

# IMPERVIOUS SURFACE MAPPING FOR THE STATE OF CONNECTICUT<sup>1</sup>

Daniel L. Civco<sup>2</sup> and James D. Hurd<sup>3</sup>

Department of Natural Resources Management and Engineering  
The University of Connecticut  
Box U-87, Room 308, 1376 Storrs Road  
Storrs, CT 06269-4087  
860-486-2840 (p)  
860-486-5408 (f)

## ABSTRACT

A method is described by which percent impervious surface, including concrete, asphalt, and varying roof tones, is quantified at the Landsat Thematic Mapper sub-pixel level. This technique is based on an artificial neural network, which is capable of nonlinear, complex mappings of input patterns into output percentages. The neural network is trained with highly calibrated reference data acquired from heads-up interpretation and digitizing of land cover features as depicted in 2-meter digital aerial imagery. The neural network, using data from the six reflective bands from two different seasons of TM, as well as the Kauth-Thomas transform and all within-date two-band ratios, for a total of 48 input features, was able to predict percent pixel composition for 10 different land cover classes, five of them being different impervious surfaces. Correlations with impervious surface calibration data ranged from 0.624 to 0.728, and a correlation with the five-class impervious surface composite of 0.714. The results are promising for the creation of a Connecticut statewide percent impervious surface layer for use in nonpoint source pollution modeling, watershed quality assessment, as well as other environmental and engineering applications.

## INTRODUCTION

Explaining environmental concepts to the public and reaching them with current information has always been a difficult task. Project NEMO, or Non-point Source Education for Municipal Officials, was created and designed in an effort to bridge this gap (Arnold *et al.*, 1994). NEMO's focus has been the explanation of nonpoint sources and their link to different land uses. Particular

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<sup>2</sup> Associate Professor, NRME and Director, Laboratory for Earth Resources Information Systems, dcivco@canr1.cag.uconn.edu

<sup>3</sup> Research Assistant, NRME, jhurd@canr1.cag.uconn.edu

attention is paid to the role of impervious, or paved, surfaces in the transport and concentration of pollutants. To guide towns, NEMO outlines a three-tiered strategy of natural resource-based planning, site design, and the use of stormwater best management practices that towns can use to address their land use and cope with nonpoint source pollution. NEMO is a joint venture of the University of Connecticut Cooperative Extension System, with the University of Connecticut Department of Natural Resources Management and Engineering and the Connecticut Sea Grant College Program collaborating. Other cooperating agencies include the Environmental Protection Agency, the Connecticut Department of Environmental Protection, The Nature Conservancy, Connecticut Chapter, and EnviroGraphics, Inc.

Nonpoint source (NPS) pollution has many origins. Water washing over the land, whether from rain, car washing, or the watering of crops or lawns, picks up an array of contaminants, including oil and sand from roadways, agricultural chemicals from farmland, and nutrients and toxic materials from urban and suburban areas. This runoff finds its way into our waterways, either directly or through storm drain collection systems. The term nonpoint is used to distinguish this type of diffuse pollution from point source pollution, which comes from specific sources, such as sewage treatment plants or industrial facilities. Scientific evidence shows that although huge strides have been made in cleaning up major sources, our precious water resources are still greatly threatened by polluted runoff. In fact, the 1994 National Water Quality Inventory Report to Congress states that this type of pollution is the leading cause of impairment in our Nation's rivers and streams. Urban runoff, in particular, is the leading source of pollution in estuaries and is the third and fourth leading source of pollution in lakes and rivers.

