Using Evidence Theory in Land Cover Change Prediction to Model Imperfection Propagation with Correlated Inputs Parameters

Ahlem Ferchichi, Wadii Boulila and Imed Riadh Farah
Ecole Nationale des Sciences de l'Informatique, Laboratoire RIADI, Manouba, Tunisia

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Abstract: The identification and the propagation of imperfection are important. In general, imperfection in land cover change (LCC) prediction process can be categorized as both aleatory and epistemic. This imperfection, which can be subdivided into parameter and structural model imperfection, is recognized to have an important impact on results. On the other hand, correlation of input system parameters is often neglected when modeling this system. However, correlation of parameters often blurs the model imperfection and makes it difficult to determine parameter imperfection. Several studies in literature depicts that evidence theory can be applied to model aleatory and epistemic imperfection and to solve multidimensional problems, with consideration of the correlation among parameters. The effective contribution of this paper is to propagate the imperfection associated with both correlated input parameters and LCC prediction model itself using the evidence theory. The proposed approach is divided into two main steps: 1) imperfection identification step is used to identify the types of imperfection (aleatory and/or epistemic), the sources of imperfections, and the correlations of the uncertain input parameters and the used LCC prediction model, and 2) imperfection propagation step is used to propagate aleatory and epistemic imperfection of correlated input parameters and model structure using the evidence theory. The results show the importance to propagate both parameter and model structure imperfection and to consider correlation among input parameters in LCC prediction model. In this study, the changes prediction of land cover in Saint-Denis City, Reunion Island of next 5 years (2016) was anticipated using multi-temporal Spot-4 satellite images in 2006 and 2011. Results show good performances of the proposed approach in improving prediction of the LCC of the Saint-Denis City on Reunion Island.

1 INTRODUCTION

Propagation of the imperfections existing in a system and the corresponding reliability analysis have become an essential task for current product design processes, especially, in LCC prediction process (Boulila et al., 2014). Generally, imperfection in a system can be classified into aleatory and epistemic (Hoffman and Hammonds, 1994). Aleatory imperfection results from randomness (e.g. uncertainty). However, epistemic imperfection stems from the lack of knowledge (e.g. imprecision, conflict). Imperfection types can be roughly split into two categories: parameter and structural model (Duy et al., 2013)(Droguett. and Mosleh, 2012). Imperfection in model parameter is due to natural variability, measurement inaccuracy, and errors in handling and processing data (Duy et al., 2013). Model structure shows imperfection from model assumptions/approximations, hypotheses, and scale effects. On the other hand, Correlated parameters are often neglected when modeling a natural system. However, parameters correlation often blurs the model imperfection and makes it difficult to determine parameter imperfection. In review of literature, model parameter imperfection has received the most attention in previous studies (Boulila et al., 2014)(Eckhardt et al., 2003). (Boulila et al., 2014) focuses on the imperfection in LCC prediction model parameters, and explores how those imperfection propagate through to model responses using probabilistic method to model only random imperfections, and have not taken into account the correlation among parameters. The focus here partly reflects a consensus that model parameter is an important source of imperfection in simulation predictions. However, it also reflects the relative ease with which imperfection in model parameter can be quantified in comparison to assessments of structural im-

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perfection in models. In practice, structural imperfection may be more important than parameter imperfection in evaluating model performance (Gong et al., 2013)(Rohmer et al., 2014). For example, (Gong et al., 2013) show the importance of using the imperfection of hydrological model structure in the imperfection processing. In LCC prediction process, the correlated parameters and structural model imperfections are generally treated by probability theory. Moreover, numerous authors conclude that there are limitations in using probability theory in this context (Droguett. and Mosleh, 2012). So far, several non-probabilistic methods have been developed, which include evidence theory (Shafer, 1976), possibility theory (Zadeh, 1965), etc. As a generalization of all the above probability and non-probability imperfection models, evidence theory combines random and epistemic imperfections in a very straightforward way, and is capable to solve multidimensional problems, with consideration of the correlation among parameters (Jiang et al., 2013). Based on the flexibility of evidence theory, the main aim of our work is to propagate the imperfection associated with both correlated input parameters and LCC prediction model itself using the evidence theory. The proposed approach is divided into two main steps: 1) imperfection identification step is used to identify the types of imperfection (aleatory and/or epistemic), the sources of imperfections, and the correlations of the uncertain input parameters and the used LCC prediction model, and 2) imperfection propagation step is used to propagate aleatory and epistemic imperfection of correlated input parameters and model structure using the evidence theory. The remainder of this paper is organized as follows. A brief introduction of evidence theory is given in Section 2. The proposed framework is presented in section 3. Section 4 presents our results. Finally, section 5 concludes the paper with summary and future works.

