SUBPIXEL IMPERVIOUS SURFACE MAPPING

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Abstract

Identified by the EPA as the leading threat to surface water quality in the United States, nonpoint source (NPS) pollution is channeled into rivers and streams via impervious surfaces. Impervious surfaces are anthropogenic features, such as roads, buildings, and parking lots, through which water cannot infiltrate into the soil. Research from the past 15 years shows a consistent, inverse relationship between the percentage of impervious surfaces in a watershed and the health of its receiving stream. In conjuction with remote sensing satellite imagery, this relationship may be utilized as a time- and cost-effective indicator of overall ecosystem health and water quality. Impervious estimates are typically calculated by multiplying a land use specific percent impervious coefficient by the total area of that land use within a drainage basin. Though a widely used method, this approach does little to promote accurate, standardized, measures upon which to base land use planning decisions. Artificial neural networks and the ERDAS Imagine SubPixel Classifier were investigated as methods for the improved characterization and quantification of impervious surface cover. The principal goal of this research was to develop an accurate, standardized, and geographically extensible impervious surface prediction model. This model was based upon Landsat Thematic Mapper data and was used to quantify, by land cover type, the percent imperviousness at the subpixel (30 m) level. High accuracy planimetric data, in the form of an impervious footprint, were used to calibrate both models for four municipal study areas in Connecticut. Considering only impervious-pervious detection at the pixel level, overall accuracies for the artificial neural network and the ERDAS Imagine Subpixel Classifier predictions, respectively, were 92% and 94% for Marlborough, 90% and 92% for Waterford, 84% and 86% for Woodbridge, and 74% and 71% for West Hartford. At the local watershed level, the RMSE for the four towns for the neural network approach and Subpixel Classifier, were, respectively: Marlborough, 1.29 and 0.66; Woodbridge, 2.51 and 0.99; West Hartford, 4.97 and 5.97; and Waterford, 1.24 and 2.98. Results from this research will provide the foundation for subsequent efforts to quantify impervious surface cover using satellite remote sensing imagery.

Introduction

The accurate mapping of impervious surfaces within a watershed is essential to our ability to monitor urban-related non-point source pollution (NPS). Non-point source pollution, or polluted runoff, has been recognized as the leading threat to surface water quality in the United States (Environmental Protection Agency 1994). Because impervious surfaces provide one of the primary means for the conveyance of runoff into waterways, they are intimately linked to issues of water quality. Research indicates that the percentage of impervious surface within a watershed is a viable indicator of watershed health and ecosystem quality (Booth and Reinfelt 1993, Schueler 1994, Arnold and Gibbons 1996). As a result, a need has developed for the ability to map accurately impervious phenomena at a watershed scale. Traditional satellite remote sensing classification methods, while able to discern general spatial pattern, extent, and distribution of land cover features, are unable to resolve mixed pixels, which occur when the material of interest occupies an area smaller than the sensor's resolution. As a result, subpixel

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classification techniques are emerging that specifically address the mixed pixel problem. It was the purpose of this research to compare two subpixel classification methods for impervious surface characterization, using Landsat Thematic Mapper data. Impervious surface maps were derived using both an artificial neural network and a commercially available subpixel classifier, and were calibrated using high-accuracy planimetric data for four Connecticut towns.

Methods

Introduction

Two per pixel impervious surface prediction models were constructed based upon: (1) artificial neural networks and (2) the ERDAS[3] Imagine Subpixel Classifier. These models were calibrated using planimetric data for structures, roads, driveways, parking lots, and other built surfaces, and further post-processed by applying an urban-related land use / land cover mask, and by recoding the initial continuous output into binary and categorical impervious layers. Spatial data processing occurred at all stages of the research and was performed using numerous software packages. IMAGINE 8.4 is a geographic image processing package and was used at every stage of the research. ESRI[4] ArcInfo 7.2.1 is a fully functional geographic information system and was used for data preparation, construction, manipulation, and editing. ESRI ArcView 3.2 is a desktop GIS package and was used for data visualization and basin summary analysis, and Microsoft Access97 is a relational database management system (RDBMS), which was used for data summarization. The impervious surface models were developed using NeuralSIM[5], a Microsoft Excel-based neural network development and deployment package, and the ERDAS IMAGINE Subpixel Classifier[6] module. The Subpixel Classifier module is fully integrated with IMAGINE 8.4 and was used for subpixel impervious surface characterization.

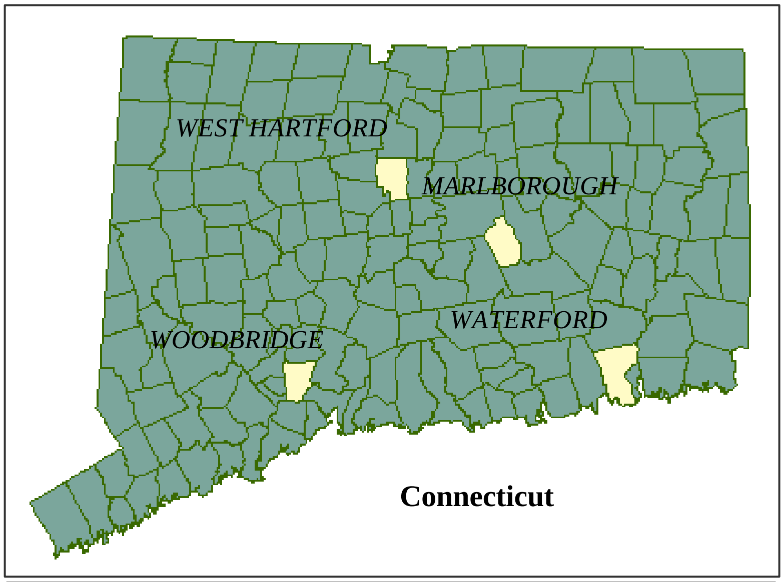

Figure 1. The study area was comprised of the four Connecticut towns of Marlborough, West Hartford, Waterford, and Woodbridge.

Study Area

The Connecticut towns of Marlborough, West Hartford, Waterford, and Woodbridge comprised the study area for this research (Figure 1). The four towns are situated in three different physiographic regions of the state, and each is in a different developmental stage. Marlborough is located in the Eastern Highlands and is a rural community, and West Hartford is located in the Central Valley, and represents the most urbanized town of the study area. Waterford is located along the Coastal Plain and is a suburban town, as is Woodbridge, which is located in the Central Valley. It was considered essential that the study towns, as a whole, represent the developmental continuum from rural, to

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[5] NeuralWare, 230 E. Main Street, Suite 200, Carnegie, PA 15106 (*www.neuralware.com*)
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suburban, to urban, so as to represent land cover features of the highest variability. Data availability, however, was the primary reason for the four towns comprising the study area. High-accuracy data were needed in order to calibrate both the artificial neural network and the Subpixel Classifier models, and at the commencement of this research, these were the only towns with planimetric data of acceptable quality.