The need for information concerning the percentage of impervious surfaces has become increasingly more important due to growing concern over water quality in this country. The accurate mapping of impervious surfaces therefore plays an important role for the management of water quality. Increased impervious surface coverage can be a prime indicator of nonpoint source pollution and water quality degradation. NEMO investigators measure the impervious area in a town and compare it to a zoning-based build-out analysis to help highlight potential pollution problems. Zoning maps, local basins, and land cover information are combined to create the final images. Currently, Project NEMO and other programs in Connecticut derive impervious information from land use and land cover data (Arnold and Gibbons, 1996). These estimated values tend to be too generalized and do not depict the true spatial pattern of impervious surfaces in an area. This has led to the need for the development of a model which would allow analysts to generate an impervious surface map for a given study area at a finer level of biophysical discrimination, such as described by Ridd (1995). This paper overviews a method for the generation of percentage impervious surface data from Landsat Thematic Mapper (TM)

imagery, at the per-pixel level, using an artificial neural network as the modeling tool and high-resolution digital aerial imagery for sub-pixel calibration. Neural networks have proven to be effective analysis mechanisms that involve complex relationships between remote sensing measurements and biophysical parameters (Civco, 1993; Ridd *et al.*, 1992; Stocker *et al.*, 1995; Wang and Civco, 1995).

## DATA SOURCES AND PREPROCESSING

Landsat Thematic Mapper (Path 13, Row 31) image data from May 8, 1995 and August 28, 1995 were the principal source of data for impervious surface mapping. These images, geometrically corrected and geocoded by EOSAT, Inc., have the following properties: 30 meter pixel resolution, UTM Zone 18, Clarke 1866 spheroid, and NAD27 datum. Both springtime and summertime imagery was selected for impervious surface mapping because of their respective merits. The May imagery (leaf off) allows for improved penetration of forest canopies and better detection of potentially obscured impervious surfaces, whereas the August imagery permits the distinction between some springtime bare soil conditions, often resembling inert or impervious surfaces, and their vegetated state during the growing season.

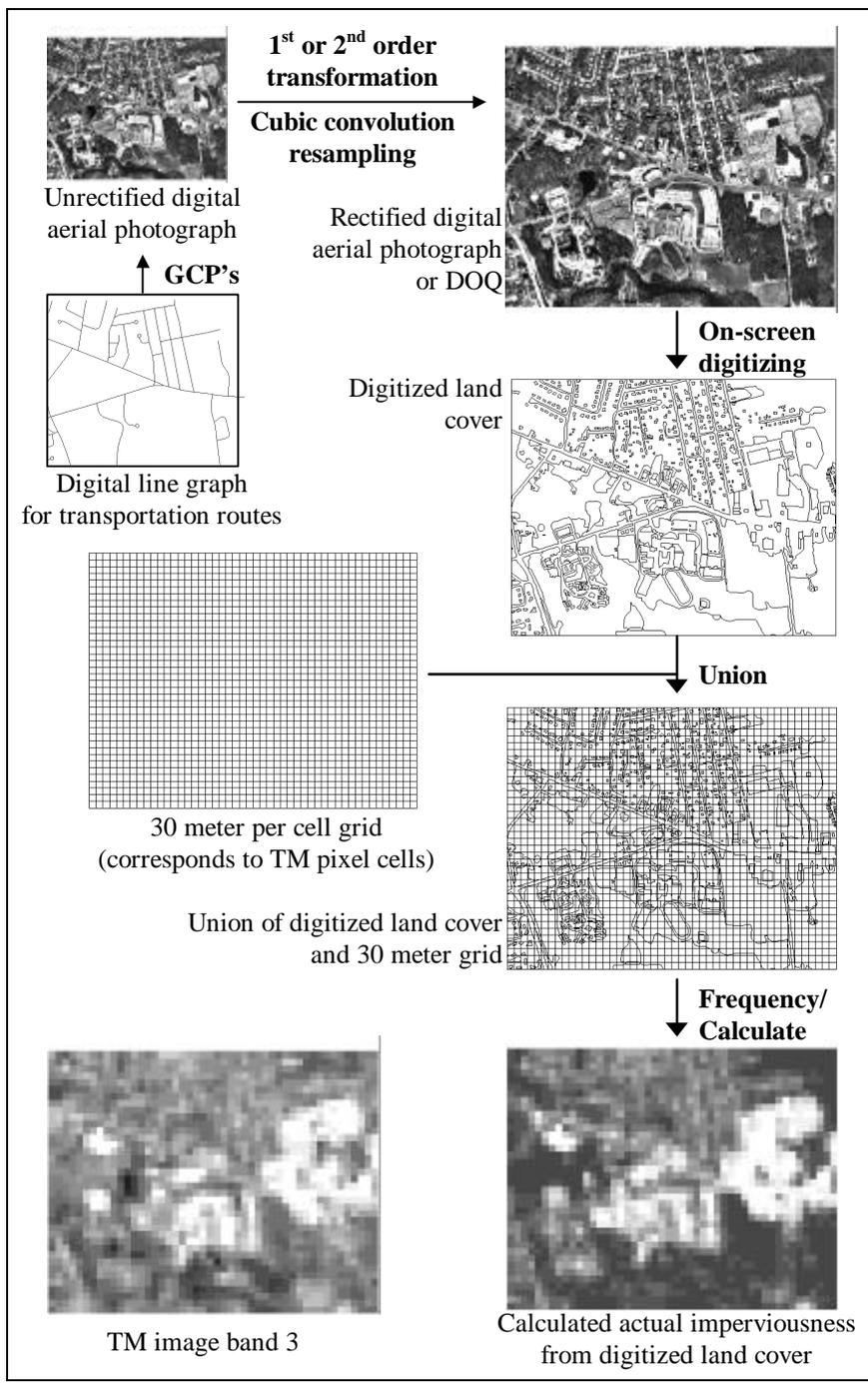
In addition to the Landsat digital data, aerial photographs and Digital Orthophoto Quarter-Quadrangles (DOQQ's) were also utilized for the digitization of training sites. The aerial photographs were flown for the state of Connecticut during the spring of 1990. These photographs are black-and-white and at a nominal scale of 1:12000. The photographs were scanned into a digital format at 150 dpi, resulting in a pixel size of approximately 2 meters on a side. Georeferencing was performed by selecting ground control points (GCPs) from transportation Digital Line Graphs (DLGs). Coordinate locations for road intersections were identified from the DLGs and these GCPs were likewise identified in the aerial photographs. Geometric correction was performed with either a 1<sup>st</sup> or 2<sup>nd</sup> order level polynomial and cubic convolution was used for a resampling method. Aerial photographs were rectified with projection properties the same as those of the Landsat TM data being used. The quality of the rectification was assessed by overlaying the transportation DLGs on the rectified aerial photograph as well as superimpositioning with the TM imagery. It was imperative that the two dates of TM data and the digital aerial photographs be as precisely co-registered as possible to ensure accurate sub-pixel characterization of land use and land cover types, especially impervious surfaces.

