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Project Report

Improving Urban Land Cover Maps through Resolution Merge and Decision-rule Classification

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INTRODUCTION

The Casco Bay Estuary Project in Maine is currently engaged in the environmental monitoring of Casco Bay. Environmental monitoring is important to establish baseline information, assess the current state of the environment, and to detect environmental change. Increasingly, satellite imagery, remote sensing, and Geographic Information Systems (GIS) have become key tools for environmental monitoring. Satellite imagery in conjunction with remote sensing techniques and GIS permit a highly accurate and detailed spatial representation of environmental features.

One task of the Casco Bay Estuary Project is to describe and delineate urban land cover. Urban land cover is characterized by spatially heterogeneous areas that contain a large variety of small structures at a high spatial frequency (Jensen 1983). These land cover or land use types include single family housing, multiple family housing, commercial buildings, industrial areas, transportation networks, parking lots, parks and lawns. The spatial resolution of a multispectral satellite image may be too coarse to accurately delineate such land cover types. In addition, urban structures are often indistinguishable from natural structures solely based on spectral reflectance. An example of this problem would be the similarity in reflectance of the concrete of buildings and intertidal rock.

In 1995 the company Earthsat produced a land cover classification from a Landsat Thematic Mapper (TM) scene for the Casco Bay Estuary Project. Unsupervised classification was used to create a land cover map with 25 classes, including 4 urban land cover types (high density urban, dense urban, moderate density urban, and residential/bare). Due to the limited resolution of Landsat TM (pixels 30m on a side), and the spectral similarity between some urban surfaces and other types of bare surfaces, the classification did not differentiate between urban and commercial land cover types.

The Spatial Analysis Lab at the Smithsonian Institutions' Conservation and Research Center entered into a contract with the Casco Bay Estuary Project to develop and produce an improved land cover classification for urban land cover classes in Casco Bay. This classification included the merging of data from different satellite sensors, image processing, unsupervised classification, selection of training sites, evaluation of classification, ground truthing, and an

accuracy assessment. In addition, we performed decision-rule based classification using the results of our image classification and ancillary data. The major steps in the production of this improved land cover map included:

1. **Resolution Merge:** Multiple sensors can be used to produce a composite image that allows for more detailed interpretation. We merged a Landsat Thematic Mapper and a SPOT Panchromatic image to combine the spatial content of the high resolution SPOT Panchromatic image (10m on one side) with the spectral information from the Landsat Thematic Mapper image.

2. **Multispectral Classification:** We used an image processing system to perform a classification on the merged image.

3. **Decision-rule Classification:** This form of classification employs the registration of image data with ancillary data sets. After visual interpretation and comparisons between satellite data and ancillary data sets, we developed rules in a decision tree that were applied during classification.

4. **Accuracy Assessment:** In this analysis, we used data from the field to evaluate the classification, and to determine the classification accuracy for urban classes.

The following four sections explain the techniques and discuss the results for each one of the four major steps. To keep data sets manageable, all analyses were performed on a subsetted data set that contained the City of Portland and surrounding lands. This approach allowed us to evaluate each technique before applying it in the final classification. In the fifth section, we discuss the results of the final classification. All image processing and remote sensing analyses presented in this report were performed with ERDAS IMAGINE software. We used ARC/INFO software for all GIS operations and analyses and TRIMBLE software for the registration and differential correction of ground truthing points.

SECTION 1: RESOLUTION MERGE

INTRODUCTION

In a resolution merge a satellite image with high spatial resolution is merged with a satellite image that has a lower spatial resolution but spectral characteristics that are desirable for the surfaces structures of concern. Resolution merge techniques can be divided into different categories: 1) techniques that retain as much of the spectral information as possible, and 2) techniques for display that increase visual interpretability of the image. In current remote sensing, research focuses on resolution merge techniques that preserve most of the spectral information (Chavez et al. 1991). These techniques include: forward-reverse Principal Components transform (PCA transforms), multiplicative transform, and forward-reverse Intensity Hue Saturation transform (IHS transforms).

We merged a SPOT Panchromatic image with a Landsat Thematic Mapper image. Landsat TM sensors have six bands with a spatial resolution of 28.5 m (Figure 1). The SPOT Panchromatic sensor has one broad band with a very high spatial resolution of 10 m (Figure 2). Combining these two images to yield a six band data set with 10 m resolution combines the best characteristics of both sensors. For the remainder of the report the Landsat Thematic Mapper and the SPOT Panchromatic image are referred to as TM and SPOT, respectively.

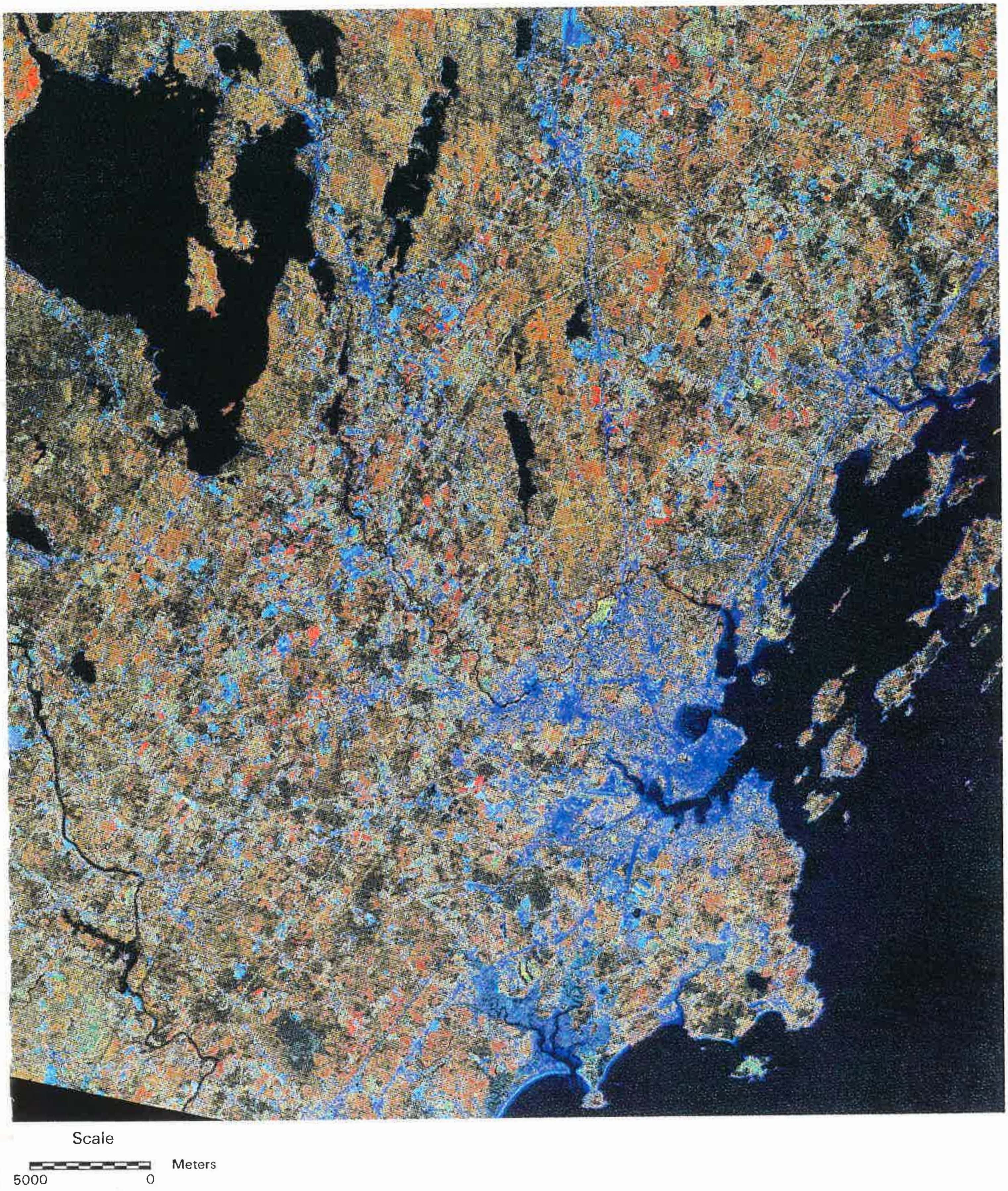


Figure 1. Color composite of Landsat TM image (bands 4, 5 and 3) displaying the Casco Bay Area.

