TEMPORAL CHARACTERIZATION OF IMPERVIOUS SURFACES FOR THE STATE OF CONNECTICUT

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ABSTRACT

Impervious surfaces (IS) such as asphalt, concrete and rooftops prevent percolation of water into the soil, creating water quantity and water quality impacts that have been extensively documented in the literature. Impervious surfaces can therefore be considered a direct indicator as to the quality of surrounding surface water including streams, lakes, and estuaries. Simply put, as the amount of IS increase for a given area, water quality will decrease. As such, it is necessary to develop accurate estimates of IS to improve our ability to monitor the potential impact of developed land on water resources. Remote sensing imagery provides an ideal medium from which to directly estimate IS.

Researchers at the Center for Land use Education And Research (CLEAR) at the University of Connecticut have been long involved in investigating ways to measure impervious surfaces. One technique is through the use of the ERDAS Imagine Subpixel Classifier (SPC) applied to Landsat TM and ETM imagery. The SPC is a supervised classifier that enables the detection of materials of interest (MOIs) as whole or fractional components of individual pixels, with a minimum detectable threshold of 20 percent and in increments of 10 percent (i.e., 20-30%, 30-40%, ... 90-100%). Results of several pilot projects indicate the SPC technique generates improved accuracy and greater geographic extensibility than land cover-based IS coefficients. This paper details the development of a consistent set of impervious surface estimates using the SPC on four dates (1985, 1990, 1995, 2002) of Landsat TM imagery for Connecticut.

INTRODUCTION

Nonpoint source pollution (NPS) has been cited as one of the top contributors to water quality problems in the United States (U. S. EPA, 1994). Nitrogen and phosphorus have been identified as the primary nutrients responsible for algal blooms caused by eutrophication which results in fish die-off, endangers human health, and impacts the economic and recreational use of riverine, palustrine, and estuarine waters (U.S. EPA, 1996). Urban runoff has been found to contribute a significant amount of these and other nonpoint source pollutants to our water resources (Beach, 2002; Boyer et al., 2002; U.S. EPA, 2002). It has been well documented that urbanization increases the volume, duration, and intensity of stormwater runoff (Booth and Reinfelt, 1993). Additional research has also suggested that the amount of urban runoff and its impacts on stream conditions and water quality are strongly correlated to the percent area of impervious surfaces within a watershed (Schueler, 1994; Arnold and Gibbons, 1996; Clausen et al., 2003). Imperviousness influences hydrology (e.g., an increase in imperviousness is directly related to increase in the volume and velocity of runoff), stream habitat (e.g., the hydrological impacts of increased imperviousness lead to increased stream bank erosion, loss of riparian habitat, and degradation of in-stream habitat), chemical water quality (e.g., increases in imperviousness and runoff directly effect the transport of non-point source pollutants including pathogens, nutrients, toxic contaminants, and sediment), and biological water-quality (e.g., all the above changes have an adverse impact on the diversity of in-stream fauna) (Schueler, 1994; Arnold and Gibbons, 1996). The hydrological impacts of urbanization, particularly impervious surfaces are depicted in Figure 1. This strong

relationship shows impervious surfaces can serve as an important indicator of water quality, not only because imperviousness has been consistently shown to affect stream hydrology and water quality, but because it can also be readily measured at a variety of scales (*i.e.*, from the parcel level to the watershed and regional levels) (Schueler, 1994).



Figure 1. Hydrologic impact of urbanization. Gray boxes identify impacts directly related to impervious surfaces (adapted from Hall, 1984).

Understanding the degree and location of impervious surfaces and limiting the amount of impervious surface in a watershed is an important component of overall watershed management. Coastal resource and land use managers need to be able to determine the existing percent imperviousness for an area in order to develop appropriate watershed management and/or NPS mitigation plans. While much research has focused on determining the relationship between watershed impervious surface coverage and water resource impacts, work has only recently been undertaken to develop methods to measure impervious surfaces at the watershed scale or larger (Ji and Jensen, 1999; Bird *et al.*, 2000; Wang *et al.*, 2000; Ward *et al.*, 2000; Bird *et al.*, 2002; Justice and Rubin, 2003; Yang *et al.*, 2003). Past efforts to determine watershed imperviousness have been hampered by inconsistent methods and outdated or unavailable data. There remains a need for a consistent and replicable technique to calculate easily and quickly watershed imperviousness from readily available and cost effective remote sensing information that achieves an acceptable level of accuracy.