## CALIBRATION DATA COLLECTION

Training data were collected from the rectified aerial photographs and DOQQ's for sites within the towns of Waterford, Mansfield, Hartford, Manchester, Putnam, Torrington, West Torrington, and Winsted. Areas in these towns were selected based on familiarity by the analysts, and also for the variety of impervious and non-impervious land covers existing in each. It was important to incorporate into the training data as much variability as possible in terms of reflectance characteristics of land cover features and also areal extent of impervious surfaces (large and small expanses of impervious surfaces) while maintaining a manageable training data set for use in the neural network. A grid, with cells of 30 meters square, was created for each training area and coregistered to each of the respective Landsat TM images. A bounding box was also created to match the outside edge of the grid. In ArcView, the bounding box was displayed over the rectified aerial photograph to highlight the area to be digitized. Using the on-screen interpretation and digitization capabilities of ArcView, land cover features within the bounding box were digitized into separate *shape files* based on the land cover features listed in Table 1. The shape files were converted to ArcInfo *coverages* and erroneous line segments and other errors were cleaned. This coverage was then *unioned* with the grid coverage, therefore providing information on the amount of each land cover feature falling within its corresponding TM pixel. From the unioned digitized and grid coverages, the percentage of each land cover feature within each pixel was calculated. Lastly, the six reflective bands from each of the two dates of TM imagery for the training data sites were converted to an ASCII tabular format. These data, in conjunction with the actual percentage of each land cover, were preprocessed and used to train an artificial neural network to model the percent impervious and other cover at the per-pixel level. The overall calibration data collection procedures for one of the study sites are illustrated in Figure 1.