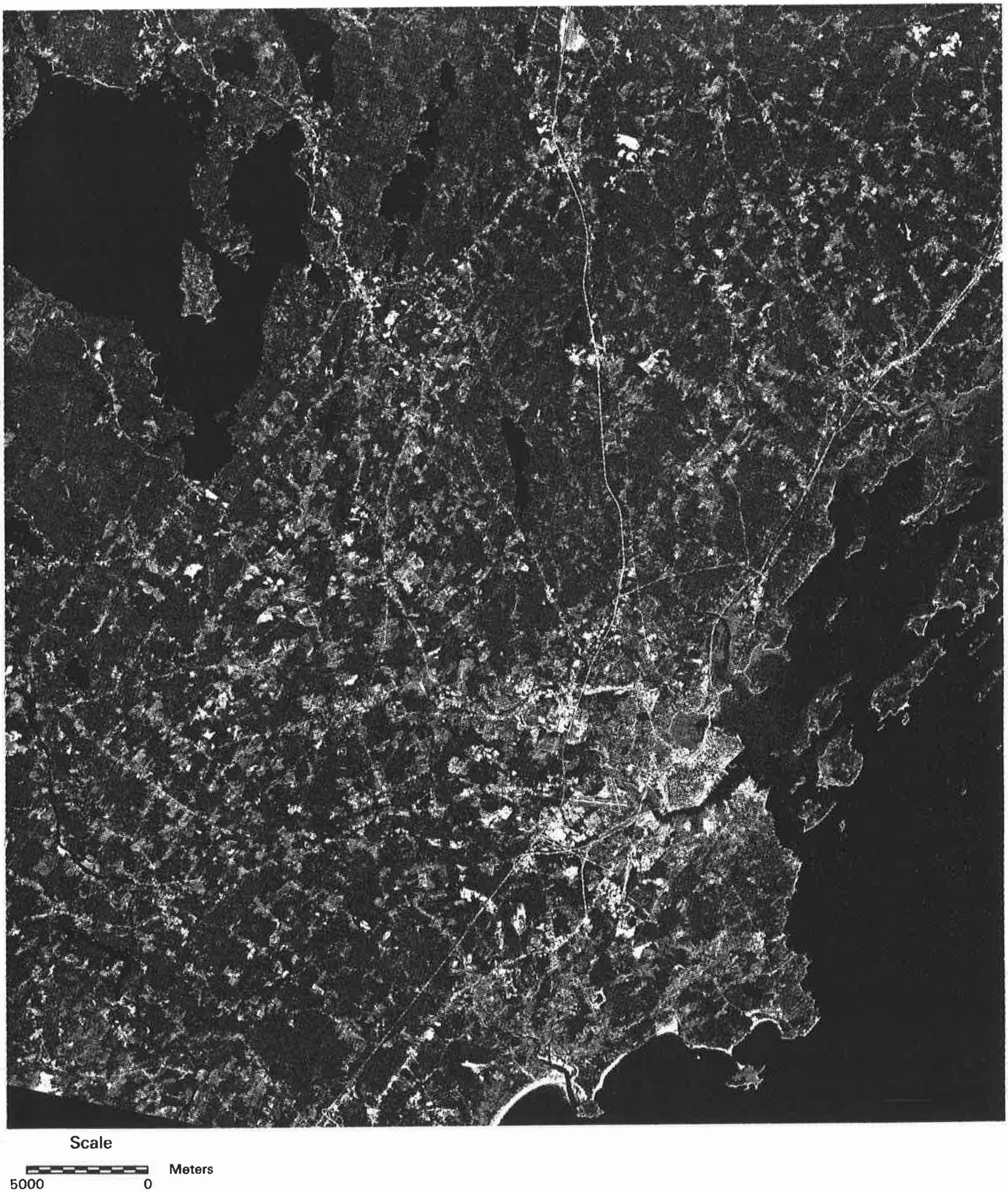


Figure 2. SPOT Panchromatic Image displaying the Casco Bay Area.

Data Sources

The TM and SPOT images used in our analyses were previously rectified and geocoded to a Universal Transverse Mercator projection and the North American Datum 1927. The TM image has a spatial resolution of 30 m and consists of seven spectral bands. We subsetted the TM image to 6 layers leaving out the thermal infra-red layer.

The SPOT image has a spatial resolution of 10 m. For this study we only utilized the panchromatic band of a SPOT scene, which registers reflectance in the visible range of the spectrum.

Image Preprocessing

Georeferencing: In order to merge the TM with the SPOT data, the TM image needed to be resampled to a 10 m resolution and cross-referenced to the SPOT image using ground control points. We located five ground control points in the TM image, used them as source coordinates and cross-referenced them to five pixels in the SPOT image. After computing a first-order transformation matrix, we resampled the TM image with a nearest neighbor algorithm. The accuracy of the cross-referencing and resampling was improved until we achieved a root mean square error of below 1.0.

Subsetting: The TM and SPOT data set were reduced in size to restrict analyses to parts of the data sets that covered a common geographic area. Because of the large data volume, we also decided to conduct preliminary analyses on a subsetted image that covered the south-east quadrant of the study area, including Portland and surrounding areas. We chose the Portland area of the images because we were most concerned with the differentiation of urban land cover. All analyses were first conducted on the south-east quadrant and then subsequently applied to the full data set. This approach kept data sets manageable in the initial analytical processes and allowed us to create and evaluate spectral signatures before applying them to the entire data set.

Resolution Merge Techniques

We employed three different techniques: Principal Components, Intensity Hue Saturation, and Brovey Transform. The first two techniques assume that the intensity component (Principal Component 1 or Intensity) is spectrally equivalent to the SPOT Panchromatic image, and that all

the spectral information is contained in the other Principal Components or in Hue and Saturation. Since SPOT data do not cover the full spectral range that TM data do, this assumption does not strictly hold true.

Principal Components Transform: Principal Components Analysis is used to analyze the variance in the 6 spectral bands, excluding the thermal band. The first Principal Component (PC-1) is removed and its minimum and maximum are determined. In the next step the SPOT image is remapped so that the histogram of its spectral values is constant, but it is in the same numerical range as PC-1. The high resolution image is substituted for PC-1 and the Principal Components Analysis is then reversed.

Intensity Hue Saturation Transform: This method uses three bands of the lower resolution data set and transforms these data into Intensity Hue Saturation (IHS) space. IHS is an alternate color space to the normally used three additive colors red, green and blue (RGB). RGB is commonly used in image processing systems that have three color guns. In IHS the three positioned parameters are Intensity, Hue, and Saturation. This system presents colors more closely to the way they are perceived by the human eye. Intensity is the overall brightness of the scene (like PC-1), Saturation represents the purity of color, and Hue is representative of the dominant wavelength of the pixel. As in the PCA transform, the SPOT image is remapped so that the histogram of its spectral values is constant, but it is in the same numerical range as the Intensity band. Following this contrast stretch the SPOT data replaces the Intensity band and a RGB transform is applied that reprojects the merged image into RGB color space.

Brovey Transform: This technique uses all bands of the TM image and multiplies the data from the high resolution image with the fraction between the spectral values for the respective band and the sum of all spectral values for all other bands. Such simple arithmetic and multiplicative approaches to resolution merge have been demonstrated to retain most of the spectral information contained in the TM imagery. The Brovey Transform follows the following formula:

$$[DN_{B1}/(DN_{B1}+DN_{B2}+DN_{Bn})] \times [DN_{\text{high res. Image}}] = DN_{B1\_new}$$
$$[DN_{B2}/(DN_{B1}+DN_{B2}+DN_{Bn})] \times [DN_{\text{high res. image}}] = DN_{B2\_new}$$

etc.

Results of the Resolution Merge and Comparison of Techniques

For the classification of urban land cover, the merged image should display urban classes that can be easily differentiated using classification algorithms and visual interpretation. Ideally the resolution merge should add spatial information without distorting spectral information contained in the low resolution image. Visual interpretation and unsupervised classification were performed on merged images produce by the PCA, IHS, and Brovey transform, to evaluate and compare their usefulness for image enhancement (Figure 3). We found that urban land cover was more easily differentiated in images produced by the Brovey transform than images produced by the other techniques. The PCA transformed image was good for differentiation of vegetation and forest types but lacked detail in the urban areas. The IHS transformed image showed considerable distortions of the spectral information and was also visually not as enhanced as the other two. Based on these observation, we decided to use the Brovey transform for the resolution merge and all subsequent analyses.

