Comparing ARTMAP Neural Network with the Maximum-Likelihood Classifier for Detecting Urban Change

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Abstract
Urbanization has profound effects on the environment at local, regional, and global scales. Effective detection of urban change using remote sensing data will be an essential component of global environmental change research, regional planning, and natural resource management. This paper presents results from an ARTMAP neural network to detect urban change with Landsat TM images from two periods. Classification of urban change, and, in particular, conversion of agriculture to urban, was statistically more accurate with ARTMAP than with a more conventional technique, the Bayesian maximum-likelihood classifier (MLC). The effect of different levels of class aggregation on the performance of change detection was also explored with ARTMAP and MLC. Because ARTMAP explicitly allows "many-to-one" mapping, classification using coarse class resolution and fine class resolution training data generated similar results. Together, these results suggest that ARTMAP can reduce labor and computational costs associated with assembling training data while concurrently generating more accurate urban change-detection results.

Introduction
The world is undergoing an urban transformation unprecedented in human history. Human settlements, which for tens of thousands of years were mainly rural, are becoming increasingly urban. Globally, urban agglomerations have expanded into the countryside, transforming natural ecosystems, converting agricultural land, and enveloping agrarian communities. Although urban areas cover less than 2 percent of the Earth's total land surface (Grübler, 1994), half of the world's population reside in urban regions, and, according to recent United Nations estimates, 60 percent of global population will reside in urban areas by 2030 (United Nations, 2001). This urban revolution has profound environmental impacts at multiple scales, including local and regional climate change, loss of wildlife habitat and biodiversity, and increases in pressure on water, energy, and agricultural resources. From the provision of clean drinking water to the construction of transportation infrastructure, every aspect of the urbanization process presents huge environmental challenges. Successful monitoring of temporal and spatial patterns of urban change will be imperative to anticipate—and hopefully mitigate—negative environmental, social, and economic impacts of urban development. There is a need to monitor not only urban expansion, but also changes within built-up areas, such as intensification of land use within urban regions. Therefore, the use of remote sensing to detect both expansion and intensification of urban areas will be an essential component of global environmental change research, regional planning, and natural resource management.

Among the myriad studies that have assessed urban land-use change with remote sensing (Barnsley and Barr, 1996; Ridd and Liu, 1998; Zhang and Foody, 1998; Jensen and Cowen, 1999; Masek *et al.*, 2000; Ji *et al.*, 2001; Lopez *et al.*, 2001; Stefanov *et al.*, 2001; Yeh and Li, 2001; Seto *et al.*, 2002), three common issues emerge. First, the detection of urban change often is confounded with variations in vegetation and ground reflectance associated with the agricultural crop cycle of planting, growth, and harvesting. This confusion is pervasive throughout tropical and subtropical regions, in areas with multi-crop fields, and in places where agricultural plot size is small. Fallow or barren fields confound the classification of urban areas or urban change. Accurate estimates of agricultural land loss to urban expansion are vital, yet difficult to acquire, even through annual compendium (Seto *et al.*, 2000). Because agriculture by definition is diverse and includes a variety of crops and cropping patterns, it can be easily misclassified as urban change. In Asia, where a majority of the urban growth in the 21st century will occur, multi-crop fields, agricultural terracing, and small field sizes produce textures and tones that can be difficult to differentiate from patches of urban expansion. Separation of urban change from agricultural phenology has been achieved with the use of synthetic aperture radar (SAR) and fusion techniques (Henderson and Xia, 1997; Kuplich *et al.*, 2000; Dell'Acqua and Gamba, 2001), but there has been limited success using only optical data.

Second, the spatial and temporal patterns of urban features are difficult to characterize. Urban land use occurs along a continuum and is manifested in different shapes, sizes, styles, and trajectories. As such, there is no sole archetype for urban change. Inter- and intra-class spectral and land-cover variability of urban and agriculture types limit the success of a single approach to urban change mapping. For example, urban development in the western United States often involves the complete removal of existing land cover and replacement with concrete (Jensen and Cowen, 1999). This suburban model of urban change usually occurs along roads and other infrastructure development. In contrast, urbanization in

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Photogrammetric Engineering & Remote Sensing
Vol. 69, No. 9, September 2003, pp. 981–990.

0099-1112/03/6909–981$3.00/0

developing countries may not be temporally linear or spatially adjacent. In east and southeast Asian countries, the urbanization experience has been largely defined by *desakota*, or the intensive mixture of agricultural and non-agricultural land uses in a pattern of patch-like mosaics across the landscape (McGee, 1991). It has been argued that the Asian urban growth process is inherently different from the western experience because the former is regionally based while the latter is city-based (Webster, 2001).

Third, urban change may constitute only a small fraction of the total study area, but may be the dominant class of interest. For supervised classification, training data must be a representative sample across all land-cover classes in the study area. For example, given N number of land-cover classes, if all possible combinations of change are possible, the total number of unidirectional change classes is $N(N-1)/2$. In cases where bi-directional change can occur (e.g., forest to agriculture and agriculture to forest), the total number of change classes is $N(N-1)$. A large number of land-cover categories increases the amount of training data required and yet urban change classes may comprise only a small portion. Because broad, aggregated class definitions (e.g., agriculture) are comprised of more detailed classes (e.g., irrigated paddy, winter wheat), class definition and the level of aggregation impact both the labor costs for training data collection and classification accuracy. If classes are very aggregated, this lends itself to "many-to-one" mapping, or the presence of many spectral categories for any single map class. For example, a single agriculture map class must encompass all spectral variations inherent in the suite of possible crop types. The "many-to-one" mapping can complicate classification, because, for each "from" class, there are multiple "change to" classes.

