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Classification of a complex landscape using Dempster–Shafer theory of evidence

L. CAYUELA*†‡, J. D. GOLICHER‡, J. SALAS REY§ and J. M. REY BENAYAS†

†Departamento de Ecología, Universidad de Alcalá, C.P. 28871 Alcalá de Henares, Madrid, Spain

‡Departamento de Ecología y Sistemática Terrestre, División de la Conservación de la Biodiversidad, El Colegio de la Frontera del Sur, Carretera Panamericana y Periférico Sur s/n, C.P. 29290, San Cristóbal de las Casas, Chiapas, Mexico

§Departamento de Geografía, Universidad de Alcalá, C.P. 28801Alcalá de Henares, Madrid, Spain

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The landscape of the Highlands of Chiapas, southern Mexico, is covered by a highly complex mosaic of anthropogenic, natural and semi-natural vegetation. This complexity challenges land cover classification based on remotely sensed data alone. Spectral signatures do not always provide the basis for an unambiguous separation of pixels into classes. Expert knowledge does, however, provide additional lines of evidence that can be employed to modify the belief that a pixel belongs to a certain coverage class. We used Dempster–Shafer (DS) weight of evidence modelling to incorporate this information into the classification process in a formal manner. Expert knowledge-based variables were related to: (1) altitude, (2) slope, (3) distance to known human settlements and (4) landscape perceptions regarding dominance of vegetation types. The results showed an improvement of classification results compared with traditional classifiers (maximum likelihood) and context operators (modal filters), leading to better discrimination between categories and (i) a decrease in errors of omission and commission for almost all classes and (ii) a decrease in total error of around 7.5%. The DS approach led not only to a more accurate classification but also to a richer description of the inherent uncertainty surrounding it.

1. Introduction

Complex mosaic landscapes in which heterogeneity is apparent at a very fine grained level of resolution are frequent in many tropical regions around the world (Imbernon and Branthomme 2001, Pedroni 2003). Two major determinants of this complexity are land use and abrupt topography. Land use frequently includes timber extraction, slash and burn agriculture, fuel wood production and cattle ranching, all of which are associated with fragmentation of natural forests and the initiation of complex succesional stages of vegetation development (Meyer and Turner II 1992, Imbernon 1999a, b, Imbernon and Branthomme 2001, Ramírez-Marcial *et al.* 2001). Additionally, population growth and the social structure of

*Corresponding author. Email: luis.cayuela@uah.es

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communities lead to the division of land into extremely small units, often less than 1 ha in extent (Ochoa-Gaona 2001).

Remotely sensed information is an important tool for documenting and understanding the resulting patterns of land cover. However, landscape complexity poses particular challenges for image classification. There is an inevitably high degree of misclassification, particularly if various categories are interspersed within a small spatial area (Foody 2002b) or some of the land cover categories have overlapping spectral signatures (Pedroni 2003). In such circumstances, subjective image interpretation or time-consuming photo-interpretation (Dirzo and García 1992, Turner *et al*. 1996, Ochoa-Gaona and González-Espinosa 2000, Peralta and Mather 2000) has traditionally been preferred to automated supervised or unsupervised image classification. This has several drawbacks. It takes time to classify images manually, and skilled interpreters may not always be available. Furthermore such classification is inevitably subjective, making independent replication and verification of the results extremely difficult. Context operators have also been used to improve classification by removing errors caused by signal noise (Booth and Oldfield 1989). However, in heterogeneous landscapes they can smooth out genuine landscape features.

In attempting to solve the problem of misclassification in fine-grained complex landscapes, soft classifiers have become increasingly popular (Foody 1996, 2002a, Ji 2003). In addition, some researchers have investigated the possibility of including environmental data in the classification process, often through prior probabilities (Mather 1985, Cibula and Nyquist 1987, Frigessi and Stander 1994, Maselli *et al*. 1995, McIver and Friedl 2002, Pedroni 2003). We investigated a method for the classification of land cover by the fusion of multi-spectral data and expert knowledge based on Dempster–Shafer (DS) theory of evidence. The DS approach has the advantage of integrating different pieces of information through formal probabilistic reasoning in a well-documented manner. We applied this method to a case study, the Highlands of Chiapas, Mexico. Our study asked whether the inclusion of field-knowledge-based lines of evidence could improve classification accuracy at least as much as noise reduction through context-based filtering.

2. Material and methods

2.1 *The study area*

The Highlands of Chiapas extend over 11 000 km^2 (figure 1). They form a biologically diverse region which includes 30% of the approximately 9000 vascular plant species of the flora of Chiapas (Breedlove 1981). Several forest formations are found in the Highlands, including oak, pine–oak, pine–oak–liquidambar, pine, and evergreen cloud forests (Miranda 1952, Rzedowski 1988, González-Espinosa *et al*. 1991). The region is densely populated by Mayan peasants who have cleared forest both permanently and temporarily for shifting cultivation and used firewood and other forest resources since pre-Columbian times (Cowgill 1962, Collier 1975).

Our study area was the San Cristóbal de las Casas watershed, located in the central Highlands of Chiapas (figure 1). The area covers around 542 km^2 and extends mainly over the municipalities of San Cristóbal de las Casas and Chamula. Maximum temperatures are between 16 and 22°C. Minimum temperatures can fall below freezing. Rainfall is between 800 and 1200 mm with moist summers and dry winters. Elevations range from 1600 to 2900 m.a.s.l. The underlying geology of the

