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Application of DSmT for Land Cover Change Prediction

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Abstract: *This chapter presents an environmental application of DSmT for the land cover prediction. The spatial prediction of land cover at the field scale in winter is useful to reduce the bare soils in agricultural intensive regions. Fusion process with the Dempster-Shafer theory (DST) proved to have limitations with the increase of conflict between the sources of evidence that support land cover hypotheses. Several modifications may be used such as source weighting or the hedging methods, but with no benefit in the considered case studied since the conflict may not explain by itself all the bad decisions. Actually, sources of evidence may induce all together a wrong decision. Then, it is necessary to introduce paradoxical information. Nevertheless, sources of evidence that are in use, are defined according to hypothesis "covered soil" or "bare soil" in the frame of DST. We investigate several points of view to define the belief assignments of the hyper-power set of the DSmT from the initial power set of DST. So, smart belief assignments induce a better prediction of bare soils.*

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17.1 Introduction

In intensive agricultural areas, water quality may be improved by reducing bare soil surfaces during the winter months. In this context, the knowledge of the spatio-temporal variations of the land use and cover as well as the spatial prediction of the land cover at the field scale appear essential for the issue of bare soils reduction. Land-cover prediction, that is useful for stakeholders that manage water-quality programs in focusing on the areas where the probability to find a bare soil is high, requires the identification and characterization of the driving factors of observed land-cover changes. The high variability of the driving factors that motivate land-cover changes between two successive winters induces the integration of uncertainty in the modelling of the prediction process.

Several short-term predictions have been simulated with the Dempster-Shafer (DS) theory in previous studies to assess land-cover distribution in winter on a relatively intensive farming watershed of 61.5km^2 [1]. This study area, located in western France, produces significant amounts of nitrogen before winter infiltration of water. Fusion process with the DS theory proved to have limitations with the increase of conflict between the sources of evidence that support land cover hypotheses. Several modifications may be used (such as source weighting or the Hedging methods) but with no benefit in our application. It appears that conflict may not explain by itself all the bad decisions. Actually, each sources of evidence may induce all together a wrong decision. Then, paradoxical information was introduced to improve the prediction accuracy.

A first application of the Dezert-Smarandache theory on the study area has pointed some results a little bit better than the DS, but the rate for the hypothesis "bare soil" was still inferior to 40% of good prediction. An improvement of the fusion process must be performed specially for this hypothesis. In this application, sources of evidence that are in use, are still defined according to hypothesis "Covered soil" or "Bare soil" in the frame of the Dempster-Shafer theory. Mass functions assignment determined from statistical analysis and expert knowledge are defined to support the hypotheses but the high level of conflict between sources requires a finest mass attribution and a "contextual" fusion process to manage the uncertainty and the paradoxical.

This chapter focuses on the application of the Dezert-Smarandache theory for the land-cover prediction in winter, and more precisely on the transfer from evidence to plausible and paradoxical reasoning. Our objective is to improve the land-cover prediction scores in investigating several points of view to define the belief assignments of the hyper-powerset of the Dezert-Smarandache theory from the initial powerset of the Dempster-Shafer theory. A first part concerns the identification and hierarchization of the driving factors that drive the land cover changes on the studied watershed for their transformation in pieces

of evidences for the selected working hypothesis. The other one presents the process of the land cover modelling with the Dezert-Smarandache theory comparatively to the Dempster-Shafer theory and its adaptation for this specific environmental study.

17.2 Determination of information sources

The land cover in winter has been classified from remote sensing images in two land cover categories, "Bare soil" and "Covered soil" that correspond to the two hypotheses of work. The determination of the information sources for each hypothesis for the fusion process consists in identifying and hierarchizing the factors that motivate the land cover changes between winters for the studied period (1996-2003).

17.2.1 Identification of the driving factors of land cover change

The land-cover changes between winters in intensive agricultural regions are characterized by an high spatio-temporal variability depending on factors of several origin (economical, social, political, physics constraints) that need to be carfully defined in the modelling process. The identification of the driving factors of land-cover changes requires to study the land use on a quite long period. A set of 10 satellite images (9 SPOT images and 1 IRS-LISS III —2 per year over 5 years since 1996—) has been acquired, pre-processed and classified. Winter land cover change trajectories were produced by merging successively all classifications [2]. All this data have been integrated in a GIS (Geographic Information System) to identify the crop successions spatially and the land-cover changes between winters on the field scale. A statistical analysis and a meeting with the agricultural experts provided four main driving factors of land-cover changes, namely the field size, the crop successions, the agro-environmental actions and the distance of the fields from farm buildings. All this factors explain the winter land-cover distribution in the categories "Bare soil" or "Covered soil". Then, a hierarchization of the identified driving factors of land-cover change was needed in the fusion process to predict the future land-cover (Mass belief assignment to the sources of evidence), to assess the respective "weight" of each explicative factors.

