ANALYSIS OF CONVERGENT EVIDENCE IN AN EVIDENTIAL REASONING KNOWLEDGE-BASED CLASSIFICATION

Y. Cohen[a] and M. Shoshany[b]

[a] Institute of Agricultural Engineering, Agricultural Research Organization (A.R.O), the Volcani Center Bet Dagan 50250 ISRAEL, yafitush@volcani.agri.gov.il

[b] Department of Transportation and Geo-Information Engineering , Faculty of Civil and Environmental Engineering, Technion, Haifa, ISRAEL, maximsh@techunix.technion.ac.il

Commission TS ThS 8

KEY WORDS: Remote-sensing, Agriculture, Classification, Knowledge-base, Reasoning, Convergent.

ABSTRACT:

The use of KBSs based on evidential reasoning, for land-cover mapping based on remotely-sensed images is spreading widely. In recent years, KBS utilizing Dempster-Shafer Theory of Evidence (D-S ToE) were found most successful in wide range of remote sensing applications. One important feature of the D-S ToE is that it provides a measure for the evidential support (belief) accumulated for each object class at each pixel. Although cumulative belief values (CBVs) play a major role in classification decisions, their analysis has received little attention in the literature. The objective of the present study was to investigate and to characterize the added value of the KBS by the analysis of the CBV. For that purpose we applied a KBS based on D-S ToE to crop recognition in a wide heterogeneous region and compared its results with those of the application of ISODATA classification. We investigated the relationships between the distribution of the CBV of the different classes and their corresponding classification accuracy/reliability. The CBVs were found to be good indicators of levels of classification complexity in both the pixel and the class scales. In addition to that, levels of two class properties could be analyzed according to the distribution of CBVs of each class: heterogeneity and uniqueness. Moderate and high correlations (r^2=0.69 and r^2=0.94) were found between these two properties and classification efficiency of an unsupervised classification (US). Lower correlations were found between these properties and the KBS classification efficiency (r^2=0.59 and r^2=0.75). Moreover, US classification was highly affected by heterogeneity and uniqueness as referred from much higher slope coefficients (5 times higher): US classification efficiency decreased with increasing heterogeneity levels and decreasing uniqueness levels. These findings are suggesting that in contrast to the US classification the KBS facilitates identification of a class with little affect of its internal variability (heterogeneity) and its similarity with other classes (lack of uniqueness).

1. INTRODUCTION

1.1 General Instructions

The use of KBSs based on evidential reasoning, for land-cover mapping based on remotely-sensed images is spreading widely. In recent years, KBS utilizing Dempster-Shafer Theory of Evidence (D-S ToE) were found most successful in wide range of remote sensing applications (e.g. Wilkinson and M´egier. J., 1990; Kontoes et al., 1993; Peddle, 1995; Adinarayana and Rama-Krishna, 1996). One important feature of the D-S ToE is that it provides a measure for the evidential support (belief) accumulated for each object class at each pixel. Although cumulative belief values (CBVs) play a major role in classification decisions, their analysis has received little attention in the literature. One important feature of the D-S algorithm is that it provides a measure of the accumulated evidential support or cumulative belief value (CBV) for each recognition class (Ci) inferred at each image pixel (Xi,j). The advantage of KBSs lies in achieving recognition of a class despite incomplete, missing and conflicting evidences. The CBV for Ci at Xi,j depends on the overall applicable evidences (rules) for Xi,j supporting and/or conflicting Ci. For different compositions of environmental conditions different compositions of evidences will be applicable. The CBV increases with increasing number of supportive evidences and decreasing number of conflicting evidences and vise versa. There are few published researches regarding the relationship between KBS recognition accuracy and reliability of a class and the level of its CBV. It is to be expected that for classes or sites with no conflicting and/or incomplete evidences, high reliability and accuracy will be accompanied by a high accumulation of supporting evidence. In such cases it is expected that there is little or no need for the KBS approach. This assumption can be assessed by comparing the classification results of the KBS with those of an unsupervised classification (US). In complex classes or sites there are more conflicting and/or incomplete evidences and low supporting evidence is accumulated. It is important to determine how the KBS performs in these complex situations and whether low CBVs are necessarily accompanied by low accuracy or reliability. Also, recognition systems perform differently within a class, i.e. the same class in different sites may gain different CBVs. Analysis of the distribution of the CBV within a class will facilitate the determination of how unique and/or heterogeneous a class is. This in turn, will enable the investigation of whether heterogeneity and/or lack of uniqueness limit the classification accuracy and reliability of the KBS. The objective of the present study was to investigate and to characterize the added value of the KBS by the analysis of the accumulated supporting evidence. For that purpose we applied a KBS based on D-S ToE to crop recognition in a wide heterogeneous region and compared its results with those of the application of ISODATA classification. We first describe the study area and its heterogeneity. In the subsequent two sections we outline the principles of the D-S ToE and the GSA and describe the construction of the KBS. We conclude with the results and conclusions.