The urgent need for efficient and accurate mapping of urban change at local, regional, and global scales necessitates reliable change detection algorithms that address the aforementioned issues. In this paper, we evaluate an artificial neural network, ARTMAP, to evaluate the following questions: (1) how effective is ARTMAP at identifying urban change from agricultural phenology? (2) how does class resolution affect classification accuracies of urban change? and (3) how does ARTMAP compare to a more conventional technique, the Bayesian maximum-likelihood classifier?

ARTMAP Neural Network

In the last decade, artificial neural networks (ANNs) have gained momentum in remote sensing due to numerous successful applications (Paola and Schowengerdt, 1995; Atkinson and Tatnall, 1997). Neural network models have two important properties: the ability to "learn" from input data and to generalize and predict unseen patterns based on the data source, rather than on any particular *a priori* model. Commonly used neural network models in remote sensing include multilayer perceptron (MLP) (Benediktsson *et al.*, 1990; Benediktsson *et al.*, 1993; Foody, 1997), ARTMAP (Carpenter *et al.*, 1997; Carpenter *et al.*, 1999; Gopal *et al.*, 1999), radial basis function (Rollet *et al.*, 1998), and learning vector quantization (Ito and Omatu, 1999). Results from studies that use MLP models for land-cover change detection indicate that the MLP neural network generates more accurate results than does a traditional maximum-likelihood classifier (Gopal and Woodcock, 1996; Dai and Khorram, 1999). However, the MLP with the backpropagation training algorithm has several limitations, such as finding sub-optimal solutions by getting trapped in a local minima, overfitting, and difficult selection of proper parameters (Foody, 1997). An alternative neural network, ARTMAP, has been used in remote sensing applications for spatial data mining (Gopal *et al.*, 2001; Liu *et al.*, 2001), land-cover mapping (Gopal *et al.*, 1999), and change detection (Gopal *et al.*, 1994). Direct comparisons between ARTMAP and MLP show that the former generates more accurate results than does the latter (Carpenter *et al.*, 1997; Gopal *et al.*, 1999).

The Adaptive Resonance Theory (ART) family of pattern recognition algorithms was developed by Carpenter and Grossberg (Carpenter *et al.*, 1991a; Carpenter *et al.*, 1991b). ART is a match-based learning system, the major feature of which is its ability to solve the "stability-plasticity dilemma" or "serial learning problem," where successive training of a network interferes with previously acquired knowledge. That is, learning a new pattern usually involves replacing or modifying the existing information base. The modification of training data can be done with relative ease if the network can learn all existing patterns in the training data. However, the real world environment likely is more complex and dynamic than the training data. Training data are supposed to represent the possible range of variability within and among land-cover types, but rarely do because they usually only include "pure" archetypes. ART networks maintain the stability of keeping previously learned patterns, while simultaneously being flexible, or plastic, enough to master new patterns.

Among the ART family models, fuzzy ARTMAP is a supervised learning system that has been used widely in many fields. A comprehensive description of the model is detailed in Carpenter and Grossberg (1992) and Carpenter *et al.* (1995) from which the synopsis of the basic architecture of the fuzzy ARTMAP model is drawn (Figure 1). It consists of a pair of fuzzy ART modules, ART_a and ART_b, connected by an associative learning network called a map field. The architecture uses a learning rule that minimizes the predictive error while concurrently maximizing the predictive generalization – or the ability to predict previously unseen patterns. The "hidden units" in ART_a and ART_b are called F_2 nodes, which represent learned recognition categories. Each category, or F_2 node, extracts and generates common spectral properties from input training data.

During the training phase, the ART_a and ART_b modules are given input data a^p and desired output pairs b^p. As the two modules classify the a^p and b^p vectors into various map categories, the map field makes the association between ART_a and ART_b categories. If there is a discrepancy between the observed and predicted values of b^p, a memory search occurs in the ART_a module. The match tracking component within the module increases the sensitivity of the ART_a vigilance parameter, ρ_a, to activate a memory search. A new memory search increases the probability that an ART_a category will generate a better predicted value of b^p. If none of the existing categories can minimize the predictive error or match the statistics of the input vector, a new category is generated. This allows

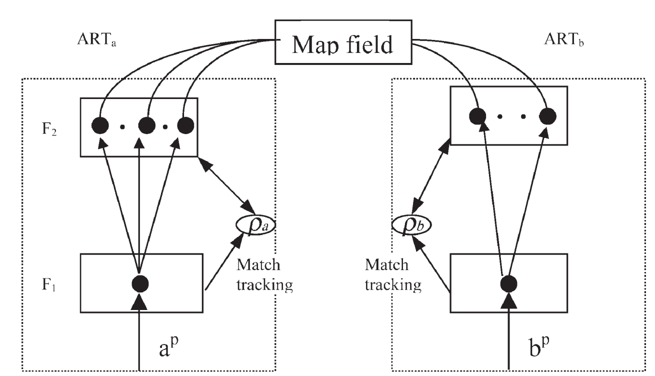

Figure 1. The architecture of fuzzy ARTMAP

intra-class variability to be captured through the creation of new categories. Alternatively, if there is a match, the spectral characteristics of the new input vector will be incorporated to redefine the attributes of the category. This weighting function in effect generalizes the category. Thus, an important attribute of fuzzy ARTMAP is that it can capture both intra- and inter-class variability, facilitating "many-to-one" mapping.

