CONSIDERATION OF THE UNCERTAINTY IN UNCERTAIN KNOWLEDGE FOR KNOWLEDGE BASED IMAGE CLASSIFICATION

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ABSTRACT

A key issue in knowledge based remotely sensed image classification is the approach to deal with the uncertainty existing in inexact knowledge. The uncertainty problem can be differentiated into two types: one is the uncertainty directly associated with uncertain knowledge; the other refers to the uncertainty existing in the certainty values of inexact knowledge. Expert system research has provided numerous theories for dealing with the former type of uncertainty, while few endeavors are found to address the latter type. This paper is devoted to the second type of uncertainty, namely, the Uncertainty In Uncertainty (UIU) problem. Based on an analysis of the importance of this issue, the paper presents a mathematical model for dealing with the uncertainty in uncertainty values, and discusses the methods to estimate various variables and parameters involved in the model. A case study is presented which has preliminarily proven the effectivity of the uncertainty model.

Key Words: Uncertainty reasoning, Uncertainty in uncertainty, Knowledge-based system, Expert system, Image classification, Mathematical modeling, Remote sensing.

INTRODUCTION

The incorporation of ancillary data into the classification of remotely sensed images has proven to be effective in improving classification accuracy (Middelkoop and Janssen, 1991; Skidmore, 1989; Kenk et al. 1988; Wu et al, 1988). Ancillary data, such as topographic information, soil maps and temporal relationships, can be applied effectively only if they have known relationships to the classes in the images. This implies that the utilization of ancillary information in image classification requires the incorporation of declarative knowledge that indicates such relationships into spectrally-based classification. Thus, the knowledge based system approach has been widely applied to multi-source image classification. Meanwhile, knowledge on the relationships between ancillary data and image classes is usually acquired from relevant specialists or based on statistics, therefore, the declarative knowledge inevitably encapsulates uncertainty or ambiguity. This makes the methodology for uncertainty reasoning an important issue in multi-source remote sensing image classification.

Research in the expert system domain has provided a variety of methods for dealing with the uncertainty problem. Among them are probability theory, uncertainty theory, the Dempster/Schafer theory, possibility theory, plausibility theory, etc. (Frost, 1986; Payne and McArthur, 1990). These theories, though differing from each other, all deal with the representation of inexact (or uncertain) knowledge and reasoning based on inexact knowledge. However, beneath the uncertainty values of inexact knowledge, there actually exists another type of uncertainty, namely, the reliability of the uncertainty values. For example, a certainty factor associated with a rule stated by an expert may have uncertainty related to the sufficiency and representativity of the sample used by the expert to derive this rule; the probability of certain diseases' occurrence given certain symptom has its inherent uncertainty related to the data accuracy and sufficiency in the database where the probability is derived. This type of uncertainty is not handled in all those theories dealing with uncertainty.

This paper addresses the uncertainty in uncertainty (UIU) problem of inexact knowledge. The necessity of addressing this topic is discussed through the analysis of the sources that cause the UIU problem, and the inadequacy of uncertainty reasoning methods commonly used in knowledge-based systems to the UIU problem. An approach for dealing with this problem is then given. It includes the definition of the UIU concept, the establishment of a mathematical model for dealing with the uncertainty, and the estimation of variables and parameters involved in the model. Based on the uncertainty model, a case study is presented in order to demonstrate the utilization and effectivity of this model. A preliminary conclusion is drawn based on the experiment that, by taking the UIU problem into account, the classification accuracy can be improved.

NECESSITY OF CONSIDERING THE UNCERTAINTY IN UNCERTAINTY VALUES

The Uncertainty in Remote Sensing Image Classification

Much of the knowledge with which humans reason is inexact or uncertain in some respect or other. As analyzed by Frost (1986), this is due to several factors: a) the universe of discourse is truly random; b) the universe of discourse is not strictly random but for some reason there is insufficient data; c) available knowledge represents a 'gut feeling' and such judgmental knowledge can be useful when more sound knowledge is not available; d) available knowledge is couched in terms which are themselves vague (e.g. the word 'usually' in 'Canary grass usually will not follow canola'); and e) the knowledge source is imperfect.