2. STUDY AREA

Two agricultural areas in Israel, which comprise 33% of the overall cultivated areas in the country, were investigated. The southern area lies along the Coastal Plain. It covers 700 km^2 and is characterized by topographic fluctuations between sea level and 240 m. Annual precipitation ranges between 400 and 500 mm and over 60% of the soils are suitable for agriculture. Agriculture is the main land use (over 50%), and developed areas form approximately one-third of the total. There are relatively wide natural habitats on both the eastern and western sides of the study area. The northern area covers 1600 km^2, and there are steep west-east topographic and climatic gradients. The height of the Jordan Valley on the east is 300 m below sea-level, and 17 km to the west of the valley the Gilbo'a Mountains rise to 570 m above sea level. In addition, to the west, the proximity of the Yizra'el Valley to the Carmel Mountains creates enormous height differences over limited horizontal distances. The annual average rainfall decreases along this gradient from approximately 650 mm/year in the west to less than 200 mm/year in the east. Soil types vary between Terra-Rossa, brown and light rendzina, groumosoils, red-loam, dark-brown soils and sandy soils. Cultivated areas form 50% of this study area, in which the environmental variations cause wide variability in natural vegetation types, crop types, and in the crop seeding and harvesting periods.

3. METHODOLOGY

3.1 KBS and the Dempster-Shafer Theory of Evidence

KBSs as a type of expert systems address real-life problems and, therefore, they must deal with uncertain data, information, and knowledge. During the mid-1970s Shafer (1976) crystallized and formalized the mathematical theory of evidence based on earlier ideas of Art Dempster, which since then has been known as the "Dempster-Shafer Theory of Evidence" (D-S ToE). D-S ToE and its Gordon and Shortliffe approximation (GSA) (Gordon and Shortliffe, 1985), when applied to a body of evidence, have domain-independent inference capabilities to combine evidence while representing some levels of ignorance, bias and conflicts. The fundamental aspects of the D-S ToE will be described here in most general terms, with reference to its application to crop recognition in remote sensing images, following the work of Gordon and Shortliffe (1985) and Cohen (2000).

3.1.1 Frame of Discernment

Suppose an interpreter needs to analyze a satellite image of an agricultural site. To his knowledge, this area contains only two summer crops: cotton (cn) and sunflower (cf); and two winter crops: wheat (wh) and pea (pe). The set of possible hypotheses, which is called a Frame of Discernment (FoD) is defined as:

$\Theta = \{cn, sf, wh, pe\}$ Where each compatible possibility (crop) in Θ is called a singleton. Since the hypotheses in □ are exhaustive the empty set, ", is considered as a false hypothesis in Φ. In addition to the singletons there are subsets of Θ representing hypothetical possibilities of combinations such as summer crops or {cn, sf} in our example. The set of all subsets of Θ is denoted 2^{Θ}, and a set of size n has 2^n-1 true hypotheses.

3.1.2 Basic Probability Assignment

Suppose that there is a body of evidence in support of the non-empty subset A of 2^{Θ}. A function m{A}, called the Basic Probability Assignment (BPA), assigns to hypothesis A, a degree, denoted m, to which the evidence supports the hypothesis. Degrees of support are numbers in the range of [0,1] and must sum to 1 over all possible hypotheses.

3.1.3 Combination of Belief Functions

Dempster's rule of belief functions combination enables the computation of the degree of support gained by combining multiple belief functions that refer to a set of possible hypotheses A of 2^{Θ}. Suppose that one piece of evidence supports summer crops and one supports cotton to degrees of 0.4 (m_1) and 0.7 (m_2) respectively. Three new BPAs' are defined by the D-S combination rule, denoted $m_1 \oplus m_2$ calculated by means of the following table:

m_2 \ m_1	{cn}(0.7)	Θ(0.3)
{cn, sf}(0.4)	{cn}(0.4*0.7)=(0.28)	{cn, sf}(0.4*0.3)=(0.12)
Θ(0.6)	{cn}(0.6*0.7)=(0.42)	Θ(0.6*0.3)=(0.18)

where: $m_1 \oplus m_2$ {cn} = 0.28+0.42 = 0.7; $m_1 \oplus m_2$ {cn,sf} = 0.12; $m_1 \oplus m_2$ {Θ} = 0.18.

