Computational theory of perceptions applied to automatic analysis of forest degradation

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Abstract - **In the field of environmental preservation, one important challenge consists of the constant monitoring of the vegetation cover degradation. Satellite images are important tools employed in environmental studies. Unfortunately, these images depend on the analysis and interpretation made by human experts. Due the large amount of data to analyze and the insufficient number of experts, the decision process may become slow. Therefore, new computational tools that make possible the automatic description of these image contents are desirable to support this task. This paper presents a contribution to tackle this problem through an application based in the Computational Theory of Perceptions. The implemented software tool allows us to produce accurate linguistic descriptions of the vegetal cover degradation degree using multispectral images. We also include different results achieved using real satellite imaging data.**

Keywords—Computational Theory of Perceptions, Fuzzy Logic, Image Analysis, Linguistic Report, Environmental Degradation, Vegetation Monitoring.

I. INTRODUCTION

Forests are an important reserve of biodiversity, source of natural resources and carbon stocks. They protect soil from erosion and regulate the hydrological cycle, and also ensure the ecological and climatic equilibrium. In consequence, forests have a key role in maintaining the quality of life of populations. Forest degradation refers to the reduction of the capacity of a forest to produce goods and services [1]. In consequence, a degraded forest produces a reduced supply of goods and services and it maintains only limited biological diversity. It has lost the structure, function, species composition and/or productivity normally associated with the natural forest type expected at that site [1]. The degradation causes may be natural (i.e. fires or drought), human-induced (i.e. agriculture or urban expansion), or a combination of both.

Because of the need for environmental preservation, governments have created stricter laws and increased surveillance to fight against ecological crimes. Accurate information on the forest condition and the extension of its degradation will enable the prioritization of human and financial resources to prevent further degradation and to restore and rehabilitate degraded forests [2]. Among the control measures, the use of satellite images in monitoring of the forests has been widely used [3-4]. Such images are important in the study of the distribution and temporal evolution of vegetation cover. Although satellite images are an important source of information for understanding the geographic space, for inspection actions and for decision making, they depend on the analysis and interpretation of specialists.

Humans have the ability to produce linguistic descriptions of complex and imprecise situations. Through natural language (NL), their perception of a phenomenon can be described in different levels of granularity to hide irrelevant aspects of the problem. However, the automatic generation of linguistic descriptions from non-trivial digital images and/or video sequences is still a difficult problem that has challenged the scientific community [5].

The Computational Theory of Perception (CTP), introduced by Zadeh [6] and developed in later works [7-12], was inspired in the use of natural language by humans. CTP provides a framework to develop computer systems able to produce imprecise descriptions of phenomena similarly as humans do.

This paper describes a prototype of novel system based on the CTP framework to support the automatic analysis of forest degradation. First, digital image processing techniques were applied to extract relevant attributes from the satellite images. Next, these attributes were used as input variables for adapting to the considered application of the Granular Linguistic Model of a Phenomenon (GLMP) [13-14]. Finally, a linguistic description of the degradation of vegetation cover was created using fuzzy logic to calculate the relevance of a set of sentences.

Successful examples of GLMP model application to produce linguistic descriptions of different types of phenomena can be found for the behavior of traffic in a roundabout [13], in the reporting of financial data [15], in descriptions about relevant features of the Mars' Surface [14], or in the assessing of reports produced by truck driving simulators [16].

This paper is organized as follows. Section II describes in a general manner the structural model applied to create linguistic descriptions of a given phenomenon. Section III explains how to instantiate this model to automatically produce the linguistic reports corresponding to environmental degradation using satellite images. Section IV shows the experimentation carried out using Landsat satellite images from Mato Grosso (Brazil), captured in the period 2000-2005. Finally, Section V presents the conclusion of this study and outlines future works.