<b>VEGETATED</b>	<b>ROOF</b>
1.Forest	8.Bright Roof (TM <i>dn</i> value > 140)
2.Grasses	9.Medium Roof (TM <i>dn</i> value <140, > 50)
3.Forest/Grass Mix	10. Dark Roof (TM <i>dn</i> value < 50)
<b>WATER</b>	<b>PAVEMENT</b>
4.Water	11.Concrete
5.Wetlands	12.Asphalt
<b>BARREN LAND</b>	<b>SHADOW</b>
6.Exposed Soil	13.Shadowed Impervious
7.Sand	14.Shadowed Non-impervious

**Table 1.** Digitized land cover features.



**Figure 1.** Training data collection procedures.

## ARTIFICIAL NEURAL NETWORK PROCESSING

The data stream produced from calibration data collection consisted of 12 brightness values, six from each of the two seasons of TM data, and a vector of sub-pixel percent composition of the 14 cover types listed in Table 1. Preliminary studies indicated that water and wetlands could be combined into a single class, and that the attempt to distinguish between shadowed impervious surfaces and other land covers in shadow would be less than successful. This remains a problem, however, in urban areas with tall structures casting long shadows on impervious surfaces, but is rather inconsequential given the cityscapes of Connecticut.

These data were further preprocessed by DataSculptor<sup>4</sup> to create TM image derivatives as well as to prepare the data for use with the NeuralWorks Pro II+ neural network development tool. In DataSculptor, the Landsat TM data were transformed into the Kauth-Thomas measures of Brightness, Greenness, and Wetness. Also, all pairwise band ratios were calculated for each of the two dates. These data transformations resulted in an augmented vector of 48 measurements for each calibration pixel: six brightness values, three K-T measures, and 15 ratios for each of the two dates. These data were accompanied also by the per-pixel composition of each of ten cover types: forest; grass; forest and grass mix; water; barren; bright, medium, and dark roof; concrete; and asphalt. This dataset, consisting of 7,563 observations, was divided into a training set of 5,042 points and a testing set of 2,561. From DataSculptor, these two datasets were export into an ASCII format compatible with the NeuralWorks Pro II+ neural network software.

A number of neural network paradigms and architectures, as well as different combinations of input (the TM data and their transforms) and output data (the per-pixel percent cover), were examined. The paradigms explored included Back Propagation, Modular Neural Networks, Learning Vector Quantization, and General Regression Neural Networks. Architectures included both single and two hidden layer designs, as well as a varying number of neurons (processing elements) per hidden layer. Input data streams ranged from the use of the six brightness values from only a single date (May) to the full complement of two-date TM data and their respective transforms and ratios. Through systematic evaluation of the performance of each neural network design, by way of monitoring root mean square error (RMSE) during the training phase as well as assessing accuracy of the results during the independent testing phase, it was determined that a single hidden-layer, populated with 20 elements, back propagation network, with 10 outputs and all

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<sup>4</sup> NeuralWare, Inc., Pittsburgh, PA