Data Types and Sources

This research utilized three different data types: (1) high-accuracy planimetric data were used as reference, or calibration, data; (2) Landsat Thematic Mapper data were used to construct the impervious surface model; and (3) a statewide land use / land cover (LULC) thematic layer was utilized as a mask in post-processing.

Impervious surface planimetric data layers consisting of buildings and houses, roads, driveways, parking lots, sidewalks (for West Hartford and Marlborough only), and recreation areas (for Marlborough and Woodbridge only) were used as calibration data for the impervious surface models. Figure 2 is an illustration of these data for the town of Waterford The planimetric data were digitized from 1"=200' aerial photographs, using stereographic techniques, by independent firms contracted by each of the towns. The flight dates for each town were: Marlborough, 1997; West Hartford, 1989 (western portion), 1990 (eastern portion); Waterford, 1994; and Woodbridge, 1996.

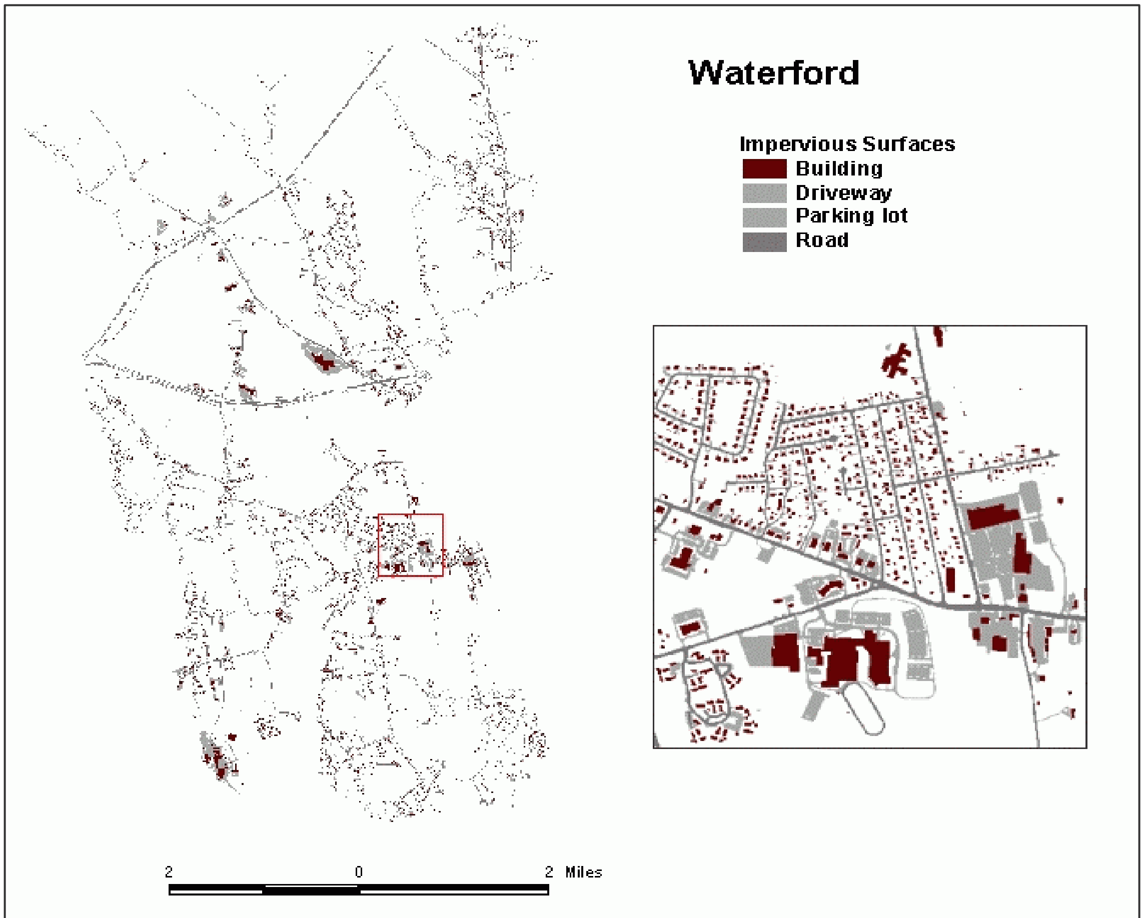

Figure 2. Impervious planimetric footprint for the town of Waterford, Connecticut, showing buildings, driveways, parking lots, and roads.

Statewide Landsat Thematic Mapper imagery from May 5, 1995 and April 28, 1994, were used for the development of the impervious surface prediction models. Two images were used since the 1995 data did not cover the state in its entirety. The 1995 TM data were of Path 13, Row 31, and the 1994 data were of Path 12, Row 31. These images, geometrically corrected and geocoded, had the following properties: 30 meter pixel resolution, UTM Zone 18, Clarke 1866 spheroid, and NAD27 datum. Springtime imagery was selected for impervious surface mapping because of its ‘leaf-off’ condition, allowing for greater penetration of tree canopies and better detection of potentially obscured impervious surfaces. While these images were classified independently, an image mosaic was produced in order to create a TM scene that represented the full extent of the state.

A statewide LULC thematic map (Civco and Hurd 1999) was utilized as a post-processing method in order to mask impervious surface pixel classifications occurring beyond the extent of already acknowledged urban land use. The initial LULC thematic image represented 28 classes and was recoded into a binary layer representing only urban-related. This image was later used as a multiplication operator input layer in order to mask the output from both impervious surface prediction methods.

Calibration Data Processing

Impervious surface planimetric data were used to derive the per pixel impervious surface percentage (*i.e.*, fractional composition) for all corresponding 30m x 30m Landsat TM whole pixel occurrences within each town. After co-registering the impervious planimetric and the statewide TM data, a grid was generated using ESRI ArcInfo 7.2.1, the cell size and geographic location of which corresponded to those of the TM image. This coverage was then ‘*unioned*’ to the impervious planimetric data. In ArcView 3.2, these intermediate layers were respectively overlaid upon town boundary polygons, from which all whole pixels, existing within the town boundary, were selected. The result of this selection was then used to ‘*clip*’ each impervious planimetric layer to create a final layer that consisted of all impervious surfaces, delineated by the same coordinate space as the TM image, wholly within each town.