II. STRUCTURAL MODEL APPLIED

This section describes the Granular Linguistic Model of a Phenomenon (GLMP) and the structural model applied to the development of the computational system. Figure 1 sketches the processing modules in the implemented: Data Acquisition Module (DAM), Data Processing Model (DPM), Linguistic Description Module (LDM) and Template Module (TM), respectively. We describe these modules and the associated data structures in the following subsections.

A. Granular Linguistic Model of a Phenomenon (GLMP)

This subsection summarizes the GLMP model as described in [14]. A GLMP consists of a multi-layer network of interlaced layers of Perception Mappings (PMs) and Computational Perceptions (CPs). Each PM receives a set of input Computational Perceptions (CPs) and produces a higher-level CP. Each CP of the network has a certain degree of granularity and covers some specific aspects of the phenomenon. The GLMP paradigm allows to model particular perceptions of complex phenomena by using different linguistic expressions and aggregation functions.

1) Computational Perception (CP)

A CP is a computational model of a unit of meaning about the phenomenon to be described. In general, CPs correspond with specific parts of the phenomenon at certain degree of granularity. Formally, a *CP* is a set of 2-tuples:

$$(A,W)=\{(a_1,w_1),(a_2,w_2),\ldots,(a_n,w_n)\},$$

where:

$A = \{a_1, a_2, \ldots, a_n\}$ is a set of linguistic expressions (words or sentences in natural language) that represents the meaning of a CP. Each a_i describes a possible value of CP with specific degree of granularity. During the process, the designer defines the linguistic domain A.

$W = \{w_1,w_2, \ldots ,w_n\}$ is a set of validity degrees $w_i \in [0,1]$ associated to each a_i. The values of w_i are instantiated during the on-line process, i.e., they change according with the state of the monitored phenomenon. The concept of validity depends on the truthfulness and relevancy of each sentence in its context of usage.

2) Perception mapping (PM)

The *PM* is a 4-tuple (U, y, g, T) used to create new CPs by aggregating CPs, where:

U is a set of input CPs, $U = (u_1, u_2, \ldots, u_n)$, where u_i is a variable defined in the input data domain;

y is the output CP with values $y = \{(a_1,w_1), (a_2,w_2),\ldots, (a_n,w_n)\}$;

g is an fuzzy aggregation operation: $W_y = g(W_{u1}, W_{u2}, \ldots ,W_{un})$ where: W_y is a vector $(w_1,w_2,\ldots ,w_n)$ of degrees of validity assigned to each element in y, and W_{ui} are the degrees of validity of the input perceptions. In case of 1-PM, g is built using a set of membership functions; and

T is a linguistic template used to describe the current state of the monitored phenomenon, e.g., "The degradation of the forest area is {high | medium| low}".

B. Computational Perception System (CPS)

Computational Perception System (CPS) is inspired by the GLMP. CPS allows the automatic generation of linguistic descriptions of a phenomenon from using an Expert Knowledge Base. It can be structured into three domains: application, computational perception and linguistic, respectively.

In the considered application domain, CPS includes both acquisition modules (DAM) and data processing modules (DPM). These modules are responsible for the extraction and manipulation of the relevant characteristics of the phenomenon (i.e. the input data), that will be used by the Linguistic Description Module to build the linguistic report associated to the phenomenon.

In the domain of Computational Perception, the Linguistic Description Module (LDM) is responsible for creating the perception of a phenomenon organized in different levels of granularity.

In the domain of Linguistic, the Language Template Module (TM) provides the syntactic structures to generate the sentences used in the linguistic reports, and it is dependent on the application and on the experts's knowledge.

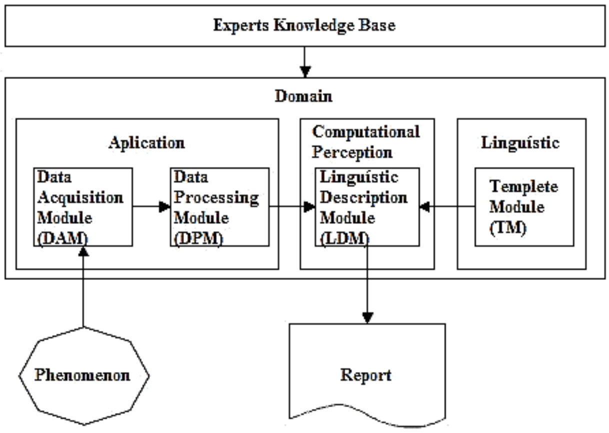


Fig. 1. Main components of the proposed Computational Perception System.