2 EVIDENCE THEORY

Evidence theory, also called as Dempster-Shafer theory, was initially developed by (Klir, 1994) and formalized by (Shafer, 1976). The evidence theory has the potential to quantify aleatory and epistemic imperfections. This theory has also become the accepted method for propagating correlated and uncorrelated input parameters imperfection through LCC prediction models. In this section, the basic notations of the evidence theory are introduced.

Frame of Discernment (FD). The FD is defined by the finest possible subdivisions of the sets, and the finest possible subdivision is called the elementary proposition.

Basic Probability Assignment (BPA). Let Θ be a finite set of mutually exclusive and exhaustive hypotheses, and 2^Θ be the power set of Θ. The fundamental concept for representing imperfection is the BPA, which defines a mapping function (m) of 2^Θ to the interval between 0 and 1. The measure m, BPA function, must satisfy the following axioms:

$$m(A) \geq 0, \quad \forall A \subseteq \Theta. \tag{1}$$

$$m(\emptyset) = 0 \tag{2}$$

$$\sum m(A) = 1. \quad \forall A \subseteq \Theta. \tag{3}$$

Belief and Plausibility Functions. The measures of imperfection provided by evidence theory are known as belief (Bel) and plausibility (Pl), which also lie in the interval $[0,1]$. Given a body of evidence, the (Bel) and (Pl) can be derived from the BPA by

$$Bel(B) = \sum_{A \subseteq B} m(A). \tag{4}$$

$$Pl(B) = \sum_{B \cap A \neq \emptyset} m(A). \tag{5}$$

The formulas make it easy to see that the belief function, (Bel), is calculated by summing the BPAs that totally agree with the event B, while the plausibility function, (Pl), is calculated by summing BPAs that agree with the event B totally and partially. These two functions can be derived from each other. For example, the belief function can be derived from the plausibility function in the following way:

$$Bel(B) = 1 - Pl(\overline{B}) \tag{6}$$

The relationship between belief and plausibility functions is

$$Bel(B) \leq Pl(B) \tag{7}$$

which shows that as a measure of event B is true, if $P(B)$ is the true value of the measure of set B is true, then $Pl(B)$ is the upper bound of $P(B)$,and $Bel(B)$ is the lower bound, so

$$Bel(A) \leq P(A) \leq Pl(A) \tag{8}$$

Dempster's Rule of Combining. The Dempster's rule of combination is an operation that plays a central role in the evidence theory. The BPAs induced by several sources are aggregated using this rule in order to yield a global BPA that synthesizes the knowledge of the different sources. Take two BPA structures, m_1 and m_2 , for instance, the combined structure m_{12} is calculated in the following manner:

$$m_{12}(A) = \frac{\sum_{B \cap C = A} m_1(B) m_2(C)}{1 - K} \quad when \quad A \neq \emptyset \tag{9}$$

$$m_{12}(\emptyset) = 0, \quad when \quad K = \sum_{B \cap C \neq \emptyset} m_1(B) m_2(C) \quad (10)$$

The coefficient K represents the mass that the combination assigns to $\emptyset$ and reflects the conflict among the sources. The denominator in Dempster's rule, $1-K$, is a normalization factor, which throws out the opinion of those experts who assert that the object under consideration does not exist.

3 METHODS AND DATA

3.1 Study Area and Data

Reunion Island is a French territory of 2500 km^2 located in the Indian Ocean, 200 km South-West of Mauritius and 700 km to the East of Madagascar (Fig. 1). Mean annual temperatures decrease from 24 deg$C$ in the lowlands to 12 deg$C$ at ca 2000 m. Mean annual precipitation ranges from 3 m on the eastern windward coast, up to 8 m in the mountains and down to $1m$ along the south western coast. Vegetation is most clearly structured along gradients of altitude and rainfall (Cadet, 1980). Reunion Island has a strong growth in a limited area with an estimated population of 833,000 in 2010 that will probably be more than 1 million in 2030 (Reunion, 2011). It have been a significant changes, putting pressure on agricultural and natural areas. The urban areas expanded by 189% over the period from 1989 to 2002 (Durieux et al., 2008) and available land became a rare and coveted resource. The landscapes are now expected to fulfil multiple functions i.e. urbanisation, agriculture production and ecosystem conservation and this causes conflicts among stakeholders about their planning and management (van der Valk, 2002). Saint−Denis is the capital of Reunion Island, and the city with the most inhabitants on the island (Fig. 1). It hosts all the important administrative offices, and is also a cultural center with numerous museums. Saint-Denis is also the largest city in all of the French Overseas Departments.

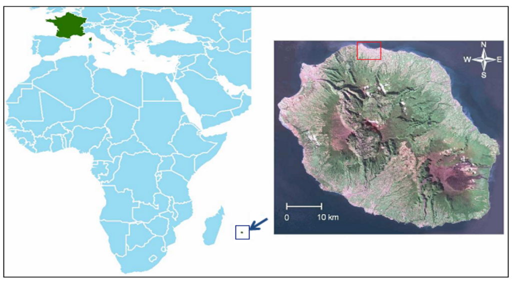

Figure 1: Location of the study area.