ArcView 3.2 was then used to calculate, given the 900 m^2 area of each pixel, the impervious surface percentage for each pixel. The output was a DBF table that included for each town, the easting-northing coordinates, and subpixel impervious surface percent for each pixel. These tables were subsequently imported into a Microsoft Access database. The per pixel imperviousness DBF file was also converted to ASCII table format, and further converted into an image, using the IMAGINE ‘*Convert ASCII to Pixel*’ utility. In this manner, the actual per pixel percent imperviousness for each town was converted to a continuous value, raster image {0,100}. This image file was then recoded into a thematic image whose values corresponded to the Subpixel Classifier output image format, which represents eight class values, of 10% increments, greater than 20%. This final, recoded layer for each of the four study towns comprised the reference, or calibration, data for both the artificial neural network and the subpixel classifier impervious surface prediction models.

Artificial Neural Networks

The artificial neural network impervious surface prediction model consisted of a two-tier neural network series, wherein the output from the first network comprised the input to the second. The final output consisted of per pixel impervious predictions for each of the four study towns. These were then converted into a thematic image layer and recoded to depict eight classes of 10% imperviousness, greater than 20%; corresponding to the output format of the ERDAS Imagine Subpixel Classifier. Artificial neural network training data consisted of Landsat TM band reflectance values for geographic subsets throughout the state, as had been processed by Civco and Hurd (1997), as well as for the corresponding impervious Areas of Interest (AOI) that constituted the training file for the ERDAS Imagine Subpixel Classifier.

In the case of the TM subsets, small areas depicting a variety of impervious and non-impervious land cover features, were used from the towns of Hartford, Manchester, Mansfield, Putnam, Torrington, and Waterford. Civco and Hurd (1997) had obtained the actual land cover class values of the corresponding geographic areas by digitizing aerial photographs and Digital Orthophoto Quarter-Quadrangles. The percent fractional composition for each of the following land cover classes was then calculated for each 30m by 30m grid corresponding to the geographic space of the TM pixels: vegetation, water, bare soil, bright impervious, medium impervious, and dark impervious. The TM pixel brightness values that comprised the ERDAS Imagine Subpixel Classifier impervious training areas were also appended. Using the Area of Interest (AOI) tool, whole pixel occurrences of bright, medium, and dark impervious areas were selected throughout the state, and their brightness values were then extracted from the image, converted to ASCII table format, and appended. The TM brightness values for the entire training file were then converted to five normalized ratios: a normalized difference vegetation index (NDVI); a water index; an iron oxide index; a clay mineral index; and a ferrous content index. These ratios, which incorporated information from all six reflective TM bands, were chosen so as to reduce any topographically-induced reflectance variability within the TM data, as well as to allow for the greatest degree of spectral separability among the represented land use classes. Further, these transformations had the effect of normalizing the TM brightness values {0,255} over the range of {-1,+1} or {0,1}, magnitudes of data more amenable to neural processing.

An artificial neural network was developed for the purposes of mapping the relationships from the TM ratios to the subpixel land use classes, using NeuralWare. The network architecture included five input nodes, corresponding to the five TM ratios, 14 hidden nodes, and six output nodes, corresponding to the six types of cover and impervious classes, for which the actual pixel percentages were known. Internal network correlation during the training stage was 0.8036. Running the network on the training data resulted in output predictions for each of the class categories of vegetation, water, bare soil, bright impervious, medium impervious, and dark impervious. The output values from this first neural network subsequently comprised the input data for a second neural network.

A second neural network was developed that utilized as inputs, the output predicted values for the six class categories of vegetation, water, bare soil, bright impervious, medium impervious, and dark impervious from the first network. The rationale in developing a two-tiered neural network model was to allow the second neural network to learn the *mistakes* of the first and refine the transforms, resulting in a more accurate prediction values. The pixel values for the three categories of bright impervious, medium impervious, and dark impervious were then summed, resulting in a per pixel estimation of imperviousness. The second network architecture consisted of six input nodes, corresponding to the output from the first network, six hidden nodes, and one output node – representing the predicted imperviousness for each pixel. Internal correlation during the training stage of the second network was 0.8902, and running the network on the training data resulted in a correlation of 0.895 between the actual and the predicted subpixel percent imperviousness. TM data, transformed into the five ratios, for each of the study towns were then processed through the two-tiered neural network series, resulting in subpixel impervious surface predictions for each town. These continuous {0,100} data were subsequently recoded into eight, 10% classes, greater than 20%, corresponding to the output format of the ERDAS Imagine Subpixel Classifier.

ERDAS Imagine Subpixel Classifier

The ERDAS Imagine Subpixel Classifier module is comprised of four required steps: preprocessing, environmental correction, signature derivation, and MOI classification. The first two steps are autonomous – preprocessing resulting in a hidden, companion file to the original image being classified, and environmental correction resulting in a CORENV companion file that contains information pertaining to atmospheric and environmental correction factors. Signature derivation and MOI classification are detailed below. Additional information can be found in Flanagan (2000) and Flanagan and Civco (2001).

Impervious training areas throughout the state were manually selected using the ERDAS IMAGINE Areas of Interest (AOI) tool, for each of the three categories of bright, medium, and dark imperviousness. Previous research (Civco and Hurd 1997) indicated that the diverse reflectance characteristics of anthropogenic impervious features were best represented by considering imperviousness a composite class comprised of three sub-classes. These sub-classes were considered to represent the varying spectral characteristics of concrete and asphalt, the two major components of anthropogenic impervious features. Using the optional Signature Combiner function in the ERDAS Imagine Subpixel Classifier, these impervious sub-classes were subsequently grouped into a multi-signature file called a '*family*', so that each sub-class was treated independently during classification. Signature families typically represent variations in the signature for a single material of interest, and are used to detect more accurately the material despite these variations.

The final step in the ERDAS IMAGINE Subpixel Classifier, Material of Interest (MOI) classification utilized as inputs the initial TM image data, the corresponding environmental correction file derived from the Environmental Correction step, and the impervious signature '*family*' file. A classification tolerance of 1.50 and eight output classes of 0.1 increments were selected. Signature tolerance is a parameter that can be used to adjust the number of MOI detections, and its value can be increased to include more pixels in the classification result, or decreased to reduce false detections. Output from this final step resulted in a four-band thematic overlay detection file – one band showing impervious detections for each of the sub-class signature files, and one band showing detections for the combined contribution of the three sub-classes. The final ERDAS Imagine Subpixel Classifier image consisted of the fourth band of this detection file.