Researchers at The University of Connecticut's Center for Land use Education And Research (CLEAR) have long been involved in investigating ways to measure impervious surfaces (IS), and to use these data in educational programs such as the Nonpoint Education for Municipal Officials (NEMO) Project (Arnold *et al.*, 1993; Stocker *et al.*, 1999). One direction of research has continued to improve upon traditional techniques of assigning percent IS coefficients as a function of land cover type (Prisloe *et al.*, 2000; Sleavin *et al.*, 2000, Prisloe *et al.*, 2001). Another direction of research has been aimed at sub-pixel percent IS modeling directly from Landsat TM and ETM data (Civco and Hurd, 1997; Flanagan, 2000; Flanagan and Civco, 2001a, Civco *et al.*, 2002). The research presented here focuses on this latter method of impervious surface estimation and its application to a temporal dataset of Landsat imagery (1985, 1990, 1995, and 2002) to derive four consistent impervious surface estimates for the State of Connecticut that can be compared to observe changes in impervious surfaces over the 17-year period

SUB-PIXEL CLASSIFIER OVERVIEW

One of the more promising methods for sub-pixel estimation of percent IS has been the application of Leica Geosystems' ERDAS Imagine Sub-Pixel ClassifierTM (SPC) to Landsat TM and ETM image data. The SPC, engineered by Applied Analysis Inc., is a supervised classifier that enables the detection of materials of interest (MOIs) as a whole or fractional component of an image pixel, with a minimum detectable threshold of 20 percent and in increments of 10 percent (*i.e.*, 20-30%, 30-40%, ... 90-100%) (Flanagan and Civco, 2001a; Flanagan and Civco, 2001b). The process consists of identifying and removing the unwanted spectral contribution of materials that make up the background of the pixels and comparing the remaining spectrum to the signature of the material of interest. (Huguenin *et al.*, 2004). The pixel is considered to contain some portion of the MOI if the remaining spectrum matches the signature spectrum.

As a brief description of the process, the SPC module is comprised of four required steps. These are image preprocessing, image 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 is conducted manually using the Imagine Area Of Interest (AOI) tool to identify pixels with a minimum of 90 percent imperviousness. Because of the diverse reflectance characteristics of impervious surfaces, signatures were individually created for bright, medium, dark, and very dark sub-classes of impervious surfaces. These sub-classes were grouped into a single signature file called a 'family' using the optional Signature Combiner function in the SPC. The final step is MOI Classification. This step utilizes the initial preprocessed image, corresponding environmental correction file, and the 'family' signature file. Additional parameters that can be set by the user are the classification tolerance and number of output classes. 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. The number of output classes can vary from two, four, or eight. Because of the combination of signatures, the output image contains five thematic layers, one for each of the sub-class signatures and one showing detections for the combined contribution of the four sub-classes. It is this composite layer that is used as the impervious surface estimation.

The following sections describe the iterative procedure used to derive impervious surface estimates for Connecticut for the years 1985, 1990, 1995, and 2002.

IMPERVIOUS SURFACE ESTIMATION

Initial Classification

Initial sub-pixel classification was conducted on the August 30, 1995 Landsat TM image. This image was selected based of the existence of planimetric data that corresponded closely to the collection date of the TM imagery. The planimetric data were used to assess the validity of the IS estimate and is discussed later in this paper. The remaining three dates (1985, 1990, and 2002) of impervious surfaces were derived based on the results of this 1995 classification. To begin, a principal components image of the entire scene was generated from the 1995 TM image. The first principal component channel (PC1) is known to represent an overall brightness image of the Landsat TM scene and was generated to serve solely as a visual guide for the selection of training pixels representing the four brightness conditions of impervious surfaces. The PC1 image was divided into four levels to

identify bright, medium, dark, and very dark reflective pixels within the scene. The four brightness levels represent various spectral characteristics of concrete and asphalt from newly paved conditions to older, more aged conditions, and various reflective characteristics of different roofing and construction materials. It should be noted that these distinctions among impervious surface classes are spectrally-based and do not imply the function of the impervious surface (*i.e.* roof, road, parking lot, etc...) (Flanagan and Civco, 2001a). From this point, the process of deriving an IS estimate from the 1995 Landsat image was an iterative one, with each step serving to improve the overall result.

