Land Use and Land Cover Change Prediction with the Theory of Evidence : A Case Study in an Intensive Agricultural Region of France

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Abstract – *In intensive agricultural regions, accurate assessment of the spatial and temporal variation of winter vegetation covering is a key indicator of water transfer processes, essential for controlling land management and helping local decision making. Spatial prediction modeling of winter bare soils is complex and it is necessary to introduce uncertainty in modeling land use and cover changes, especially as high spatial and temporal variability are encountered. Dempster's fusion rule is used in the present study to spatially predict the location of winter bare fields for the next season on a watershed located in an intensive agricultural region. It expresses the model as a function of past-observed bare soils, field size, distance from farm buildings, agro-environmental action, and production quotas per ha. The model well predicted the presence of bare soils on 4/5 of the total area. The spatial distribution of misrepresented fields is a good indicator for identifying change factors*

Keywords: Theory of evidence, prediction, spatial modeling, land cover changes.

1 Introduction

Regional and local land use and cover changes have multiple influences on our environment and more generally on global change. Driven factors of changes are multiple, variable in time and scale dependent. Land use and land cover change modeling cannot be more accurate than the knowledge and data that produce them. However, most land use and cover changes do not take uncertainty into account in their model processing. Uncertainty is inherent in land use and land cover change predictive studies and its evaluation is real challenge.

In intensive agricultural regions, short-term lands use and cover changes – from a few days to a few years - is a key indicator of water transfer processes. The presence of fields with no or little vegetation during the winter increases pollutant fluxes towards the rivers. Accurate assessment of the spatial and temporal variation of winter vegetation covering is essential for controlling land management and helping local decision making. Spatial prediction modeling of winter bare soils is complex due to the intricate interactions between biophysical and socio-economic factors operating at various scales from the field to the watershed. In some cases the uncertainty level can be significant, as far as meteorological constraints or economic and/or political events like subsidy allocation for certain crops are concerned. Therefore, it is necessary to introduce uncertainty in modeling land use and cover changes, especially as high spatial and temporal variability is encountered.

Unlike methods generally used (e.g. Bayesian techniques), the Dempster-Shafer theory, also named the theory of evidence, introduces uncertainty in modelling, allows the expression of ignorance in the body of knowledge, and states that belief in a hypothesis is not necessarily the complement of its negation. This theory has been applied in multisensor data fusion including remotely sensed images with the main objective being to improve classification in remote sensing by integrating multiple data sources (Lee and al, 1987; Le Hegarat-Mascle *et al*, 2000, Leduc *et al*, 2000).

In most studies, the thematic application of Dempster-Shafer theory concerns land use and land cover mapping, sometimes, by considering temporal changes (Leduc *et al*, 2001).

The double objective of this study is to evaluate the interest of the theory of evidence in producing land use-land cover prediction for winter land cover and to confirm the preliminary results achieved on a small and highly human-controlled watershed to predict corn presence in fields (L. Hubert-Moy *et al*, 2001).

2 Decision fusion using 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 (i.e. in Richards, 1993 and in Srinivasan *et al,* 1990). Detailed applications of the Dempster-Shafer theory can be found in Eastman (1997) and in Mertikas and Zervakis (2001).

The Dempster-Shafer theory is based on the use of two types of information imperfection : *probabilistic uncertainty* and *imprecision*. Let us assume that a domain reference, *called the frame of discernment* Ω, that is composed of a set of exhaustive and mutually exclusive hypotheses (i.e. one and only one hypothesis must occur). The lake of knowledge of the hypothesis concerned is referred to as the *probabilistic uncertainty*. The probabilistic approach attributes to each elementary hypothesis a "belief" value that we call its probability of occurrence. Thus, the probability that a compound sub-set occurs (i.e. the only one occurring elementary hypothesis belongs to this sub-set) is obtained by adding the probabilities of occurrence of all the elementary hypotheses forming the sub-set. In other words, the probabilistic approach has no means to manage an elementary hypothesis by forming sub-sets that cannot be *distinguished* by a given sensor or a given recognition algorithm. This incapacity of distinguishing elementary hypotheses, even when they cannot occur simultaneously, is referred to as the *imprecision* type of information imperfection.