17.2.2 Hierarchization of the factors of land cover change

The mutual information between the variables has been used to hierarchize the explicative factors of land-cover change. The mutual information analysis is based on the information theory [3]. It is used to outline relations between the variables [4]. For this study, three indicators have been chosen to characterize the relationship between variables that may explicit the land cover evolution between the winters.

- Entropy $\mathcal{H}$: the main property of the information concept is that the quantity of information is maximum when the events are distributed uniformly. It allows to calculate the information quantity

between the set of events.

$$\mathcal{H} = \sum_{i=1}^{N} p_i \log p_i,$$

with N number of possible events and p_i probability of event i.

- Mutual Information $\mathcal{I}$: it represents the mutual information between two variables X and Y; it is obtained through the difference between the entropy $\mathcal{H}$ of X, Y and the joint entropy $\mathcal{H}(X,Y)$ as follows.

$$\mathcal{I}(X,Y) = \mathcal{H}(X) + \mathcal{H}(Y) - \mathcal{H}(X,Y).$$

- Redundancy $\mathcal{R}$: It is issued from the entropy and the mutual information. It measures the heterogeneity rate of two variables X, Y.

$$\mathcal{R} = \frac{\mathcal{I}(X,Y)}{\mathcal{H}(Y)}.$$

The process provides a hierarchization of the information quantity for the explicative variables with the variable to explain. The results of the mutual information test (Table 17.1) show that the most representative variable is "Crop successions (1996-2002)", followed by "Size of the fields", "Agro-environmental actions" and "Distance from farm buildings" in decreasing representative order. These results allow to optimise the mass belief assignment for the hypotheses "Bare soil" and "Covered soil", in comparison with an empirical "expert knowledge" method.

	Classes	$N_F(\%)$	$\mathcal{R}$	$\mathcal{I}$
Distance from	1: < 1.25	1255 (67.6 %)	0.14 %	0.0006
farm buildings	2: > 1.25	601 (32.4 %)		
Agro-environmental	1: without	1619 (87.2 %)	0.2 %	0.0008
actions	2: with	237 (12.8 %)		
Field size	1: < 1.5 ha	1517 (81.7 %)	0.97 %	0.0039
	2: > 1.5 ha	339 (18.3 %)		
	1: (SC W)	1046 (56.4 %)		
	2: (BS 1W)	301 (16.2 %)		
Crop rotation	3: (BS 2W)	186 (10 %)	5.19 %	0.0211
(1996–2002)	4: (BS 3W)	179 (9.64 %)		
	5: (BS 4W)	89 (4.8 %)		
	6: (BS 5W)	55 (2.96 %)		

Table 17.1: Explicative variables hierarchization with the mutual information analysis.

Column $N_F(\%)$ of the Table 17.1 indicates the numbers N_F of fields (and their percentage). Column 5 of the table indicates the values of redundancy $\mathcal{R}$ and column 6 the values of mutual information $\mathcal{I}$. In the last row (i.e. crop rotations during 1996-2000) of Table 17.1, six cases have been identified and correspond to

1. (SC W) : soils covered during all winters
2. (BS 1W) : bare soil during one winter
3. (BS 2W) : bare soil during two winters
4. (BS 3W) :bare soil during three winters
5. (BS 4W) : bare soil during four winters
6. (BS 5W) : bare soil during five winters

17.3 Land cover prediction with the Dempster-Shafer Theory

The theory of evidence proposed by Dempster was developed by Shafer in 1976 and the basic concepts of this theory have often been exposed [5, 6]. Detailed applications of the Dempster-Shafer theory can be found in [7]. Previous applications of the DS theory for our study [1] showed that 45% of the information sources were highly conflicting and generate misprediction results. Performances decrease when the conflict between the evidences is rising ($k < 0.6$). In our case, only 75% of the fields concerned by a high degree of conflict are correctly predicted. On the contrary, results become clearly better (91% of right prediction) when the conflict is low ($k < 0.2$).