First Iteration of Sub-pixel Classification. Image preprocessing and generation of an environmental correction file were performed as required by the SPC. Training pixels were selected that represent at minimum 90 percent imperviousness. This was done separately for each of the four brightness sub-classes with approximately 50 pixels selected for each sub-class. For a successful sub-pixel classification, the quantity of training pixels is less important then the quality of the pixels (i.e., pixels that represent nearly 100 percent imperviousness), but it is important to try to select pixels that represent the full spectral range of impervious surfaces. The signatures for each sub-class were combined using the SPC Signature Combiner then MOI Classification was performed. Based on tests conducted on a subset of Landsat TM data, a classification tolerance of 1.4 was used. The number of output classes was eight (i.e., class 1 = 20-29%, class 2 = 30-39%, ... class 8 = 90-100%). The results were visually examined and it was readily apparent that the classification result needed improvement, due primarily to a number of highly impervious pixels not being detected by the SPC. An example of the results is shown in Figure 2b.



(a) August 28, 1995 Landsat TM image displaying bands 4, 5, 3.



(b) Sub-pixel classification following first iteration.



(c) Sub-pixel classification following signature refinement and second iteration.



Figure 2. Results of initial Sub-pixel Classification and signature refinement for a portion of Waterford, CT.

Signature Refinement and Second Iteration of Sub-pixel Classification. The SPC has a component that allows for signature evaluation and refinement. In this process additional pixels were selected for each of the four subclasses that represented correctly classified pixels, falsely classified pixels, and missed pixels. These files were created using the AOI tool and applied to the existing signature files to produce a modified signature file for each brightness sub-class. These files were again combined and a new MOI Classification performed using a classification tolerance of 1.4 and eight class output. Visually, the results showed a further decline in the number of pixels detected, but, the quality of those pixels detected appeared to improve slightly (Figure 2c). However, with the lack of detected pixels experienced, additional steps were needed.

Identification of Impervious Surfaces Through Supervised Classification. To increase the detection of 100 percent impervious pixels that were missing from the sub-pixel classification, a supervised classification approach was applied. A signature file was created that contained signatures of various conditions of 100 percent impervious pixels. Supervised classification was performed using a parallelpiped decision rule. In using a parallelpiped decision rule, any pixel falling within the upper and lower limits of the class signature would be identified as belonging to

that particular signature class otherwise the pixel would remain unclassified; a pixel not containing 100 percent imperviousness. If class boundaries overlapped, a maximum likelihood decision rule was followed. The supervised result was combined with the result of the Sub-pixel Classifier to produce a visually improved impervious surface estimate. An example of the results can be viewed in Figure 3a.

Application of a 3x3 Majority Filter. Because there still existed undetected pixels that should contain high levels of imperviousness, and many of these pixels were surrounded by pixels that were detected as containing high levels of imperviousness through either the sub-pixel process or supervised classification process, a 3 x 3 majority filter was employed to fill in many of these missing pixels. For the majority filtering process, only impervious class values of 0, 5, 6, 7, 8 were used for computation and changes were only applied to pixels with a value of zero. The rationale behind this was that if a pixel was not detected as containing a high level of imperviousness, but was surrounded by pixels with high levels of imperviousness, then the undetected pixel would be given a value similar to its eight neighbors, but not influenced by pixels detected as having lower levels of imperviousness. This allows for a slight gradation of imperviousness if the majority of pixels within the window are not 100 percent. An example of the results of this process is provided in Figure 3b.



(a) Classification following addition of supervised results.

(b) Classification following 3x3 majority filter.

20% - 29 %	60% - 69%
30% - 39%	70% - 79%
40% - 49%	80% - 89%
50% - 59%	90% - 100%

Figure 3. Results of the application of supervised derived 100 percent pixels and subsequent 3x3 majority filter function.