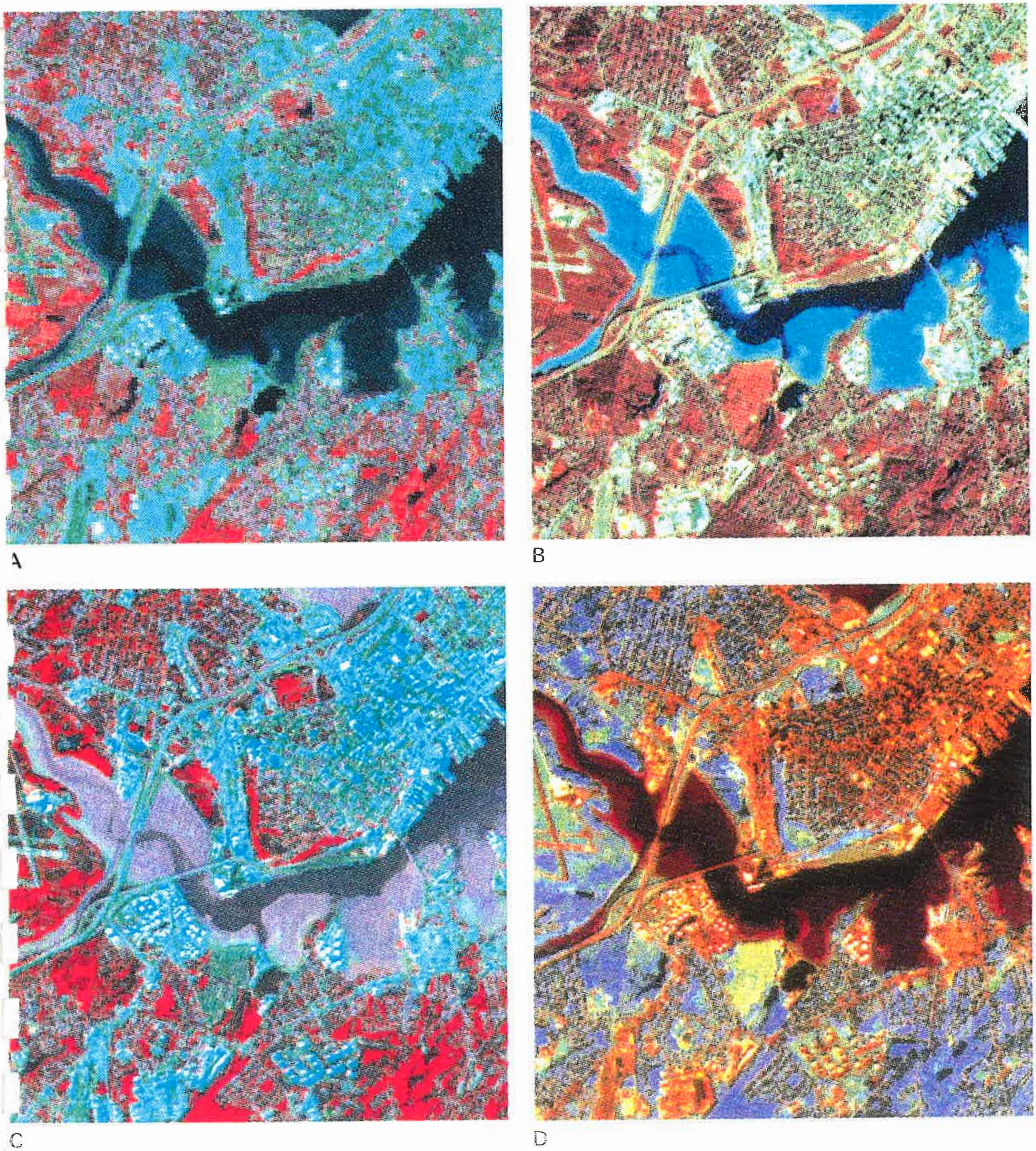


Figure 3. Visual comparison of resolution merge techniques. A = color composite of original Landsat TM image, B = resolution merge with IHS transform, C = resolution merge with PCA transform, D = resolution merge with Brovey transform.

SECTION 2: MULTISPECTRAL CLASSIFICATION

INTRODUCTION

In multispectral classification, pixels of an image are assigned to a predefined number of categories based on their data values for all bands used in the analyses. Statistical, mathematical, or context criteria can be used for this sorting process. Commonly, spectral reflectance is employed in the classification of multispectral images. Statistics are derived from spectral characteristics of all pixels in an image. These statistics can then be used to detect specific spectral patterns. In subsequent analyses the computer is trained to recognize these patterns in the data and assign pixels to the appropriate categories. This training can be performed in a supervised or unsupervised method. We used an hybrid classification approach in which unsupervised training and supervised classification were utilized.

CLASSIFICATION

Unsupervised Training: Unsupervised training was performed using an ISODATA clustering algorithm that divided pixels into classes based on the minimum Euclidian distance between their spectral values (ERDAS Field Guide 1991). For analyses on the south-east quadrant of the scenes we created 40 initial classes using ISODATA. These classes were then evaluated, merged and assigned to specific land cover categories. Data sources used for the assignment of a class to a land cover category included ground-truth points that were collected in November 1995, the land cover map produced by Earthsat and other available ancillary data sets.

Ground Truthing and Collecting Training Pixels: In November 1995, we ground truthed 120 locations in the Casco Bay area. Points for ground truthing were selected from the unsupervised classification of the TM image. These points were distributed among statistical clusters. We used stratified random sampling to select points in urban classes and classes that are spectrally similar such as sand beaches, bare/sand, gravel, intertidal rock, rock gravel, scrub shrub, and wetland classes. In the field we were able to use the TM image and topographic maps to find the points.

During ground truthing each point was assigned to a land cover class according to a classification scheme explained later in this chapter. To determine the exact geographic location of each point,

we used a Global Positioning System (GPS). The Maine Surveyor Service in Yarmouth, Maine, operated a community base station at the same time, and provided us with the data for the differential correction of our GPS rover files. The differential correction was performed at the Spatial Analysis Lab, and increased the accuracy of GPS to the meter level.

Signature Statistics and Classification: Information from ground truthing was entered into a database and attached to training pixels. Training pixels in urban areas were used to calculated statistics for spectral signatures. After creating spectral signatures for urban classes we performed a supervised classification applying a maximum likelihood decision rule. This rule determines the probability that a pixel belongs to a particular class. Maximum likelihood decision rules are based on the assumption that probabilities are equal among classes and that the input bands have a normal distribution (ERDAS Field Guide 1992).

Classification Scheme

The classification of satellite imagery to produce land cover maps should be performed with a set of target classes in mind. Such a classification has to be tailored to the available data sources, the future use of the land cover map, and the earth features of interest. Our classification scheme followed closely the scheme used for the production of the first land cover map by Earthsat. In addition, we refined classes and added higher level categories for urban land cover (Table 1).

In principle, our classification scheme represents a modification of schemes previously suggested by the United States Geological Survey (Anderson et al. 1976). This classification system was devised to identify land use and land cover from remote sensor data. It effectively mixes two different approaches to derive as much information as possible from remote sensor data. Land cover classification deals with the type of feature present on the earth surface. Land use is related to the human activity or economic function within areas and can not always be distinguished from remote sensor data. The classification system we created has three hierarchical levels (I, II, III) of which only levels II and III are displayed in the final land cover maps.

Table 1. Land Use/Land Cover Classification Scheme

Level I	Level II	Level III
Urban	Residential	Low Density Residential
		Residential
		High Density Residential
	Commercial	Commercial Buildings
		Commercial Bare
	Mixed Industrial/Commercial	
	Roads	
Barren Land	Sand Beaches	
	Mud Flat	
	Bare/Sand	
	Exposed Rock or Gravel	Gravel
		Intertidal Rock
	Mixed Barren	Gravel/Rock
Rangeland	Grassland	
	Scrub Shrub	
	Emergent	
Forest Land	Deciduous Forest	Hardwood
		Hardwood/Beech
	Coniferous Forest	Softwood/Spruce
		Softwood/Pine
		Softwood/Pine/Wet
	Mixed Forest Land	Hardwood Mix
		Softwood Mix
		Hardwood Tolerant
Wetland	Forested Wetland	
	Non-forested Wetland	Marsh
		Marsh/Grassland
		Scrub Shrub Wet
Water	Deep Water	
	Turbid Water	
	Shallow Water	

As suggested by the U.S.G.S., we used a classification system in which categories can be divided in higher level categories and subcategories. In addition, higher level categories can be aggregated into lower level categories. We made an effort to differentiate urban land cover as finely as possible. Therefore we defined the following level III urban classes in our classification scheme:

Low Density Residential: Single family houses spaced over 30 m from each other. This includes single family houses in urban as well as in rural areas. The class can occur by itself in outlying areas, which indicate farm housing. It is also frequently seen along back streets in urban areas.

Residential: Single family houses spaced between 5 m and 30 m apart. This class is predominantly found in urban areas. It is usually associated with High Density Residential.

High Density Residential: Single and multiple family houses adjoining one another or in very close proximity. Found in the downtown areas of Portland.

