Combining Decision Fusion and Uncertainty Propagation to Improve Land Cover Change Prediction in Satellite Image Databases

Wadii Boulila[1], Imed Riadh Farah[1], Karim Saheb Ettabaa[1], Basel Solaiman[2]
[1]Laboratoire RIADI
Ecole, Nationale des Sciences de
l'Informatique
Tunisia
[2]Laboratoire ITI
TELECOM-Bretagne
France
{Wadii.Boulila, karim.sahebettabaa}@riadi.rnu.tn, riadh.farah@ensi.rnu.tn, Basel.Solaiman@telecombretagne.eu

ABSTRACT: *The interpretation of remotely sensed images in a spatiotemporal context is becoming a valuable research topic. It helps predicting future trends and behaviors, allowing remotely sensed users to make proactive and knowledge-driven decisions. These decisions are useful for urban sprawl prevention, estimation of changes regarding productivity, and planting status of agricultural products, etc. However, the process of change prediction is usually characterized by several types of imperfection, such as uncertainty, imprecision, and ignorance. Fusion of several decisions about changes helps improve the change prediction process and decrease the associated imperfections. In this paper, we propose to use an adaptive possibility fusion approach to take into account the reliability of each change decision. This reduces the inuence of unreliable information and thus enhances the relative weight of reliable information. Decisions about changes are obtained by applying previous works and represented as spatiotemporal trees. These trees are combined to obtain more accurate and complete ones. In addition, an uncertainty propagation module is developed to estimate the uncertainty in the output of the knowledge fusion module from the uncertainty in the inputs. This helps us to identify robust conclusions. The proposed approach is validated using SPOT images representing the Saint-Denis region, capital of Reunion Island. Results show good performances of the proposed approach in predicting change for the urban zone in the Saint-Denis region.*

Keywords: Adaptive Possibility Fusion, Land Cover Change Prediction, Decision Fusion, Satellite Images

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1. Introduction

Land cover change is an important subject in global environmental change [16] [18][17].

Modeling land cover change helps analyzing causes and consequences of land change in order to support land cover planning and policy. It also allows the exploration of future land cover changes under different scenario.

Several studies have been devoted to modeling land cover changes. The commonly used models for estimating land cover changes are: analytical equation-based models [10], statistical models [15], evolutionary models [1], cellular models [14], multi-agent models [2], hybrid models [16], Markov models [13], and expert system models [20].

However, most studies considering the issue of predicting land cover changes focus on predicting change in terms of analytical equation, statistical, evolutionary, cellular, multiagent, hybrid based models, or Markov models. Although these models offer a powerful mathematic framework, modeling imperfection related to the process of predicting land cover changes is not well considered in these models. Imperfection can be of various forms such as imprecision, uncertainty, ambiguity, incompleteness, unreliability, conflict, ignorance, etc. It can be related to data (series of satellite images), processing methods (methods of processing image, methods of prediction, etc.) or interpretation of results.

Modeling a source of imperfection means to assign a mathematical structure to the imperfection. In literature, several methods are proposed to model imperfection such as the probability, the possibility and the evidence methods.

In previous works, the issue of land cover change prediction is discussed [5] [8]. A soft-computing method based on a fuzzy data mining process is proposed. The combination of the two concepts (fuzzy logic and data mining) offers potential for mapping and understanding environmental changes.

They can be used for several fields such as disaster prevention and monitoring, planting status of agricultural products, and tree distribution of forests. An application of the proposed approach is to follow the eects of urban sprawl in the Reunion Island [8].

In previous works, we explain how the proposed approach allows building spatiotemporal change trees which depict changes of a particular land cover type [8] [9]. However, each spatiotemporal change tree depicts a partial view about changes for a particular land cover type. Combining these trees can help improve the prediction of land cover changes and decrease the associated imperfections. It provides potential advantages over using a single tree in terms of change prediction accuracy.

In this paper, we investigate the issue of combining several spatiotemporal change trees to provide more accurate decisions about land cover changes. Tree combination is ensured by an adaptive possibility fusion method. Fusion is applied at the decision level and aims to integrate the reliability of each change tree in the fusion process. This reduces the influence of unreliable information and thus enhances the relative weight of reliable tree in the change prediction process.

Another important issue addressed in this paper is the uncertainty propagation or uncertainty analysis. The goal of the uncertainty propagation module is to estimate the uncertainty in the output of the knowledge fusion module from the uncertainty in the inputs. This helps us to identify robust conclusions. Indeed, structural assumptions or parameters are systematically varied to discover the degree to which conclusions depend on uncertain inputs of knowledge fusion module.

In this paper, we start by presenting a review of the spatiotemporal change tree. Then, we propose our approach for fusing spatiotemporal change trees. Later on, we describe the uncertainty propagation module. We conclude our paper with a validation section which depicts a real-world application and an interpretation of the results.

