MODELLING UNCERTAINTY IN HIGH RESOLUTION REMOTELY SENSED SCENES USING A FUZZY LOGIC APPROACH

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ABSTRACT:

This contribution concentrates on the determination of thematic uncertainty after the classification process. It is shown that in this context – in particular when evaluating remotely sensed scenes showing high spatial resolution – severe problems arise due to indeterminate boundaries in both, reference data and classification results. This effect occurs between mostly natural objects or are due to blurred or overlapping definitions of classes or related attributes in a given classification scheme. Based on some approaches in the literature and not satisfying tools in existing software packages we propose the introduction of a new characteristic value, the Fuzzy Certainty Measure (FCM), that is able to model and quantify the indeterminate boundaries in reference data and classification results.

1. INTRODUCTION

The evaluation of thematic uncertainty after the classification of remotely sensed scenes is a standard task in order to determine the quality of the input data and the classification process as such. In general, respective quantitative methods compare reference data ("ground truth") and the classification result from which error matrices and related measures like overall accuracy or Kappa coefficient can be derived.

By doing this, one assumes discrete boundaries between regions of a scene for which one and only one topographical object is attached and which is not subject of temporal changes. Furthermore, the reference data are assumed to be error-free which is obviously not the case with most applications. Instead of this, we have to deal with some effects of fuzziness, i.e. indeterminate boundaries between neighbouring objects. These effects are even amplified with the use of spatial high resolution data like those from the new digital airborne camera systems or from satellite systems.

Section 2 will elaborate on the just indicated problems in uncertainty determination from which the motivation arises to introduce some fuzzy uncertainty measures. Section 3 gives an overview of such measures from the literature, but also looks at the available tools within the software package *eCognition*™. From this survey it can be concluded that the existing characteristic values do not fulfil all demands with respect to uncertainties in reference data as well as to fuzziness in both, reference and classification results. Hence, our goal is to develop and to test a more profound methodology to determine the classification uncertainty. The resulting Fuzzy Certainty Measure (FCM) is presented in section 4. Section 5 summarizes these results and presents recommendations for further developments.

2. PROBLEMS IN UNCERTAINTY DETERMINATION

When accuracy is known objectively then it can be expressed as *error*, where it is not, the term *uncertainty* applies (Hunter & Goodchild, 1993). Thus, uncertainty covers a broader range of doubt or inconsistency and includes errors. In the following we concentrate on *thematic uncertainty* which shall be determined after the classification process.

Respective quantitative methods generally compare reference data ("ground truth") and the classification result from which error matrices and related measures like overall accuracy or Kappa coefficient are derived. Applying this procedure, some problems become evident which are even amplified with the use of spatial high resolution data like those from the new digital airborne camera systems (like ADS 40, DMC or UltraCam) or from satellite systems (like Ikonos, QuickBird or OrbView).

In general, we have to handle indeterminate boundaries or spatial transition zones between mostly natural objects (e.g., between forest and meadow), which are in some cases also a function of time (e.g., the boundary between beach and water). On the other hand we have also to consider blurred or overlapping definitions of classes or related attributes in a given classification scheme.

With high resolution data the absolute number of pixels describing spatial transition zones also increases. Due to the smaller ground pixel sizes the spectral variance within regions representing a topographical object is increased, which leads to mixed elements (e.g., forest consists of trees, bare soil and others).

Furthermore it becomes more difficult to obtain a reference data set that is able to serve as a reasonable, "true" description of the reality. It is obvious that the assumption of error free reference data becomes even more critical with high resolution data.

The higher degree of details which can be derived from those high resolution scenes must also lead to more complex classification schemes. With that, the chance of overlapping object and attribute descriptions increases in the same way as the (even visual) interpretation gets more error-prone.

Finally, an adoption of the number and size of sample units has to take place. In particular the conventional acquisition on per pixel basis is not suitable anymore due to too small elements and neglecting the neighbourhood.

In conclusion, it is obvious that due to the increasing importance of remotely sensed data with high spatial resolution on one hand, and the above described problems on the other hand, there is a significant necessity to develop uncertainty measures that consider uncertainties in reference data as well as indeterminate boundaries in both, reference data and classification results.

3. PREVIOUS WORK

3.1 Literature

While for the application of conventional, statistically founded methods a variety of papers exist (e.g., Thomas, Hendrix & Congalton, 2003; Foody, 2004), approaches for the determination of fuzziness have been considered rather rarely.

