Multi-source Information Fusion: Monitoring Sugarcane Harvest Using Multi-temporal Images, Crop Growth Modelling, and Expert Knowledge

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Abstract — This paper deals with the automatic detection of sugarcane harvesting using multi-source information fusion. Information extracted from multi-temporal imagery is fused with indicators from crop growth modelling, and are combined with expert knowledge. The introduced decision support system uses the fuzzy sets theory to cope with uncertainty and imprecision. Fuzzy inference is based on Mamdani's method. The output belongs to three possible classes, and it is accompanied by membership values. The system was evaluated on an irregular time series of Spot5 images acquired on Reunion Island with significant acquisition gaps. Daily climatic data were used to run the growth model. Results obtained were satisfactory; an overall accuracy of 93% is obtained.

I. Introduction

Multi-temporal high spatial resolution remotely sensed imagery is an important source of information for several agricultural applications [1-4]. It offers great potential for detecting changes in large zones at once and at a fine scale. Therefore, it can be used to provide socioeconomic and political actors useful information to plan and improve resource allocation in cropped areas [5, 6].

Many investigators reported the capacity of multi-temporal imagery in monitoring sugarcane harvesting through multi-spectral classification [5, 7-9]. The major drawbacks of this method are:

- the subjective and time-consuming photo-interpretation phase necessary to reduce the number of classes resulting from the classification;
- the radiometric confusion between different status that have the same spectral responses. For instance, when the delay between two cloud-free images is too large, it is difficult to differentiate between a standing crop and the regrowth of a field harvested at the beginning of season.

Thus, we must seek an automatic and a more robust method that satisfies the need expressed by the sugar industry which is to have credible information on the harvest progress throughout the milling season.

The quantity of information extracted from the multi-temporal images is, by itself, generally restricted, in particular by the acquisition gaps, the atmospheric conditions and imperfections in radiometric normalization. Therefore, this information must be supplemented with indicators coming from other sources in order to arrive to more credible decisions. The modelling of crop growth dynamics and expert knowledge can meet this need.

Several studies combined multi-source information, using various methods, to make better decisions. Ref. [10] used the Dempster-Shafer method to fuse multi-temporal images for land use recognition. Ref. [11] used the same theory to combine numerical data with symbolic systems (expert knowledge), and Ref. [12] used it to develop a new unsupervised classification method. The theory of fuzzy subsets and the theory of possibilities, usually used in the field of medical imagery, has been extended to land use classification [13, 14]. Ref. [13] used fuzzy fusion to integrate numerical data and symbolic systems. Starting from the probability distribution of a class, given by its samples, he calculates the equivalent distribution of possibilities. The data symbolic systems relate to the geographical context and they are provided by the expert in the form of rules. They are also translated in the form of distributions of possibilities and are combined with the numerical data using a conjunctive mode. The method was adapted and applied recently to the cartography of the reefscapes, a field characterized by its heterogeneousness [15].

Until now, outputs of biophysical or agronomical models have not often been used as an information source that goes with remote sensing data. However these outputs can provide important complementary information.

In this study, we present a novel decision support system that deals with information coming from multi-temporal imagery, crop growth modelling, and expert knowledge in order to automatically detect sugarcane harvesting in Reunion Island.

This system is based on the theory of possibilities which is an appropriate tool for combining uncertain and imprecise information, and to associate a confidence factor to each decision.

II. Background

Sugarcane is a semi-perennial tall grass belonging to the "Graminae" family and is a crop that propagates vegetatively. The seed materials used are the stem cuttings. After the harvest of the plant crop (aged between approximately 18 and 24 months), buds on the left-over underground stubbles germinate again and give rise to another crop. This crop is called ratoon crop, and is harvested about every 12-months

for up to four years or more, before the crop is renewed due to decreasing yield.

Harvesting is done when the crop has fully matured and ripened. Early varieties and ratoon crops are the first to be harvested, either by hand or mechanically. The harvest season generally lasts several months, depending on the tonnage of cane to be processed, the capacity of the mills and the climate.