III. LINGUISTIC DESCRIPTION OF ENVIRONMENTAL DEGRADATION

In order to evaluate the applicability of the proposed model for describing enviromental degradation, we considered the description of forest area destruction based on satellite images. These images correspond to the Amazon Basin region that covers an area of approximately 6,600,000 km^2 and extends by Brazil, Colombia, Ecuador, Peru, Bolivia and Venezuela. This region contains the largest continuous rain forest in the world. Although deforestation is a problem common these countries, in Brazil its occurrence is even more intense.

Due to the dimension of the region and to the great difficulty of accessing it, the study of the dynamics of deforestation in the Amazon requires the application of remote sensing techniques for analyzing the land use. However, the automatic and accurate interpretation of satellite images corresponding to very extense and complex areas is still a difficult problem that requires from skilled human resources [17].

This section describes the implementation of our proposed Computational Perception System (CPS) applied to the analysis and linguistic description of forest degradation using satellite images from the Amazon region.

A. Data Acquisition Image Module (DAM)

The dataset used contains multispectral images provided by the sensors of the TM (Thematic Mapper) Landsat 5 and Landsat 7 satellites. These images obtained for free at the website of the National Institute for Space Research of Brazil (INPE) [18].

The spatial resolution of the images is 2,000×2,000 pixels and its geometrical resolution in the bands 1, 2, 3, 4, 5 and 7 is 30 m (i.e. each "pixel" of the image represents an area of 0.09 hectares). For the band 6, the resolution is 120 m (i.e. each "pixel" represents 1.4 hectares).

Each band corresponds to a range of the electromagnetic spectrum captured by the satellite and it has specific features and applications. In order to tackle the environmental degradation study is necessary to perform the proper combination of spectral bands in order to highlight the properties of water, vegetation and soil. For this purpose, INPE recommends the use of the following RGB composite images: RGB-432 and RGB-543; respectively. In the RGB-432 (color infrared composite) image, two visible bands and the near infrared band are combined as follows: R = near IR, G = visible red, and B = visible green. This composite contains the near infrared waveband and therefore vegetation types are better distinguished compared to a true color composite (i.e. the RGB-321 images). In the RGB-543 (false color composite) image, one visible band and two infrared bands are combined as follows: R = near IR, G = mid IR, and B = visible red. Although the colors are not natural to human eyes, the RGB-543 band composition is the best for distinguishing different forest and vegetation types.

The Data Acquisition Module (DAM) allows the system user to select and combine the multispectral bands of the scene that will used by the Data Process Model. Figure 2(a) shows an example of the composite RGB-432 image.

B. Data Process Module (DPM)

The Data Processing Module (DPM) is responsible for performing the segmentation, classification, filtering and extraction of the relevant characteristics of the classes considered. The process of image segmentation consists in partitioning the image into homogeneous regions, according to some specific features.

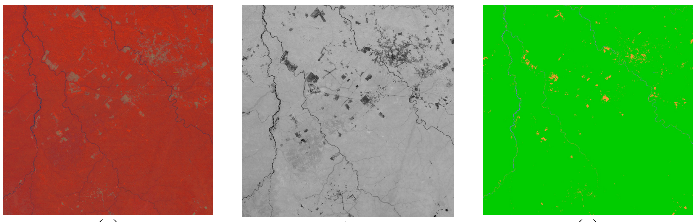
To analyze the presence and the localization of vegetation, the Normalized Difference Vegetation Index (NDVI) proposed in [19] was used. This index allows a better visualization of plant biomass (i.e. the higher the value of NDVI, the denser the green biomass is).This index is calculated from the values of the bands of the spectrum of the red (band 3) and of the near infrared (band 4), as in (1).

$$NDVI = \frac{(NIR - R)}{(NIR + R)} \tag{1}$$

where: NIR = near infrared (0,75 – 0,90 μm); and R = red (0,63 – 0,69 μm).