Inclusion of Developed Land Cover Information. Given the similarities in spectral reflectance among many impervious features and barren land (or bare soil), an urban-related land cover mask was employed as an additional processing step to eliminate those pixels that were falsely detected as containing some level of imperviousness. A 1995 statewide land cover thematic layer that was developed as part of CLEAR's¹ on-going mission of creating landscape characterization information and derived from the same August 28, 1995 Landsat image, was used to mask out pixels detected as containing imperviousness but not identified as belonging to the developed category. In addition, pixels that were classified as developed in the 1995 land cover but not detected as containing imperviousness were assigned to a new 10 percent impervious class (class 1). Because the Sub-pixel Classifier only detects the occurrence of component MOIs to a minimum threshold of 20 percent, it was believed that by including this new, lower level impervious class, that the impervious surface estimation would more closely resemble the true extent of imperviousness within an area. Figure 4a provides an example of this process.

Sub-pixel Classification of 10 Percent Impervious Pixels. Comparing Figure 3b to Figure 4a, it is apparent that the SPC failed to detect a significant number of pixels that obviously contain some degree of imperviousness but are now assigned a value of 10 percent impervious following the inclusion of the developed land cover category. The

¹ <u>http://clear.uconn.edu/</u>

result is an excessive number of 10 percent impervious pixels, which essentially serves to underestimate the total amount of impervious surfaces for a given area. In order to correct for this issue, only pixels identified as 10 percent imperviousness (class 1) were extracted from the Landsat TM image. Image preprocessing was performed, but the original environmental correction file was used since the same image was used. New signatures using pixels that represent only bright and dark occurrences of impervious surfaces were selected using the AOI tool. These signatures were combined into a single signature file and MOI classification performed. The result was an increase in the detection of impervious pixels over the 10 percent value, with the number of pixels in the 20 to 60 percent impervious (classes 2 through 5) range showing a significant increase. The result is a more realistic estimate of impervious surfaces for a given area. An example can be viewed in Figure 4b where the increase in impervious levels can be seen, particularly along transportation routes.



10% - 19 %
20% - 29 %
30% - 39%

40% - 49%



70% – 79% 80% – 89% 90% - 100%

Figure 4. Results if the inclusion of developed land cover pixels and final sub-pixel analysis.

Sub-pixel Classification of Subsequent Dates

The remaining three dates of Landsat imagery (April 26, 1985, August 30, 1990, and September 8, 2002) were classified independently following the same procedures used under the first iteration of the 1995 Landsat image. For each date, preprocessing and environmental correction were applied and a principal component image was derived. Signatures were selected for bright, medium, dark, and very dark impervious pixels. These were combined into a single signature file and MOI classification performed. Since these classifications were built upon each other (*i.e.* the 1990 IS estimate was derived from the 1995 IS estimate, the 1985 IS estimate was derived from the final result of the 1990 IS estimate, and the 2002 IS estimate was derived from the 1995 IS estimate), the classification threshold was set to 1.5 to increase slightly the number of pixels detected as containing impervious surfaces. The resulting IS classification was combined with the corresponding land cover image, classified from the same Landsat image, to mask out erroneously detected impervious pixels and to generate the 10 percent impervious class.

Creation of Final IS Estimates. A fundamental principal in developing IS estimates for multiple dates was to maintain consistency in IS estimates among the four dates. Models were developed that would combine each adjacent pair of IS estimates to maintain this consistency. The primary concern was to eliminate the chance of a given pixel to fluctuate between dates, such as losing imperviousness between 1985 and 1990, then gaining imperviousness between 1995 and 2002, or to show unlikely increases or decreases in imperviousness over time. The first step was to derive a difference image between the completed IS estimate (i.e., 1995) and the date of IS to be modified (i.e., 1990). Since there are nine classes for each IS estimate, a constant of 10 was added to the difference to derive positive values ranging from one to 19. If a pixel contained a value of one, then that pixel had a class value of 0 (no imperviousness) in 1995 and a class value

of nine (high imperviousness) in 1990, essentially a condition that should not occur and is a case of misclassification in one or both IS estimates.

