An Approach based on Adaptive Decision Tree for Land Cover Change Prediction in Satellite Images

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Abstract: Decision tree (DT) prediction algorithms have significant potential for remote sensing data prediction. This paper presents an advanced approach for land-cover change prediction in remote-sensing imagery. Several methods for decision tree change prediction have been considered: probabilistic DT, belief DT, fuzzy DT, and possibilistic DT. The aim of this study is to provide an approach based on adaptive DT to predict land cover changes and to take into account several types of imperfection related to satellite images such as: uncertainty, imprecision, vagueness, conflict, ambiguity, etc. The proposed approach applies an artificial neural network (ANN) model to choose the appropriate gain formula to be applied on each DT node. The considered approach is validated using satellite images representing the Saint-Paul region, commune of Reunion Island. Results show good performances of the proposed framework in predicting change for the urban zone.

1 INTRODUCTION

The DTs are used in many practical application areas (Kumar et al., 2011)(Levashenko and Zaitseva, 2012). The concept of DTs was popularized by Quinlan with ID3 (Quinlan, 1986). DTs have emerged as an important tool for addressing many problems related to remote sensing images (Fried et al., 1999)(Boulila et al., 2011). Several advantages have encouraged the use of DTs for land cover prediction (Boulila et al., 2011). First, DTs are simple to understand and interpret. Second, they perform well with large amounts of data in a short time. Moreover, a DT prediction generates rules that are accurate and easily interpretable with little user intervention. DT is a widely used data prediction technique for both certain and uncertain data. Data uncertainty arises in many applications during the data collection process. In remote sensing, satellite images are characterized by several imperfection types.

Many decision tree approaches under imperfection were proposed in the literature, namely, probabilistic DTs, belief DTs, fuzzy DTs and possibilistic DTs which were proposed to deal with uncertainty in data represented, respectively, by means of probability distributions, basic belief assignments, degree of membership, and possibility distribution. The difference between the existing approaches mainly lies in the type of imperfection related to the problem at hand (e.g. uncertainty, conflict, imprecision, etc.) and especially in the way of dealing with that imperfection when building the tree. The probabilistic DT is used to classify instances with missing or uncertain attribute values where uncertainty is represented by a probability (Ozols et al., 2006)(Anuradha et al., 2012). For example, in the field of remote sensing, (McIver et al., 2002) use the DTs (C4.5 algorithm) with prior probabilities to classify land cover. The second type of DT is the belief DT. It can represent both imprecision and uncertainty. This method is also suitable to solve problems where a conflict between different sources arises. Many studies have been proposed in this context (Trabelsi et al., 2007)(Elouedi et al., 2001). In the field of remote sensing, (Xuerong et al., 2010) use the DTs with evidence theory for satellite image classification. The third type of DT is the fuzzy DT. It is used to represent the imprecision and also allows modeling vagueness. Most works in the literature apply the fuzzy DT for classification and prediction of imperfect data (Chang et al., 2010)(Levashenko and Zaitseva, 2012). In the field of remote sensing, many studies have been developed (Boulila et al., 2011). Authors in paper (Boulila et al., 2011) use fuzzy ID3 algorithm with the aim of determining the fitting of a given state to the different land cover types (water, urban, forest, etc.). The forth type of

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DT is the possibilistic DT. It allows manipulation of uncertainty, imprecision and ambiguity. Several studies have been developed for classification and evaluation of imperfect data using possibilistic DT such as (Hullermeier, 2002)(Amor et al., 2008).

Despite the significant role that DT plays in many domains, most works in the literature use only one type of DT whatever the nature of imperfection related to data is. The main goal of this study is to propose an adaptive DT for change prediction in satellite image databases. The adaptive DT integrates several types of DTs and it adapts the choice of DT to the type of imperfection related to treated data. This allows taking into account different types of imperfection related to satellite images such as uncertainty, imprecision, conflict and ambiguity. The proposed approach consists of four main processing steps: testing gain type by neural network, selection of attribute measure, partitioning strategy and stopping criteria.

2 THE PROPOSED APPROACH

This paper presents an approach for land-cover change prediction in remote-sensing imagery. This approach is based on an adaptive DT. The purpose of adaptive DT is to choose the appropriate DT method to be applied according to the type of imperfection related to data. An adaptive DT is a DT with the same representation of a standard decision tree. However, on each tree node, we integrate a testing module to select the type of gain to be applied to choose the selection attribute. The testing module is based on neural networks. This model takes as input the values that affect the satellite objects characteristics. Figure 1 illustrates the general architecture of the proposed approach. It is composed of two modules including objects database and predicting of changes.