Commercial Buildings: A class which is clearly defined by medium to large-sized commercial buildings. No overlap with asphalt parking lots or other high reflectance industrial buildings occurs. This class can be found along major streets and at major shopping complexes (malls and strip complexes). It is usually found in association with Commercial Bare areas which demarcate it as buildings.

Commercial Bare: A class that encompasses asphalt and other high reflectance surfaces such as parking lots, and paved roofs of buildings. This is a mixed class that can include buildings but usually is restricted to large parking lots found in the downtown area and around shopping complexes.

Mixed Commercial/Industrial: A mixed class that represents large buildings with high reflectance roof tops. These buildings include portions of shopping complexes and large buildings in the downtown Portland area. The class also comprises large industrial complexes in outlying areas.

Results and Discussion

The classification of the initial clusters resulted in 28 classes including six urban classes (Figure 4). We were able to differentiate and delineate urban classes more finely than was done in previous classifications. Much of this is due to the spatial information added by the SPOT image. The classification of heterogeneous areas that have the high frequency of urban structures was especially improved by the resolution merge.

The higher resolution provided by the SPOT image allowed us to more accurately distinguish urban trees and grassy areas from buildings and parking lots. This increase in accuracy becomes very apparent when the original land cover classification of a TM image is compared with the classification produced from the resolution merged image (Figures 4 and 5).

The classification accuracy for classes that have similar spectral characteristics to urban classes is a major limitation for the use of satellite remote sensing in the mapping of urban land use and cover. The resolution merge reduced some of these inaccuracies, but there is still a considerable amount of misclassification for urban classes. An example would be the single family housing pixels in the intertidal zones of the image.

Our project focused on the differentiation of urban classes or sealed surfaces. Due to spectral distortions that were induced by the resolution merge, we were not able to finely distinguish between forest categories and some other vegetation classes. In addition, wet vegetation classes, such as scrub shrub wet and marshland were frequently misclassified as urban.

In summary, we found that the resolution merge increased accuracy and detail for urban classes but caused misclassification for some of the vegetation classes. To resolve these problems we decided to perform a decision-rule classification utilizing other ancillary data.

Figure 4. (Displayed on the next page) Land cover map produced by hybrid classification of resolution merged image.

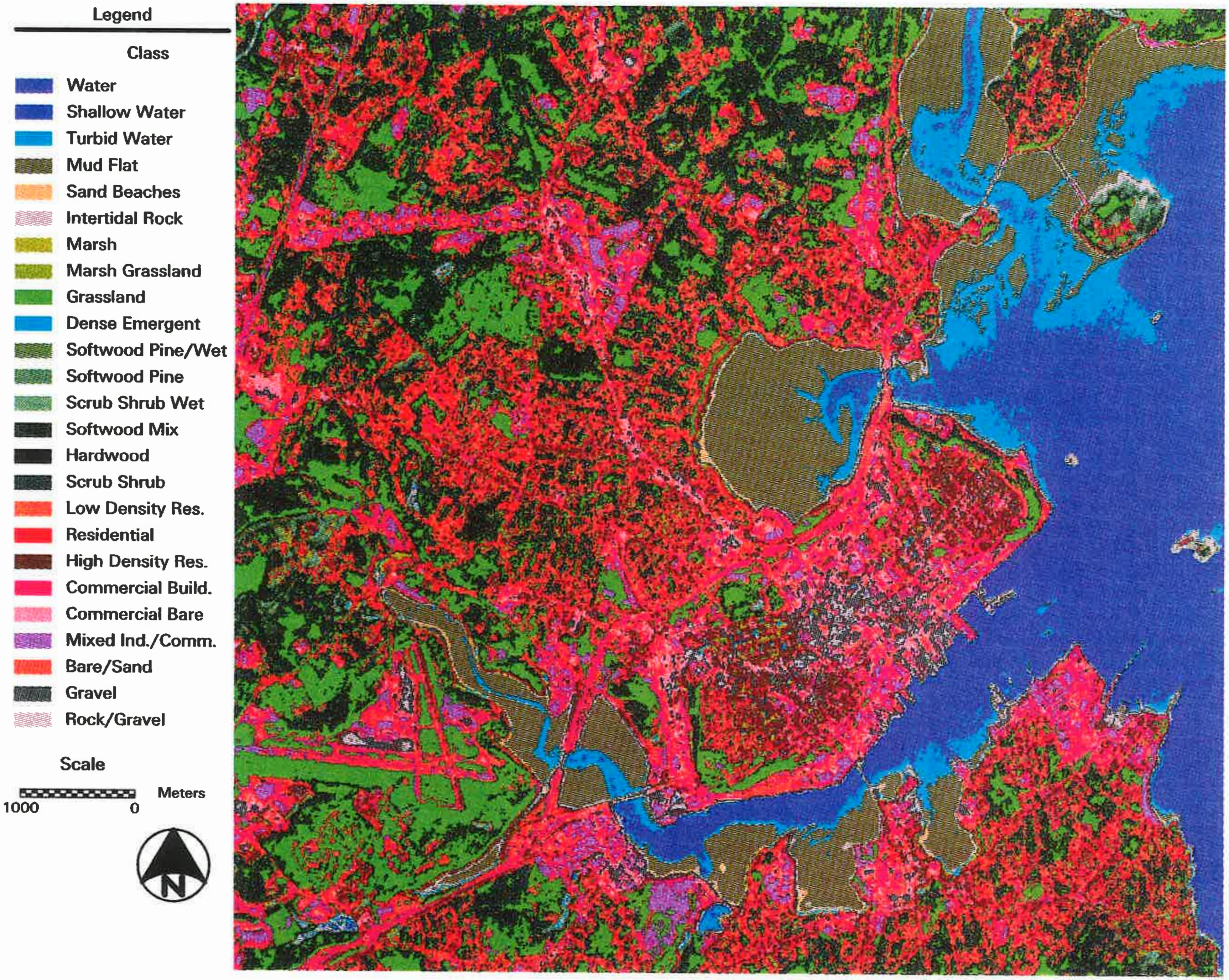
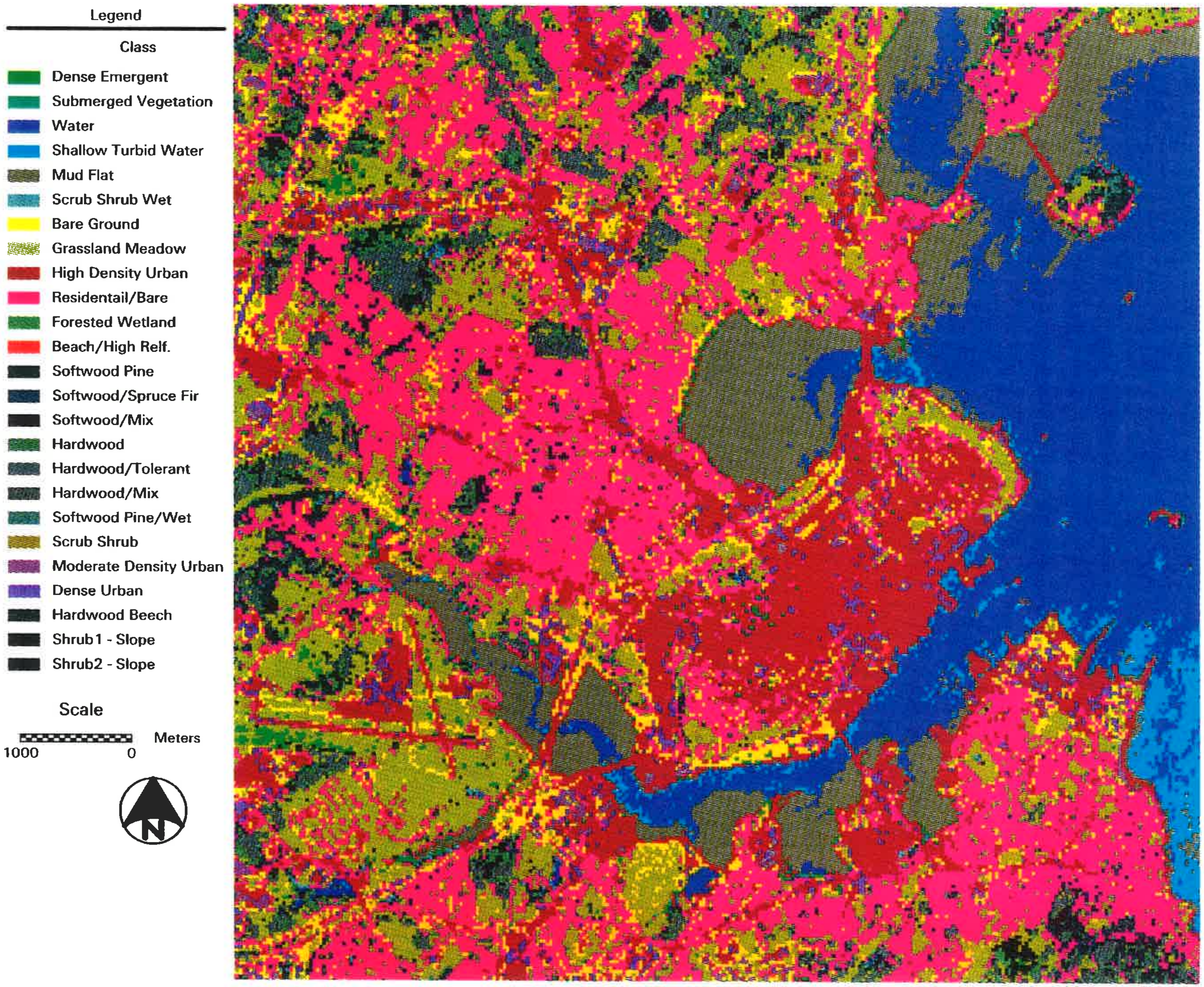

