A HIERARCHICAL APPROACH TO LAND USE AND LAND COVER MAPPING USING MULTIPLE IMAGE TYPES

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ABSTRACT

The main objective of this project was to derive digital land use and land cover information from satellite remote sensing data for Connecticut, Long Island, and those watersheds contributing to Long Island Sound. In doing so, four methods of land use and land cover classification were evaluated on two test quadrangles to determine which method was best suited, in terms of time and costs balanced with spatial and thematic accuracy. These four methods are: a single date Landsat Thematic Mapper (TM) computer-assisted classification, a TM/SPOT panchromatic image fusion and automated classification, a TM classification combined with on-screen digitization of SPOT panchromatic data, and a TM classification combined with on-screen digitization of Digital Orthophoto Quarter-Quadrangles (DOQQs). For Connecticut statewide land cover mapping, a layered approach was used, with each stage concentrating on a related set of land cover types. Twenty-eight detailed land use and land cover classes were mapped with an overall accuracy of nearly 80%. An accuracy of better than 88% was achieved for the six Level I categories found in Connecticut.

INTRODUCTION

In 1990, under a grant from the Joint Long Island Sound Study (LISS) of the Connecticut Department of Environmental Protection and the United States Environmental Protection Agency, land cover maps of the state of Connecticut were prepared by scientists from the University of Connecticut's Laboratory for Earth Resources Information Systems (LERIS) through computer-assisted analysis of satellite digital remote sensing data. Land cover information was extracted from multiseasonal Landsat Thematic Mapper (TM) and Multispectral Scanner (MSS) for 23 land cover types (Civco and Hurd, 1991; Civco *et al.*, 1992). The accuracy of these data has proven to be adequate for the initial purposes for which they were intended, *i.e.,* area-wide nonpoint pollution modeling using land use-dependent coefficients (Frink *et al.*, 1993). The quality of the information has been confirmed both spatially and thematically in comparison with land cover maps developed through conventional aerial photointerpretation in border quadrangles with Massachusetts. However, categories of urban and suburban land cover, particularly low density development, were found to be some of the least accurate, yet most essential categories for the development of nonpoint load estimates (Computing Solutions, Inc., 1993). Urban regions have been found to be a major source of nutrients to rivers, lakes, and estuaries. It became apparent that it was necessary to develop a procedure to create a new land cover map which better identifies the densities of urban areas, particularly low density developed areas and provide an up-to-date map for the state of Connecticut.

Research to improve upon the thematic depth and accuracy of satellite imagery has been conducted by investigators at the LERIS. Investigations have resulted in the development of innovative techniques for extracting land cover information from remote sensing and ancillary data (Wang and Civco, 1992a; Wang and Civco, 1992b; Wang and Civco, 1994; Civco *et al.*, 1995). This has proven essential in order to characterize better the degree of

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urbanization, with particular relevance to the identification of low-density development and estimates of impervious cover. Techniques have been developed to improve the spatial sensitivity of 30 meter Landsat TM multispectral data by *merging* them with 10 meter SPOT panchromatic imagery (Civco *et al*., 1995; Zhou and Civco, 1998). In theory, the merging of these two data types provides the opportunity to create more spatially accurate and detailed land cover maps while still maintaining a high degree of automation to the classification procedure. Another innovative technique has been the development of a paradigm for the quantification of per-pixel percent impervious surface cover from TM data. This model uses neural networks to predict the percentage of imperviousness for each 30 meter TM pixel in a study area (Civco and Hurd, 1997).

To evaluate best how these image enhancement techniques would perform for classification over a large area, four methods of classification were selected for comparison. These methods were chosen to take advantage of improved spatial image data available in the form of SPOT panchromatic images and DOQQ's (Digital Orthophoto Quarter-Quadrangles):

1. A multi-season spring/summer Landsat TM computer-assisted classification.
2. A fused Landsat TM and Spot panchromatic image computer-assisted classification.
3. On-screen digitizing of SPOT panchromatic images to highlight urban regions followed by a merging with a Landsat TM classification.
4. On-screen digitizing of DOQQs to highlight urban regions followed by a merging with a Landsat TM classification.

EVALUATION OF CLASSIFICATION TECHNIQUES

Study Areas and Data

The four classification techniques were evaluated on two USGS $7^{1/2}$-minute topographic quadrangles prior to statewide implementation to determine which method would be best suited for statewide classification. These study areas were the Essex quadrangle located in the neo-coastal region of Connecticut and the West Torrington quadrangle located in the northwest hills of Connecticut (Figure 1). The Essex quadrangle contains an abundance of estuarine marshes, inland wetlands, residential and commercial development of varying densities, and forest land. The West Torrington quadrangle contains sizable areas of residential and commercial development, forest land, wetlands, and agriculture. In addition, the West Torrington quadrangle contains areas of substantial relief ranging in elevation from approximately 600 feet to 1600 feet. Studying this type of terrain is important for evaluating the effect of topography on each of the data types and classification methods in terms of geometric properties and thematic accuracy.

For this evaluation, three types of remote sensing image data were used as sources for land use and land cover mapping. Landsat TM image data served as the basis for land cover mapping in all four methods. Although lacking a high degree of spatial resolution compared to other remote sensing products, the TM possesses higher multispectral resolution, thereby enabling improved distinction among many cover types. This makes TM data a more effective source of remote sensing information for the classification of large geographic areas such as Connecticut and the Long Island Sound watershed area.

