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Technical Report No.173
March 2003

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A Rapid Land Cover Classification Method For Use in Urban Watershed Analysis

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INTRODUCTION

Modifications of the land surface during urbanization can produce tremendous changes in the patterns and the processes of stormwater runoff. These changes result from clearing vegetation, compacting soil, ditching and draining, and finally covering the land surface with impervious roofs and roads. The infiltration capacity of these covered areas is lowered to zero, and much of the remaining soil-covered area is trampled to a near-impervious state. Compacted, stripped, or paved-over soil also has lower storage volumes, and so even if precipitation can infiltrate, the soil reaches surface saturation more rapidly and more frequently. This results in pervasive changes to water quantity, water quality, and the associated ecological function of streams and riparian areas.

In addition to changes in how rainfall is absorbed or runs off of hillslopes, urbanization affects other elements of the drainage system. Gutters, drains, and storm sewers are laid in the urbanized area to convey runoff rapidly to stream channels. Natural channels are often straightened, deepened, or lined with concrete to make them hydraulically smoother. Each of these changes increases the efficiency of the channel, transmitting the flood wave downstream faster and with less retardation by the channel and destroys the habitat for stream biota.

Because of the profound effect of urban development on aquatic systems, characterizing the land cover of a region is critical for a variety of resource-management applications. In the Pacific Northwest, this characterization has been used most commonly to correlate the intensity of human activity with observed stream or wetland conditions, in order to predict the health of the stream system or to guide the allocation of mitigation efforts. For example, measured biological conditions in lowland streams are regularly presented in terms of “impervious area percentage” of the contributing watershed. Land cover is a primary input parameter for numerical hydrologic models (such as the Hydrologic Simulation Program Fortran [HSPF], widely used by the surface-water management agencies of King County, Snohomish County, the cities of Seattle and Bellevue, and the consultants of these and smaller jurisdictions throughout western Washington). Every one of the $20+ million in capital projects planned or under construction by King County Water and Land Resources Division, for example, is designed using HSPF with land cover as a primary, determining input.

Unfortunately, there is little consistency or quality control in how land-cover data are collected and analyzed. Some of this variety is entirely appropriate—the methods and the products for assessing wilderness-area potential in the Cascade Range have little overlap with those used to plan optimal siting of commuter-rail stations, for example. Yet certain applications constantly reemerge, and so typical procedures have been developed but only on an *ad hoc* basis.

The characterization of land cover for purposes of evaluating and assessing aquatic-system conditions is one such application. Yet the imprecision of the methodology currently used to classify land cover belies the significance of the results: typically, recent 1:12,000-scale airphotos (within the last 2-3 years) are manually discriminated by a technician into eight or so different "classes," of which four discriminate urban development of different densities and the remainder characterize the unbuilt areas. Discrimination is at the judgement of the operator, following established guidelines; typical minimum unit areas are one to five acres (about 100 m minimum dimensions); and subsequent ground truthing is nonexistent. Typical analyses require about 1 person-week for a 10-mi^2 area, and once the operator is trained there are no opportunities for greater speed—every new area requires an equivalent level of effort. ***This*** is the procedure against which any alternative method should be compared.

Remotely sensed data from satellites provide an alternative source of information on land cover over very large areas. The traditional approach to classifying remotely sensed data from satellites into discrete classes of land cover involves a lengthy process of automated classification, clustering of spectral signatures, much fine-tuning, and an eventual supervised classification. This process can be both time and resource-intensive. It is also continually being refined, and so the methodologies are not consistent.

We have developed an alternative approach using Landsat satellite imagery to produce the same general type of land-cover characterization as has currently found widespread acceptance and use across the region. However, our methodology does so in a way that achieves maximum utility and consistency for a particular group of users—individuals and agencies needing to assess watershed conditions in the urban, and urbanizing, parts of western Washington. The classes of land cover produced have been chosen to reflect the categories that can be readily distinguished in the satellite data and to have important differences in their associated runoff and watershed characteristics.