The main concept of the theory of evidence is to distribute the total unitary mass of certainty over all the sub-sets of Ω instead of making this distribution over the elementary hypothesis only. In this way, the belief, that is called the *mass function*, in the occurrence of one of two hypotheses that cannot be distinguished by a given sensor will be attributed to the compound set with these two hypotheses and no belief will be affected to them independently.

The frame of discernment corresponds to a hierarchical structure and includes all possible combinations between the sets of hypotheses. For example, for the three hypotheses {A, B, C}, the possible combinations are [A], [B], [C], [A, B], [A, C], [B, C], [A, B, C]. (The compound hypotheses, or sub-sets, represent the evidential type of imperfection, i.e. probabilistic uncertainty and imprecision). The commitment between these hypotheses is expressed through different functions:

- First, mass functions are defined such that each subset of Ω is associated with a basic probability assignment, also called the mass function. For example, the mass function *m* (A) represents the strength of some evidence that supports the hypothesis A. One mass between 0 and 1 is assigned for each combination of the set of hypotheses. The sum of all basic probability assignments or masses is always equal to 1, and *m* for the empty set is 0. Thus :

$$\sum_{A \subseteq \Omega} m(A) = 1 \qquad (1)$$

$$m_\Omega(\emptyset) = 0$$

Then Dempster evidence functions, belief and plausibility, are derived from mass functions. For example, the belief function *Bel* (A) summarizes all the reasons to support A. The belief function corresponds to the sum of masses of belief of the subsets that involve A. *Bel* of a subset A of Ω is defined by :

$$Bel(A) = \sum_{E \in \Omega \text{ such that } E \subseteq A} m(E) \qquad (2)$$

Plausible belief *Pl* (A) expresses how much we should believe in A if all currently unknown facts were to support A. Plausibility represents the degree to which a hypothesis cannot be disbelieved. Thus :

$$Pl(A) = \sum_{E \in \Omega \text{ such that } E \cap A \neq \emptyset} m(E) \qquad (3)$$

M (A), *Bel*(A) and *Pl*(A) have one value in the interval [0,1]. The true belief in A lies somewhere in the interval [*Bel*(A)-*Pl*(A)] which represents uncertainty (**Figure 1**). An area of great interest can be defined in the lower part of this interval insofar as it corresponds to the values for which the degree of uncertainty in establishing the presence of hypothesis A is the lowest.

When mass functions are defined, they are combined according to the Dempster rule, also called Dempster's orthogonal sum, to aggregate probability statements from different sources of evidence, as follows :

$$\text{Bel}(A) = \text{Bel}_1(A) \oplus \text{Bel}_2(A) \qquad (4)$$

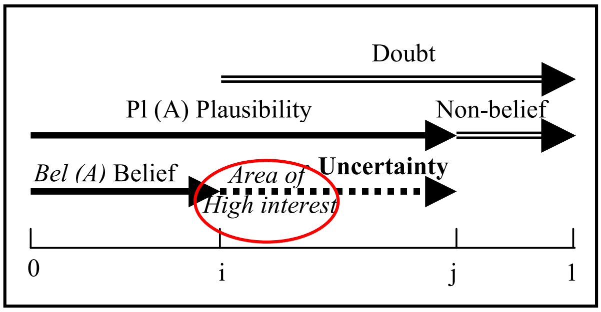


Fig. 1. Representation of Belief, Plausibility and Uncertainty for a given hypothesis in the interval unit

In other words, if we are given two basic probability assignments $m1$ and $m2$ from two evidence sources to support hypothesis A, they combine into a third basic probability assignment $m1+m2$ defined as :

$$m1+m2\ (A) = \frac{\sum m1\ (X) * m2\ (Y)^{(1)}}{\sum m1\ (X) * m2\ (Y)^{(2)}} \qquad (5)$$

$^{(1)}$for all X,Y with intersection A
$^{(2)}$ for all X,Y with empty intersection.