2. The Proposed Approach

2.1 Review of the spatiotemporal change tree

Let us suppose that we have an object *obj* extracted from a satellite image acquired at a date *t* using previous work [7]. *Obj* can be a lake, vegetation zone, urban area, etc. In [7], ve types of features (radiometry, geometry, texture, spatial relations and acquisition context) are used to identify objects extracted from satellite images. Each feature is described through a set of attributes A_i $(1 \leq i \leq N)$. At a given date, the set of attribute values of an object *obj* defines the state of this object. In the proposed approach, a model M_p is composed by a set of states representing, each one, the same object but at a different date. For example, in the equation (1), the state S_{t_1} represents the object *obj* at the date t_1 whereas the state S_{t_2} represents the object *obj* at the date t_2. Equation (1) presents the form of a model M_p (equation (1), left part) and the form of a state (equation (1), right part). Here, the model M_p is composed by *n* states describing each one the object *obj* at *n* different dates.

$$M_p = \begin{pmatrix} t_1 \begin{pmatrix} A_1 \\ A_2 \\ \vdots \\ A_N \end{pmatrix} = S_{t_1} \\ t_2 \begin{pmatrix} A_1 \\ A_2 \\ \vdots \\ A_N \end{pmatrix} = S_{t_2} \\ \vdots \\ t_n \begin{pmatrix} A_1 \\ A_2 \\ \vdots \\ A_N \end{pmatrix} = S_{t_n} \end{pmatrix}, S_{t_i} = \begin{pmatrix} A_1 \\ A_2 \\ \vdots \\ A_N \end{pmatrix} \tag{1}$$

Let us suppose that we have a spatiotemporal change tree obtained by previous works [8]. The spatiotemporal tree depicts changes of the object *obj* between two dates *t* and *t'*.

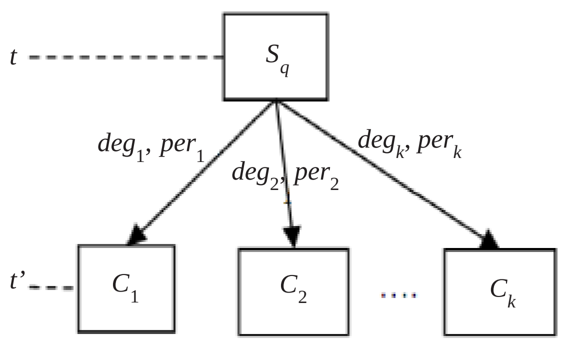


Figure 1. The spatiotemporal change tree of the S_q state between *t* and *t'*

Figure 1 shows the spatiotemporal change tree of a state S_q between two dates *t* and *t'*.

Where

S_q denotes the state relative to *obj* at the date *t* (S_q is the set of attributes identifying *obj* at the date *t*). C_1, C_2,..., C_k are the possible land cover types to which the object *obj* can evolve.

per_1, per_2 ,..., per_k are respectively the percentages of changes of the state S_q to C_1, C_2,..., C_k.
deg_1, deg_2,..., deg_k are respectively the condence degrees of changes of the state S_q to C_1, C_2,..., C_k.

The proposed approach generates for the object obj a set of spatiotemporal change trees. Each one provides a partial view about changes made throughout time for *obj*. A condence degree conf is accorded to each tree to illustrate its reliability in describing changes of *obj*.

2.2 The knowledge fusion module

In the proposed approach, the fusion step is applied at the decision level. In fact, the use of possibility theory fits with our needs. This approach is used to model either uncertain or imprecise information through the use of possibility degrees [12]. The knowledge fusion module allows handling imperfections related to the KDD process. Let $D = \{C_1, C_2,..., C_n\}$ be the set of possible decisions; C_r ($1 \leq r \leq n$) representing the possible land cover types to which a query state can evolve. Information is modeled by a possibility distribution, i.e., the degree of possibility that the land cover type to which S_q evolves is C_r when referring to a particular change tree *i* [4]. Here, each spatiotemporal change tree has a confidence degree (also known as a reliability degree). The need of an adaptive fusion seems to be necessary to take into account the reliability of each change tree. This reduces the influence of unreliable information and thus enhances the relative weight of reliable information.

To better explain the fusion concept, let us consider that a query state S_q (at date t) is similar to S_1 with 0.95 at a date t_1' and to S_2 with 0.9 at a date t_1'' .

Let us also suppose that S_1 evolves to C_1, C_2 and C_3 at a date t_2' and S_2 evolves to C_1 and C_2 at a date t_2''. Here, t_2''- t_1''= t_1'- t_1'.

We obtain the following transition trees:

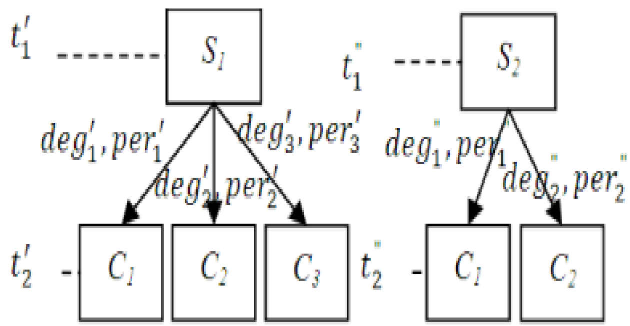


Figure 2. Examples of Spatiotemporal Models Change

The degree of confidence accorded to the first tree (figure 2, left part) is 0.95, whereas, the confidence degree accorded to the second tree (figure 2 right part) is 0.9.

The focus of the knowledge fusion module is to provide a spatiotemporal tree which results from combining the two trees in Figure 3 and which depicts global changes of the query state S_q.

Figure 3 depicts the spatiotemporal change of the state S_q between two dates t and t'; where t is the present date of the query state S_q and $t' = t + t_2' - t_1'$.

