IMPROVING RICE CLASSIFICATION USING MULTI-TEMPORAL DATA WITH FUZZY LOGIC AND GENETIC ALGORITHMS

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ABSTRACT: Rice is the most important food crop for the society and the economy of Thailand. Information on the area of rice is essential for agricultural land use planning and analysis, for example, crop prediction. If the calculated area is close to the real area, forecasts will be more accurate. The Office of Agricultural Economics (OAE) currently uses visual interpretation of a single LANDSAT TM epoch to classify rice area. However the process is time consuming and requires highly trained people. It is also error prone because it considers only a single point in time; rice fields that have not yet been planted will be omitted.

The purpose of this study is to investigate methods for improving the accuracy of rice area classification using LANDSAT TM imagery. Rice is difficult to classify correctly because the rice fields have different spectral signatures during different periods of growth (transplanting, growing, reproducing, mellowing, harvesting) but multiple periods may be present in a single scene. Fuzzy logic classification is one technique which can deal with multi-temporal data and can have multiple rules per class for different signatures. To find appropriate fuzzy logic rules, we used an optimization technique modeled on evolutionary biology called 'genetic algorithms' (GA). Preliminary results demonstrated that with appropriate parameters, GA produced a stable set of fuzzy rules based on the training data. Using the fuzzy rules to classify rice areas results in class assignment that is fairly close to the visual interpretation. An evaluation comparing results with maximum likelihood classification is planned.

1.0 INTRODUCTION

Rice is the most important food crop for the society and the economy of Thailand. Information on the area of rice is essential for agricultural land use planning and analysis, for example, crop prediction. If the estimate of rice area is close to the actual area, the agricultural analysis will be more accurate. Remote sensing and Geographic Information Systems (GIS) can be useful for analyzing the extent of rice cultivation and showing the result. It is often simpler to see and understand a map than a table of numbers from calculations.

Currently, the Office of Agricultural Economics (OAE) within the Thai Ministry of Agriculture and Cooperatives uses visual interpretation of rice cultivation from remotely sensed images to identify the boundaries of rice areas and uses the result for data analysis. The OAE has problems with this process. One problem is inaccuracy due to temporal factors. Because all farmers do not plant at the same time in all areas, a single image does not show all of the actual rice fields in the region covered by the image. An image acquired earlier or later would show different areas as rice. A second problem is effort and expertise required for classifying land use.

2.0 BACKGROUND

The primary objective of this research is to find ways to improve the accuracy of the manual rice area estimation process practiced by OAE. We have attempted to improve classification accuracy and reduce labor requirements by using more sophisticated methodology to estimate area of rice based on the remotely sensed imagery. Specifically, we have applied multi-temporal classification, fuzzy logic and genetic algorithms to produce a new and more effective methodology.

2.1 Multi Temporal Classification

For rice inventory using remote sensing imagery, the following items of the domain knowledge should be taken into account: the local crop calendar, the timetable of rice growing, and the variations of spectral reflectance of a rice field within a rice season.

The rice growing season can the divided into five periods:

1. Transplanting: fields are covered by water with little vegetation;
2. Growing: vegetation density is increasing;
3. Reproducing: vegetation density reaches the maximum and starts to decrease slowly;
4. Mellowing: vegetation density continuously declines;
5. Harvesting: fields become bare soil with a little crop residue.

Thus the land cover of a rice field and hence the spectral characteristics are changing during a rice growing season. While it may be hard to identify a rice field in any one image, the pattern of the temporal spectral variation of a rice field provides solid evidence to identify rice fields. This is the most important reason that we suggest the use of multi-temporal images. Some useful information could be extracted from the temporal profile for distinguishing rice fields, for example the curve shape of the profile or the NDVI differences among epochs. (Huang et al., 1985)

Tseng, et al. (1998) investigated using the multi-temporal NDVI profile to detect rice fields in Taiwan. Compared to traditional supervised classification using a single image epoch, the difference classification method improved the accuracy and worked well even if there were only two or three periods available.

2.2 Fuzzy Logic Rule-Based for Classification

Fuzzy logic classification treats class membership as approximate. Instead of simply specifying that a particular pixel belongs to a particular class, fuzzy logic classification allows us to evaluate the strength or degree of the pixel to class association and to compare this across classes. Fuzzy rule-based classification generally comprises three principle steps, The first step, fuzzification, involves the division of the input feature space into fuzzy subspaces, each specified by a fuzzy membership function. Fuzzy rules are then generated from each fuzzy subspace. The second step, inference, requires the calculation of the strength of each rule being triggered. The final step, defuzzification, combines all triggered rules and generates a non-fuzzy outcome. (Tso and Mather, 2001)

Bárdossy and Samaniego (2002) investigated the applicability of fuzzy-rule-based modeling to classify a LANDSAT TM scene. The expected outputs of their research were a land cover map with four different categories (forest, impervious areas, permeable areas, and water bodies) and an image depicting the degree of ambiguity of the classification for each pixel. The fuzzy classification algorithm used a rule system derived from a training set using simulated annealing as an optimization algorithm. The results showed that their methods perform slightly better than the maximum likelihood classifier (MLC). However a great advantage of fuzzy-rule-based modeling when compared to other standard methods, such as MLC, is its open rule system, as well as the fact that it can incorporate multiple image epochs. Also fuzzy-rule-based classification can produce multiple rules for a single class, reflectively the fact that a single conceptual class may have several distract spectral profiles. Due to the variation across its growing season, this is likely to be true for rice.

