A Neural Network Method for Land Use Change Classification, with Application to the Nile River Delta

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Abstract

Detecting and monitoring changes in conditions at the Earth's surface are essential for understanding human impact on the environment and for assessing the sustainability of development. In the next decade, NASA will gather high-resolution multi-spectral and multi-temporal data, which could be used for analyzing long-term changes, provided that available methods can keep pace with the accelerating flow of information. This paper introduces an automated technique for change identification, based on the ARTMAP neural network. This system overcomes some of the limitations of traditional change detection methods, and also produces a measure of confidence in classification accuracy. Landsat thematic mapper (TM) imagery of the Nile River delta provides a testbed for land use change classification methods. This dataset consists of a sequence of ten images acquired between 1984 and 1993 at various times of year. Field observations and photo interpretations have identified 358 sites as belonging to eight classes, three of which represent changes in land use over the ten-year period. A particular challenge posed by this database is the unequal representation of various land use categories: three classes, *urban, agriculture in delta,* and *other*, comprise 95% of pixels in labeled sites. A two-step sampling method enables unbiased training of the neural network system across sites.

Index terms – Neural network, ARTMAP, Landsat Thematic Mapper TM, change detection

Introduction

Change classification is the process of identifying state transitions of an object or phenomenon observed over time [1]. A method that uses remote sensing data for change detection or identification needs to be able to distinguish significant variables such as radiance and local texture from distractors such as atmospheric conditions, illumination, viewing angle, and soil moisture. In addition, changes of interest need to be separated from temporal variations in seasons, weather, tides, or night and day. A number of researchers have developed change detection methods for remotely sensed satellite data [2]. However, these methods often do not take full advantage of the information available in the images.

An early review by Singh [1] describes simple image differencing and thresholding, principal component analysis (PCA), and change vector analysis (CVA). These methods typically estimate change on the basis of linear combinations of spectral bands in the input image [3]. Some of the methods (e.g., PCA) use statistical properties of the image to extract change components based on the assumption that image variations caused by changes in the states of objects are different from variations caused by extraneous sources. Image classification is frequently used for change detection, either by comparing independent classifications from two or more dates or by making multidate classifications. Other traditional methods, such as those based on differencing images of derived indices, including NDVI, monitor a single image index to estimate change in the landscape. Neural networks that can utilize large quantities of on-line information from multiple high-dimensional sources have potential to significantly improve change detection methodologies.

The question of which method is best suited to a given problem is complicated by the many types of changes that can occur in landscapes and how those changes are manifested in images. A taxonomy of landcover change might begin by separating landcover changes that are *continuous* from those that are *categorical*. In *continuous* landcover changes, the amount or concentration of some attribute of the landscape is measured as a continuous variable. Examples include changes in forest attributes such as vegetation cover, basal area, and leaf area index. The goal of change detection would here be to track the change in a given quantity through time. Continuous change detection methods include image differencing, change vector analysis [4], principal component analysis [5], multitemporal Gramm-Schmidt orthogonalization [6], and some neural networks [7-9].

Categorical change monitors temporal variations in landcover or land use categories, including descriptors of deforestation, urbanization, expansion of agriculture, and reforestation. Methods to identify categorical landcover change include post-classification comparisons and multidate classification [10], and the use of thresholds in combination with image differencing [11]. Abuelgasim et al. [12] introduced a Change Detection Adaptive Fuzzy (CDAF) network for environmental change detection and classification to monitor landcover changes resulting from the Persian Gulf War. This ARTMAP-based neural network assesses quantitative change in class likelihood or class intensity within a region.

Lenney et al. [13] used a multitemporal NDVI thresholding method to classify land use changes in the Nile River delta. This labor-intensive technique required a great deal of hand crafting and expertise. The present article develops a land use change classification methodology that employs an ARTMAP neural network classifier to automate change identification across a sequence of images. These images need not be taken under uniform seasonal, atmospheric, or illumination conditions, and sensor calibration need not be consistent across the sequence. The ARTMAP change classification system overcomes inconsistencies by learning to identify the multidate spectral signatures of image pixels. It also uses internal measures to estimate confidence in classification accuracy.