The advantages of such an approach are obvious. The algorithm is developed only once; after completion, it can be applied rapidly to any other selected area through GIS software. It does not depend on the discretion of individual operators and so the results are reproducible. These advantages have not been lost on public agencies, but those agencies are not equipped to pursue such efforts systematically, given project-related geographic boundaries, time constraints, staff turnover, and the difficulty of inter-agency communication. With suitable testing and documentation, the release of these data layers through the University of Washington may encourage agencies across the region to adopt a uniform methodology, resulting in a degree of uniformity in data collection, analysis, and reporting of these data that is currently unavailable.

METHODOLOGY

The methodology used in this project is summarized in Figure 1. The area of this analysis was a portion of the Puget Sound lowlands of northwestern Washington State. The area extends from the city of Olympia in the south to Everett in the north, and it includes the entire Seattle-Tacoma-Everett metropolitan area from Puget Sound east to the foothills of the Cascade Mountain range. The study site was chosen to cover a broad range of urban, suburban, and rural areas while excluding those areas with extreme topographic relief and little or no urban development.

Our classification scheme followed a multi-step process that was designed to be intuitive while yielding accurate results. It consisted of:

1. Combination and manipulation of the raw satellite images;
2. Selection of training sites, where different land-cover categories could be defined;
3. Extraction of the “typical” Landsat signatures for each coverage;
4. Classification of the entire image, following the characteristics defined for each class; and
5. Assessment of the classification’s accuracy by checking actual field conditions at selected locations.

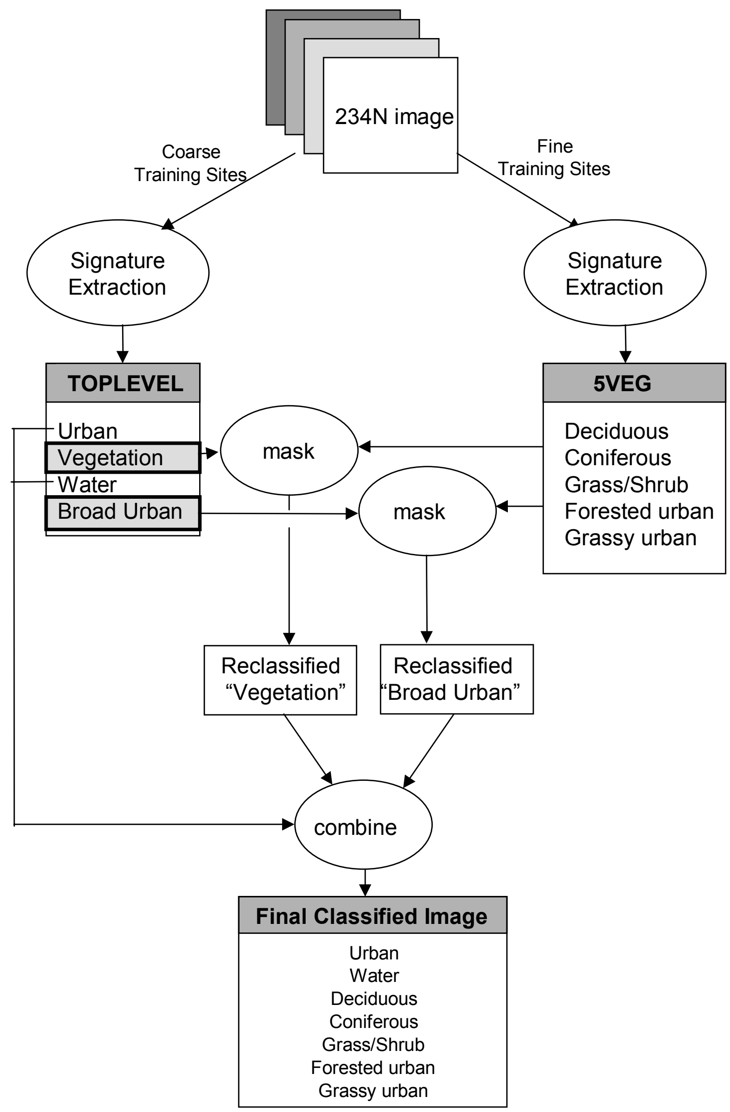

Figure 1. Classification Process

STEP 1: Image Manipulation

Landsat satellite images from 1991 and 1998 were obtained for northwestern Washington State. The resolution of these images was 30 meters, meaning that each pixel represented an area of 900 m^2. The raw Landsat images were imported into the ERDAS Imagine software package and geocorrected to the UTM projection (zone 10N, spheroid Clarke 1866, datum NAD27) utilizing digital orthophotos (DOQQ's) as the reference projection source. This allowed the raw Landsat and classified images to be compared directly to the DOQQ's using the geographic linking function in the Imagine viewer.