If $\sum m1\ (X) * m2\ (Y) = 0$ for $X \cap Y = \emptyset$, then the equation becomes :

$$m1+m2\ (A) = \sum m1\ (X) * m2\ (Y) \text{ for } X \cap Y \neq \emptyset \qquad (6)$$

All basic probability assignments are aggregated for all subsets of Ω, before final belief, plausibility and the belief interval can be calculated for each hypothesis. Thus, uncertainty is measured at different levels of the full hierarchy of hypotheses.

When compared with traditional probability theory, the main attribute of this theory is the ability to assign non-additive belief to subsets of Ω and therefore to express the degree of ignorance in a decision rule for handling uncertainty that involves ignorance (Srinivasan and Richards, 1990). In Bayesian probability theory, only singleton subsets of Ω are considered and as they are assumed to be exhaustive, they are affected one single value without taking into account uncertainty. With the theory of evidence, as a result of being able to assign belief and uncertainty values to a set, it is possible to suspend judgment.

When considering application of this theory, some critical points can be raised. First, the choice of pieces of evidence and their relationship with the hypotheses leads to several questions (i.e. Are they direct or indirect pieces of evidence? Which hypothesis (es) do they support? How do they support one or several hypotheses?). In fact, these choices appear to be highly expert-knowledge dependent and therefore they should always be validated, even though it is not always easy to validate decisions derived from subjective judgment or empirical data. Second, conflicts between sources of evidence are badly-managed when data are combined by normalization. The greater the number of data to fuse, the more crucial the problem becomes. Third, the choice of criterion decision for a given hypothesis is subjective too, and should be clearly justified, which is not easy in general.

3 Change prediction based on the Dempster Shafer theory of evidence

3.1 Change prediction design

Dempster's fusion rule is used in the present study to spatially predict the location of winter bare fields for the next season on a watershed located in an intensive agricultural region. Land use and cover change driven factors have been defined to support the three following hypotheses : [soils with little or no vegetation cover], [soils with vegetation cover], [soils with little or no vegetation cover; soils with vegetation cover].

The land cover change model processing can be divided into different steps (**Figure 2**):

- *Identification and hierarchization of driven factors of change.* First, an analysis of spatial and temporal changes in intensive farming regions was produced (**Figures 3 and 4**). Then, the definition and hierarchization of change variables for winter land cover distribution were made by experts and validated with past-observed data.

- *Selection of multisource data* also called "sources of evidence". This includes expert data and multitemporal sensor data (a thematic map resulting from the classification of a series of satellite images).

- *Data transformation through fuzzy membership functions into mass function maps.* The assignment of basic probabilities (shape of membership function) on the selected indicators were also determined by experts and from the evidence image distribution. They were finally and validated with past-observed data and expert's knowledge.

- *Data fusion with Dempster's rule.* Probability images were aggregated with Dempster's orthogonal sum to produce belief, plausibility and interval belief images