Figure 2(b) shows the NDVI image generated from the image of Figure 2(a). To perform classification, the domain of values in the NDVI image is divided into ranges (see Table I). The values of these ranges correspond to the three classes considered in the PRODES Project (i.e. “Forest”, “Non Forest” and “Hydrography”, respectively). These values may vary depending on the properties of the scene under study.

Figure 2(c) shows the Thematic Image (TI) generated from the NDVI image of Figure 2(b) by using these ranges (adapted from [19]).



(a) (b) (c)

Fig. 2. Proposed preprocessing of multispectral images: (a) initial composite RGB-432 image; (b) NDVI image; and (c) resulting thematic image

TABLE I. RANGES OF VALUES OF THE NDVI IMAGE

Range	Class
0.3 <= NDVI <= 1	Forest
0 <= NDVI < 0.3	Non Forest
-1 <= NDVI < 0	Hidrography

The study of the evolution of vegetation cover can be carried out from the comparison of NDVI images obtained at different periods of time. Therefore, the proposed system will works with pairs of images captured at different dates. These respective images will be represented by the superscripts *t* and *t*+1, respectively. Figure 3 outlines the images and processes involved in the application modules included in our system (DAM and DPM, respectively).

The last task of the Data Processing Module (DPM) is to extract the relevant information for the application, in order to pass these parameters to the Language Description Module (LDM). For each of the three classes considered (“Forest”, “Non Forest”, and “Hydrography”, respectively) the parameter values computed by the equations (2)-(4), are determined. These classes are considered in the images of the Brazilian Amazon Deforestation Monitoring Project (PRODES Project) [20].

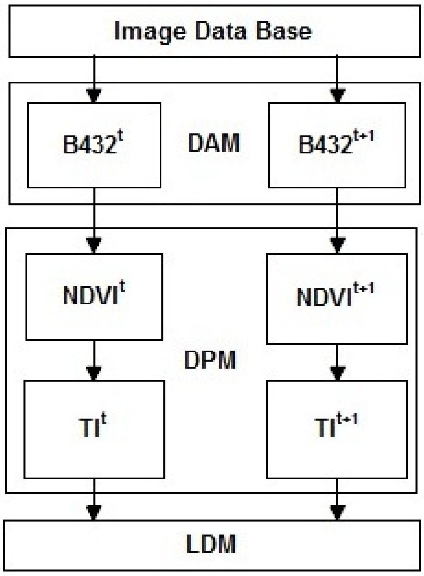


Fig. 3. Structure diagram of the application modules in our system.

- **Coverage Area Percentage of the class i at the image t+1 (CAP_i):**

$$CAP_i = \frac{100 * CA_i}{AI} \tag{2}$$

where CA_i is the coverage area of class i at the image t+1 and AI is the total area of the image.

Variation Percentage of each class i between images t and t+1 (VP_i):

$$VP_i = \frac{100 * \left(\sum_j^n Count_{j \to i} - \sum_j^n Count_{i \to j} \right)}{CAP_i} \tag{3}$$

where $Count_{j \to i}$ represents the number of pixels of the class i that are transformed into pixels of the class j between the images t and t+1, $Count_{i \to j}$ represents the corresponding count of pixels from class i transformed into pixels of class j, and CAP_i is the index computed by the previous equation (2).

- **Interclass Impact for classes i and k ($II_{k \to i}$):**

$$II_{k \to i} = \frac{100 * \left(Count_{k \to i} - Count_{i \to k} \right)}{CAP_i} \tag{4}$$

where k is the class that has caused impact in the considered class i, and the '→' means the change of the class pixels relative to previous and subsequent images.

