Application of evidential reasoning to improve the mapping of regenerating forest stands

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1. Introduction

Forest inventory information is usually mapped based on the interpretation of aerial photographs and is represented by homogeneous polygons according to a set of guidelines (Avery and Burkhart, 2002). Forest companies and government services involved in forest management are faced with the challenge of obtaining subpolygon information, especially for regenerating stands without any stand attribute information other than location. A report focused on forest management in the province of Quebec, Canada (CEGFPQ, 2004) mentioned the lack of accuracy in provincial inventories for predicting timber quality and accessibility. More specifically, the report mentions that the species composition of regenerating stands is a key parameter for estimating the efficiency of future volume growth. The authors suggested that the current information on regenerating stands does not allow a reliable estimation of this critical parameter for forest management (Chapter 5). In addition, forest inventories tend to be updated decennially. At a local scale, forest companies need the best available information to evaluate the accessibility of resources and to efficiently manage their lands. Stringent management requirements demand improved maps of regenerating stands beyond what is presently available.

The most common mapping methods used in forestry are photo-interpretation (Hall, 2003), satellite image classification with maximum likelihood methods (Rogan and Yool, 2001), and k nearest-neighbour algorithms (Finley and McRoberts, 2008). Some studies also employed image segmentation (Magnussen et al., 2004), which can reduce map accuracy at a local scale through pixel aggregation but can increase the general quality of the map with an extended set of metrics and flexible statistical rules. Frequently, mapped attributes include stand extent, vegetation type (i.e., stand type and species), stand height or age, and stand density. Some studies have proposed expanding mapping methods for forest stands by integrating multiple data sources using Markov random fields (Schistad-Solberg, 1999), decision trees (Sesnie et al., 2008), or neural networks (Blackard and Dean, 1999). The expansion of current automatic classification methods beyond the spectral information associated with an image is not widely adopted due to the lack of a working framework for efficient data integration.

For forest regeneration mapping, very high spatial resolution imagery (2 and 6 cm) with leaf-off conditions has been employed successfully for hardwood and shrub competition characterization in conifer stands (Pouliot et al., 2006). However, covering large forest extents with an aerial camera remains costly. Individual tree-crown delineation followed by crown classification has also been
applied to characterize regenerating stands (Leckie et al., 2003). In such a case, vegetation such as ferns and shrubs were not considered in the final classification. Fiorella and Ripple (1993) showed that the Spectral Index (ratio: band 4/band 5) from Landsat TM images could be used to identify poorly regenerating conifer stands as compared to well-regenerated stands. However, the discrimination was efficient only for stands older than 15 years. Moreover, finer spatial resolution is often required to map clear-cuts where regeneration patches have dimensions smaller than 30 m. Van Lier et al. (2008) mapped the areal extent of ericaceous shrubs in coniferous stands with IKONOS and Landsat TM images.

A study on deciduous stand regeneration in southern Quebec provides a good test case for assessing improvements to traditional classification methods and for testing a new framework for the integration of heterogeneous data sources. Many parameters affect stand regeneration and growth success including soil conditions (Park and Yanai, 2009; Gasser et al., 2010), light availability (Hane, 2003; Gasser et al., 2010), temperature (Raulier et al., 2000), the presence of particular wildlife with consequent damage to vegetation (Frelich and Lorimer, 1985), and species competition (Pouliot et al., 2006).

As the main objective of our study, we first propose a method that improves the accuracy of maps of regenerating forests as compared to traditional classification methods based on satellite images and potentially on large spatial extents (regional scale). Secondly, we demonstrate how the evidential reasoning (ER) method integrates heterogeneous geospatial data sources, such as satellite images and attributes describing biophysical parameters. Development of the ER method to map forest attributes both improves the accuracy of the maps and provides a more general working framework for data integration. Therefore, we apply the Dempster–Shafer theory (DST) and the Dezert–Smarandache theory (DSmT) to map naturally regenerating forest stands within the Watopeka forest located in southern Quebec. In addition, different mass function configurations are tested and their advantages and limitations are discussed. This study strengthens preliminary work which consisted of a basic application of the DST to the data sources used in this paper (Mora et al., 2008).

2. Material

2.1. Study area

The Watopeka forest is located in the Appalachian ecoregion (Ecological Stratification Working Group, 1995) and is located 25 km north of Sherbrooke, Quebec, Canada (Lat. 45° 35’ N, long. 71° 50’ W). The forest is exploited for paper production. The rectangular 50 km² study area contains 2.5 km² of regenerating forest stands (Fig. 1) that are primarily composed of sugar maple (Acer saccharum), yellow birch (Betula alleghaniensis Britton) and coniferous species such as balsam fir (Abies balsamea), jack pine (Pinus banksiana) and black spruce (Picea mariana). The area offers a complex combination of several biophysical parameters. These are drainage, surface deposits, slope, aspect, and slope position (e.g., bottom slope, mid-slope and ridgetop). The terrain altitude varies from 250 to 400 m above sea level with gentle hills. The annual mean precipitation rate varies between 1000 and 1100 mm and the annual snow cover from 250 to 400 cm (Robitaille and Saucier, 1998). The growth season varies from 170 to 180 days per year and the number of growing degree days varies from 2400 to 3400 °C.

