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Modelling farmers' choice of miscanthus allocation in farmland: a case-based reasoning model

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Abstract: The spatial extension of perennial biomass crop, like miscanthus, seems to be unavoidable to face the decrease of fossil fuel. However, the risk of a food / non food competition due to land use change has to be anticipated. Several models of biomass crops allocation have been already performed. Most of these models simulate large-scale allocation processes, taking into account numerous biophysical variables but only few true-to-life human variables. In this paper, we present a modelling framework of miscanthus allocation in farmland. We use a case based reasoning model in order to compute both biophysical and human variables. An *ad hoc* similarity measures framework and the comparison of two adaptation techniques are presented. First results of one application based on a french case study are discussed. They show the necessity to take into account stakeholders' knowledge of miscanthus allocation process in the modelling.

Keywords*:* artificial intelligence; decision-making support; miscanthus; modelling; land use

1 INTRODUCTION

To face the decrease of fossil energy supplies, new renewable energy resources like perennial biomass crops are of a great interest (R.E.D., 2009). Their spatial extension and allocation seem then unavoidable, like anticipating global issues as food / non-food competition (Karp, Richter, 2011). Several land-use change models deal with biomass crops allocation (Hellmann, Verburg, 2008; Lovett *et al*., 2009). Most of these models simulate large-scale allocation processes, taking into account numerous biophysical variables but only few true-to-life human variables. Thus, our aim is to model farmers' allocation choice regarding miscanthus, as a complex agricultural management system, coupling social, technical or environmental variables to assess biomass spatial distribution.

As, coupling human and biophysical variables in a modelling framework raises knowledge acquisition and knowledge integration methodological questions, we propose to model biomass crop allocation relying on the case-based reasoning model (Riesbeck, Schank, 1989; Aamodt, Plaza, 1994). The choice of this model is explained and tested in a case (Burgundy biomass cooperative). This work is part of the FUTUROL project which deals with industrial process of ligno-cellulosic biomass resources.

This article presents successively the case based reasoning method, the first application to miscanthus allocation modelling, and focus the results on two main scientific questions: (i) how to retrieve a similar case, (ii) how to reuse retrieve case's solution to predict miscanthus allocation? We close this paper through a short conclusion on the model status in human decision making.

2 MATERIAL AND METHOD

2.1 Case-based reasoning theory and assets

Case-based reasoning (CBR) is a problem solving paradigm based on analogy reasoning. CBR consists in solving new problems by reusing the solutions of already solved problems (Riesbeck, Schank, 1989). A *Case* corresponds to a problem-solving episode represented by the pair *Problem-Solution* and by all the information related to the path dependency between the *Problem* and its *Solution*. Cases are recorded in a *Case Base*. The CBR process consists in solving a new problem, called a *Target problem,* according to the following four stages (cf. figure 1): 1. retrieve the most similar case - called a *Source case* - to the *Target problem* based on similarity measures between problems, 2. adapt the solution of the *Source case* thanks to inference processes and adaptation knowledge, 3. revise the *Target solution* (the inferred solution) if necessary and 4. retain the *Target case* as a new *Case* into the *Case Base* (Aamodt, Plaza, 1994, Watson, Marir 1994).
For instance in land design, a *Target problem* can be the prospective allocation of miscanthus into farmlands of a small region, and a retrieved *Source* case is a farmland where miscanthus was allocated on maize plots. In stage 2, CBR can either use directly the *Source solution* to allocate miscanthus on maize plots for the *Target solution*, or adapt the *Source solution* to the *Target problem* constraints. In our example, the constraint can be the non suitability for miscanthus harvesting in flood risk areas. CBR can then adapt the *Source solution* regarding this constraint to infer the *Target solution* (i.e. the miscanthus allocation in the problem farmland).