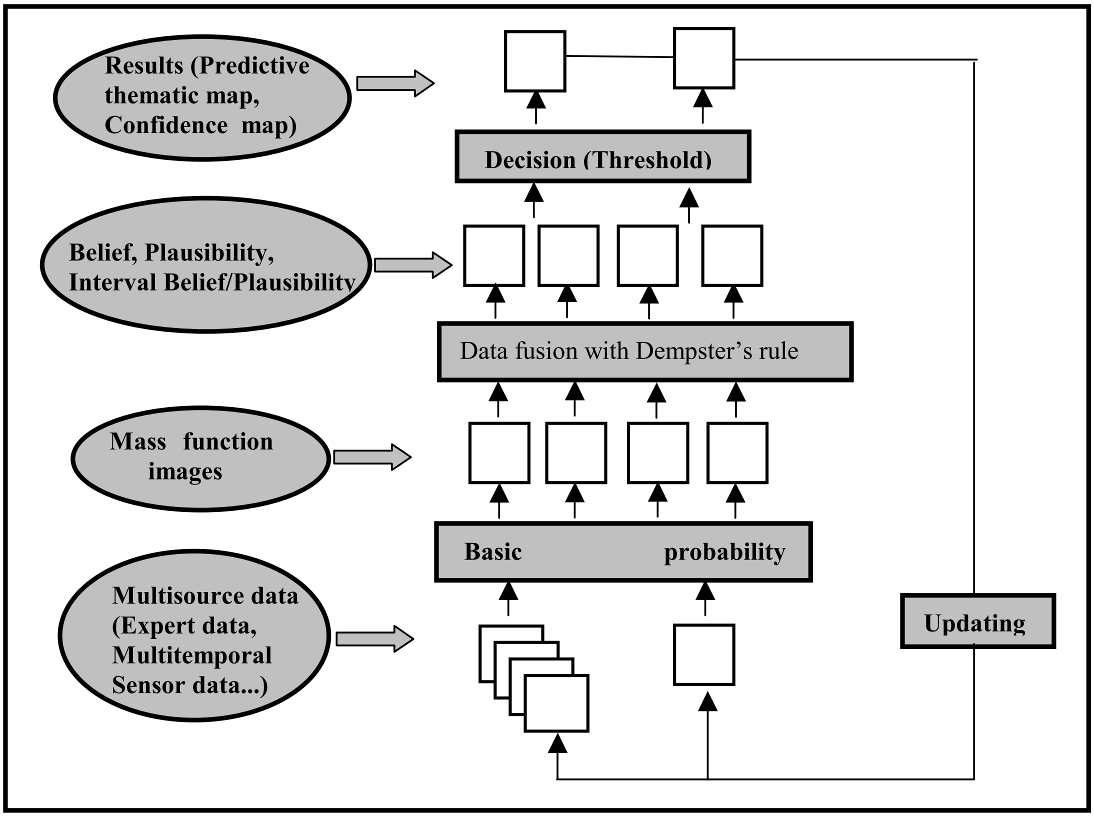


Fig. 2. Classifier integrating uncertainty in multisource data fusioning for predictive land use and land cover approaches

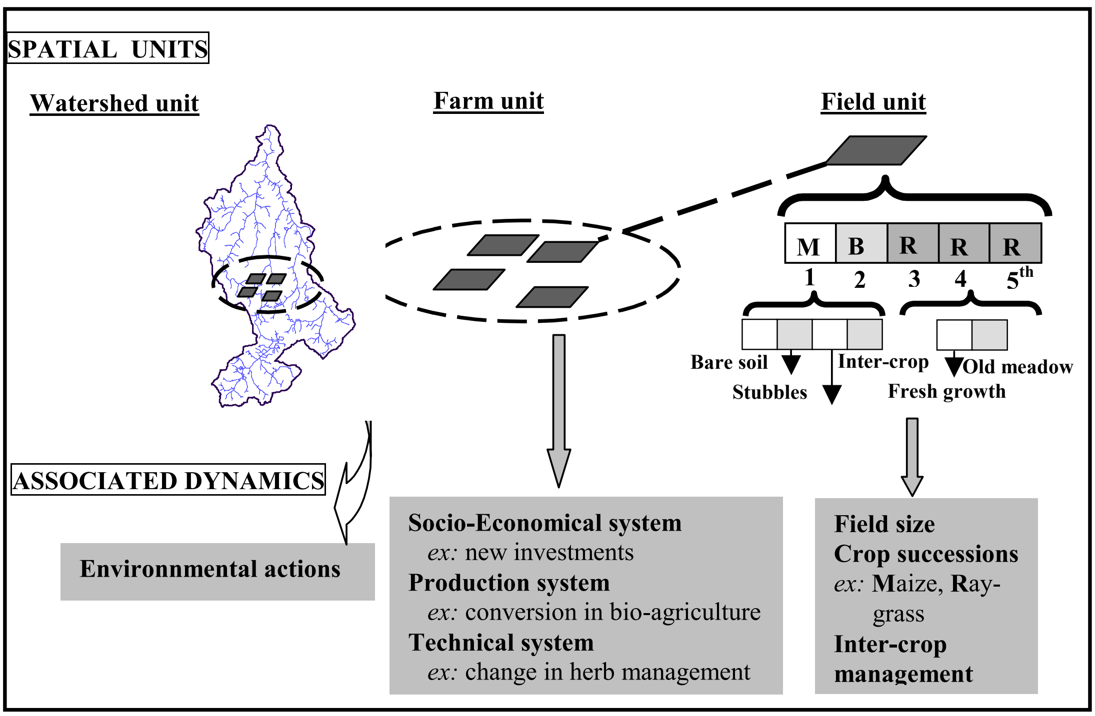


Fig. 3. Spatial units involved in winter land use and cover changes in intensive agricultural regions

- *Result validation*. A confidence map was produced to evaluate the prediction accuracy.