2.2. Data sources

2.2.1. Satellite imagery

We orthorectified a multispectral SPOT-5 HRG image taken on September 9, 2002. For this step, we used a DEM interpolated with a Spline method applied on contour lines (1:20000) extracted from the provincial topographic database. No atmospheric correction was applied to the image because the sky was perfectly clear that day. The atmospheric pressure was 995 hPa at the time of acquisition of the image. The SPOT-5 image has a 10 m spatial resolution...
which offers a good compromise between the cost of the image and
the surface covered by the image.

2.2.2. Sample plots

We adopted a map stratification tailored to provide details spe-
cific to the regenerating stands. During preliminary tests carried out
to classify the satellite image, we observed that Commercial decid-
uous (ComD) classes such as sugar maple and yellow birch were not
distinguishable from other deciduous trees having no economic
interest like the cherry tree (*Prunus pensylvanica*). Consequently, all
deciduous species were placed in the same class. As a complement
class, the Non-commercial species (NonCom) class was composed
of shrubs (*Rubus* sp.), ferns (*Demnaestidia* sp., *Pteridium* sp.),
and typical species from wetlands like lycopus (*Lycopodium* sp.)
and horsetails (*Equisetum* sp.). As a third class, the Conifers included
areas dominated by balsam fir, jack pine and black spruce.

We randomly selected field sample plots from the regenerating
stands within the study area for the three classes of the stratifica-
tion. We documented 61 sample plots for ComD, 53 for NonCom,
and 36 for Conifers. The following measurements were taken for
each sample plot: the plot location with a Differential Global Posi-
tioning System (DGPS), species composition, species projection
density, average tree species age, overall dominant tree height,
and the approximate radius of stand homogeneity from the centre.
The mean geometric error in the registration of the plot locations
was about 4 m. The sample plot diameter could vary depending
on plant homogeneity and the species distribution. Minimum and
maximum sample plot radii were 12 m and 25 m respectively.
We superimposed the satellite image over all the sample plots in order
to assign the corresponding pixels to the appropriate class thus
allowing the spectral signatures of the classes to be built.

The normality of the spectral value distributions for each class
was tested with the Jarque–Bera test (*Jarque and Bera*, 1987). Half of
the distributions were found to be normal. However, all of the dis-
tributions were unimodal. In addition, the Bhattacharyya distance
was applied to study the spectral separability of each class and it
revealed a good separability level between 1.3 and 1.45 given that
a perfect separability is equal to 2. Therefore, we decided to use
the Maximum Likelihood Algorithm (MLA) with a normal distri-
bution as the first reference test in order to evaluate the fusion
algorithms. Finally, we randomly divided each class of the dataset
into two parts to obtain a dataset to train the MLA (66% of the sam-
ple plots) and another one for the validation of the classification
results (remaining 34%).

2.2.3. Ancillary data

Drainage and surface deposit maps were obtained from the for-
est inventory produced by the provincial government of Quebec. It
was produced by the interpretation of aerial photography (1:50 000
scale), *Gagnon and Roy* (1994), *MRNQ* (1999), and *Roy et al.* (1985,
2002) showed the important influence of surface deposits and
Drainage on the spatial distribution of tree species and stand type.
Soil moisture, especially during the growth season, plays a signif-
icate role not only on site quality but also on forest composition
Roy* (1994) emphasized the major role of site drainage on sugar
maple dieback.

The aspect, slope and slope position maps were computed from
the DEM that was used to orthorectify the satellite image. Note
that we did not use the altitude in the ancillary data because of
its low variation in the study area. Statistics from *MRNQ* (1999)
showed a strong link between the slope, the slope position and, to
a lesser extent, the aspect with the spatial distribution of decidu-
ous species in the Eastern Townships Region (location of our study
area). *Roy et al.* (1985) also showed the significant influence of the
slope on regeneration. Lower slope values will decrease drainage
response times leading to soil moisture accumulation (*Niemann,
1991*). Slope position is also another important factor influencing
regeneration. Moisture increases with distance from ridgetops and
saturation occurs more frequently at the base of slopes (*Calver et al.,
1972*). A report from the Government of Quebec (1995) also showed
a statistical link between the aspect and the spatial distribution of
species. *Houston et al.* (1990) described the role of site aspect on
stand health. Finally, the slope and aspect influence the degree days
that the vegetation receive (*Bennie et al.*, 2008), which is a major
factor for plant growth.

3. Methods

The DST is an ER method that is a generalization of the Bayesian
theory of subjective probability (*Bayes*, 1763). The DST is derived
from the works of *Dempster* (1968) and *Shafer* (1976). The major
contribution of this theory compared to the Bayesian framework is
that it permits the possibility of considering classes which repre-
sent the union of singleton classes (*θ1 ∪ θ2*), such as “Deciduous OR
Conifers”. Therefore, this framework explicitly permits the notion
of uncertainty. ER methods can combine data from heterogeneous
sources through mass functions specifically established to repre-
sent the influence of each data source for each potential hypothesis
(i.e., classes of the stratification).