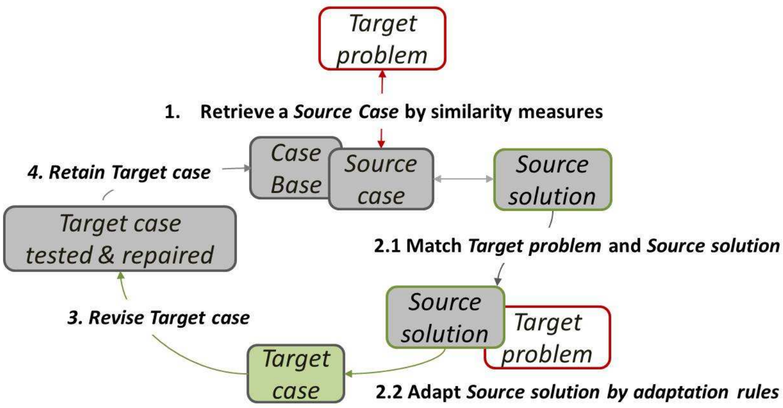

Figure 1: the CBR process (adapted from Aamodt, Plaza, 1994)

The major asset of CBR is to be able to model complex mechanisms like environmental ones (Mota *et al*, 2008) without the necessity to fully understand driving mechanisms (Du *et al*., 2010). Indeed, the analogy reasoning is able to solve problems by few data. CBR allows to take into account different types of knowledge (Leake, 1996) and is mainly used in complex domains like medicine or industry. CBR is also used in Land Use Change Science, even if there are still few published results (Du *et al*., 2010). Finally, this asset seems perfectly adapted to perennial biomass allocation issues which are too recent and not numerous enough to be fully understood, or represented by statistics. Furthermore our aim is to understand the allocation practices of farms regarding perennial biomass and to transpose these observations to other regions where there is no perennial, biomass, in a prospective way. Accordingly, CBR appears to be more adapted than agent-based models (Matthews *et al*., 2007) as its reasoning model is global rather than distributed and can be easily used with less data.
Thus, we consider the use of CBR to model the allocation of perennial biomass crop as an innovative approach to integrate complex local stakeholders' knowledge.

The following sections present one specific application case: the CBR miscanthus model.

2.2 Case-based reasoning to model miscanthus allocation

2.2.1 Study area

The CBR Miscanthus model (CBRMM) is based on a case study located in Burgundy (Côte d'Or), a region area situated in the east of France, where substantial process of miscanthus implantation is currently observed (cf. figure 2). As a matter of fact, in this area, european subsidies are given to farmers to support miscanthus.

This case study includes several research teams from the FUTUROL project, gathered together to mutualize research progresses and results.
Therefore, our application is based on pooled data coming from two INRA (French National Institute for Agricultural Research) research teams: Public Economy and SAD-ASTER. Both research teams carried out respectively 111 individual farm surveys and 10 comprehensive interviews of farmers, in 2010 and 2011 (cf. table 1).

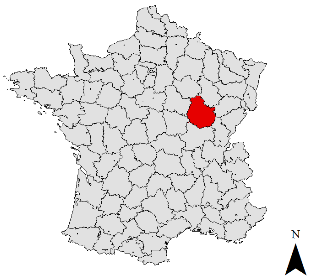

Table 1: samples of survey and comprehensive interviews

	Number of farmers by main activity			
Survey kinds	Cereal grower	Cattle breeder	Other	**Total of farmers**
Individual farm's surveys	85	22	4	**111**
Individual comprehensive interviews	6	4	0	**10**

Figure 2: localisation of the study area in France

Case description values are based on survey data and comprehensive interviews (cf. table 2). Knowledge from the comprehensive interviews is also used to define adaptation rules and to retrieve cases (cf. figure 1, stages 1 and 2.2).
Indeed, a comprehensive interview differs from a survey because it includes no leading questions (Kaufmann, 1996). It is adapted to catch all factors influencing farmers' choice from diverse kinds (social, technical) and from diverse degree of complexity (mono-factors and multi-factors). The interview is recorded, fully transcribed and analyzed, enabling to catch decision rules (cf. table 2, table 7) and driving factors explaining both the miscanthus adoption and its allocation into farmland - like the distance to the farm-stead, farmer's perception of biophysical and spatial farmland features, the cropping plan etc. (Martin *et al*., 2012).

2.2.2 Case description

A *Case* is represented by objects which are described by a set of "attribute-values" (Bergmann *et al*., 1998). Some objects belong to the *Problem* part of the *Case* and others to the *Solution*.
In the CBRMM, *Problem* corresponds to the driving factors expressed by farmers for which the modeler has selected correspondent attributes to describe them in a relevant way. In our study, the *Problem* is composed of four attributes classes: farmer's attributes, cropping plan, farm biophysical and spatial farmland features (cf. table 2). Two classes can then be considered as linked to socio-technical driving factors (farmer's attributes, cropping plan), while the two remaining classes are linked to biophysical driving factors (farm biophysical and spatial farmland features).