Post-processing

Given the similarities in spectral reflectance between bright impervious features and barren land (or bare soil) and clouds, an urban-related LULC mask was employed as an additional post-processing step. The 1995 statewide LULC (Civco and Hurd 1999) thematic layer had a Level I overall classification accuracy of 88.7%, and omission and commission accuracy percentages for the 'urban' category of 85.5% and 85.9%, respectively. A binary layer was generated from the initial 28 classes, representing only the four urban-related categories. The ERDAS Imagine *Operators* utility was subsequently used to multiply the binary urban-related thematic layer with the output from the impervious surface prediction models to create a new *'masked'* image, which included only those predicted impervious values that occurred within areas accepted to be urban-related land use.

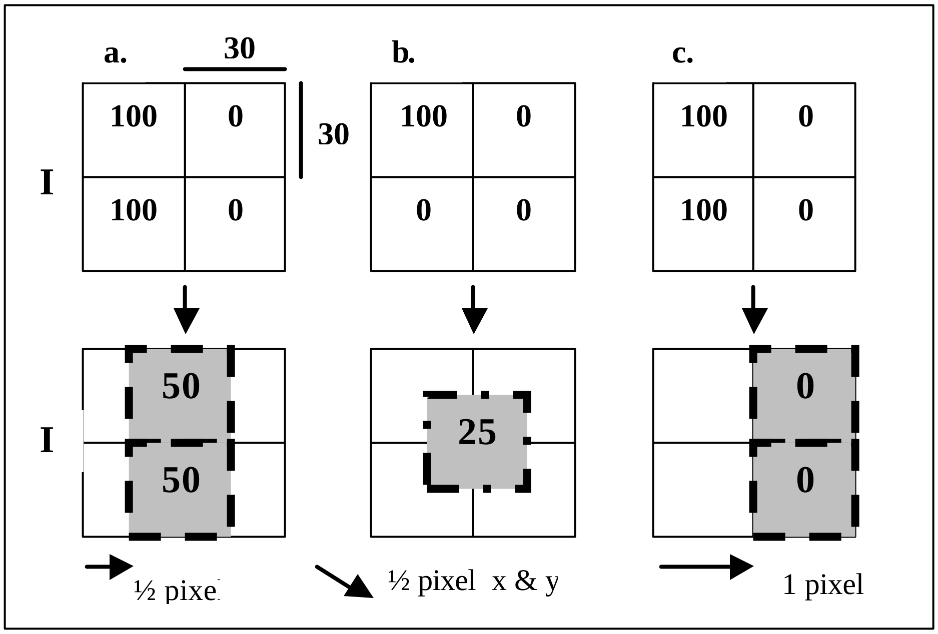

Figure 3. Misregistration can significantly affect classification accuracy even at a relatively small scale. Given the per pixel impervious percentages (I.) overall accuracy can be seen to decrease (II.) as an effect of misregistration by 50% with a shift of half a pixel (a.), 75% with a diagonal shift of half of a pixel (b.), or 100% with a shift of one pixel (c.).

From a scientific perspective, how well each model predicted actual percent imperviousness at the subpixel level, as expressed by the calibration planimetric data, is of principal interest. However, even slight mis-registration between the reference and TM data could result in potentially large differences between actual and predicted values, as illustrated in Figure 3. Also, from the management perspective, the assessment of impervious surfaces is more meaningful when reported on a landscape management unit such as a drainage basin. Therefore, per pixel-based impervious surface data were summarized over the local drainage basin unit. In ArcView, this is a matter of: (1) converting the ERDAS Imagine image (.img) files into ArcView GRID (Spatial Analyst) files; (2) reclassifying the eight intervals {1,8} of imperviousness into increments of 10%, starting at the 20-30% lower threshold {0%, 25%, 35% … 95%}, (3) intersecting each town boundary theme with the statewide drainage basins; and (4) calculating the average percent impervious surface (and other statistics), from the reclassified GRID, by summarizing zones of the town-constrained local basins.

Results and Discussion

Binary Impervious Predictions

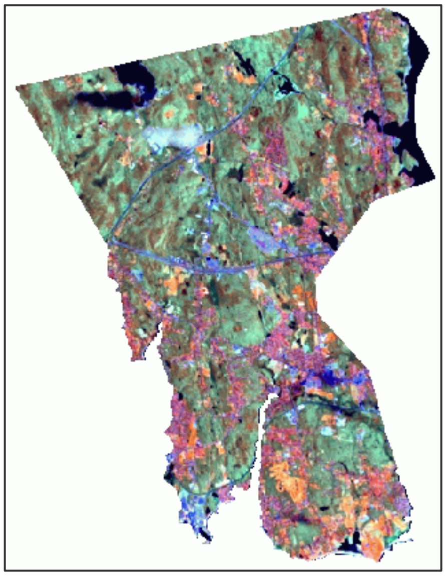

Figure 4.a. Waterford TM source data. RGB of Bands 4,5, and 3.

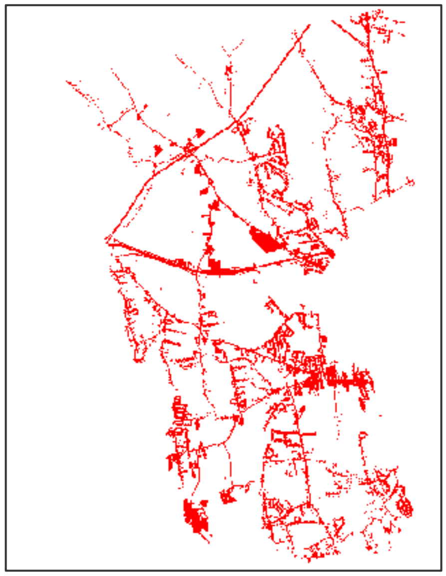

Figure 4.b. Rasterized planimetric footprint, representing greater than 20% imperviousness per pixel, in two classes.