The SPOT panchromatic image data were used for two purposes. First, the SPOT data fused with the TM data to improve the spatial properties of the TM data. Thematic Mapper data possess moderately high multispectral resolution enabling improved distinction among cover types, whereas SPOT panchromatic data possess moderately high spatial resolution, enabling discrimination at a finer level of detail. This finer level of detail would, therefore, allow for the identification of lower density residential areas, isolated buildings, and other small land cover features which may be indicative of a land use contributing the the degradation of water quality. Together, the *fused* TM-SPOT data would maximize the accuracy and precision of the land use and land cover map. A refined data merging techniques based on principal component analysis (Civco *et.al.*, 1995) and another based on the wavelet transformation (Zhou and Civco, 1998) were used to render a high quality TM-SPOT fusion. A second use of the SPOT data was for on-screen digitizing of primarily urban areas. This visual interpretation was performed to enhance detailed information of interest which is not discernible using automated techniques.

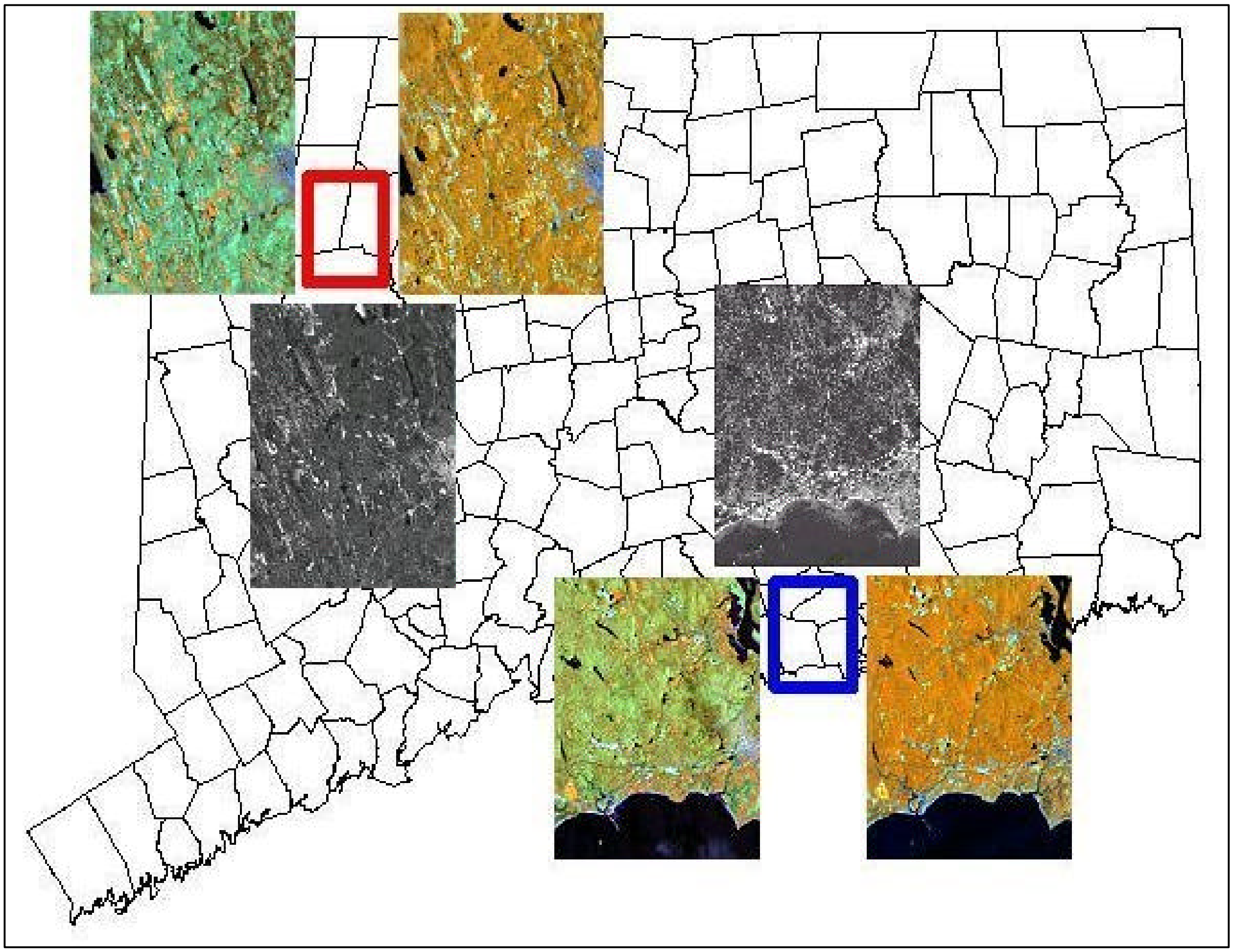


Figure 1. Locations of the West Torrington and Essex $7^{1/2}$ minute quadrangles in Connecticut. Landsat TM data are shown in Bands 4,5, and 3 for both spring (leaf off) and summer (full leaf). SPOT Panchromatic data are shown in grayscale.

The DOQQs were also used for on-screen digitizing of primarily urban areas. The one-meter spatial resolution of the DOQQs allows for easier interpretation of land use and land cover features than with 10-meter SPOT panchromatic data. Figure 2 provides a visual contrast among the spatial properties of Landsat TM, SPOT panchromatic, and DOQQ images for an area within Torrington, Connecticut.