Solution corresponds to miscanthus allocation practices and miscanthus plot features (cf. table 6, part 3.2.2).

Table 2: *Problem* description: attributes linked to socio-techical (in dark) and biophysical (in light) driving factors

Farmer's attributes
main activity and land tenure system of plots
farmer's allocation rules
farmer's perceptions of biophysical and spatial farmland features
farmer's perceptions of miscanthus

***Data source : Comprehensive interviews /* Number of cases : 10/111**

Cropping plan	**Farm biophysical features**
usable agricultural area (ha) - UAA	textural soil classification
arable land area (ha & % of UAA)	area (ha) without/with slope (from 5 to 10%)
land under permanent grass area (ha & %)	**Spatial farmland features**
set-aside area (ha & %)	number of plots and area (ha) located at different distances to the farm-stead
permanent crops (ha & %) - e.g. vineyard	number of plots from different size
perennial crops area (ha & %) - e.g. miscanthus	number of plots and area (ha) located near forests, rivers and houses

Data source : Surveys & geographically referenced data / Number of cases: 111

One of the key problems of CBR frameworks is finding similar cases in the C*ase Base*. The choice of similarity measure is important for the success of the adaptation process. A similarity measure frequently used in CBR is the nearest neighbor like in the iCOLIBRI framework (Recio Garcia, 2008), but the difficulty is the selection of the attributes (and weight) to compare. As they need to be well adapted to the problem-solving issue, similarity measures must be adapted to each CBR application and cannot be completely generic or imported from other CBR frameworks.
For the CBRMM, an *ad hoc* similarity measures framework have been chosen.

3 RESULTS

3.1 *Ad hoc* similarity measures framework

To define the *ad hoc* similarity measures framework, we assume that similar farm management and biophysical constraints of farmland enable analogue farmers' choices regarding crops allocation. The comparison of the *Target* case and cases of the *Case Base* is based on a combination of three of the four components of the *Problem* part: cropping plan, farm biophysical features and spatial farmland features. Retrieve a similar *Case* based on each component is a major step.
We first detail the similarity measure of cropping plans, then the similarity measure of soils.

3.1.1 Similarity measure of cropping plan

Retrieve similar cropping plan is a major step, considering it drives farmers' choices about crop dynamics and miscanthus allocation. To compare cropping plans, we compare the crops proportions in each farm. We assume that a similar cropping plan indicates a similar crop production activity of the farm, similar cropping schedule and work calendar, close crop rotations and similar crop requirements (e.g. water and soil).
To compare cropping plans, we use two indexes. The first one compares the proportions of common crops between the *Target* case (*tgCase*) and the *Cases* of

the *Case Base* (*bsCases*). The second one compares the proportions of non-common crops.
As our goal is to retrieve not only a similar cropping plan but a similar crop allocation management, we use weighted coefficient for computing the two indexes, as follow for non-common crops:

$$nonCommonCropsIndex = \sum_{i=1,\, j=1}^{n,m} \left(\left| nCCrop\_tgCase(i) + nCCrop\_bsCase(j) \right| \times wc(i,j) \right) \quad (1)$$

Where:
n = number of crops (i) only produces by *bsCase* and not by *tgCase*
m = number of crops (j) only produce by *tgCase* and not by *bsCase*
nCrop_tgCase(i) = proportion of crops (i) in the *tgCase* cropping plan
nCrop_*bsCase* (j) = proportion of crops (j) in the *bsCase* cropping plan
wc (i,j)= weighted coefficient

The aim is to strengthen the retrieve process to similar crops requirement management by considering "more similar" two crops having close agronomical and/or technical requirements. For instance, if the *tgCase* produces maize, thanks to weighted similarity measures we retrieve both *Cases* which produce maize and *Cases* which produce similar crops regarding moisture content requirements (e.g. soya, miscanthus) (cf. table 3).