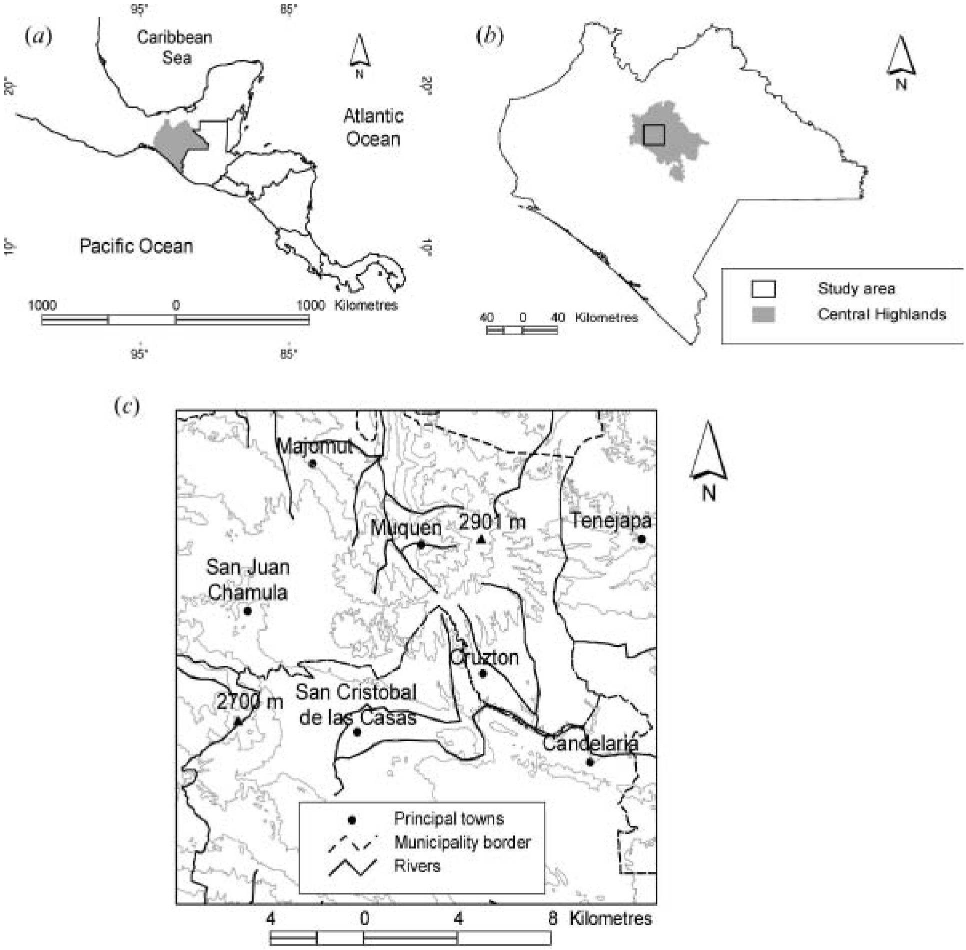

Figure 1. (*a*) The state of Chiapas, southern Mexico, and northern Central America. (*b*) Geographical allocation of the highlands of Chiapas and the central Highlands within the state. (*c*) Characteristics of the study area: municipalities, rivers, principal towns and topographical features.

area is carboniferous limestone with many rocky outcroppings. San Cristóbal and Chamula are two of the most populated districts of the Highlands. Most of the rural population belong to the Maya Tzotzil ethnic group. The main economic activities are agriculture and forestry, with oak forest coppicing being a common management practice.

2.2 *Preliminary data processing*

A subset from a Landsat ETM+ (Enhanced Thematic Mapper) image (path 21 row 48, taken on 3 April 2000) was used in this study. Geometrical corrections were performed using control points from a digital 1 : 50 000 roadway map (LAIGE 2000) with a second-order polynomial algorithm (root mean square error: x-axis$=$0.53 pixels; y-axis$=$0.52 pixels). Removal of atmospheric effects and variations in solar irradiance were achieved using an algorithm based on the Chavez reflectivity model (Chavez 1996). Digital numbers were then transformed to reflectivity values. Effects on shaded slopes were accounted for by performing topographic corrections using a C model (Teillet *et al*. 1982), which is recommended for high solar angles as was the case for our image (solar angle=58.82°). Most of the processing work was performed using PCI 7.0 software package (PCI 2001).

2.3 *Identification of land cover categories*

Classification categories were defined following Miranda (1952), Breedlove (1981), González-Espinosa *et al*. (1997), Ochoa-Gaona and González-Espinosa (2000) and Ochoa-Gaona (2001). We distinguished the following categories: (i) non-classified (NA), (ii) cloud forest (CF), (iii) oak forest (OF), (iv) pine–oak forest (POF), (v) pine forest (PF), (vi) developed areas (DA) and (vii) agriculture and pasturelands (AP). As we will make constant references to these abbreviations throughout the text we advise the reader to refer to table 1 when necessary. Water bodies were not included as a separate class as there were no large rivers, dams or ponds within the study area. Most small water bodies were dry at the time the satellite image was taken.

2.4 *The Dempster–Shafer classification procedure*

The DS theory of evidence is a generalization of the Bayesian theory of subjective probability which allows for combination of different independent lines of evidence derived from various sources in order to obtain degrees of belief for different hypotheses (Kontoes *et al*. 1993, Mertikas and Zervakis 2001). It is based on Dempster–Shafer's rule for combining degrees of belief (Shafer 1982). The procedure constructs and stores the current state of knowledge for the full hierarchy of hypotheses. For example, for three hypotheses {CF, OF, POF}, the possible combinations are [CF], [OF], [POF], [CF, OF], [CF, POF], [OF, POF], [CF, OF, POF]. This allows evidence to be incorporated in favour of occurrence of compound hypotheses when knowledge is not sufficient to discriminate between single hypotheses. It is a potentially powerful approach for aggregating indirect evidence and incomplete information into the classification process. Detailed applications to remote sensing may be found in Srinivasan and Richards (1990), Kontoes *et al*. (1993) and Mertikas and Zervakis (2001).

In our study, the DS classification procedure was implemented by combining different probability images from the evidence derived from both multi-spectral data and expert knowledge-based lines of evidence (table 2). After combining all evidence by means of the DS algorithm, results were obtained in the form of layers that defined the degree of belief or probability of each pixel belonging to each of the

Table 1. Classification categories and their corresponding abbreviations used throughout the text.

Abbreviation	Class
CF	Cloud forest
OF	Oak forest
POF	Pine-oak forest
PF	Pine forest
DA	Developed areas
AP	Agriculture and pasturelands
NC	Non-classified

hypotheses or classification categories (figure 2). A land cover classification map was then obtained by assigning each pixel to the category that was the most probable after the spectral and ancillary information had been combined. Additionally, a layer containing the classification uncertainty was produced.

Multi-spectral data were incorporated into the analysis in the form of Bayesian probabilities based on the variance/covariance matrix derived from training sites (table 2). Informative prior probabilities were not used at this stage as we incorporated the additional information during the subsequent stage of our classification procedure. The probabilities were therefore based on the likelihoods. Training sites were created by on-screen digitizing polygons from control points taken in the field using as pure a sample of the information class as possible. Training sites were selected to account for at least 10 times as many pixels for each training class as bands were used in the image classification. Spectral signatures for each training class were then extracted using information on bands 1, 2, 3, 4, 5 and 7. Bayes classification procedure outputs a separate image for each considered class containing the probability of each pixel of belonging to that class (figure 2). In essence, Bayes is a confident classifier. Lack of evidence for an alternative hypothesis constitutes support for the hypotheses that remain. Thus, a pixel for which reflectance data only very weakly support a particular class is treated as belonging to that class if no support exists for any other interpretation.

In addition to multi-spectral information, probability images were derived from expert knowledge-based evidences and included in the classification process in support of singleton or compound hypotheses (table 2). Expert knowledge represented the formalized opinion of local scientists with regard to the occurrence

Table 2. Lines of evidence in support of different single or compound hypotheses used in the DS classification procedure.