3.1. Theoretical basis of the DST

The scientific literature provides a limited but increasing num-
ber of DST examples applied to map production. Among them,
*Le Hégarat-Mascle et al.* (1997) used SAR and the fusion of optical
images for land cover mapping. In addition, *Ahmadzadeh and
Furthermore, *Rogge et al.* (2003) used a DST method to define
lineament trends that may represent potential gold mining sites.
In forestry, the DST has been applied for land cover classification
(*Franklin et al.*, 2002), for the analysis of the quality of some spectral
training sites prior to image classification (*Göttlicher et al.*, 2009),
and for decision making regarding whether or not to apply fertilizer

Here, we present a summary of the theoretical principles that
are useful for understanding the link between the DST and the Free
DSm model. The first step of the DST consists of defining a frame of
discernment Θ that includes all of the *θ* states under consideration
(Eq. (1)). Then a power set 2^Θ is defined including all of the subsets
of Θ and the empty set ∅ (Eq. (2)):

\[
Θ = \{θ_1, θ_2, θ_N\},
\]

\[
2^Θ = 2^{2^Θ}(θ_1, θ_2, θ_1 ∪ θ_2 ∅).
\]

The combination rule allows the fusion of the information
sources with the mass functions describing for each state of each
source the confidence given to each element of the power set with
non null mass. Thus, for a frame of discernment Θ composed of two
hypotheses θ1 and θ2, the mass functions m (·) for each hypothesis
of 2^Θ must satisfy the following requirements for a given source:

\[
\sum_{A \subset 2^Θ} m(A) = 1, \quad m : 2^Θ → [0, 1],
\]

\[
m(∅) = 0
\]

In addition, we designed the mass functions using the discounting
framework (*Shafer*, 1976). This method helps to weaken the
mass sources believed to be less reliable or of lesser importance
before the subsequent fusion. In our case, the framework is defined
as follows: $\forall i \in 2^{\Theta}$, $\theta_i \neq \emptyset$,

$m'(\theta_1) = am(\theta_1)$, 
$m'(\theta_2) = am(\theta_2)$, 

$m'(\theta_1 \cup \theta_2) = (1 - \alpha) + am(\theta_1 \cup \theta_2)$,

with $\alpha$ being the discounting coefficient.

Because we first designed the mass functions so that the sum of the masses of the singleton classes is equal to 1 (Eq. (6)), a normalization to unity (i.e., 1) by a rule of three was required (Eq. (3)) to integrate the mass of the union class after the use of the discounting framework.

\[ m(\theta_2) = 1 - m(\theta_1) \]  

(6)

Then, the combination rule (Eq. (7)) combines the sources two by two. For two distinct sources characterized by their belief masses $m_1(\cdot)$ and $m_2(\cdot)$, the combination rule is written as $m(\emptyset) = 0$ and $\forall C \in 2^\Theta/(\emptyset)$:

\[ m(C) = [m_1 \oplus m_2](C) = \sum_{A' \subseteq B \subset C} m_1(A)m_2(B) \]  

(7)

The denominator in Eq. (7), also named $K$ in the literature, equals zero if the sources are completely contradictory. In such a case, the conflict $(K-1)$ equals 1.

However, the efficiency of the DST is low when attempting to apply fusion to high conflicting cases, as explained by Zadeh (1979, 1986). In such cases, the DST can provide counter intuitive results. Other authors have proposed various solutions to solve this problem (Smarandache and Dezert, 2006). Thus, we decided to test the DSmT which has been designed specifically to assess conflicting cases.

### 3.2. Theoretical basis of the Free DSm model

The DSmT allows “plausible and paradoxical” reasoning and is a generalization of the DST allowing the consideration of paradoxical hypotheses (Smarandache and Dezert, 2006). This method takes into account the conflict existing between sources in a more flexible framework as compared to the DST. We chose the Free DSm model among several other potential methods because we only had two hypotheses and also for its ease of implementation (Smarandache and Dezert, 2006). The term Free refers to the fact that no constraint is applied to the fusion model (i.e., no exclusive hypothesis is defined). Otherwise, the model would be called the Hybrid DSm model.

The Free Dsm combination rule retains the properties of commutativity and associativity of the DST. A hyper-power set is now derived from the frame of discernment (1). This set is built with disjunctive and conjunctive operators: $\cup$ and $\cap$. The operator $\cap$ represents the intersection of two hypotheses ($\theta_1 \cap \theta_2$, meaning for example Deciduous AND Conifers). Thus for the frame of discernment presented in (Eq. (1)), the derived hyper-power set $D^\Theta$ is represented as follows:

\[ D^\Theta = \{\theta_1, \theta_2, \theta_1 \cup \theta_2, \theta_1 \cap \theta_2, \emptyset\} \]  

(8)

The definition of the mass functions presented for the DST remains identical for the DSmT. The DSm classic combination rule for two distinct sources is defined as $m(C) = 0$ and $\forall C \in 2^{\Theta}/(\emptyset)$:

\[ m(C) = [m_1 \oplus m_2](C) = \sum_{A' \subseteq B \subset C} m_1(A)m_2(B) \]  

(9)

The conflict $(K-1)$ in the DSm combination rule in (Eq. (7)) disappears in (Eq. (9)). Now, the conflict is represented by every combined class resulting from the intersection of two singleton hypotheses (e.g., $\theta_1 \cap \theta_2$). Thus the paradoxical aspect of this fusion method lies in the fact that some elements $\theta_i$ of a frame $\Theta$ are not exclusive; in other words, $\theta_i$ has a non-empty intersection. The DSmT has been applied in various research fields. In signal processing, Keichichian and Champagne (2007) improved the performance of a signal filtering method using the DSmT to define a novel peak tendency estimator. Khedam et al. (2006) successfully applied the DSmT for land cover mapping. Corgne (2004) applied it to land-cover prediction over an agricultural region with its success depending on the classes of the stratification. Li et al. (2006) obtained improved results with the DSmT compared to the DST for a sonar map building application.

