INTEGRATING MULTI-SOURCE INFORMATION VIA FUZZY CLASSIFICATION METHOD FOR WETLAND GRASS MAPPING

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ABSTRACT:

Late greening vegetation has been regarded as significant indicator of flood recessional wetlands ecosystem in the Poyang lake natural reserve (PLNNR). Mapping the wetlands, especially the distribution of late greening grassland is of great importance for PLNNR managers and decision makers either for ecosystem dynamic monitoring or habitat sustainability assessment. The aim of this paper is to explore the use of fuzzy classification methods to map wetlands land cover and to better represent the vegetation landscape. The proposed fuzzy rule-based system integrates information on NDVI, wetness and elevation and expert knowledge about vegetation growth condition and phenology. Nine types of land covers were classified, with four belonging to wetland vegetation. A traditional error matrix analysis has been used for accuracy assessment. The results show that fuzzy classification provides more detailed information on the possibility of vegetation presence, rather than presence/absence information obtained from a crisp classification. Fuzzy classification thus best represents vague objects and is less sensitive to poor data quality.

1. INTRODUCTION

The seasonal dynamic pattern of wetlands ecosystem within Poyang Lake National Nature Reserve (PLNNR) is influenced by climate (rain fall, temperature and solar radiation), environmental conditions (soil moisture, terrain), and hydrological fluctuation of the five up-rivers and the Yangtze River. Every year, various wetland vegetation areas green up in spring. Some remain green throughout the summer flooding months (June to August), but become senescent in autumn (September to November). We call these *early greening grassland*. Other wetland vegetation submerges during the flooding period in dormancy, but starts to germinate at the end of September when flood water ebbs and soil is exposed gradually. We call these *late greening grassland*. Late greening grassland provides habitats that are popular among migrating birds in autumn. The growth of late greening grassland is sensitive to the recession onset, which later influences forage by the migrating birds. It has thus been regarded as a significant indicator of this flood recessional wetlands ecosystem(Liu and Xu 1994). Therefore, mapping the wetlands, especially late greening grassland distribution is of great importance for PLNNR managers and decision makers either for ecosystem dynamic monitoring or habitat sustainability assessment.

The grass wetland within PLNNR is dynamic, but its extent and presence are vague in space. Different vegetation communities are distributed in discernible ring belts around lake areas from low to higher elevations (Tan 2002; Wu and Ji 2002). Previous studies on this area combined multi-source information, to best classify early and late greening grassland(Tan 2002; Si 2006; Zeng 2006). Due to vague boundaries and highly heterogeneous of wetland grasslands, conventional crisp classification methods lack capability of providing satisfactory accuracy. Fuzzy classifiers based on the concept of the fuzzy theory (Zadeh 1965), are able to better deal with imprecise, uncertain or ambiguous data sets and knowledge, than crisp classifiers.

Fuzzy logic and fuzzy set theory have been applied in a variety of ecological mapping and prediction applications. Application examples include: fuzzy modelling of vegetation dynamics (Foody 1996; Hajj *et al.* 2007), eutrophication in a lake (Chen and Mynett 2003) and soil landscapes (McBratney and Odeh 1997; Bruin and Stein 1998; Metternicht 2003).

The aim of this paper is to explore the use of fuzzy classification to map wetlands land cover and to best represent the vague vegetation landscape in the PLNNR. More specifically, we use fuzzy inference to recognize vague patterns in a set of spatial data derived from Landsat TM image and an elevation model. We argue that fuzzy inference, in combination with multi-source information, preserves the vague nature of the physical wetlands vegetation landscape in the final mapping result.

2. METHOD

Fuzzy classification in spatial applications uses multi-source information. For example, it may include expert knowledge, DEMs and remotely sensed image. We apply Mamdani's fuzzy

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inference system to map the wetlands land covers in the PLNNR. A brief review of the definition of fuzzy set, membership function and fuzzy inference system is given first, which is followed by a fuzzy rule-based system applied to the land cover classification in the study area.