Classification Methodology

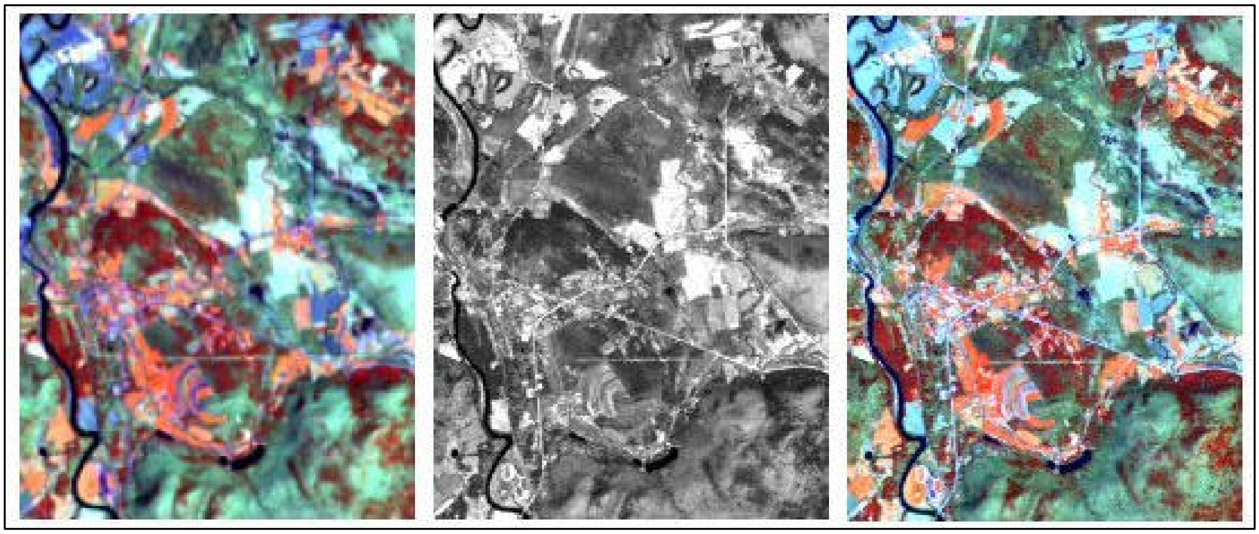
Multi-season TM Classification. Land cover mapping of the West Torrington and Essex quadrangles began with an unsupervised classification of a single date (May 8, 1995) Landsat TM image for each quadrangle. It became evident that a single season TM image would not satisfactorily separate some land cover types of interest, especially coastal marsh categories which showed considerable confusion with deciduous forests in the springtime classification. Multi-seasonal imagery has been found to be a superior source for classification than single season images because it provides greater spectral depth due to the phenological differences between (Civco and Hurd, 1991; Fuller *et al.*, 1994; Dobson *et al*., 1995). Unsupervised classification was applied to a multi-seasonal (May 8, 1995/August 28, 1995), 12-band image to produce 100 classes. These spectral clusters were identified and labeled into informational land cover categories. Supervised training signatures were then selected to augment the classes derived from the unsupervised classification. The signatures from both the unsupervised and supervised techniques were evaluated and a new set of signatures was developed by merging and appending appropriate signatures from both techniques. These signatures were used in a maximum likelihood classification to derive the final multi-seasonal classification.

30 meter Landsat TM **1 meter DOQQ** **10 meter SPOT panchromatic**

Figure 2. Image comparison of Landsat TM (Band 4), SPOT Panchromatic, and DOQQ data for an area in Torrington, CT.

TM/SPOT Fused Classification The first step in this method of classification was to fuse, or spatially enhance, the TM image with the SPOT panchromatic image. Two methods for resolution enhancement were examined in this project. These are the Brovey Transform and an inverse principal components technique. The latter technique was found to produce a better quality image and was therefore adopted for this project (see Figure 3 for an example). In the inverse principal components technique, the 30 meter TM data are resampled to 10 meter pixels and co-registered with the 10-meter SPOT image data. The synthesized 10-meter TM multispectral data are then transformed into principal components (PC). The brightness properties of the co-registered SPOT panchromatic data are matched to the first PC (PC_1), which is an overall brightness image of the original data and is then substituted for PC_1. Inverse PCA is then applied to project the data back into original Thematic Mapper spectral space which essentially results in a 10 meter Thematic Mapper image. Further detail on TM-SPOT data fusion can be found in Civco *et al.* (1995) and Zhou and Civco (1998). Unsupervised classification was applied to this image resulting in 200 classes. These were identified and labelled. Supervised signature selection was also performed and evaluated with those signatures from the unsupervised approach. Those signatures determined to provide the best classification were selected and a maximum likelihood classification was performed to produce a final classification image.