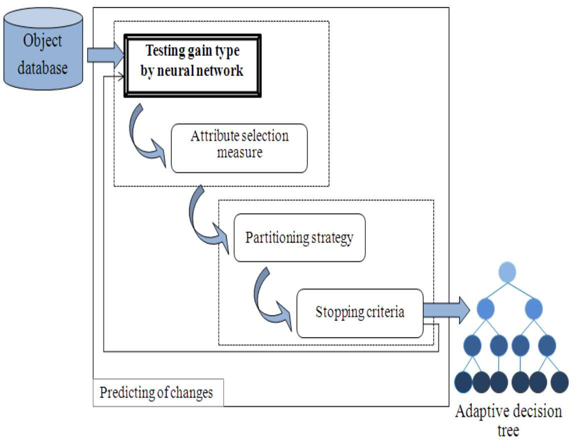

Figure 1: The proposed architecture.

2.1 Object Database

The satellite images were taken by a modeling phase. This phase consists of three steps: The first step is to segment the image into regions of homogeneous pixels. The second step is to select representative regions. The third step is to classify the objects of the database according to their degree of similarity with the query object. The similarity measure is performed between the query state representing the query object at the date t and all states stored in the base (these states are all states contained in all models in the base). Then, all models having a state which is similar to the query one are considered. Changes related to satellite image objects are stored in the temporal object database. This database is built during the off-line mode of the modeling phase. At a given date t_r, the set of attribute values of an object defines the state of this object. In the proposed approach, each object O_r is described by a set of states $S_r(t_{rn})$ each representing the same objects but at a different date ($S_r(t_{rn})$ denotes the state relative to the object at the date t_{rn}). Interested readers can refer to our previous works (Boulila et al., 2010)(Boulila et al., 2011)(Boulila et al., 2012).

So, our approach takes as input this temporal object database. It provides as output a set of knowledge describing land cover change. Since the satellite images are tainted by many imperfections types, the ignorance of these imperfections types will then be able influence on knowledge found or decisions to be made. For this, our approach takes into account the different types of imperfections that are linked to satellite images and model them at the level of prediction phase.

2.2 Predicting of Changes

2.2.1 Step 1: Testing Gain Type by Neural Network

The goal of this step is to select the type of gain to be applied to choose the selection attribute (see step 2 for the types of gain). The choice of the gain nature depends on imperfection type related attributes at each node. To achieve this task, an ANN is used. The ANNs have emerged as an important tool to solve this problem and many other problems related to remote sensing images (Neagoe et al., 2011). The objective of testing the gain type or tree type on each node is to obtain an adaptive tree that take into account several types of imperfection related to satellite imagery. To do this, the ANN model is applied on the values that have influence on the objects characteristics to determine the different imperfection types on each node. According to these imperfection types, we will define the tree type that we will use. Figure 3 shows the general architecture for the choice of DT types.

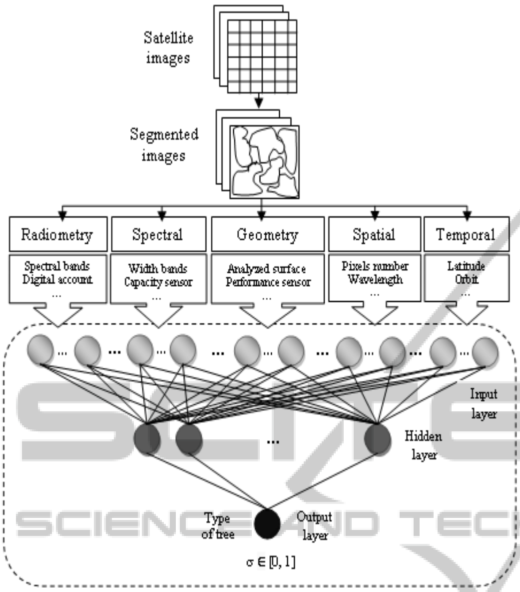

Figure 2: The proposed architecture of neural network for choose tree types.