Using the results of the difference image, all pixels in the 1990 classification that deviated one class value below that identified in the 1995 IS estimate (*i.e.*, a class value of 5 in 1995 and a class value of 4 in 1990) were identified. The spatial model then assigned the 1990 IS estimate value to these pixels and the 1995 IS estimate value to the remaining pixels. If a pixel value of zero occurred in the 1990 date, the pixel was assigned a zero value. The result is a final 1990 IS estimate that maintains the 1995 IS estimate levels unless the 1990 pixel was one class value below the 1995 level, based on the original 1990 IS sub-pixel classification and subsequent inclusion of the developed land cover information, or the pixel in 1990 was zero. The reasoning behind this procedure was to maintain a consistent set of impervious surface estimates over time based on the base 1995 IS estimate and eliminate large fluctuations between dates and also eliminate the possibility of a pixel decreasing in imperviousness, although possible, not very likely, at least for large areas. The same procedure was followed for the 1985 date using the 1990 IS estimate as the primary IS source. For the 2002 date, the 1995 IS estimate again served as the primary source, but instead of using a one class value below the 1995 IS estimate, one class value above the 1995 IS estimate was utilized. Also if the 1995 class value was zero, and the 2002 class value was greater then zero, the 2002 value was used.

Final IS Estimate Adjustment. Visual examination of the resulting IS estimates revealed there still appeared to be an underestimation of overall IS. To improve the overall IS estimate, another set of models was produced that would increase the overall IS by using the results of the 1985 sub-pixel classification and building upon each subsequent date. Essentially what this model did was combine the 1985 final IS estimate derived in the previous step with the original 1985 sub-pixel classification. If a pixel showed a higher value in the original 1985 sub-pixel classification than for the 1985 final IS estimate, then it was assigned the higher value, otherwise it remained as specified in the 1985 final IS estimate. This adjusted 1985 final IS estimate was then applied to the 1990 final IS estimate in a similar manner. This continued for the 1995 and 2002 IS estimates. The result was an increase and more realistic estimate of overall IS for all four dates. An example of the final IS estimate is provided in Figure 4c and also examples for each year are provided in Figure 5.

VALIDATION

Data used to validate the percent impervious estimates derived from the previous steps consisted of highaccuracy planimetric data for portions of seven Connecticut towns (West Hartford for circa 1990, Marlborough, Waterford, and Woodbridge for circa 1995, and Groton, Milford, and Suffield for circa 2002). These data were derived from aerial photographs collected within a couple years of the Landsat image data used to derive the percent impervious surface estimates. Planimetric data were not available for the 1985 time frame. The planimetric data consist of anthropogenic impervious surfaces such as buildings, roads, sidewalks, driveways, and parking lots. The towns with available planimetric data represent a range of different development densities from rural for Marlborough and Suffield to suburban for Waterford and Woodbridge, to urbanized for Groton, Milford, and West Hartford.

The planimetric data were co-registered to the corresponding Landsat TM image. A grid corresponding to the pixel space of the Landsat TM image was then generated for a rectangular area within each town. The grid was then *'unioned'* to the planimetric data for each town. From these *unioned* images, database tables were generated from which the percent of impervious surfaces (from 0 - 100% impervious) was calculated for each grid cell. These tables were joined with the grid file to generate images that represent percent imperviousness. The images were recoded into the nine classes whose values corresponded to the output from the IS estimation procedure *(i.e.,* class 1 = 10-19%, class 2 = 20-29%, ... class 9 = 90-100%). This final, recoded layer for each of the towns comprised the validation data that were compared to the IS estimate using an error matrix on a per pixel basis. An example for a portion of the Town of Milford is shown in Figure 6. Based on the results of the error matrix, overall accuracy for the IS estimates for the years 1990, 1995, and 2002 were 31.02 percent, 76.32 percent and 36.43 respectively.

From a scientific perspective, how well the sub-pixel classification predicted actual percent imperviousness at the sub-pixel level, compared to the calibration planimetric data, is of principal interest. However, even slight misregistration between the reference planimetric data and Landsat TM data could result in potentially large differences between actual and predicted values. Also, from a management perspective, the assessment of impervious surfaces is more meaningful when reported on a landscape management unit such as a drainage basin. Therefore, in addition



Figure 5. Examples of sub-pixel classification and pixel adjustments for each of the four dates of the Manchester, Connecticut area.

to the per pixel-based impervious surface validation process, percent impervious surface summaries were derived for each validation area. These results are displayed in Table 1.



Planimetric Truth Data



Final Impervious Surface Estimate

Figure 6. Comparison of planimetric truth data to the sub-pixel derived impervious surface estimate for a portion of the town of Milford, Connecticut.