Among these factors, b) is a typical situation in spectrally-based remote sensing image classification. For example, suppose crop types are to be identified only based on spectral information. A commonly used supervised classification method is to compute the likelihood that a field grows a type of crop using probabilistic reasoning, based on the evidence obtained from training areas.

Furthermore, ancillary information, such as soil types and digital terrain models, may be used to improve classification accuracy. This is achieved through the representation of relationships between ancillary data and crop types using certainty values such as probabilities and certainty factors, and the incorporation of these certainty values into the probabilistic reasoning. These certainty values are usually estimated from two sources, i.e. databases and human experts. Databases are used as samples to compute probability values, while the statements may be expressed in different ways by experts. For example, an expert may state: "Oats usually grow well on the land with elevation between e1 and e2, soil types t1, t2, and t3, and slope ranging from s1 to s2". This statement is an empirical rule. It is judgmental; a vague term (usually) is included in the statement; and maybe only part of the ancillary themes of concern are addressed, hence being imperfect or incomplete. Thus, in addition to the uncertainty situation b), situations c), d), and e) may all be encountered in the classification of remote sensing image based on multiple knowledge source reasoning.

The UIU Problem in Remote Sensing Image Classification

A way to examine the UIU problem in remote sensing image classification is to look into the sources where related knowledge for the classification is generated. These sources can be generalized into three types: one is non-time-serial databases, such as spectral image databases for sampling training areas; the second is historical databases or time-serial databases which are used in the elicitation of ancillary knowledge; the last is human experts who provide expertise related to the ancillary information of concern. Figure 1 outlines the major sources that cause the UIU problem.

Beneath the probabilities generated from non-time-serial databases, there exist at least two types of uncertainty. One is database accuracy, which deals

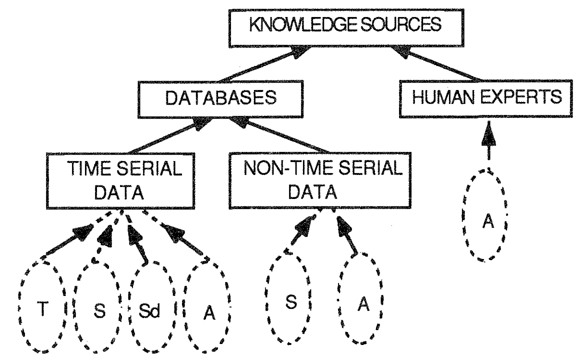

Figure 1 Major Sources Causing the UIU Problem

with data quality. The other is the sufficiency of the sample size available in the databases for statistics purpose. For example, a database with ten thousand records indicating the relationship between soil types and vegetation distributions may have over thousand records addressing soil type A, but only a few records addressing soil type B. Thus, the probabilities representing the relationship between soil types and vegetation distributions would be more reliable or certain for soil type A than for soil type B.

For time-serial databases, there are even more uncertainties existing in the probability values generated from the databases. The uncertainties of database accuracy and sample sufficiency also apply to time-serial databases. In addition, two other factors affect the probability values based on this type of databases. One is the number of time periods (e.g. the number of years), since statistics based on few time periods may be seriously biased, especially for the themes that are closely related to socio-economic situations. The other is the standard deviation of an event's occurrences during different time periods, since a large standard deviation may suggest the effect of some factors (e.g. socio-economic factors) that are not of concern in the knowledge elicitation. This can be depicted through an example, as shown in Figure 2. The height of the bar represents the number of fields that grew flax in that corresponding year. The large difference of flax field occurrences between 1986 and other years, which causes a large standard deviation, suggests a possibility that the high occurrence of flax in 1986 results from social economic factors such as the crop price. If statistics based on such a database aim to generate crop rotation rules, the result would probably be biased.