2.1 Study Area and data sets

The study area - Poyang Lake National Natural Reserve (PLNNR) is approximately 240 km^2 (29° 05′ - 29° 18′ N, 115° 53′ -116° 10′ E). The area is located to the northwest of the Poyang Lake in the JiangXi province, central China. It is situated within the middle range of the Yangtze River basin. The subtropical climate is warm and humid with abundant rainfall. Nine lakes in the PLNNR are connected to the Poyang Lake during the high water levels in summer and disconnected when water levels are low in spring, autumn and winter. Three types of vegetation dominate the wetlands: late greening vegetation, early greening vegetation and aquatic vegetation. These vegetation types are all blooming in spring and serve as important habitats and forages for spring migration birds. When winter migration birds arrive in autumn, the early greening vegetation becomes senescent. Late greening vegetation and aquatic vegetation in the lower elevation areas are shooting up gradually, and different kinds of birds feed in different elevation zones.

A Landsat TM image was acquired on November 30, 2005 during the autumn when late green vegetation is growing and pioneer migration birds start to arrive. A digital elevation model (DEM) with 0.1m vertical accuracy and 20 × 20 m spatial resolution, made in 1998 provided edaphic differences. Both TM image and DEM are geometrically corrected and geo-referenced according to Gauss-Kruger projection. The TM image was radiometrically corrected and resampled to 20m spatial resolution, to be consistent with the DEM. The Normalized Difference Vegetation Index (NDVI) and the Land Surface Water Index (LSWI) were calculated from Landsat TM image:

$$\text{NDVI} = \frac{\rho_{nir} - \rho_{red}}{\rho_{nir} + \rho_{red}} \tag{1}$$

$$\text{LSWI} = \frac{\rho_{nir} - \rho_{swir}}{\rho_{nir} + \rho_{swir}} \tag{2}$$

The NDVI is sensitive to green vegetation biomass and has been intensively used to classify land cover and monitor vegetation biomass and productivity (Hunt 1994; J. A.Gamon *et al.* 1995). The LSWI is sensitive to leaf water and soil moisture content and was chosen together with NDVI for classification (Boles *et al.* 2004). In total, 184 plots were sampled in the field between November 29 and 31, 2005. Samples were collected within 20 × 20 m observation plots and proportions of early and late greening vegetation were recorded. Late greening vegetation was further divided into vigorous and germinant according to the height of the grass. Due to some inaccessible wetland area in the field and lack of large scale map as reference, these felid plots were the only ground truth for accuracy evaluation of wetland vegetation. Testing samples of other land cover classes were collected from a 1: 100000 scale topographical map and directly from Landsat TM image by an image interpreter who is familiar with local situation.

2.2 Fuzzy sets, membership function and inference system

Fuzzy set theory has been applied in various fields, such as image clustering (Binaghi *et al.* 1999), decision making and control. Basic definitions of fuzzy sets and fuzzy logic can be found in(McBratney and Odeh 1997; Fisher 2000). A fuzzy set A is characterised by a membership function (MF), $\mu_A(x)$, that assigns to each element x a grade of membership ranging from zero to one.

$$A = \{x, \mu_A(x)\} \text{ for each } x \in X \quad \mu_A(x) \rightarrow [0,1] \tag{3}$$

$\mu_A(x) = 0$ means that x does not belong to the subset A, $\mu_A(x) = 1$ indicates that x fully belongs, and $0 < \mu_A(x) < 1$ means that x belongs to the degree μ_A. Two different but complementary approaches exist for deriving MFs: the similarity relation model and the semantic import model. The similarity relation model is based on a cluster analysis such as fuzzy c-means or on fuzzy neural networks. The semantic import model an expert or an empirical model is applied to specify a formula for the membership function without reference to data.

Fuzzy logic can be considered as a generalization of Boolean logic. Fuzzy logic uses variables with a continuous range or MFs in the interval [0,1] instead of the strict binary (0 or 1), as is the case with the Boolean logic. The soft input-output associations, when combined with an inference procedure, constitute the fuzzy rule-based systems. A typical fuzzy rule-based system consists of three components: the input defined by the MFs, the rule base method does so by means of fuzzy operations, and the output component which may be defuzzied. Fuzzy inference is the process of formatting the mapping from a given input to an output using fuzzy logic. The primary mechanism for doing so is by means of a list of if-then statements called rules. The rules of a fuzzy system describes the behaviour of the inference system based on the linguistic terms associated with the input and output variables. The rule regroups various expert knowledge by a finite collection of IF X THEN Y rules. All rules are evaluated in parallel, and the order of the rules is unimportant.