Class Resolution

We define class resolution as the level at which the physical environment is disaggregated into component units. Fine class resolution separates the landscape into detailed, precise categories while coarse class resolution provides broad, sweeping generalizations. In the most extreme example of a map with coarse class resolution, the world could be separated into only two categories: water and land. The process of classification often is an exercise in disaggregation, one in which desired final map categories are disaggregated into their constitutive spectral manifestations. The disaggregation of spectral classes into increasingly finer classes (thereby increasing class resolution) is aimed at capturing the spectral variability inherent in land cover. After classification at fine class resolution, the spectral classes can be aggregated back into the desired map classes. Accuracy assessments usually are performed on final map classes, not spectral classes, and we expect classification accuracy to be higher with coarser map classes than with more detailed map categories.

Study Area and Data

Based on fieldwork and visual interpretation of the images, we identified 809 sites divided among 6240 training and 1567 testing pixels. These pixels were extracted from two Landsat TM scenes of southern China acquired on 10 December 1988 and 03 March 1996. Located between 21°N and 23°N and crossed by the Tropic of Cancer, the region is characterized by a dry season, November through April, and a rainy season, May through October. Persistent cloud cover during the rainy season precludes acquisition of imagery during the summer months. The region is semi-tropical, and evergreen trees are common. Therefore, although the images were acquired during the dry season, there is limited variation in the phenology during the summer months. Class labels for each site were identified by an analyst who visited the study area twice and was familiar with the region.

The images were co-registered using a first-order warping function and were radiometrically corrected using a simple empirical technique that matches the 1996 image to the 1988 image (Song *et al.*, 2001). Prior work in the region revealed that differentiating urban change from agricultural phenology is difficult (Seto *et al.*, 2002). Agricultural plot sizes in southern China are relatively small, usually less than an acre (0.4 ha). The combination of small plots, multi-crops within plots, and varying crop calendars creates complex heterogeneous surfaces that can easily be confounded with urban change. Particularly difficult to differentiate are harvested rice paddies from cleared land for building construction; they are spectrally similar because both are bare plots of soil. As such, southern China provides an exemplary case study to test the efficacy of the ARTMAP neural network for distinguishing urban change from agricultural phenology.

The data were divided among 23 categories, comprised of six stable and 17 change classes (Table 1). Nine of the 17 change classes involve urban change. Recognizing that urban change occurs along a gradient, we define two urban-related classes. The *transition* class represents land in two early stages of urbanization: (1) areas that have been cleared or leveled and are ready for construction, or (2) areas on which building frames or foundations have been constructed. The *transition* class should not be confused with bare or fallow land, but rather are areas in the early stages of urbanization. The other urban class includes built-up areas, which we define as *urban*. Sites that were not *transition* in 1988 but are *transition* in 1996 are labeled as one of the nine urban change classes. The *transition to urban* class represents changes in urban density or urban structure, and is aimed to capture urban intensification. The stable *agriculture* class is comprised of a variety of crops, including citrus orchards, rice fields, and field crops.

TABLE 1. DEFINITION OF FINE CLASS RESOLUTION, TWENTY-THREE CLASSES

Class ID	Class Name	Class ID	Class Name
1	Shrub to Urban	13	Agriculture to Water
2	Water	14	*Agriculture to Urban*
3	Forest	15	*Agriculture to Transition*
4	Agriculture	16	Agriculture to Fish pond
5	*Urban*	17	*Fish pond to Transition*
6	Fish pond	18	*Transition to Urban*
7	*Transition*	19	*Shrub to Transition*
8	Shrub	20	Shrub to Water
9	Water to Agriculture	21	*Forest to Transition*
10	*Water to Urban*	22	Forest to Water
11	Water to Fish pond	23	*Forest to Urban*
12	*Water to Transition*		

Methodology

We aggregated the 23 classes into ten to compare the effects of class resolution on accuracy (Table 2). *Forest* and *shrub* were aggregated into a new class called *natural vegetation*, and the *urban* and *transition* classes were merged into a single *urban* class. The original nine urban change classes were aggregated into four: *water to urban, agriculture to urban, fish pond to transition,* and *vegetation to urban*. Because our interest is urban change, the remaining six non-urban change classes were aggregated into a single *mixed change* class. We will refer to the 23 classes as fine class resolution and the ten classes as coarse resolution.

To evaluate the effect of class resolution on the ability to detect urban change and to assess the accuracy of ARTMAP compared to a more conventional classifier, we conducted four sets of analyses. In the first analysis, the fine resolution (23 classes) data were classified using ARTMAP and the Bayesian maximum-likelihood classifier (MLC) and the results were compared. In the second analysis, the ARTMAP and MLC results from the fine resolution classification were aggregated into the ten coarse classes, and error matrices were constructed. In the third analysis, we classified the coarse resolution data (ten classes)

TABLE 2. DEFINITION OF COARSE CLASS RESOLUTION, TEN CLASSES

Class ID	Class Description
1	Other change classes
2	Water
3	Natural vegetation (Forest + Shrub)
4	Agriculture
5	Urban (Urban + Transition + Transition to Urban)
6	Fish pond
7	Water to Urban (Water to Urban + Water to Transition)
8	Agriculture to Urban (Agriculture to Urban + Agriculture to Transition)
9	Fish pond to Transition
10	Vegetation to Urban (Forest to Urban + Forest to Transition + Shrub to Transition)

using ARTMAP and MLC. We then compared the results between the second and third analyses to assess if there was a difference in classification accuracies between classifying fine resolution data and aggregating the results into coarse classes, or directly classifying coarse resolution data. For both ARTMAP and MLC, the classification accuracies were compared using overall and individual class accuracies.