C. Linguistic Description Module (LDM)

The Linguistic Description Module (LDM) is the responsible for the linguistic description of a phenomenon in different levels of granularity. The parameters sent by the DPM, which correspond to the CPs (Computational Perceptions), are the inputs of the 1-PM$_1$ to 1-PM$_4$ used in the GLMP for the application considered, as shown by Figure 4. To simplificate, the involved CPs are not represented.

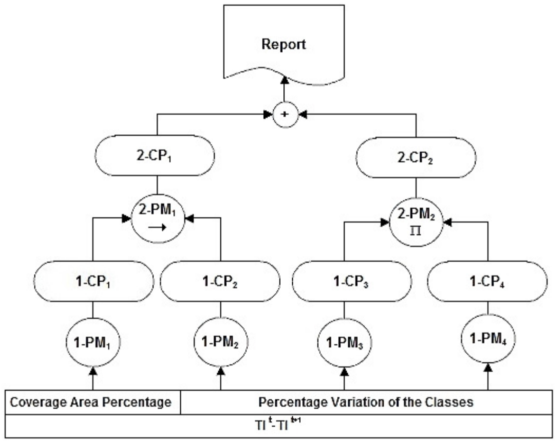


Fig. 4. GLMP for a one class of the image

The GLMP structure obtained for one of the three classes of land use at different degrees of granularity. For construction of the final report, the GLMP includes the other classes.

Each 1-PM$_1$ is structured from the fuzzification of the CAP_i variables (see Eq. (2)) by the membership functions shown in the Figure 5.

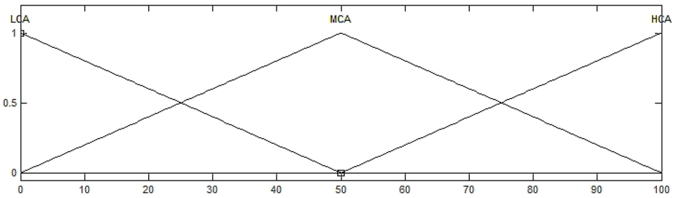


Fig. 5. Membership functions of CAP_i with labels: LCA for "Low Coverage Area", MCA for "Moderate Coverage Area", and HCA for "High Coverage Area", respectively.

Perception Mappings 1-PM$_2$ to 1-PM$_4$ are structured from the fuzzification of the variables PV_i and $II_{k \to i}$, that are respectively computed by Eqs. (3) and (4), represented by the membership functions of Figures 6 and 7.

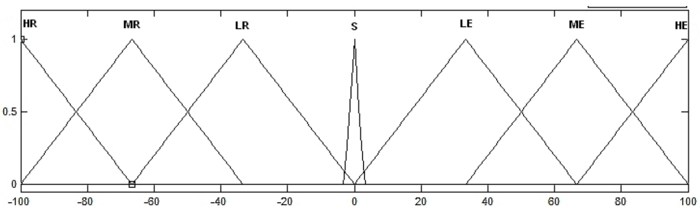


Fig. 6. Membership functions of PV_i variables with labels: HR="High Regression", MR="Moderate Regression", LR=" Low Regression", S="Stability", LE="Low Expansion", ME="Moderate Expansion", and HE="High Expansion"

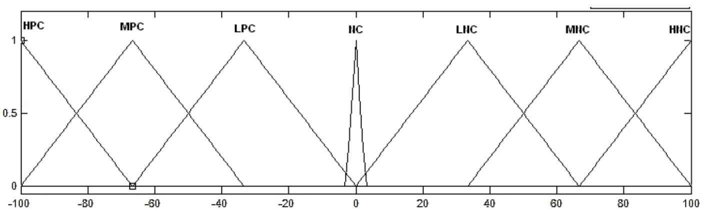


Fig. 7. Membership functions of $II_{k \to i}$ variables with labels: HPC="High Positive Contribution", MPC="Moderate Positive Contribution", LPC="Low Positive Contribution", NC="Non-Contribution", LNC="Low Negative Contribution", MNC="Moderate Negative Contribution", and HNC="High Negative Contribution".