<1 year

Therefore, winter land cover change modeling is expressed as a function of past-observed bare soils, field size, distance from farm buildings, agro-environmental actions, and production quotas per ha. In this application, the temporal dimension is introduced into the model through successions of land cover maps obtained from a series of remote sensing images.

Factors of change selection, hierarchization and definition of mass functions are highly local condition dependent. Our hypothesis is that the driven factors of change are strongly related to the farming production system. The following application concerns one of the five identified production systems of the watershed of the Yar. Fusion decision parameters will be determined in a future study.

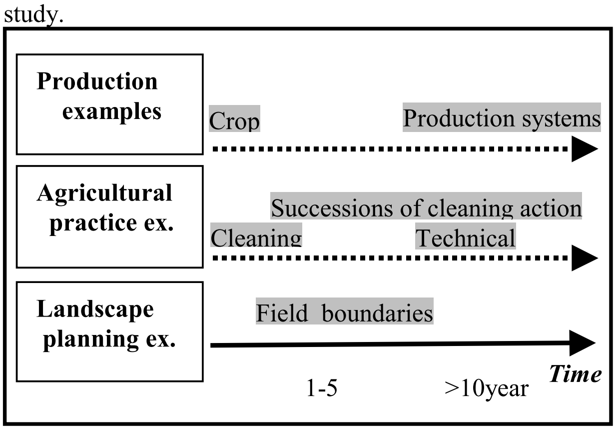


Fig. 4. Dynamics of land use and land cover changes in intensive agriculture

3.2 Study site and data

The proposed short-time predictive method is applied on a watershed, the Yar (65 km2) located on the western coast of Brittany (Western France). Intensive farming combined with wet and warm autumns produce significant amounts of nitrogen before winter infiltration of water. For several years high nitrogen rates in rivers largely due to excessive fertilization, are observed. Another effect is a phenomenon of euthrophization, which occurs in the shape of bloom algae in the spring on the coastal area, increasing yearly. Consequences on environment and tourist activities have led local authorities to take action to restore water quality. In this area, crops cover approximately 60% of the total vegetated areas. Main crops are produced in relation to industrial breeding, principally corn, wheat and artificial meadows. During winter, which corresponds here to a rainy season, fields mostly remain without any vegetation cover after corn harvesting. Nitrogen inputs are still too high, especially on bare soils in winter, following and preceding corn sowing.

Five different farming production types were defined on this watershed from expert knowledge (**Table 1**). Driven factors and their respective weight in winter vegetation cover changes were also determined by experts. As mentioned above, the selected factors and their role in change processes were validated from the observed winter land cover classification produced from a series of satellite images (**Figure 5**). A series of 10 satellite images (9 SPOT images and 1 IRS-LISS III -2 per year over 5 years since 1996-) was pre-processed. Each image was orthorectified using ground control points that were manually plotted, and calibration was also applied using a 5S Model. The pre-processed images were then classified using the classical maximum likelihood method which gives very good precision with such documents at this observation scale (Hubert-Moy *et al*, 2001). Past observed winter land cover was determined by merging successive classifications and a vector change analysis was also carried out to define more precisely vegetation cover changes on the field scale. In this way, winter land cover change trajectories were produced.

As well as past observed land cover classification, land cover change prediction modelling with the Dempster-Shafer rule was carried out in a GIS, as far as spatial information is concerned.

4 Results

Results were achieved for both hypotheses : "soils with little or no vegetation cover" and "soils with vegetation cover". Results related to the first hypothesis are detailed below.

Generally speaking, the results show quite a good correlation between expected bare fields with observed bare soils. Moreover, the maps generated for the hypothesis "soils with little or no vegetation cover" depict the spatial distribution of the predicted bare fields.