2.3 Fuzzy rule-based system

Our fuzzy rule-based system maps the wetland land cover in the PLNNR and emphasizes its late greening grassland distribution. In this section we describe the input and output variables of the system, its rule base, and the fuzzy operator that used to aggregation information.

2.3.1 System input

Three variables were defined as input to the fuzzy rule-based system for this application: Int_{NDVI}, Int_{LSWI} and Int_{DEM}.

- NDVI was used to differentiate vigorous vegetation, less vigorous vegetation and non-vegetation area. NDVI values were calculated according to (1) and are normalized to the range 0-255. NDVI values of all pixels were clustered into 20 clusters and regrouped into five classes. The minimum and maximum NDVI values of these five classes were used as parameters of the Int_{NDVI} membership function. Three categories were interpreted as “high” for vigorous vegetation, “moderate” for less vigorous vegetation and “low” for non-vegetation.

- LSWI was used to differentiate waterlogged area, less wet area and dry area. LSWI values were calculated according to (2) and normalized to the range 0-255. LSWI values of all pixels were clustered into 20 clusters and regrouped into five classes. The minimum and maximum LSWI values of these five classes were used as parameters of the Int_{LSWI} membership function. Three categories were interpreted as "high" for waterlogged area, "moderate" for less wet area and "low" for dry area.

- Elevation is the dominating environmental factor that determines the possibility of the presence of some vegetation and differentiates between similar land cover types, such as river bank and dry bare land. Local expert knowledge on the suitable elevation range for late greening vegetation growth is that it ranges from 14.2 to 16 m, with minimum 12 m and maximum 18 m. Suitable elevation range for early greening vegetation growth is from 12 to 18 m. For aquatic grass it is below 14 m, and for terrestrial vegetation above 18 m. This provides 4 categories of Int_{DEM} fuzzy membership function: "very high" for wood land, "high" for early greening grasslands, "moderate" for low wetland and "low" for water area.

2.3.2 System output

The system output is the membership value of the fuzzy set presence. Nine land cover types were defined: vigorous late greening vegetation, germinant late greening vegetation, early greening vegetation, aquatic vegetation, wet bare land, dry bare land, river bank, terrestrial vegetation, open water.

1. Vigorous late greening vegetation: mature sedge greens up after flood recession, appearing with strong vigour at the end of October when migration birds start to arrive. Carices are representative vegetation communities.
2. Germinant late greening vegetation: young sedge just germinates on the lower elevation and will grow up and provide habitat for the migration birds at November.
3. Early greening vegetation: wetland grass greens up in spring and remains green throughout summer and becomes senescent in October. Miscanthus and Cynodon are representative vegetation communities.
4. Aquatic vegetation: floating aquatic vegetation and submerged aquatic vegetation grow in the shallow water zones. Batracium and Polygonaceae are representative vegetation communities.
5. Wet bare land: non-vegetation wet land, with suitable wetness condition for late greening vegetation greens up.
6. Dry bare land: non-vegetation dry land with high or very high elevation, such as harvested crop land and sand hill.
7. River bank: non-vegetation dry land with low elevation near the river and lake open water.
8. Terrestrial vegetation: deciduous forest, evergreen forest and crop fields in high land.
9. Open water: open water in rivers and lakes.

Four categories of fuzzy membership function for vigorous late greening vegetation were interpreted as "very low" for absence, "low" for low possibility, "high" for possible to be present and "very high" for presence. Two categories of fuzzy membership function for the other 8 land cover types were interpreted as "presence" for high possibility and "absence" for low possibility.