Legend
Class
Water
Shallow Water
Turbid Water
Mud Flat
Sand Beaches
Intertidal Rock
Marsh
Marsh Grassland
Grassland
Dense Emergent
Softwood Pine/Wet
Softwood Pine
Scrub Shrub Wet
Softwood Mix
Hardwood
Scrub Shrub
Low Density Res.
Residential
High Density Res.
Commercial Build.
Commercial Bare
Mixed Ind./Comm.
Bare/Sand
Gravel
Rock/Gravel
Scale
Meters
1000
0
N

Figure 5. (Displayed on the next page) Land cover map produced by Earthsat.


Legend
Class
Dense Emergent
Submerged Vegetation
Water
Shallow Turbid Water
Mud Flat
Scrub Shrub Wet
Bare Ground
Grassland Meadow
High Density Urban
Residentail/Bare
Forested Wetland
Beach/High Relf.
Softwood Pine
Softwood/Spruce Fir
Softwood/Mix
Hardwood
Hardwood/Tolerant
Hardwood/Mix
Softwood Pine/Wet
Scrub Shrub
Moderate Density Urban
Dense Urban
Hardwood Beech
Shrub1 - Slope
Shrub2 - Slope
Scale
Meters
1000
0
N

SECTION 3: DECISION-RULE CLASSIFICATION

INTRODUCTION

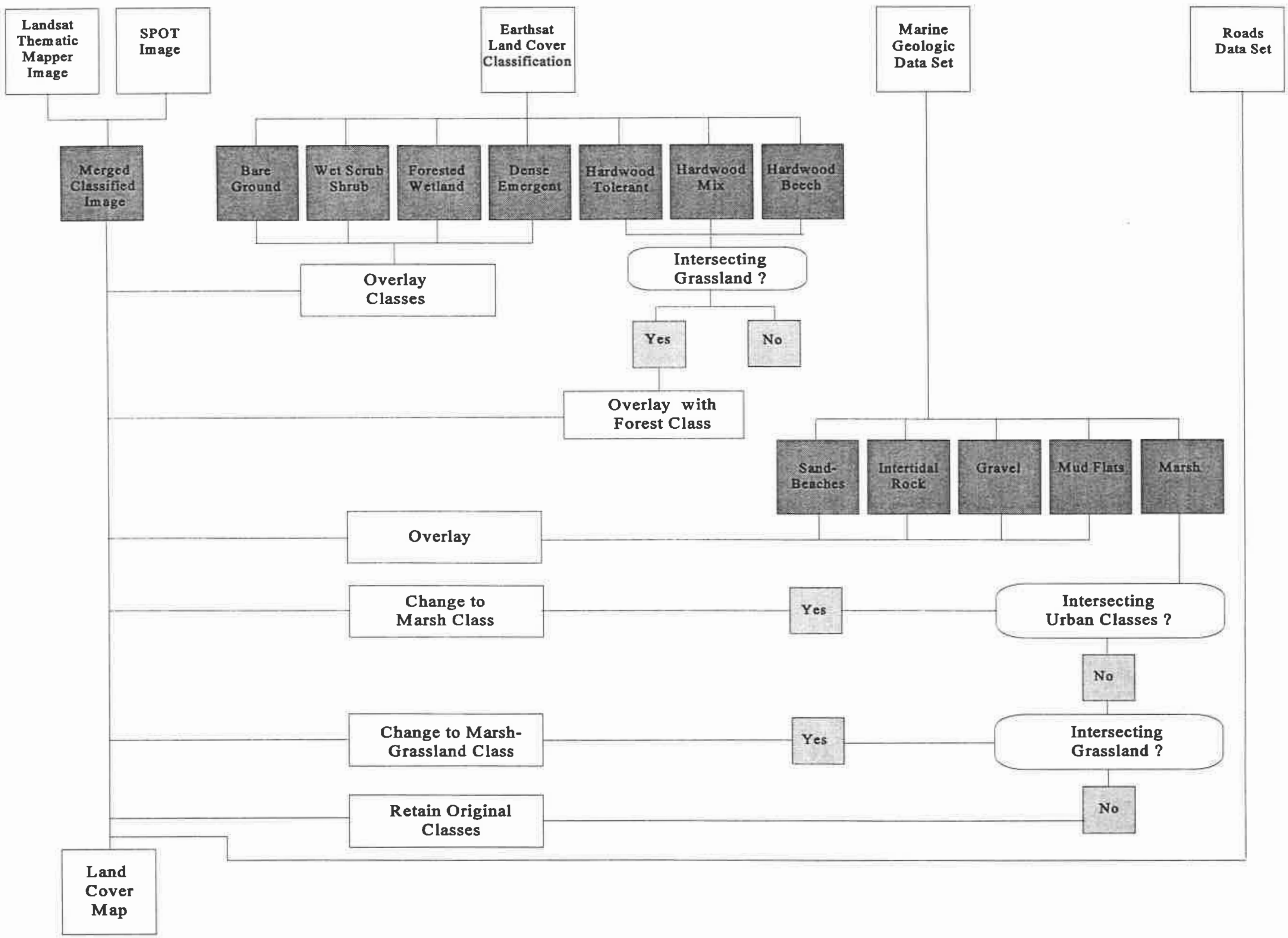
Often the identification of land cover, land use, plant communities, or man-made structures is not entirely successful using remote sensing alone. The integration of remotely sensed data, GIS, and data modeling offers the possibility of improving on the thematic mapping capabilities of both types of approaches. It is intuitive that there is not one single technique that will offer the best results for the land use mapping of many different surface types. This situation is even more apparent when the land use types of concern are spectrally relatively similar but show structurally large differences.

Incorporating ancillary data sets in remote sensing has often been adopted in previous research into land resource problems. Decision tree classifiers are one option that will allow a selectivity of techniques. Decision trees are an efficient method for separating observations into classes. We used a decision tree to improve accuracy in vegetation classes and to resolve classification problems for classes that were spectrally similar to urban cover types. This approach allowed us to maintain a high level of accuracy for the focal urban classes while we utilized already ground truthed vegetation classes from the previously produced land cover maps. All GIS operations during this part of the project were conducted using ARC/INFO software for workstations.

DATA SOURCES AND DECISION RULES

Data sources utilized in our decision-rule classification included the classification of the merged image, the Coastal Marine Geologic Environments Map (Timson 1976), the land cover classification previously produced by the Earthsat, and a digitized road map for the study area. Figure 6 displays the decision tree that we designed for the final classification.

Figure 6. (Displayed on the next page) Decision tree for decision-rule classification of the merged image.


Landsat Thematic Mapper Image
SPOT Image
Earthsat Land Cover Classification
Marine Geologic Data Set
Roads Data Set
Merged Classified Image
Bare Ground
Wet Scrub Shrub
Forested Wetland
Dense Emergent
Hardwood Tolerant
Hardwood Mix
Hardwood Beech
Overlay Classes
Intersecting Grassland ?
Yes
No
Overlay with Forest Class
Sand-Beaches
Intertidal Rock
Gravel
Mud Flats
Marsh
Overlay
Change to Marsh Class
Yes
Intersecting Urban Classes ?
No
Change to Marsh-Grassland Class
Yes
Intersecting Grassland ?
No
Retain Original Classes
Land Cover Map

Earthsat Land Cover Classification: Earthsat produced a classification using the same TM image. This classification proved to be useful and valid for most forest land and rangeland categories. We decided to utilize the Earthsat vegetation information to improve our classification of vegetation categories. The classification scheme for the Earthsat classification is given in
Table 2.