The input data of the neural network are coded and normalized in vector containing the components radiometric, spectral, geometry, spatial and temporal of each image. Assume an object,O_P, is extracted from a satellite image acquired at date t; this object can be a lake, vegetation zone, urban area, etc. Details of object extraction can be found in (Boulila et al., 2010)(Boulila et al., 2011)(Boulila et al., 2012). According to (Pulvirenti et al., 2011)(Benz et al., 2004), we determined the factors that have influence on the characteristics of O_P.

- The radiometry of the object O_P depends on: Spectral bands; Sensor calibration coefficients; Detectors; Digital account (0-255);
- The spectral characteristic depends on: Sensor capacity; Width of the interval of each band; Optical filtering device;
- The geometry depends on: Sensor performance; Stability of the satellite in its orbit; Analyzed surface;
- The spatial characteristic depends on: Pixels number; Instantaneous field of view; Wavelength; Altitude;
- The temporal characteristic depends on: Satellite capacity; Latitude; Orbit;

In the proposed approach, we worked with the multilayer perceptron (MLP) neural networks. The MLP is a structure consisting of an input layer, one or more hidden layers, and one output layer. In many cases (Panda et al., 2004), a hidden layer perceptron is sufficient to obtain satisfactory results (Fig.4).

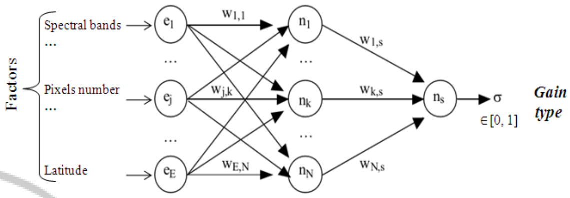

Figure 3: MLP: one hidden layer and an output neuron.

The input perceptron is a vector e of dimension E, and components e_j where j is an integer of the set $\{1,...,E\}$. The hidden layer contains N neurons; the $k-th$ neuron of the hidden layer is designated by n_k, where k is an integer of the set $\{1,...,N\}$. The perceptron being intended to classify data according to two categories, the output layer only contains a neuron, noted n_s, which provides output σ varies between 0 and 1. Each component of e is connected to N neuron of the hidden layer and each neuron of this layer is connected to the output neuron. Connections are affected synaptic weights noted $w_{j,k}$ for the connection of the input component e_j with the neuron n_k, and $w_{k,s}$ for the connection between the neuron n_k and output neuron n_s. The output s of the neuron n_s is written as

$$\sigma = f(x_s) \quad with \quad x_s = \sum_{k=1}^{N} w_{k,s} s_k + \theta_s \tag{1}$$

where the constant θ_s is the bias of neuron n_s. The function $f(u)$ is the activation function, which must be derivable to be able implement learning by back-propagation of the gradient. The most commonly used function is the sigmoid function

$$f(u) = \frac{1}{1+e^{(-u)}} \tag{2}$$

The synaptic weights of the neural network are adjusted during a learning phase, using a batch of input vectors A, considered to be representative of the application. The set of these vectors, stowed in the form $[e_1,...e_i,...,e_A]$ constitutes a matrix M of E lines and A columns, called learning matrix of perceptron. An "epoch" is the presentation, to the neural network, of the matrix M. An epoch is marked by the integer t belonging to the set $\{1,...,Q\}$. At the time t, the neuron k of the hidden layer provides A outputs $s_k^i(t)$, where i is an integer of the set $\{1,...,A\}$. Similarly, the perceptron provides A outputs $\sigma_i(t)$. An expert charged to operate the classification provides A answers h_i, where h_i belong to the interval $[0,1]$. The adjustment of the synaptic weights takes place by minimization of square error

$$\triangle_i(t) = \sigma_i(t) - h_i \quad (3)$$

considered as a function of the synaptic weights of the connections, by a back-propagation algorithm of gradient (Sawaitul et al., 2012).

2.2.2 Step 2 : Attribute Selection Measure

The first step allows the selection of the type of gain to be applied at each tree level. Before predicting changes of an object, a test of the best attribute related to this object is performed. The latter is produced by the information gain formula. In the uncertain framework, we use different types of information gain, such as: probabilistic gain, belief gain, fuzzy gain, and possibilistic gain. The difference between these gain resides mainly in the calculation of the entropy. In probabilistic case, the calculation of the entropy is as follows:

$$entropy(T) = -\sum_{i=1}^{n} p(C_i).\log_2 p(C_i) \quad (4)$$

Where T is the training set with uncertain data, $p(C_i)$ is the class probability C_i and $\log p(C_i)$ is the quantity of information that is given when the class is the expected value of this contents of the information.