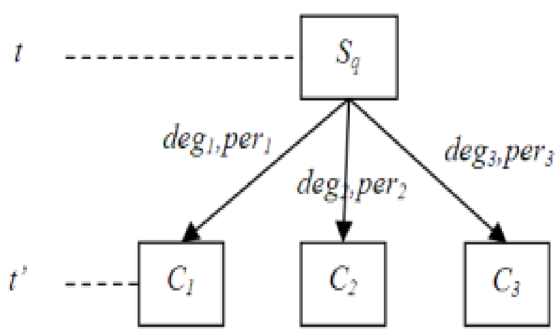


Figure 3. The Resulting Spatiotemporal Change Tree

The main challenge is to determine confidence degrees and percentages of changes for the query state S_q. *m* fuzzy sets are computed for the query state S_q as follow [12]:

$$\{\pi_1(S_q), \pi_2(S_q), ..., \pi_i(S_q), ..., \pi_m(S_q)\} \quad (2)$$

$\pi_i(S_q)$ is the membership degree of a state S_q to class C_r according to the decision tree *i*. As previously mentioned, the proposed approach generates for the object *obj* a set of spatiotemporal change trees. Each one provides a partial view about changes made throughout time for *obj*. By applying the adaptive possibility theory, we can combine confidence degrees (respectively percentages of changes) and therefore obtain a global decision about changes for *obj*. For the example in figure 3, let us suppose that $\pi_1^{lake}(S_1) = deg_1'$, $\pi_1^{urban}(S_1) = deg_2'$, $\pi_1^{vegetation}(S_1) = deg_3'$, $\pi_2^{lake}(S_2) = deg_2''$ and $\pi_2^{urban}(S_2) = deg_3''$, and the percentage of changes while considering that $\pi_1^{lake}(S_1) = per_1'$, $\pi_1^{urban}(S_1) = per_2'$, $\pi^{vegetation}(S_1) = per_3'$, $\pi^{lake}(S_2) = per_2''$, and $\pi^{urban}(S_2) = per_2''$.

The adaptive combination rule used in this paper is given as follow:

$$\pi_f^{C_r} = max\left(min\left(\omega_i \pi_i^{C_r}\left(S_q\right), f_i^{C_r}\left(S_q\right), 1 \le i \le m\right)\right) \tag{3}$$

Where $f_i^{C_r}$ is the global confidence of the change tree *i* for the land cover type C_r. ω_i is the normalization factor defined in equation (4). According to [12], this combination rule ensures that only reliable sources are taken into account for each class.

$$\begin{cases} \omega_i = \dfrac{\sum_{k=1,k\neq i}^{m} H_{\alpha QE}\left(\pi_k\right)}{\left(m-1\right)\sum_{k=1}^{m} H_{\alpha QE}\left(\pi_k\right)} \\ \sum_{i=1}^{m} \omega_i = 1 \end{cases} \tag{4}$$

where $H_{\alpha QE}(\pi_k)$ is the fuzziness degree of the spatiotemporal change tree *i*, $\pi_k = \{\pi_k^{C_r}, r = 1 \ldots n\}$. In the current example, the number of spatiotemporal change trees to combine is 2. According to [12], α ($\alpha = 0.5$) is a selective parameter. It allows having fuzzy sets with approximately the same degree of possibility or with different degrees. The fuzziness degree $H_{\alpha QE}(\pi_k)$ is defined as follow:

$$\begin{cases} H_{\alpha QE}\left(\pi_k\right) = \frac{1}{n}\sum_{r=1}^{n} S_{\alpha QE} Q\left(\pi_k^C\left(S_q\right)^{\alpha} \pi_k^C\left(S_q\right)\right) \\ S_{\alpha QE}\left(\pi_k^C\left(S_q\right)\right) = \dfrac{\pi_k^C\left(S_q\right)^{\alpha}\left(1-\pi_k^C\left(S_q\right)\right)^{\alpha}}{2^{-2\sigma}} \end{cases} \tag{5}$$

Decisions in the possibilitic approach are usually taken using the maximum possibility degree given by the following equation:

$$S_q \in C_r if\, \pi_f^{C_r}\left(S_q\right) = max\left\{\pi_f^{C_j}\left(S_q\right), 1 \le j \le r\right\} \tag{6}$$

2.3 The uncertainty propagation module

As we note previously, the proposed approach aims to model either uncertain or imprecise information through the use of the adaptive possibility method. However, the propagation of the input uncertainties through the proposed approach is not discussed. Thus, we propose to develop an hybrid methodology for uncertainty propagation. This methodology combines probability and fuzzy theories to propagate uncertain and imprecise information. The goal of the uncertainty propagation module is to estimate the uncertainty in the output of the knowledge fusion module from the uncertainty in the inputs (Figure 4). Parameters in the input of the knowledge fusion module are:

1) *per* (the percentages of changes of the state S_q to the different land cover types) and *deg* (the condence degrees of changes of the state S_q to the dierent land cover types) of each change tree.

In this paper, let us assume that an output parameter *per* is a function of several input parameters per_i (same thing can be done while considering by instead of *per deg*). Let also assume that $k < n$ random parameters (per_1,..., per_k) taking values (PER_1,...,PER_K) and possibilistic parameters (per_{k+1},...,per_n) taking values (PER_{k+1},...,PER_n) represented by possibility distributions ($\pi^{PER_{k+1}}$,...,π^{PER_n}).

In order to propagate uncertainties and imprecisions pervading the parameters $(per_i)_{i=1,\ldots,n}$ through the knowledge fusion module (denoted by F), height steps are adopted [3].