The belief map indicates that the model well predicted the presence of bare soils on 4/5 of the total area, for an overall accuracy of 78,8 %. The total amount of bare soils is under-estimated by the model and the mis-predicted fields are distributed over the whole watershed (**Figure 6**). This is mostly explained by a crop conversion from artificial meadows to corn. Converted fields are not yet covered with

Fig. 5. Winter land cover successions

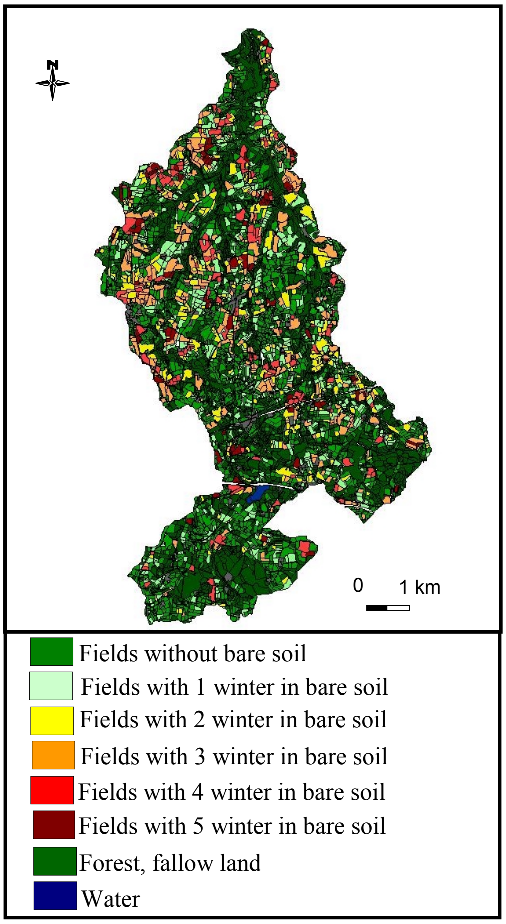
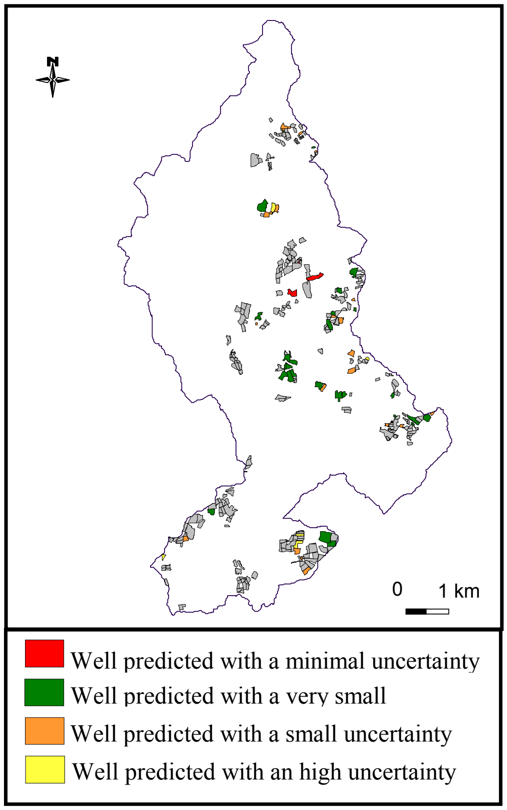


Fig. 6. Predicted bare soils' accuracy at different uncertainty levels



Factors / Production	Proximity	Size of fields	Morphology/ soils	Life's cycle	Quotas/ha of arable land	Environ- -mental actions
Cereals/pigs			2			1
Dairy milk	2	4	4	5	3	1
Suckling cows		3	2	4		1
Milk and meat	2	3	3	4		1

Table 1. Hierarchization of driven factors of land use and land cover changes for winter soil covering

landcover 2000/2002 (Bare soils) / Uncertainty hypothesis "bare soils"	Well predicted		Mis-predicted		Total	
	Ha	**%**	**Ha**	**%**	**Ha**	**%**
Maximal [0-0.1]	0	0	4.4	1.8	4.4	1.1
High [0.1-0.15]	4.4	3.1	33.6	14.1	38	10
Medium [0.15-0.2]	2.1	1.5	9	3.7	11.1	2.9
Small [0.2-0.3]	70.3	50.2	115.6	48.6	185.9	49.2
Very small [0.3-0.5]	56.2	40.1	32.9	13.8	89.1	23.6
Minimal [0.5-0.6]	7	5	41.9	17.6	48.9	12.9
TOTAL	140	100	237.4	100	377.4	100