Several methods that attempt to make the fusion operators more reliable in considering the different sources of conflict may be found in [8, 9, 10, 11]. No optimal techniques exist yet, even if an approximate adjustment of the fusion threshold can be successful for some applications. In order to deal with the conflict between the information sources, we have applied here a method based on the source weakness.

17.3.1 Basic belief assignment

The assignment of basic beliefs (membership function shape) on the selected indicators is assigned by experts and from the evidence image distribution (Fig. 17.1). They are adjusted and validated with past-observed data and expert's knowledge. Table 17.2 illustrates this stage in including the uncertainty through mass function affectation. For each evidences, denoted B for "bare soil", C for "covered soil", and $B \cup C$ for "Bare soil or covered soil", classes are defined in order to support one of the hypotheses B, C or $B \cup C$.

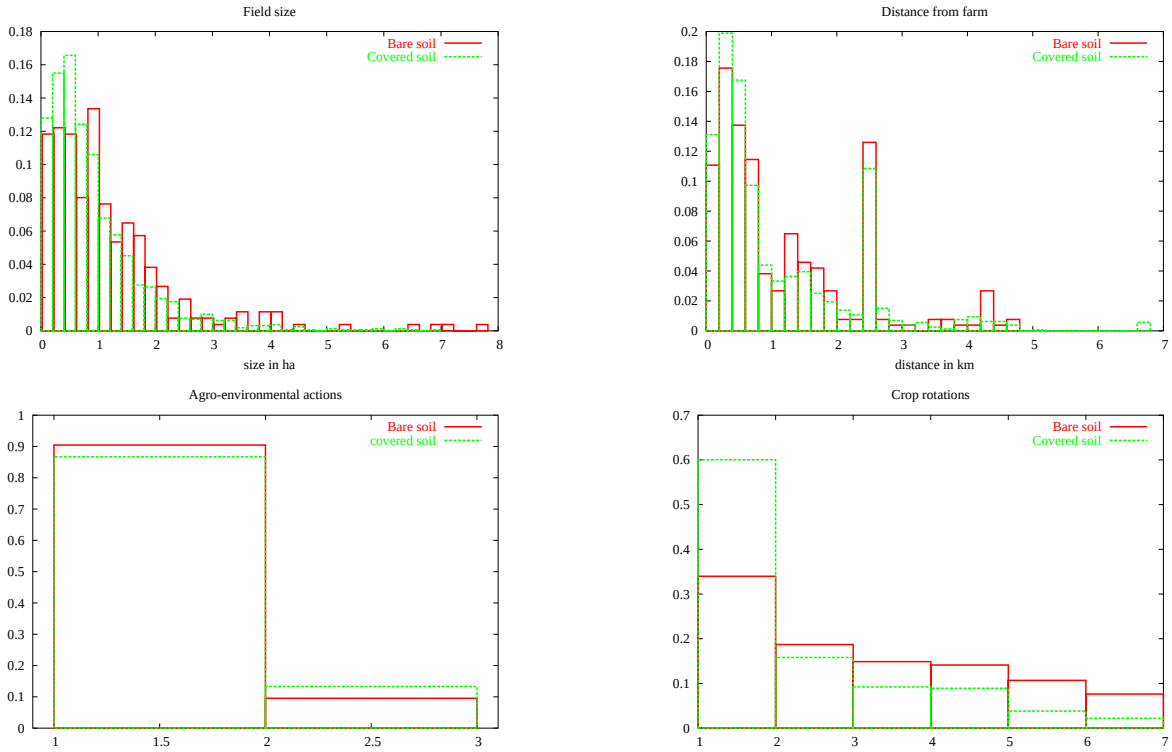

Figure 17.1: Evidence image distribution for each hypothesis.

	Classes	hyp. B	hyp. C	hyp. $B \cup C$
Distance from	1: < 1 km	0.3	0.5	0.2
farm buildings	2: > 1 km	0.6	0.2	0.2
Agro-environmental	1: without	0.6	0.3	0.1
actions	2: with	0.005	0.95	0.045
Field size	1: < 1.5 ha	0.2	0.5	0.3
	2: > 1.5 ha	0.65	0.2	0.15
	1: (SC W)	0.005	0.95	0.045
	2: (BS 1W)	0.01	0.9	0.09
Crop rotation	3: (BS 2W)	0.25	0.7	0.05
(1996–2002)	4: (BS 3W)	0.45	0.4	0.15
	5: (BS 4W)	0.65	0.3	0.05
	6: (BS 5W)	0.85	0.1	0.05

Table 17.2: Affectation of the belief masses for the DS theory.