Source	Line of evidence	Supported hypothesis	Function type	Probability range
Satellite imagery	Bayes probabilities based on spectral signatures extracted from bands 1, 2, 3, 4, 5 and 7	[CF]	Variance/ covariance matrix	0.0–1.0
		[OF]		0.0–1.0
		[POF]		0.0–1.0
		[PF]		0.0–1.0
		[DA]		0.0–1.0
		[AP]		0.0–1.0
Expert knowledge	Elevation	[OF, POF, PF, DA, AP]	Linear	0.0–0.8
	Slope	[CF, OF, POF]	Linear	0.0–0.8
		[PF, DA, AP]	Linear	0.0–0.8
	Distance to human settlements	[DA]	Distance-based	0.0–0.8
	Landscape perception regarding dominance of vegetation types	[OF, CF, DA, AP]	Fixed probability	0.0/0.6
		[POF, CF, DA, AP]	Fixed probability	0.0/0.6
		[PF, DA, AP]	Fixed probability	0.0/0.6

CF, cloud forest; OF, oak forest; POF, pine – oak forest; PF, pine forest; DA, developed area; AP, agriculture and pastureland.
Function type refers to the manner in which the knowledge regarding a certain hypothesis was shaped. Note that maximum probability for evidence derived from expert knowledge was set at 0.8 and 0.6, thus leaving sufficient room for uncertainty regarding these hypotheses.

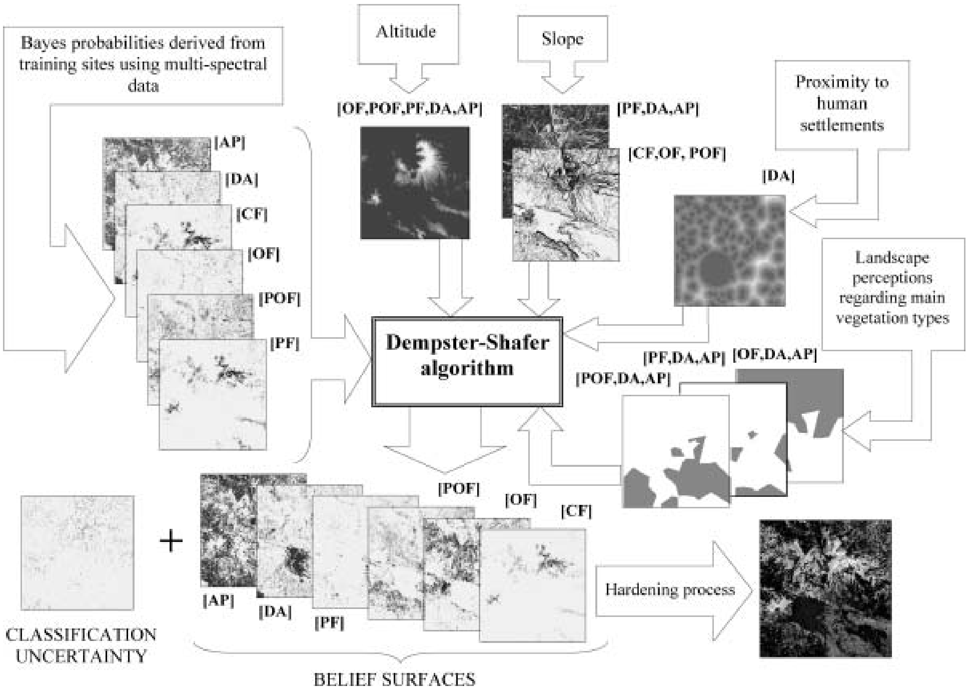

Figure 2. Dempster – Shafer classification allows the combining of different lines of evidence derived from satellite imagery and expert knowledge to produce a set of layers (belief surfaces) that define the probability of each pixel belonging to each of the classification categories. In addition, a layer showing the uncertainty associated with the classification process is generated.

of different land covers according to various characteristics of the landscape such as altitude or slope. The lines of evidence used were based on: (i) altitude, (ii) slope, (iii) proximity to human settlements and (iv) landscape perceptions regarding dominance of vegetation types through Thiessen's polygons.

(i) Altitude indirectly referred to the hypothesis cloud forest [CF]. CF in the central Highlands of Chiapas is known to occur at humid crests mostly above 2400 m (González-Espinosa *et al.* 1997). As altitude is a necessary but not sufficient condition for occurrence of CF, this evidence only supports negation of the primary hypothesis of concern. Current evidence therefore relates to occurrence of the compound hypothesis [OF, POF, PF, DA, AP] below 2400 m.a.s.l. This knowledge was incorporated using a linear function (figure 3(*a*)) where the probability for occurrence of any hypothesis but CF decreases with altitude above 2400 m.a.s.l.

(ii) Slope was used in support of two groups of hypotheses. On steep slopes a higher probability of occurrence for hypotheses [CF, OF, POF] was assumed (figure 3(*b*)). On the contrary, gentle slopes supported the hypotheses [PF, DA, AP] (figure 3(*c*)). Inclusion of PF in the latter group is due to the fact that most PF in the study area are plantations and have typically been established on gentle slopes near valley bottoms.

(iii) Proximity to known human settlements referred to the single hypothesis [DA]. This information was derived from a map of localities containing data from population censuses (INEGI 1995). As the map did not specify the size

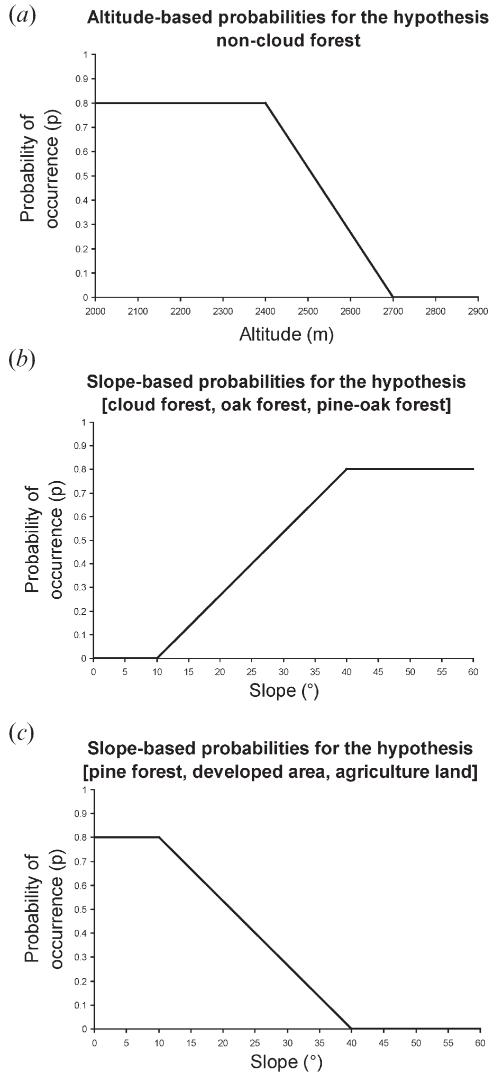

Figure 3. By means of linear functions, field knowledge is converted into probability layers. These relate: (*a*) lower altitudes to presence of any class but cloud forest [OF, POF, PF, DA, PA]; (*b*) increasingly steeper slopes to presence of forest classes [CF, OF, POF]; and (*c*) lower slopes to presence of non-forest areas and pine forests [PF, DA, PA]. CF, cloud forest; OF, oak forest; POF, pine–oak forest; PF, pine forest; DA, developed areas; AP, agriculture/pastureland.

of the settlements, only the geographical position of the settlement centre, a map representing the effect of settlement size was derived based on a function inferred from population data. As human settlements are easily discernible in satellite images, an empirical relationship was produced that related average distance from settlement centre to population number, according to the following equation:

$$y = 9.245\left(x^{0.521}\right)$$

where y is the average distance from settlement centre and x is the number of inhabitants. This approach was thought to be more accurate than a simple distance measure as it incorporates an estimation of the settlement size as a function of its population. The area close to settlements was given a probability of 0.8 for the hypothesis [DA] leaving the remaining area with a probability value of 0 (i.e. complete uncertainty for the considered hypothesis).