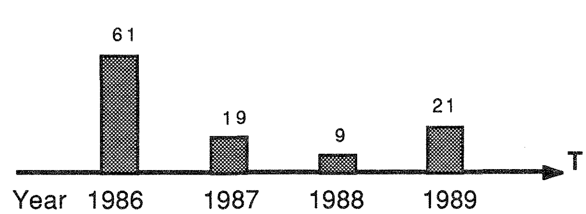

Figure 2 Occurrences of Flax Fields in An Experimental Area

The UIU problem in the knowledge provided by human experts refers to the reliability or accuracy of human expertise, which is mainly affected by the soundness of experts' knowledge.

Theories for Dealing with Uncertainty

Numerous theories have been developed to accommodate uncertainty problems in knowledge based systems. The commonly used methods are probability theory and uncertainty theory. In addition, a number of other theories, such as the Dempster/Schafer theory of evidence, possibility theory, and plausibility theory, have also been proposed, in order to solve some of the problems unable to be solved by probability and uncertainty theories. However, it can be found by looking into these theories that none of them takes into account the reliability of knowledge sources used for deriving probabilities or alike certainty measures. An exception is found in Neapolitan (1990) where the uncertainty in probabilities provided by human experts is mentioned, and a method for dealing with this uncertainty is proposed. However, as discussed previously, the UIU problem not only exists in the knowledge provided by human experts, but also in all other knowledge sources such as time-serial or non-time-serial databases. Therefore, existing theories for dealing with uncertain problems in knowledge based reasoning are inadequate, and how to solve this adequacy should become an issue in the research on uncertainty theory.

MODELING OF THE UNCERTAINTY IN UNCERTAINTY

Three issues need to be addressed in order to build a model to take into account the UIU problem in reasoning with inexact knowledge. Firstly, a formal definition needs to be given to the UIU concept, so as to formulate the scope of the problem. Based on this definition, the second step is to formulate a model to represent the defined concept. Methods for estimating variable values involved in the model then need to be developed. Further, the method for integrating the UIU measure into the reasoning of inexact knowledge should be formulated

Definition of The UIU Concept

Although different theories for dealing with uncertainty represent the uncertainty concept in different ways, they can all be transformed into such a syntax that, given certainty evidence, a certainty value refers to a measure, such as a likelihood, a probability, or a certainty factor, which indicates the certainty of an event occurrence. Thus, we can define the UIU concept as follows:

Let CV be a certainty value indicating the certainty of an event occurrence, given certain evidence. Then, the reliability of the certainty value CV or the quantitative measure of the UIU problem is termed as *Certainty In Uncertainty,* and denoted by *CIU.* If CV is provided by experts, CIU is a measure of the reliability of the expertise; if CV is extracted from an existing non-time series database, CIU is a function of database accuracy and sample size; if CV is elicited from a time series database, CIU is a function of database accuracy, sample size available in the database, the number of time periods included in the database, and the standard deviation of an event's occurrence over time periods in the database. The range of CIU is [0, 1], where 0 means that a certainty value is completely uncertain, 1 means that a certainty value is completely certainty, while values between 0 and 1 represent the varied degrees of certainty of a certainty value.

Mathematical Modeling of the UIU Problem

Based on the definition of the uncertainty in uncertainty values CIU, we can construct a function between CIU and the factors related to CIU as follows:

$$CIU = \Psi(T, S, Sd, A) \qquad (1)$$

where:

CIU - the uncertainty in uncertainty values to be evaluated;
T - the number of time periods (year, month, day, etc.) involved in the database;
S - the size of a sample available in the database for eliciting the certainty value of an evidence;
Sd - the standard deviation of occurrence of an event over time periods involved in the database;
A - the accuracy of data in a database or the reliability of an expert's statement.

In order to define the functional relationship Ψ in equation (1), we start with an analysis of the differential relationships between (CIU, T), (CIU, S), (CIU, Sd), and (CIU, A). Based on the characteristics of the variables involved, we can find that a positive ΔA would produce less increase of CIU with the increase of A; the same would be true for ΔS and ΔT., while contrary to these variables, a positive ΔSd would cause larger decrease of CIU with the increase of Sd. In addition, the function should have such a characteristic that, as CIU is getting closer to its upper or lower limits, it becomes very difficult to produce any more change in CIU. Thus, we can establish the following partial differential equation:

$$\Delta CIU = CIU(1-CIU)\,[\,(1/T)\Delta T + (1/S)\Delta S + (1/A)\Delta A - Sd\Delta Sd] \qquad (2)$$

Applying calculus to the equation, we thus obtain a mathematical model for the uncertainty in uncertainty values CIU:

$$CIU= S*T*A*\exp(-Sd^2/2 + C)/(1 + S*T*A*\exp(-Sd^2/2 + C)) \qquad (3)$$

where C is a constant. Other variables are as defined in equation (1).