Available remote sensing data for this research include classified images of land over of Saint−Denis from SPOT-4 images for the years 2006 and 2011 (Fig. 2). Selecting these images benefits from advantages such as a broad and integrated view, multispectral images and replicated coverage in different time periods. For this study, satellite data were classified after initial corrections and processing in order to prepare the data for extracting useful information. Spectral, geometric, and atmospheric corrections of images were conducted to make features manifest, increase the quality of images and to eliminate the adverse effects of light and atmosphere. According to the study objective and different land cover of the area, five categories including water, urban, forest, bare soil, and vegetation were identified and classified.

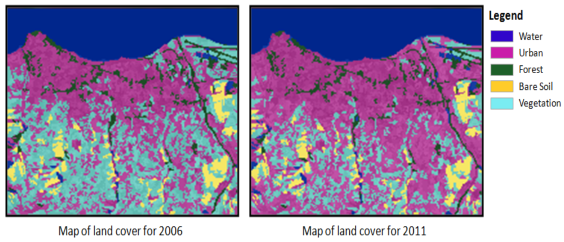

Figure 2: Satellite images.

3.2 Methodology

In this section, we propose the application of the evidence theory for propagating imperfections of correlated parameters and imperfections of structural model in the context of LCC prediction. The proposed approach is presented in the figure 3.

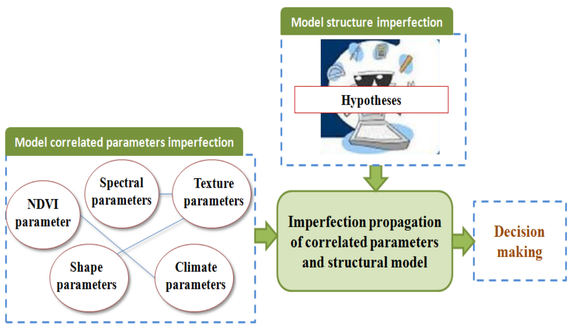

Figure 3: General modelling proposed framework.

The first step is to map sources and types of imperfection of parameter and model structure (Ferchichi et al., 2014) and to study correlation among parameters. Finally, the propagation of all sources simultaneously provides an analysis of their effect on the model response.

3.2.1 Processing and Modeling of Parameter and Model Structure Imperfection

The objective of this step is to identify imperfections related to both correlated input parameters of LCC prediction model in one hand, and imperfections related to structure of this model in the other hand.

a) Parameter Imperfection

These imperfections are related to input data of LCC prediction model.
✓ `Sources of parameter imperfection:` To better provide decisions about LCC, prediction model include several input parameters. These parameters describe objects extracted from satellite images and which are subject of studying changes. In this study, objects are extracted from images coming from SPOT-4 image, including four multispectral bands and one monospectral band:

- 10 spectral parameters: Mean values and standard deviation values of green, red, NIR, SWIR and monospectral bands for each image object;
- 6 texture parameters: These parameters generated from GLCM (Gray Level Co-occurrence Matrix) include homogeneity, contrast, dissimilarity, entropy, standard deviation and correlation. Their definitions as following:
  $Hom = \sum_i \sum_j \frac{P(i-j)}{1+(i-j)^2}$
  $Ctr = \sum_i \sum_j P(i-j)^2$
  $Ent = \sum_i \sum_j P(i-j)[-logP(i-j)]$
  $SD = \sqrt{\sum_i \sum_j P(i - \sum_i \sum_j i \bullet P(i-j))^2}$
  $Cor = \sum_i \sum_j \frac{(i-\sum_i \sum_j i \bullet P(i-j))(j-\sum_i \sum_j i \bullet P(i-j))}{SD^2}$
  where i and j are two different grey levels of the image, P is the number of the co-appearance of grey levels i and j.
- 7 shape and spatial relationships parameters: area, length/width, shape index, roundness, density, metric relations and direction relations;
- 1 vegetation parameter: The NDVI (Normalized Difference Vegetation Index) is the ratio of the difference between NIR and red reflectance.
- 3 climate parameters: temperature, humidity and pressure.