III. Data sets description

A. Study site

The study site is Reunion Island (ca. 2512 km^2) situated in the Indian Ocean, at the north-east of Madagascar (Fig.1). Sugarcane is cultivated along the coast on 26,500 ha (Source: DDAF 2004). Most of the growers are smallholders, and the average size of sugarcane fields is about 0.8 ha.

In the wet north-eastern part of the island, sugarcane is rainfed, while in the drier south-western part it is irrigated.

B. Satellite data

A time series of thirteen images acquired by Spot 5 between July 6, 2002 and October 26, 2004 were used. Both Spot 5 instruments HRG1 and HRG2 acquire radiation in four spectral bands with high spatial resolution: 10x10m in Green, Red and NIR (Near Infra-Red) bands, and 20x20m in SWIR (Short Wave Infra-Red) band.

The images belong to the KALIDEOS-ISLE REUNION database built by the CNES [16]. They are ortho-rectified and radiometrically corrected at top of canopy level (with atmospheric correction). Table I shows the characteristics of the time series. As can be seen, nine of the images are acquired during the harvest campaign (June–December), and the four others fall into the growing period (January–May).

Cloud masks were also available for each image.

C. In-situ data

Daily climatic data recorded between the first and the final dates of the time series were available (Source: Meteorological Data Base of CIRAD in Reunion). Among these data we used Rainfall (mm), Potential Evapo-Transpiration (mm), Global radiation (J/m^2), and minimum, maximum and mean temperature values (°C).

Fig. 1. The location of Reunion Island in the Indian Ocean.

Table I
Characteristics of the Spot5 Time series (Source: kalideos-isle Reunion/CNES).

Dates	Spot 5 Instrument	Incidence angle (in °) (Right = -)	Solar elevation (in °)	Phase angle (in °)
07/06/2002	HRG 2	-25.08	40.4	27.1
09/22/2002	HRG 2	-25.02	67.7	47.3
10/18/2002	HRG 2	+24.90	65.3	48.9
01/10/2003	HRG 2	-04.65	64.1	21.3
05/04/2003	HRG 1	+10.90	46.8	48.0
07/21/2003	HRG 1	+10.58	41.2	53.1
08/21/2003	HRG 1	+18.17	48.9	51.0
12/19/2003	HRG 1	-02.90	67.2	19.9
03/17/2004	HRG 2	-19.10	54.2	25.2
05/13/2004	HRG 1	-11.80	42.9	43.9
06/18/2004	HRG 2	+03.25	39.1	52.0
08/19/2004	HRG 1	+17.96	48.5	51.2
10/26/2004	HRG 2	+03.30	67.9	24.9

On the other hand, the Leaf Area Index (LAI) was estimated on twenty ratoon fields using allometric functions (for young cane canopies) and Licor LAI-2000 (for mature cane). The test fields were selected in irrigated and rainfed areas. The measurements were repeated two or three times during the crop season simultaneously with spatial acquisitions [17].

IV. Method

In this section, we present the system that we developed to automatically detect the sugarcane harvesting using multi-source information.

First, we describe each source of information, and then we introduce the decision support system that combines the information in order to make decisions.

A. Information Source

1) Multi-temporal imagery: Using the sugarcane field boundaries, we extract from the multi-temporal images the temporal profile of the NDVI (Normalized Difference Vegetation Index) at the field scale. The extraction is made after the application of a 20m buffer created in order to eliminate mixed border pixels. In general, the NDVI profile can be divided into two periods: a period with increase in NDVI values, corresponding to the vegetative development of the sugarcane, and another one with steady or decreasing values, corresponding to the maturation phase of the plant. When the field is harvested the NDVI value drops down remarkably. Therefore, a two-date difference of NDVI values can be a good indicator for harvest detection. This indicator is useful when the temporal distance between cloud-free acquisitions at field scale is low (less than two months). Fig.2 shows an example of the temporal profile of the NDVI for ratoon and planted crops.