Equation (3) can be applied to the three different knowledge elicitation cases (as discussed before) in the following ways:

1) when an uncertainty value is extracted from a time serial database, the quantitative measure of the UIU concept is as the form expressed by equation (3);

2) when an uncertainty value is extracted from a non-time serial database, the quantitative measure of the UIU concept can be derived from equation (3) by instantiating T=1 and Sd=0. Thus, the equation becomes:

$$CIU = S*A*\exp(C) / (1 + S*A*\exp(C)) \quad (4)$$

3) when an uncertainty value is based on experts' statements, the quantitative measure of the UIU concept can be derived from equation (3) by instantiating T=1, S=1, and Sd=0. Thus, the equation becomes:

$$CIU = A*\exp(C) / (1 + A*\exp(C)) \quad (5)$$

Estimation of the Variables and Determination of the Constant

Four variables (T, S, Sd, and A) are included in the generic uncertainty in uncertainty model (3). This section discusses the estimation of these variables and the determination of the constant C.

Estimation of Variable T. T relates to the time period involved in a time serial database. The time period could be, for example, the number of photograph periods for a remote sensing image database; it could also be the number of crop rotation periods for a crop inventory database. A straightforward way to valuate T might be to directly use the number of time periods included in a database. However, the number of time periods which is regarded as being sufficient for statistical purpose essentially varies with applications. For instance, more time periods would be required to elicit crop rotation knowledge based on a crop inventory database than to extract the relationship knowledge between land types and crop yields. This is because the elicitation process in the former case mainly depends on time periods, while time periods are used as a minor factor in the knowledge extraction in the latter case. Therefore, it is necessary to assign a standardized value of time periods, instead of the number of time period itself, to the variable T. Thus, T can be defined as:

$$T = Nt/SNt \quad (6)$$

where Nt represents the number of time periods involved in the database, and SNt stands for the number of time periods sufficient for eliciting an uncertainty value.

Estimation of Variable S. S deals with the sample size related to an event in a database for use in statistics. Its straightforward meaning is the sum of the occurrences of an event over the time periods involved in a database. For example, suppose that there is a crop inventory database in which crop distributions of N time periods for a certain area are included. Then, in the rule elicitation of the rotation from crop type A to crop type B based on this database, S could refer to the sum of the occurrences of crop type A in the first N-1 time periods (N-1 results from the fact that a rotation has to be based on two consecutive time periods, or in other word, the time period in the crop rotation case refers to two consecutive crop growing periods). Namely,

$$S_A = \sum_{t=1}^{N-1} S_{At}$$

where S_{At} would be the number of occurrence of crop type A in each of the first N-1 time periods. Similar to variable T, however, S is also a variable with relative meaning, since the sufficiency of a sample size is application dependent. For instance, the sample used for generating training area data would be much larger than the sample size needed for eliciting crop rotation rules. Therefore, it is necessary to standardize this variable through the division of the total sample size of an evidence by a sample size sufficient for conducting the statistics. Thus,

$$S = (\sum_{t=1}^{Nt} S_t) / SS \quad (7)$$

where S_t refers to the sample size of an evidence's occurrence in time period t, and SS represents the sample size sufficient for the statistical purpose. t ranges from 1 to Nt. Generally, Nt refers to the the number of time periods included in the database, but specific consideration should be given to the cases where a time period used as a basis for statistics is different from the straightforward number of time periods included in the database.