(iv) Landscape perceptions regarding dominance of vegetation types were introduced into the analysis by means of Thiessen's polygons. Thiessen's polygons divide space in such a way that each pixel is assigned to the nearest control point defining regions which are dominated by each point (Eastman 2001). Seventy control points were recorded on the field according to expert-knowledge-based perceptions of dominant vegetation types. Main hypotheses were referred to OF, POF and PF. Since DA and AP do not apparently follow any pattern of appearance within the study area, these categories were not considered separately but in combination with different vegetation types. CF was ascribed to similar probabilities of occurrence as OF and POF. Thus, landscape perceptions supported three groups of compound hypotheses: (a) [OF, CF, DA, AP], (b) [POF, CF, DA, AP] and (c) [PF, DA, AP]. Probability in support of the different hypotheses within the polygons was set to 0.6. This left more room for uncertainty than for all the other lines of evidence, where maximum probability of occurrence for a certain hypothesis or group of hypotheses was set to 0.8.

Different combinations of lines of evidence derived from expert knowledge were used to check their separate effect in reducing classification error. These results were then compared with those obtained with a maximum likelihood classifier based only on spectral information, with and without the use of a 3×3 modal filter. In addition, maximum likelihood classifications were performed using multi-spectral information plus: (i) digital elevation model (DEM) data, (ii) slope and (iii) both DEM and slope. This approach basically differed from the DS procedure in that the characteristics of each classification category regarding the ancillary data were automatically selected from the training sites (as with the multi-spectral data) and not based on expert knowledge. Finally, surface estimations were calculated for each individual class under the three main procedures. All these procedures were implemented using Idrisi32 (Eastman 2001).

2.5 *Accuracy assessment*

The final stage of the classification process involved an accuracy assessment. Traditionally this is done by generating a random set of locations to visit on the ground for verification of the true land cover types (Foody 2002b). However, land tenure and accessibility within the study area make this process difficult. One hundred and thirty-six verification points were collected on the ground (geo-referenced with a Garmin GPS III Plus) through pre-defined transects along principal and secondary roadways. A minimum of 10 points was recorded for each class. Criteria used in the selection of verification points were independency and representativity. For CF it was not possible to find completely independent points due to the low proportion of land surface covered by this class (19 points taken in three different forest stands). Another criterion applied was that the areas where points were taken had an extent of at least 90×90 m and were located at least 30 m from the border. This was done to avoid positional errors in geo-referencing control points (Foody 2002b). A confusion matrix was then generated and three kinds of errors were calculated: (i) error of omission for each category, which indicates how well the training points were classified; (ii) error of commission for each category, indicating the probability that a classified pixel actually represents that category in reality; and (iii) overall error with confidence intervals. In addition, producer's, user's and overall accuracy with 95% confidence intervals were calculated as the complementary of the omission, commission and overall errors, respectively. A kappa index of agreement (KIA) with 95% confidence intervals was used to estimate consistency of classification accuracy (Rosenfield and Fitzpatric-Lins 1986). KIA represents the proportion of agreement obtained after removing the proportion of agreement that could be expected to occur by chance. Thus, the lower the difference with accuracy values the lower the proportion of pixels correctly classified by chance. Finally, estimated errors and accuracies were compared between DS, maximum likelihood and filtered maximum likelihood classifications.

3. Results

3.1 *Classification accuracies*

Confusion matrixes for maximum likelihood classification with and without the use of context operators and DS classification are shown in table 3. The addition of expert knowledge reduces overall error from 33.1% to 25.7% (figure 4). The KIA follows quite closely the overall accuracy results, with an increase in accuracy from 59.8% for maximum likelihood (95% confidence intervals [50.4–69.3]) to 68.6% for DS (95% confidence intervals [59.7–77.6]). The use of a 3×3 modal filter on the maximum likelihood classification increases overall error up to 39.7% (figure 4).

In addition to overall classification accuracies, we examined the classification performance of each of the classifiers with respect to individual classes. There was an improvement in accuracy in almost all individual classes when the DS classifier is compared with maximum likelihood (table 3, figure 4). For the non-forest classes, there was a slightly decrease in user's accuracy for DA and AP and in producer's accuracy for AP. As for all the forest classes, both user's and producer's accuracies were improved when combining expert knowledge with remote sensing data through the DS theory of evidence. Accuracy was greatly improved for some classes, such as POF and PF, whereas for others, such as CF and OF, improvement was lower than 10%. Modal filtered maximum likelihood classification, on the other hand, decreased user's and producer's accuracy for almost all individual classes except for PF, DA and AP.

The upper section of table 4 shows the errors derived from maximum likelihood classification when adding DEM and/or slope data to multi-spectral information. This approach is typically used in remote sensing and we thus included it for comparative purposes. The inclusion of the DEM data increased overall error for most of the forest classes. There were two exceptions to this trend. First, the error of commission was greatly reduced for CF. This was because training sites for CF were mainly at high altitude and thus the inclusion of DEM data reduced the extent of this category and few pixels were misclassified through commission to this class. Second, the error of omission for PF was also considerably reduced. This can be explained using the opposite argument. PF training sites were recorded along a

Table 3. Confusion matrix for (*a*) maximum likelihood (ML) classifier, (*b*) ML classifier with 3×3 modal filter and (*c*) DS classifier using remote sensing in combination with expert knowledge.