The inclusion of these 27 uncertain parameters was based on previous studies (Boulila et al., 2014)(Boulila et al., 2011).
– *Spectral parameters imperfection sources:* Several studies have presented effects of spectral parameters on prediction decisions (Atanassov et al., 2013). Among these effects we list: spectral reflectance of the surface, sensor calibration, effect of mixed pixels, effect of a shift in the channel location, pixel registration between several spectral channels, atmospheric temperature and moisture profile. To reduce the spectral imperfections, (Atanassov et al., 2013) have proposed some solutions e.g. strict requirements for the instrument's design, envisaging of appropriate procedures for on-board calibration, choosing appropriate algorithms for radiometric and atmospheric correction, reducing the wavelength range of the irradiance or spectral response measurement, reducing the cloud shadows and cloud contamination effects and reducing errors of sensor system itself.
– *Texture parameters imperfection sources:* Those factors may produce a textural effect derived by the spatial interaction between the size of the object in the scene and the spatial resolution of the sensor, a border effect, and ambiguity in the object/background distinction. (Peters, 1995) (Pesaresi and Benediktsson, 2001) have proposed some solutions for reduction of texture data imperfection e.g. using high spatial resolution and choosing appropriate methods for segmentation.
– *Shape parameters imperfection sources:* Imperfection related to shape parameters can rely to the following factors (Atanassov et al., 2013): accounting for the seasonal position of the sun with respect to the Earth, conditions in which the image was acquired changes in the scene's illumination, atmospheric conditions and observation geometry. (Atanassov et al., 2013) have proposed some solutions for reduction of shape data imperfection e.g. improving the platforms' stability and the carrier's velocity, technological enhancement of the sensors themselves, reducing the effects of atmospheric conditions, improving the overall segmentation quality, reducing of the number of bad pixels and the size of bad areas, and improvement of the imperfection of pixels' response.
– *NDVI imperfection sources:* Among factors that affect NDVI, we can list: variation in the brightness of soil background, red and NIR bands, atmospheric perturbations as a function of the state of the atmosphere and the soil surface at the time of the two acquisitions and variability in the structure of sub-pixel of the vegetation, and variability in the structure of sub-pixel. To reduce the NDVI imperfections, (Miura et al., 2000) (Hird and McDermid, 2009) have proposed some solutions e.g. choosing appropriate algorithms for atmospheric correction, reducing errors in surface measurements for the NIR and red bands, reducing the temporal variations effects in the solar zenith and azimuth angles, and reducing the sun angle effects and noise contamination.
– *Climate parameters imperfection sources:* Sev-

eral studies have investigated the influence of several factors on the climate parameters accuracy (Jimenez-Munoz and Sobrino, 2006). These factors can be: atmospheric correction, noise of the sensor, land surface emissivity, aerosols and other gaseous absorbers, angular effects, wavelength imperfection, full-width half maximum of the sensor and band-pass effects. To reduce the climate data imperfections, (Jimenez-Munoz and Sobrino, 2006) (Hulley et al., 2012) have proposed some solutions e.g. choosing appropriate algorithms for atmospheric correction, reducing errors of sensor system itself, reducing the emissivity variations, reducing the sun angle effects and solar heating, reducing the errors of radiometer calibration and the errors of radiation, and reducing errors of spatial and temporal variability of clouds.

✓ `Types of parameter imperfection`: Imperfection related to input parameters to the LCC predictio model can be of two types: epistemic and random. The imperfection type for each parameter depends on sources of their imperfection. For example, for the NDVI parameter, imperfection sources are the brightness of pixels, the red and NIR bands, etc. Thus, each imperfection source provides an imperfection type for NDVI parameter. For example, the brightness of pixels on darker pixels leads to imprecise information in a vegetation zone. In this case, the NDVI parameter is marred by an epistemic imperfection.

✓ `Modeling of parameter imperfection`: The goal of this step is to determine the distribution of each uncertain parameter. For random parameters, various distributions, such as uniform, triangular, normal, or lognormal distributions, can be used in the model. For epistemic parameters, there are also many distributions such as: belief and plausibity distributions, possibility distribution, etc. Herein, each imperfection propagation method has its own specific distributions.

✓ `Analysis of parameters correlation`: Its objective is to determine the relationships between parameters. In general, input parameters in remote sensing systems are not independent of each other. The value of one parameter can affect the value of another. A LCC prediction model usually contains a large number of correlated parameters leading to non-identifiability problems. For example, the distribution and the production of vegetation are strongly influenced by temperature. Then, temperature and NDVI parameters are correlated.

b) Model Structure Imperfection

These are imperfections related to LCC prediction model structure itself. The proposed model for LCC prediction is presented in previous work (Boulila et al., 2011). In this work, we presented a model to predict spatiotemporal changes in satellite image databases. The proposed model exploits data mining concepts to build predictions and decisions for several remote sensing fields. Imperfections related to the structure of LCC prediction model can be very numerous and affect different parts of the model. Therefore necessary to identify imperfections sources that should be considered for processing. Then, imperfection related to model structure are resulting from conceptualization, simplifications, and hypotheses related to a lack of knowledge about a system, a structure, and the behavior of components in varied conditions during development. In majority, the imperfection of structural representation is the most influential imperfection on LCC prediction model. The development of LCC prediction model is based on a number of hypotheses which are decisions or judgments considered by analysts. For example, when two hypotheses H_1, H_2 are given by two different experts, then we have two different structural models M_1 and M_2. In most cases, imperfection about LCC prediction model structure is a form of epistemic imperfection because we are unsure whether their constructions are reasonable and complete. It would be aleatory imperfection only if the structure of the governing model were itself to change over time, across space, or among components in some population.