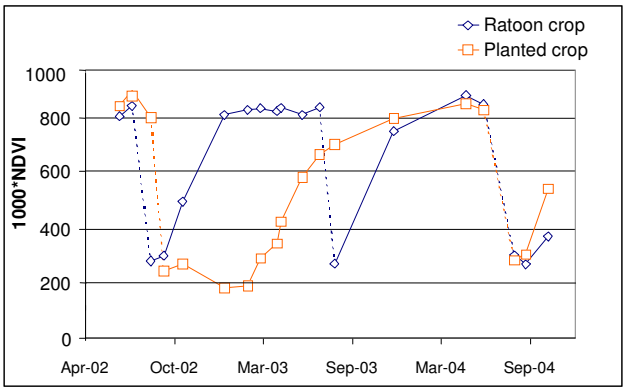

Fig. 2. Example of the temporal profile of the NDVI at sugarcane field scale.

2) Modelling: Crop growth modelling is the second source of information. We used the sugarcane ecophysiological growth model MOSICAS [18] to simulate LAI profiles at field scale. This model estimates sugarcane growth on a daily time scale. It deals with biophysical data on the environment of the sugarcane plot (soil characteristics and climatic data) and the crop management sequence. MOSICAS was calibrated and validated in Reunion for ratoons of the R570 sugarcane variety, with a 12-month cropping cycle.

Since we seek to build a field harvest indicator based on the NDVI, daily estimations of LAI made by MOSICAS were transformed to NDVI by the mean of a regression (Eq. (1)) that we established using LAI ground measurements and spatial data.

$$NDVI = 1/9.713 * Ln(LAI/0.003) \qquad (1)$$

From simulated NDVI profile, we obtained a helpful indicator *(Tn)* for the harvest detection which is the number of days required to reach a given threshold of NDVI starting with a given harvest date. This indicator, mainly based on climatic data, is used to fill the gap in radiometric information, so that it can inform us on the possibility of having sugarcane cut between two dates. For instance, when the delay between two cloud-free images of a field is significant (e.g., more than 2 months) harvesting can not be detected using the NDVI temporal profile, whereas the indicator stemming from the model can provide us with this possibility. Fig.3 illustrates an example of relations between the simulation starting date (harvest date) and the number of days required to reach a NDVI threshold of 0.5, 0.6 and 0.7 respectively. These plots were obtained using 2002 climatic data recoded in La Mare station located in the north-eastern part of the Island. We noticed that for high values of NDVI threshold (0.7 in our example) the model is very sensitive to meteorological variables such as rainfall amount.

3) Expert knowledge: Knowledge about the phenological and physiological stages of sugarcane, about the temporal behaviour of its NDVI, and about the harvest campaign evolution must be integrated in the decision support system in order to automate the harvesting detection process.

In fact, expert knowledge constitutes the basis of the rules used in the decision support system that we developed.

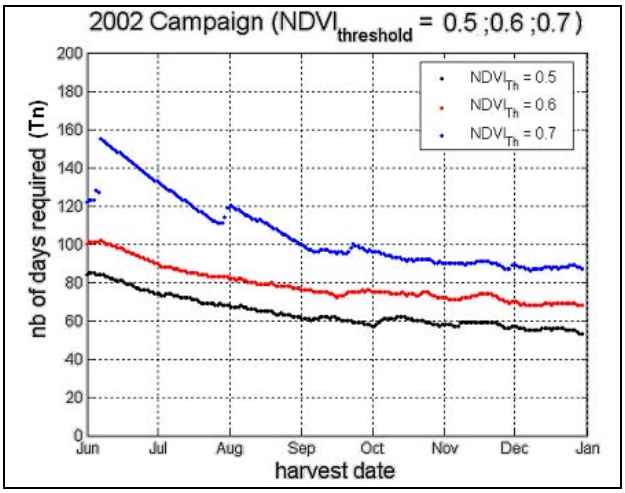

Fig. 3. Example of the plots of the number of days required to reach a NDVI threshold (Tn) as a function of the harvest date (the starting date of the simulation of NDVI). These plots were calculated using climatic data recorded during 2002 harvest campaign.