These steps are summarized as follows:

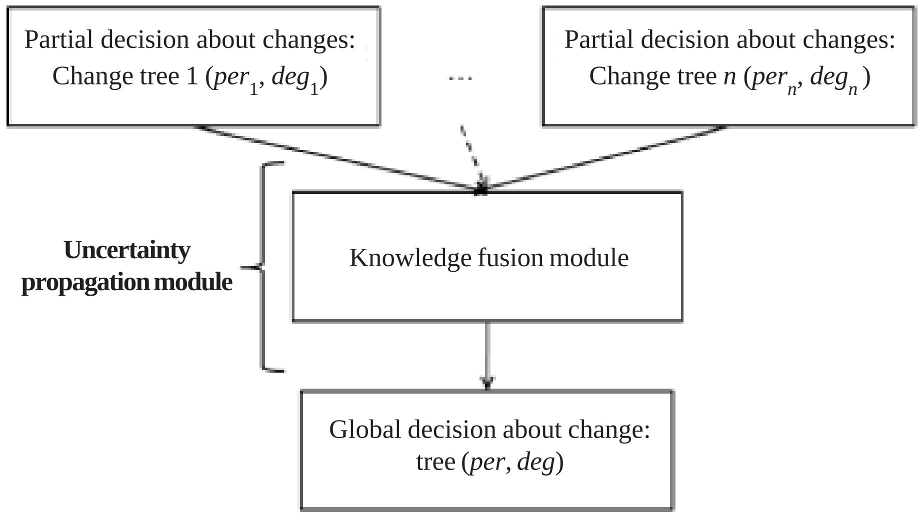


Figure 4. Position of the uncertainty propagation module

1. Generate k random numbers ($p_1,..., p_k$) from a uniform distribution on [0,1] taking account dependencies and sample the k PDF (Probability Distribution Functions) to obtain a realization of the k random variables ($per_1,..., per_k$).

2. Select a possibility degree and the corresponding cut as the selected interval.

3. Calculate the *Inf* (smallest value) and *Sup* (largest value) of F ($per_1,..., per_k, per_{k+1},..., per_n$), considering all values located within the α-cuts for each possibility distribution.

4. Assign the *Inf* and *Sup* values to the lower and upper limits of the α-cuts of F ($per_1,..., per_k, per_{k+1},..., per_n$).

5. Return to step 2) and repeat steps 3) and 4) for another-cut. The fuzzy result of F ($per_1,..., per_k, per_{k+1},..., per_n$) is obtained from the *Inf* and *Sup* values of F($per_1,..., per_k, per_{k+1},..., per_n$) for each α-cut. In this paper, is increased from 0 to 1 by step 0.1.

6. Return to step 1) to generate a new realization of the random variables. A family of fuzzy numbers ($\pi_1^F,..., \pi_m^F$) is obtained.

7. Identify focal elements: ranges of values obtained bycutting each fuzzy result.

8. Define the masses of probability to assign to each focal element.

3. Validation

The proposed approach is validated on a set of images representing the Saint-Denis region, located within the northeastern Reunion Island in the Indian Ocean, east of Madagascar (Figure 4).

Satellite image used in this study come from the SPOT-5 satellite and belong to the Kalideos[1] database set up by the CNES[2].

The validation section is divided into two parts: 1) evaluation of the role of the fusion module in improving the prediction of land cover changes. This module allows reducing imperfection related to the prediction of land cover changes and therefore giving accurate results for better decision making. 2) uncertainty propagation through the fusion module. This helps to propagate input uncertainties and to know which of the uncertain input sources contribute the most to the output uncertainty.

3.1 Knowledge fusion

Figure 5 represents a satellite image representing the the Saint-Denis region acquired on July 06, 2002.

[1]http://kalideos.cnes.fr

[2]Centre National d'Etudes Spatiales (French Space Agency)

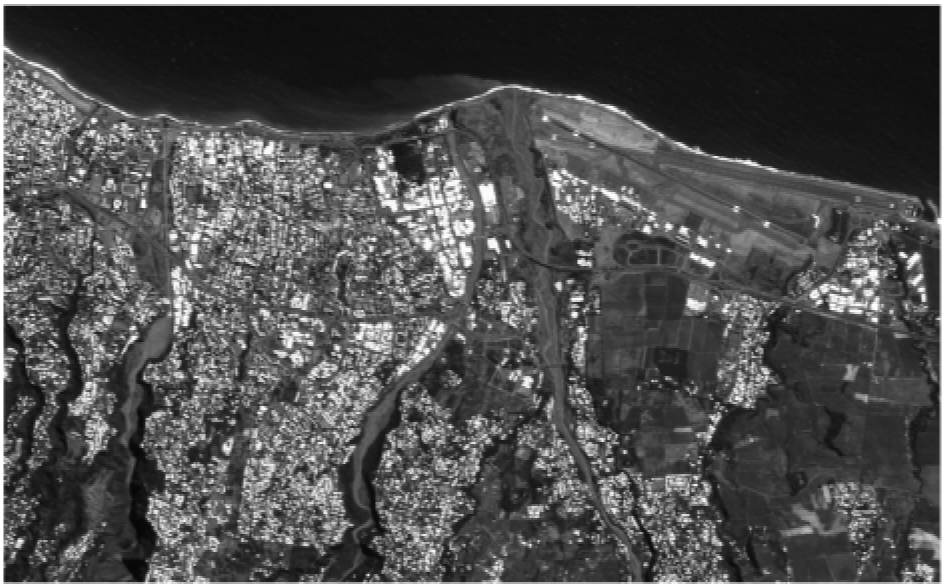


Figure 5. Satellite image acquired on July 06, 2002

Let us suppose that a query object representing the urban site is extracted after the segmentation of the satellite image (Figure 5) using previous work (Figure 6) [7].