SPOT On-screen Digitizing. The first task with on-screen digitizing of the SPOT image was to determine what areas were to be digitized since it is not feasible to interpret visually and digitize manually the entire state of Connecticut. For this purpose, road coverages and sewered areas were used to determine likely target areas for on-screen digitizing. High densities of road networks and sewered areas are indicative of an urbanized environment. Once these target areas were identified, they were compared with the multi-seasonal TM classification to determine if digitization was necessary (*i.e.,* did the TM classification alone produce enough detail for a particular urban area?). In those cases where digitization was necessary, the SPOT image was displayed on-screen and the areas of interest digitized. The land cover features were digitized into the following categories: High Density Industrial, Medium Density Industrial, High Density Commercial, Medium Density Commercial, Low Density Commercial, High Density Residential, Medium Density Residential, Low Density Residential, Turf & Grass, Turf & Tree Complex, Forest, Water, and Bare/Exposed Ground. The distinction among the different density groups is somewhat arbitrary and based strictly on visual interpretation. A high density area is roughly composed of over 90 percent roof and pavement, a medium density area is between 50 to 90 percent roof and pavement, a low density area falls below 50 percent roof and pavement. Once the digitization was complete, it was merged with the multi-seasonal TM classification to produce a seamless composite of land use and land cover information derived from different sources.



TM **SPOT** **Fused SPOT-TM**

Figure 3. Example of 30 meter TM data (Bands 4, 5, 3) fused with 10 meter SPOT Panchromatic data.

DOQ On-screen Digitizing. The same procedure was used with the DOQQ data as was used with the SPOT image. Land cover features were digitized into the same categories as used in the SPOT on-screen digitizing. Once the digitization was complete, it was joined with the multi-seasonal TM classification to produce a seamless composite of land use and land cover derived from different data sources.

Discussion

The multi-seasonal TM classification produced visually appealing results. However, as with the previous 1990 statewide land use and land cover mapping project, urban and built-up lands were not adequately classified and delineated, even though classification focused more on these land cover features than was done with the 1990 mapping project. The 30 meter resolution of the TM sensor, coupled with the aspatial, per-pixel classifier, is not fine enough to detect consistantly the low density urban features that are of importance.

The TM/SPOT fusion classification provided a vast improvement in the ability to detect visually isolated built-up areas compared to the TM classification, and is therefore better suited for detecting lower density built-up areas. However, this improved spatial detail results in a more sizable and complex image dataset. This complexity can be managed, in terms of classification, at the quadrangle level, but would become inherently difficult to classify accurately at the statewide level due to the complexity of the landscape. This would result in an increase in the number of classification training signatures required for each category, thereby adding to the potential for misclassification. In addition, the spectral and radiometric difference between the numerous SPOT scenes needed to cover the state would also add to the need for additional category training signatures.

While only attempted in a small area, using SPOT data for on-screen digitizing was found to be difficult. This was due to two reasons. First, the SPOT image is not spatially detailed enough in some areas of the urban environment to allow for easy discrimination among the different types of land cover being digitized. It is difficult to distinguish a boundary between an industrial use to a commercial use to a residential use. Second, it is difficult to determine objectively and consistently the areal extent to which an urban area should be digitized. Even through the use of the roads and sewered area coverages, isolated urbanized areas are missed, especially the rural residential and low density urban areas which are a major category of interest in this project. Further, these ancillary data predate the satellite images by as many as 12 years in Connecticut, thereby introducing substantial temporal disparity.

Lastly, the DOQQ data, while providing an excellent source of imagery for digitizing, proved to be too much data to handle. Each quarter quadrangle is approximately 45 megabytes in size resulting in one quadrangle consisting of 180 megabytes of data. Connecticut alone requires 116 quadrangles for complete coverage resulting in approximately 21 gigabytes of storage. This volume of data poses substantial logistical problems in attempting to use them in the way intended (*i.e.*, on-screen digitizing and merging with satellite derived thematic information). Therefore, the DOQ data was used in a supporting role as opposed to a source of classification.

The final result of this evaluation of the four classification techniques methods tested on the West Torrington and Essex quadrangles was the development of a hierarchical approach to land use and land cover classification. It was determined that a majority of land cover in the state of Connecticut does not require the amount of detail produced through the TM/SPOT fusion method to be adequately classified (*i.e.* forest lands, agricultural lands, and water bodies are mostly homogeneous entities and do not require high spatial detail to be classified accurately). However, some of the urban features require the additional detail for improved classification. Therefore, in the hierarchical approach, the majority of the Connecticut landscape was classified from only the multi-season Landsat TM imagery which provides adequate information for general classification, and the low density developed areas were derived from the TM/SPOT fused image and merged with the TM classification

STATEWIDE LAND COVER MAPPING

Data Types and Sources

The state of Connecticut is covered almost entirely by Landsat data collected at WRS Path 13, Row 31, with the exceptions of the eastern most tier of 7 $^{1/2}$ -minute quadrangles, covered by Path 12, Row 31. Therefore, in order to obtain full Landsat coverage for the state, partial scenes from Path 12, Row 31 were required. In order to maximize the information content and accuracy of the derived land use and land covers, data from two different seasons – spring and summer – were required. Additional criteria were that the data be as contemporaneous as possible, as cloud free as possible, and of high radiometric quality. LERIS already had in its archive a full Landsat scene for summer 1995 which ended near the southern border of Connecticut. An appropriate spring 1995 Landsat image was acquired which covered Connecticut, and Long Island. Spring 1994 and summer 1995 partial Landsat scenes were acquired to cover the eastern half of Connecticut. In addition to the Landsat data, SPOT panchromatic data were acquired covering the entire state. The SPOT data are composed of a mosaic of various dates of imagery (1994-1996) compiled into15 tiles which cover all of Connecticut.