3.2.2 Propagation of Imperfection using Evidence Theory

The objective of this step is to propagate the imperfection of correlated parameters and the imperefction of model structure using evidence theory.

a) Parameters Imperfection Propagation using Evidence Theory

Using the evidence theory to model imperfections has been studied extensively in several fields (Duy et al., 2013) (Abdallah et al., 2013). In this section, the procedures of propagating the unified structures dealing with both random and epistemic imperfection and with considering correlation among parameters will be addressed. For the proposed model, first we should identify which type of imperfection each parameter. To illustrate the proposed method, we use a simple transfer function which has two uncertain parameters

$$Y = f(E,A). \tag{11}$$

where E represents the epistemic imperfection parameter, A represents the random imperfection parameter and Y is the model response of the LCC. For E, the epistemic imperfection is generally expressed by a series of subsets of the universal set associated with a BPA structure just as $\{[E_1^L, E_1^U]/m(1), [E_2^L, E_2^U]/m(2), ..., [E_k^L, E_k^U]/m(k), ...|k \in (1,2,...,M)\}$. Where M is the total number of subintervals of E and $m(k)$ represents the BPA value associated with the kth subinterval $[E_k^L, E_k^U]$. When there are different BPA structures, we can use combining rule to integrate them into a combined BPA structure as $E_j/m(E_j)(j \in [1,2,,M])$ ultimately, where E_j is also an interval as $[E_j^L, E_j^U]$ and $m(E_j)$ is the BPA value associated with the interval E_j. For A, assuming A is normal distribution $A \sim (\mu, \sigma)$, the distribution scope can be truncated to $[\mu - \xi\sigma, \mu + \xi\sigma]$ approximately and then we can discretize the approximate interval into N subintervals $[A_i^L, A_i^U]$, $i \in [1,2,,N]$, and for each subinterval the basic probability value is defined:

$$m(A_i) = \int_{A_i^L}^{A_i^U} f(x)dx, i \in [1,2,...,N]. \tag{12}$$

where A_i is defined as $\{A_i | x \in [A_i^L, A_i^U]\}$ and $f(x)$ is the probability density distribution function (pdf) of x. Obviously for the random parameter, the equivalent BPA values within specified intervals are equal to the area under the pdf. After obtaining the BPA structures of all the uncertain parameters, we can integrate them into a joint structure. The joint BPA structure is defined by the Cartesian product, which is synthesized as:

$$C = A \times E = \{c_{ij} = A_i \times E_j\} \tag{13}$$

where C denotes the Cartesian set of all the uncertain parameters and c_{ij} is the element of C.

– When the uncertain parameters, E and A, are independent, the joint BPA for c_{ij} is defined by multiplying the BPA of A_i to the BPA of E_j.

$$m(c_{ij}) = m(A_i) \times m(E_j) \tag{14}$$

The focal element c_{ij} is included by the joint FD, and its BPA is just equal to the multiplication of the corresponding marginal BPAs.

– When the uncertain parameters, E and A, are correlated, we will develop a new evidence theory model which takes into account the correlation among parameters based on ellipsoidal model (Luo et al., 2008). Then, the ellipsoidal model is originally proposed for non-probabilistic imperfection analysis. Here the ellipsoidal model is extended to deal with the correlated evidence parameters. For this purpose, a multidimensional ellipsoid is constructed by making all possible realizations of the N-dimensional inter-correlated evidence parameters fall into a joint FD:

$$\Omega = \{\mathbf{X} | (\mathbf{X} - \mathbf{X}^c)^T \mathbf{G} (\mathbf{X} - \mathbf{X}^c) \leq 1\} \tag{15}$$

where the ellipsoidal center $\mathbf{X}^c$ is obtained through the marginal FDs:

$$X_m{}^c = \frac{X_m{}^L + X_m{}^R}{2}, m = 1,2,...,N \tag{16}$$

where $X_m \in c_{ij}$ is the evidence parameters (random and epistemic parameters).

The symmetric positive-definite characteristic matrix $\mathbf{G}$ determines the size and orientation of the ellipsoid, reflecting the degree and the manner of correlation between the evidence parameters. Obviously, one should assign the belief probabilities only to the elements c_{ij} that are partially or totally falling into the ellipsoid model. Thus, a joint BPA is formulated as:

$$m(c_{ij} \cap \Omega) = \frac{m(A_i) \times m(E_j)}{S}, c_{ij} \cap \Omega \neq 0 \tag{17}$$

where S is a normalization factor to make the total BPAs of m equal to 1.0, which is given by

$$S = \sum_{c_{ij} \cap \Omega \neq 0} m(c_{ij}) \tag{18}$$

Then, get the upper and lower CDFs of system response y via evidence reasoning.