	Verification points							User's accuracy (%)	Error of commission (%)
	CF	OF	POF	PF	DA	AP	Total		
(a) Maximum likelihood classified land cover									
NC	0	0	1	0	2	1	4		100.0
CF	15	0	2	2	0	0	19	78.9	21.0
OF	4	20	4	0	0	0	28	71.4	28.6
POF	0	3	12	6	0	0	21	57.1	42.9
PF	0	2	2	4	0	0	8	50.0	50.0
DA	0	0	0	0	16	5	21	76.2	23.8
AP	0	3	2	1	5	24	35	68.6	31.4
Total	19	28	23	13	23	30	136		
Producer's accuracy (%)	78.9	71.4	52.2	30.8	69.6	80.0		OA	66.9 [58.3–74.6]
Error of omission (%)	21.0	28.6	47.8	69.2	30.4	20.0		OE	33.1 [25.2–41.0]
(b) 3 × 3 modal filtered ML classified land cover									
NC	0	0	0	0	2	0	2		100.0
CF	11	1	2	1	0	0	15	73.3	26.7
OF	7	17	5	0	0	1	30	56.7	43.3
POF	0	2	9	5	0	0	16	56.2	43.7
PF	0	0	3	5	0	0	8	**62.5**	37.5
DA	0	0	0	1	12	1	14	**85.7**	14.3
AP	1	8	4	1	9	28	51	54.9	45.1
Total	19	28	23	13	23	30	136		
Producer's accuracy (%)	57.9	60.7	39.1	**38.5**	52.2	**93.3**		OA	60.3 [52.1–68.5]
Error of omission (%)	42.1	39.3	60.9	61.5	47.8	6.7		OE	39.7 [31.5–47.9]
(c) DS classified land cover									
NC	0	0	0	0	0	0	0	**100.0**	0.0
CF	15	0	1	1	0	0	17	**88.2**	11.8
OF	4	22	2	0	0	1	29	**75.7**	24.1
POF	0	1	16	3	1	0	21	**76.2**	23.8
PF	0	2	2	8	0	0	12	**66.7**	33.3
DA	0	0	0	0	17	6	23	73.9	26.1
AP	0	3	2	1	5	23	34	67.6	32.3
Total	19	28	23	13	23	30	136		
Producer's accuracy (%)	**78.9**	**78.6**	**69.6**	**67.5**	**73.9**	76.7		OA	**74.3** [65.9–81.2]
Error of omission (%)	21.0	21.4	30.4	38.5	26.1	23.3		OE	25.7 [18.4–33.1]

Ninety-five per cent confidence intervals are shown for overall accuracy (OA) and error (OE). Bold numbers in (*b*) and (*c*) indicate an increase in accuracy with regard to the ML classification.

NC, non-classified; CF, cloud forest; OF, oak forest; POF, pine–oak forest; PF, pine forest; DA, developed areas; AP, agriculture/pastureland.

broad altitudinal range. Thus including DEM data led to an increase in PF extent and a consequent reduction in the error of omission. With regard to slope, overall error is somewhat reduced. However, errors for most forest classes increased with the exception of the error of commission for CF. The explanation for this

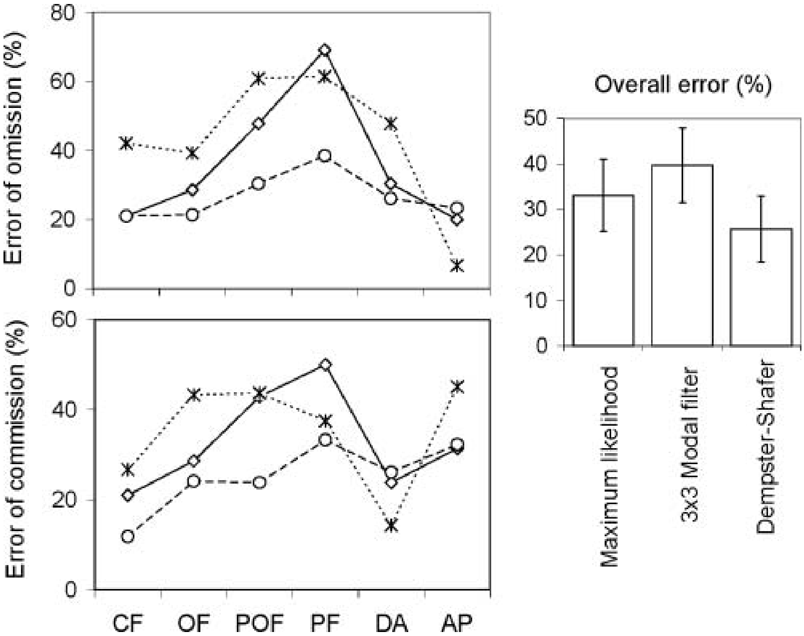

Figure 4. Errors of omission, and commission and overall error (%) obtained when using maximum likelihood (continuous line with diamonds), a modal filtered maximum likelihood (dotted line with crosses) and Dempster–Shafer (dashed line with circles) classification procedures. Overall error is shown (right side) with 95% confidence intervals.

observation is similar to that mentioned for the case of DEM data. In combination, DEM and slope do not lead to better results, causing an increase in error in most forest classes as well as an increase in overall error.

The contrast between results obtained through simple inclusion of DEM and slope data in the maximum likelihood classification and the inclusion of the same information when shaped by expert knowledge and combined using the DS method is apparent when table 4 is considered in its entirety.

The relative importance of different combinations of lines of evidence in improving classification accuracy can be seen in the lower section of table 4. When combined separately with multi-spectral data, only landscape perceptions regarding vegetation types succeeded in reducing total error (by around 4%). The use of this line of evidence also led to a reduction of errors of omission and commission for OF, POF and PF and did not increase error for any other individual class. Evidence regarding altitude slightly increased the error of omission for CF but decreased its error of commission. Likewise it hardly increased the error of commission for POF but decreased the error of omission for this class. Evidence concerning slope decreased the error of commission for CF and the errors of omission and commission for PF, but increased the error of omission for POF. All these changes reduced overall error by about 1%. Distance to known human settlements reduced the error of omission for DA but slightly increased its error of commission and both the errors of omission and commission for AP. Again, overall accuracy was not improved.

Increasingly complex combinations of these lines of evidence showed the same trends, i.e. better performance of Thiessen's polygons compared with other lines of

Table 4. Accuracy assessment for: (i) maximum likelihood classifications with and without the addition of environmental variables (digital elevation model (DEM) and/or slope) (upper section); and (ii) increasingly complex combinations of lines of evidence in addition to reflectance data using DS classifier (lower section).