Estimation of Variable Sd. Sd stands for the standard deviation of S_t over the time periods used in statistics. As generally defined, Sd can be obtained as follows:

$$Sd = Sqrt\{ \sum_{t=1}^{Nt} [S_t - Mean(S_t)]^2 / Nt \} \quad (8)$$

Where S_t is the sample size of an evidence's occurrence in time period t, Nt is the number of time period used in statistics, and Mean(S_t) is the average of S_t over the Nt periods.

Estimation of Variable A. A refers to the accuracy of a database or the reliability of expertise provided by experts. In the database case, the accuracy mainly deals with data quality, which is often case-dependent. For example, the accuracy of a crop distribution database generated from remote sensing image classification is the image classification accuracy performed for identifying crop distributions, while the accuracy of crop inventory can be regarded as the accuracy of a crop inventory database. The case-dependent property determines that the assignment of values to A in the database case could only be conducted on a case-by-case basis.

In the case where an uncertainty value is generated from experts' statements, however, it is possible to provide a generic method for quantifying A, since experts' judgment is the dominant factor affecting the uncertainty value. Examining the judgment-making process, we can find that experts' confidence in making a judgment is a key factor that contributes to the UIU problem included in the judgment, and essentially, this confidence is mainly based on the sample size used by the expert in making the judgment. This analysis allows us to directly apply the approach addressed by Neapolitan (1990) for obtaining the uncertainty in probabilities .

Consider first the case where a propositional variable, say D, has precisely two alternatives, d_1 is the presence of a particular event, and $P(d_1)$ is the probability of d_1's occurrence. If we let x be a variable which represents a possible value of $P(d_1)$, then the general formula for the beta distribution is given by

$$\beta(a,b) = \frac{(a + b + 1)!}{a!\, b!} \times x^{a} (1-x)^{b} \qquad (9)$$

where a, b >= 0. This function is a probability density function $\mu(x)$ for the possible values of $P(d_1)$. For all a,b >= 0, it is proven that

$$\text{if} \qquad \mu(x) = \beta(a, b) \qquad (10)$$

$$\text{then} \qquad \int_0^1 \mu(x)\, d(x) = 1 \qquad (11)$$

$$\text{and} \qquad P(d_1) = \int_0^1 x\, \mu(x)\, d(x) = (a + 1) / (a + b + 2) \qquad (12)$$

Neapolitan (1990) points out that the values of a and b are based on the expert's confidence with the estimate of probability $P(d_1)$, and a+b can be liken to the sample size Se essentially used by the expert in the estimation, namely:

$$a + b = Se \qquad (13)$$

Using equations (12) and (13), we can solve for a and b. Replacing the values of a, b and $P(d_1)$ in equation (9), we thus obtain a probability value that indicates the certainty of the estimated probability by the expert. The obtained probability value can be regarded as the accuracy of expert's knowledge in the case where the propositional variable has two alternatives.

Furthermore, Neapolitan (1990) extends the case of two alternatives of the propositional variable to t alternatives, and concludes that the density function for the possible value of $P(d_i)$ is the Dirichlet distribution:

$$Dir_i\,(a_1, a_2, ..., a_t) = \frac{(b_i + a_i + t - 1)!}{a_i!(b_i + t - 2)!} \times x^{a_i}(1-x)^{(b_i+t-2)} \qquad (14)$$

where

$$b_i = \sum_{j=1}^{t} a_j - a_i. \qquad (15)$$

Similar to the two alternative case, if $\mu(x)= Dir_i\,(a_1, a_2, ..., a_t)$, then

$$\int_0^1 \mu(x)\, dx = 1 \qquad (16)$$

and

$$P(d_i) = \int_0^1 x\, \mu(x)\, dx = (a_i + 1) / (a_1 + a_2 + ... + a_t + t) \qquad (17)$$

To estimate the value of Dir_i , the expert needs to specify values, $a_1, a_2, ...,$ and a_t, which are all >= 0, such that his experience is approximately equivalent to having seen d_1 occuring a_1 times, d_2 occuring a_2 times, ..., and dt occuring a_t times in $a_1 + a_2 + ... + a_t$, total occurrences. Thus, the estimate of Dir_i can be used as the accuracy value being addressed in the case where the propositional variable has multiple possible values.