B. Decision support system

Our decision support system attempts to give a decision on the presence of a sugarcane harvest between two acquisition dates *t* and *t'* at the field scale.

In this subsection we describe the input/output variables of the system, its rule base, and the fuzzy operator that we used to aggregate information.

1) System Input/Output: Twelve parameters constitute the inputs of the system. Seven of them are fuzzy and five are non-fuzzy. These inputs are calculated using information coming from the three different sources: multi-temporal imagery, crop growth modelling, and expert knowledge.

First, the system makes a temporal classification of acquisition dates *t*, *t'* and *t''* (*t''* = all the dates preceding *t'*). Three intervals are defined using the beginning dates and ending dates of the current and the last harvest campaigns (Fig.4). The date *t* is classified among the intervals "No Campaign" or "Current Campaign". The dates *t'* and *t''* are classified among the intervals "No Campaign", "Current Campaign", or "Last Campaign". For simplification reasons, the selection of *t''* was restricted to acquisition dates preceding *t'* and belonging to the same temporal interval.

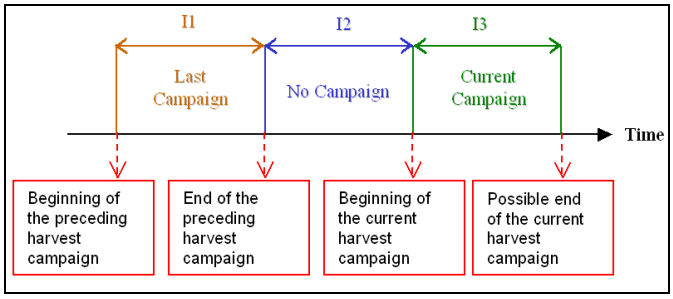

Fig. 4. The temporal intervals used for the classification of the acquisition dates.

* The temporal classes of acquisition dates constitute the first two inputs of the inference system:

- "In1" is the class of acquisition date *t*.
- "In2" is the class of acquisition date *t'* (and *t"* if it exists).

* In a fuzzy framework, three other inputs are calculated using acquisition dates, the last harvest date, the date of the beginning of the harvest campaign, the nominal cycle length, and the indicator *Tn* (Time needed) stemming from the growth modelling. Here is the role of each of these inputs:

- "In3" checks if the temporal distance (in number of days) between *t* and the last harvest date is higher than or equal to the nominal cycle length (which is fixed in this study to 9 months ±1 month).
- "In4" compares the temporal distance (*t-t'*) to *Tn* in order to examine the possibility of field harvest between *t* and *t'*. This input, calculated using the model indicator, includes an ambiguity range of ±1 month.
- "In5" compares the difference between *t* and the date of the beginning of harvest campaign to *Tn*. This parameter is useful when *t* belongs to the "Current Campaign" period and *t'* belongs to "No Campaign". The ambiguity range is ±1 month.

The membership functions of these fuzzy inputs are represented in Fig.5.

* On the other hand, the system assigns to NDVI values membership degrees to three possible sets: "Low", "Medium", and "High". We conceived these sets according to the different status of sugarcane field. Fig.6 shows the fuzzy sets of the NDVI, and an example of NDVI profiles plotted according to the thermal time (calculated as the accumulation of daily mean temperature since January 1, 2003 minus a base temperature of 12°C). Using the NDVI profiles, the configuration of the sets were defined by photo-interpretation and expertise:

- "Low" NDVI values (< 0.30) correspond generally to residues and bare soil after field harvesting.
- In growth phase, the NDVI values are "Medium" (between 0.30 and 0.75). They are also 'Medium" in the senescence phase.
- At the end of the growth stage and before senescence, the NDVI values are "High" (>0.75).

