest because of the frequent floods that sweep the country and cause displacement of residents and loss of life and material damage. Sentinel-1 images and information from a database are used in our experiments. The experimental results prove the effectiveness of the proposed approach. It shows also how coupling Dempster-Shafer approach with qualitative relationships offers a useful solution for modeling and managing spatio-temporal uncertainty of flood events.
As future work, first, we plan to more rigorously address the similarity of flood events part. For example, according to our approach, if the relation between two flooding events is disconnected or meets, then their degree of similarity is 0 although the meets relation seems to reflect a small similarity between the events because their distance contrary to the disconnected relationship is zero. This notion of distance is therefore to be taken into consideration for our future work. Then, we plan to extend our proposed approach for the 2-dimensional (2D) problem.

References

Allen, J. F. (1983). Maintaining knowledge about temporal intervals. *Communications of the ACM 26*(11), 832–843.

Cai, S., J. Fan, and W. Yang (2021). Flooding risk assessment and analysis based on gis and the tfn-ahp method: a case study of chongqing, china. *Atmosphere 12*(5), 623.

Chehibi, M., M. Chebbah, and A. Martin (2018). Independence of sources in social networks. In *International Conference on Information Processing and Management of Uncertainty in Knowledge-Based Systems*, pp. 418–428. Springer.

Das, S. (2020). Flood susceptibility mapping of the western ghat coastal belt using multi-source geospatial data and analytical hierarchy process (ahp). *Remote Sensing Applications: Society and Environment 20*, 100379.

Dempster, A. P. (1967). The annals of mathematical statistics. *Upper and Lower Probabilities Induced by a Multivalued Mapping 38*, 325–339.

Dubois, D. (1988). Théorie des possibilités; applications a la représentation des connaissances en informatique. Technical report.

Goguen, J. (1973). La zadeh. fuzzy sets. information and control, vol. 8 (1965), pp. 338–353.- la zadeh. similarity relations and fuzzy orderings. information sciences, vol. 3 (1971), pp. 177–200. *The Journal of Symbolic Logic 38*(4), 656–657.

Ha, H., C. Luu, Q. D. Bui, D.-H. Pham, T. Hoang, V.-P. Nguyen, M. T. Vu, and B. T. Pham (2021). Flash flood susceptibility prediction mapping for a road network using hybrid machine learning models. *Natural hazards 109*(1), 1247–1270.

Hu, S., Y. Fan, and T. Zhang (2020). Assessing the effect of land use change on surface runoff in a rapidly urbanized city: A case study of the central area of beijing. *Land 9*(1), 17.

Kurte, K., A. Potnis, and S. Durbha (2019). Semantics-enabled spatio-temporal modeling of earth observation data: An application to flood monitoring. In *Proceedings of the 2nd ACM SIGSPATIAL International Workshop on Advances on Resilient and Intelligent Cities*, pp. 41–50.

Merwade, V., F. Olivera, M. Arabi, and S. Edleman (2008). Uncertainty in flood inundation mapping: current issues and future directions. *Journal of Hydrologic Engineering 13*(7), 608–620.

Miau, S. and W.-H. Hung (2020). River flooding forecasting and anomaly detection based on deep learning. *IEEE Access 8*, 198384–198402.

Moreira, L. L., M. M. de Brito, and M. Kobiyama (2021). A systematic review and future prospects of flood vulnerability indices. *Natural Hazards and Earth System Sciences 21*(5), 1513–1530.

Randell, D. A., Z. Cui, and A. G. Cohn (1992). A spatial logic based on regions and connection. *KR 92*, 165–176.

Shafer, G. (1976). *A mathematical theory of evidence*, Volume 42. Princeton university press.

Shen, X., D. Wang, K. Mao, E. Anagnostou, and Y. Hong (2019). Inundation extent mapping by synthetic aperture radar: A review. *Remote Sensing 11*(7), 879.

Zadeh, L. A. (1978). Fuzzy sets as a basis for a theory of possibility. *Fuzzy sets and systems 1*(1), 3–28.

Zhang, Y., Y. Wang, Y. Chen, Y. Xu, G. Zhang, Q. Lin, and R. Luo (2021). Projection of changes in flash flood occurrence under climate change at tourist attractions. *Journal of Hydrology 595*, 126039.