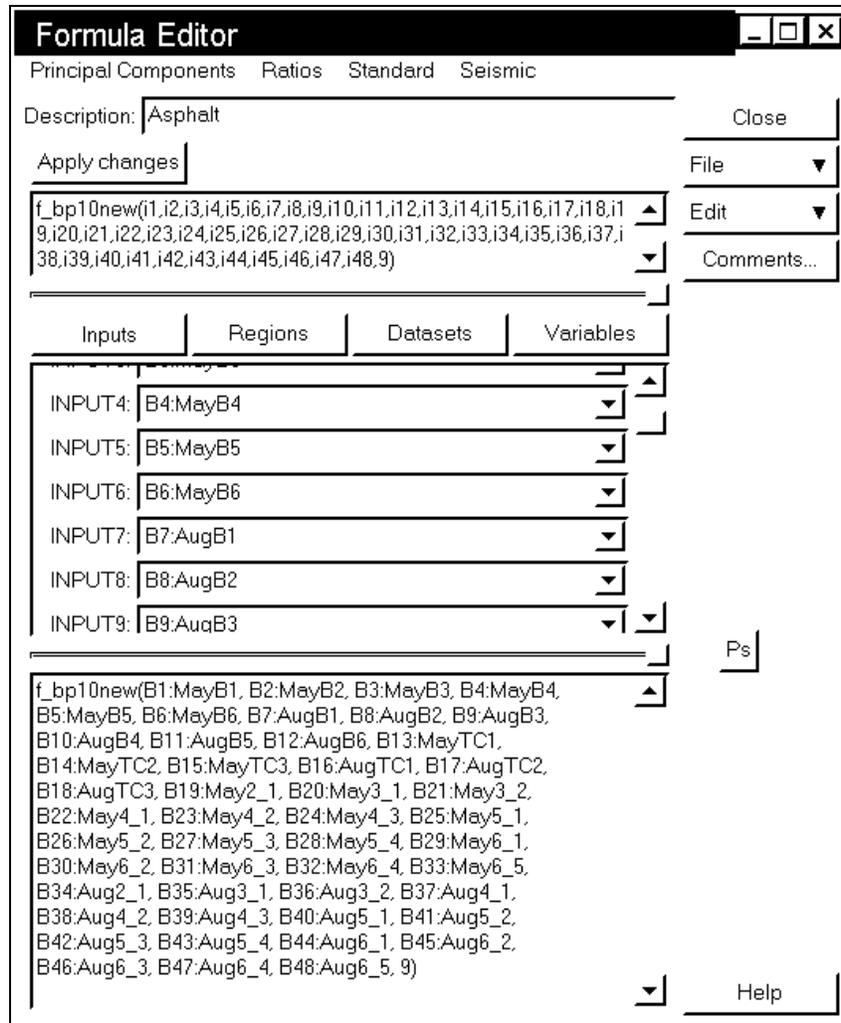
48 inputs, and using a sigmoid transfer function, was the most appropriate paradigm-architecture for this problem. The final neural network design was trained with these data for more than 500,000 iterations, achieving an RMSE of 0.099. The RMSE obtained with the test data was 0.103, a good balance between the accuracy achieved with the training data and that of the test data, indicating favorable generalization of this network. One concern that might be expressed is that of over-training the network such that it *remembers* the input patterns nearly-perfectly, but does not perform well with slightly different or noisy data. This is not such a concern here, since the calibration data were selected from around Connecticut and complete-statewide impervious surface characterization will use these same dates of Landsat TM data.

The final neural network classification scheme was exported from NeuralWorks into C-language source code, which was compiled into a DLL<sup>5</sup> using Microsoft Visual C++ version 4.0. This DLL can be addressed by ERMMapper's<sup>6</sup> function calls as a formula to be used in an ERM algorithm (for a discussion of the ERMMapper software and its capabilities, refer to Civco, 1996). In ER Mapper, the physical datasets for the May and August Landsat TM data were combined to create a virtual dataset (VDS), which included also, each date's Kauth-Thomas transforms and all pairwise band ratios, for a total of 48 data layers in the virtual dataset. Another algorithm was created which calculated the pixel-level percent cover for each of the 10 classes being analyzed using the DLL from the trained neural network. An example of the ERMMapper dialog box illustrating this operation is shown in Figure 2. The syntax for the classifier is {*f\_name*,*Input*<sub>1</sub>...*Input*<sub>*n*</sub>,*Output*<sub>*m*</sub>}, where *f\_name* is the compiled neural net-generated DLL, *Input*<sub>1</sub> through *Input*<sub>*n*</sub> are the 48 input data, in this case, and *Output*<sub>*m*</sub> is the index of the output neuron, ranging from 1 to 10 (actually 0 to 9) in this design. After the ER Mapper Virtual DataSet is processed by the compiled neural network generated C-code, the product is an algorithm, or alternatively physical or virtual datasets, predicting the percentage cover for each class (*m*={1,10}). In our case, we summed the predictions for the five related categories (concrete, asphalt, and the three brightnesses of rooftop) to render a composite of percent impervious surface per pixel. Individually and aggregately, the correlations between each of the five individual impervious surface predictions with their calibration data are shown in Table 2, as is the correlation between the aggregate impervious surface class.