17.3.2 Conflict managing with the source weakness

17.3.2.1 Principle

Sources weakness method (i.e. discounting technique presented in chapter 1 consists in taking in account the reliability of the evidences by using reliability factor α for each source as a value such as $0 \leqslant \alpha \leqslant 1$. This way, a source may be considered as totally reliable if $\alpha = 1$, or on the contrary completely unreliable if $\alpha = 0$. Damping rule is defined as follows:

$$\begin{cases} m'(A) & = \alpha\, m(A) \qquad \forall A \neq \Theta \\ m'(\Theta) & = (1-\alpha) + \alpha\, m(\Theta). \end{cases}$$

The weakness process is performed when the conflict is too high (relatively to a threshold, such as $k < 0.4$). Two rules have been investigated:

- α is set to a value so that the source does not interfere in the decision process. Then,

$$\begin{cases} m'(\theta_{\text{bare soil}}) & = 0.01 \\ m'(\theta_{\text{covered soil}}) & = 0.01 \\ m'(\theta_{\text{bare soil}} \cup \theta_{\text{covered soil}}) & = 0.98. \end{cases}$$

- α is set to a value linked to the conflict level k. So that the more the conflict, the more the weakness. We remind the conflict between two sources is defined as:

$$k = \sum_{A \cap B \neq \varnothing} m_1(A) m_2(B).$$

17.3.2.2 Results and partial conclusion

The results provided with this method are a little better than the simple application of the DS theory for the hypothesis "bare soil" since 84 fields are correctly predicted against 73 for the DS. But the analysis of the results showed that the conflict does not necessary take place in the mispredictions for the "bare soil" hypothesis. Also, Plausibility-Belief interval can not be helpful for the accuracy of the predictions. Then, an ambiguity between the sources must be taken into consideration in the process. Than is why, prediction process has been moved to the DSm theory in order to deal with paradoxical.

17.4 Land cover prediction with DSmT

The Dezert-Smarandache theory (DSmT) can be considered as a generalization of the Dempster-Shafer. In this new theory, the rule of combination takes into account both uncertain and paradoxical information, see chapter 1 of this book and [12]. Let be the simplest frame of discernment $\Theta = \{\theta_{\text{bare soil}}, \theta_{\text{covered soil}}\}$ involving only two elementary hypotheses with no more additional assumptions on $\theta_{\text{bare soil}}$ and $\theta_{\text{covered soil}}$.

DSm theory deals with new basic belief assignments $m(\cdot) \in [0,1]$ in accepting the possibility for paradoxical information such that:

$$m(\theta_{\text{bare soil}}) + m(\theta_{\text{covered soil}}) + m(\theta_{\text{bare soil}} \cup \theta_{\text{covered soil}}) + m(\theta_{\text{bare soil}} \cap \theta_{\text{covered soil}}) = 1.$$

Recently, a hybrid rule of combination issued of the DSm theory has been developed by the authors of the theory, see chapter 4 of this book. The fusion of paradoxical and uncertain evidences with the hybrid DSm rule of combination combines several masses of independent sources of information and takes into consideration the dynamics of data sets. Thus, hybrid DSm model can be considered as an intermediary model between the DS and the DSm theory. The capacity to deals with several hyper-power set makes the hybrid model an interesting alternative in various fusion problems.

17.4.1 Mass belief assignment

17.4.1.1 Fuzzy mass belief assignment

the mass belief assignment follows the same process as the DS theory. Nevertheless, a fuzzy mass belief assignment is here applied for two sources of evidence: "size of fields" and "distance from farm buildings" because of their specific characteristics (Fig. 17.1). For the variable "Size of fields" for example, the size evolves to 0.05 to 7.7 ha. Then, a continuous mass belief affectation appears pertinent for fusion process, by integrating paradoxical information when experts had introduced threshold instead. It is achieved by smoothing the actual bi-level assignment (Fig. 17.2).