2.3.3 Rules and fuzzy operators

Among all the combinations of input variables, 19 rules were defined based on expert knowledge. All the IF THEN rules can be built in a decision tree logical way showed in figure 3. All the rules are assigned equal weight. Here are some examples:

- If Int_{NDVI} is high and Int_{DEM} is moderate, Then possibility of vigorous late greening vegetation presence is very high.

- If Int_{NDVI} is moderate, Int_{LSWI} is low and Int_{DEM} is high, Then Early greening vegetation is presence and possibility of vigorous late greening vegetation presence is high.

- If Int_{NDVI} is low, Int_{LSWI} is high and Int_{DEM} is low, Then River bank is presence and possibility of vigorous late greening vegetation presence is very low.

The fuzzy rule-based system is based on Mamdani's fuzzy inference method that uses the MIN t-norm as the conjunction operator for each rule and the MAX s-norm as aggregation operator, centroid as defuzzification operator.

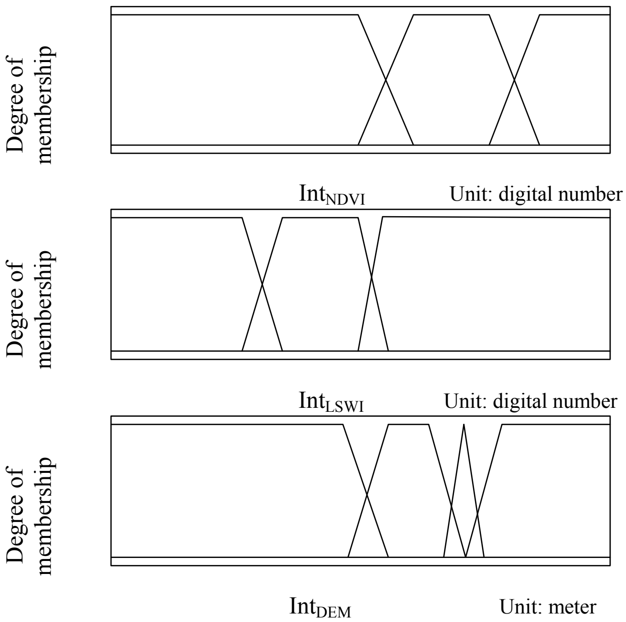


Fig. 1. Membership functions of system inputs

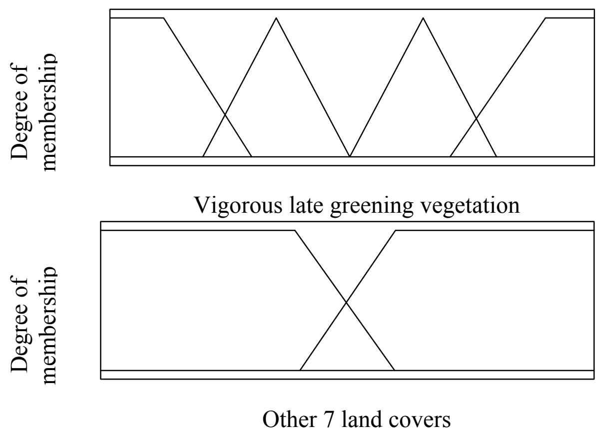


Fig. 2. Membership functions of system outputs

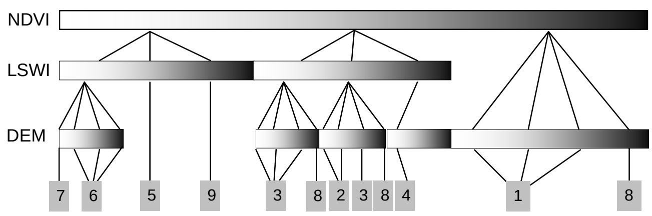


Fig. 3. Decision tree for rules establishment.(numbers are land cover serial numbers in section 2.3.2)