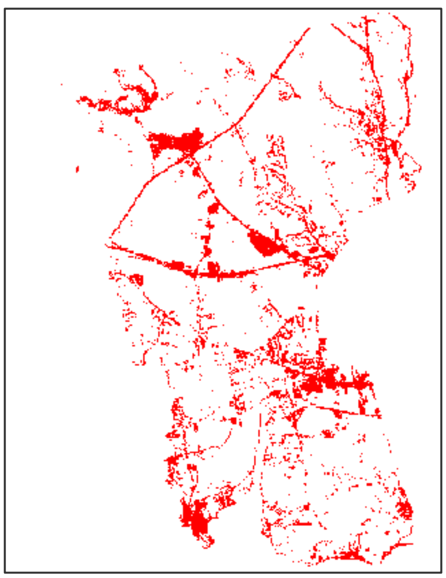

Figure 5.c. Initial artificial neural network impervious prediction, in two classes.

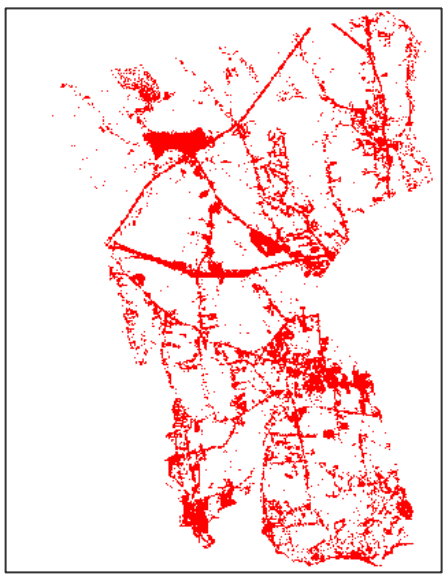

Figure 5.d.. Initial ERDAS Imagine Subpixel Classifier impervious prediction, in two classes.

For the purposes of discerning whether the impervious surface prediction models were viable methods of ascertaining impervious surfaces, the first stage of analysis compared the output from both impervious surface models to the planimetric data on a binary scale - both for its initial output, and after masking the initial output with the binary, urban-related, 1995 LULC layer.

Binary layers were calculated by recoding the planimetric data and the model output data such that pixels with subpixel impervious occurrences, or predictions, greater than 20% were given a value of ‘1’, and pixels having an impervious value of less than 20% were given a value of ‘0’. This resulted in each of the planimetric, neural network prediction, and ERDAS Subpixel Classifier prediction layers being represented on the same scale. Figure 4 shows the TM source data, the binary planimetric impervious footprint, the initial binary artificial neural network output, and the initial binary ERDAS Subpixel Classifier output for Waterford.

These images may be assessed on a qualitative level by visually comparing both the neural network and the ERDAS Imagine Subpixel Classifier output with the planimetric data. Qualitative analysis of the initial output from both models, in binary format, for all four study towns indicates that both models were largely successful in discerning major road features and the larger impervious areas – particularly for the two more developed towns of the study area. In West Hartford and Waterford, the larger contiguous patches of impervious surfaces and road networks appear to have been successfully detected by both models. In contrast, there appears to be relatively inadequate impervious detection for the two rural towns of Marlborough and Woodbridge. Although the major road (CT Route 2) running through the center of Marlborough was detected by both models, and particularly by the ERDAS Imagine Subpixel Classifier, this is less the case for the minor roads. A similar effect can be seen for the town of Woodbridge, for which the major impervious area towards the southeastern portion of the town was detected but again, this is less the case for the minor roads and road networks. As a result of qualitative analysis, it may be hypothesized that the further along the developmental scale a town, the more amenable that town may be towards impervious surface mapping. It is noteworthy that both models have classified the cloud, visible in Figure 4.a., in the northwestern corner of Waterford, as being an impervious feature. This is due to the similarity in reflectance values from both cloud cover and impervious features. Other land cover features that are commonly misclassified for the same reason are agricultural land, or barren land, and sand.

Overall accuracies for both the artificial neural network and the ERDAS Imagine Subpixel Classifier impervious predictions, respectively, were 91% and 93% for Marlborough, 87% and 88% for Waterford, 83% and 85% for Woodbridge, and 73% and 71% for West Hartford. These results would indicate that the rural town of Marlborough was most accurately classified for impervious surfaces, followed by the suburban town of Waterford, followed by the rural town of Woodbridge, followed by the suburban-urban town of West Hartford. The ERDAS Imagine Subpixel Classifier obtained higher overall accuracy values for three towns, while the artificial neural network model obtained a higher overall accuracy value for the town of West Hartford, though only with a 2% difference. Despite the relatively consistent level of classification accuracy between the two models, it should be noted that the overall accuracy values are inflated due to the inclusion of the '0' class. Since overall accuracy is calculated by dividing the sum of the total number of correctly classified pixels by the total number of reference pixels, the resultant value not only indicates how well the prediction models classified impervious pixels, but also how well the prediction models successfully classified non-impervious pixels.

Qualitative assessment of the masked artificial neural network and ERDAS Imagine Subpixel Classifier output revealed the removal of many of the smaller, isolated, impervious-predicted areas. Since these data represent the masked initial data, this is directly attributed to the LULC mask, the effect of which would have removed any pixels occurring outside areas already mapped as an urban-related land use (Civco and Hurd, 1999). There was also the noticeable removal of the misclassified cloud pixels in the northwestern portion of Waterford, which had been classified as impervious because of their similarly high reflectance values. Pixels along the southern coastline of Waterford were also '*cleaned up*', their having been misclassified due to the high reflectance values of sand.

Sand, bare soil, and barren land were problematic features for both impervious surface prediction models due to the similarity in their signature reflectance curves. The misclassification of these features provided the primary motivation for utilizing a LULC mask, as it represented a means with which to remove these misclassified pixels from the impervious images. Although there is a high degree of temporal continuity - both the TM image and the LULC being from 1995 - a shortcoming of this method is that the masked impervious surface prediction model results would then be related to the 88.68% (Level I) overall classification accuracy of the LULC layer. In order to reduce errors of commission, however, it was thought that the benefit of removing the misclassified pixels of similar reflectance value from the impervious images, outweighed the cost of them remaining. Overall accuracies for the artificial neural network and the ERDAS Imagine Subpixel Classifier impervious predictions, respectively, were 92% and 94% for Marlborough, 90% and 92% for Waterford, 84% and 86% for Woodbridge, and 74% and 71% for West Hartford. Compared to the initial results, these overall accuracy values represent a slight increase in classification accuracy for both methods. As was the case for the initial un-masked results, the ERDAS Imagine Subpixel Classifier better classified the three towns of Marlborough, Waterford, and Woodbridge, and the artificial neural network better classified the town of West Hartford though again, only with a 3% difference.