One approach for modelling transition zones is to introduce the so called ε–bands, as defined by Blakemore (1994; cited after Ehlers & Shi, 1997). Here, the different chances of a point-in-polygon-relation are described by five *qualitative* measures ("definitively in", etc.). Ehlers & Shi (1997) propose to use a probabilistic model in order to give a *quantitative* description which also allows for the combination with values of thematic uncertainty: Applying the so called S-band model positional and thematic uncertainty values are linked by using the product rule. Other options to treat indeterminate boundaries (e.g., least squares polynomial fitting, corridor techniques, etc.) are mentioned by Edwards & Lowell (1996).

The application of fuzzy set theory for the determination of classification accuracy has been significantly influenced by Gopal & Woodcock (1994). They added certainty values on a linguistic scale ("absolutely safe", etc.) to their visually classified elements. Those linguistic values can be combined using fuzzy logic theory for a better understanding of the resulting map. Similar approaches are reported by Wang & Hall (1996), Townsend (2000) or Lowell et al. (2005).

Edwards & Lowell (1996) concentrate on the definition of a membership function which in their case describes spatial uncertainties. For this purpose they introduce fuzzy transition zones whose widths are defined for all pairs of object classes ("twains"). In this case the corresponding zone width values had been derived from the mean deviations resulting from multiple digitizations in aerial images. The authors also found that not only the thematic class memberships but also the area sizes of the polygons under consideration have a significant influence on the width of the transition zone (the smaller the area, the larger the fuzziness).

3.2 Implementation under *eCognition*™

The software package *eCognition*™ (Definiens, 2006) offers conventional methods for the determination of classification accuracy by using reference data and the classification result („Error matrix based on TTA mask“, or "Error matrix based on samples"). Besides that we also find the option for an evaluation of classification results based on fuzzy set methods. The concept of the „advanced classification evaluation based on fuzzy classification“ assumes that the larger the deviation of all membership values (for all classes, for one pixel or segment) is, the more uncertain the classification is. With that, uncertainties in the classification scheme and indirectly also measurement errors can be addressed, while the acquisition and processing methods themselves cannot be assessed, because uncertainties of the reference data are not considered.

In this context the following characteristic values, which are only derived from the classification result (respectively, the corresponding membership values), can be taken into account with *eCognition*™:

- „Classification stability“: For each pixel the difference between the largest and second largest membership values is computed and summed up for the entire class (or even the entire scene) – in the literature also known as *ambiguity*.
- „Best classification result“: This gives the visual representation of the corresponding largest membership value for each pixel. The mean value of all membership values can be interpreted as indicator of the total uncertainty.
- For each pixel one can determine the standard deviation of the membership values which again can be summed up for the entire scene.

4. FUZZY CERTAINTY MEASURE (FCM)

Based on the above outlined problems and the current state of implementations as presented in the previous section our goal is to develop and to test a more profound methodology to determine a posteriori the classification accuracy considering uncertainty in reference data as well as indeterminate boundaries in the reference and the classification result. We will end up with the new, so called *Fuzzy Certainty Measure (FCM)*.

Our approach starts with the **assumptions** that the classification schemes between reference and classification are identical and that no discrepancies occur due to different pixel sizes or temporal changes. Furthermore we assume that an appropriate sampling procedure has been taken into account.

In order to demonstrate the overall process as described above, we have applied our proposed method to a **data set** of the digital airborne camera system HRSC-AX which delivers image and elevation data in very high spatial resolution (in our case ground pixel size equals to 15 cm; see figure 1, first row).

By considering **uncertainties in the given reference data set,** which is actually nothing else than another classification result, we have to state that in most cases the underlying measurements, attributes and decision rules are not known anymore. In order to model the inherent fuzziness, transition zones are introduced. Those are defined a posteriori using a buffering zone along a given boundary between two topographical objects. Based on the above cited investigations by Edwards & Lowell (1996) the width of this zone depends on the combination of objects (e.g., the transition zone between forest and meadow is obviously larger than those between building and road) as well as on the size of the object areas. We end up with membership values $\mu_{REF}(c)$ for each pixel (or region, if desired) separately for each object class c (figure 1, middle row, right).