3. RESULT AND DISCUSSION

3.1 Classification and Accuracy assessment

Figure 5 shows the nine land cover distribution within the PLNNR area, based on the fuzzy rule-based classification of the Landsat TM image and DEM and expert knowledge on the phenology of wetland vegetation. Pixels excluded by the 19 rules were assigned to unclassified. The membership values from all the land covers were compared and the class with the highest membership value was assigned to the pixel label. The accuracy assessment for all the 9 classified land covers shows a 71.69% overall accuracy and kappa value equal to 0.68 (table 1). This wetlands land cover map provides more detail location information on different wetland vegetations than previous studies (Zheng 2001; Zhao *et al.* 2003; Si 2006; Leeuw *et al.* 2007). Dominant wetland vegetation including late greening vegetation, early greening vegetation and aquatic vegetation were differentiated from terrain vegetation. Moreover, germinant late greening vegetations which still do not appear blooming in October and wet bare lands which have suitable wetness condition for late greening vegetation shooting up have been detected.

From the classification result, we notice that 108 plots have been classified as early greening vegetation, among which only 55 were correct, leading to 50.93% users accuracy. Since early greening vegetation grows in a wide range of elevations and soil wetness conditions, other land covers can be easily misclassified to it. Obvious misclassification happened between vigorous late greening vegetation and early greening vegetation. The suitable growth elevation of early greening vegetation ranges wider than that for late greening vegetation. Therefore, they have distinct phenology but still are highly mixed at the moderate elevation level. In Miscanthus + Cynodon + Carex vegetation community, for instance, taller Miscanthus and Cynodon grows in the superstratum and Carex is the undergrowth (Wu and Ji 2002). Some germinant late greening vegetation was misclassified as early greening vegetation. The reasons are that they have similar NDVI values of image pixels which reflect both of them appearing less vigorous in the fields, and that they possibly mix in their growth in lower elevation near the shortly exposed river bank. Some terrestrial vegetation was misclassified as early greening vegetation mainly due to the similar spectral characteristics and suitable elevation of crop fields and early greening vegetation. River bank area and wet bare land near the river both have a low NDVI and a low elevation. They only differ in wetness degree. Sample plots of river bank and wet bare land collected from Landsat TM image are imprecise by nature, thus underestimating the accuracy of the assessments on these two classes.

To produce a more general land cover map, four broader land cover classes are used: wetland vegetation, terrestrial vegetation, bare land and water. Vigorous late greening vegetation, germinant late greening vegetation, early greening vegetation and aquatic vegetation were regrouped to wetland vegetation class. Wet bare land, dry bare land and river bank were regrouped to bare land, whereas terrestrial vegetation and open water classes remained. this general land cover map shows a 89.33% overall accuracy and a kappa value of 0.84.

Figure 6 shows the vigorous late greening vegetation and the membership values of presence possibility from 0 to 1. Visually, this soft classification result explicitly reflects the vague characteristics and contains more detail information instead of “yes or no” on a crisp classification map. If we change the soft classification into a hard classification by letting $B = \{x|\ x = 1, \mu_B(x) > 65\%\}$, and compare it with field samples, then we observe a 74.55% overall accuracy and a kappa value of 0.48

3.2 Uncertainty map and analysis

A fuzzy classification has the advantage that a measure of uncertainty factor $C(\mu)$ can be defined for each pixel as

$$C(\mu) = 1 - \max \mu_m(x) \tag{4}$$

This measure indicates whether or not the classification has yielded a clear response. The highest value of uncertainty factor is 0.5, which indicates the unclassified pixels. The lowest occurring value equals 0.11 instead of zero, since membership value of each output has not successfully captured 1. The reason is that centroid operator was used for defuzzification of the system output. It confines the range of vigorous late greening vegetation value from 0.89 to 0.1 and the range of other land covers value from 0.75 to 0.25. Membership values outside this range are impossible to be reproduced by fuzzy inference. The system output variables were divided into four or two categories. The number of divisions has an impact on the possible range of output values. A fine divisions corresponds with a large range of output membership values. Considering all uncertainty factors, we considered pixels with $C(\mu) < 0.25$ as certainly classified and pixels with $C(\mu) > 0.35$ as having a high potentiality of misclassification. The uncertainty map in figure 7 thus provides us with a good opportunity to highlight the deficiencies in the rule-based system and can be referenced as priori sampling locations for validation.