Eight-class Impervious Predictions

For the purposes of determining the within class impervious discrimination of the artificial neural network and ERDAS Imagine Subpixel Classifier impervious surface prediction models, the second stage of analysis compared the output from both impervious surface models to the planimetric footprint on a categorical scale. A more refined analysis, the accuracy of the impervious surface prediction models was calculated after recoding the initial prediction values into eight 10% subpixel prediction increments, greater than 20%.

Since the default output format for the ERDAS Imagine Subpixel Classifier is in eight 10% classes greater than 20%, the planimetric data and the artificial neural network output were correspondingly recoded so as to have the same format as the subpixel classifier output. Figure 5 shows the TM source data, the eight-class planimetric impervious footprint, the initial eight-class artificial neural network output, and the initial eight-class ERDAS Imagine Subpixel classifier output, for Waterford. With the exception of their having been recoded into eight classes, these data represent the same pixel occurrences as the binary impervious predictions.

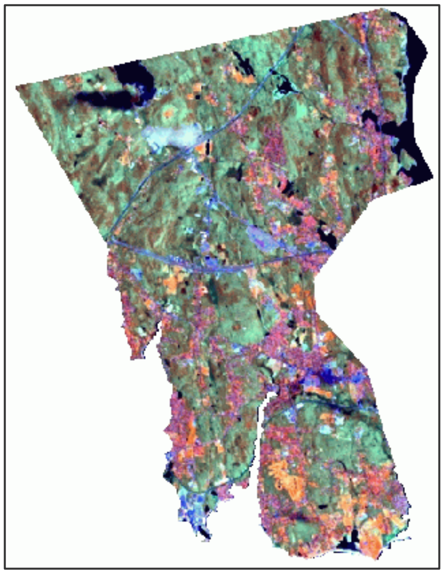

Figure 5.a. Waterford TM source data. RGB of Bands 4,5, and 3.

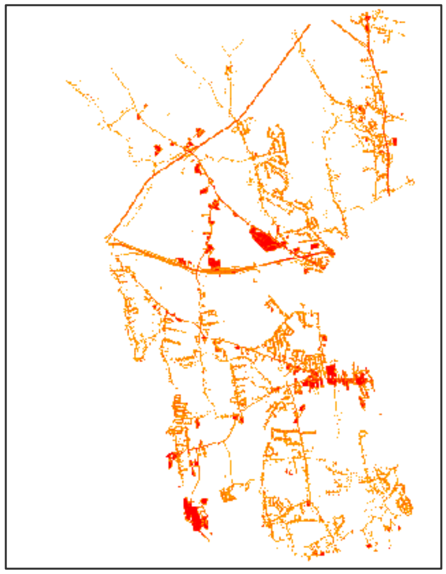

Figure 5.b. Rasterized planimetric footprint, representing greater than 20% imperviousness per pixel, in eight classes.

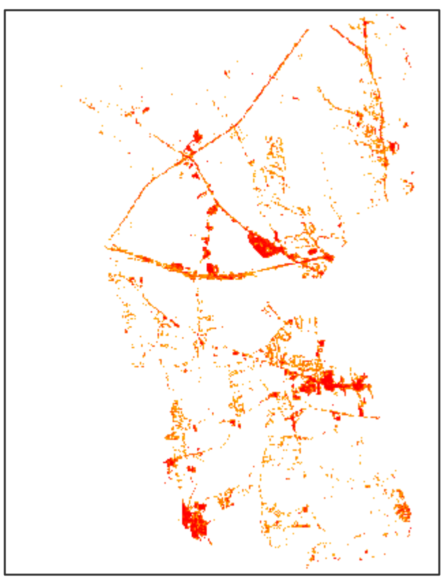

Figure 5.c. Artificial neural network impervious prediction after applying 1995 LULC mask, in eight classes.

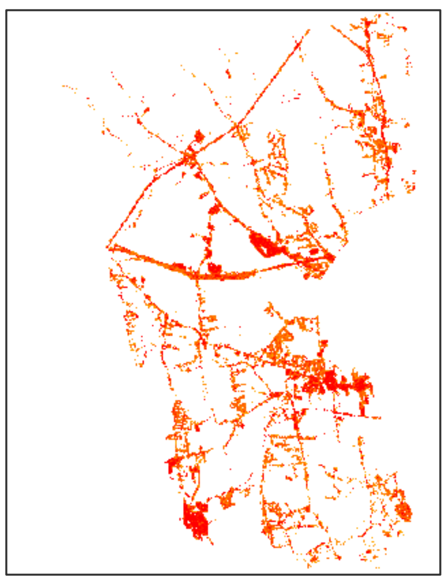

Figure 5.d. ERDAS Imagine Subpixel Classifier impervious prediction after applying 1995 LULC mask, in eight classes.

Unlike for the binary impervious prediction layers, qualitative analysis for the eight-class artificial neural network and ERDAS Imagine Subpixel Classifier output considered, for each pixel, the respective class to which that pixel was assigned. By comparing the color intensity of the output images in relation to the color intensity of the planimetric data (increasing imperviousness represented by intensity) both models appeared to over-predict the degree of imperviousness for those pixels for which impervious surfaces were predicted.

Overall accuracy for the eight-class artificial neural network and the eight-class ERDAS Subpixel Classifier imperviousness predictions, respectively, were 22% and 23% for West Hartford, 24% and 20% for Waterford, 23% and 21% for Woodbridge, and 20% and 18% for Marlborough. Significantly lower than the overall accuracy values obtained for the output in binary form, these results implied that both impervious surface models were unsuccessful in determining the per pixel percentage of impervious surfaces. However, inspection of the error matrices reveal that much of the confusion is among adjacent Percent impervious surface classes. Futher, as alluded to previously, even a slight misregistration between planimetric reference data and sub-pixel percent impervious predictions can produce large errors in accuracy, when comparing on a pixel-by-pixel basis. A more meaningful assessment of the value of the results is to examine them at the drainage basin level, a unit commonly used in non-point source pollution modeling.