The raw Landsat images contain 7 layers, or bands, that correspond to reflectances received by the satellite sensors in various wavelength ranges.

Bands 2, 3 and 4 (corresponding to the visible blue, near infrared, and mid-range infrared portions of the EM spectrum) were extracted from the raw image. These bands were selected for their ability to discriminate and detect characteristics of vegetation such as chlorophyll absorption, biomass content, and vegetation vigor (Lillesand and Kiefer 1994). Using Imagine's Model Maker module, bands 3 and 4 were used to create a Normalized Difference Vegetation Index (NDVI) layer. The NDVI layer is particularly useful in discerning vegetation vigor and subtler variations in vegetative land cover and is commonly used in remote sensing research. The NDVI layer was then combined with the individual bands 2, 3 and 4 using the STACKLAYER function to yield one composite image with 4 layers. This image is hereafter referred to as the "234N image." The 234N image was clipped to the extent of the study area and the remainder of the image was discarded.

STEP 2: Training Sites

The next step in the process was the identification of and delineation of training sites used to define the characteristic pattern, or "signature," in the 234N image for each land-cover category. "Training sites" are areas of known land cover, usually no more than 1000 m^2 in size, determined from ground truthing in the field or from inspection of digital orthophoto quarter quadrangles (DOQQ's). We used a combination of both methods to obtain a series of suitable training sites for each desired class. Training sites were digitized onto a separate layer in Imagine that could be overlaid onto the Landsat and DOQQ images.

Separate training sites were created for a total of 9 classes, using a two-tier scheme (Table 1). The top scheme, called ***Toplevel***, consisted of 4 broad land cover classes: "intense urban" (land nearly completely paved or built upon), "water," "vegetation," and "broad urban" (essentially everything remaining). The second tier, called ***5Veg***, consisted of 5 finer classes that subdivided the "vegetation" and "broad urban" classes of Toplevel into "deciduous vegetation," "coniferous vegetation," "grassy/shrubby vegetation," "forested urban" (developed land with significant canopy coverage), and "grassy urban" (developed land with few trees but significant grass coverage).

Toplevel
• Intense urban • Water • Vegetation • Broad urban
5Veg
• Deciduous vegetation • Coniferous vegetation • Grass/shrub vegetation • Forested urban • Grassy urban

Table 1. Classes used in the land-cover classification.

STEP 3: Signature Extraction

Once selected, the outlines of the training sites were overlaid on the 234N image. Using the Signature Editor module in Imagine, spectral signatures were simultaneously extracted from each of the 4 layers of the 234N image, yielding "signatures" for each training site within each class. Signatures correspond to a cluster of reflectance values within each band. Signatures within each class were then combined to obtain a single spectral signature range in 4-dimensional space for each class. The output of this step thus consisted of 9 distinct sets of signatures.

STEP 4: Supervised Classification

The first supervised classification was conducted on the 234N image using the Toplevel, or first-tier, signatures (*i.e.* intense urban, water, vegetation, and broad urban). The classification utilized the parallelepiped non-parametric rule and the maximum-likelihood parametric rules in classification of individual pixels of the Landsat image. Remote sensing software packages, such as Imagine, construct bounding boxes, or parallelpipeds, around clusters of signatures collected from the training sites. The limits of these parallelpipeds represent each individual class in multi-spectral space. In classifying the entire image, certain decision rules govern how pixels are classified (see chapter 7 in Lillesand and Kiefer [1994] for a more thorough explanation of classification decision rules). Pixels whose multi-spectral reflectance values fall within the limits of a parallelpiped are immediately classified to that parallelpiped's corresponding class. In areas where parallepipeds overlap or for pixels that fall outside parallepiped limits, the maximum likelihood decision rule determines the classification. This rule calculates the statistical probability of a pixel belonging to a particular class, based on the variance and covariance of the spectral signatures. The combination of the parallepiped and maximum-likelihood decision rules results in an output map in which no pixels are left unclassified.