Table 2. Prediction accuracy at different uncertainty levels for the hypothesis" bare soils"

vegetation. This type of conversion, which is very injurious for water quality in relation to high nitrogene release, is difficult to predict because the life cycle of artificial meadows generally varies from 2 years to 8 years. To some degree, the relative under-estimation of bare fields by the model can also be explained by climatic conditions: precipitations were exceptionally high during the winter 2000/2001, and soils were too saturated to sow wheat in the fields. Therefore in some places fields with corn will this year be more numerous than expected, as fields with wheat will be far less represented than usual. This explains that some fields which were expected to have vegetation cover last winter (wheat and meadows) were in fact sown with corn during spring 2001.

The interval belief/plausibility image allows us to locate the fields where uncertainty is very low. The regions of particular interest are associated with the minimal level of uncertainty. In this application, only 7 ha are concerned (**Table 2**). At this level of minimal uncertainty, which represents 12. 9% of the overall uncertainty, mis-predicted fields represent 17.6 ha, which is quite high. The fields concerned were converted to rye grass. At the farm scale, this conversion is related to the inverse conversion from meadows to corn, as farmers are encouraged to cover fields with vegetation between two successions of corn. Very small and small levels of uncertainty concern a higher number of fields covered with vegetation during winter and reflect the application of environmental action. As expected, high and maximal levels of uncertainty correspond to low prediction accuracy. The spatial distribution of these different uncertainty levels does not indicate a relation between field location in the watershed and the uncertainty level. This is an indicator of the impact of environmental action. Such a relationship perceptible through a progressive reduction of bare spatial cover extending from the river up to the watershed limits, is expected by the local authorities in the next few years.

These first results show that the number of bare fields does not significantly decrease, compared to the past-observed variations during the period 1996-2000.

They also confirm that the proportion of bare soils between two annual corn crops is affected by high inter-annual variability. This should be reduced under the influence of present environmental action. Nevertheless, temporal changes are not regular. This shows that prediction has to be updated as new parameters like climatic conditions or economic events modify agricultural practices.

5 Conclusions

In this study, Dempster-Shafer's theory of evidence is used to multisource data fusion in order to produce a short-time winter land cover prediction. The temporal dimension as well as the spatial dimension are introduced into data fusion processing. This method aims to integrate expert knowledge and multitemporal sensor data into a homogeneous and consistent framework. To achieve land cover prediction, driven factors of change are first identified, then hierarchized according to their respective weight in land use and land cover change processes before being validated with past-observed land cover data. Selection of entry parameters and their formalization through basic probability map production is complicated by the fact that spatio-temporal variability of the studied process is high and human and biophysical factors of change are great.

Uncertainty associated with the results is of great interest for the experts. Each final classification decision is produced with a degree of confidence obtained from belief and plausibility maps. Thus, predictions are more realistic. However, uncertainty is reduced as new data are integrated in the system, and therefore prediction accuracy increases as long series of data are processed.

The analysis of differences between prediction and reality produces additional information. Global differences show the extent of "non predicted" changes due to unexpected transformations or changes related to still approximate modeling. In some cases, change factors can be considered as "hidden variables" which are revealed by mispredictions. Furthermore, the spatial distribution of misrepresented fields is a good indicator for identifying factors of change. For example, misprediction distributed over the whole watershed will preferentially be assigned to meteorological conditions whereas differences limited to one or two farm territories could be explained by individual behaviour such as agricultural production system conversion.

These results have been achieved for a dairy milk production system. The model will be applied to other agricultural systems first on the watershed scale and then on a regional scale. If validated, this method could contribute to defining a useful assessment and planning tool for restoring water quality in intensive agricultural regions. Furthermore, this approach supports spatio-temporal monitoring and projections of land use and land cover changes.

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