Classification procedure	CF		OF		POF		PF		DA		AP		Total error	KIA
	O	C	O	C	O	C	O	C	O	C	O	C		
Maximum likelihood (ML) procedures:														
ML (6 bands)	21.0	21.0	28.6	28.6	47.8	42.9	69.2	50.0	30.4	23.8	20.0	31.4	33.1 [25.2–41.0]	59.8 [50.4–69.3]
ML (6 bands + DEM)	31.6	**0.0**	35.7	37.9	78.3	44.4	**38.5**	52.9	**26.1**	26.1	46.7	**20.0**	37.5 [29.4–45.6]	54.2 [44.3–64.0]
ML (6 bands slope)	26.3	**6.7**	28.6	33.3	47.8	50.0	76.9	57.1	**21.7**	**14.3**	**13.3**	33.3	31.6 [23.8–39.4]	61.2 [51.7–70.7]
ML (6 bands + DEM + slope)	26.3	**0.0**	32.1	38.7	82.6	42.9	**38.5**	50.0	30.4	23.8	**16.7**	46.8	36.8 [28.7–44.9]	55.0 [45.1–64.8]
Dempster–Shafer procedures														
Alt	26.3	**12.5**	28.6	28.6	**43.5**	45.8	69.2	50.0	30.4	23.8	20.0	31.4	33.1 [25.2–41.0]	59.8 [50.3–69.3]
Sl	21.0	**16.7**	28.6	28.6	52.2	42.1	**53.8**	**45.4**	30.4	23.8	20.0	31.4	32.3 [24.5–40.2]	60.8 [51.4–70.2]
Dist	21.0	21.0	28.6	28.6	47.8	42.9	62.9	50.0	**26.1**	26.1	23.3	32.3	33.1 [25.2–41.0]	59.8 [50.3–69.3]
Thies	21.0	21.0	**21.4**	**21.4**	**39.1**	**30.0**	**61.5**	**44.4**	30.4	23.8	20.0	31.4	29.4 [21.7–37.1]	64.3 [55.2–73.5]
Alt + Sl	26.3	**12.5**	28.6	28.6	47.8	42.9	**53.8**	**45.4**	30.4	23.8	20.0	31.4	32.3 [24.5–40.2]	60.7 [51.3–70.2]
Alt + Dist	26.3	**12.5**	28.6	28.6	**43.5**	45.8	69.2	50.0	**26.1**	26.1	23.3	32.3	33.1 [25.2–41.0]	59.7 [50.2–69.3]
Alt + Thies	21.0	**11.8**	**21.4**	**21.4**	**34.8**	**28.6**	**53.8**	**40.0**	30.4	23.8	20.0	31.4	27.9 [20.4–35.5]	66.1 [57.0–75.2]
Sl + Dist	21.0	**16.7**	28.6	28.6	52.2	42.1	**53.8**	**45.4**	**26.1**	26.1	23.3	32.3	32.3 [24.5–40.2]	60.7 [51.3–70.2]
Sl + Thies	21.0	**16.7**	**21.4**	**21.4**	**39.1**	**22.2**	**38.5**	**33.3**	30.4	23.8	20.0	31.4	27.2 [19.7–34.7]	67.0 [58.1–76.0]
Dist + Thies	21.0	21.0	**21.4**	**21.4**	**39.1**	**30.0**	**61.5**	**44.4**	**26.1**	26.1	23.3	32.3	29.4 [21.7–37.1]	64.3 [55.1–73.5]
Alt + Sl + Dist	26.3	**12.5**	28.6	28.6	47.8	42.9	**53.8**	**45.4**	**26.1**	26.1	23.3	32.3	32.3 [24.5–40.2]	60.7 [51.3–70.2]
Alt + Sl + Thies	21.0	**11.8**	**21.4**	**24.1**	**30.4**	**27.3**	**38.5**	**33.3**	30.4	23.8	20.0	31.4	25.7 [18.4–33.1]*	68.6 [59.7–77.6]*
Alt + Dist + Thies	21.0	**11.8**	**21.4**	**21.4**	**34.8**	**28.6**	**53.8**	**40.0**	**26.1**	26.1	23.3	32.3	27.9 [20.4–35.5]	66.1 [57.0–75.2]
Sl + Dist + Thies	21.0	**16.7**	**21.4**	**21.4**	**39.1**	**22.2**	**38.5**	**33.3**	**26.1**	26.1	23.3	32.3	27.2 [19.7–34.7]	67.0 [58.0–76.0]
Alt + Sl + Dist + Thies	21.0	**11.8**	**21.4**	**24.1**	**30.4**	**23.8**	**38.5**	**33.3**	**26.1**	26.1	23.3	32.3	25.7 [18.4–33.1]*	68.6 [59.7–77.6]*

Errors of omission (O) and commission (C) are given for each thematic category in addition to total error and kappa index of agreement (KIA) with 95% confidence intervals. Reductions (bold) and increases (underline) in error are shown in the table for individual classes with regard to maximum likelihood classification. Combinations of lines of evidence that minimize total error are marked with an asterisk.

CF, cloud forest; OF, oak forest; POF, pine – oak forest; PF, pine forest; DA, developed areas; AP, agriculture/pastureland; Alt, altitude; Sl, slope; Dist, distance to known human settlements; Thies, Thiessen's polygons.

evidence. Furthermore, classification accuracy was considerably improved when all these lines of evidence were combined. Total error was least when two combinations of lines of evidence were used: (i) all lines of evidence and (ii) all lines of evidence except distance to known human settlements. When these were used in combination with remote sensing data total error was reduced by 7.4%. Differences were found at the individual class level. When using all lines of evidence, the error of commission for POF and the error of omission for DA were lower, whereas there was a slightly increase in the errors of omission and commission for AP compared with that classification which uses all lines of evidence except distance to known human settlements. As one of our objectives was the improvement of classification accuracy for vegetation types, the former result is preferred. The thematic map resulting from hardening DS classification using all lines of evidence is shown in figure 5. A richer description of the classification process is given by the underlying belief surfaces and the uncertainty associated with the classification process (see figure 2). Space restrictions prevent a full presentation of all belief layers The overall uncertainty image associated with the results is shown in figure 6. Inspection shows that uncertainty is greatest on steep slopes and within forest areas where natural vegetation gradients exist. The pattern of uncertainty is itself fragmented over the image. The uncertainty image is thus an accurate representation of the inherent difficulty involved in assigning pixels to land use classes in this extremely complex and heterogeneous landscape.

3.2 *Land cover estimation*

From any image classification, the estimated area associated with each type of land cover can be derived. Land cover estimates for the three main classification techniques used in this study are reported in table 5. The use of a 3×3 modal filter tends to favour the most frequent class at the expense of the least frequent or the most fragmented ones. AP, with a surface of 24 295 ha estimated from the maximum likelihood classification, increased its area up to 27 026 ha after applying a 3×3 modal filter. On the contrary, NC, CF, PF and DA decreased their estimated

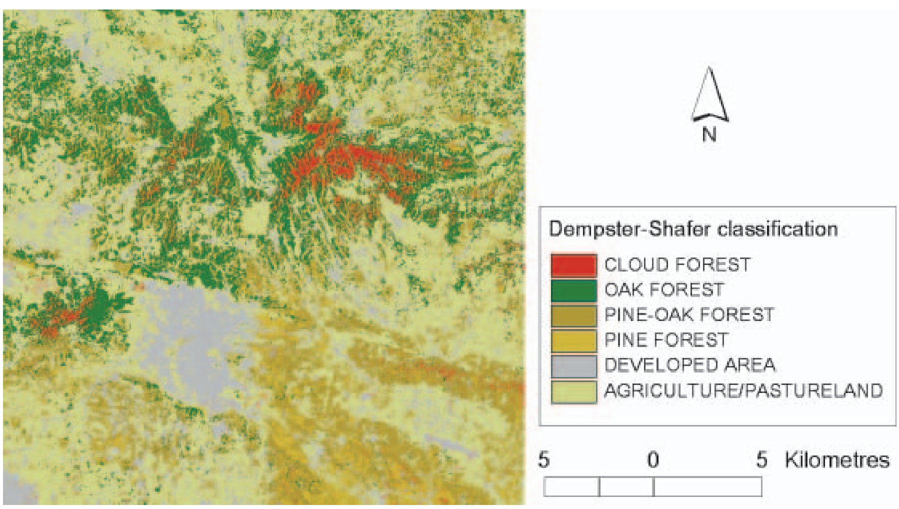

Figure 5. Hardened Dempster – Shafer classification using all lines of evidence in addition to multi-spectral data.