Thus, in belief case, the calculation of the entropy is equal to:

$$entropy(T) = -\sum_{i=1}^{n} BelP^{\Theta}\{T\}(C_i).\log_2 BelP^{\Theta}\{T\}(C_i) \quad (5)$$

where $BelP^{\Theta}\{T\}(C_i)$ is the average pignistic probability function taken over the set of objects T. For each $C_i \in \Theta$, this function equal to:

$$BelP^{\Theta}\{T\}(C_i) = \frac{1}{|T|}\sum_{I_j \in T} BelP^{\Theta}\{I_j\}(C_i) \quad (6)$$

where $BelP^{\Theta}\{I_j\}(C_i)$ is the pignistic probability of each instance I_j which applies applying the pignistic transformation to $m^{\Theta}\{I_j\}$.

In fuzzy case, the entropy of a set of data items, represented as $\{t_1, t_2, , t_x\}$, is given by:

$$entropy(T) = -\sum_{i=1}^{n}\{\frac{\sum_{h=1}^{x}\mu(C_i,t_h)}{|T|}.log_2\frac{\sum_{h=1}^{x}\mu(C_i,t_h)}{|T|}\} \quad (7)$$

Then, in possibilistic case, given an ordered possibility distribution $\pi = \{\pi_{(1)}, \pi_{(2)}, ..., \pi_{(n)}\}$ such that $1 = \pi_{(1)} \geq \pi_{(2)} \geq ... \geq \pi_{(n)}$ the entropy of π is given by:

aa

$$entropy(\pi) = [\sum_{i=1}^{n}(\pi_{(i)} - \pi_{(i+1)}.log_2 i)] + (1 - \pi_{(1)}).log_2 n \quad (8)$$

Where $\pi_{(n+1)} = 0$. Note that the range of entropy is $[0, \log_2 n]$. $entropy(\pi) = 0$ is obtained for the case of complete knowledge (precise information) and is reached for the case of total ignorance. For each set containing n possibility distributions, must induce a representative possibility distribution of that set π_{Rep}. This possibility distribution is obtained via the arithmetic mean of $\pi_i(i = 1..n)$ and it is given by:

$$\pi_{AM}(w_q) = \frac{1}{n}\sum_{i=1}^{n}\pi_i(w_q) \quad (9)$$

Then, we should normalize π_{AM} to obtain:

$$\pi_{Rep}(w_q) = \frac{\pi_{AM}(w_q)}{\max_{q=1}^{|\Omega|}\pi_{AM}(w_q)} \quad (10)$$

Finally, we can measure the discriminate between different sets of possibility distributions using equation (18).

2.2.3 Step 3: Partitioning Strategy

The partitioning strategy consists in partitioning the training set according to all possible attribute values which leads to the generation of one partition per attribute value. In the construction of an ordinary DT, there is no alternative to partition the training base. During the construction of a node N, the A_l attribute associated to m_j possible values. Then, the training set T witch composed of e_i samples is partitioned into m_j subset T_j^N such as:

$$\forall e_i \in T^N, if \quad e_i(A_l) = v_{lk}, \quad then \quad e_i \in T_k^N, \quad 1 \leq k \leq m_j \quad (11)$$

where v_{lk} is a value among the set of possible values of the attribute A_l.

and

$$T^N = \bigcup_{k=1,...,m_j} T_k^N \quad (12)$$

and

$$\forall x, \quad k = 1, ..., m_j, \quad x \neq k, \quad T_x^N \bigcap T_k^N \quad (13)$$

However in the case uncertain, various strategies can be used depending on the gain type of attribute. Then, we will divide all elements of the training set in all subset by giving them a probability distribution, basic belief assignment, degree of membership or possibility distribution.

2.2.4 Step 4: Stopping Criteria

They determine the conditions of stopping the partitioning process. The stopping criterion used to decide whether it is necessary to continue for a training set to develop the tree. The reasons can be related to a low number of the example in the considered set or if all examples of the set have the same class, or at least a sufficient number relative to the examples number of the set. The criteria are the same for adaptive decision tree by adapting the evaluation of these criteria.