ARTMAP has previously been shown to be an effective tool for landcover classification of individual images [14-16]. A straightforward extension of this method might analyze landcover change by first establishing categorical classifications for each date. Postclassification comparisons of single-date class labels would then show how landcover had changed during the study period. Unfortunately, such a straightforward method gives poor results, since errors in single-date classifications are compounded when multiple images are considered [1].

Multidate classification combines spectral bands from a series of dates to form a single spectral signature. This method does not rely on single-date classifications, but rather constructs a classifier system to extract spectral signatures that differentiate constant land use from changing land use. Multidate classification has previously been implemented using the K-means technique [12].

A drawback of multidate classification is that the dimension of the input vectors increases with each date represented in the spectral signature. It is therefore desirable to use a classifier system that scales well with high-dimensional data. The ARTMAP neural network is one such system. It has been applied successfully to classification problems involving hundreds of input features [17, 18], as well as to a number of remote sensing landcover classification problems [12, 14-16, 19]. The multidate ARTMAP classification method developed here extends single-date neural network landcover classification methods, using feature vectors from a sequence of ten satellite images as inputs to the neural network system.

ARTMAP Classification of Land Use Change

Data

Ten Landsat TM images of the Nile River delta region and surrounding areas were taken at various times of year between 1984 and 1993. The images form the dataset used by Lenney et al. [13] to classify land use changes based on multitemporal NDVI vegetation index features. The images were geometrically registered and normalized as described in that study. Field data were collected during the summer of 1993 at 88 sites in the study area. Ground truth labels for 270 additional sites were determined by expert image analysis at the Boston University Center for Remote Sensing. This information was combined to form a database of 358 sites. In order to make full use of the limited number of labeled sites, the present study employs four-fold cross-validation. To this end, the database was partitioned into four subsets, each containing 89, 90, or 91 sites. Each of the four subsets was then used, in turn, as a test set to evaluate the performance of an ARTMAP classifier which had been trained on the sites in the other three subsets. Carpenter et al. [15] describe the use of such a cross-validation method to evaluate machine learning systems for remote sensing applications.

Method

Data preprocessing: Prior to performing model selection, input vectors were preprocessed. This preparation consisted of computing transformations and scaling each input component to the interval [0,1].

In order to investigate which input variables would be most useful for ARTMAP neural network identification of land use change categories, several feature sets were prepared using different transformations of the spectral data. The first feature set, SPECTRAL, contained untransformed spectral values from all available spectral bands and dates, for a total of 59 features. The second feature set, BGW, contained spectral data transformed by the Tasseled Cap transformation, which transforms spectral values into coordinates known as Brightness (B), Greenness (G), and Wetness (W) [3, 20]. This linear transformation reduces the dimension of the spectral data from six to three while preserving most of the non-redundant information. It was possible to compute the BGW transformation for only 9 of the 10 dates due to a missing band in one image. Concatenating the BGW data from these 9 dates resulted in a vector of 27 features. The third feature set, NDVI, contained the normalized difference vegetation index values [21]. These were derived from Landsat TM spectral values for each of 10 dates, for a total of 10 features.

Results of prior ARTMAP remote sensing applications suggested that auxiliary variables (pixel location coordinates and geographic zone designations) might also contribute to neural network classification performance [15, 16]. The feature set COORDINATES consisted of the x and y coordinates of each pixel. The feature set ZONE consisted of 4 mutually exclusive indicator variables: the variable corresponding to the designated geographic zone was assigned a value of 1 and all others were assigned a value of 0.

Table 1

2) *Model selection*: For each of the four training/testing partitions, input variables and parameters were selected by evaluation on the training set (Table 1). The Tasseled Cap transformation (BGW feature set) gave the best performance of the three transformations under consideration. Performance also improved when the BGW information was supplemented with geographic zone information and image pixel locations.