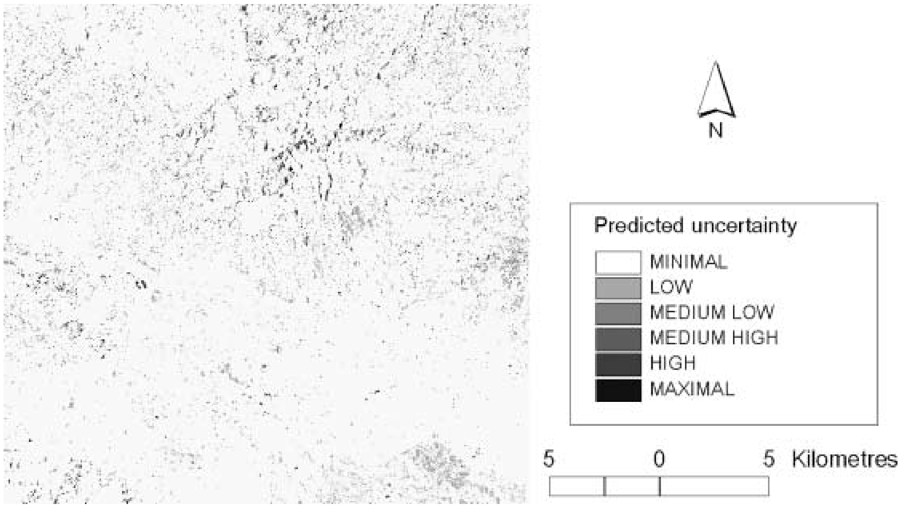

Figure 6. Overall uncertainty associated with the Dempster – Shafer classification of land cover.

surface by 755, 239, 640 and 1228 ha, respectively. OF and POF, the most common categories after AP, showed no quantitative distinction in estimated areas with and without the use of modal filters.

DS classification reduced uncertainty where multi-spectral data are not sufficient to assign a pixel to a certain category. Thus, compared with the non-classified 1309 ha estimated in the maximum likelihood classification, we report only 257 ha when using the DS classifier. Similarly, there was a reduction in estimated cover for CF and POF of 431 and 1187 ha, respectively. On the contrary, there was an increase in estimated cover for OF, PF, DA and AP, the largest corresponding to OF with 1210 ha. PF and DA showed an increase of 540 and 553 ha, respectively, compared with the results from maximum likelihood classification, whereas AP showed the lowest increase with 365 ha. The relative values of these changes are important. Whereas a change in the estimated surface of 500 ha only represents 2% for AP, the same change in the estimated area is equivalent to about 40% for CF.

Table 5. Estimated areas (ha) for different land covers using three different classification techniques: maximum likelihood (ML), modal filtered maximum likelihood (ML3 $\times$ 3), and Dempster–Shafer (DS).

	ML	ML3 $\times$ 3	DS
NC	1309	554	257
CF	1824	1585	1393
OF	8572	8782	9782
POF	10593	10513	9406
PF	1886	1246	2426
DA	5680	4452	6233
AP	24 295	27 026	24 660

(NC, non-classified; CF, cloud forest; OF, oak forest; POF, pine–oak forest; PF, pine forest; DA, developed areas; AP, agriculture and pastureland)

4. Discussion

The inclusion of expert knowledge through the DS procedure leads to better discrimination of some forest classes and thus an improvement in overall accuracy of classification. DS does not favour the most frequent and the least fragmented classes, as modal filters do. Differences in estimated surface between maximum likelihood and DS classification largely depend on the use of evidence derived from expert knowledge.

4.1 *Classification accuracies*

Because the decrease of 7.4% in overall error when using DS procedure as compared with maximum likelihood is within the 95% confidence interval we refer to a tendency towards DS improving classification with regard to traditional classifiers rather than a significant improvement. A formal test of significance and associated p value is not included as we considered the null hypothesis (no difference between classification methods) to be uninformative in the context of comparing methods of classification that were assumed *a priori* to have some effect (Johnson 1999).

Although the effect size measured as a reduction in overall error is not large, we emphasize that errors of omission and commission for some individual classes, e.g. PF and POF, were considerably reduced (figure 4). Confusion between categories occurs mainly within the group of forest and non-forest classes separately, although there are a few pixels belonging to some forest classes misclassified as AP. CF is confounded with OF in about 20% of cases. Addition of expert knowledge did not reduce this error of omission, probably due to lack of direct evidence in favour of CF. However, errors of commission are reduced when using the DS classifier due to the use of direct evidence in favour of the hypotheses that are most commonly confused with CF, e.g. POF and PF. The classes that are more commonly confused under the maximum likelihood classification are OF, POF and PF. Since training sites were allocated in sites representing as pure a sample of the training class as possible, it is reasonable to expect a high spectral separability between these categories. However, these training classes represent the extremes of a natural vegetation gradient (González-Espinosa *et al.* 1991, Galindo-Jaimes *et al.* 2002) but do not consider mixed classes along the gradient. Therefore, despite high spectral separability among training sites, we must assume mixing of forest categories under certain successional conditions (Kent *et al.* 1997). Some examples are misclassifications of disturbed CF with mature OF or POF (see Ramírez-Marcial 2001 for a plant community study in cloud forests) or pine-dominated canopy POF with PF (e.g. Ramírez-Marcial *et al.* 2001). An additional problem is that complex topography causes varying spectral responses of land covers, mainly by influencing sun illumination angles (Helmer *et al.* 2000).

When performing maximum likelihood classification, accuracy for some particular classes is quite low but improves when adding consecutive lines of evidence in support of different hypotheses. Expert knowledge in these cases can reduce the number of mixed pixels more than traditional remote-sensing-based classifiers. Environmental variables *per se*, however, do not necessarily lead to an improvement in the results, as shown when combining DEM and slope data with multi-spectral information through the maximum likelihood procedure. However, once filtered through our experience and visual perception of landscape patterns this information does help to discriminate between certain categories that are particularly challenging to traditional methods.