The output from this process, termed the "Toplevel image," consisted of 4 classes corresponding to the 4 Toplevel signatures in Table 1. This image was then recoded, using the RECODE function in Imagine, to create masks for each of the 4 classes. From this process, we created 4 masks, one for each Toplevel category. Masks only contain pixel values of 0 and 1 and are useful in cropping other maps.

A second supervised classification was then conducted on the 234N image using the second-tier signatures (deciduous vegetation, coniferous vegetation, grass/shrub, forested urban, and grassy urban). This classification used the same parallelepiped-maximum likelihood classification rules and produced a classified image with 5 classes corresponding to the 5Veg signatures in Table 1. This image is referred to as the "5Veg image."

This new five-class image took all pixels in the study area and assigned them to one of the 5Veg categories. Some misclassification occurred during this step as areas of water or intense urban cover were classified to one of the 5Veg classes. To eliminate these misclassified pixels, we used the Toplevel broad urban mask to crop the 5Veg image to the areas not originally classified as water, vegetation, or intense urban. The resulting image contained a 5-class classified image of the broad urban study area. We then used the Toplevel vegetation mask to crop the original 5Veg image to the areas that were classified as vegetation in the Toplevel classification. This step allowed us to break the coarse Toplevel classes of vegetation and broad urban into the finer 5Veg classes.

At this point we had four images: a single-class "intense urban" image, a single-class "water" image, and two images with five classes for the vegetated and broad urban areas. Each of the images was mutually exclusive, with their own unique coverage within the study area. The final step was to combine each of these images into a final composite seven-class image (Table 2). Each of the four images was recoded using the RECODE function in Imagine to give each class a unique value. All the images were then combined to obtain a final image called "Final-classed"(Figure 2).

Final Classes--1991	Final Classes--1998
Intense urban	Intense urban
Open water	Open water
Deciduous vegetation	Forested
Coniferous vegetation	Bare earth
Grass/shrub	Grass/shrub
Forested urban	Forested urban
Grassy urban	Grassy urban

Table 2. Final classes used in classification.