### 3.3. Decision rule

Several decision rules have been proposed for choosing the best hypothesis after the combination of the data sources. The most common decision rules are defined by Shafer (1976): the maximum credibility and the maximum plausibility. The credibility (Eq. (10)) of hypothesis $A$ is based upon the sum of the mass products $B$ strictly supporting the hypothesis $A$ whereas the plausibility function (Eq. (11)) considers the mass products $B$ intersecting the hypothesis $A$.

\[ Cr(A) = \sum_{B \subseteq A} m(B) \]  

(10)

\[ Pl(A) = \sum_{B \in 2^\Theta, A \cap B \neq \emptyset} m(B) \]  

(11)

For each decision rule, the hypothesis maximizing the decision statistics is adopted as the most credible or plausible answer. In a scenario where there are only two singleton hypotheses, the decision (choice of final hypothesis) between the maximum credibility and the maximum plausibility will always be the same. Therefore maximum credibility was selected for this study.

### 3.4. Mass function establishment

We used the Fuzzy Statistical Expectation Maximization (FSEM) algorithm to define the mass functions for the satellite image (Germain et al., 2002). This is a multi-iterative classification method based on Gaussian distribution classes. The method produces union classes from the original input singleton classes and computes posterior probabilities. This algorithm could only be applied on the satellite image as normal distributions are required.

For the ancillary data sources, mass functions were assigned manually, based upon scientific and technical references. First, the references indicated whether the ancillary data had a positive influence on the growth development of the deciduous species, most particularly on sugar maple which was the most common species of interest in the area. In other words, we were able to depict a general shape for the mass functions without having absolute values for mass allocation. We therefore had to estimate the influence of each state when the scientific and technical references did not provide such information (e.g., Southern aspect: favourable, Northern aspect: adverse). As this was done empirically for some sources, we applied sensitivity tests to evaluate the influence of a range of mass values on the quality of the fusion (see Section 4.4). Note that many studies have employed empirical rules (i.e., expert-knowledge based rules) to establish mass functions, such as Corgne (2004) and Cayuela et al. (2006).

Mass function values assigned to the site drainage parameter were deduced from Roy et al. (1985). The study was carried out on 62 maple stands distributed within a rectangular 2500 km² area in southern Quebec. They established a curve linking the dieback rate to the drainage of forty deciduous forest stands in southern
Quebec. We used this curve to quantify the influence of the drainage parameter on the potential growth of sugar maple (Table 1). We noticed that the two levels referred to as Excessive and Fast were not found in our study area. The codes in Table 1 correspond to the provincial forest inventory standards.

Mass function values applied to the surface deposit parameter were determined according to the references cited in Section 2.2.3. We estimated the influence of the amount of clay and the thickness of the soils on the growth development of sugar maple (Table 2). Note that the codes correspond to the provincial forest inventory standards.

Mass function values applied to the aspect parameter were selected based on information found in Gagnon et al. (1990) and a report from the Government of Quebec (1995). This information allowed us to create a hierarchy of the various aspects. The values were fixed empirically (Table 3).

Mass function values applied to the slope parameter were deduced from Roy et al. (1985). They provided a classification of the slopes according to the dieback rate found on each of them. We empirically evaluated the dieback susceptibility into a quality criterion for the growth development of sugar maple (Table 4).

Implementing the discounting framework, we empirically fixed the coefficient $\alpha$ to a value of 0.5 given the uncertainty related to the data sources (i.e., scale digitization and quality of the manufacturing process). This is equivalent to considering the mass of the union class as the mean of the masses of the singleton classes (Eq. (6)). On the one hand, this choice appeared to be the best compromise for modelling the uncertainty of the sources.

### 3.5. Data fusion procedure

The first step in the data fusion procedure consisted of the delineation of the regenerating stands in the satellite image using the provincial forest inventory in order to create a mask. The forest inventory updated by Domtar Corporation was used to identify the location of the regenerating stands. We therefore created the regeneration mask and applied it to the satellite image. As a second step, we identified in the regenerating stands the isolated pixels dominated by Conifers. These pixels were then included in the mask created in step 1. This allowed us to simplify the following fusion procedures, by only considering the ComD, NonCom and their union class. Moreover, Conifers were not dominant in the study area and could be easily classified with the MLA.