The following categories were used in the new classification as complete overlays: dense emergent, scrub shrub wet, forested wetland and bare ground. The first three categories were under-represented in our classification. The bare ground class enhanced the accuracy of fields and bare surfaces by cutting out incorrectly classified urban areas. Each class was recoded to a separate mask which was then overlaid onto the classified, merged image (Figure 6). To assess the impact of this operation on other land cover classes, we calculated the number of effected pixels.

In the merged image, some forest types were not adequately separated from grassland. These forest classes included hardwood tolerant, hardwood mix and hardwood beech. To improve the accuracy for forest classes, we constructed forest masks from the Earthsat classification. We created a classification rule that overlaid these forest classes from the Earthsat image wherever they intersected the grassland class of the merged image (Figure 6).

Table 2. Classification Scheme used by Earthsat.

Class Name
Moderate Density Urban/High Reflectance
Dense Urban/High Reflectance
High Density Urban/High Reflectance
Residential/Bare
Beach/High Reflectance
Mud Flats
Bare Ground
Shrub 1 - Slope/Exposed Soil/Rock
Shrub 2 - Slope/Exposed Soil/Rock
Grassland Meadow
Scrub Shrub
Dense Emergent
Hardwood
Hardwood Beech/Poplar/Ash
Softwood Spruce/Fir
Softwood Pine
Softwood Pine/Wet
Hardwood Mix
Softwood Mix
Hardwood Tolerant
Forested Wetland
Scrub Shrub Wet
Submerged Vegetation
Water
Shallow Turbid Water

Coastal Marine Geologic Environments: Many coastal marine classes have similar spectral characteristics to man-made structures and urban land cover. This problem was prevalent in the Earthsat classification. Due to increased spatial resolution, we were able to reduce inaccuracies in these areas during our classification process. However, there was still a substantial area within the coastal zone of the merged image that was misrepresented as urban. We decided to use the Coastal Marine Geologic Environments map, produced by the U.S.G.S. in 1976, to improve our classification in these areas. This data set includes higher level classes than we could differentiate in our classification. To include these classes in our decision-rule classification, we grouped them into lower level categories that were present in our classification scheme. Table 5 displays the marine geologic classes we utilized and the lower level category to which they were assigned.

Sand Beaches, Intertidal Rock, Marsh, Gravel and Mud Flats were the land cover categories we extracted from the Coastal Marine Geologic Environments map. The first four classes were overlaid on top of the merged image covering all classes underneath (Figure 6). The Marsh category was treated differently. We created a marsh mask, and overlaid onto the classified merged image according to the following decision-rules:

1. If the marsh mask intersected urban classes in the merged image, we assigned these areas to the category marsh.
2. If the marsh mask intersected grassland, we assigned these areas to the category marsh-grassland.
3. If the marsh mask intersected other vegetation categories, the original category was retained.

The first decision rule is justified because of the problems we encountered in differentiating urban categories from marsh. The Coastal Marine Geologic Environments map only delineated

Table 5. Original and Assigned Categories for Land Cover Classes Derived from the Coastal Marine Geologic Environments Map.

Assigned Lower Level Category	Original Higher Level Category
Sand Beach	Dunes and Vegetated Beach Ridges
	Sand Beach
	Mixed Sand and Gravel Beach
	Low Energy Beach
	Spits
Intertidal Rock	Boulder Beach
	Boulder Ramp
	Mussel Bar
	Ledge
Marsh	Fresh-Brackish Marsh
	Fuvial Marsh
	High Salt Marsh
	Low Salt Marsh
	Marsh Levee
	Salt Pannes and Salt Ponds
Gravel	Gravel Beach
	Washover Fans
Mud Flats	Mud Flats
	Coarse-Grained Flat
	Seaweed-Covered Coarse Flat
	Algal Flats

marsh in coastal areas, and was unlikely to introduce error into urban classes in areas distant from the coast. Decision rules 2 and 3 were designed to retain information on vegetation classes from the other data sets.

Road Data Set: Linear land features, such as roads, utility corridors, and railroad tracks, usually cannot usually be discerned in multispectral classification of satellite imagery. Due to differences in orientation towards the sun and resulting differential shading, these linear structures can vary enormously in their spectral characteristics. Nevertheless, these structures can cover large areas and are of interest in a land cover classification. We decided to use a digital data set of roads to account for their presence, and to be able to quantify the area that is sealed by these structures. Roads were overlaid onto the merged image, covering all classes underneath (Figure 6). Visual interpretation of the resulting map demonstrates that spatial accuracy of the road coverage was within the limits of the overall spatial accuracy of the merged image.

RESULTS AND DISCUSSION

Decision-rule classification greatly improved the overall quality of the land cover map (Figure 7). Accuracy of most land cover classes seemed to be increased based on visual comparison. Decision-rule classification also helped to define land cover categories that are difficult to distinguish based on remote sensing alone. We were able to increase accuracy for urban classes, and also increase the number of higher level categories in the final classification.

Figure 7. (Displayed on the next page) Land cover map produced from merged image using decision-rule classification.

Legend

Class

- Water
- Shallow Water
- Turbid Water
- Mud Flat
- Sand Beaches
- Intertidal Rock
- Marsh
- Marsh Grassland
- Grassland
- Dense Emergent
- Scrub Shrub Wet
- Scrub Shrub
- Forested Wetland
- Softwood Pine/Wet
- Softwood Pine
- Softwood Mix
- Hardwood
- Hardwood Tolerant
- Hardwood/Mix
- Low Density Res.
- Residential
- High Density Res.
- Commercial Build.
- Commercial Bare
- Mixed Ind./Comm.
- Roads
- Bare/Sand
- Gravel
- Rock/Gravel

Scale

Meters

1000 0

N

SECTION 4: ACCURACY ASSESSMENT

INTRODUCTION

The quality of land cover classifications derived from remote sensing can be estimated using an accuracy assessment. Accuracy assessment is accomplished by comparing the classification to land cover information from known geographic locations. This process is usually achieved by collecting ground truth information for all classes at sampling points and recording the exact geographic position of these points with a GPS. The ground truth information can then be assigned to reference pixels, and the true land cover can be compared to the land cover assigned during the classification.

The number of reference pixels is an important factor in determining the accuracy of a classification. It has been demonstrated that more than 250 pixels are needed to estimate the mean accuracy of a class to within plus or minus five percent (Congalton 1991). However, financial and time constraints rarely allow for such extensive data collection. We collected ground truth data for 154 ground control points in six urban classes.

To assess the accuracy of urban classes we generated an error matrix, and calculated producer's and user's accuracy. We also used a Kappa coefficient to assess the reduction in error generated by the classification process to the error of a completely random classification.

GROUND TRUTHING FOR THE ACCURACY ASSESSMENT

In April 1996, we collected ground truth information for urban land cover at 154 locations in the Casco Bay area. Stratified random sampling was used to predetermine the geographic location for ground truthing. The points were distributed across all urban land cover categories. The protocol for collecting land cover information and determining the exact geographic position for the location was the same as described for the collection of ground truth data for training pixels in section 2. The data from ground truthing was entered into a database, and merged with the classification to create reference pixels.

RESULTS AND DISCUSSION

The results of the accuracy assessment are listed in the error matrix (Table 6). The performance of the classification is described in different ways in this error matrix. All diagonal elements of the matrix represent pixels that were correctly classified. All non-diagonal elements represent misclassification and can further be divided in omission and commission errors. Omission error occurs when a pixel is excluded from its correct category, while commission error occurs when a pixel is included into the wrong category. Overall accuracy of urban classes is computed by dividing the total number of correctly classified pixels by the number of reference pixels. Producer's accuracy expresses this figure for each of the categories separately. User's accuracy can be considered a measure of commission error for each class. To calculate user's accuracy the number of correctly classified pixels for each category is divided by the total number of pixels that were assigned to this class.

The overall accuracy for urban classes was 85.06%. The producer's accuracy is very high for three of the urban classes, indicating that there is little omission error for low density residential, commercial bare, and roads. Omission error is also acceptable and below 15 % for roads and bare/sand. The other urban classes have relatively high omission errors. However, when taking a closer look at the error matrix, it is apparent that all errors of omission occurred only between urban land categories. For example, the high density residential classes were omitted for 4 pixels that were assigned to commercial bare and mixed industrial and commercial. This procedure seems acceptable since these classes have a tendency to be located relatively close to each other.