Some of the ARTMAP parameters chosen via the cross-validation process were the same for all four partitions. Namely, an option called *instance counting* had a consistently detrimental effect on network performance on this problem, and so was never used; and setting the baseline vigilance parameter $\bar{\rho}$ equal to 0 minimized cross-validated classification error. On the other hand, other system options, including the values of the choice parameter α, the number of networks combined in a voting system, and the duration of training, varied across the four partitions.

3) *Training*: Each ARTMAP network was trained by presenting a random sequence of pixels from the training subset. A major challenge encountered with this database was that the number of pixels in individual sites varied considerably, with sites ranging in size from 4 to 3,440 pixels. Optimal prediction required that small sites be adequately represented in the neural network training set while still exploiting information contained in all pixels of large sites. This goal was achieved via a two-step pixel sampling process. Each training pixel was determined by first selecting a random training site and then selecting a random pixel from that site. The number of times each site was presented, via representative pixels, was determined during the parameter selection phase.

4) *Model testing*: Multiple trained ARTMAP networks were combined to form a committee voting system to improve classification performance and stability [22]. Combining

two or more networks in a committee and making a classification decision on the basis of the average output of these committee members is a proven way of improving the expected performance of neural network systems [23]. The number of voting networks (V) was determined during parameter selection, with each voter weighted equally. The net vote for each class k was taken to be the average analog output across the V voters. A classification decision was made by selecting the class with maximum average output value.

The analog values assigned to pixels by the voting system may be thought of as estimates of their fuzzy membership in various classes. Averaging these values across all the pixels within a site gives membership estimates for the site. The system labels a site as belonging to the class with the maximum fuzzy membership value.

Results and Discussion

Figure 1
Table 2

The present analysis shows how an ARTMAP system can automate the classification of land use change from remote sensing data, to produce the map shown in Figure 1. The *user's accuracy*, defined as the rate of correct classification of test set sites in the ground truth database, averaged 84.6% for the four systems (Table 2), compared to user's accuracy of 87.55% reported by Lenney et al. [13]. The *producer's accuracy*, which adjusts classification rates in proportion to the estimated true fractions of land use change categories in the map, averaged 86.4%. During training, each neural network attempts to optimize user's accuracy, having no knowledge of underlying class probabilities that might enable higher performance on producer's accuracy, such as the 95.85% obtained by Lenney et al. Note, however, that Lenney et al. used a somewhat different assessment dataset and testing methodology.

Table 3
Table 4

Confusion matrices (Tables 3 and 4) provide details of system predictive accuracy for each of the nine output classes. Two of the land use change classes, *urbanization* and *wetlands reclaimed*, had insufficient data for training the neural network. In particular, the entire ground truth dataset included only three *wetlands reclaimed* sites. Not surprisingly, the learning systems consistently failed to identify these sites when they had not been seen at all during training. Like the NDVI-based classification system developed by Lenney et al. [13], the ARTMAP classifier had substantial difficulty distinguishing between *urban* and *reduced productivity* classes. These classes evidently have similar spectral signatures which are easily confused.

Figure 2

A benefit of using ARTMAP neural networks to generate land use change classification maps is that the confidence of classification decisions is readily available via the variables $\square_k$, which provide the system's class probability estimates. A map of classification confidence thus accompanies each primary map of land use changes. Note that large areas in the southwest quadrant of the study area are incorrectly classified by the ARTMAP system as *urban*. Figure 2 shows that the ARTMAP system is least certain of its predictions in these regions. Identifying the areas in which the network's classifications are most likely to be incorrect could be used to guide manual editing of a land use change map. These areas could further be used to guide collection of additional ground truth data.