As a third step, we used the data fusion methods. The DST was employed to combine the satellite image with each ancillary data source separately. Then, we combined the satellite image with each possible combination of two ancillary data sources. We added a third ancillary data source to the best combination obtained with the satellite image and two ancillary data sources. In addition, we discarded the SPOT-5 image and fused the ancillary data sources that provided the best results when combined with the satellite image. The power set for the DST was defined as follows:

$$2^\Theta = \{\text{ComD}, \text{NonCom}, \text{ComD} \cup \text{NonCom}, \emptyset\}. \quad (12)$$

Then, we applied a Hill–Smith test (Hill and Smith, 1976) to study the link between the masses, the quality of the result obtained by the DST, and the conflict level. This test allows the consideration of numerical and categorical data. In Fig. 2, each vector of the correlation circle is associated with a specific parameter. Vectors in the same direction and close to each other are positively correlated, whereas vectors in the opposite direction to each other are negatively correlated, and vectors that are orthogonal are independent to each other. Theoretically, vectors with the same direction provide redundant information while orthogonal vectors may provide conflicting but complementary information. The results showed that the use of the Free DSm model was justified because a positive correlation between the conflict and the misclassified pixels was found.

The application of the Free DSm model followed the same procedure as the DST fusion process. We started to fuse the data sources with a total transfer of the mass from the union class to the intersection class. This is a classical way to use the Free DSm model (Corgne, 2004). A second test consisted of conditioning the transfer of the mass of the union class depending on the conflict level computed during the DST fusion. The conflict level gives important information about the possibility of getting a false result from the DST, as explained by Zadeh (1978, 1986). Therefore, the mass transfer should only be used for high values. The threshold was fixed con-

<table>
<thead>
<tr>
<th>Table 1</th>
<th>Mass function values for the drainage parameter.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level</td>
<td>Code</td>
</tr>
<tr>
<td>Excessive</td>
<td>0</td>
</tr>
<tr>
<td>Fast</td>
<td>1</td>
</tr>
<tr>
<td>Good</td>
<td>2</td>
</tr>
<tr>
<td>Moderate</td>
<td>3</td>
</tr>
<tr>
<td>Imperfect</td>
<td>4</td>
</tr>
<tr>
<td>Bad</td>
<td>5</td>
</tr>
<tr>
<td>Very poor</td>
<td>6</td>
</tr>
</tbody>
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<table>
<thead>
<tr>
<th>Table 2</th>
<th>Mass function values for the surface deposit parameter.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type</td>
<td>Code</td>
</tr>
<tr>
<td>Thin organic deposits</td>
<td>7T</td>
</tr>
<tr>
<td>Thin glacial deposits</td>
<td>1aM</td>
</tr>
<tr>
<td>Medium thickness glacial deposits</td>
<td>1aY</td>
</tr>
<tr>
<td>Thick glacial deposits</td>
<td>1a</td>
</tr>
<tr>
<td>Juxtaplacial deposits</td>
<td>2A</td>
</tr>
<tr>
<td>Proglacial deposits</td>
<td>2B</td>
</tr>
<tr>
<td>Ancient fluviatil deposits</td>
<td>3AN</td>
</tr>
<tr>
<td>Glaciolacustral deposits</td>
<td>4GS</td>
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<table>
<thead>
<tr>
<th>Table 3</th>
<th>Mass function values for the aspect parameter.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aspect</td>
<td>ComD</td>
</tr>
<tr>
<td>Flat</td>
<td>0.5</td>
</tr>
<tr>
<td>North</td>
<td>0.4</td>
</tr>
<tr>
<td>East</td>
<td>0.65</td>
</tr>
<tr>
<td>South</td>
<td>0.75</td>
</tr>
<tr>
<td>West</td>
<td>0.5</td>
</tr>
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<table>
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<tr>
<th>Table 4</th>
<th>Mass function values for the slope parameter.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slope rate</td>
<td>Dieback level</td>
</tr>
<tr>
<td>0–1%</td>
<td>High</td>
</tr>
<tr>
<td>1–30%</td>
<td>Small</td>
</tr>
<tr>
<td>&gt;30%</td>
<td>High</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 5</th>
<th>Mass function values for the slope position parameter.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level</td>
<td>ComD</td>
</tr>
<tr>
<td>Bottom slope</td>
<td>0.40</td>
</tr>
<tr>
<td>Gentle slope</td>
<td>0.95</td>
</tr>
<tr>
<td>Steep slope</td>
<td>0.95</td>
</tr>
<tr>
<td>Ridge</td>
<td>0.40</td>
</tr>
</tbody>
</table>
considering that the unimodal conflict distribution was Gaussian. As a result, the threshold was fixed in order to carry out the transfer for the 2.5% highest conflict values. The maximum credibility decision rule was also employed. The hyper-power set for the Free DSm model was defined as follows:

\[ D^{\phi} = \text{ComD}, \text{NonCom}, \text{ComD} \cup \text{NonCom}, \text{ComD} \cap \text{NonCom}, \varnothing. \] (13)

3.6. Reference methods

We compared the results of the fusions with two reference methods: the MLA and Linear Spectral Unmixing (LSU). As a reference, we first used the results from the MLA method applied to the area of the satellite image covered by the regeneration mask in order to evaluate the performance of the fusion methods. The MLA was applied to the first four bands resulting from a principal component analysis, so that the results are comparable to those obtained with the FSEM and the fusion algorithms. The bands represented more than 80% of the variance. We also used this result to identify the coniferous pixels in the regenerating stands in order to mask them (step 2 of the methodology presented above).