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<sup>5</sup> A dynamic-link library (DLL) is an executable module containing functions that Windows-based programs can call to perform tasks and operations, such as executing a run-time neural classifier, in this case.

<sup>6</sup> Earth Resources Mapping, Inc., San Diego, CA.

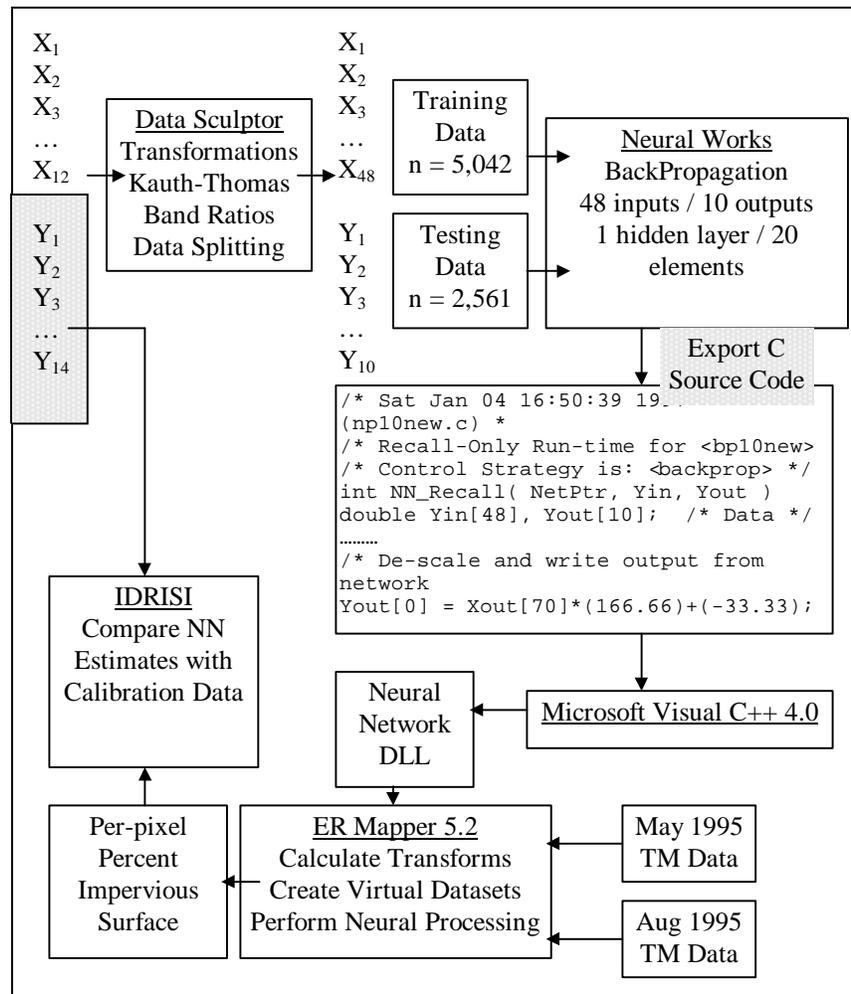


**Figure 2.** ER Mapper 5.2 Algorithm Equation Dialog Box for Neural Network Impervious Surface (Asphalt Condition) Classifier.

Bright Roof	Medium Roof	Dark Roof	Concrete	Asphalt	All Five
0.664	0.728	0.624	0.702	0.699	0.714

**Table 2.** Correlations between Neural Network Predictions of Impervious Surface with Entire Calibration Test Dataset

The predicted percent impervious estimates were exported to a generic ASCII file for import in IDRISI<sup>7</sup>, a fully-functional, very capable, general purpose spatial data analysis software system. In IDRISI, the calibration images, with actual percent cover by category derived from the 2-meter digitized aerial photographs, were compared with the estimates derived from the neural net process. Figure 3 illustrates the overall neural processing impervious surface estimation and evaluation procedure.