Suppose m_2 was attached to wheat, i.e., m_2{wt} = 0.7. In such cases of conflicting evidence, the support in each hypothesis is raised by 1/(1-k), where k is the support committed to Φ:

$m_1 \oplus m_2$ {wt} = 0.58; $m_1 \oplus m_2${cn,sf} = 0.16; $m_1 \oplus m_2$ {Θ} = 0.25.

A pairwise addition of the following form allows more than two BPAs' to be combined:

$m_1 \oplus m_2 >>> (m_1 \oplus m_2) \oplus m_3 >>> ((m_1 \oplus m_2) \oplus m_3) \oplus m4\ldots$

3.1.4 Cumulative Belief Value (CBV)

Integration of all applicable rules (evidence) for each pixel provides the formal basis for the calculation of cumulative belief values (CBV) of each class (hypothesis). In this way, each pixel initially has a CBV for each class. Final recognition requires application of decision criteria for selecting the most probable class, i.e., the class with the highest CBV is selected.

3.2 Knowledge-based crop recognition system: Construction and Implementation

An evidential reasoning mechanism based on the Gordon-Shortliffe Algorithm was realized in C++. The operation of the GSA is carried out on the basis of three input files, which represent the knowledge base: Database, Rule-Base and Hierarchic Representation. In each operation of the GSA program, the evidential values of all applied rules for each class, for each pixel, are combined in order to calculate the class convergent belief value (CBV). Each pixel is then classified into the most probable class, i.e., the class with the highest CBV.

3.2.1 Database construction

Information layers required for the database formation were derived from three main sources: imagery data, Israeli GISs, and existing maps. The spatial database comprised a total of nine layers:

- 5 multi-temporal NDVI layers generated from Landsat TM images (Table 1);
- 1 unsupervised classification layer based on the NDVI layers;
- 1 averaged annual rainfall data layer from the Israeli Meteorological Service;

- 1 soil types layer from the GIS of the Ministry of Agriculture of Israel; and
- 1 land use layer from the Israeli National GIS.

Sensor	Image date
Landsat TM	10-Nov-96; 14-Feb-97; 19-April-97; 21-May-97; 22-Jun-97
Spot-panchromatic	20-Jun-96

Table 1. Images available to study area.

3.2.2 Hierarchic representation

The GSA makes it possible to use evidence, which may apply not only to a single hypothesis (e.g., sunflower), but also to sets of hypotheses (e.g., sunflower, cotton), that together comprise a concept of interest (e.g., summer crops). A specific KBS hierarchic representation should relate to semantic affinity between classes, and to indicative information which can be obtained from the database sources. Figure 1 displays the hierarchic representation of crop types and their generalized super-classes. It can be inferred from the tree that there are only 9 final classes (underlined): other (non-vegetated formations), mixed natural vegetation, shrubs/forests, citrus, wheat, legume, other crops, cotton, and sunflower. Each relates to different number of super-classes.

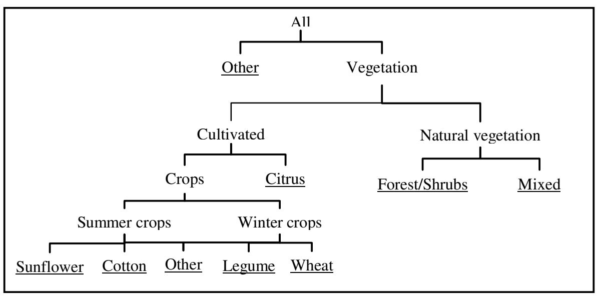

Figure 2: Hierarchic tree representation of land-cover/use and crop types.