2.3 Genetic Algorithm Optimization

Genetic Algorithm is a computing technique used to find a true or approximate optimization of some data set. GA is implemented as a computer simulation in which a population of abstract representations of candidate solutions to the problem (called chromosomes or the genome) evolves toward better solutions. GA requires a genetic representation of the solution domain and a fitness function to evaluate candidate solutions. GA procedures have three steps: initialization, reproduction, and selection. Initialization randomly generates solutions to create an initial population. Reproduction is used to generate next population of solutions by “crossover” and/or “mutation” of old population members to create the next population. Selection involves the evaluation of all population members to find best solution in the current of generation. The generational process repeats until a solution is found that satisfies minimum criteria.

Benton (1995) used a GA procedure to classify 512 by 512 satellite images with four bands. The results indicated that genetic algorithms can be used to classify pixels from satellite images more quickly, compared with the fuzzy k-nearest neighbor algorithm, and give a good degree of reliability.

3.0 METHOD

We used LANDSAT-5 ETM images from four dates: 2004/05/22, 2004/08/26, 2004/10/13, and 2004/12/16, from scene 128/49 (path/row) that is located in Khon Kaen Province in Thailand. Each image included bands 2, 3, 4, and 5 which are the most useful bands for agricultural classification. We used Fuzzy Logic classification with Genetic Algorithm optimization for classification.

For training the fuzzy classification and for evaluating results, we used polygons obtained from OAE. These polygons identified the location of different classes including rice, water, and forest. They were defined from OAE’s manual interpretation of a single image.

The OpenDragon image processing package was used for standard operations such as image registration and polygon rasterization. Custom algorithms for fuzzy rule processing and GA optimization were programmed by the first author using the OpenDragon programmer’s toolkit.

3.1 Fuzzy Logic Classification with Genetic Algorithms

3.1.1 Preprocess images and training data: We prepared the 16 images as follows:

1. Registered our images to OAE background image so that their polygons would be located correctly.

2. Imported polygons into OpenDragon and rasterized them into mask images that identified the locations of pixels in each class.

3. Used erosion to reduce edge errors due to registration or rasterization and to eliminate very small polygons.

4. Used thresholding to develop cloud masks in order to reduce impact of training pixels obscured by cloud in the May and August images.

5. Separated remaining training pixels into two sets, one to use for training and one for evaluation

6. Extracted and stored data values for these pixel sets for all 16 bands from four dates and four bands in each date.

3.1.2 Define candidate fuzzy functions: We defined fuzzy numbers (FN) as ranges of image data values for each band. Each FN consists of three values: minimum, center, and maximum. A FN will have a membership value of 1.0 at the center and 0 at minimum and maximum limits. We explored defining different numbers of FNs per band based on overlapping percentile ranges. Specifically, we experimented with 3, 4, 5 and 6 FNs per band. We extracted and stored data of fuzzy boundaries for all 16 bands.

3.1.3 Rule selection and GA optimization: We used the following process to select and evaluate rules:

1. *Initialization.* Create a random initial rule set by randomly choosing one of the available FN for each of the 16 bands. Duplicate rules were discarded.

2. *Reproduction.* Randomly select pairs of rules from the current generation and randomly select a crossover point. Then swap the rule contents after that point. According to the mutation probability parameters, randomly change at most one FN in each of the resulting rules. During this process, we protected the top N parent rules from any change.

3. *Selection.* Use training pixels to evaluate each rule. Treat each training pixel as a vector of band values. For each band value, compute its degree of membership (DOM) in the rule's FN for that band. Average the DOM across all the FN in the rule to get a measure of how well the rule fits the training pixel. Find the rule which has the highest fit for this training pixel and add that fit value to the total fit value for that rule. Add 1 to the total fit count for the rule.

Select the best rules for next generation by sorting the result of ratio between total fit count and total fit. Keep the top N rules as parents to create the next generation.

4. Stop the iteration when the top three rules do not change for M iterations.

Parameters in this optimization process include the mutation probability, the number of candidate FNs, the number of rules in each generation, the number of parents to keep and the stopping criterion. We tried a number of different parameter sets. The results that we report used a mutation probability of 10%, a population size of 16 rules per class, and a choice of the top three parent rules in each generation. Our stopping criterion was 50 iterations during which the top three rules for a class did not change.