Methodology for Connecticut Land Use and Land Cover Mapping

The following discussion overviews the procedural aspects associated with the Connecticut land use and land cover mapping portion of the project. In this approach, picture elements (pixels) from the TM imagery were separated into general land cover groupings based on the spectral characteristics of the land cover types. The purpose of this was to focus signature selection training on spectrally similar categories, thereby, reducing the number of signatures and subsequent classes containing mixed land cover types. The groupings fall into the following three broad categories: Vegetation, Water and Wetlands, Urban and Barren.

Vegetation. The Vegetation pixels were extracted using the Normalized Difference Vegetation Index (NDVI). In general, this image enhancement technique measures the amount of vegetation biomass present for a given pixel. The NDVI was calculated for both the spring and summer images. Various areas known to contain different vegetation types (*i.e.* forest, agriculture, turf, etc,) were examined from each of the NDVI images and transects were used to extract NDVI values. These values were used to develop upper and lower thresholds which would identify pixels likely to contain vegetation. A binary map was created, based on these thresholds, containing all pixels likely to be vegetation. The binary map was used to mask a 10 band (bands 1, 2, 3, 4, 5, 6, and 7 from the spring image and bands 3, 4, and 5 from the summer image) multitemporal TM image to eliminate non-vegetative pixels and extract only those pixels identified as having a vegetative cover. Training area selection was derived using supervised, unsupervised, and guided clustering techniques. Supervised signature selection involves digitizing areas of interest (aoi's) around locations of known land cover and using the pixels within the aoi to generate signature statistics which are used in classification. Another method of supervised signature selection is through the use of pixel seeding and region growing. In this technique, a seed pixel is selected within an area of known land cover, and any adjacent pixels that fall within set parameters are selected to create signature statistics and used in classification. In unsupervised training selection, the user specifies the number of signatures to be created. Pixels are then grouped into the specified number of signatures based on the spectral characteristics of each pixel and which group it most closely resembles. In guided clustering, a small area of known land cover types is selected from the imagery. Unsupervised clustering is performed to derive signature statistics for the land cover types. Once several signatures are created, those signatures producing apparently satisfactory results based on their statistics, mean plots, and visual identification were used in a maximum likelihood classification.

Water and Wetland. The Water and Wetland pixels were extracted using a Tasseled Cap transformed image in conjunction with the Thermal band from the TM sensor. A Tasseled Cap transformation changes the TM image data into channels of brightness, greenness, and wetness where the brightness channel highlights areas of high reflectance, the greenness channel highlights areas which are vegetated, and the wetness channel highlights areas that have a high water or moisture content. Areas known to be water and wetlands were examined from the Tassel Cap image and the TM thermal band and pixel values were extracted for the brightness, greenness, wetness, and thermal channels. These values were used to develop upper and lower thresholds which would identify pixels likely to be water and pixels likely to be wetland areas. These thresholds were used to create two binary maps highlighting all pixels within the image being considered water and wetlands. In addition, for the wetland mask, since most wetlands contain vegetation, a majority of wetland pixels (primarily forested wetlands) were also identified as vegetation and therefore classified in the vegetation classification procedure. In order to narrow the number of pixels to be classified and to eliminate a double classification of wetland pixels, the vegetation binary map was used to mask the wetland binary mask to eliminate those pixels that exist in both binary maps. The water binary map was used to mask the springtime seven band TM image to extract only those areas identified as water. Training area selection was done using both supervised and unsupervised techniques. Those signatures producing apparently satisfactory results based on their statistics, mean plots, and visual identification were used in a maximum likelihood classification. The wetland binary map was used to mask the 10 band multitemporal TM image to extract only those areas identified as wetland. Training area selection and classification were performed the same as for the water classification.

Merge vegetation, water, and wetland. The three classified images for vegetation, water, and wetland were combined into one classified image. Where two classifications overlapped, an expert decision was used to determine which classification was to have priority.

Cloud and Cloud Shadow. There were some clouds present in the TM imagery, primarily with the springtime data. Fortunately most of these occurred where the springtime images overlapped and were therefore able to be eliminated, using the cloud-free portions of one of the two images. However, some clouds and shadow areas did exist in other areas of the images. In order to classify land cover for these areas, cloud and cloud shadow signatures were included during the classification of the vegetation, water, and wetland layers. These classes were then used to create a mask which was applied to the summertime images thereby extracting cloud and shadow-free pixels from the summertime images for which cloud and cloud shadow existed in the springtime images. A supervised signature selection was used to derive training signatures followed by a maximum likelihood classification. This classification was then merged with the vegetation, water, and wetland classification replacing those areas classified as cloud or cloud shadow. On-screen editing was performed to eliminate apparent errors.

Urban and Barren. Potential urban and barren pixels were extracted using the vegetation, water, and wetland classification as a guide. All pixels previously classified as vegetation, water, and wetland were used to create a mask. This mask was applied to the 10 band multitemporal TM image to identify areas which consisted only of non-vegetated urban, barren and exposed soil areas. Supervised signature selection was used to generate training signatures. Those signatures producing apparently satisfactory results based on their statistics, mean plots, and visual identification were used in a maximum likelihood classification. A 5-by-5 majority filter was used to generalize slightly this classification to eliminate some apparent errors, followed by on-screen editing to reduce further the occurrence of errors. The urban and barren classification was merged with the vegetation, water, and wetland classification to nearly complete the statewide classification. Filtering using a 3-by-3 majority filter was then applied iteratively six times on selected categories in an attempt to spatially generalize the classification while maintaining the highest level of thematic and spatial detail possible. The classification was then recoded into the final 28 classes (Table 1).