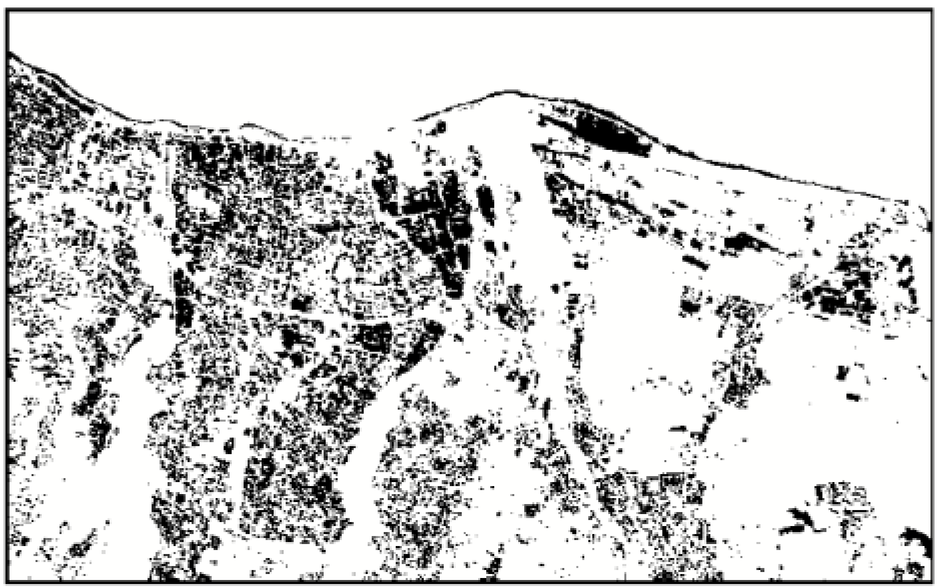


Figure 6. “*Urban*” object extracted from the classified image acquired on July 06, 2002

Let also suppose that urban changes between the date 2002 and a date 2009 are computed using previous work [8]. The process of predicting changes allows the generation of spatiotemporal change trees for urban site between 2002 and 2009 as shown in figure 1.

Table 1 presents percentages of the urban changes and confidences degrees accorded to these changes on 2009. Here, ten change trees are presented. Each one depicts a partial view about changes made throughout time for the urban site on 2009. A confidence degree *conf* is accorded to each tree.

The goal of the fusion module is to apply the adaptive possibility fusion method to combine percentages of changes and confidence degrees of the ten change trees. Table 2 presents these percentages of changes and confidence degrees. They describe urban changes between 2002 and 2009 to lake, vegetation, bare soil, forest and urban.

		C1	C2	C3	C4	C5	conf
CT1	per	0.05	4.2	6.56	19.17	70.02	99.83
	deg	84.82	81.15	90.5	67.81	88	
CT2	per	0.1	2.71	10.12	15.34	71.73	99.71
	deg	71.04	79.93	52.34	85.61	90.80	
CT3	per	0	1.78	6.01	18.12	74.09	99.68
	deg	50.77	74.05	88.76	69.4	86.22	
CT4	per	0.06	4.29	9.12	13.57	72.96	99.54
	deg	85.75	77.96	65.75	78.05	95.08	
CT5	per	0.09	7.11	6.02	14.6	72.18	99.42
	deg	83.40	47.1	87.9	79.5	97.56	
CT6	per	0.02	6.21	7.1 1	7.91	68.76	99.17
	deg	81.57	46.03	92.87	60.11	60.23	
CT7	per	0.67	1.32	5.88	20.1	72.03	98.82
	deg	68.23	53.29	78.90	50.10	96.26	
CT8	per	0.37	2.65	5.9	14.05	77.03	98.66
	deg	70.64	83.27	88.5	79	72.55	
CT9	per	1.2	5.44	10.17	16.2	66.99	98.58
	deg	49.34	62.9	55.25	95.7	61.77	
CT10	per	0.94	3.9	5.85	8.98	80.33	98.35
	deg	53.21	91.1	84.34	58.03	48.90	

Table 1: Urban changes between 2002 and 2009 according to ten change trees (C1 = lake, C2 = vegetation, C3 = bare soil, C4 = forest,C5 = urban. $CTi_{i=1,...,10}$ is the change tree number *i*. conf is the confidence degree accorded to each change tree. *deg* are the confidence degrees of changes of the urban site to C1, C2, C3, C4, and C5. per are the percentages of changes of the urban site to C1, C2, C3, C4, and C5)

		C1	C2	C3	C4	C5
Proposed	per	0.68	2.54	8.77	16.25	71.76
changes	deg	86.38	82.03	84.31	94.80	93.89

Table 2. Urban changes between 2002 and 2009 after applying the fusion module (C1 = lake, C2 = vegetation, C3 = bare soil, C4 = forest,C5 = urban. deg is the confidence degrees of changes of the urban site to C1, C2, C3, C4, and C5. per are the percentages of changes of the urban site to C1, C2, C3, C4, and C5)

In order to evaluate performances of the fusion process in predicting urban changes, real changes based on an image presenting the same zone and acquired on March 21, 2009 (Figure 6) are computed.