2-PM$_1$ and 2-PM$_2$ are built using different aggregation functions. 2-PM$_1$ employs an aggregation function based on rules. The degrees of validity of 1-PM$_1$ and 1-PM$_2$ are used as antecedents of the rules. The consequents are obtained by the membership function of the Figure 8. This aggregation function uses a Mamdani-type fuzzy inference system [21].

2-PM$_2$ uses an aggregation function based on the Cartesian product of the degree of validity to the fuzzy sets. The label with largest validity degree is chosen to compose the sentence.

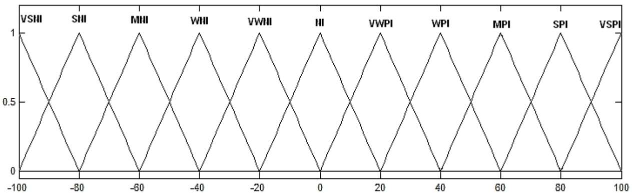


Fig. 8. Membership functions of the consequent of 2-PM$_1$ with labels: VSNI="Very Strong Negative Impact", SNI="Strong Negative Impact", MNI= "Moderate Negative Impact", WNI="Weak Negative Impact", VWNI="Very Weak Negative Impact", NI=" No Impact", VWPI="Very Weak Positive Impact", WPI="Weak Positive Impact", MPI="Moderate Positive Impact", SPI="Strong Positive Impact", and VSPI="Very Strong Positive Impact".

IV. EXPERIMENTATION

A. General characteristics of the study area

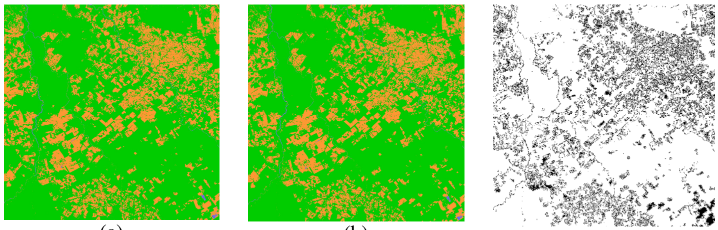
The Amazon Deforestation Monitoring Project (PRODES), developed by the Brazilian National Institute For Space Research (INPE), analyzes the annual rates of deforestation of the Amazon since 1988 [20]. According to the annual estimates of deforestation generated based on satellite images, the Brazilian Amazon presents an accumulated deforestation of 396,857 km^2 in the period 1988-2012. The main deforested areas coincide with the agricultural frontier advances [22], called "arc of deforestation" [19]. The state of Mato Grosso (MT) is in the first position of the list, with an area of 136,122 km^2 accumulated deforestation for this same period.

In our experimentation, we used satellite images from Landsat TM 5 and Landsat 7, bands 432, orbit 1804, Path 228, Row 068, with the following dates: July 01, 1985/July 26, 2000/ July 24, 2005/July 25, 2011. These images were selected because the analyzed region covers the area from Juara, municipality from the Mato Grosso that presented the largest area of accumulated deforestation of the state. Table II shows the rates observed in five years. The accumulated deforestation rate (i.e. "Forest" area converted into "Non Forest") in the period 2000-2005 was 7.8%.

TABLE II. RATES IN DEFORESTATION ON JUARA-MT

Increase	Until 2000	Until 2001	Until 2002	Until 2003	Until 2004	Until 2005
	0,0	1,0	1,9	1,5	1,5	1,9
Forest	67,1	66,1	64,2	62,7	61,2	59,3
Non Forest	32.2	33.2	35.1	36.6	38.1	40.0
Hydrography	0,7	0,7	0,7	0,7	0,7	0,7

Figures 9(a) and 9(b) show the Thematic Images generated from the images of Juara, composition RGB-543, from July 24, 2000 and July 24, 2005, respectively. The black pixels of Figure 9(c) show the extension of the devastation of the forest



(a) (b) (c)

Fig. 9. Juara-MT images: (a) RGB-543 compositon at July 24, 2000; (b) RGB-543 composition at July 24, 2005; and (c) accumulated deforestation.