The ARTMAP and MLC methods' classification accuracies were evaluated three ways. First, we compared the overall accuracy of the two methods by evaluating the percentage of the testing data that were classified correctly. Next, we compared the percentage classified correctly for individual classes. Because we are concerned about the quality of the results from the perspective of the user, not the producer, of the map, this was done using the user's accuracy. Lastly, we calculated Z-statistics using the user's and overall accuracies to test the statistical significance of differences in results between ARTMAP and the MLC. The Z-statistic was calculated as follows:

$$Z = \frac{p_A - p_M}{\sqrt{p_{AM}(1 - p_{AM})\frac{1}{n_A} + \frac{1}{n_M}}} \qquad (1)$$

where p_A is the overall or individual class accuracy of ARTMAP, p_M is the overall or individual class accuracy of the MLC, p_M is the pooled accuracy of the two results, and n_A and n_M are the sample sizes for the ARTMAP and MLC classifications, respectively. The Z-statistic tests the null hypothesis that, for a particular class, the accuracy of the ARTMAP classification is equal to the accuracy using the MLC. Values of Z that exceed the critical threshold indicate that the accuracies are different. The more accurate classification is identified by the sign on Z. A positive sign indicates that results from the ARTMAP classification are more accurate than results from the MLC. The ARTMAP algorithm was written in C and implemented with the Image Processing Workbench (IPW) software program.

Results

Plots of the mean, minimum, and maximum spectral characteristics for the coarse resolution data are shown in Figure 2. Each plot shows the range in digital number (DN) values of a training sample across the six reflective TM bands for the two images. The plots indicate that the *urban*, *agriculture,* and *agriculture to urban* classes have the largest intra-class variance. The large within-class variability in the *agriculture* class effectively causes a large inter-class variability between agriculture and urban. This indicates that conversion of agriculture to urban will be difficult to classify due to the large spectral variability inherent in both classes.

Error matrices were generated with results from the ARTMAP neural network and MLC based on the fine resolution, 23 class data set (Tables 3a and 3b). Z-statistics were calculated on the user's and overall accuracies to evaluate statistically the difference between the ARTMAP and MLC results (Table 4). The overall accuracy of the ARTMAP approach (84.43 percent) is significantly higher ($Z = 6.0$, $p < 0.01$) than that for the MLC method (75.88 percent). In terms of user's accuracy for individual classes, the ARTMAP approach was more accurate ($p < 0.10$) for six out of the nine urban change classes, and significantly higher ($p < 0.05$) for the *agriculture to urban* (85.51 percent versus 58 percent, $Z = 3.808$, $p < 0.01$) and *agriculture to*

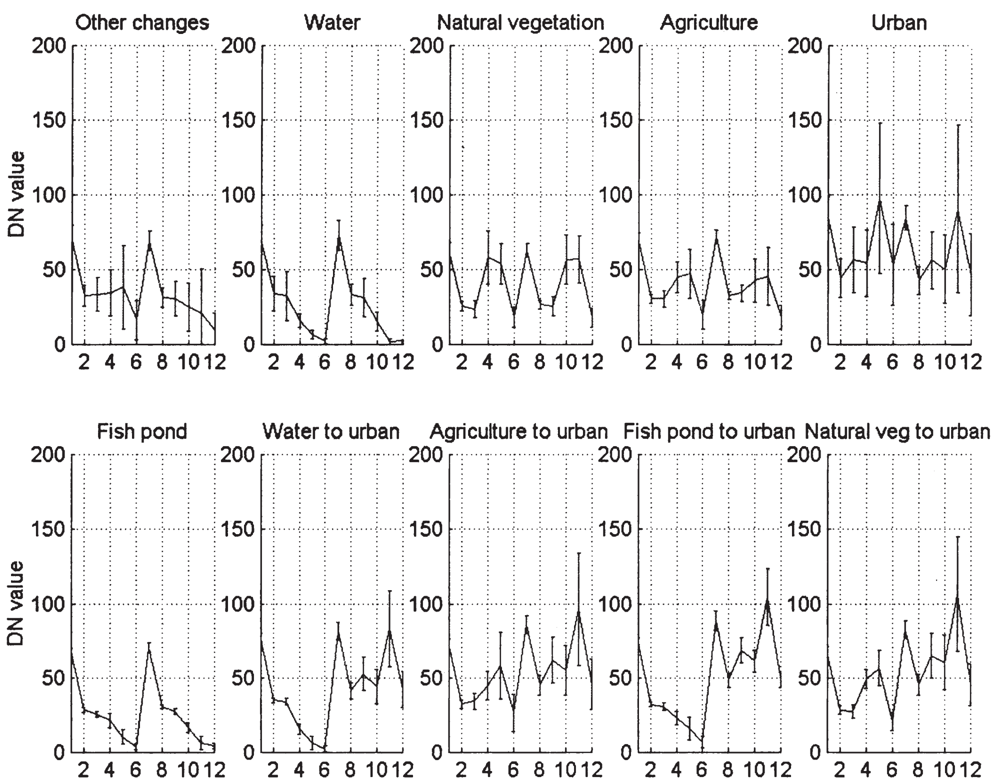

Figure 2. Plots of mean, minimum, and maximum DN values for ten classes (coarse resolution). On the X-axes are TM bands 1-5, and 7 of the 1988 image, and TM bands 1-5, and 7 of the 1996 image. DN values are shown on the Y-axis.