3.2.3 Rule base Formation

In general terms, a rule here represents the support value m given to a hypothesis A, assuming that indicators X, Y, Z are valid:

if X and Y and Z and… then A with m

Rule base formation involves learning the relationships between potential indicators and object classes (potential hypotheses). The learning process was conducted through analysis of domain literature and interviews with experts from the Ministry of Agriculture. The results of this process were used to learn growth rates of crop types, optimal environmental conditions for crop growth in the various climatic areas of Israel, and the effects of environmental modifications on crop growth rate and quality. In addition, field survey plots were used to learn how growth rates and quality are reflected in imagery data. This was achieved by both visual interpretation and GIS analysis. Rules were related to all classes from all levels. Indications of various kinds and with various affinities (support values) were found, and selection was applied in order to exclude indications with poor affinity. In terms of support values, only indications with more than 50% support were included. The resulting rule-based composition demonstrates the priority given to imagery data, as 90% of the rules included imagery indicators. In addition, 20% of the rules utilized soil type properties, 20% used precipitation properties, and 13% used INGIS land-use information.

4. RESULTS

The KBS generates two outputs for each pixel: its recognition class and its CBV. The present section will describes classification results and the CBV distribution separately.

4.1 Classification results

Assessment of the confusion matrix for an US classification is most important, since it indicates the locations of phenological conflicts between crop types and thus facilitates assessment of the resolved and unresolved confusion introduced by using the KBS. Application of the US ISODATA classification yielded good results for four crop categories and very poor results for orchards, shrubs and mixed natural vegetation categories (Table 2). These results demonstrate the high information content in the NDVI phenologies (Cohen and Shoshany, 2002).

Reference→ Class.↓	wheat	legume	cotton	sun-flower	orchards	shrubs	nat. veg
wheat	**77.8%**	8.9%			0.5%	3.4%	1.6%
legume	4.0%	**72.2%**			4.7%	6.0%	28.3%
cotton			**99.7%**	5.6%	0.6%	1.1%	0.1%
sunflower				**91.3%**	0.3%	0.6%	0.0%
orchards	1.7%				**65.0%**	32.0%	0.4%
shrubs					3.5%	**28.9%**	12.2%
nat. veg	7.1%	5.5%			1.7%	3.6%	**30.1%**
other crop				3.1%	0.9%	1.8%	
other	9.3%	13.3%	0.3%		22.8%	22.6%	27.2%
Reliability	87.1%	67.4%	94.0%	98.8%	55.7%	81.4%	42.6%
No. of pixels	9529	7058	9315	7653	10897	7085	3890

Table 2: Confusion Matrix of US Classification.

Reference→ Class.↓	wheat	legume	cotton	sun-flower	orchards	shrubs	nat. veg
wheat	**89.9%**	7.9%			3.9%	0.3%	3.5%
legume	6.4%	**91.3%**			2.5%	0.2%	0.6%
cotton			**99.7%**	5.6%	0.9%	0.2%	0.1%
sunflower				**91.3%**	0.6%		
orchards	3.2%				**77.0%**	0.5%	0.3%
shrubs					1.5%	**80.6%**	1.3%
nat. veg					0.3%	1.4%	**82.8%**
other crop				3.1%	1.4%		
other	2.5%	0.8%	0.3%		12.0%	16.7%	11.5
Reliability	88.0%	87.5%	94.6%	99.1%	96.0%	96.3%	96.1%
No. of pixels	9529	7058	9315	7653	10897	7085	3890

Table 3: Confusion Matrix of KBS Classification.

The recognition achieved by applying the GSA is best characterized by the following principle cases:

- Considerably better recognition of legume, orchards, shrubs and natural vegetation;
- Considerably better distinction between winter crops and natural vegetation;
- Better distinction between orchards areas and shrubs;
- Better distinction between cultivated areas and 'other';

4.2 Convergent belief values

Distributions of CBV of the different classes are presented in Figure 2. This distribution reflects a hierarchy among these classes:

1. Crops present dominancy of high CBVs in which summer crops (cotton and sunflower) exhibit very high proportions of high belief level (PHBL; ~95%), whereas winter crops (wheat and legumes) gained only moderate PHBLs (68% and 51% respectively).
2. Orchards presented a mixture of high, medium and low CBV figures.
3. Natural vegetation areas and shrubs/forest areas present dominancy of low and poor levels, with low proportions of PHBL.