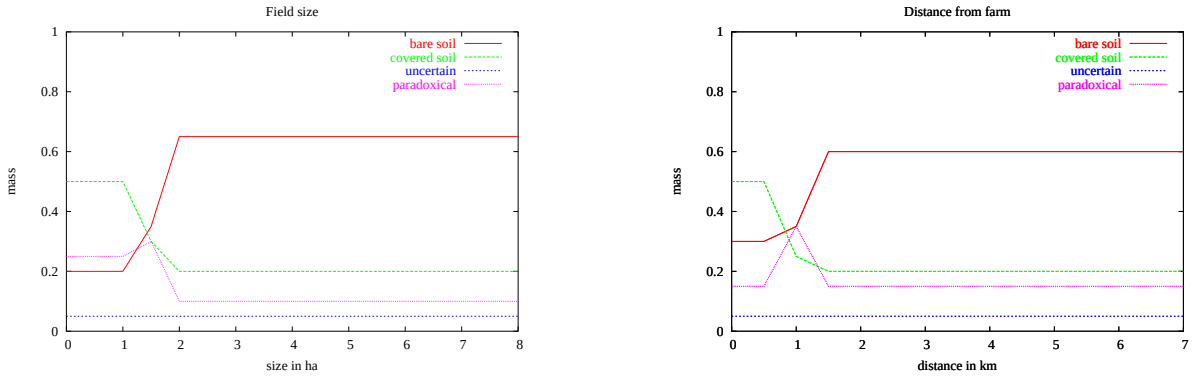

Figure 17.2: Fuzzy mass belief assignment for the evidences "Distance" and "Field size".

17.4.1.2 Contextual damping of source of evidence

since the conflit level between sources is not necessary involved in the misprediction for the "bare soil" hypothesis, a contextual damping strategy is applied depending on the decision that is about to be taken. Actually, we consider that when the decision is about to be taken to the "bare soil" hypothesis, distance to farm and field size are completely paradoxical when crop rotation belongs to class 1 or 2. Furthermore,

when the decision is to be taken to the "covered soil" hypothesis, all the sources become paradoxical when crop rotation is greater than 3 (bare soil during two winters at least).

In order to make sources of evidence paradoxical, a partial damping is applied as follows:

$$\begin{cases} m'(\theta_{\text{bare soil}}) & = \alpha\, m(\theta_{\text{bare soil}}) \\ m'(\theta_{\text{covered soil}}) & = \beta\, m(\theta_{\text{covered soil}}) \\ m'(\theta_{\text{bare soil}} \cup \theta_{\text{covered soil}}) & = m(\theta_{\text{bare soil}} \cup \theta_{\text{covered soil}}) \\ m'(\theta_{\text{bare soil}} \cap \theta_{\text{covered soil}}) & = 1 - \alpha\, m(\theta_{\text{bare soil}}) - \beta\, m(\theta_{\text{covered soil}}) - m(\theta_{\text{bare soil}} \cup \theta_{\text{covered soil}}). \end{cases}$$

The couple (α, β) allows to remove the mass of an hypothesis to the benefit of the paradoxical. Here, $(\alpha, \beta) = (0.1, 1)$ is applied when the decision "bare soil" is about to be taken with crop rotation of 1 or 2 (bare soil during no more than one winter). Also, (α, β) is set to $(1, 0.1)$ when deciding a "covered soil" while crop rotation is greater than 3 (bare soil during 2 winters at least).

Here, this contextual partial damping allows the DSm rule to take into consideration a kind of contional mass assignment.

17.4.2 Results

The application of a contextual DSm rule of combination provides better results for the hypotheses "bare soil". 121 fields (Table 17.4.2) are correctly predicted against 73 with the DS and 84 with the source weakness process. The "bare soil" hypothesis still generates a high level of mispredictions, which is not the case for the "covered soil" hypothesis. Several factors can explain the weak rate of right prediction for the hypothesis "Bare soils". It is strongly linked to the high spatio-temporal variability of the land-use. Actually, an important number of fields covered with meadows during four or five years are ploughed in autumn and re-integrated in a cycle of crop successions. This kind of change is difficult to model since it can be due to unexpected individual human decisions, or exceptional and isolated weather-events. The spatial distribution of the results can be analyzed on the Fig. 17.3. The west part of the watershed corresponds to more intensive system farming than the east part. In the context of intensive system, the variability of land cover changes is higher than the others systems, it depends mostly on economics constraints that are difficult to model. On the contrary, the south part of the watershed is characterized by dairy milk production system. In this part of the watershed, the land cover evolution is better known and highly depends of the crop successions. Its integration into DSm theory is easier and the prediction process yields finest results.