TABLE 3A. ERROR MATRIX COMPARING FINE RESOLUTION (TWENTY-THREE CLASSES) ARTMAP RESULTS WITH REFERENCE CATEGORIES

ARTMAP	Reference Categories																								User's
Results	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	Total	Accuracy
1	48	0	0	7	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	7	63	76.19%
2	0	49	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	51	96.08%
3	0	0	70	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	70	100.00%
4	10	0	0	203	2	6	0	2	0	0	0	0	0	5	0	6	0	0	0	0	0	1	4	239	84.94%
5	0	0	0	2	53	0	0	0	0	0	0	0	0	7	0	0	0	1	0	0	0	0	0	63	84.13%
6	0	8	0	5	0	47	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	64	73.44%
7	0	0	8	0	0	0	53	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	61	86.89%
8	0	0	8	20	0	0	0	74	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	102	72.55%
9	0	0	0	1	0	0	0	0	106	7	0	0	0	2	0	0	0	0	0	0	0	0	0	116	91.38%
10	0	1	0	0	0	0	0	0	0	52	0	2	0	3	0	0	0	0	0	0	0	0	0	58	89.66%
11	0	0	0	0	0	0	0	0	0	0	26	0	0	0	0	0	0	0	0	0	0	0	0	26	100.00%
12	0	0	0	0	0	0	0	0	0	2	0	19	0	0	0	0	5	0	0	0	0	0	0	26	73.08%
13	0	0	0	0	0	0	0	0	0	0	0	0	72	0	0	8	0	0	0	6	0	2	0	88	81.82%
14	1	1	0	0	4	0	0	0	0	0	0	0	0	59	3	0	0	1	0	0	0	0	0	69	85.51%
15	0	0	0	0	0	0	0	0	0	0	0	0	0	5	84	0	0	0	6	0	3	0	0	98	85.71%
16	0	0	0	5	0	0	0	0	0	0	0	0	1	0	0	65	0	0	0	0	0	1	0	72	90.28%
17	0	0	0	0	1	0	0	0	0	2	0	0	0	0	0	1	30	0	0	0	0	0	0	34	88.24%
18	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	37	0	0	0	0	0	39	94.87%
19	0	0	0	0	0	0	0	0	0	0	0	0	0	3	4	0	0	0	57	0	20	0	0	84	67.86%
20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	4	100.00%
21	0	0	0	0	0	0	0	0	0	0	0	0	0	1	3	0	0	0	9	0	73	0	0	86	84.88%
22	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	2	0	25	0	30	83.33%
23	4	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	17	24	70.83%
Totals																								1567	84.43%

TABLE 3B. ERROR MATRIX COMPARING FINE RESOLUTION (TWENTY-THREE CLASSES) MLC RESULTS WITH REFERENCE CATEGORIES

MLC	Reference																								User's
Results	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	Total	Accuracy
1	47	0	0	4	0	0	0	0	0	0	0	0	0	3	4	0	0	0	0	0	0	0	7	65	72.31%
2	0	44	0	6	0	4	0	0	1	0	3	0	0	0	0	3	0	0	0	0	0	0	0	61	72.13%
3	0	0	75	6	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	82	91.46%
4	3	11	0	152	2	2	0	4	0	0	0	0	0	4	0	3	0	0	0	0	0	0	2	183	83.06%
5	0	0	0	1	48	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	50	96.00%
6	0	3	0	5	0	45	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	55	81.82%
7	0	0	8	0	0	0	46	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	54	85.19%
8	1	0	3	28	0	0	0	71	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	105	67.62%
9	0	0	0	9	0	0	0	0	107	0	0	0	0	0	0	0	0	0	0	0	0	0	0	116	92.24%
10	0	0	0	0	0	0	0	0	0	47	0	9	0	1	0	0	0	0	0	0	0	0	0	57	82.46%
11	0	0	0	0	0	0	0	0	0	0	23	0	0	0	0	0	0	0	0	0	0	0	0	23	100.00%
12	0	0	0	0	0	0	0	0	0	16	0	12	0	0	0	0	4	0	0	0	0	0	0	32	37.50%
13	1	0	0	0	0	0	0	0	0	0	0	0	42	0	0	6	0	0	0	0	0	4	0	53	79.25%
14	2	0	0	20	8	0	0	0	0	0	0	0	0	58	4	5	0	2	0	0	0	0	1	100	58.00%
15	2	0	0	0	0	0	0	0	0	0	0	0	0	12	78	6	3	0	2	0	12	0	0	115	67.83%
16	0	1	0	6	2	2	0	0	0	0	0	0	2	7	0	54	0	0	0	0	0	1	0	75	72.00%
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	28	0	0	0	0	0	0	28	100.00%
18	0	0	0	0	0	0	9	0	0	0	0	0	0	0	0	0	0	37	0	0	0	0	0	46	80.43%
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	64	0	16	0	0	86	74.42%
20	0	0	0	0	0	0	0	0	0	0	0	0	25	0	0	4	0	0	0	11	0	4	0	44	25.00%
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	63	0	1	70	90.00%
22	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	1	0	0	0	1	0	20	0	29	68.97%
23	7	0	0	9	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	3	0	17	38	44.74%
Totals																								1567	75.88%

Table 4. Comparison of Fine Resolution (Twenty-Three Classes) ARTMAP and MLC User's Accuracies