Table 1. Connecticut Statewide Land Use and Land Cover Categories

	Land Cover Class Name	Area (hectares)	Percent Area
1	Commercial & Industrial & Pavement	56474	3.92
2	Commercial &Residential	84072	5.84
3	Rural Residential	20969	1.46
4	Turf & Tree Complex	62873	4.36
5	Turf and Grass	20503	1.42
6	Pasture & Hay & Grass	110734	7.69
7	Pasture & Hay/Cropland	213	0.01
8	Pasture & Hay/Bare Soil	9404	0.65
9	Bare Soil/Cropland	23031	1.60
10	Bare Soil	12356	0.86
11	Shade-grown Tobacco	395	0.03
12	Nursery Stock	520	0.04
13	Scrub & Shrub	7938	0.55
14	Deciduous Forest	647040	44.91
15	Deciduous Forest & Mountain Laurel	18328	1.27
16	Coniferous Forest	131195	9.11
17	Dead/Dying Hemlock	126	0.01
18	Forest Clear-cut	1198	0.08
19	Mixed Forest	12548	0.87
20	Deep Water	183285	12.72
21	Shallow Water & Mud Flats	7097	0.49
22	Non-forested Wetland	7423	0.52
23	Shrub Wetland	3660	0.25
24	Deciduous Forested Wetland	5342	0.37
25	Coniferous Forested Wetland	3868	0.27
26	Low Coastal Marsh	1967	0.14
27	High Coastal Marsh	3200	0.22
28	Bare Rock and Sand	4903	0.34
		1440662	100.00

<u>*SPOT/TM Fused Image*</u>. In order to locate and identify isolated residential and commercial areas which tend to be too small to be depicted by the Landsat TM sensor, yet are a numerous component of the Connecticut landscape, a TM/SPOT fused image was created. This image was closely examined, and thresholds developed, based on the spectral characteristics, to identify urban structures and, alternatively, other features with spectral characteristics which are similar to the urban features (*e.g.,* barren land, bare soil, exposed rock, etc.). A binary map was generated based on these thresholds. This 10 meter binary map was then resampled to a 30 meter dataset that corresponds to the 30 meter vegetation, water, wetland, urban and barren classification. The urban structure binary map was then fused with the classification. To eliminate the errors associated with the development of the urban structure layer due to the inclusion of pixels other than structures (*e.g.,* barren areas), the urban structure pixels had to fall within certain land cover classes. If an urban structure pixel fell within the following classes, it was considered rural residential, otherwise it was kept as originally classified: Turf & Grass, Deciduous Forest, Deciduous Forest & Mt Laurel, Coniferous Forest, Mixed Forest.

<u>Post Classification Editing</u>. On-screen, interactive, post-classification editing was performed to eliminate any remaining apparent errors. These edits consisted primarily of converting major highways into Commercial &

Industrial & Pavement from Residential & Commercial, utility rights-of way from Rural Residential to Scrub Shrub, and from Rural Residential to Forest types where rural residential was classified due to snow and ice being present in some of the SPOT panchromatic scenes. Post-classification editing was performed quadrangle by quadramgle using the source digital image data as a base for on-screen editing and USGS topographic maps as an additional reference to assist in editing. Figure 3 portrays the final land use and land cover map for Connecticut, and Figures 4 and 5 depict land cover in the West Torrington and Essex quadrangles, respectively.

Accuracy Assessment. Accuracy was determined by selecting a stratified random sample of pixels throughout each classified image. For the Connecticut statewide classification, 1149 pixels were selected. In the case of this classification, each of the pixels was examined using the spring and summer TM images in conjunction with the SPOT image to identify the true land cover of each pixel. The product of the accuracy analysis was an overall classification accuracy and a Kappa coefficient of agreement. The overall classification accuracy is a percentage expressed as the number of correctly classified sample pixels over the total number of sample pixels. This percentage indicates how accurate the classification is with respect to the reference data (Story and Congalton, 1986). The Kappa coefficient of agreement is a measure of the actual agreement minus chance agreement. This value provides a better measure of how the classification performs compared to the reference data because it takes into account those pixels omitted into other categories, not just those pixels correctly classified (Congalton *et al*., 1983) Tables 2 and 3 provide accuracy values for the Connecticut statewide classification.