The varying lines of evidence used in the DS procedure had a different weight in increasing classification accuracy. Thiessen's polygons, as representations of landscape perceptions regarding dominant vegetation types, seemed to have the largest effect. Thiessen's polygons have been used in previous works to characterize landscape patterns (Parresol and McCollum 1997). The use of this line of evidence reduced errors of omission and commission of the three forest classes that were supported by this line of evidence. The creation of Thiessen's polygons is a partially subjective exercise that can only be attempted if good knowledge of the landscape is available. We feel that the comparative success of the Thiessen's polygon approach in our case can be attributed to very reliable knowledge about the distribution of the main vegetation types at the landscape level. We also point out that we used verifiable control points taken in the field; thus this line of evidence can be easily and objectively evaluated. We also included a comparatively high degree of uncertainty associated with this line of evidence. This means that giving a high spectral probability for any pixel to belong to a certain class, the inclusion of this new line of evidence in support of a different hypothesis is not enough to trigger a shift to a different class. However, when spectral data provide a similar probability of a pixel belonging to more than one class, our perception regarding dominant vegetation types helps to tilt the balance to one particular class and no other. The line of evidence slope is also important in reducing errors of omission and commission for PF and the error of commission for CF. Altitude and distance to human settlements simultaneously reduced one kind of error for some individual classes and increased other errors for the same or different classes. Overall, they do not modify total error or accuracy. However, when combined with other lines of evidence they contributed positively to increasing the accuracy for an individual class as well as the total accuracy. In general, there is no line of evidence derived from expert knowledge that worsened our results, and all combined reduced overall error as well as errors of omission and commission for all individual forest classes. The DS procedure did increase some individual errors for DA (error of commission) and AP (both types of error) compared with the maximum likelihood results, but these changes were never larger than 4% and were always counterbalanced by reductions in error for individual forest classes.

The way in which the lines of evidence derived from expert knowledge relate to the probability generated from multi-spectral information is difficult to assess due to the complexity of the algorithm used. One suggested approach to explore this question is by running the DS procedure several times using different thresholds for the various lines of evidence. Unfortunately the algorithm currently used to implement the DS procedure is computationally intensive. This currently constrains formal sensitivity analysis. Our observations suggested that probability derived from remote sensing data is by far the most decisive factor when assigning one pixel to a certain class. There are two reasons for this. First, as mentioned before, Bayes is a confident classifier. Thus very weak support for one hypothesis still provides the most probable classification if no support exists for any other interpretation. Secondly, probabilities derived from multi-spectral data support individual classes whereas evidence derived from expert knowledge mostly supports compound hypotheses. As a result the latter are not as conclusive in assigning a pixel to a certain class as remote-sensing-based probabilities. This effect, however, is highly desirable because our initial intention was to use expert knowledge to discriminate categories only in those cases where multi-spectral information on its own was ambiguous.

The choice of ancillary variables is obviously of great importance to correctly discriminate between different thematic classes (Pedroni 2003). We observed from the confusion matrices that there is no reduction in the error of omission for CF. It would therefore be convenient to collect more evidence regarding this hypothesis. Although expert knowledge considerably decreased the errors of omission and commission in the case of PF, this forest type remained the least well classified of all classes. Thus, it would also be necessary to either further refine the training sites or add new lines of evidence to reduce misclassification of this category.

4.2 *Land cover estimation*

Differences in estimated surfaces from maximum likelihood and DS classification largely depend on the use of evidence derived from expert knowledge. Some lines of evidence tended to favour some hypotheses and not others, and this would lead to an increase in the estimated surface of such classes. However, there is no general trend (as occurs with the use of modal filters) that automatically favours the most frequent and least fragmented classes. CF, for example, would be overestimated when using only spectral data. This is due to the fact that most of the remaining patches of CF extend over steep slopes, giving this class a closer resemblance to PF. This occurs despite topographical corrections which can not fully counterbalance these effects. In consequence, the spectral signature for this class becomes mixed with PF, which is more prone to be found at lower altitudes. Introducing altitude-based evidence against CF clearly reduces the estimated surface for this class in what ground-based experience confirmed to be an accurate manner. It also noticeably reduced the number of non-classified pixels when adding expert knowledge to remote sensing data. Estimation of PF increased after the use of DS classification chiefly at the expense of reducing the extent of POF. These classes follow a natural gradient and it is difficult to determine — even in the field — whether a certain pixel belongs to the former or the latter.

4.3 *Final remarks*

The use of contextual techniques is being increasingly used with success in a number of different classification problems (Frigessi and Stander 1994, Hubert-Moy *et al.* 2001, McIver and Friedl 2002). This allows researchers to specify and flexibly manipulate probability laws over large sets of random variables that interact with each other on a local basis. In theory the choice of a classification method should be done according to landscape structure, but in practice analysts often apply the same classification algorithm to various areas without considering the particular features of a given landscape (Hubert-Moy *et al.* 2001). This can lead to a high level of misclassification and low accuracy. DS classification allows the incorporation of expert knowledge into the classification procedure in a formal and well-documented manner, increasing accuracy with regard to traditional classifiers based uniquely upon remote sensing data. Other techniques, such as inclusion of prior probabilities into a maximum likelihood classification (Mather 1985, Cibula and Nyquist 1987, Frigessi and Stander 1994, Maselli *et al.* 1995, Pedroni 2003), would probably lead to similar results.

The DS algorithm offers some advantages beyond a tendency to improve classification accuracy. First, because conflicts of evidence are resolved through probabilistic reasoning, logical inconsistencies are avoided. This allows greater flexibility in the use of evidence. Second, the formalized use of probability to express uncertainty associated with the information used in the classification procedure reflects the inevitably dynamic nature of landscapes. Uncertainty associated with the results (figure 6) is of itself of interest to users of the information. Third, sensibility analysis can be performed upon estimation of the area of the varying thematic classes by changing our levels of belief. An example can be found in Cayuela *et al.* (2006) for the highly threatened cloud forest in the central Highlands of Chiapas. Fourth, the classification procedure accepts the natural complexity of fine-grained mosaic landscapes without smoothing over genuine features. This last point is particularly important in the context of fragmented tropical forests (Turner and Corlett 1996).

Despite this tendency of the DS procedure to improve classification compared with traditional classifiers, it is important to stress that landscape transitions are rarely sharp. Many boundaries between landscape units must be subjective, as classification itself is a subjective exercise. These limits must be considered as guidelines for further assessing and improving the classification techniques (Hubert-Moy *et al*. 2001). Although a thematic map is often treated as a definitive depiction of a single reality by users of the information it contains, it is better regarded as a model based on our perceptions of reality (Woodcock and Gopal 2000). The overt use of subjective information helps to make this clear.

5. Conclusions

Under a natural transitional vegetation gradient, it is difficult to distinguish between different forest classes from satellite imagery alone. DS classification and surface estimations in thematic maps generated throughout this procedure offer some advantages over traditional remote-sensing-based classifiers, particularly in complex and heterogeneous landscapes. Inevitably many difficulties remain, but we found (i) a decrease in errors of omission and commission for almost all classes and (ii) a decrease in total error of around 7.5% when compared with traditional classifiers. A particular advantage of this classification technique over context operators, such as modal filters, is that it does not either distort landscape patterns or decrease the amount of information contained in the satellite image. The DS approach led not only to a more accurate classification but also to a richer description of the inherent uncertainty surrounding the classification process.

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