B. Descriptions Obtained

Based on the images described, that represent part of the municipality of Juara, the proposed system estimated the following interclass variation rates presented in Table III.

TABLE III. RATES IN THE PERIOD 2000 TO 2005

Forest Area	Forest Variation	Impact of Non Forest	Impact of Hydrography
73,3%	-7,9%	7,8%	0,1%
Non Forest Area	**Non Forest Variation**	**Impact of Forest**	**Impact of Hydrography**
26,4%	31,1%	-31,0%	-0,1%
Hydrography Area	**Hydrography Variation**	**Impact of Forest**	**Impact of Non Forest**
0,3%	9,1%	-18,2%	9,1%

Figure 10 shows the obtained GLMP for the "Forest" class. From de values listed in the Table III, which are inputs of 1-PM, the model generates automatic linguistic descriptions at different levels of granularity.

The temporal evolution of the region of cover in the current image is described as follows:

Region of Forest : Moderate Coverage Area and Low Regression of Forest area, resulting in Weak Negative Impact for this class, due the Low Negative Contribution of the Non-Forest area and Non-Contribution of the Hydrography area.

Region of Non-Forest : Moderate Coverage Area and Low Expansion of Non-Forest area, resulting in Weak Positive Impact for this class, due the Low Positive Contribution of the Forest area and Non-Contribution of the Hidrography area.

Region of Hydrography : Low Coverage Area and Low Expansion of Hydrography area, resulting in Very Weak Positive Impact for this class, due the Low Positive Contribution of the Forest area and Low Negative Contribution of the Non-Forest area.

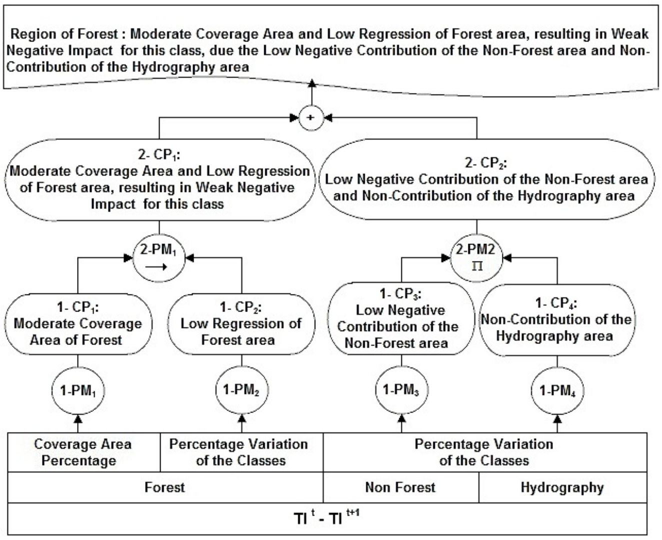


Fig. 10. GLMP for the Forest class

V. CONCLUDING REMARKS

This paper presented an application-oriented prototype for analyzing the environmental degradation. Our system is based in applying the Computational Theory of Perceptions (CTP) to interpret the temporal variations between two multispectral images of the same region, which are registered and then compared. We explore the possibility of automatically producing linguistic descriptions about the level of forest degradation and assessing the impact between the classes present.

The linguistic descriptions, generated using satellite images that were acquired on different dates, reflect the mutual interference among the classes of forest, non-forest and hydrography. From the parameterization of the membership functions, linguistic descriptions can be adjusted to reproduce the knowledge provided by experts.

As future work the authors intend to conduct new assessments based on the perceptions on human experts in enviromental degradation. The experimentation with more complex images includes a higher number of classes in the automatic analysis and description is another natural line of study.

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