The LSU could be applied based on the proportion of each class identified on each sample plot from in situ measurements. The first four bands resulting from a principal component analysis were used as input data. These proportion values were used to initiate the calculation and allowed the algorithm to define each end-member. The final map was derived by allocating to each pixel the class with the highest proportion. Foody (1995) suggests that the best way to evaluate the LSU results is to apply the cross-entropy measurement (Klir and Folger, 1988). For the result of an \( N \) class spectral unmixing, the cross-entropy \( H_c \) is defined as follows:

\[ H_c = - \sum_{i=1}^{N} (p_i)' \ln(p_i'). \] (14)

with \( p_i \) being the proportion of class \( i \) in the ground truth data and \( p_i' \) the proportion of class \( i \) in the result.

4. Results and their interpretation

4.1. Reference methods

Results were obtained for the MLA with the three classes of the original stratification and also for the two remaining classes by using a mask to remove the Conifers from the regenerating stands (Table 6). These last results were compared to those obtained with the fusion algorithms. The MLA provided better results in the two class case (82.75%) compared with the three class case (70%). These results can be explained by the removal of the Conifers class, which reduced the level of confusion; for the two class case, both classes were well classified. Such good results were expected since the

**Table 6** Results for the MLA according to the number of classes.

<table>
<thead>
<tr>
<th></th>
<th>ComD</th>
<th>NonCom</th>
<th>Conifers</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Three class case</td>
<td>83%</td>
<td>40.96%</td>
<td>81.48%</td>
<td>70.03%</td>
</tr>
<tr>
<td>Two class case</td>
<td>90.83%</td>
<td>71.08%</td>
<td>/</td>
<td>82.75%</td>
</tr>
</tbody>
</table>
sample distributions were assumed to be normal and the Bhattacharyya distance demonstrated good class separability. Note that in this study we computed the weighted means in order to take into account the number of pixels in each class.

A hard classification was developed based upon the results from the LSU (Table 7). Although the hard classification provided better results than the MLA, these results must be put into perspective with the cross-entropy values (Table 8), which indicate a poor evaluation of the proportions for the NonCom class and a very bad result for the Coniferous class. Consequently, the MLA results will be used to evaluate the results of the fusion algorithms.

4.2. Fusion with the DST

The classification results for the satellite imagery obtained with the MLA were more favourable compared to those from the FSEM (Table 9). Consequently, we decided to stop the FSEM after one iteration in order to obtain a Fuzzy MLA classification and the evaluation of the mass functions. Indeed, the first iteration of the FSEM fixes the prior probabilities for each of the n classes at 1/n. When compared to the FSEM, the Fuzzy MLA provided an improvement of 6.4% on the overall accuracy. When the MLA was used as a reference, the result was lower than the one obtained with the Fuzzy MLA (1%). This can be explained by the fact that the last method computed the masses for a third class (the union class). This induced a new distribution of mass values which could lead to a new hierarchy between the singleton classes.

The results obtained when the satellite image was fused with one ancillary data source showed that half of the fusions were improved with the use of a Fuzzy MLA (Table 10). The fusion between the PCA bands of the satellite image with the surface deposit parameter provided the best result. Fusion of the SPOT-5 image with the drainage data provided the second best results. According to these results, we decided to keep using the Fuzzy MLA for the satellite image to be input into the next DST fusion test.

The DST was further applied to combine the satellite image with all possible combinations of two ancillary data sources from the available layers. The Fuzzy MLA was also used to compute the mass functions for the satellite image. Only the best results are shown in Table 11. The layer that provided the best results for the one ancillary data source case (i.e., surface deposit parameter) proved to be always included in the best combination using two ancillary data sources. The addition of the drainage parameter and the surface deposit parameter with the SPOT-5 image provided an improvement to the overall accuracy of 2.4%. The second best combination using the aspect parameter did not provide an improvement to the results compared to the one ancillary data source combination tests. Finally, we added a third ancillary data source to the best combination of the satellite image and two ancillary data sources. All of these supplemental combinations induced a decrease in the overall accuracies.

The fusion of the best ancillary data sources (i.e., the drainage and surface deposit parameters) provided an overall accuracy of 73.3%. The ComD class and NonCom class had an accuracy of 100% and 35% respectively.

4.3. Fusion with the Free DSm model

The first set of results with the Free DSm model was obtained by entirely transferring the mass from the union class to the intersection class. Fusing the satellite image with one or two ancillary data sources with the Free DSm model led to an improvement of 0.5% to the overall accuracy for the combination with the drainage parameter and an improvement of 1% for the fusion with the aspect parameter (Table 12). All of the other one ancillary data source combinations provided worse results. Finally, the best result was obtained again with the combination of the satellite image with the drainage parameter and the surface deposit parameter. It induced a small improvement of 1% to the overall accuracy compared to the DST. Fig. 3 shows the map obtained with the best combination.