Table 3: weighted coefficients values

wc Values	Level of similarity / dissimilarity with crops of *Target problem*
0 < wc < 1	similar allocation requirements with close cropping systems
wc = 1	dissimilarity of allocation requirements
wc > 1	dissimilarity of allocation requirements with a different farming management (e.g. cropping system, farm activity)

3.1.2 Similarity measure of soil types

For our application, we would only use the information about soil texture to account for biophysical farm features attributes (cf. table 2). First we compare the proportion of soil texture between *tgCase* and *bsCases*. Then, according to the procedure done for cropping plan similarity measures, we established weight to account for the proximity between different kinds of soils. To compare soil textures we built a taxonomy (a hierarchical set of concepts) based on the FAO soil textural classes, where the final sheets correspond to textural classes and where upper nodes correspond to more general textures (cf. figure 3). The similarity between soil types is expressed by a path length to a common parent. The distance is calculated by the number of nodes between two soil textures according to figure 3. This one represents a path length from the *tgCase* (in bold) to the *bsCase* (in bold and underlined).

The similarity measure of soil types can be calculated as follow:

$$soilSimilarityIndex = \sum_{i=1,j=1}^{n,m} \left(\left| soil\_tgCase(i) + soil\_bsCase(j) \right| \times wc(i,j) \right) \quad (2)$$

Where:
n = number of soil textural classes of *tgCase* farmland
m = number of soil textural classes of *bsCase* farmland
soil_*tgCase*(i) = proportion of soil textural classe (i) in *tgCase* farmland
soil_*bsCase*(j) = proportion of soil textural classe (j) in the *bsCases* farmland
wc (i,j)= weighted coefficient

For spatial features, similarity measures have been computed by comparing the proportion of each spatial feature between *tgCase* and *bsCases* (cf. table 5).

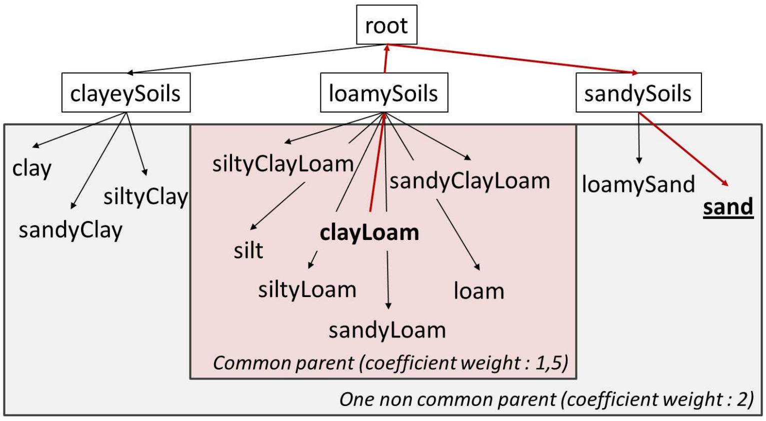

Figure 3: textural soil hierarchy and weighted coefficient values.

3.2 Application first results

3.2.1 Retrieve process results

The aim of our application is to retrieve the similar *Case* to the *Target case E4*, for which one, *Problem* and *Solution* have been caught by survey and comprehensive interview (cf. table 5, table 6, table 7).
The final score measuring the global similarity between *tgCaseE4* and *bsCases* is the sum of the different measures for each *Case*. The most similar *Case* regarding *tgCaseE4* is the *Case13* described in table 5 (for cropping plan and spatial farmland features).

Table 5: *Target case E4* and *Source Case* 13 descriptions and dissimilarity results

Cropping plan	***tgCaseE4***	***Case13***	***Dissimilarity***
proportion of arable land over Usuable Agricultural Area (%)	*94,4*	98	-3,6
proportion of set-aside over UAA (%)	*5,6*	2	3,6
maize proportion of arable land (%)	*10,9*	14,5	-3,6
Spatial farmland features	***tgCaseE4***	***Case13***	***Dissimilarity***
number of field blocks	25	45	-20,0
total area (ha) of distance plots to the farm-stead ≤ 1 km	95	0	95,0
tot.area of distance plots to farm-stead:]1 km,10 km[	60	211	-151,0
total area (ha) of distance plots to the farm-stead ≥ 10 km	25	0	25,0
number of plots located near woodland	2	8	-6
number of plots located near rivers	12	5	7