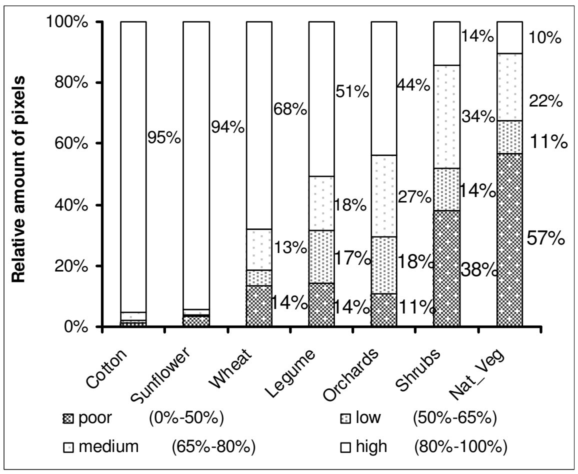

Figure 2: Proportions of cumulative belief levels.

In spite of this, as presented in Table 3 orchards, shrubs and natural vegetation achieved by the KBS accuracy of around 80% and reliability of 95%. These accuracy and reliability figures leads to a proposition that medium and low CBVs do not necessarily imply for wrong classification decisions by the KBS.

5. DISCUSSION

Relationships between recognition accuracy/reliability of both classification methods and CBVs for each class were assessed. Two characteristics of a class have attracted attention through the analysis of these relationships:

Heterogeneity: In similar way to ecological characterization of species diversity, the CBVs attributed to pixels of a certain land-cover class, represent the different variants of this class. Heterogeneity of an ecological system is examined among other indexes by its species' diversity. Analogues to that, heterogeneity of a class may be examined through its CBV diversity. CBV diversity of a certain class was measured according to Shannon-Weiner information index:

$$\text{CBV Diversity (CBVD)} = \sum_{i=1}^{20} p_i * \ln p_i \quad (1)$$

where i stands for the 5% intervals of the CBV (e.g., i=1 is 0%-5% CBV and i=20 is 95%-100%) and p stands for the proportion of each interval relative to the overall class.

	CBVD	PHBL	US-CEM	KBS-CEM
Cotton	0.75	95%	94%	95%
Sunflower	1.17	94%	91%	92%
Wheat	2.00	68%	78%	88%
Legume	2.53	51%	67%	88%
Orchards	2.19	37%	65%	77%
Shrubs	2.42	14%	29%	81%
Nat_Veg	2.76	10%	30%	83%

Table 4: Values of CBVD, PHBL, US-CEM and KBS-CEM for each class.

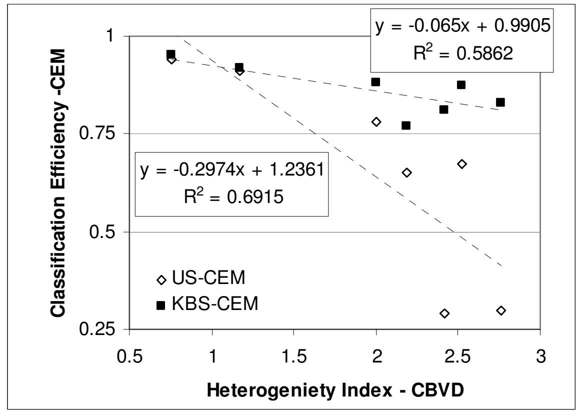

Figure 3: Relationships between heterogeneity index (CBVD) and classification efficiency measures (CEM) of US and KBS classifications.

A high CBVD is expected when there is a wide range of CBV values attributed to a class, which indicates heterogeneity and, conversely, a low CBVD is expected for cases in which there is dominancy of a certain signature. As inferred from Table 4, summer crops are very homogeneous, whereas wheat, orchards, legumes and shrubs are more heterogeneous. It may be hypothesized that as class heterogeneity increases, the recognition ability of a classification decreases. This hypothesis is partially supported by the classification results. When the classification efficiency (CEM) is regarded as a measure representing the lower value between accuracy and reliability of each class, there was found moderate correlations (r^2 = 0.69) between CBVD and CEM for the US and lower for the KBS (r^2 = 0.59; Figure 3). However, the US classification efficiency is highly more affected by the heterogeneity. Slope of linear trend-line of the US is five times higher then this of the KBS (0.3 vs 0.065). These moderate correlations indicate that heterogeneity alone does not fully characterize the limitedness of the US classification, and there is a need to analyze how unique is each class.

Uniqueness: is represented by the PHBL obtained for each class (Table 4). Wherever a class is composed solely of unique variants it gains a relatively high PHBL (e.g., cotton) as there are negligible conflicts in most of its pixels. High correlation (r^2 = 0.94) was found between the CEM of the US and the PHBL (Figure 4). In addition to the moderate correlation found with the CBVD it can be concluded that the success of an 'off-the-shelf' US classification diminishes with increasing heterogeneity of a class, and to a greater extent than its diminution with decreasing uniqueness.