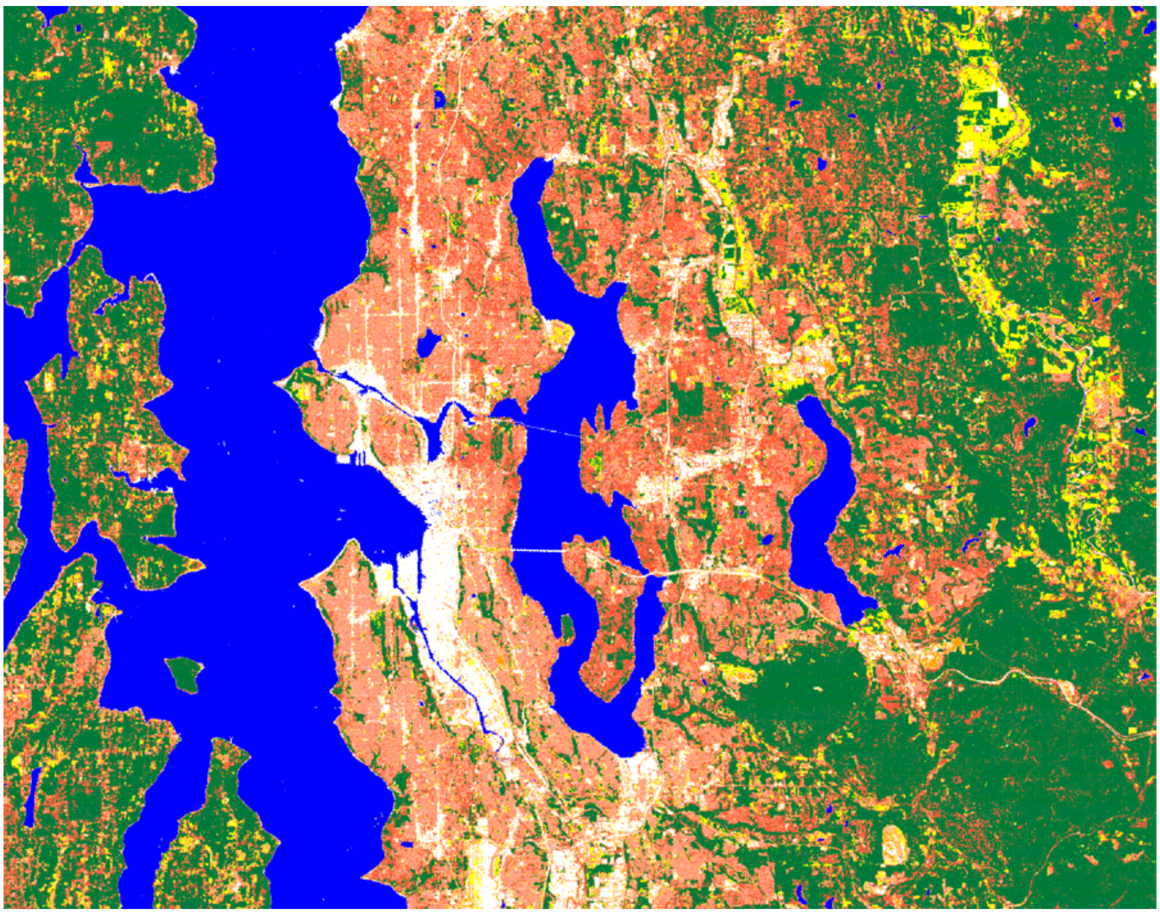

Figure 2. A portion of the final classified image, centered on Lake Washington and the City of Seattle.

STEP 5: Accuracy Assessment

The final step involved an accuracy assessment of the classed images for 1991 and 1998. We took two approaches, both using digital and printed overlays of the classified images and the DOQQ's (see Appendix). One hundred

(1991 image) or 50 (1998 image) pixels from each of the seven categories were randomly selected; they were chosen from clusters of 25 (5-by-5) uniformly classified pixels to ensure that minor mis-registration of the orthophotos did not skew the analysis. The orthophoto corresponding to the center pixel in each 5-by-5 group was displayed on the computer monitor and divided into a 10-by-10 grid. Each of the one hundred grid cells of the orthophoto was visually identified into one of four (1991) or seven (1998) categories (1991: open water, trees, shrubs/ grass, and pavement or bare earth; 1998: open water, trees, shrubs/ grass, pavement, bare earth, pavement or bare earth, and shadows) (Figure 3).