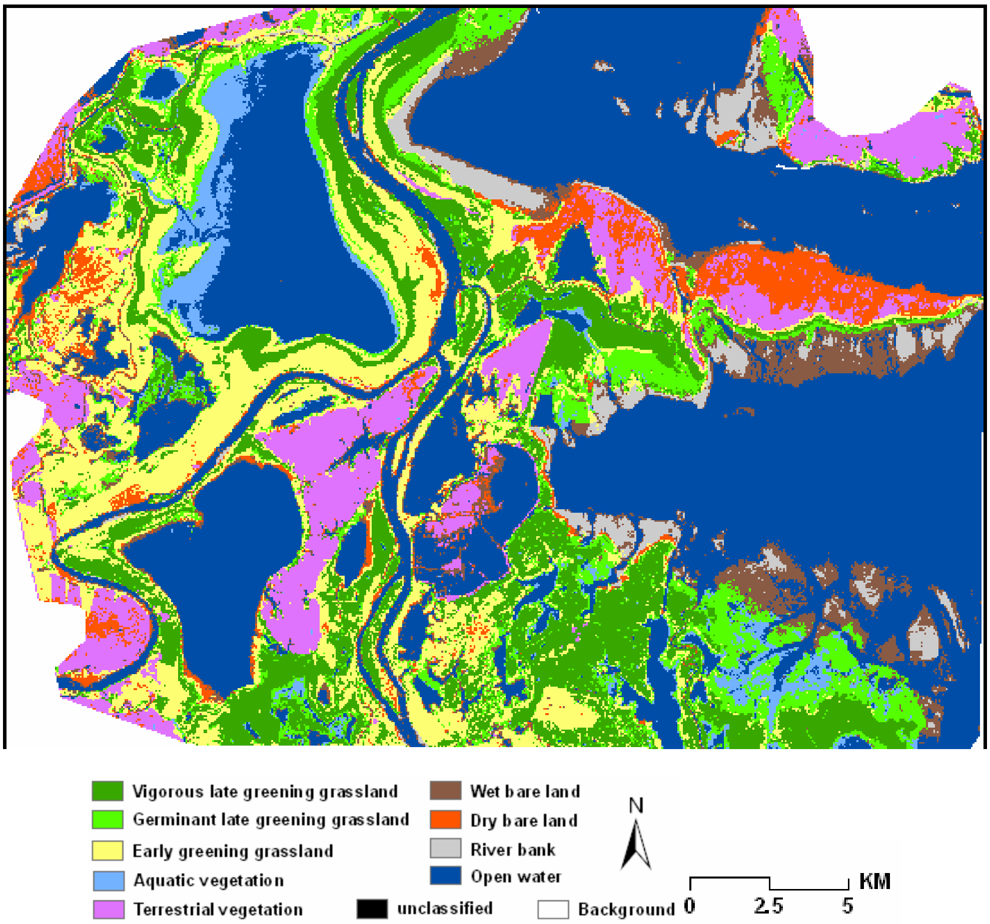


Fig. 5. Wetland land cover map classified by fuzzy rule-based system

Classified	Reference Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9	CT	NC	PA	UA
Class 1	57	7	14	0	0	0	1	5	0	84	57	62.64%	67.86%
Class 2	11	55	1	8	5	0	1	0	0	81	55	66.27%	67.90%
Class 3	17	14	55	6	2	4	0	10	0	108	55	73.33%	50.93%
Class 4	3	4	0	43	0	0	0	0	0	50	43	57.33%	86.00%
Class 5	1	2	1	4	47	0	14	0	0	69	47	56.63%	68.12%
Class 6	2	0	2	6	3	44	1	3	0	61	44	77.19%	72.13%
Class 7	0	1	0	0	18	3	45	0	0	67	45	71.43%	67.16%
Class 8	0	0	1	0	0	6	0	68	0	75	68	79.07%	90.67%
Class 9	0	0	1	8	8	0	1	0	90	108	90	100.00%	83.33%
Reference Total	91	83	75	75	83	57	63	86	90	703	504		

Overall Classification Accuracy = 71.69%
Overall Kappa Statistics = 0.6809

Table 1. Wetlands land cover map accuracy report (RT= reference total, CT= classified total, NC= number correct, PA= producers accuracy, UA= users accuracy)