A key feature of ARTMAP neural network classifiers is that large-scale datasets can be analyzed rapidly and automatically, once enough sample field identifications have been made to form the training set. Virtually every function of the current system, including cross-validated parameter selection, feature set selection, training, testing, and map generation, could be performed by a single integrated software package. The user would need to provide only candidate feature vectors and ground truth training set labels to the system. Thus ARTMAP is a natural choice among candidate systems for development of efficient land use change classification systems.

The methods described in this paper are useful for identifying known types of change and nonchange pixels in the image database. A second type of categorical change detection is the identification of new landcover classes, as discussed by Abuelgasim et al. [12]. The latter type of detection was not within the scope of this study but might is a promising area for further analysis of multidate neural network change detection systems.

Conclusions

Like other change classification methods, the ARTMAP system presented in this paper has attributes that recommend it for certain types of problems. In particular, the multidate ARTMAP neural network classifier accepts high-dimensional spectral signatures containing features from a number of different dates, and produces a confidence map.

The development of new methods for change detection and classification would be accelerated by the parallel development of benchmark databases for training and testing. Such resources would help researchers to compare properties of various systems and to assign different methods to different problem types.

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	Partition 1	**Partition 2**	**Partition 3**	**Partition 4**
Parameters determined a priori				
β (learning rate parameter)	1.0			
ε (match tracking control)	-.001			
p (CAM decision rule power)	1.0			
Parameters determined by cross-validation				
Feature set	BGW + ZONE + LOCATION			
Instance counting?	No			
$\bar{\rho}$ (baseline vigilance)	0			
α (choice parameter)	.0025	.001	.01	.001
V (number of voters)	3	2	5	4
Average number of training presentations of each site via representative pixels	190	70	106	62

Table 1. Parameters of the ARTMAP systems used for four cross-validation partitions.

	Partition 1	**Partition 2**	**Partition 3**	**Partition 4**	**Mean of four partitions**
User's accuracy (%)	89.9	85.4	84.3	79.1	**84.6**
Producer accuracy (%)	88.5	86.9	90.2	80.1	**86.4**

Table 2. Performance of the ARTMAP land use change classifier on four cross-validation partitions.

		Field assessments								
Land use classifications	Sites	Urban	Urbanization	Reduced productivity	Agriculture in delta	Agriculture in desert/coast	Reclamation	Wetlands reclaimed	Other	User's accuracy
Urban	83	**63**	2	10	3		2		3	*75.9%*
Urbanization	1		**1**							*100.0%*
Reduced productivity	20	2	1	**17**						*85.0%*
Agriculture in delta	147	4	6	4	**132**				1	*89.8%*
Agriculture in desert/coast	15					**12**	1		2	*80.0%*
Reclamation	13					2	**10**		1	*76.9%*
Wetlands reclaimed	1								1	*0.0%*
Other	78					1	6	3	**68**	*87.2%*
Total	358	69	10	31	135	15	19	3	76	**Overall** ***84.6%***

Table 3. User's Accuracy Assessment: a composite of the performance of the ARTMAP land use change classifier on the four cross-validation partitions.

		Field assessments								
Land use classifications	Sites	Urban	Urbanization	Reduced productivity	Agriculture in delta	Agriculture in desert/coast	Reclamation	Wetlands reclaimed	Other	Map proportions
Urban	25	**5.055%**		0.689%						*5.744%*
Urbanization	0									
Reduced productivity	4			**1.804%**						*1.804%*
Agriculture in delta	35		2.619%		**43.214%**					*45.833%*
Agriculture in desert/coast	4					**4.411%**				*4.411%*
Reclamation	2					2.223%	**2.223%**			*4.446%*
Wetlands reclaimed	0									
Other	19						3.968%	1.984%	**31.742%**	*37.694%*
True proportions		*5.055%*	*2.619%*	*2.493%*	*43.214%*	*6.634%*	*6.191%*	*1.984%*	*31.742%*	
Producer's accuracy		100.0%	0.00%	72.36%	100.0%	66.49%	35.91%	0.00%	100.0%	**Overall 88.45%**

Table 4: Producer's Accuracy Assessment: This performance assessment is for the system developed for the first cross-validation partition. Table 2 indicates that the performance on this partition is typical.