Let $\Theta_Y = \{d_{ij} : d_{ij} = f(c_{ij}), c_{ij} \subset \Theta_{\mathbf{X}}\}$ denote the frame of discernment of Y, where d_{ij} is its focal element, f is the LCC prediction model in (11), and $\Theta_{\mathbf{X}}$ is the frame of discernment of $\mathbf{X}$. After determining the sets, c_{ij} and d_{ij}, the belief and plausibility functions are evaluated by checking all propositions of the joint BPA structure, as given in the following equations (Joslyn and Helton, 2002).

$$Bel_Y(d_{ij}) = Bel_{\mathbf{X}}[f^{-1}(d_{ij})] = \sum_{c_{ij} \subset f^{-1}(d_{ij})} m_{\mathbf{X}}(c_{ij}) \tag{19}$$

$$Pl_Y(d_{ij}) = Pl_{\mathbf{X}}[f^{-1}(d_{ij})] = \sum_{c_{ij} \cap f^{-1}(d_{ij}) \neq \emptyset} m_{\mathbf{X}}(c_{ij}) \tag{20}$$

Then

$$Bel_Y(y < v) = Bel_{\mathbf{X}}[f^{-1}(Y_v)] = \sum_{c_{ij} \subset f^{-1}(Y_v)} m_{\mathbf{X}}(c_{ij}) \tag{21}$$

$$Pl_Y(y < v) = Pl_{\mathbf{X}}[f^{-1}(Y_v)] = \sum_{c_{ij} \cap f^{-1}(Y_v) \neq \emptyset} m_{\mathbf{X}}(c_{ij}) \tag{22}$$

$$Y_v = \{y : y < v, y \in \Theta_Y\} \tag{23}$$

From (8),

$$Bel_Y(y < v) \leq P(y < v) \leq Pl_Y(y < v) \tag{24}$$

Obviously, Bel_Y is the lower CDF of the LCC prediction system response Y, and Pl_Y is the upper CDF.

- *Algorithm of the ellipsoidal model construction:* Assuming that there are t experimental samples $X^{(r)}$, $r = 1, 2, ..., t$ for the N evidence parameters and each sample is an N-dimensional vector, the ellipsoidal model can be established as follows:

1. Take a pair of evidence parameters X_m and X_n $(m \neq n)$ at a time from the uncertain parameter set.
2. Extract the values of X_m and X_n from the t experimental samples and construct a corresponding bivariant sample set $(X_m^{(r)}, X_n^{(r)})$, $r = 1, 2, ..., t$.
3. Create a minimum ellipse enveloping the obtained bivariant samples and obtain the corresponding rotation angle θ as shown in Fig. 5.

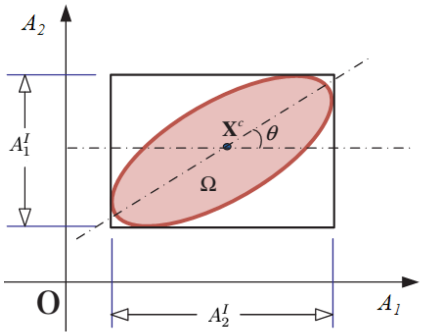

Figure 4: Ellipsoidal-model-based joint FD.

4. Compute the covariance (Cov) and correlation coefficient (ρ) of the two uncertain parameters X_m and X_n based on the value of θ:
   - $Cov(X_m, X_n) = \frac{tan(\theta)}{1-tan^2(\theta)}((X_m^w)^2 - (X_n^w)^2)$ where $X_m^w = \frac{X_m{}^L + X_m{}^R}{2}$ and $X_n^w = \frac{X_n{}^L + X_n{}^R}{2}$ represent the radii of X_m and X_n, respectively.
   - $\rho_{X_m X_n} = \frac{Cov(X_m, X_n)}{X_m^w X_n^w}$, $-1 \leq \rho_{X_m X_n} \leq 1$.
5. Repeat the above process for all pairs of uncertain parameters, and obtain a total of $N(N-1)/2$ covariances and correlation coefficients for all the parameters.
6. Create a covariance matrix C based on the calculated covariances.
7. Finally, an ellipsoidal model can be obtained:

$$\Omega = \{\mathbf{X} | (\mathbf{X} - \mathbf{X}^c)^T \mathbf{C}^{-1} (\mathbf{X} - \mathbf{X}^c) \leq 1\} \quad (25)$$

b) Model Structure Imperfection Propagation using Evidence Theory

The model structure imperfection propagation is implemented in combination with the propagation of the parametric imperfection. In this section, as parametric imperfections are modeled by evidence theory, we use this technique in this framework (Ferchichi et al., 2014). Therefore, the final imperfection representation of output variable Y can be obtained by the following formulas.

$$Bel^*(Y) = min(Bel_1(Y), Bel_2(Y), ..., Bel_K(Y)) \quad (26)$$

$$Pl^*(Y) = max(Pl_1(Y), Pl_2(Y), ..., Pl_K(Y)) \quad (27)$$

The belief and plausibility functions $[Bel^*(Y), Pl^*(Y)]$ take into account both parameter and structural model imperfection in the final output result.