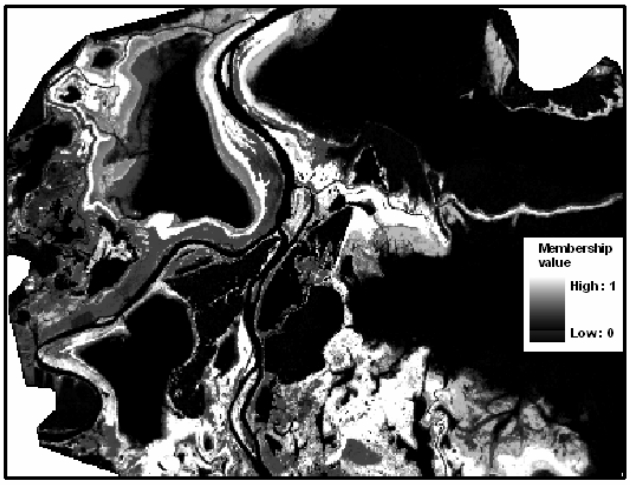


Fig. 6. Membership values of possibility of vigorous late greening vegetation presence

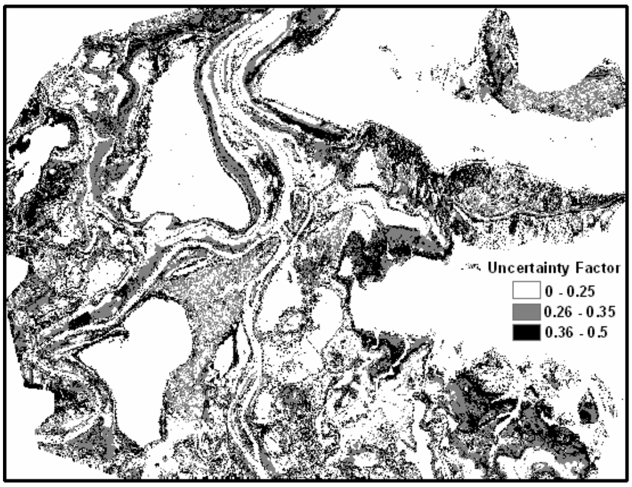
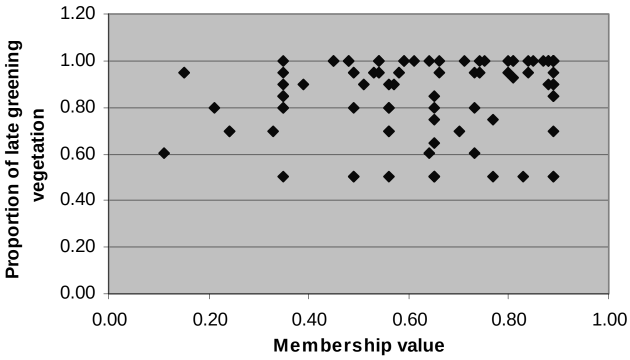


Fig. 7. Locations of pixels with high uncertainty (in black)



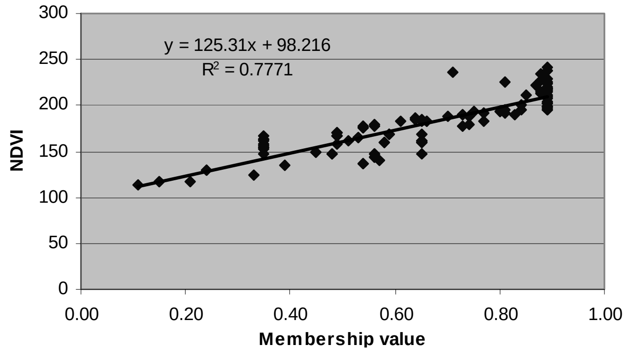


Fig. 8. Correlation between membership values and vegetation proportions (a), membership values and normalised NDVI values (b)