Table 3 depicts real changes of the urban site between 2002 and 2009.

Figure 8 depicts a comparison between real changes, proposed changes (after applying the adaptive fusion of the ten change trees) and the tree estimating the best urban changes (CT1).

As we note, the proposed urban changes are the closest changes to the real ones. Error in predicting urban changes is equal to 4.36% for the proposed approach whereas is equal to 5.6% for CT1.

	C1	C2	C3	C4	C5
Real urban changes	0.08	3.74	7.19	16.83	72.16

Table 3. Real changes of the urban site between 2002 and 2009

Figure 7. Satellite image acquired on March 21, 2009

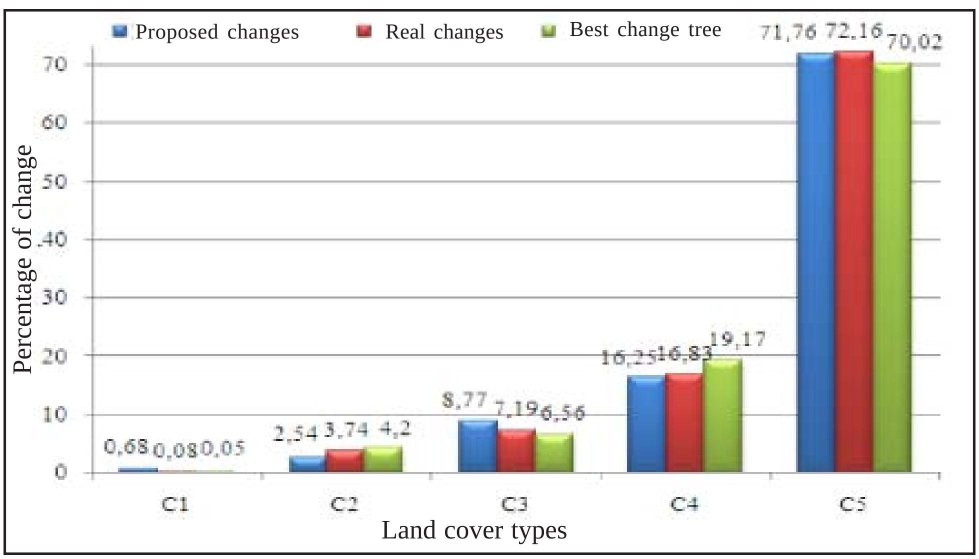


Figure 8. Comparison between real, proposed and best tree changes for the urban site between 2002 and 2009

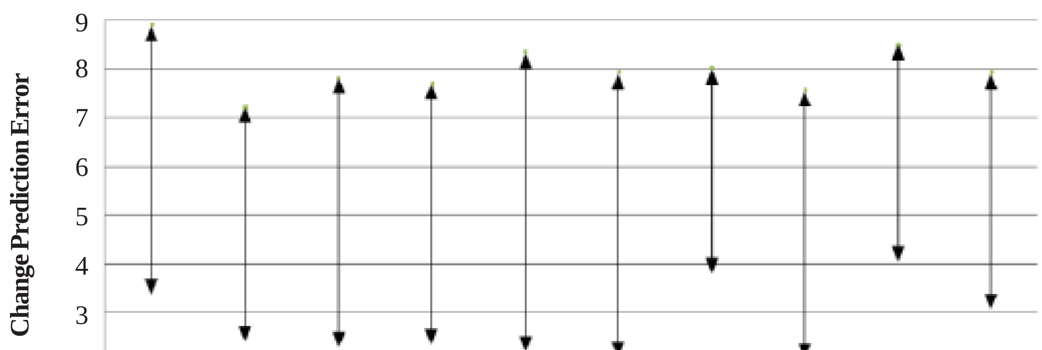
In order to better evaluate performances of the adaptive fusion method, 12 experiments are performed. Twelve different periods are considered. Predicted land cover changes for these 12 periods are estimated through the proposed approach. Then, real urban changes are evaluated based on images representing the same dates in each period. Table 4 depicts the error calculated between adaptive possibility method (1) and the tree estimating the close urban changes (2), and real urban changes for each period.

From the table 4, the number of time having the minimum of prediction error according to the 12 previous experiments can be discerned. The adaptive fusion method has 9 times minimum of error prediction for the water zone, 7 times for the forest zone, 6 times for the bare soil zone and 9 times both the vegetation and urban zones.

	Water		Forest		Bare soil		Vegetation		Urban	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
D1	6.77	4.73	4.13	7.69	2.67	3.73	6.12	5.74	4.15	3.16
D2	7.21	2.49	5.8	3.73	5	6.9	5.99	6.12	4.12	4.28
D3	4.33	7.11	4.7	7.33	6.06	7.91	6.78	6.06	5.55	3.66
D4	5.11	5.37	5.9	2.61	5.5	2.1	8.01	7.26	4.07	6.63
D5	6.62	3.92	2.91	2.39	6.75	6.92	4.5	2.08	4.9	3.88
D6	3.39	4.25	2.32	3.41	7.05	5.73	6.06	3.86	5.9	5.83
D7	3.39	4.25	2.32	3.41	7.05	5.73	6.06	3.86	5.9	5.83
D8	6.11	4.23	5.04	2.38	4.11	3.46	6.04	3.84	6.24	5.02
D9	7.02	2.44	4.08	3.59	8.33	6.93	7.6	7.56	6.88	7.69
D10	7.2	4.73	4.43	7.69	2.22	3.73	5.95	5.74	8.5	3.16
D11	5.2	4.7	7.1	7.29	3.62	4.03	4.61	7.1	8.24	5.98
D12	8.9	6.34	6.3	5.8	5.1	4.7 3.	82 3.	2	5.72	3.07

Table 4. Error for the prediction of land cover change for 12 period tests ((1) denotes the adaptive possibility method, (2) denotes the tree estimating the close urban changes and $Di_{i=1...12}$ denotes the Twelve experiments)

Figure 9 illustrates the minimum, mean and maximum values of the error rate in predicting land cover changes for the adaptive possibility method and the tree estimating the close urban changes for the twelve previous experiments.