3.1.4 Evaluation of rule sets: We planned to use two methods to evaluate the result rule set of all classes from GA optimization:

1. Use the resulting rule set to classify the evaluation pixel data set (reserved half of pixels from the rasterized polygons). The result should represent the class correctly for all evaluation pixels.

2. Use resulting rule set to classify the whole image and compare with the maximum likelihood method.

Since this research is still in progress, in this paper we report only the results of method 1.

4.0 RESULTS AND CONCLUSION

A fuzzy number represents a data range in which we expect to find the data values for some class. The broader the range of a FN, the more likely that a particular value will have some non-zero degree of membership. A priori, there is no way to determine the best set of FN to use. Bárdossy and Samaniego (2002) used candidate FNs centered on the mean, minimum and maximum values of the image, as well as a "don't care" FN that covered the full range of image values. We found that including a "don't care" FN caused rules to be dominated by this FN. We experimented with using three, four, five and six fuzzy numbers, based on equal percentile ranges. Our results, in terms of the final fit value for the best rule, and the number of iterations to stability, are shown in Tables 1 and 2.

	Rice		Forest		Water		Urban	
FN	Fit	Iterations	Fit	Iterations	Fit	Iterations	Fit	Iterations
3	0.65	3001	0.54	10000	0.29	10000	0.59	1277
4	0.63	388	0.53	10000	0.35	10000	0.54	2626
5	0.55	4437	0.49	10000	0.32	10000	0.55	6300
6	0.67	588	0.54	10000	0.33	10000	0.51	2567

Table 1: Best Rule Fits and Iterations to Stability for Four Image Epochs

	Rice		Forest		Water		Urban	
FN	Fit	Iterations	Fit	Iterations	Fit	Iterations	Fit	Iterations
3	0.77	158	0.63	1186	0.36	94	0.68	117
4	0.60	593	0.71	833	0.38	109	0.66	264
5	0.59	1507	0.73	2934	0.39	1169	0.57	1943
6	0.53	5038	0.68	10000	0.37	2698	0.57	5342

Table 2: Best Rule Fits and Iterations to Stability for Two Image Epochs (October and December)

These tables shows several trends. First, fit values tend to be higher for the two-epoch solutions. Furthermore, the two-epoch results almost always converge, while the four-epoch solutions do not (10,000 means that we stopped GA iterations without reaching our stability criterion). We believe that this is due to the large amount of cloud in the May and August images. Although we attempted to reduce the cloud effect by masking out training pixels completely covered by cloud, we could not correct for the spectral distortion caused by partial cloud cover.

Second, for the two-epoch results, the fewer the possible fuzzy numbers, the faster the GA optimization tend to converge, and the higher the fit ratios. Fewer candidate FNs means that the "gene pool" is less diverse. The best solutions should thus be found more quickly. On the other hand, a rule in which there are only three possible FNs per band will not discriminate as well between pixels that do and do not belong to the class; it is less specific.

We used the rule sets from the various conditions above to classify our evaluation data set. The results are shown in Table 3. These results confirm the notion that the four-epoch rules are not reliable. Percent correct for individual classes are mostly quite low for the four-epoch classifications, and the Kappa coefficients, which take into account errors of both omission and commission, are poor. Results from the two-epoch rule sets are more encouraging, especially for water and forest classes, but the accuracy of rice classification is lower than the other classes.

The research described here is currently in progress. We want to examine several modifications to our algorithms to try to improve fit values and classification accuracy. First, we will consider competitive training, in which all training pixels are tested against all rules. Incorrect assignments will reduce the fit for a rule. Currently, rules for each class are considered separately; a rule that is chosen as a good fit for one class may also create confusion errors with other classes. Second, we want to investigate alternatives to our fit ratio criterion for rule goodness. This measure has several weaknesses. It defuzzifies the DOM at an early stage of the processing, throwing away information about rules that might fit almost as well. Furthermore, it gives inordinate weight to rules that produce high fit values for a very small number of training pixels.

Epoch	*FN*	*% Correct Rice*	*% Correct Forest*	*% Correct Water*	*% Correct Urban*	*Kappa Overall*
4	3	26.56	48.01	8.02	39.26	0.069
	4	19.32	58.55	93.89	28.27	0.341
	5	32.88	86.87	39.08	29.01	0.315
	6	17.03	69.08	80.76	47.53	0.389
2	3	63.28	98.70	83.97	73.95	0.740
	4	62.27	98.96	96.79	70.12	0.769
	5	53.11	97.58	96.79	70.99	0.738
	6	61.80	84.97	99.70	52.47	0.673

Table 3: Classification Results Applying Rules to Evaluation Pixels

Finally, we want to classify the entire image with our best rule sets, and compare the results to maximum likelihood classification. Since the fuzzy rules allow incorporation of multi-temporal data and support multiple spectral patterns for a single conceptual class, we expect the accuracy to be higher than for maximum likelihood. Of course, limitations in our training data (such as digitizing errors and clouds) will negatively effect both the fuzzy-rule-based and the maximum likelihood results.

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