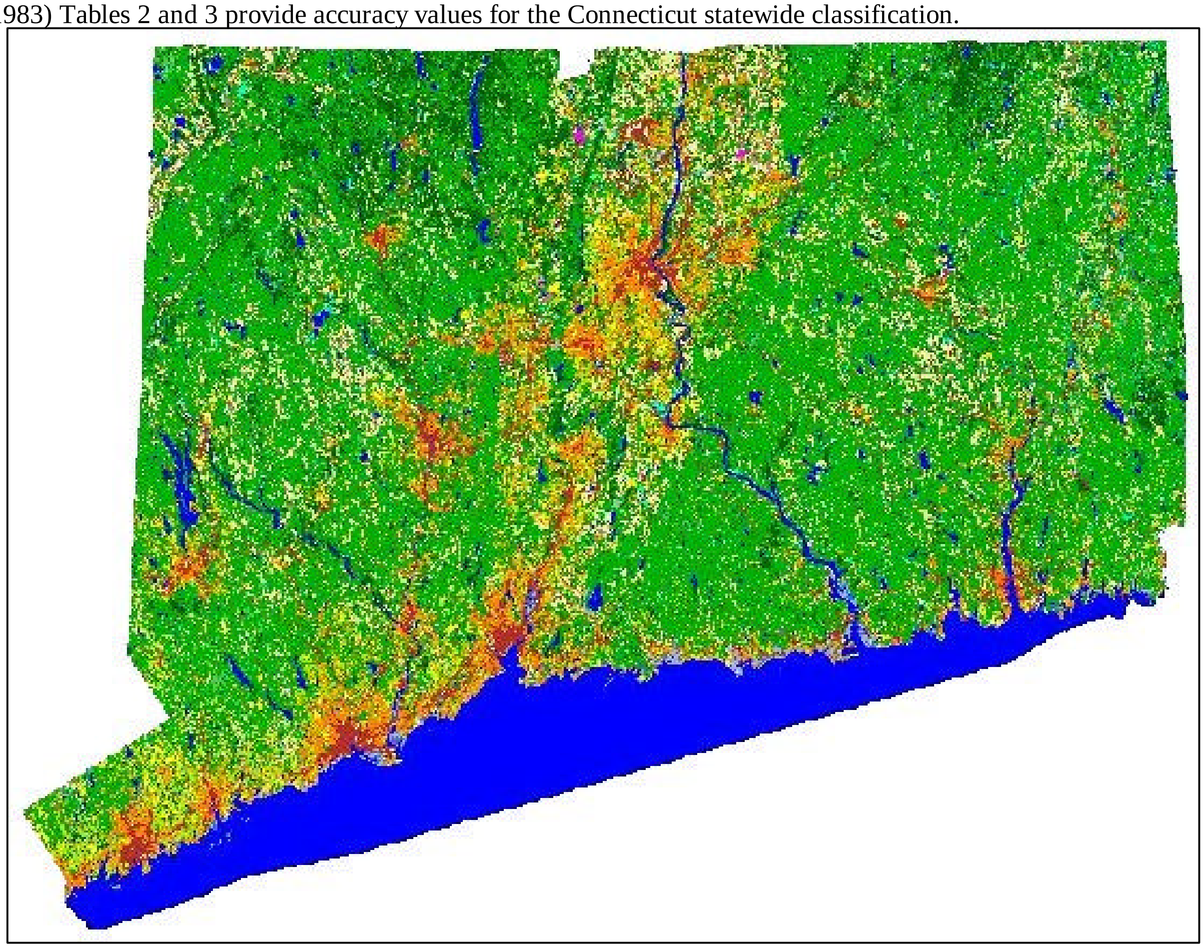


Figure 4. Connecticut Land Use and Land Cover.

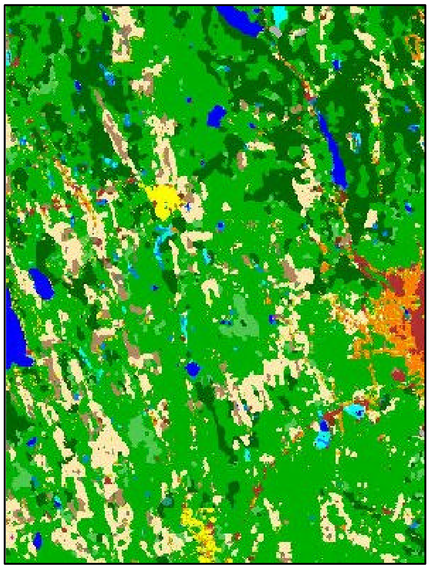


Figure 5. Land Cover for West Torrington.

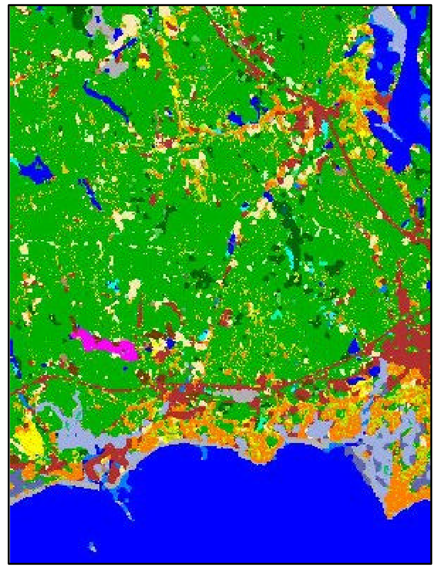


Figure 6. Land Cover for Essex.

Table 2. Overall classification accuracy for Connecticut statewide classification.