Local Drainage Basin Predictions

Figure 6 illustrates an example of the actual (from the planimetric data) and predicted (from neural processing and Subpixel Classification) percent imperviousness for the local drainage basins of Waterford. Even a cursory inspection of a graphical rendition of the results reveals a high degree of correspondence between the basin-level impervious surface measures based on the planimetric (reference) data and the model predictions. In general, in the case of Waterford, the neural network under estimated imperviousness in moderately developed basins (>5% IS); whereas the Subpixel classifier over estimated some of the more highly developed basins (>15% IS). The neural net agreed better with the reference data in low urban density watersheds (<3% IS), whereas the Subpixel Classifier tended to overestimate the percent imperviousness in those basins.

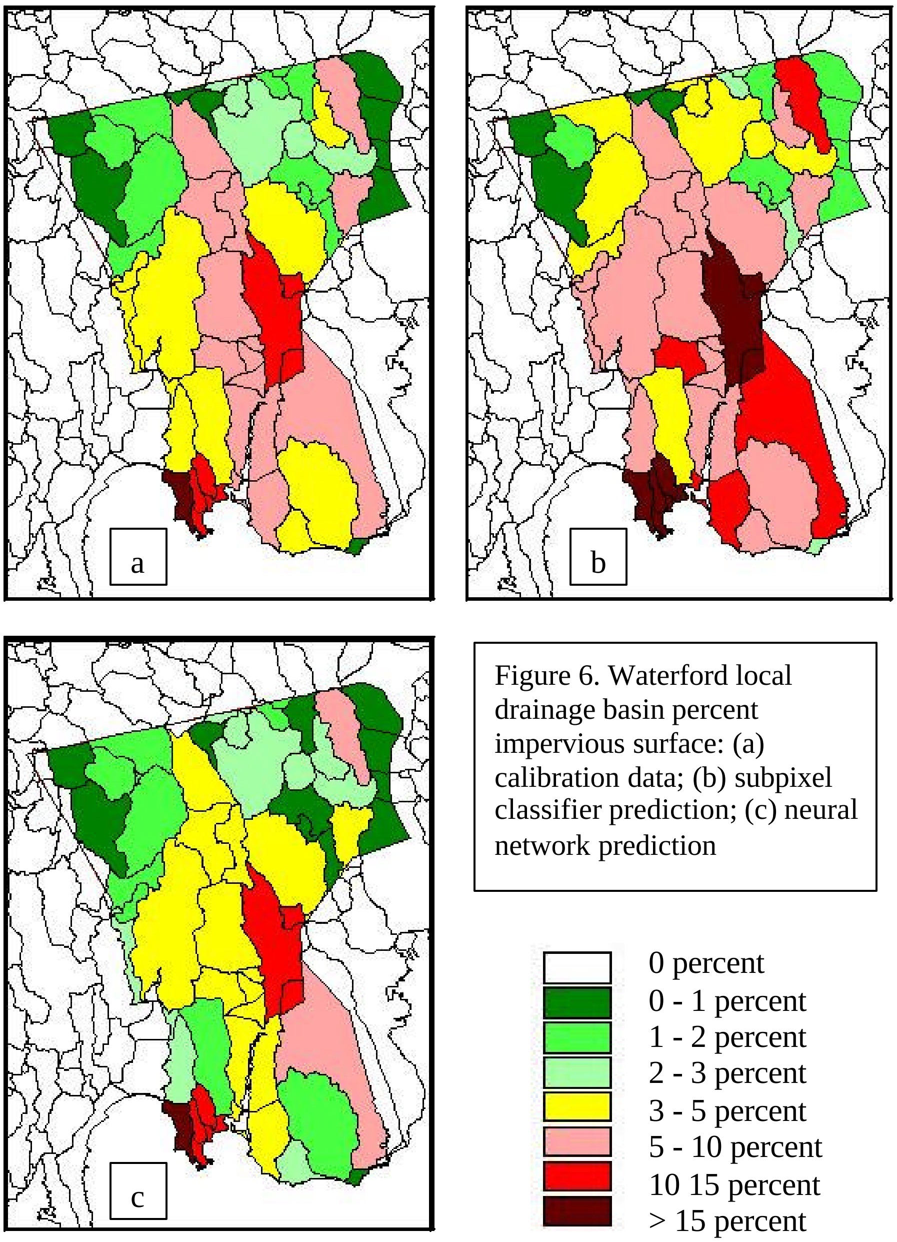

Figure 6. Waterford local drainage basin percent impervious surface: (a) calibration data; (b) subpixel classifier prediction; (c) neural network prediction

A standard root mean square error (non-weighted) was calculated between the local drainage basin percent impervious surface coverage as derived from the reference planimetric data and that derived from the results of each the neural network model and the Subpixel Classifier. This was done for the basins falling wholly or partially within Marlborough (n=22), Woodbridge (n=16), West Hartford (n=19), and Waterford (n=54). The RMSE for the four towns for the neural network approach and Subpixel Classifier, were, respectively: Marlborough, 1.29 and 0.66; Woodbridge, 2.51 and 0.99; West Hartford, 4.97 and 5.97; and Waterford, 1.24 and 2.98.

Discussion

There are a number of potential sources of error that could have contributed to the predictions of the artificial neural network and the ERDAS Imagine Subpixel Classifier impervious surface prediction models. In general, these may pertain to the planimetric and Thematic Mapper data themselves, the study areas, the impervious prediction models themselves, and the LULC mask layer.

In terms of the data, it may be the case that high-resolution planimetric data and coarse resolution TM satellite data are simply too dissimilar for use in impervious surface mapping. It may be hypothesized that the relatively high degree of omission and commission errors observed in the eight class impervious predictions were an artifact of using such high-resolution data as an accuracy assessment reference for what are coarse-resolution prediction models.

Misregistration among the different data types may also have negatively influenced the results. This research was wholly predicated upon all of the data exhibiting near-perfect subpixel co-registration. However, given the coarse resolution of the TM data, even slight misregistration may introduce large error. Figure 3 illustrates the effect pixel misregistration can have on overall accuracy - an effect that may particularly pertain to linear features, such as roads, where a shift of one pixel can result in reduction in accuracy value of 100%. Data availability, or the contemporaneousness of the data, was also a possible source of error. Although the Thematic Mapper data were of 1995, the date of the reference data varied by town. Waterford planimetric data were from 1994 - a fact that undoubtedly contributed to Waterford's consistently obtaining higher accuracy values – and Woodbridge and Marlborough data were from 1996 and 1997, respectively. In comparison to the date of the planimetric data, their later dates were a potential source of error. Planimetric data for West Hartford were from, for the western portion of the town, 1989, and for the eastern portion of the town, 1990. While these predate the Thematic Mapper data, it may be argued that West Hartford also obtained higher accuracy values because of its already-existing urban infrastructure.