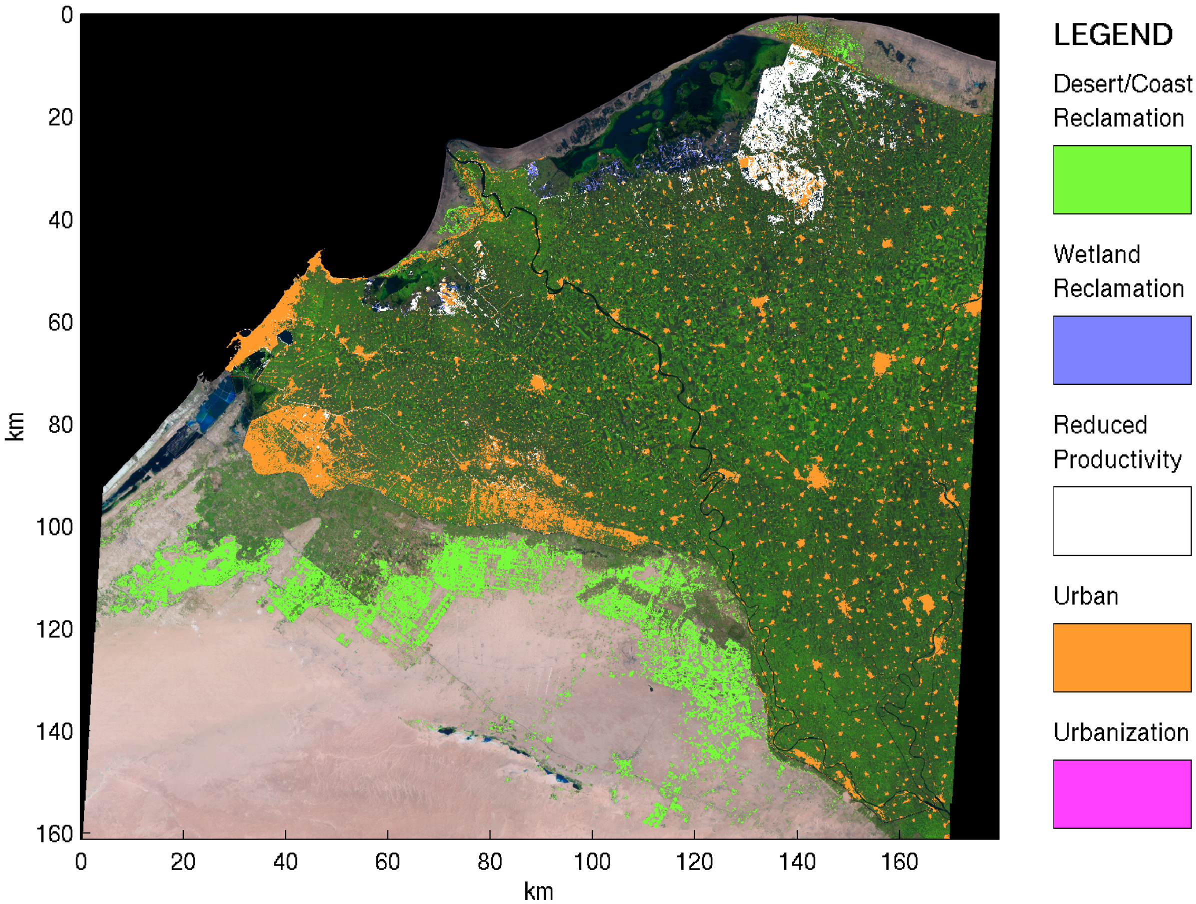

Figure 1. Composite map showing ARTMAP classifications of land use changes, after water had been separated from land via a linear threshold mask. Classes are superimposed on a false color image acquired in 1993. Four systems, each of whose performance has been determined by cross-validated testing, were combined to create this map.