A second set of results with the Free DSm model was obtained by transferring the mass from the union class to the intersection class according to the conflict level. The conditions for the mass transfer did not provide an improvement over the previous best results. A decrease of 1% for the overall accuracy was observed. However, for less favourable combinations from the first set of results, 6 of these 21 possible combinations had an increase in their overall accuracy. Overall, when compared to the DST, the Free DSm model provided equal results for half of the possible combinations with two ancillary data sources. Firstly, this is explained by the fact that for these cases the conflict rate was not high enough to induce the transfer of the mass to the intersection class. Secondly, the theoretical advantages of the Free DSm model did not operate due to a low conflict rate (about 0.25 with both ancillary data sources) which provided results identical to those from the DST.

Table 7

Results for the “Hard” classification with LSU according to the number of classes.

<table>
<thead>
<tr>
<th></th>
<th>ComD</th>
<th>NonCom</th>
<th>Conifers</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Three class</td>
<td>90%</td>
<td>75.90%</td>
<td>81.48%</td>
<td>83.65%</td>
</tr>
<tr>
<td>Two class</td>
<td>89.16%</td>
<td>77.10%</td>
<td>/</td>
<td>84.23%</td>
</tr>
</tbody>
</table>

Table 8

Results for the LSU with cross-entropy.

<table>
<thead>
<tr>
<th></th>
<th>ComD</th>
<th>NonCom</th>
<th>Conifers</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.2</td>
<td>27.5</td>
<td>211</td>
<td></td>
</tr>
</tbody>
</table>

Table 9

Results obtained using the MLA and the FSEM.

<table>
<thead>
<tr>
<th></th>
<th>ComD</th>
<th>NonCom</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>MLA</td>
<td>90.83%</td>
<td>71.08%</td>
<td>82.75%</td>
</tr>
<tr>
<td>FSEM</td>
<td>96.67%</td>
<td>49.40%</td>
<td>77.34%</td>
</tr>
<tr>
<td>Fuzzy MLA</td>
<td>85%</td>
<td>81.93%</td>
<td>83.74%</td>
</tr>
</tbody>
</table>

Table 10

Overall accuracy obtained using the DST with one ancillary data source.

<table>
<thead>
<tr>
<th></th>
<th>Fuzzy MLA</th>
<th>FSEM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slope position</td>
<td>66%</td>
<td>77.33%</td>
</tr>
<tr>
<td>Drainage</td>
<td>87.19%</td>
<td>86.20%</td>
</tr>
<tr>
<td>Slope</td>
<td>67.98%</td>
<td>71.92%</td>
</tr>
<tr>
<td>Aspect</td>
<td>80.78%</td>
<td>76.84%</td>
</tr>
<tr>
<td>Surface deposit</td>
<td>87.68%</td>
<td>80.29%</td>
</tr>
</tbody>
</table>

Table 11

Best results obtained using the DST with two ancillary data sources.

<table>
<thead>
<tr>
<th></th>
<th>ComD</th>
<th>NonCom</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drainage/surface deposit</td>
<td>95.83%</td>
<td>81.93%</td>
<td>90.14%</td>
</tr>
<tr>
<td>Surface deposit/aspect</td>
<td>90%</td>
<td>79.52%</td>
<td>85.71%</td>
</tr>
</tbody>
</table>

Table 12

Best results obtained with the Free DSm model with a total transfer of the Fuzzy mass to the paradoxical class.

<table>
<thead>
<tr>
<th></th>
<th>ComD</th>
<th>NonCom</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drainage</td>
<td>93.33%</td>
<td>79.51%</td>
<td>87.68%</td>
</tr>
<tr>
<td>Surface deposit</td>
<td>89.16%</td>
<td>84.33%</td>
<td>87.19%</td>
</tr>
<tr>
<td>Aspect</td>
<td>85%</td>
<td>77.10%</td>
<td>81.77%</td>
</tr>
<tr>
<td>Drainage/surface deposit</td>
<td>95%</td>
<td>85.54%</td>
<td>91.13%</td>
</tr>
<tr>
<td>Drainage/aspect</td>
<td>91.66%</td>
<td>77.10%</td>
<td>85.71%</td>
</tr>
<tr>
<td>Slope/surface deposit</td>
<td>66.66%</td>
<td>71.08%</td>
<td>68.47%</td>
</tr>
</tbody>
</table>
4.4. Sensitivity tests

The first sensitivity test consisted of varying the mass function values that were empirically chosen from the ancillary data sources. The range of values was selected to preserve the shape of the mass functions which represents the hierarchy between the state values of the source. The tests carried out on one and two ancillary data sources showed that the original mass values were the most efficient in providing the best overall accuracies and the most balanced class accuracies. The tests showed that increasing the mass of one hypothesis automatically increased its accuracy while decreasing the accuracy of the other class.