Certainly, issues regarding the study areas themselves were possible sources of error. It would have been advantageous to include a greater number of study areas, across a greater physiographic and developmental spectrum. At the time of this research, however, the four towns utilized were the only towns within the state of Connecticut with digital data readily available to these investigators, of the resolution needed. It also would have been advantageous were high-resolution, planimetric data available from an entirely urban town.

The impervious surface training data may have included possible sources of error. In the case of the artificial neural network, the variability of impervious features may not have been adequately represented by the Civco and Hurd (1997) training areas. This would have meant that the neural network was unable to identify certain types, or conditions, of imperviousness, ultimately contributing to low accuracy values. In the case of the ERDAS Imagine Subpixel Classifier, the bright, medium, and dark Areas of Interest (AOIs) may also not have captured the variability of impervious features found throughout the state.

Also, being a relatively new and unproven image processing technique, the performance of the ERDAS Imagine Subpixel Classifier needs further evaluation since there are few studies documenting its use and effectiveness. The fact that its output is forced into 10% bins significantly reduces the opportunity to perform many types of accuracy assessment. This would not be the case were the software to allow continuous {0,100} output. An alternative method to perform accuracy assessment would be to consider each pixel as having the midpoint value of the class to which it was assigned (*e.g.*, a pixel assigned to Class 8 would have the equivalent real value of 95). Or ancillary data may be recoded so as to correspond to the ERDAS Imagine Subpixel Classifier output format - such as was done in this research.

The urban-related LULC mask layer was also a potential source of error. Although it was derived from contemporaneous 1995 Thematic Mapper data, its inherent error could be seen to affect the producer's and user's accuracy of the masked impervious surface model output. On the other hand, using the LULC mask for the binary predictions did result in an increase in producer's and user's accuracy, indicating that it successfully removed those errors of commission caused by the spectrally similar land cover features of agricultural land, bare soil, and sand (and clouds).

Conclusion

Building upon the previous endeavors of Civco and Hurd (1997), Sleavin (1999) and Sleavin *et al*. (2000), this research represents a forward step in our ongoing efforts toward developing methods with which to extract impervious cover at the TM subpixel level. It was the purpose of this research to compare two Landsat Thematic Mapper subpixel classification methods for impervious surface characterization. For the most past, results indicated that to the extent that coarse resolution satellite imagery may be used to map impervious features, the ERDAS Imagine Subpixel Classifier prediction model was more accurate than the artificial neural network for the purposes of impervious surface mapping. There appeared to be some evidence that towns further along the developmental spectrum were more amenable to impervious surface detection, but this may have been an artifact of the relatively small number of towns that constituted the study area. Although the impervious surface models did not obtain accuracy values sufficient to allow their being deployed as a stand-alone application, the models themselves may not be the cause. This is particularly the case given the significantly large effects that mis-registration among the data can have upon classification accuracy. As there was no systematic attempt to quantify or determine the degree to which mis-registration affected the results, it is recommended that further consideration be given to develop methods with which to do so.

Results from this research will provide the foundation for subsequent efforts to quantify impervious surface cover using remote sensing satellite imagery[7]. The purpose of this study was to investigate two additional methods for subpixel land cover mapping - in particular, a spectral unmixing model using maximum entropy and the Mahalanobis Distance algorithm - and will integrate Landsat Thematic Mapper data with Landsat ETM+, IKONOS, and ADAR 5500 data. Results indicate that the integration of higher resolution image data into the model itself might facilitate impervious surface detection.

The utility of using advanced techniques in geospatial data processing for the purposes of addressing natural resource management problems is an increasing practice among today's land use planners and decision-makers. Projects like the Nonpoint Education for Municipal Officials (NEMO)[8] and the Northeast Applications of Useable Technology in Land Planning for Urban Sprawl (NAUTILUS)[9], have been hugely successful in using the power of remote sensing technology for the purposes of addressing the impact of urban sprawl on our communities and on our natural systems, such as monitoring watershed dynamics for ecosystem health.

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References

Arnold, C.A. Jr. and C.J. Gibbons. 1996. Impervious surface coverage: the emergence of a key urban environmental indicator. *Journal of the American Planning Association*, 62(2):243-258.

Booth, D.B., and L.E. Reinfelt. 1993. Consequences of urbanization on aquatic systems – measured effects, degradation thresholds, and corrective strategies. Proceedings of Watershed 1993: A National Conference on Watershed Management. March 21-24, Alexandria, VA. *pp*. 545-550.

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[7] *Extraction of land cover information at the Landsat TM subpixel level: A systematic evaluation*. Civco, D.L., Principal Investigator, Storrs Agricultural Experiment Station Project CONS00728, October 1, 2000 through September 30, 2002.
[8] http://nemo.uconn.edu
[9] http://resac.uconn.edu

Civco, D.L. and J.D. Hurd. 1997. Impervious surface mapping for the state of Connecticut. Proc. 1997 ASPRS/ACSM Annual Convention, Seattle, WA. 3:124-135.

Civco, D.L. and J.D. Hurd. 1999. A hierarchical approach to land use and land cover mapping using multiple image types. Proc. 1999 ASPRS Annual Convention, Portland, OR. *pp*. 687-698.

Environmental Protection Agency. 1994. The Quality of Our Nation's Water: 1992. United States Environmental Protection Agency. EPA-841-S-94-002. USEPA Office of Water, Washington, D.C.

Flanagan, M.C. 2000. Subpixel Impervious Surface Modeling using Landsat Thematic Mapper Data. M.S. Thesis, Department of Natural Resources Management and Engineering, The University of Connecticut, Storrs, CT. 125 p.

Flanagan, M.C. and D.L. Civco. 2001. Imagine Subpixel Classifier Version 8.4: Software Review. Photogrammetric Engineering and Remote Sensing 67(1):23-28.

Schueler, T.R. 1994. The importance of imperviousness. Watershed Protection Techniques, 1(3):100-11.

Sleavin, W.J. 1999. Measuring impervious surfaces in Connecticut using planimetric GIS data. M.S. Thesis, Department of Natural Resources Management and Engineering, University of Connecticut, Storrs, CT.

Sleavin, W., S. Prisloe, L. Giannotti, J. Stocker, and D.L. Civco. 2000. Measuring Impervious Surfaces for Non-point Source Pollution Modeling. Proc. 2000 ASPRS Annual Convention, Washington, D.C. 11 p.