The choice of these components (the testing tree type, the attribute selection measure, the partitioning strategy, and the stopping criteria) makes the major difference between DT algorithms. The algorithm used in our approach for the change prediction is the C4.5 algorithm (Quinlan, 1993). This type of algorithm has proven its effectiveness in the field of remote sensing (Jiang et al., 2011). It provides a predictive model represented as a DT easily understandable and interpretable.

2.3 Complexity of Constructing Adaptive Decision Trees

Finding optimal strategies via an exhaustive enumeration is a highly computational task. For instance, in a standard decision tree with n objects and m attributes the complexity is $O(n \times m \times \log(n))$. For adaptive decision trees, where the goal is to test the choice of imperfection types on each node by neural model which is $O(m^2)$. The complexity is:

$$O(m^2) + O(n \times m \times \log(n)) = O(m^2 + (m \times n \times \log(n))) \tag{14}$$

then, the algorithm complexity for constructing a kind of smallest-scale adaptive decision tree is NP-hard. Details of NP-hard problems can be found in (Garey and Johnson, 1979).

3 EXPERIMENTAL RESULTS

The experimental results section is devoted to evaluate the quality of the land cover change prediction of the proposed approach.

3.1 Study Zone and Data

The study site is the Saint-Paul region, located in the Indian Ocean, east of Madagascar, about 200 kilometers from the south west of Mauritius, the nearest island (Fig.5). Saint-Paul is the second-largest commune in the French overseas department of Reunion. It is located on the extreme west side of Reunion Island.

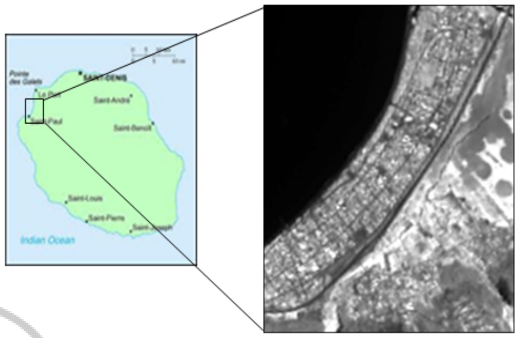

Figure 4: The studied area.

The satellite images used for the experiments are coming from the SPOT-5 satellite and acquired on 30 April 2007 and 30 October 2012 (Fig. 7).The second image is used to test the performance of the proposed approach in predicting change at the date of October 2012. Generally, we used 483 images SPOT-5 to predict land cover change.

3.2 Validation of the proposed Approach

The validation of the proposed approach is divided into two parts. The first part aims to validate the ANN module for selection of the DT type. The second part presents a land-cover change prediction through the application of the adaptive DT.

3.2.1 First Part: ANN Module

The ANN module uses factors that influence the radiometric, spectral, geometric, spatial, temporal features for satellite images. To validate this model, a variety of network structures has been implemented: 1) the choice of a more hidden layers architecture has allowed us to infer that a single hidden layer is sufficient, 2) the number of neurons in this single hidden layer influences the accuracy of the result despite its convergence, several tests have revealed that a total of 15 neurons is sufficient. We could show that the choice and the structure of multilayer neural network inputs based primarily on the characteristics of objects that strongly influence on the quality of the output. To predict the tree type based on the characteristics of images, we assigned the value 0.2 to Probabilistic tree, the 0.4 to Belief tree, 0.6 to Fuzzy tree and 0.8 to Possibilistic tree. For this study, the neural networks were simulated in the Neural Network module of NeurophStudio with NetBeans IDE 7.2.1 (Fig.6).

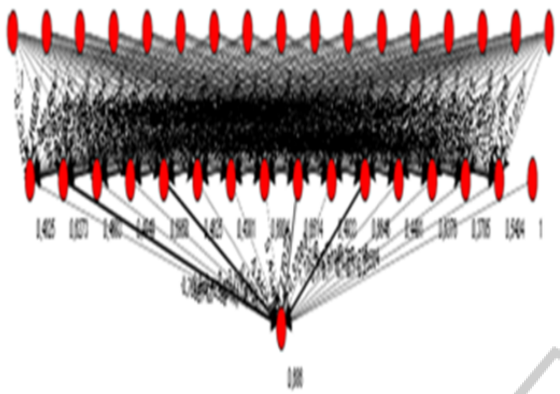

Figure 5: Representative schematic of an artificial neural network.