3.2.2 Adaptation results and validation

In order to adapt the *Solution source* to *tgCaseE4*, several more or less complex techniques can be used (Watson, Marir, 1994). As the *Solution* of *tgCaseE4* is known, we compared 2 adaptation techniques by the validation of adaption results.
We first tested a "null adaptation" technique. Crucial differences between the inferred and real *Solutions* were pointed out as the surface of miscanthus plots (cf. table 6). This situation reveals differences of practices between both farmers and shows us the necessity to take into account dissimilarity between *Cases* to infer *Solution*. Another "simple" technique that was applied is to adjust attribute-values pairs according to the dissimilarity (cf. Table 6) as following adaptation rules:
r1. if "*tgCaseE4* number of plots < *Case13* number of plots" then "*tgCaseE4* number of miscanthus plots < *Case13* number of miscanthus plots"

r2. if "*tgCaseE4* distance of most far-off plots > *Case13* distance of most far-off plots" then "*tgCaseE4 distance of* miscanthus > *Case13 distance of* miscanthus"
r3. if "*tgCaseE4* number of plots located near river > *Case 13* ones" then "*tgCaseE4* miscanthus will be allocated near a river".
The area of miscanthus plots (miscA) is calculated based on the arable land area (arableLA) as follow:

$$miscA\_tgCase = \left(miscA\_bsCase / arableLA\_bsCase\right) \times arableLA\_tgCase \tag{3}$$

Table 6: comparison of adaptation results from two adaptation techniques

	real *Solution* of the *Target case* E4		*Solution* from null adaptation (⇔case 13 sol)			*Solution* from simple adaptation	
numb. of miscanthus plots	2		3			2	
area of plots (ha)	15	5	**3,2**	**1,21**	**1,81**	**2,63**	**1,24**
soil type	Clay		Clay loam (CL)	*CL*	CL	CL	CL
land tenure system	owner occupancy		owner occupancy			owner occupancy	
past 3 years covers	maize	set-aside	set-aside	maize	maize	set-aside	maize
dist. to farm-stead	20 km		**7 km**			**> 10 km**	
slope pourcentage	0		0			0	
flood-risk of plots	yes		no			no	
neighborhood feature	woodland, river		river	woodland	river	river	

Results show that both adaptation techniques are not sufficient to adapt correctly the *Solution source* (see area of miscanthus plots, in table 6). More elaborate methods as integrating farmers' decisions rules (cf. table 7) should be applied, as they explain allocation practices of *tgCase*. A feedback can also be necessary to change similarity measures.

Table 7: decisions rules of *Target problem* E4

Farmer's attributes	
miscanthus allocation decision rule 1	allocation in nitrate-vulnerable zone
miscanthus allocation decision rule 2	allocation in far-off plots
miscanthus allocation decision rule 3	flood risk of plot
miscanthus allocation decision rule 4	good agronomical value of the plot
management decision rule	compensate sugar beet production stopping
perception of miscanthus	crop friendly environmental
perception of farmland textural soils	good agronomical value of textural soils
perception of spatial farmland feature	transport costs constraint of far-off plots

4 DISCUSSION AND CONCLUSION

In this paper, we described a preliminary CBR application to predict allocation dynamics of miscanthus in farmland. An *ad hoc* similarity measures framework has been built to retain the most similar *Cases* regarding land use change management of farmer and its ability to allocate miscanthus in farmland.
At the present time, similarity measures and adaptation process are based on three attributes groups: copping plan, biophysical farmland features and spatial farmland features. But as we saw in part 3.2.2, it is necessary to take into account farmers' rules for the adaptation process and for similarity measures. Thus, our future work will consist to enrich our model by farmers' decision rules and perceptions, in an iterative way. Even if we do not build the CBRMM in a participative way, we are going to use farmer's choices to calibrate adaptation rules and to validate them by feedbacks. A second period of interviews with farmers is planned to catch their

adaptation practices, according to different scenarios (built by the researcher beforehand). On the other hand, similarity level between crops has been defined according to crops requirements and major features that broadly influence farmer allocation rules. To increase the validity of the model to local application, it could be interesting to use the observation of local cropping system for several years. The use of Terruti data (Mari, Le Ber, 2006) can be a work perspective.
To conclude, case based reasoning provides an interesting opportunity to integrate various data, like survey data but also like stakeholders' rules and choices. More than being an alternative to model land use change, we hope that the use of CBR could also be an efficient way to fully understand current and future practices of biomass allocation, in order to anticipate the food/ non food competition risk.

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