Class	User's Accuracy ARTMAP	User's Accuracy MLC	Z-statistic
Shrub to urban	76.19%	72.31%	0.502
Water	96.08%	72.13%	3.363***
Forest	100.00%	91.46%	2.503**
Agriculture	84.94%	83.06%	0.523
Urban	84.13%	96.00%	−2.035**
Fish pond	73.44%	81.82%	−1.088
Transition	86.89%	85.19%	0.263
Shrub	72.55%	67.62%	0.774
Water to agriculture	91.38%	92.24%	−0.239
Water to urban	89.66%	82.46%	1.115
Water to fish pond	100.00%	100.00%	0
Water to transition	73.08%	37.50%	2.701***
Agriculture to water	81.82%	79.25%	0.376
Agriculture to urban	85.51%	58.00%	3.808***
Agriculture to transition	85.71%	67.83%	3.049***
Agriculture to fish pond	90.28%	72.00%	2.821***
Fish pond to transition	88.24%	100.00%	−1.877*
Transition to urban	94.87%	80.43%	1.976**
Shrub to transition	67.86%	74.42%	−0.944
Shrub to water	100.00%	25.00%	3.098***
Forest to transition	84.88%	90.00%	−0.951
Forest to water	83.33%	68.97%	1.297
Forest to urban	70.83%	44.74%	2.011**
Overall accuracy	84.43%	75.88%	6.001***

***Statistically significant at $p < 0.01$
**Statistically significant at $p < 0.05$
*Statistically significant at $p < 0.10$

transition (85.71 percent versus 67.83 percent, $Z = 3.049$, $p < 0.01$) classes. It is apparent from the error matrices that the majority of misclassification was caused by agriculture and agricultural change samples.

Three results from the fine resolution analysis are particularly noteworthy. First, ARTMAP was able to differentiate the conversion from transition to urban with greater accuracy than did the MLC ($Z = 1.976$, $p < 0.05$). This implies that ARTMAP is a promising method for identifying not only urban expansion, but also changes in urban structure and differentiating between older buildings and newer construction. Second, the MLC classified stable urban more accurately than did ARTMAP (96 percent versus 84.13 percent, $Z = -2.035$, $p < 0.05$). This suggests that the MLC method may be more appropriate for applications that aim to identify urban areas and not urban change. Third, both techniques generated similar accuracy with regard to distinguishing stable agriculture (84.95 percent for ARTMAP versus 83.06 percent for MLC, $Z = 0.523$). This last result is surprising. The *agriculture* class has the largest intra-class spectral variability. Because ARTMAP does not assume normality in the data, it was expected to generate more accurate results than the MLC at classifying agriculture.

The results from the fine resolution analysis were aggregated into ten coarse classes (Tables 5 and 6). As expected, the differences in accuracy between the two methodologies were heightened once the results were merged. The overall accuracy of the ARTMAP model (89.92 percent) is still statistically different ($Z = 3.855$, $p < 0.01$) from the MLC method (85.39 percent), although aggregation of the results improved the overall accuracy for MLC (9.51 percent) more than for ARTMAP (5.49 percent). The ARTMAP approach was expected to, and did, produce more accurate results than the MLC for the *agriculture to urban* class ($Z = 3.109$, $p < 0.01$), which was a combination of the *agriculture to urban* and *agriculture to transition* classes from the fine resolution analysis.

For the coarse-resolution, ten-class data set, error matrices and Z-statistics (Tables 7 and 8) show that ARTMAP also generated significantly more accurate classification results

Table 5. Error Matrices Comparing Aggregated Fine Resolution (Twenty-Three to Ten Classes) ARTMAP and MLC Classification Results with Reference Categories

ARTMAP Results	Reference Categories 1	2	3	4	5	6	7	8	9	10	Total	User's Accuracy
1	321	0	0	6	0	0	7	2	0	0	336	94.72%
2	2	49	0	0	0	0	0	0	0	0	51	96.08%
3	0	0	152	20	0	0	0	0	0	0	172	87.79%
4	7	0	2	203	2	6	0	5	0	14	239	84.81%
5	0	0	8	2	146	0	0	7	0	0	163	90.12%
6	4	8	0	5	0	47	0	0	0	0	64	74.29%
7	0	1	0	0	0	0	75	3	5	0	84	88.37%
8	0	1	0	0	5	0	0	151	0	10	167	84.27%
9	1	0	0	0	1	0	2	0	30	0	34	88.57%
10	0	0	0	10	0	0	0	12	0	235	257	90.21%
Totals											1567	89.92%

MLC Results	Reference Categories 1	2	3	4	5	6	7	8	9	10	Total	User's Accuracy
1	312	1	0	15	2	2	0	7	0	1	340	91.76%
2	7	44	0	6	0	4	0	0	0	0	61	72.13%
3	0	0	150	34	0	0	0	0	0	3	187	80.21%
4	3	11	4	152	2	2	0	4	0	5	183	83.06%
5	0	0	8	1	140	0	0	1	0	0	150	93.33%
6	2	3	0	5	0	45	0	0	0	0	55	81.82%
7	0	0	0	0	0	0	84	1	4	0	89	94.38%
8	11	0	0	20	10	0	0	152	3	19	215	70.70%
9	0	0	0	0	0	0	0	0	28	0	28	100.00%
10	0	0	0	13	0	0	0	15	0	231	259	89.19%
Totals											1567	85.39%

TABLE 6. COMPARISON OF AGGREGATED ARTMAP AND MLC USER'S ACCURACIES

Class	User's Accuracy		
	ARTMAP	MLC	Z-statistic
Other change	94.72%	91.76%	1.530
Water	96.08%	72.13%	3.363***
Natural vegetation	87.79%	80.21%	1.949*
Agriculture	84.81%	83.06%	0.487
Urban/Transition	90.12%	93.33%	−1.026
Fish pond	74.29%	81.82%	−0.985
Water to urban	88.37%	94.38%	−1.414
Agriculture to urban	84.27%	70.70%	3.109***
Fish pond to urban	88.57%	100.00%	−1.848*
Vegetation to urban	90.21%	89.19%	0.382
Overall accuracy	89.92%	85.39%	3.855***

***Statistically significant at $p < 0.01$
**Statistically significant at $p < 0.05$
*Statistically significant at $p < 0.10$

than did the MLC in terms of overall accuracy ($Z = 4.768$, $p < 0.01$). Perhaps the most important result from the coarse resolution analysis is that the ARTMAP model has significantly higher accuracies than does the MLC approach for the *agriculture* (89.35 percent versus 78.7 percent, $Z = 4.357$, $p < 0.01$) and *agriculture to urban* (90.27 percent versus 78.7 percent, $Z = 2.672$, $p < 0.01$) classes.