Class Name	Reference Totals	Classified Totals	Number Correct	Omission Accuracy	Commission Accuracy	Kappa
Commercial & Industrial & Pavement	50	45	40	80.00%	88.89%	0.8838
Residential & Commercial	66	57	48	72.73%	84.21%	0.8325
Rural Residential	28	31	21	75.00%	67.74%	0.6694
Turf & Tree Complex	31	45	27	87.10%	60.00%	0.5889
Turf & Grass	32	28	23	71.88%	82.14%	0.8163
Pasture & Hay & Grass	97	74	64	65.98%	86.49%	0.8524
Pasture & Hay/Cropland	4	4	3	75.00%	75.00%	0.7491
Pasture & Hay/Exposed Soil	15	31	13	86.67%	41.94%	0.4117
Exposed Soil/Cropland	23	35	20	86.96%	57.14%	0.5627
Exposed Soil	24	26	20	83.33%	76.92%	0.7643
Shade-grown Tobacco	5	5	5	100.00%	100.00%	1.0000
Nursery Stock	3	4	3	100.00%	75.00%	0.7493
Scrub & Shrub	17	23	8	47.06%	34.78%	0.3380
Deciduous Forest	356	326	288	80.90%	88.34%	0.8312
Deciduous Forest & Mt Laurel	27	28	13	48.15%	46.43%	0.4514
Coniferous Forest	86	86	70	81.40%	81.40%	0.7989
Dead & Dying Hemlock	1	2	1	100.00%	50.00%	0.4996
Forest / Clear Cut	0	16	0	---	---	0.0000
Mixed Forest	35	27	15	42.86%	55.56%	0.5416
Deep Water	103	101	100	97.09%	99.01%	0.9891
Shallow Water & Mud Flats	22	21	14	63.64%	66.67%	0.6602
Non-forested Wetland	20	24	15	75.00%	62.50%	0.6184
Deciduous Shrub Wetland	11	20	11	100.00%	55.00%	0.5457
Deciduous Forested Wetland	27	20	14	51.85%	70.00%	0.6928
Coniferous Forested Wetland	19	21	14	73.68%	66.67%	0.6611
Low Coastal Marsh	9	10	6	66.67%	60.00%	0.5968
High Coastal Marsh	15	17	13	86.67%	76.47%	0.7616
Exposed Rock & Sand	23	23	20	86.96%	86.96%	0.8669
Totals	**1149**	**1149**	**889**	**77.37 %**		**0.7424**

Omission Accuracy = (Number Correct / Reference Totals); Commission Accuracy = (Number Correct / Classified Totals)

Table 3**. Overall Level I classification accuracy for Connecticut statewide classification.**

Class Name	Reference Totals	Classified Totals	Number Correct	Omission Accuracy	Commission Accuracy
Urban	207	206	177	85.51%	85.92%
Agriculture	171	179	150	87.72%	83.80%
Forest	522	507	476	91.19%	93.89%
Water	125	122	115	92.00%	94.26%
Wetland	101	112	81	80.20%	72.32%
Barren	23	23	20	86.96%	86.96%
Totals	**1149**	**1149**	**1019**		
Overall Classification Accuracy = 88.68% (Kappa = 0.8436)					

Omission Accuracy = (Number Correct / Reference Totals); Commission Accuracy = (Number Correct / Classified Totals)

CONCLUSIONS

The primary objective of the Connecticut statewide and Long Island mapping project was to derive the most accurate and useful land use and land cover information possible given the use of the most cost effective techniques available. The initial research performed in this project lead to the development of a hierarchical approach to land use and land cover classification. This classification approach was based on the spatial analysis and classification performed on the Essex and West Torrington quadrangles. It was discovered during this classification analysis that a vast majority of the land cover in Connecticut does not require a high degree of spatial resolution to be classified accurately. For example, water, forested areas, and agricultural fields are fairly homogeneous over large areas. These categories, therefore, did not require the more detailed, larger, and computationally demanding 10 meter image to classify accurately. It was in the urban and isolated developed areas that the more detailed 10 meter dataset would have proven useful. Because of the radiometric differences among the SPOT images comprising the statewide mosaic, it was not possible to use the TM/SPOT fused image to its full potential. Therefore this technique was not utilized as anticipated. However, by using the hierarchical classification technique, specific, spectrally related, land cover groupings were isolated from the primary image and signature selection was focused on each of the grouping types minimizing the effect of misclassification between spectrally similar classes of other groups.

Overall, the hierarchical classification technique was found to be a useful technique. The benefits allowed the analyst to focus attention on spectrally similar land cover types (*i.e*. water, wetland and vegetation), and had the overall quality of the TM/SPOT fused image been better, would have allowed for the use of different image types to classify various land cover features depending on the detail required. However, the technique was not without drawbacks. The largest of these was the amount of space required for the storage of several statewide images of Connecticut depicting each of the land cover groupings, and their respective classifications and iterations. These images required over four times the space needed as opposed to using a single all inclusive image. Additionally, the amount of time spent classifying several images might have been reduced by classifying a single image (TM alone) or two types of images (TM for certain land cover types, and TM/SPOT fused image for land cover types requiring more detail). However, classifying one or two images and trying to capture the major land cover types within them would have required more effort to create land cover signatures which accurately characterized the land cover features they represented while minimizing the effects of category misclassification. There was some inclusion of other category types (especially along edges where two types of groups border one another) These tended to be minimized and were easily classified into an appropriate category while most of the signatures from the image group where focused on the image grouping in question.

Unfortunately, the TM/SPOT fused image did not provide a reliable enough image for statewide classification due to the radiometric differences between the several SPOT panchromatic images required to create a composite image to cover the state of Connecticut. The image was sufficient enough to use, however, in identifying isolated developed areas which are characterized in the rural residential category. In the future, as new sensor become available, such as Landsat 7 which will contain a multispectral sensor and a smaller resolution panchromatic sensor, image fusion and classification will become more easily accomplished. This is due to the fact that the images to be fused will be collected at the same time, over a larger area, reducing the differences in radiometric qualities.

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