The NDVI classes constitute the inputs "In6", "In7" and "In8" of the inference system:

- "In6" is the class of NDVI(*t*).
- "In7" is the class of NDVI(*t'*).
- "In8" is the class of NDVI(*t"*) (if it *t"* exists).

The membership functions of these three inputs correspond to Fig.6.

* Another input obtained using NDVI is "In9". It is a fuzzy input based on the two-date difference of NDVI calculated at *t* and *t'*. It checks if the difference value (NDVI(t) – NDVI(t')) is higher than a specific threshold $\Delta NDVI_{Threshold}$. In our calculation, the threshold was fixed to 0.3 with an ambiguity range of ±0.1. The membership function of this input is showed in Fig.7.

* Two ternary inputs are integrated to describe the NDVI behavior before the date *t*: "In10" and "In11" check if the sign of the gradient between NDVI(t') and NDVI(t") is negative or positive respectively. Each of these inputs takes a single label [No t"], [For at least one t"], or [For all t"].

* The last input "In12" is integrated to indicate if the image of the field acquired at date *t* is cloud free or not. One of two labels [Yes] or [No] can be assigned to this input.

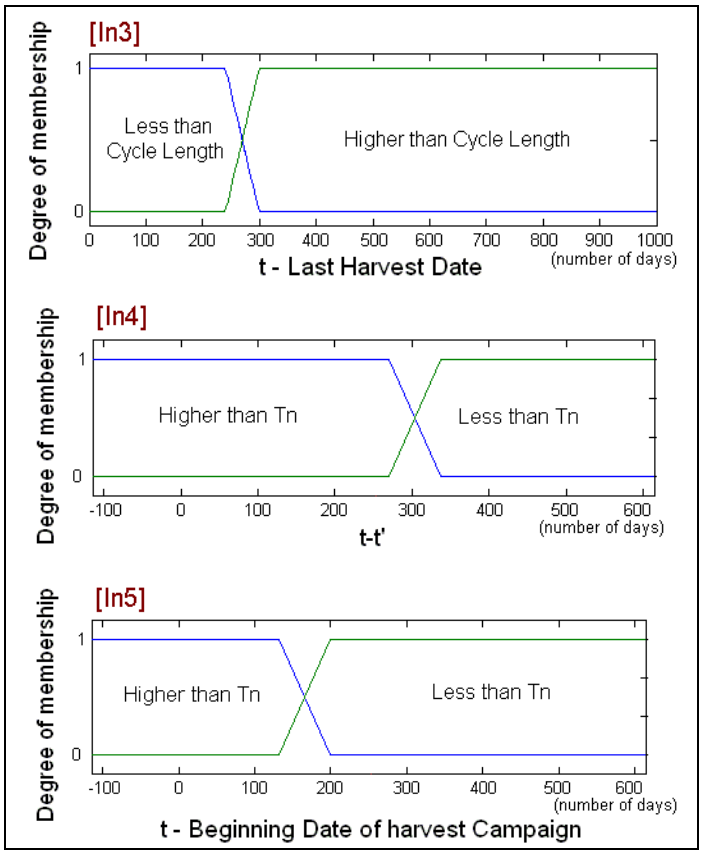

Fig. 5. Membership functions of inputs "In3", "In4" and "In5".