To assess the effects of class resolution on urban change detection, we compared the classification results from the aggregated and coarse resolution data (Table 9). In terms of overall accuracies, the results indicate that there is no significant difference between using fine or coarse resolution classes for either the ARTMAP or MLC approach. One interesting result is that, for the *agriculture* class, the ARTMAP approach generated more accurate ($p < 0.10$) results with coarse class resolution training data (90.27 percent) than with the fine resolution training data (84.81 percent). One possible explanation is that the ability of ARTMAP to distinguish both intra- and inter-class variability means that it can assess spectral differences with greater precision than an analyst who divides the data set. The reverse is true for the classification of *agriculture* using the MLC method, where the fine resolution training data produced more accurate ($p < 0.05$) results (83.06 percent) than did the coarse classes (74.79 percent).

Finally, an assessment of the F_2 categories generated from ARTMAP indicates that the neural network produces more spectral categories when given fine resolution data than with coarse resolution data (Table 10). ARTMAP neural network trained with 23 classes created more categories than did the network trained with only ten classes. For example, 40 F_2 nodes were generated for class 8 (*agriculture to urban*) using coarse resolution data, but 61 categories were generated using fine resolution classes. Although ARTMAP generated fewer categories with coarse resolution data, the overall accuracy was not statistically different from classification with fine resolution data (Table 9). Indeed, in the only case (*agriculture*) where the accuracy was statistically different ($p < 0.10$) between the two resolutions of input data, there was little difference between the number of F_2 categories generated (28 versus 29). This suggests that ARTMAP can automatically find the patterns of categories regardless of the class resolution of the input data. Because the computational cost of ARTMAP is proportional to the number of F_2 categories, use of coarse class resolution data can increase computational efficiency with very little cost to accuracy.

Discussion

Taken together, the results from this research reveal several trends. First, ARTMAP consistently identifies urban change with greater accuracy than does the MLC approach. This

TABLE 7. ERROR MATRICES COMPARING COARSE RESOLUTION (TEN CLASSES) ARTMAP AND MLC CLASSIFICATION RESULTS WITH REFERENCE CATEGORIES

ARTMAP Results	Reference Categories										Total	User's Accuracy
	1	2	3	4	5	6	7	8	9	10		
1	327	14	0	8	0	0	3	4	0	0	356	91.85%
2	1	34	0	0	0	0	0	0	0	0	35	97.14%
3	0	0	150	20	0	0	0	0	0	0	170	88.24%
4	0	0	4	204	2	7	0	1	0	8	226	90.27%
5	0	0	8	0	145	0	0	6	0	0	159	91.19%
6	6	9	0	3	0	46	0	0	0	0	64	71.88%
7	1	2	0	0	0	0	80	3	4	0	90	88.89%
8	0	0	0	0	6	0	0	151	0	12	169	89.35%
9	0	0	0	0	1	0	1	0	31	0	33	93.94%
10	0	0	0	11	0	0	0	15	0	239	265	90.19%
Totals											1567	89.79%

MLC Results	Reference Categories										Total	User's Accuracy
	1	2	3	4	5	6	7	8	9	10		
1	288	16	1	13	0	1	1	0	0	4	324	88.89%
2	3	33	0	2	0	1	0	0	0	0	39	84.62%
3	0	0	149	36	0	0	0	0	0	4	189	78.84%
4	22	10	4	175	4	3	0	12	0	4	234	74.79%
5	5	0	8	3	144	0	0	5	0	0	165	87.27%
6	2	0	0	5	0	48	0	0	0	0	55	87.27%
7	1	0	0	0	0	0	83	3	4	0	91	91.21%
8	13	0	0	4	5	0	0	133	2	12	169	78.70%
9	0	0	0	0	0	0	0	0	29	0	29	100.00%
10	1	0	0	8	1	0	0	27	0	235	272	86.40%
Totals											1567	84.05%

Table 8. Comparison of Coarse Resolution ARTMAP and MLC User's Accuracies

Class	User's Accuracy ARTMAP	User's Accuracy MLC	Z-statistic
Other change	91.85%	88.89%	1.313
Water	97.14%	84.62%	1.838*
Natural vegetation	88.24%	78.84%	2.383***
Agriculture	90.27%	74.79%	4.357***
Urban/Transition	91.19%	87.27%	1.137
Fish pond	71.88%	87.27%	−2.056**
Water to urban	88.89%	91.21%	−0.521
Agriculture to urban	89.35%	78.70%	2.672***
Fish pond to urban	93.94%	100.00%	−1.348
Vegetation to urban	90.19%	86.40%	1.365
Overall accuracy	89.79%	84.05%	4.768***

***Statistically significant at $p < 0.01$
**Statistically significant at $p < 0.05$
*Statistically significant at $p < 0.10$