The user's accuracy is in most cases higher than the producer's accuracy except for commercial bare and mixed industrial/commercial. Both of these classes can occur in close proximity to commercial buildings and high density residential, which were the classes most often incorrectly assigned to pixels of the category commercial bare and mixed industrial/commercial. Merging all commercial classes would greatly improve user's and producer's accuracy. All other classes fare very well in the classification, and can be differentiated with good accuracy.

Similar results are achieved when calculating the Kappa coefficient (Table 7). The Kappa statistics describe to what percentage of correct values in the error matrix are due to truly correct classification as opposed to a correct classification by chance.

Table 6. Error Matrix for Accuracy Assesment

	Reference Data Set								
	Low Density Residential	Residential	High Density Residential	Commercial Buildings	Commercial Bare	Mixed Ind./Comm.	Roads	Bare/Sand	Row Total
Low Density Residential	36	3							39
Residential	1	9					1	1	12
High Density Residential		1	6						7
Commercial Buildings				8				1	9
Commercial Bare			2	3	11	2		2	20
Mixed Industrial/Commercial	1		2		1	5			9
Roads	1						31		32
Bare/Sand				1				25	26
									0
Column Total	39	13	10	12	12	7	32	29	154

Producer's Accuracy

Low Density Residential	=	36/39	=	92.31%
Residential	=	9/13	=	69.23%
High Density Residential	=	6/10	=	60.00%
Commercial Buildings	=	8/12	=	66.66%
Commercial Bare	=	11/12	=	91.66%
Mixed Industrial/Commercial	=	5/7	=	71.43%
Roads	=	31/32	=	96.87%
Bare/Sand	=	25/29	=	86.21%

User's Accuracy

Low Density Residential	=	36/39	=	92.31%
Residential	=	9/12	=	75.00%
High Density Residential	=	6/7	=	87.72%
Commercial Buildings	=	8/9	=	88.89%
Commercial Bare	=	11/20	=	55.55%
Mixed Industrial/Commerci	=	5/9	=	55.55%
Roads	=	31/32	=	96.87%
Bare/Sand	=	25/26	=	95.15%

Overall Accuracy for Urban Casses = (36 + 9 + 6 + 8 + 11 + 5 + 31 + 25) / 154 = 85.06%

The overall Kappa for urban classes is a little below the overall accuracy for urban classes. Partial Kappa is high for low density residential, high density residential, commercial buildings, and roads. The Kappa values for the other urban classes are low, indicating that some of them are mixed and probably should be merged.

Table 7. Kappa Values for Urban Land Cover Classes

Land Cover Category	**Kappa**
Low Density Residential	0.8764
Residential	0.6186
High Density Residential	0.8503
Commercial Buildings	0.8825
Commercial Bare	0.5240
Mixed Industrial/Commercial	0.5409
Roads	0.9634
Bare/Sand	0.8070
Overall Kappa	**0.7954**

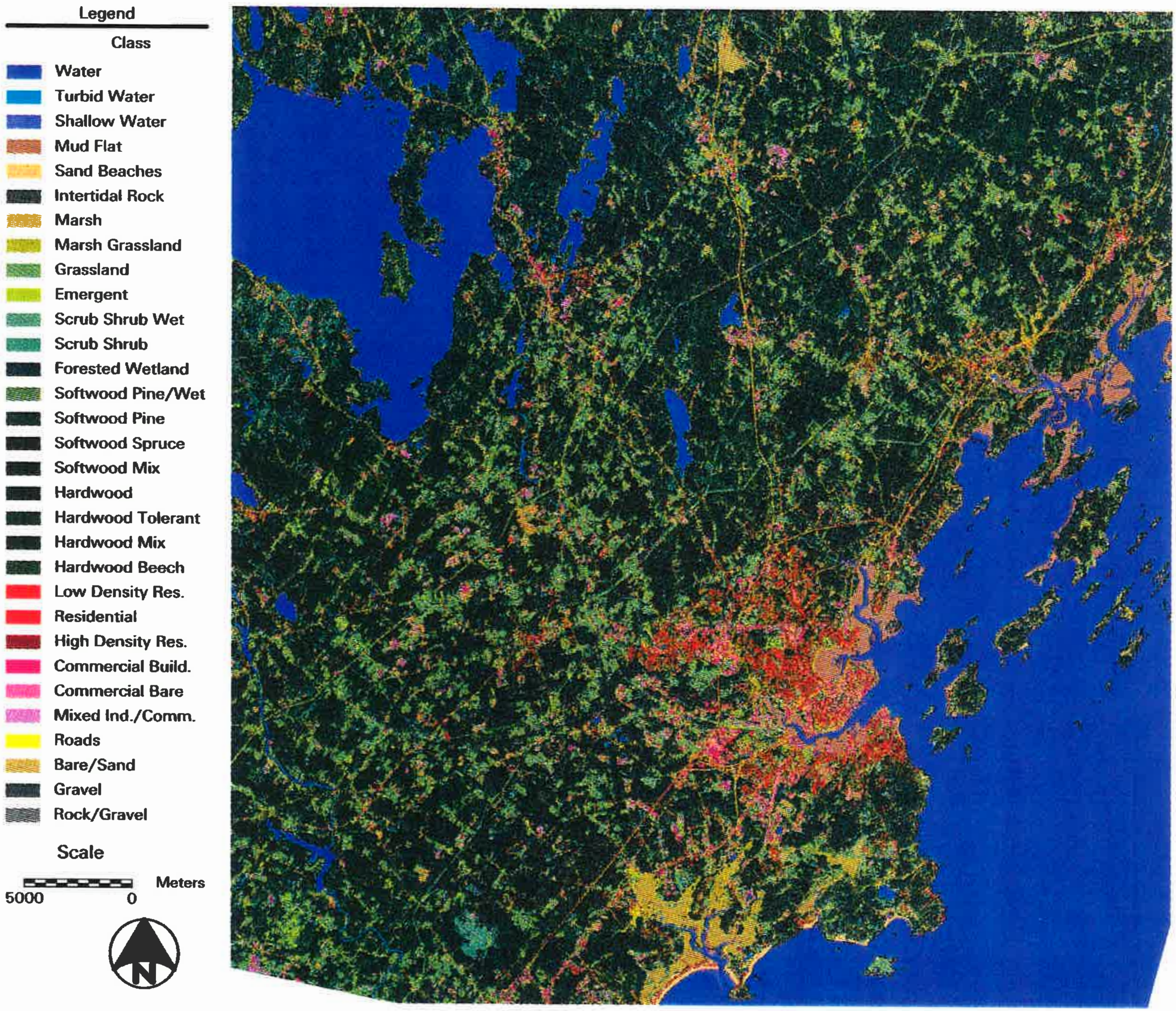
The prinicipal limitations of our accuracy assessment are due to the relatively small number of reference pixels for each class and the fact that we could not collect information for other land cover classes. However, we believe that the results of our accuracy assessment would improve if we could include more reference pixels. If out of 10 reference pixels one is misclassified by chance, this can reduce the user's accuracy by 10 percent.

SECTION 5: FINAL CLASSIFICATION

RESULTS AND DISCUSSION

All previous sections described the development and application of our classification methods to a restricted data set that covered the south-east quadrant of the study area. The analyses conducted on the restricted data set could be refined in many steps and evaluated. We were able to do this efficiently because we kept the data volume manageable. After we had designed, evaluated and refined all techniques, we applied them to the entire data set. However, the larger data set also included a wider range of spectral variation and we had to adjust to the larger data volume. This process made changes necessary for the unsupervised training. We specified 60 initial clusters in the unsupervised training instead of 40 as described in section 2 of this report. As a result, we were able to create better signature statistics for urban classes as well as for some of the wet classes. All other procedures followed the same methodology as described in previous sections. Attached to this section are two figures that display the Earthsat classification of the TM image and our final product. Visual comparisons as well as the previously described accuracy assessment demonstrate the usefulness of resolution merge for the classification of urban land cover. A major improvement was achieved by combining remote sensing of satellite imagery with ancillary data sets in a GIS environment using decision-rule classification.