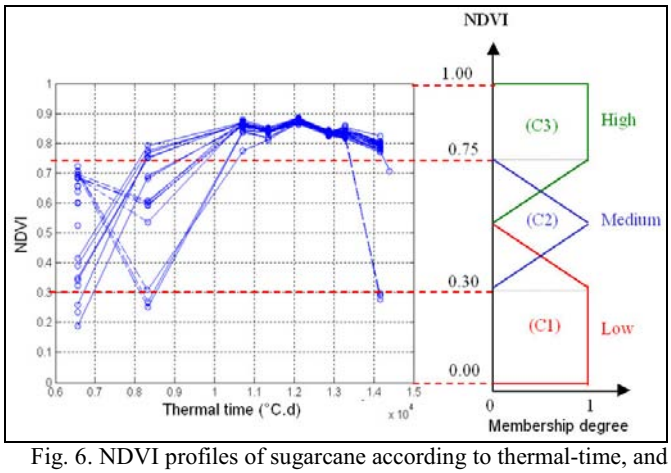

Fig. 6. NDVI profiles of sugarcane according to thermal-time, and the configuration of the membership functions of NDVI fuzzy sets. This configuration of membership functions corresponds to the inputs "In6", "In7" and "In8".

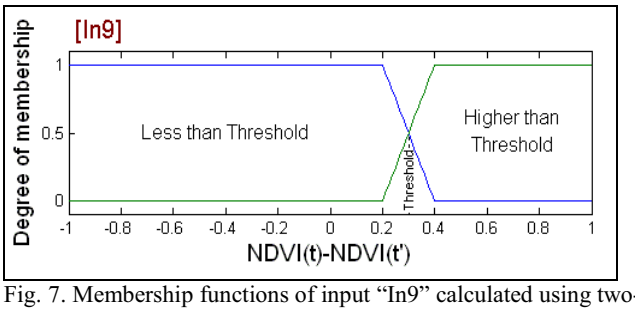

Fig. 7. Membership functions of input "In9" calculated using two-date NDVI difference.

Concerning the system output, we decided that it might be fuzzy in order to exploit the tolerance for imprecision and uncertainty, and to associate to each decision a confidence value. So, the decision can belong to three possible categories:

- "HARVESTED" when the system detects that the sugarcane field is harvested between *t* and *t'*.
- "NOT HARVESTED" when the system does not detect a field harvesting between *t* and *t'*.
- "NO DECISION" when the system is unable to decide if the sugarcane field has been harvested between *t* and *t'* or not.

The membership functions of the output are represented in Fig.8. In order to avoid contradictory decisions, we configured the output sets so that "HARVESTED" and "NOT HARVESTED" sets do not overlap. In the other hand, "NO DECISION" set overlaps with the two other sets. According to the chosen configuration, if a decision has a membership value μ for the class "HARVESTED", his membership value for the classes "NO DECISION" and "NOT HARVESTED" are (1 – μ) and 0 respectively. Similar when the decision belongs to the class "NOT HARVESTED".

2) Rules: The rule base of a fuzzy system describes the behavior of the inference system based on the linguistic terms associated with the input and the output variables. It regroups the various possible knowledge-based scenarios by a finite collection of IF *X* THEN *Y* rules; e.g.

Rule 1: if x_1 is A_1^1 and x_2 is A_2^1 … and x_n is A_n^1 then y is B^1
Rule 2: if x_1 is A_1^2 and x_2 is A_2^2 … and x_n is A_n^2 then y is B^2
…
Rule r: if x_1 is A_1^r and x_2 is A_2^r … and x_n is A_n^r then y is B^r
(Eq.2)

where A_k^r is the class of the input "In*k*" assigned to x_k and B^r is the output class.

While being based on expert knowledge, we defined a set of 118 rules covering the maximum of possible cases that the system can affront to make decisions. Here are some examples:

- if *In1* is *No_Campaign* and *In2* is *No_Campaign* then Decision is *NOT_HARVESTED*
- if *In1* is *Current_Campaign* and *In2* is *No_Campaign* and *In3* is *Higher_than_Cycle_Length* and *In6* is *Low* and *In7* is *High* and *In12* is *No* then *Decision* is *HARVESTED*
- if *In1* is *No_Campaign* and *In2* is *Last_Campaign* and *In6* is *Low* and *In7* is *Medium* and *In9* is *Less_than_Threshold* and *In12* is *No* then Decision is *NO_DECISION*