Table 1. Comparison of calculated percent impervious surfaces from planimetric data and IS estimate for the seven
town, nine validation areas.

	Planimetric % Impervious	Estimated % Impervious	Sample Area Size
Town	Surface	Surface	(acres)
Groton	21.68	23.65 (year 2002)	1,412
Marlborough	3.85	2.95 (year 1995)	6,667
Milford	24.60	27.39 (year 2002)	3,529
Suffield	7.46	5.94 (year 2002)	1,985
Waterford (area 1)	4.07	3.91 (year 1995)	6,697
Waterford (area 2)	8.61	9.31 (year 1995)	7,052
Woodbridge	6.74	4.27 (year 1995)	7,394
West Hartford (area 1)	34.06	37.75 (year 1990)	4,122
West Hartford (area 2)	16.51	14.99 (year 1990)	4,467

DISCUSSION AND CONCLUSION

While the results presented here provide a consistent set of impervious surface estimates of Connecticut for four dates of time over a 17-year period, there is noticeable room for improvement, particularly in terms of per-pixel accuracy. As reported in the validation section, the overall accuracy results varied for each year. For the years 1990, 1995, and 2002, the overall accuracy was 31.02 percent, 76.32 percent and 36.43 percent respectively. These percent accuracies increased substantially when the number of pixels in adjacent classes were included in the assessment (*i.e.*, include the number of pixels from classes 2 and 4 when assessing impervious class 3). The overall accuracy in this case increased to 51.70 percent, 88.29 percent, and 57.39 percent for the years 1990, 1995, and 2002 indicating that a significant number of estimated pixels are approximating the truth data, but there is still a need for improvement. The higher accuracy for the 1995 IS estimate was due to the existence of a large number of zero impervious pixels. Out of 121,140 pixels used in the assessment, 88,316 were correctly classified as containing no impervious surfaces (72.90 percent of the total). While this could be considered a minor success by not erroneously

identifying impervious pixels where no imperviousness existed, the accuracy of pixels actually detecting the nine classes of imperviousness remained quite low. The 1990 assessment used a total of 37,416 pixels with 7, 994 being correctly classified as containing no impervious surfaces (21.37 percent), and the 1995 assessment used 39,334 pixels with 10,334 being correctly classified as having no impervious surfaces (26.27 percent). Again, it is difficult to compare these results on a per pixel basis due to probable misalignment issues between the planimetric and estimate impervious results.

For estimation of impervious surfaces summarized over a given area, the results closely relate to the impervious surface values derived from the planimetric truth data for the same area (Table 1). There does, however, appear to be a noticeable trend in terms of areas that contain lower levels of imperviousness versus those containing higher levels of imperviousness. For those areas having overall lower levels of impervious surfaces (*i.e.*, more rural development densities), the IS estimate tends to under-estimate the actual impervious level with the exception of the Waterford area 2. The reverse is found for the higher impervious surfaces present with the exception of the Waterford area 2. This suggests a need to revise further the Sub-pixel Classifier to try to increase the detection and amount of impervious MOIs in lower level impervious pixels and decrease the detection and amount of impervious MOIs in the higher level impervious pixels. This is most likely a function of both the Sub-pixel Classifier not being able to detect levels of MOIs below a 20 percent threshold and therefore relying heavily on the land cover to derive the 10 percent impervious class (class 1), and the overall procedures used to derive the final IS estimates, such as the use of the supervised parallelpiped classification to increase the number of 100 percent impervious pixels.

This research represents a first step in producing consistent impervious surface estimates of the State of Connecticut over a 17-year period. Based on this work, two major areas are identified where improvement is warranted. First, as mentioned previously, is the adjustment of pixels with lower levels of imperviousness and higher levels of imperviousness. Continued refinement of signatures and MOI classification will serve to improve the overall results. In addition, focusing on the use of land cover to extract un-detected impervious pixels then performing sub-pixel analysis on these pixels should also serve to increase the level of imperviousness of these pixels and improve the overall results. The second area in need of improvement is to smooth the overall classification. Referring to Figures 4 and 5, it is apparent that, especially along transportation routes, there is significant variability in the level of imperviousness among neighboring pixels. One would expect a more uniform level of imperviousness along the transportation route with the level of imperviousness decreasing along the edges of the route. Options on how to obtain this level of consistency require further examination.

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