Neapolitan's approach to the estimation of the UIU value included in experts' knowledge can be applied to the situation where time dimension is not involved in the estimation. When this is not the case, a better approach is to include the variable of time periods in the estimation, thus, the Neapolitan's approach needs modification, or a new approach needs to be devised. This is a topic remained for further research.

Determination of constant C. C is the constant included in function (3). To determine the value of the constant, we can suppose an ideal condition where T = 1, S = 1, A = 1, and Sd = 0. Based on the meaning of the variables involved, there should be CIU(T=1, S=1, A=1, Sd=0) = 1, which means that the certainty in an uncertainty value elicited from a database or from an expert reaches a maximum in the ideal situation. Replacing the values of CIU, T, S, A, and Sd to in equation (3), the constant of C can then be obtained.

Adjustment of Certainty Values Using CIU

Once the value of CIU is obtained, the next step is to adjust the certainty value generated from a database or provided by experts using the CIU value. Let the certainty value be CV, and the adjusted certainty value be ACV, then ACV can be obtained using the following simple function:

$$ACV = CV * CIU \qquad (18)$$

This is reasonable since CV and CIU are essentially independent from each other. If CV is measured in probability and CIU < 1, then CV is reduced to some extent. If CV is represented as a certainty factor which has range [-1, 1] or [-100, 100], and CIU < 1, then equation (18) results in the decrease of the absolute value of CV.

A CASE STUDY

A case study was conducted in order to test the effectivity of the proposed UIU model. The basic objective of the case is to classify crop types using Synthetic Aperture Radar (SAR) imagery. To improve classification accuracy, crop rotation rules with certainty factors were generated based on a five-year crop inventory database, and were integrated into the crop classification. For the purpose of experimentation, two sets of crop rotation rules were presented as matrices in Tables 1 and 2, one based on two year's rotation data, and the other on five year's data. The classification accuracy with and without the integration of crop rotation rules is shown in part of Table 6.

Applying equation (3) to each of crop types involved in this case, we obtain the values of certainty in uncertainty CIU, as shown in Table 3. The same operation was applied to the case of two year's crop rotation data. The variable values as well as CIU values are also presented in Table 3.

Multiplying five years' and two years' r values presented in Table 3 with the certainty factors in Table 1 and Table 2 respectively, we obtain the adjusted certainty factors, as shown in Tables 4 and 5.

Table 6 summarizes the classification accuracy based on spectral information (MLM), on the integration of two-year-based and five-year-based crop rotation knowledge, and on the integration of adjusted crop rotation knowledge for both the two-year and five-year cases. The classification accuracy was computed using two different methods: one is based on the whole set of crop field, while the other on the set of crop fields where crop rotation rules were applied (notice that part of the cells in Tables 1 and 2 have certainty factors of 0, which resulted that some of the crop fields were classified without the use of crop rotation rules).

Table 1: Crop Rotation Rules with Certainty Factors Based on Two Years' Crop Inventory Data

	Oats	Wheat	Peas	Canola	Canary	Barley	Flax	Fallow
Oats	0	0	0	0	0	0	0	0
Wheat	0	0	0	0	0	0	0	0
Peas	0	52.3	-83.0	-100	0	25.3	0	-100
Canola	-100	0	0	-84.6	-98.2	0	0	-96.3
Canary	0	0	0	0	0	0	0	0
Barley	0	-76.0	0	0	0	17.4	0	0
Flax	0	0	0	0	0	0	-100	16.5
Fallow	0	0	-100	52.6	0	-100	0	-100

Table 2: Crop Rotation Rules with Certainty Factors Based on Five Years' Crop Inventory Data

	Oats	Wheat	Peas	Canola	Canary	Barley	Flax	Fallow
Oats	0	0	0	0	0	0	0	0
Wheat	0	0	0	0	0	0	0	0
Peas	0	24.0	-97.7	-74.0	0	15.7	0	-40.9
Canola	-100	0	0	-83.0	-78.6	0	0	-33.3
Canary	0	0	0	0	0	0	0	0
Barley	0	-69.2	0	0	0	6.7	0	0
Flax	0	0	0	0	0	0	-100	1.3
Fallow	0	0	-95.5	50.5	0	-82.4	0	-100

Let i denote any type of crop growing in the studied area, we can instantiate the variables included in equation (3) by:

$T = 5/SNt$, where SNt is assigned a value of 10,
$S_i = S_{ti}/SS$, where SSt is assigned a value of 500,
Sd_i is computed based on S_i and T (equation (8)),
A = 1, based on the fact that the data used are ground inventory data.