4. DISCUSSION

4.1 Validation of soft classification result

Soft classification approaches based on fuzzy set theory or probability statistic theory are expected to give more information than only yes or no by hard classification. How to evaluate the soft classification result, however, has been proposed as a research and practical question(Gopal and Woodcock 1994; Foody 1996; Binaghi *et al.* 1999; Townsend 2000). When using historical images and field collected data, as in this study, validation will be confined by the existing data and soft results can not be fully assessed. Even if there is an opportunity to collect test samples in the fields for a particular soft classification validation, we may question what kind of information in the sample point will correspond to the soft result. In this study, taking the vigorous late greening vegetation output as an example, membership functions to map possibility degree of vegetation presence have values between

0 and 1. Membership values close to 1 indicate high possibility to present, those close to 0 indicate high possibility of absence,

and those around 0.5 indicate highly uncertain decisions. The uncertainty map in figure 6 thus gives a rough impression where high certainty happens, i.e. in the homogeneous vegetation zones, and where large uncertainty occurs, i.e. in vegetation transition zones. This does not necessarily mean that membership values can be regarded to corresponding vegetation proportion in the fields. In fact, output membership functions describe possibility instead of proportion. A total of 109 field sample plots with late greening vegetation proportion higher than 50% has been used to extract membership values on soft result map in figure 6. Figure 8(a) shows that the correlation between membership values and vegetation proportion is not significant. In the absence of a directly corresponding test measurement, validation of the soft result becomes difficult. In figure 8 (b), membership values and normalised NDVI values appear highly positively correlated. It shows that NDVI values can serve as indicator of late greening vegetation presence. Possibility values in figure 6, however, contain more comprehensive information about vegetation presence than the NDVI values, since it not only considers vegetation index (NDVI) but also the wetness index (LSWI) and elevation. In summary, it is no problem to compare different possibility values and to select the land cover with maximum one as classification label, but to use the single soft result of one land cover deserves more attention.

4.2 Limitations and further improvement

From the low users accuracy of early greening vegetation, we notice that fuzzy rule-based system works less efficiently if the classification object has loose constraints, as may apply for widely distributed vegetation without growth limits,. Part of the classification error can be corrected by an image from another time. For example, in the late November image, early greening vegetation and germinant late greening vegetation can be classified with more certainty, when most of early greening vegetation withered versus germinant late greening vegetations blooming. The fuzzy rule-based system is flexible to add the multi-temporal image data, only at the price of additional computing time.

The rules in the fuzzy rule-based system are based on expert knowledge on the vegetation growth conditions and phenology. Therefore, mapping natural land covers can benefit from the extra information besides the image data. If existing knowledge about the classification targets is insufficient or implicated in the data, the explicit rules definition used in this study can not applied any more. In addition, if the number of system inputs is large, there is no possibility to try out each possible inputs combination. Other data mining methods, such as neural networks and optimizing methods such as simulating annealing can be the alternatives for rules construction (Zheng 2001; Bardossy and Samaniego 2002).

The fuzzy rule-based classification in this study is an unsupervised classification. It integrates expert knowledge and multi-source data by means of fuzzy inference. Other researches on precise membership function definition (Vlag and Stein 2007) and rule importance measurement (Zheng 2001) can provide further improvements on this classification method. If more samples exist for supervised classification, the possibility values given to each land cover can be used as priori probability instead of equal probability value in maximum likelihood classification approach.

5. CONCLUSION

Wetland ecosystem is characterised by high dimensionality, complexity and non-linearity. Ecosystem knowledge is usually semi-qualitative, and a large field dataset is difficult to obtain due to high sampling cost and inaccessible plots. This makes classification approaches solely depending upon expert experiences rather subjective and let alone purely data-driven approaches such as artificial neural network. The fuzzy rule-based system applied in this study is a practical approach to deal with semi-qualitative knowledge and semi-qualitative data. This research shows that land cover mapping in the PLNNR wetland ecosystem can benefit from a fuzzy rule-based classification method by combining expert knowledge, DEM, and remotely sensed image. This method provides more detail information on possibility rather than only presence or absence information in a crisp classification. It has the powerful capability of representing vague objects and is less sensitive to data quality problems.

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