4 EXPERIMENTAL RESULTS

The aim of this section is to validate and to evaluate the performance of the proposed approach in propagating imperfection related to correlated parameters and structural model. The proposed approach was used that subdivided the database into training (60%), validation set (10%), and test set (30%). The training data set is used for building the LCC prediction model. A validation set was used to stop the training procedure, and a test set was used to validate the performance of the LCC prediction model.

4.1 Validation of the Proposed Approach

4.1.1 Validation of the Imperfection Propagation of LCC Prediction Model

In proposed changes prediction model, the processing and propagating imperfections associated with 27 input parameters in the framework of evidence theory are realized. To validate the proposed approach, consider that the all parameters are independent. The cumulative distribution function (CDF) of output representing only the imperfection in parameters is obtained via evidence theory. In fact, Figure 6 shows this distribution based on 10,000 samples. Now, consider that the parameters are correlated. The CDF of output representing only the imperfection in parameters is obtained in figure 6. Here, the difference in both distributions representation presents the effect and the impact of parameters correlation.

Also, Figure 7 shows the belief (Bel*) and plausibility (Pl*) functions representing the integrated parameter and structural model imperfections about the LCCs.

Note that the combined effect of structural model and parameter imperfection lead to a wider imperfection bound of the LCC when compared against the parameter imperfection case.

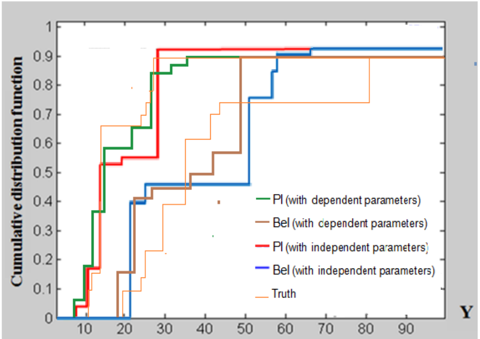

Figure 5: Distributions of model output (LCCs) of only parameter imperfection with (in)dependence parameters.

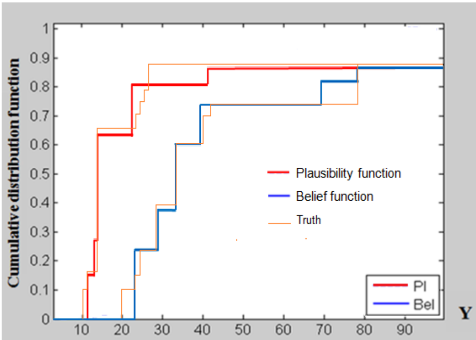

Figure 6: Belief and plausibility functions of the combined parameter and structural model imperfections for LCCs.

4.1.2 Validation of LCC Prediction Maps

The validation of LCC prediction maps consisted of two phases. First, the 2011 LCC was simulated using the 2006 datasets, which was then compared with the actual LCC in 2011 to evaluate the accuracy and the performance of the proposed approach. Second, the future changes was simulated using the actual 2011 datasets. Figure 8 compares the actual and the simulated percentages occupied by the different land cover types (water, urban, forest, bare soil, and vegetation) between 2006 and 2011; it shows that the simulated changes generally matched that of the actual changes. These results confirms that the LCC prediction model were reasonable to describe the LCC and the proposed approach can simulate the prediction of LCC with an acceptable accuracy.

After the validation of the proposed approach, the next step was to simulate the LCC in 2016, assuming the changes between 2006 and 2011 will continue during the next time interval. In this simulation, the LCC and input parameters acquired in 2011 were used as input to simulate the LCC in 2016. Figure 9 shows that the simulated changes between 2006 and 2016. There have been significant LCC where urban land covered 26,5% of simulated changes in 2011 and 37,4% in 2016. This could be attributed to the increase in population by increased demands for residential land. The resulting effect was the decrease in forest land from 27,8% of simulated changes in 2011 and to 20,1% in 2016. From these results, it can be found the replacing the land natural cover (forest land) in the study area by residential land (urban land).

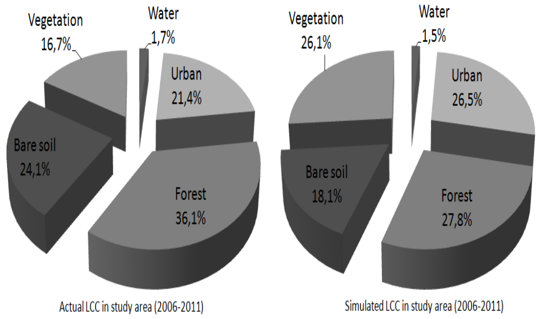

Figure 7: Categorical distribution of the actual and simulated LCC between 2006 and 2011.