The same procedure applies for the **classification result**, leading to membership values $\mu_{CLASS}(c)$ (figure 1, bottom row,

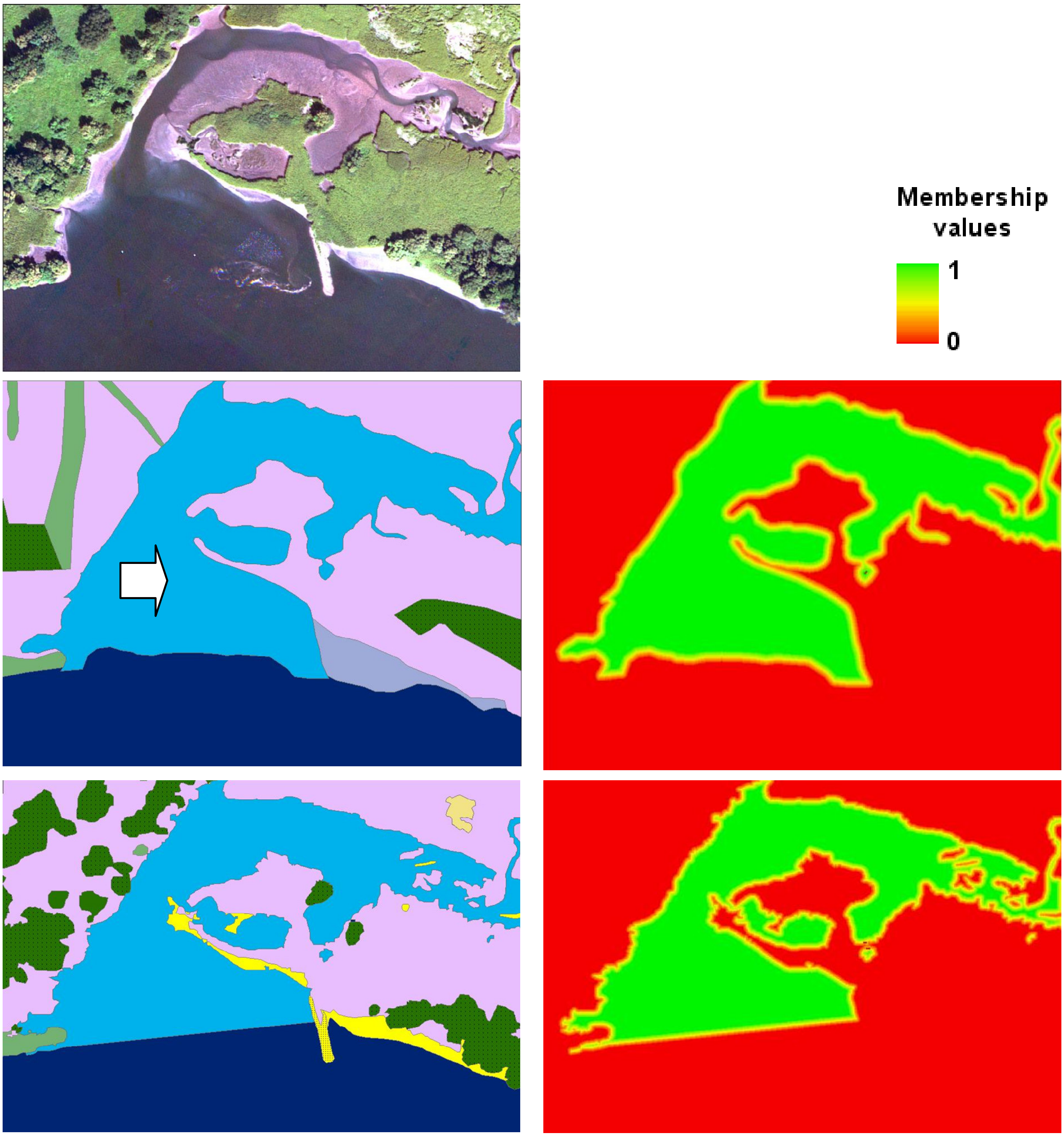

Figure 1. Top row: Digital aerial photo for comparison purposes.

Middle row: Reference data (left, with arrow indicating object class under consideration) and visualization of membership values $\mu_{REF}(c)$ for class c under consideration (right)

Bottom row: Classification result (left) and visualization of membership values $\mu_{CLASS}(c)$ for class c under consideration (right)

right). Presently, we use the same rules for building the transition zones as outlined above for the reference data. However, if more information is available, also a combination of traceable observation errors as well as different fuzzy measures could be applied.