	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2
	Water		Forest		Bare Soil		Vegetation		Urban	
Min Value	3, 39	2, 44	2, 32	2, 38	2, 22	2, 10	3, 82	2, 08	4, 07	3, 07
Mean Value	6, 31	4, 79	4, 72	5, 13	5, 18	5, 13	5, 95	5, 44	6, 02	5, 02
Max Value	8, 90	7, 21	7, 81	7, 69	8, 33	7, 91	8, 01	7, 56	8, 50	7, 92

Figure 9. The Min, Mean and Max values of the error rate in predicting land cover changes for the adaptive fusion method (M2) and the tree estimating the close urban changes (M1) for the 12 experiments

Figure 10 describes changes of the urban at the date 2009 to the five land cover types: water, forest, bare soil, non-dense vegetation and urban. The important changes are concerning the non-dense vegetation (yellow) and forest (green). These zones are considered as the best agricultural lands in the Reunion Island because of their accessibility and their productiveness. This needs an intervention of national authority to preserve these zones.

3.2 Uncertainty propagation

In order to evaluate the module of the uncertainty propagation, we consider the case of evaluating the percentages of changes of the urban between 2002 and 2009 to the five land cover types. The same work can be done in the case of the confidence degrees (*deg*).

Let us consider that $deg_j = F(deg_{ij}) 1 \le i \le m$ and $1 \le j \le k$. deg_{ij} are the confidence degrees of changes of the urban site to the land cover type C_j according to the change tree CT_i. They represent the uncertain inputs of the fusion module. deg_k are the confidence degrees of changes of the urban site to the land cover type C_j . They represent the output of the fusion module. The goal of this section is to propagate input uncertainties related to deg_{ij} and to know which input sources contribute the most to the output uncertainty.

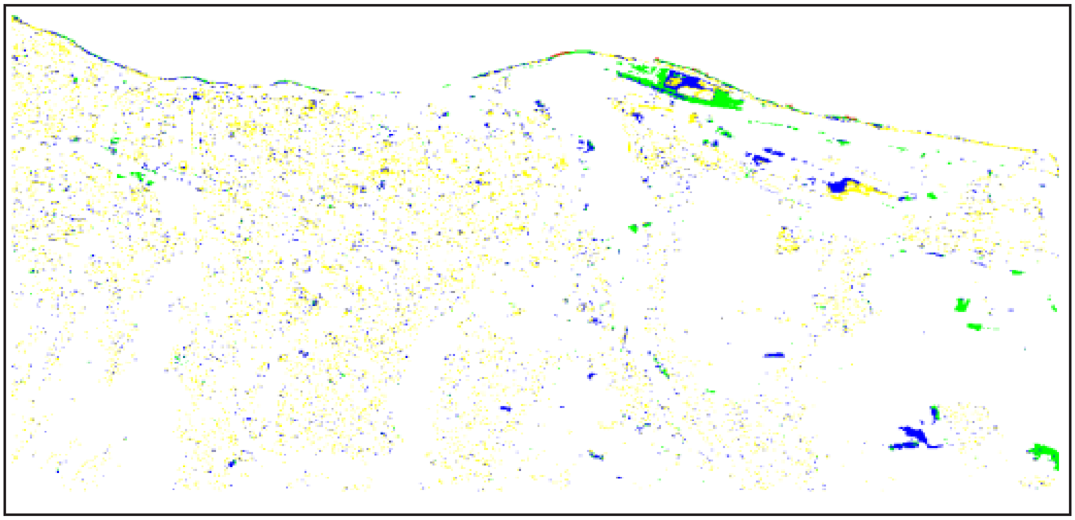


Figure 10. Urban changes between 2002 and 2009

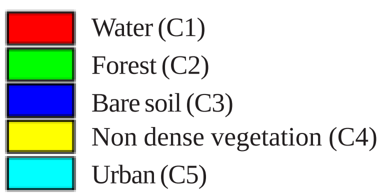


Figure 11. Land cover types

To determine the distributions of uncertain variables of the degrees of confidences, we conduct random sampling distributions using the Monte Carlo method [19].

In this paper, we use 1000 samples. Focal elements are obtained by using outer discretisation sampling and cutting each fuzzy result. Then, masses of probability are assigned to each focal element. Here, we take the case of 10 slices and a realization frequency which is a function of the number of iterations used in the Monte Carlo process equal to 1000.

The probability mass assigned to each interval is 1/10000 = 0.1*1/1000.

Figure 12 shows the prediction on belief and plausibility of the fusion module.