The network was tested with different numbers of learning stages or epochs, different learning rates, and different numbers of neurons in the hidden layer. The model runs using 80% of data for training and 20% for predicting. In addition, generalization techniques, methods to reduce over-fitting, were analyzed including technique such as early stopping by adjusting the training mean square error (MSE). The MSE is described by the following equation:

$$MSE = \frac{1}{2}\sum_{i=1}^{A}(\sigma_i(t) - h_i)^2 \tag{15}$$

h_i and $\sigma_i(t)$ represent the desired output and the output of neuron i in the output layer. Fig.7 depicts that when iteration times were 37, the error curve had no more great drop. This denotes that the performance of the network had been steady. Thus, the training of the network could be stopped with 37 iteration times, and it had perfect performance (0.0098131).

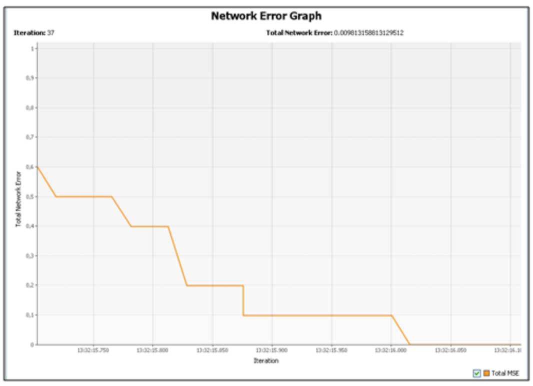

Figure 6: Iteration times and prediction error of the ANN training.

The impact of the contribution of neural networks for testing tree type on each node from satellite images by back-propagation was implemented. The proposed algorithm uses the factors affecting image features forming an input layer of 17 elements. It was found that there is no need to design more than 15 neurons in the hidden layer, increasing the number of neurons significantly improves the results but greatly increases the calculation time.

3.2.2 Second Part: Land Cover Prediction by the Adaptive Decision Tree

The second part of the validation section aims to validate the model of the land cover change prediction of the proposed approach. The urban changes between the two dates 2007 and 2012 are estimated based on the proposed approach. Then, these changes are compared to the real changes computed based on the two images representing the two dates 2007 and 2012 (Fig.8).

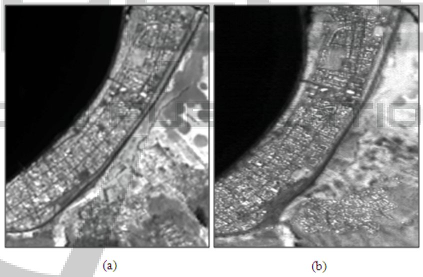

Figure 7: Satellite images: (a)image acquired on 30 Apr 2007 and (b)image acquired on 30 Oct 2012.

Fig. 9 shows the segmented images, acquired on 30 Apr 2007 and 30 October 2012. Five thematic classes are identified which are the following: (1) urban; (2) water;(3) forest; (4) bare soil; and (5) non-dense vegetation areas.

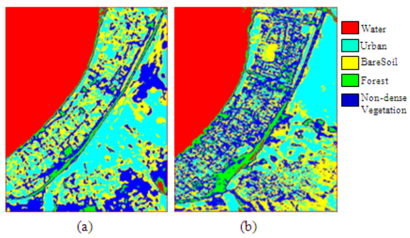

Figure 8: Segmented images: (a) image acquired on 30 Apr 2007, (b) image acquired on 30 Oct 2012.

After image segmentation, the object representing the "Urban" area is extracted (Fig. 10) and five features (radiometric, geometric, textural, spatial and acquisition context)are calculated. Next, these features are converted to generate a state representing the "Urban" object at the date of 30 Apr 2007.The proposed approach looks for the most similar states to the query state and which have a change after five years and six months. The model of predicting changes for the query state is performed. It allows the generation of a change tree for urban site in the Saint-Paul region between 2007 and 2012. Table 1 presents the proposed changes of the ”Urban” site on October 2012. Urban site will evolve to water with a percentage of change equals to 0.54%, to bare soil with a percentage of change equals to 8.09 %, to non-dense vegetation with a percentage of change equals to 17.26%, to forest with a percentage of change equals to 10.78% and to urban with a percentage of change equals to 63.33 %. Table 2 shows the real changes on 30 October 2012. The important changes are concerning the forest and the non-dense vegetation zone.