A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Class
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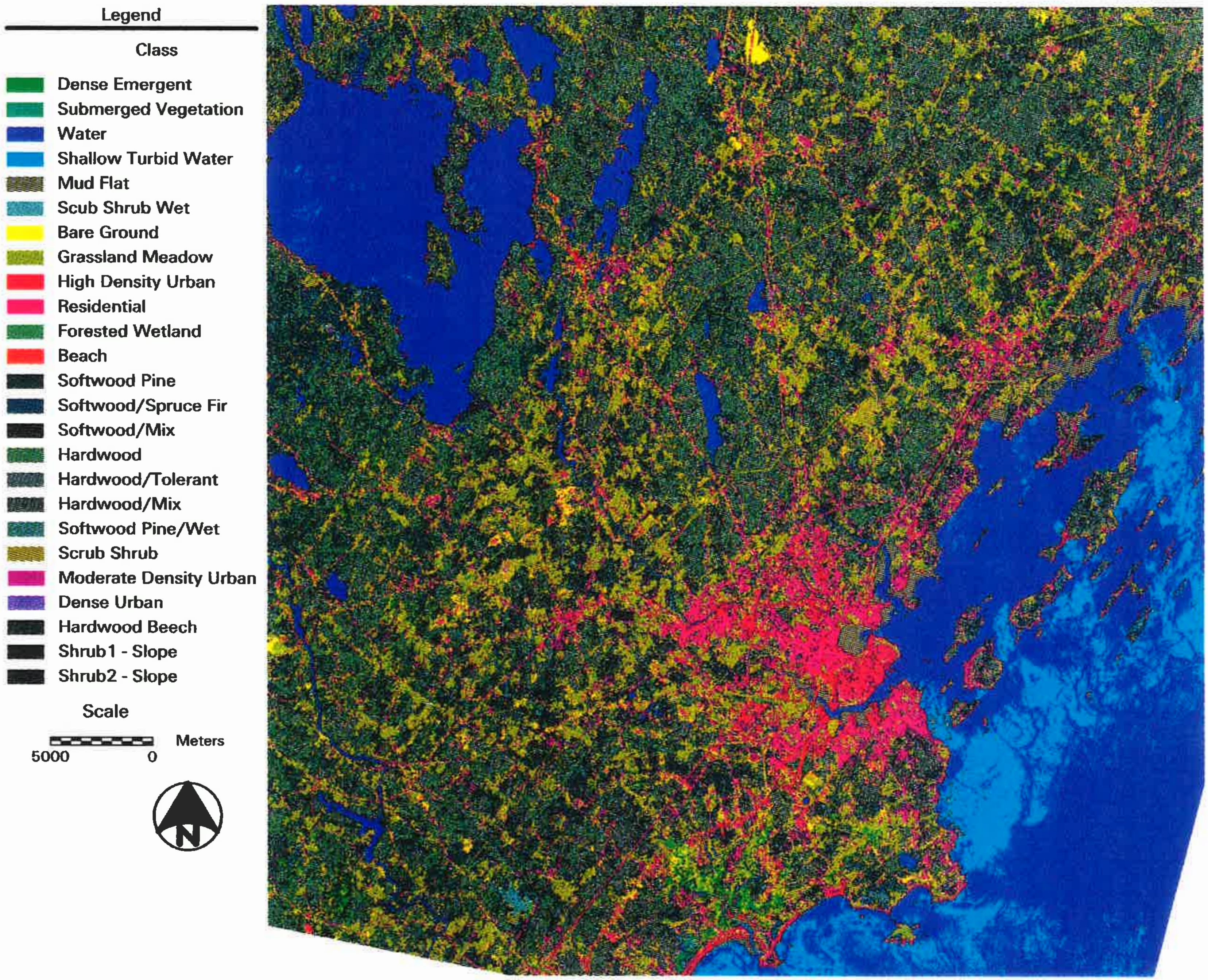
Turbid Water
Shallow Water
Mud Flat
Sand Beaches
Intertidal Rock
Marsh
Marsh Grassland
Grassland
Emergent
Scrub Shrub Wet
Scrub Shrub
Forested Wetland
Softwood Pine/Wet
Softwood Pine
Softwood Spruce
Softwood Mix
Hardwood
Hardwood Tolerant
Hardwood Mix
Hardwood Beech
Low Density Res.
Residential
High Density Res.
Commercial Build.
Commercial Bare
Mixed Ind./Comm.
Roads
Bare/Sand
Gravel
Rock/Gravel
Scale
Meters
5000
0
N

B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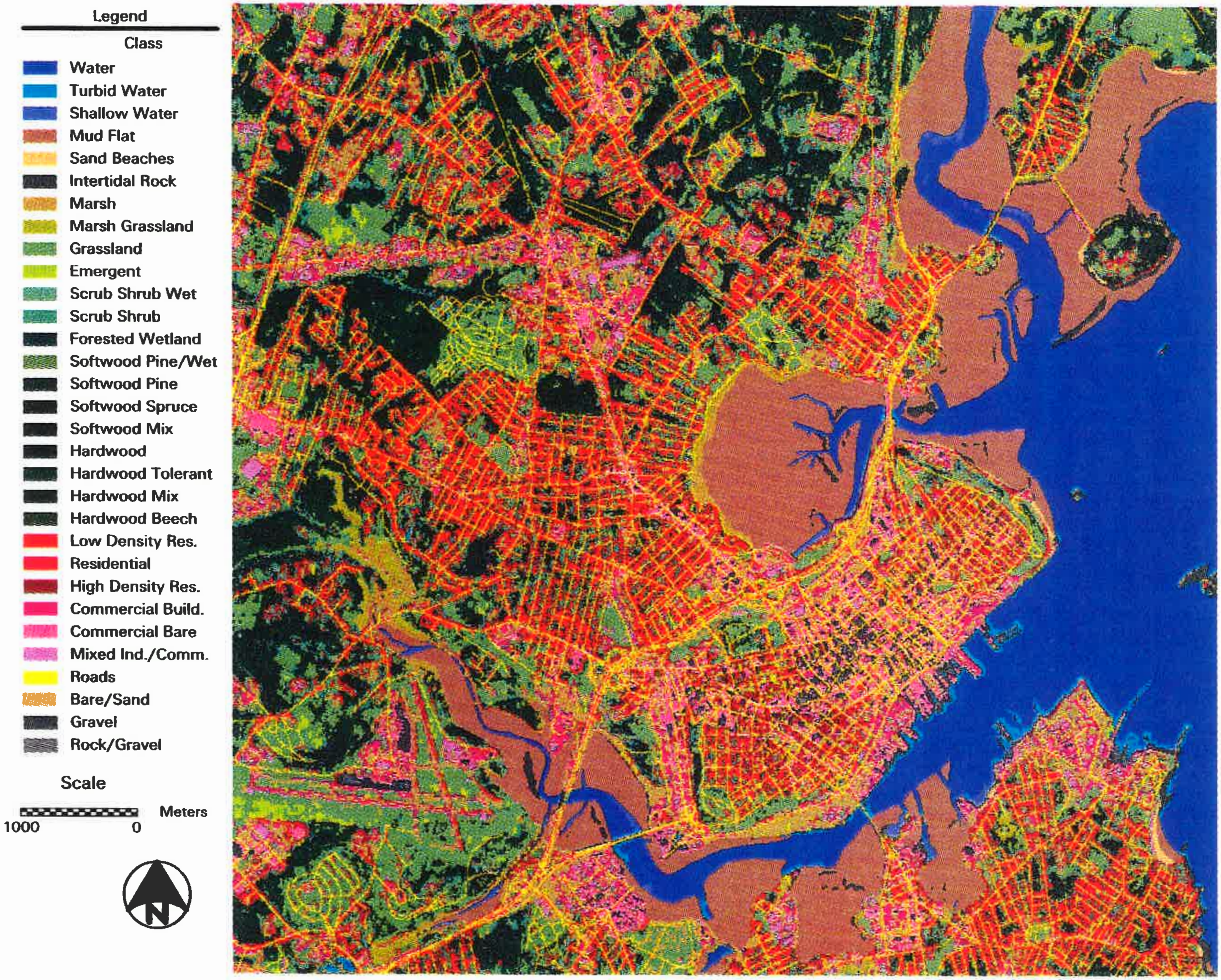
Submerged Vegetation
Water
Shallow Turbid Water
Mud Flat
Scub Shrub Wet
Bare Ground
Grassland Meadow
High Density Urban
Residential
Forested Wetland
Beach
Softwood Pine
Softwood/Spruce Fir
Softwood/Mix
Hardwood
Hardwood/Tolerant
Hardwood/Mix
Softwood Pine/Wet
Scrub Shrub
Moderate Density Urban
Dense Urban
Hardwood Beech
Shrub1 - Slope
Shrub2 - Slope
Scale
Meters
5000
0
N

C


Legend
Class
Water
Turbid Water
Shallow Water
Mud Flat
Sand Beaches
Intertidal Rock
Marsh
Marsh Grassland
Grassland
Emergent
Scrub Shrub Wet
Scrub Shrub
Forested Wetland
Softwood Pine/Wet
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Softwood Spruce
Softwood Mix
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Hardwood Beech
Low Density Res.
Residential
High Density Res.
Commercial Build.
Commercial Bare
Mixed Ind./Comm.
Roads
Bare/Sand
Gravel
Rock/Gravel
Scale
Meters
1000
0
N

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