As a second test, we looked at the justification for the use of a discounting coefficient value $\alpha$ of 0.5. We tested this decision by applying a full range of values. When $\alpha$ was equal to zero (i.e., $m'(\theta_1 \cup \theta_2) = 1$) the ancillary data sources provided no information. Therefore, the accuracies were equal to those obtained with the Fuzzy MLA. Values between 0.1 and 0.9 did not change the accuracies for the one ancillary data source case. Improvements of 0.5% and 1% for the overall accuracy were obtained with values of 0.1 and 0.2 for the combination produced with two ancillary data sources. When $\alpha$ was equal to 1 (i.e., $m'(\theta_1 \cup \theta_2) = 0$) a Bayesian belief configuration was obtained. For both fusion cases, this mass configuration did not change the accuracies compared to other neighbouring values of $\alpha$.

5. Discussion

As already shown in previous studies (Franklin et al., 2002; Cayuela et al., 2006), our work confirmed that ER methods can lead to an improvement of the classification results when compared to classical methods, such as the MLA and LSU. The sensitivity tests showed the difficulty in translating scientific knowledge about the influence of the biophysical parameters that we considered into quantifiable values in the fusion algorithms, as also described by Srinivasan and Richards (1990). Some sources did not provide the expected improvement, such as the topographic parameters. Therefore, the selection of data input, their quality and their associated mass functions are crucial in order to successfully apply data fusion methods.

We suggest several steps to help address the selection of input data and to select the mass function values. Firstly, we found that a reliable way to automatically compute the masses of the spectral bands of a satellite image was to adopt the Fuzzy MLA based on the FSEM when stopped after one iteration. Therefore, the FSEM should be considered for datasets representing classes with normal distributions. Secondly, the sensitivity tests showed the low influence of the discounting coefficient on the accuracies of data fusion with the exception for $\alpha = 0$ and $\alpha = 1$, which are particular cases. In this study, we established that a constant discounting coefficient $\alpha$ at a value of 0.5 is the best way to deal with our lack of knowledge regarding the influence of each ancillary data source and their quality. Nonetheless, for other case studies, the selection of different $\alpha$ values for each data input should probably be done based on data quality and relevance. For example, it is plausible that input data of varying precision (e.g., scale, accuracy) may involve adjusting $\alpha$ for each data source. In the case of our study, all data sources had the same scale. The Bayesian configuration of the masses ($\alpha = 1$) revealed that in our study the discounting framework may not be wholly appropriate for modelling uncertainty in the model, as a Bayesian belief configuration provides equivalent results as one taking into account such information (i.e., uncertainty).

We assessed which data sources were best to improve the classification results from conventional methods. Among six ancillary data sources those that provided the best results were the drainage and surface deposit parameters. These data are available from the provincial forest inventory and therefore can be easily accessed by foresters and researchers thus leading to greater reproducibility of our approach for larger areas. The other ancillary data such as the topographic parameters (i.e., aspect, slope and slope position parameters) did not improve the results. Furthermore, the fusion
of the ancillary data involved in the best fusion case showed, firstly, how important the satellite image information is to get high and balanced class accuracies; and, secondly, the test showed the limits (production standards) of the ancillary data to provide information enabling an accurate mapping of the potential spatial extent of the classes considered in this study.

The Free DSm model provided only a slight improvement (1%) in the results compared with DST resulting from its ability to deal with higher conflict values than the DST. This small improvement may be partially due to the fact that the validation plots were not taken in high conflict areas (i.e., locations where the sources provide contradictory mass values). This situation highlights the importance of plot distribution and the inclusion of areas presenting high conflict.

Further studies should focus on the evaluation and structuring of the mass function values prior to data fusion. When high conflict values occur, the Free DSm model or its derivatives like the Propor- tional Redistribution Conflict methods (Smarandache and Dezert, 2006) should be considered. Moreover, additional classes could be added to the stratification in order to broaden the mapping area and reduce the preprocessing steps (mask application). Finally, additional sources of information could be considered such as the type of former forest stand and the type of adjacent stands combined with the main wind direction (especially for anemochore species). These two potential data layers would allow the consideration of seeds in the soil which influence the regeneration stand (Marks, 1974).

6. Conclusion

Important objectives were met in our study: (1) we developed and applied a new analytical framework for the application of two ER methods (DST and Free DSm model), (2) the framework provided a practical tool to include biophysical information from spatial layers in addition to satellite imagery, and (3) we showed that the accuracy of a stand regeneration map could be improved with ER, compared to reference methods (MLA and LSU). Experienced foresters know that many environmental factors interact to influence the process of stand regeneration. The ER framework provided a formal mechanism allowing a quantification of the influence of biophysical parameters on the growth potential of regenerating forest stands in southern Quebec. We obtained an improvement of 7.4% and 8.4%, respectively, for the DST and the Free DSm model compared with the MLA. The Free DSm model gave slightly better results than the DST, but the improvement of only 1% indicated that both models could be used with only small differences. In addition to the satellite image, the two spatial variables in our study that provided the best results were the surface deposit and drainage variables. Both variables are often easily accessible in developed regions of the world like in Canada. The study showed the central importance of the information provided by the satellite image and that the biophysical parameter maps can be considered as ancillary data sources only. In this study, accuracy improvements were sufficient to facilitate operational forest planning. Both DST and DSmT can be implemented following the examples provided in Smarandache and Dezert (2006). The implementation of both fusion methods does not require in-depth knowledge about information theory. In fact, DST is increasingly becoming available through a number of software tools such as MATLAB® and IDRISI®, to name a few.

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References