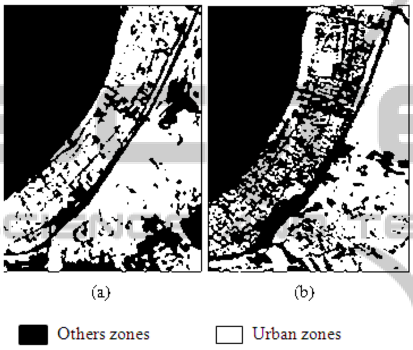

Figure 9: ”Urban” object extracted: (a) image acquired on 30 Apr 2007, (b) image acquired on 30 Oct 2012.

Table 1: Proposed change for the ”Urban” site at the date 2012.

Land cover type	Percentage of change
Water	0.54
Bare soil	8.09
Non-dense vegetation	17.26
Forest	10.78
Urban	63.33

Table 2: Real change detection for the ”Urban” site between 2007 and 2012.

Land cover type	Percentage of change
Water	0.69
Bare soil	6.96
Non-dense vegetation	21.95
Forest	9.11
Urban	61.29

Saint-Paul is among regions in the Reunion Island that presents problems of urban sprawl. In fact, natural and agricultural areas are being rapidly converted to urban which affects agricultural activities.

3.3 Evaluation of the proposed Approach

In order to evaluate the proposed approach, we compared their performance in predicting land cover changes to the approaches presented in (Mishra et al., 2011)(Mitra et al., 2002). The evaluation is carried out through the Kappa coefficient computed from a visual assessment followed by a statistical analysis through the calculation of a confusion matrix that established between the ground truth and different classifications. From this matrix, we compute the statistical parameter ”Kappa” which is an indicator of the overall accuracy (Congalton, 1991). This coefficient is defined by the following equation:

$$Kappa = \frac{N\sum_{i=1}^{M} X_{ii} - \sum_{i=1}^{M}(X_{i+} \times X_{j+})}{N^2 - \sum_{i=1}^{M}(X_{i+} \times X_{j+})} \quad (16)$$

Where
X_{ij}: the elements of the confusion matrix; X_{i+}: the total sum of the elements in rows; X_{+i}: the total sum of the elements in columns; X_{ii}: the diagonal elements; N : the total number of pixels of the matrix; M : the number of classes considered.

The results in Table 3 indicate that the Adaptive decision tree model produces better prediction results compared to the benchmark approaches.

Table 3: Interpretation of proposed approach.

Approach	Kappa
Proposed approach (adaptive DT)	0.8621
Approach Mishra et *al.* (Probabilistic DT)	0.8200
Approach Mitra et *al.* (Fuzzy DT)	0.8222

4 CONCLUSIONS

DT is one of the successful data mining techniques used in classification or prediction. However, most works within the literature uses only one method of DT to process all types of imperfection related to data.

In this study, an adaptive DT method for land cover change prediction is discussed. The proposed approach allows modeling several imperfection types such as uncertainty, imprecision, conflict and ambiguity using neural model. The combination of DT with different logics offers the potential for mapping and understanding environmental changes. The application of the ANN module allows retrieving the appropriate DT method. This allows for a better modeling of imperfection related to attributes at each node of the DT. The application of the proposed approach is estimate urban changes at the Saint-Paul region in the Reunion Island. The same process can be replicated to compute changes for the others land cover types. The proposed approach presents a useful tool for disaster prevention and monitoring, planting status of agricultural products, and tree distribution of forests. The evaluation depicts good results of the proposed approach in predicting urban changes.

Future prospects are primarily research and extraction of other relevant descriptors and indicators that affect objects features of satellite images and improve the complexity of our algorithm. Another challenge is to apply the proposed approach on others sites.

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REFERENCES

Amor, N. B., Benferhat, S., and Elouedi, Z. (2008). Decision trees as possibilistic classifiers. In *International Journal of Approximate Reasoning*.

Anuradha, K., Radha, N. T., and Kumar, T. P. (2012). A decision tree algorithm for uncertain data. In *International Journal of Engineering and Advanced Technology*.

Benz, U., Hofmann, P., Willhauck, G., Lingenfelder, I., and Heynen, I. (2004). Multi-resolution, object-oriented fuzzy analysis of remote sensing data for gis-ready information. In *ISPRS Journal of Photogrammetry and Remote Sensing*.

Boulila, W., Farah, I., Ettabaa, K., Solaiman, B., and Ghzala, H. B. (2010). Spatio-temporal modeling for knowledge discovery in satellite image databases. In *Conference en Recherche d'Information et Applications*.