3) Fuzzy inference: Our system is based on Mamdani's fuzzy inference method [19] that uses the MIN t-norm as the conjunction operator for each rule *"r"* and the MAX s-norm as aggregation operator. We point out that the input of the aggregation process is the list of truncated output functions returned by the conjunction process for each rule. The inferred conclusion μ'_B, in the form of a membership function according to Eq. (2), is given by:

$$\mu'_B(y) = \max_r(\min(\alpha^r, \mu_{B^r}(y))) \qquad (3)$$

Where the activation degree of the r-rule is:

$$\alpha^r = \min(\mu_{A_1^r}(x_1),...,\mu_{A_n^r}(x_n)) \qquad (4)$$

The system outputs are the membership values for the three fuzzy sets "HARVESTED", "NOT HARVEST", and "NO DECISION".

V. Validation

We assessed the decision support system using our thirteen images time series acquired between July 6, 2002 and October 26, 2004, and the daily climatic data (for the model). Results have been compared to ground truth data of a sugarcane estate composed of 33 fields situated in the North-east of the Island. For this estate we have the harvest dates of each field during the harvest campaign of 2002, 2003 and 2004. The average field size is equal to 5.4 ha, and the average altitude is about 70 m.

By considering that for each output having a membership value for the class "HARVESTED" different from zero this one is retained as a "HARVEST" decision, and similar for the outputs with membership values for the class "NOT HARVESTED" different from zero, the overall accuracy of the system, according to the confusion matrix (Table II), is 93%, with 85% of good harvested field detection and 96% of good non-harvested field detection. The errors of commissions are 14% and 3% for the "HARVEST" and "NO HARVEST" decisions respectively, and the percentage of "NO DECISION" is 1.3%.

If we look at decisions that have membership values for the classes "HARVESTED" and "NOT HARVESTED" higher than 60%, we obtain an overall accuracy of 90% with 5.8% of the decisions belonging to the class "NO DECISION". For decisions with membership values higher than 70%, 80%, and 90% the overall accuracy values are 90%, 73% and 72% respectively and the percentages of "NO DECISION" are 6%, 23.8% and 24.8% respectively.

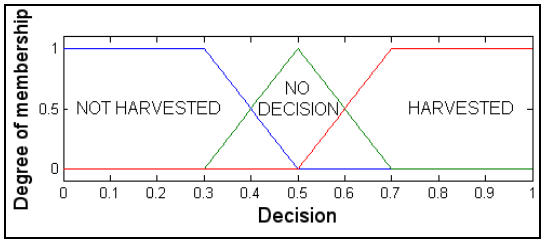

Fig. 8. Membership functions of the system output.

TABLE II

THE CONFUSION MATRIX OF THE SUGARCANE HARVESTING DETECTION (GIVEN IN NUMBER OF FIELDS).

		Expert system decision					
		HARVEST (μ > 0)	NO HARVEST (μ > 0)	NO DECISION	Row total	System's accuracy	Errors of Omission
Reference data base	HARVEST	71	9	3	83	**0.85**	0.15
	NO HARVEST	12	299	2	313	**0.96**	0.04
	Column total	83	308	5		Global precision **0.93**	
	Errors of Commission	0.14	0.03				

VI. CONCLUSION

This work presents a decision support system for automatic detection of sugarcane harvesting. In a fuzzy framework, the system deals with information coming from three different sources: multi-temporal imagery, crop growth modelling, and expert knowledge. The inference is based on Mamdani's fuzzy method that exploits an IF-THEN rule base. The system output belongs to three possible fuzzy sets.

The evaluation was done using an irregular series of high spatial resolution images with significant acquisition gaps, and the results obtained were very satisfactory.

The next step consists of analysing the output errors and adjusting the configuration of the fuzzy inputs. It would also be interesting to integrate other indicators that use SWIR reflectance, which is very sensitive to crop residues, in order to improve system performance especially in dry zones.

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