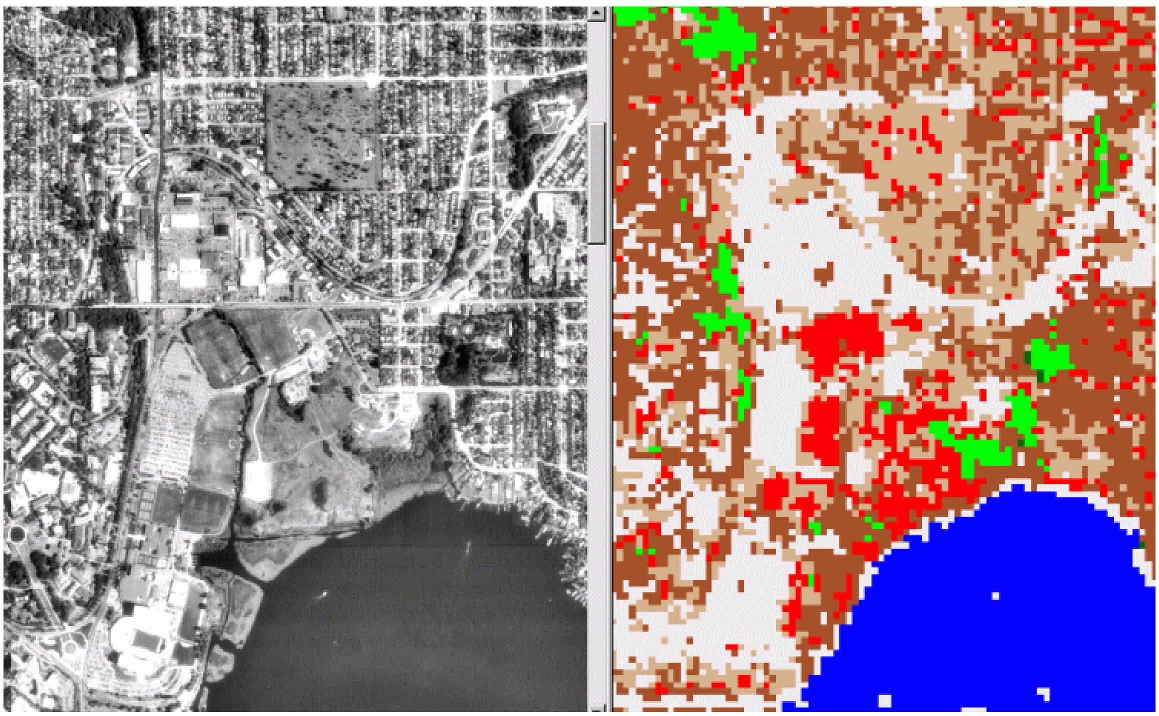

Figure 3. An example of the pairing of orthophoto and classified image, centered on the University Village area of Seattle.

The first accuracy assessment was a classic error check, wherein classified pixels are judged to be “correctly” or “incorrectly” identified. The criteria, determined from the results of the signature extraction for the 1998 image, are listed in Table 3. The analysis for the 1998 image (Table 4) shows an overall accuracy of 77 percent, with the worst performance for the two classes with the greatest mixture of land covers: *grassy urban* (most pixels were “more urban” than anticipated) and *forested urban* (the misclassified pixels were both more and less urban than expected).

	Water	Trees	Grass	Bare earth	Paved
Forested Urban		≥25%			≥20% & <60%
Grassy Urban		<25%	≥25%		<60%
Paved Urban					≥60%
Grass/Shrub/ Crops			≥50%		<20%
Water	≥80%				<20%
Bare Soil			<20%	≥75%	
Forested		≥70%			<20%

Table 3: Criteria for “correct” land-cover classification.

		OBSERVED (from orthophotos)								
EXPECTED (i.e. pixels as classified)		forested urban	grassy urban	paved urban	grass/ shrub/ crops	water	bare soil	forested	**Row Total**	Consumer's accuracy:
	forested urban	27	5	4	9	0	0	5	**50**	54%
	grassy urban	0	9	35	6	0	0	0	**50**	18%
	paved urban	0	0	47	1	0	0	2	**50**	94%
	grass/shrub/ crops	0	0	0	49	0	0	1	**50**	98%
	water	0	0	0	0	50	0	0	**50**	100%
	bare soil	0	1	7	3	0	39	0	**50**	78%
	forested	0	0	0	1	0	0	49	**50**	98%
	Column Total	**27**	**15**	**93**	**69**	**50**	**39**	**57**	**350**	
Producer's accuracy:		100%	60%	51%	71%	100%	100%	86%		**77% = overall accuracy rate**

Table 4. Error matrix for the 1998 classification.

However, we were less concerned with a correspondence with preestablished categories than with having a robust characterization of land cover. We therefore took a second approach to accuracy assessment—accepting the pixel classification as a given, and simply characterizing *a priori* the land cover associated with each of the seven categories (open water, coniferous vegetation, deciduous vegetation, grass/shrub, intense urban, grassy urban, and forested urban). From this approach, values for each of the 100 (1991) or 56 (1998) pixels in each category were combined to yield averages and standard deviations for the different *land covers*, visible in an orthophoto, for each of the seven *classes*. Values are tabulated in the Appendix. In particular, impervious-area percentages (combining pavement and bare earth) for the seven classes are listed in Table 5.