Boulila, W., Farah, I., Ettabaa, K., Solaiman, B., and Ghzala, H. B. (2011). A data mining based approach to predict spatiotemporal changes in satellite images. In *International Journal of Applied Earth Observation and Geoinformation*.

Boulila, W., Farah, I., Ettabaa, K., Solaiman, B., and Ghzala, H. B. (2012). Combining decision fusion and uncertainty propagation to improve land cover change prediction in satellite image databases. In *Journal of Multimedia Processing and Technologies*.

Chang, P., Fan, C., and Dzan, W. (2010). A cbr-based fuzzy decision tree approach for database classification. In *International Journal: Expert Systems with Applications*.

Congalton, R. (1991). A review of assessing the accuracy of classifications of remotely sensed data. In *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews*.

Elouedi, Z., Mellouli, K., and Smets, P. (2001). Belief decision trees: Theoretical foundations. In *International Journal of Approximate Reasoning*.

Fried, M., Brodley, C., and Strahler, A. (1999). Maximizing land cover classication accuracies produced by decision trees at continental to global scales. In *IEEE Transactions on Geoscience and Remote Sensing*.

Garey, M. and Johnson, D. (1979). Computers and intractability: A guide to the theory of np-completeness. In *Printed in the United States of America*.

Hullermeier, E. (2002). Possibilistic induction in decision-tree learning. In *ECML '02 Proceedings of the 13th European Conference on Machine Learning*.

Jiang, L., Wang, W., Yang, X., and N. Xie, Y. C. (2011). Classification methods of remote sensing image based on decision tree technologies. In *Computer and Computing Technologies in Agriculture IV*.

Kumar, U., Kerle, N., Punia, M., and Ramachandra, T. (2011). Mining land cover infor-mation using multilayer perceptron and decision tree from modis data. In *Journal of the Indian Society of Remote Sensing*.

Levashenko, V. and Zaitseva, E. (2012). Fuzzy decision trees in medical decision making support system. In *Proceedings of the Federated Conference on Computer Science and Information Systems*.

McIver, D., Friedl, M., and Dzan, W. (2002). Using prior probabilities in decision-tree classification of remotely sensed data. In *Remote Sensing of Environment*.

Mishra, P., Singh, D., and Yamaguchi, Y. (2011). Land cover classification of palsar images by knowledge based decision tree classifier and supervised classifiers based on sar observables. In *Progress In Electromagnetics Research B*.

Mitra, S., Konwar, K., and Pal, S. (2002). Fuzzy decision tree, linguistic rules and fuzzy knowledge-based network: generation and evaluation. In *Remote Sensing of Environment*.

Neagoe, V., Neghina, M., and Datcu, M. (2011). Neural network techniques for automated land-cover change detection in multispectral satellite time series imagery. In *International Journal of Mathematical Models and Methods in Applied Sciences*.

Ozols, M., Mancinska, L., Berzina, I., Agadzanjans, R., and Rosmanis, A. (2006). Principles of optimal probabilistic decision tree construction. In *International Conference on Foundations of Computer Science*. Las Vegas, Nevada, USA.

Panda, S., Garg, V., and Chaubey, I. (2004). artificial neural networks application in lake water quality estimation using satellite imagery. In *Journal of Environmental Informatics*.

Pulvirenti, L., Pierdicca, N., and Marzano, F. (2011). Prediction of the error induced by topography in satellite microwave radiometric observations. In *IEEE Transactions on Geoscience and Remote Sensing*.

Quinlan, J. (1986). *Induction on decision trees*. Machine Learning.

Quinlan, J. (1993). *C4.5 : Programs for machine learning*. Morgan Kaufmann, San Mateo, ca edition.

Sawaitul, S., Wagh, K., and Chatur, P. (2012). Classification and prediction of future weather by using back propagation algorithm-an approach. In *International Journal of Emerging Technology and Advanced Engineering*.

Trabelsi, S., Elouedi, Z., and Mellouli, K. (2007). Pruning belief decision tree methods in averaging and conjunctive approaches. In *International Journal of Approximate Reasoning*.

Xuerong, L., Qianguo, X., and Lingyan, K. (2010). Remote sensing image classification method based on evidence theory and decision tree. In *Proceedings of the SPIE: Multispectral, Hyperspectral, and Ultraspectral Remote Sensing Technology, Techniques, and Applications III*.