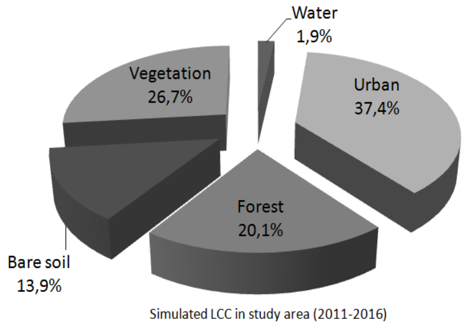

Figure 8: Categorical distribution of the simulated LCC between 2011 and 2016.

Figure 11 maps the simulated future changes compared with land cover maps for the years 2006 and 2011. These results indicate usefulness and applicability of the proposed approach in predicting the LCC.

4.2 Evaluation of the Proposed Approach

In order to evaluate the proposed approach in LCC prediction, we apply the proposed method and the methods presented by (Boulila et al., 2014) [1] and (Gong et al., 2013) [5]. Then, we compare the proposed prediction changes to these two methods.

Table 1 depicts the error calculated between real LCCs, proposed method and methods presented in [1] and [5] between dates 2007 and 2011. As we note, the proposed approach provides a better results than

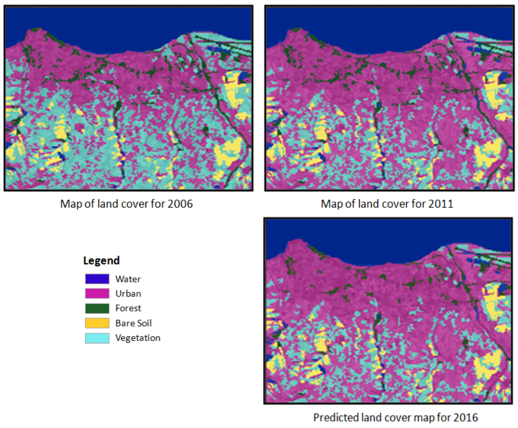

Figure 9: Comparison between the land cover maps for years 2006 and 2011 and the predicted land cover map for 2016.

Table 1: Error for the prediction of LCCs between dates 2007 and 2011.

Approach	predicting LCCs (%)
Approach in [1]	0.18
Approach in [5]	0.23
Proposed approach	0.09

the methods presented in [1] and [5] in predicting LCCs. This shows the effectiveness of the proposed approach in reducing imperfection related to the prediction process. Indeed, figure 10 shows the difference between real changes and changes prediction for the three approaches: proposed approach, approach in [1] and approach in [5]. For example, as we note, the proposed approach predicts a change of 72.15% for forest object, while the real image shows a change of 72.21%.

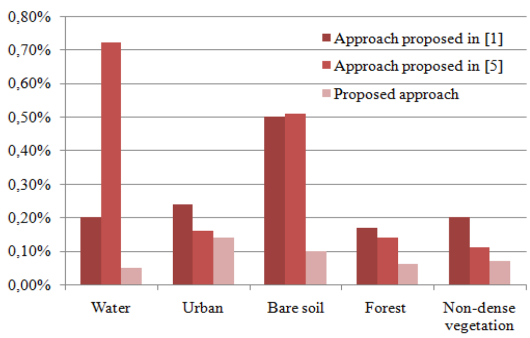

Figure 10: Comparaison between real changes and changes prediction for the three approaches: proposed approach, approach proposed in [1] and approach proposed in [5] .

This provides a difference in the order of 0.06%. This result confirms the effectiveness of the proposed approach in improving LCC prediction. This is made by reducing the effect of imperfection related to parameters and model structure and the effect of their propagation on LCC prediction model.

5 CONCLUSION

This article has expanded the evidence theory framework for propagating correlated parameters and structural model imperfections through a LCC prediction model. We used the ellipsoidal model to analyze correlated parameters. The proposed approach has also modeled both imperfections types (random and epistemic) that are associated with input parameters and model itself.

The results show the importance to propagate both aleatory and epistemic imperfection and to consider correlation among input parameters in LCC prediction model. Proposed approach studied the changes prediction of land cover in Saint-Denis City, Reunion Island of next 5 years (2016) using multi-temporal Spot-4 satellite images in 2006 and 2011. Results indicated that the urban land covered 26,5% of simulated changes in 2011 and 37,4% in 2016 and the forest land covered 27,8% of simulated changes in 2011 and 20,1% in 2016. From these results, it can be found the replacing the land natural cover (forest land) in the study area by residential land (urban land).

Proposed approach was compared on error prediction to existing propagation methods. Results show good performance of the proposed approach in improving prediction of the LCC. More work, however, is needed to understand how to reduce the computational cost in our proposed approach. LCC prediction model with a large number of uncertain input parameters is more complex. To optimize, it is important to study the sensitivity of input parameters and also the sensitivity of model structure.

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