Now the obtained membership values for each pixel (or region) and for each topographical class are compared with the **Fuzzy Certainty Measure FCM(c) per class c** as follows:

$$FCM(c) = 1 - \frac{1}{n}\sum_{i=1}^{n} | \mu_{i,REF}(c) - \mu_{i,CLASS}(c) |$$

$$\forall i \,|\, \mu_{i,REF} > 0 \vee \mu_{i,CLASS} > 0$$

with:

$\mu_{REF}(c)$: membership value of a pixel (or region) for class c in reference data

$\mu_{CLASS}(c)$: membership value of a pixel (or region) for class c in classification result

n: number of pixels (or regions) under consideration

The FCM(c) values vary between 0 and 1 – the larger the coincidence between reference and classification, the larger FCM(c) becomes. In our example we obtain the values as given in table 1. Figure 2 visualizes the measure for a selected class (KPS, refer to figure 1).

Class c_i		**FCM(c_i)**
BAT	Shrubs (Salix)	0.97
FWR	Reed (Phragmites)	0.86
FZT	Tidal River	0.97
KPS	Tidal Creek / Tideland	0.95
WWT	Willow Forest (Salix)	0.91

Table 1. Feature Certainty Measure for object classes under consideration (class names according to specific object catalogue, referring to example from figure 1, top row).

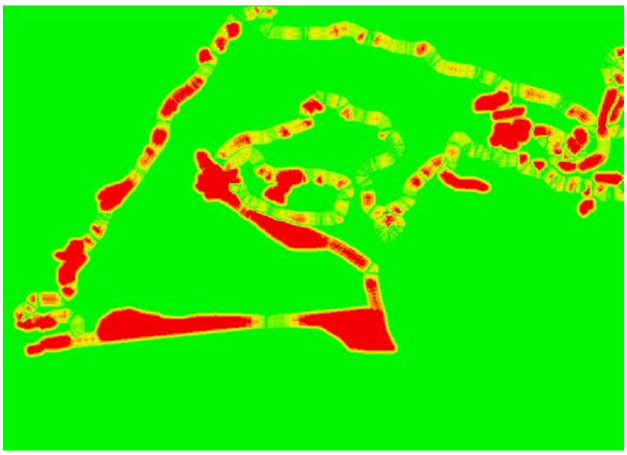

Figure 2. Visualization of FCM(class=KPS): red colours indicate higher uncertainty (compare legend in figure 1)

Based on this it is also possible to compute the values $FCM(c_{jk})$ for a **confusion matrix** by comparing $\mu_{REF}(c_j)$ and $\mu_{CLASS}(c_k)$ considering different classes (j≠k).

Finally a **total FCM** can be obtained, e.g. by using the area A weighted average of all *FCM(c)*:

$$FCM = \sum_{i=1}^{k} \frac{A_i}{\sum_{i=1}^{k} A_i} FCM(c_i)$$

With that one obtains a characteristic value that considers the influence of the reference data and gives an indication of the quality of the classification procedure as such.

However, in order to give an idea of the total uncertainty we recommend to specifying also the parameters

- *vagueness* (difference of total classification membership from maximal value 1.0) and
- *ambiguity* (difference between maximum and second largest membership value for a pixel or region).

Finally we also favour a suitable graphical representation of the obtained quantities using methods of geo visualisation (e.g., interactive attribute brushing methods).

5. SUMMARY AND FUTURE WORK

Various basic research work (e.g., Hunter & Goodchild, 1995; Ehlers & Shi, 1997; Congalton & Green, 1999) has pointed out that it is not possible to define a generally valid or optimal model for determining the classification accuracy based on remotely sensed scenes. In fact, a variety of parameters like available data sources, systems or processes which shall be described, user demands, etc., have to be taken into account for every specific case.

In this overall context our contribution concentrates on thematic uncertainty which shall be determined after the classification process. Here, we addressed the problems of indeterminate boundaries in both, reference and classification results, which occur between mostly natural objects or are due to blurred or overlapping definitions of classes or related attributes in a given classification scheme. These problems are even amplified with the use of remotely sensed data showing high spatial resolution as given with the new digital airborne or spaceborne systems.

We propose the introduction of a new characteristic value, the *Fuzzy Certainty Measure (FCM)* which considers the influence of the reference data and gives an indication of the quality of the classification procedure as such. With that, comparisons between different classifications (with respect to different methods, time stamps etc.) can be evaluated more reliably. The procedure can be characterized as flexible and quite simple to apply.

Our future work is concerned with a sensitivity analysis of the parameters (in particular with the width of transition zones based on object class combination and area sizes). Furthermore, empirical investigations will be performed for the combination of fuzzy with additional probabilistic measures. Finally, also the extension towards a change analysis is taken into consideration by introducing thresholds for FCM values for the classifications of different time stamps.

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