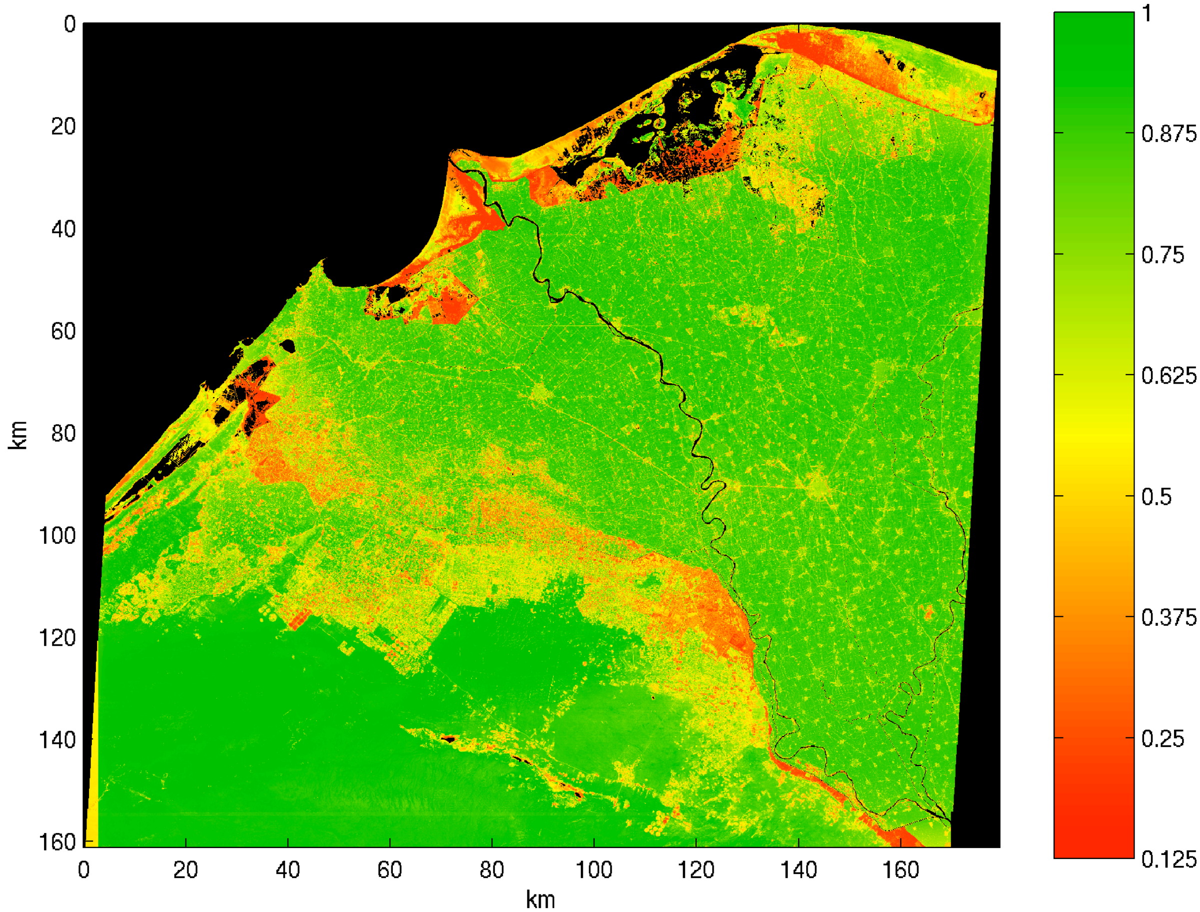

Figure 2. Composite map showing confidence of ARTMAP land use change classifications, with red indicating regions of lowest confidence. Four systems, each of whose performance has been determined by cross-validated testing, were combined to create this map. The confidence measure, which is based on ARTMAP output values, reflects the degree of system confusion between two or more classes.