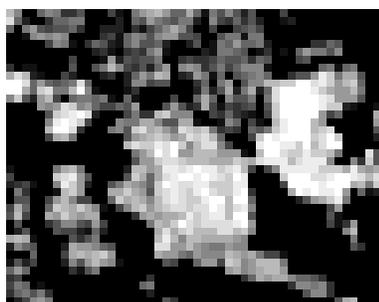


**Figure 3.** Overview of Neural Network-based Impervious Surface Modeling and Evaluation

<sup>7</sup> The IDRISI Project, Graduate School of Geography at Clark University, Worcester, MA.

## RESULTS AND DISCUSSION

Figure 4 presents the results of the aggregated-class percent impervious surface neural network prediction for one of the study sites, and Figure 5 is of that of the calibration data for that area. Figure 6 is a difference image showing the magnitude and spatial distribution of error between the neural network percent imperviousness and that derived from on-screen interpretation and digitizing. Figure 7 is a histogram of that difference image, with the frequency depicted on a log scale. Note that a large proportion of the error (differences) are at or near zero, and that there are relatively few large differences.

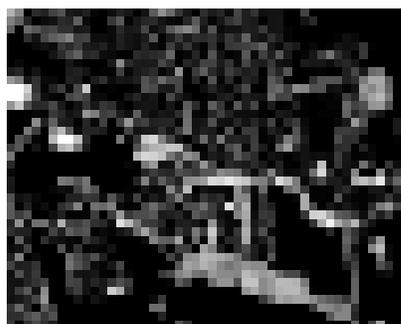


**Figure 4.** Neural Net Percent Impervious Surface Prediction

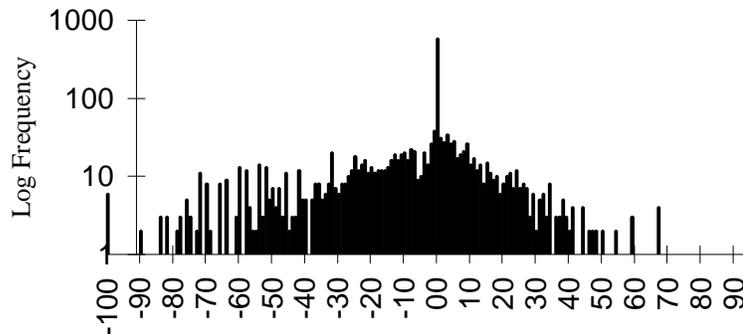


**Figure 5.** Calibration Data Percent Impervious Cover

*(darker tones indicate lower percent impervious surface cover, whereas brighter tones indicate higher impervious surface cover {0,100%})*



**Figure 6.** Difference Image between NN Prediction and Calibration Data *(brighter tones indicate greater magnitude of difference between calibration data and neural prediction)*



**Figure 7.** Calibration Data minus Neural Prediction

Most of the errors in this sample impervious surface prediction stem from the inclusion of some barren features into one or more of the impervious classes, often with low percentages, but sometimes with high ones. Also, there is some spatial overestimation of the spatial extent of impervious surfaces in medium to high density residential areas. High degrees of correspondence, however, were achieved for the high density impervious covers, such as the parking lots and shopping centers, in the right-hand side and just below middle of Figure 4 (or 5), for example.

## CONCLUSIONS

Artificial neural networks are a viable modeling tool for predicting percent impervious cover at the sub-pixel level. The results were best for the aggregated impervious surface categories, and of varying success with the individual classes. Highest degree of agreement with the calibration data among the five types of impervious cover was medium brightness roof surfaces, followed by concrete, asphalt, bright roofs, and lastly dark roof surfaces. These estimates, although imperfect, are far better than the current method of quantifying impervious surface, which is based on assigning literature estimates to land cover types as derived from satellite image classification. As a work in progress, research will continue into refining neural network design to improve both the precision and accuracy of this predictive model, especially before implemented statewide.

## ACKNOWLEDGMENTS

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