	Land use for winter 2001/2002 (from remote sensing data)	Prediction (rate)
bare soils	266 fields	121 (0.46 %)
covered soils	1588 fields	1239 (0.78 %)
Total	1856 fields	1360 (0.73 %)

Table 17.3: Performance of hybrid DSm rule for land prediction

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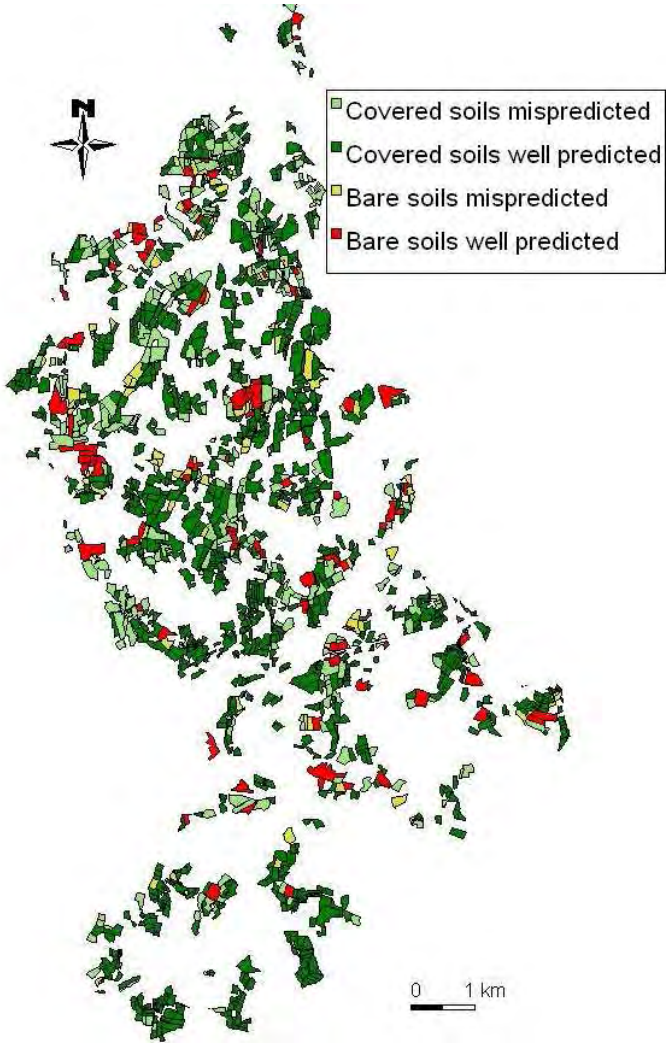

Figure 17.3: Prediction performance with the hybrid DSm rule on the Yar watershed (Brittany).

17.5 Conclusion

Two studies have been analyzed in this chapter for the prediction of land cover on a watershed subject to environmental problems. The land cover prediction with DS proved to have limitations with the increase of conflict between the sources of evidence that support land cover hypotheses. Several modifications may be used such as source weighting or the Hedging methods, but with no benefit in our case. To manage the conflict, the DSm has been applied with a little improvement of the accuracy of predictions. Actually conflict may not explain by itself all the bad decisions since the sources of evidence may induce all together a wrong decision. That is why, a contextual fusion rule appeared necessary for this environmental problem where information sources can be paradoxical or/and uncertain. This new fusion process required first the identification of the driving factors of land cover changes. Then, a mass belief assignment is built for the two hypotheses "covered soil" and "bare soil" through expert knowledge and a mutual information analysis that yield a hierarchization of the source of evidences. A fuzzy affectation is performed for two of the information sources and a "contextual" combination rule is applied to manage the uncertainty and the paradoxical characteristics of the information sources into the DSm decision process. The results for the "bare soil" hypothesis, which still generates too many mispredictions, are better than the prediction through DS decision rule (46% of correct "bare soil" predictions against 36% issued from the previous study). The hypothesis "covered soil" yields 78% of right prediction; this difference between the hypotheses can be explained with the weak rate of bare soil on the watershed and especially with the high variability of the land cover changes that characterized the intensive farm systems located on the north-west part of the watershed. Nevertheless, the fusion process appears to be robust and doesn't require specifics data as input. Thus, prediction system developed with the DSm theory can be apply on different watersheds in Brittany and provides a useful tool for assessing and planning land use. The knowledge of land use is one of the key for restoring water quality intensive agricultural regions.

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