In addition, a sensitivity analysis is performed to see which inputs contribute most to overall uncertainty. Sensitivity is measured by reducing the input variable uncertainty and detecting the change in the overall uncertainty. In the proposed example, there are 10 inputs. The sensitivity analysis performed shows which decision tree requires more attention. As can be seen in Figure 13, the change trees CT3 and CT6 are the most involved trees in the overall output uncertainty.

4. Conclusion

Land cover change prediction is a challenging issue in the remote sensing field. It allows estimating changes that are useful for

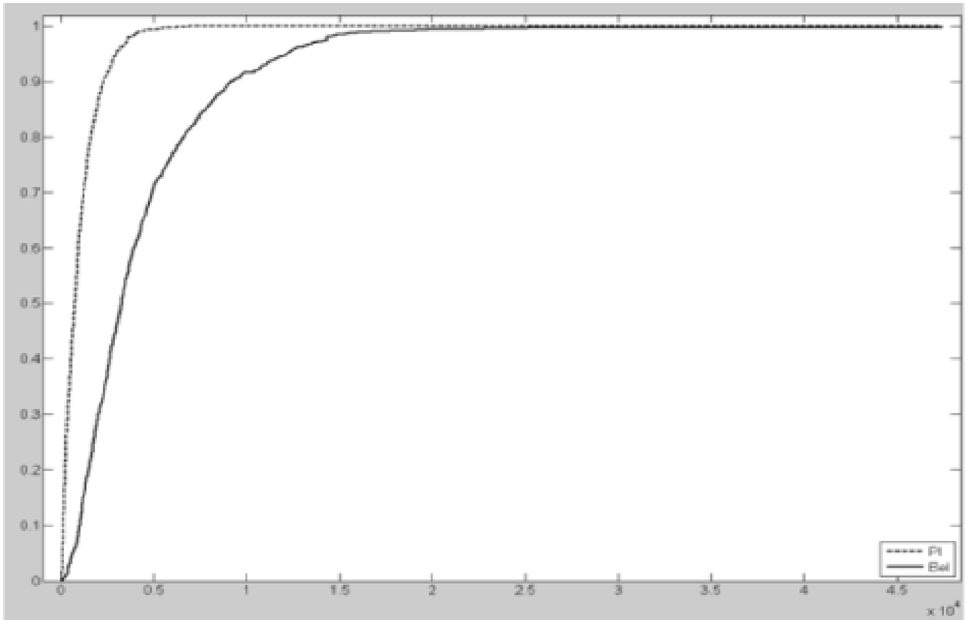


Figure 12. Behavior of the belief and plausibility functions

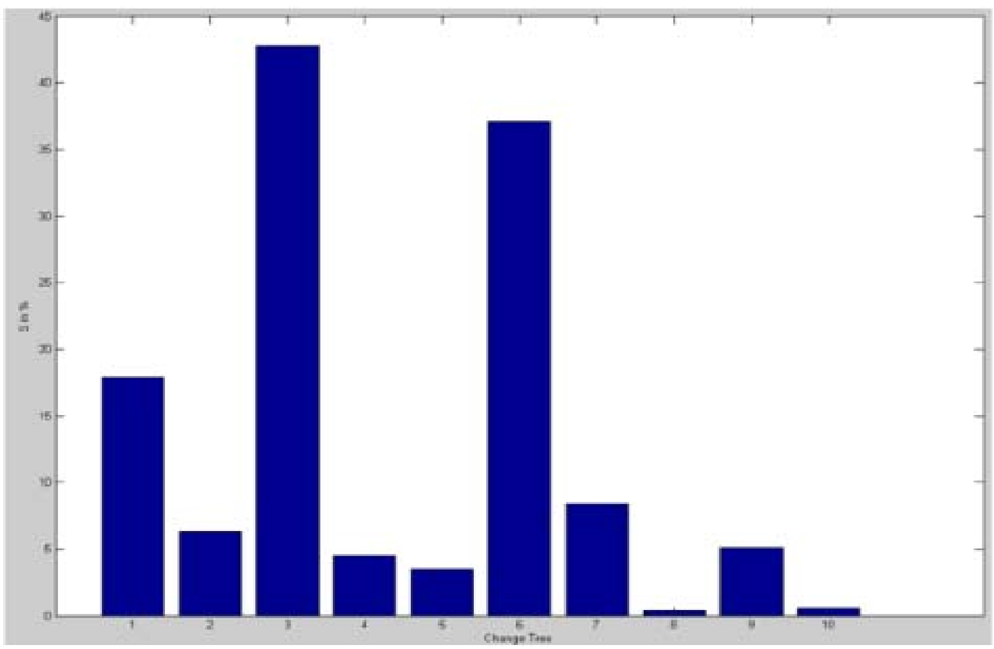


Figure 13. Contribution of the change trees in the overall output uncertainty

disaster prevention and monitoring, estimation of changes regarding productivity, planting status of agricultural products, and tree distribution of forests. However, making decisions related to land cover changes requires accurate predicted changes. In this paper, an approach for combining several predicted land cover changes is proposed. The proposed approach is based on an adaptive fusion method to take into account the reliability of partial land cover change decisions. It allows reducing imperfections related to the process of land cover change prediction.

In addition, an hybrid methodology for uncertainty propagation is developed. This methodology combines probability and fuzzy theories to propagate uncertain and imprecise information through the fusion module.

In order to evaluate the performances of the developed system, we compared proposed urban changes to real ones. Results show good performances of the proposed approach. As future works, we consider testing the proposed approach on several images of different domains such as medical one.

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