In contrast, the CEM of the KBS presented moderate correlation with PHBL (Figures 4), and with five times lower slope. Together with the moderate correlation eith the CBVD and low slope it is suggested that the KBS facilitates identification of a class beyond its internal variability (heterogeneity) and its similarity to other classes (lack of uniqueness).

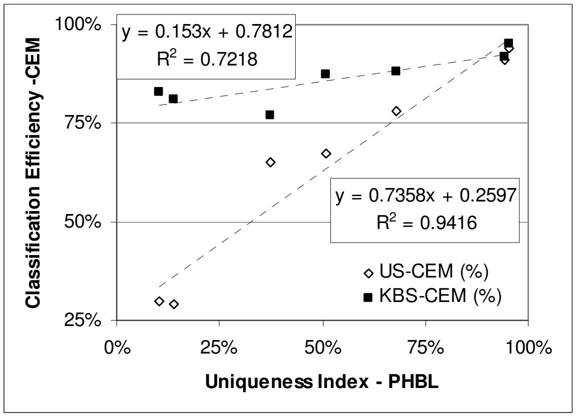

Figure 4: Relationships between uniqueness index (PHBL) and classification efficiency measures (CEM) of US and KBS classifications.

6. SUMMARY AND CONCLUSIONS

The use of KBSs based on evidential reasoning, for land-cover mapping based on remotely-sensed images is spreading widely. Secondary products of such classification techniques are the CBVs which are unique features of the Dempster-Shafer algorithm. However, despite the major role of CBVs in KBS classification decisions, their analysis has received little, attention in the literature. In the present study relationships between CBVs of the different classes and the accuracy/reliability of their corresponding classifications were investigated. The CBVs were found to be good indicators of the level of classification complexity on both the pixel and the class scales. In this framework we added two new parameterizations for the CBV distribution: PHBL and CBVD, two parameters which contribute to the analysis of the heterogeneity and the uniqueness of a class.

Correlations were found between US and KBS classification efficiency and levels of heterogeneity and uniqueness of a class. However, US classification efficiency was much more affected by the heterogeneity and uniqueness levels of a class as referred by five times higher slopes of the trend-lines. In other words, the KBS facilitates identification of a class beyond its internal variability (heterogeneity) and its similarity with other classes (lack of uniqueness). Finally, contrary to the intuitive expectation, CBVs do not indicate the reliability of classification. Low CBVs are indicative of complex situations or difficulties but do not necessarily imply that they cannot be resolved by the KBS.

7. AKNOWLEDGEMENT

We thank Arik Solomon and Eyal Sarid for realizing the Gordon-Shortliffe algorithm. We thank also to Dr. Victor Alchanatis for his helpful comments.

8. REFERENCES

Adinarayana, J., and Rama-Krishna, N. .1996. Integration of multi-seasonal remotely sensed images for improved land use classification of hilly watershed using geographical information systems. *International journal of remote sensing*, 17, pp. 1679-1688.

Cohen, Y., 2000. *Knowledge-based crop recognition by data sources integration in a Mediterranean environment*. PhD Dissertation. Israel: Bar-Ilan University.

Cohen, Y., and Shoshany, M., 2002. A national knowledge-based crop recognition in Mediterranean environment. *International Journal of Applied Earth Observation and Geoinformation*, 4, pp. 75-87.

Gordon, J., and Shortliffe, E. H., 1985. A method for managing evidential reasoning in hierarchial hypothesis space. *Artificial Intelligence*, 26, pp. 323-357.

Kontoes, C. C., Wilkinson, G. G., Burrill, A., Goffredo, S., and M´egier, J., 1993. An experimental system for the integration of GIS data in knowledge-base image-analysis for remote sensing of agriculture. *International Journal of GIS*, 7, pp. 247-262.

Peddle, D. R., 1995. Knowledge formulation for supervised evidential classification. *Photogrammetric engineering and remote sensing*, 61, pp. 409-417.

Shafer, G., 1976. *A mathematical theory of evidence.* Princeton, New Jersey: Princeton University Press. pp. 302.

Wilkinson, G. G., and M´egier. J., 1990. Evidential reasoning in a classification hierarchy a potential method for integrating image classifiers and expert system rules based on geographic context. *International journal of remote sensing*, 11, pp. 1963-1968.