Table 9. Comparison of Classification Accuracies from Different Class Resolutions

	Class	User's Accuracy Aggregated (23 to 10 classes)	User's Accuracy Coarse Resolution (10 classes)	Z-statistics
ARTMAP	Other change	94.72%	91.85%	1.502
	Water	96.08%	97.14%	−0.264
	Natural vegetation	87.79%	88.24%	−0.127
	Agriculture	84.81%	90.27%	−1.776*
	Urban/Transition	90.12%	91.19%	−0.330
	Fish pond	74.29%	71.88%	0.307
	Water to Urban	88.37%	88.89%	−0.107
	Agriculture to Urban	84.27%	89.35%	−1.376
	Fish pond to Urban	88.57%	93.94%	−0.776
	Vegetation to Urban	90.21%	90.19%	0.009
	Overall accuracy	89.92%	89.79%	0.118
MLC	Other change	91.76%	88.89%	1.260
	Water	72.13%	84.62%	−1.450
	Natural vegetation	80.21%	78.84%	0.330
	Agriculture	83.06%	74.79%	2.040**
	Urban/Transition	93.33%	87.27%	1.800
	Fish pond	81.82%	87.27%	−0.790
	Water to Urban	94.38%	91.21%	0.820
	Agriculture to Urban	70.70%	78.70%	−1.780*
	Fish pond to Urban	100.00%	100.00%	0.000
	Vegetation to Urban	89.19%	86.40%	0.980
	Overall accuracy	85.39%	84.05%	1.040

***Statistically significant at $p < 0.01$
**Statistically significant at $p < 0.05$
*Statistically significant at $p < 0.10$

Table 10. Number of ARTMAP F_2 Categories Generated for Different Class Resolutions

	Class Label 1	2	3	4	5	6	7	8	9	10	Total
10 classes	14	5	12	28	9	4	5	40	4	39	160
23 classes	52	6	38	29	14	5	9	61	3	47	264

was true for the fine resolution, coarse resolution, and aggregated data. The ARTMAP approach was able to classify various urban land-use changes with 84 to 90 percent accuracy. In our study area, the most complex urban change category is the *agriculture to urban* class. In all cases, the ARTMAP approach was able to successfully differentiate urban change from agricultural phenology and it also produced more accurate classifications than did the maximum-likelihood classifier. One possible explanation is that the MLC approach assumes normality in the data, while ARTMAP does not, allowing ARTMAP to better characterize the data set. The large spectral variance within the *agriculture to urban* class generates confusion between it and the *agriculture* class, making accurate characterization difficult. Nonetheless, ARTMAP was able to classify *agriculture to urban* with 84 to 89 percent accuracy. Using the more conventional MLC approach, the accuracies for this class varied between 71 and 79 percent.

One of the strengths of the ARTMAP neural network model is that it explicitly allows for "many-to-one" mapping. This feature is especially suitable for data with large intra- and inter-class variance, such as change from agriculture to urban. In these cases, the large intra-class variance forces ARTMAP to generate additional new categories, all of which are associated with one class. Detailed analysis of the internal structure of ARTMAP indicates that the ability to represent a single class through multiple manifestations can minimize misclassifications (Gopal *et al.*, 2001). For example, if the observed and predicted values of b^p do not match, several new categories will be generated. ARTMAP can then separate the confused, or mixed, categories from categories that are created using "pure" training data. This learning mechanism ensures that only mixed samples will be classified into a mixed category. Pure samples will have very low probability of misclassification.

We anticipated that classification would be more accurate with coarse class resolution than with fine class resolution. Yet, one unexpected result is that class resolution, as defined for our study area and data, does not appear to affect the overall and individual classification accuracies. This was especially the case using the ARTMAP approach, where there were no statistical differences between the classification accuracies using the fine or coarse resolution data. Applying the ARTMAP neural network to coarser class resolution data has two main advantages. First, with coarser data, ARTMAP generates fewer categories. This reduces the computation time required for classification. Second, collection of training data, especially fieldwork, is labor intensive. Hence, the use of coarser resolution training data can reduce both computational and labor costs. Finally, the methodologies tested in this paper were applied only to training data, not the entire image. Further tests will be required to evaluate whether the methodology performs as well when pixels are not as "pure" as the training data.

Conclusions

Efficient and accurate mapping of urban change at multiple scales will be an important component of global environmental change research. Currently, one of the biggest challenges to urban remote sensing is the generation of reliable urban change estimates. Due to intra- and inter-class variability, urban change and urban change from agriculture are difficult to characterize. The main objectives of this research were to evaluate and compare the efficacy of ARTMAP at identifying urban change, and to assess the effects of class resolution on classification accuracy. The most important result from this research is that ARTMAP generated more accurate classifications of urban change and, in particular, urban change from agriculture, than did the Bayesian maximum-likelihood classifier. The overall and individual user's accuracies from the two approaches were statistically different, suggesting that ARTMAP is a superior method for identifying urban change and intensification of urban areas.

The results also indicate that ARTMAP can achieve similar accuracies for urban change using either coarse or fine resolution data. This indicates that the use of coarser resolution training data may increase computational efficiency without compromising accuracy. However, this finding should be taken with caution, because the results are dependent on the study area and definition of classes. Further analysis is required to investigate the extent to which these findings hold true in other regions and for different class definitions.

Acknowledgments

The authors would like to thank Curtis Woodcock and Suchi Gopal for invaluable discussions at earlier stages of the research, and the helpful comments of two anonymous reviewers. This research was supported by a NASA New Investigator Program grant NAG5-10534 to K. Seto.

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