It can be seen from the Table 6 that by integrating crop rotation rules based on five-year's crop inventory data into classification, the accuracy is improved by 6.7% based on the whole field set, while it increases to 9.5% if only looking at the crop fields where crop rotation rules were used. By adjusting the certainty factors of crop rotation rules based on five-years crop inventory data, the classification accuracy is slightly further improved (0.6%). The experiment also shows that the use of rotation rules based on two years inventory data

Table 3: Estimates of CIU for each crop type

	Oats		Wheat		Peas		Canola		Canary		Barley		Flax		Fallow	
T	2	5	2	5	2	5	2	5	2	5	2	5	2	5	2	5
A	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S	0	8	171	691	70	365	191	516	17	74	188	740	21	110	45	180
Sd	0	3	0	5	0	46	0	55	0	12	0	13	0	23	0	24
CIU	*	*	*	*	.58	.87	.79	.89	*	*	.79	.95	.29	.74	.41	.83

* means that the CIU is not calculated, since there is no rule for the corresponding crop.

Table 4: Crop Rotation Rules with Adjusted Certainty Factors Based on Two Years' Inventory Data

	Oats	Wheat	Peas	Canola	Canary	Barley	Flax	Fallow
Oats	0	0	0	0	0	0	0	0
Wheat	0	0	0	0	0	0	0	0
Peas	0	30.4	-48.2	-58.1	0	14.8	0	-58.1
Canola	-79.1	0	0	-66.9	-77.7	0	0	-76.2
Canary	0	0	0	0	0	0	0	0
Barley	0	-60.0	0	0	0	13.7	0	0
Flax	0	0	0	0	0	0	-29.4	4.9
Fallow	0	0	-41.2	21.7	0	-41.2	0	-41.2

Table 5: Crop Rotation Rules with Adjusted Certainty Factors Based on Five Years' Inventory Data

	Oats	Wheat	Peas	Canola	Canary	Barley	Flax	Fallow
Oats	0	0	0	0	0	0	0	0
Wheat	0	0	0	0	0	0	0	0
Peas	0	20.9	-85.2	-64.5	0	13.7	0	-35.7
Canola	-89.3	0	0	-74.1	-70.2	0	0	-29.7
Canary	0	0	0	0	0	0	0	0
Barley	0	-66.0	0	0	0	6.4	0	0
Flax	0	0	0	0	0	0	-74.4	1.0
Fallow	0	0	-78.8	41.5	0	-67.9	0	-82.5

Table 6: Accuracy of classification results

Channel	Time	Basis	MLM	2 year	2 year *	5 year	5 year *
CHH	1989	whole field set	57.8%	57.4%	63.5%	64.5%	64.9%
		Rule applied field set	55.1%	54.5%	63.1%	64.6%	65.2%

*: where the adjusted certainty values were used in the classification.

results in a slightly lower classification accuracy than that of the MLM method; however, the accuracy is significantly increased (by 8.6%) after the certainty factors are adjusted using the values of CIU. This suggests a possibility that the less time periods are used in eliciting time-dependent knowledge, the greater increase in classification accuracy could result through the consideration of the UIU problem.

CONCLUSIONS

Consideration needs to be given to the Uncertainty In Uncertainty (UIU) problem existing in the knowledge either generated from databases or provided by human experts. A model has been developed in this paper in order to estimate the UIU values. Methods have also been addressed for estimating the variables involved in the model. A case study has shown that the proposed model is effective in improving classification accuracy based on multiple knowledge sources. Further research is needed to estimate the reliability or accuracy of time-dependent knowledge provided by human experts. More experiments are also needed to further test the effectiveness of the proposed model.

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