Categories from the classified Landsat image:	Observed impervious-area percentages: 1991	1998
"UNDEVELOPED"		
Open water	0	0
Coniferous vegetation	1	—
Deciduous vegetation	4	—
Forested	—	3
"DEVELOPED"		
Grassy/shrubby vegetation	29	5
Bare earth	—	98
Forested urban	23	38
Grassy urban	31	74
Intense urban	62	92

Table 5. Average values of impervious-area percentages, determined from orthophotos for each of the seven classes.

These average values follow the expected trends for the different classes, and in general the 1998 classification does a better job of discriminating developed from undeveloped land uses. However, actual land covers for individual pixels of the same class can vary widely. The standard deviations for each cover type in each class are generally of the same magnitude of the average values themselves (see Appendix for the 1998 values), and so estimates of land cover for a single (or a small number) of pixels have a high probability of diverging significantly from the average values.

The magnitude of this uncertainty, and the number of pixels needed to reduce it to a predetermined level, can be estimated using the expectation of normally distributed variability in the range of measured values (an expression of the central limit theorem in statistical analysis). For a given pixel, its estimated mean should lie within two standard deviations (2s) of the "true" mean (m). In developing the estimates of the class averages we evaluated a large number (n) of pixels (n = 56 in the case of the 1998 data, for example). For a presumed normally distributed population, we can have a 95-percent confidence that:

$$\text{estimated mean} - 2(s/\sqrt{n}) < \text{true mean} < \text{estimated mean} + 2(s/\sqrt{n})$$

To then estimate the land-cover percentages of a new classified pixel from the tabulated average values, we need to include the potential variability of observations about the mean for this *new* sampling. This results in:

$$\text{estimated mean} - 2(s + s/\sqrt{n}) < \text{true mean} < \text{estimated mean} + 2(s + s/\sqrt{n})$$

The large magnitude of the standard deviations makes the classification useless for single pixels—95-percent confidence intervals, in some cases, span over 60 percentage points!

Yet by aggregating "enough" pixels, N, of a single class, the estimated mean value (for which we will use the values in Table 4 [imperviousness] or the Appendix [all classes]) should converge more closely about the mean value of the (presumed) normally distributed population. In this instance, the estimated mean of the *aggregated* pixels has the following relationship to the true mean (again, with 95-percent confidence):

$$\text{estimated mean} - 2(s + s/\sqrt{n})/\sqrt{N} < \text{true mean} < \text{estimated mean} + 2(s + s/\sqrt{n})/\sqrt{N}$$

If we explicitly define a maximum acceptable range for the 95-percent confidence interval for specific land-cover types (trees, impervious area, etc.), the minimum number of aggregated pixels (N_{min}) needed to achieve that range can be calculated. Consider a maximum permitted range of $\pm$ 1 percent for the estimate of total impervious area contributed by each class. Thus, for an area that is uniformly classified (i.e. all the pixels are the same class), this criterion is:

$$1 \geq 2(s_i + s_i/\sqrt{n})/\sqrt{N_i}, \text{ or}$$

$$N_i \geq [2(s_i + s_i/\sqrt{n})]^2$$

where s_i is the measured standard deviation of impervious-area percentage for each of the seven classes of pixels (i = 1 for water, i = 2 for coniferous, etc.).

In any real mixed-land-cover area, most if not all of the seven classes will be present, with each contributing only a fractional error scaled by their proportion N_i/T (where T = the total number of pixels in the area of interest). If we including this factor, then limiting the contribution of any one class to an error of $\pm$ 1 percent will require that

$$1 \geq (N_i/T) \times 2(s_i + s_i/\sqrt{n})/\sqrt{N_i}, \text{ or}$$

$$T^2/N_i \geq [2(s_i + s_i/\sqrt{n})]^2$$

This relationship is shown graphically below for the values of s_i determined for impervious-area percentage. As a general rule, low-development watersheds of just a few hundred acres should have estimates of total imperviousness within a few percent; more urban areas will require areas of one-half to one square mile for equally reliable results. The most urban areas should be evaluated over areas of one to two square miles (or more).

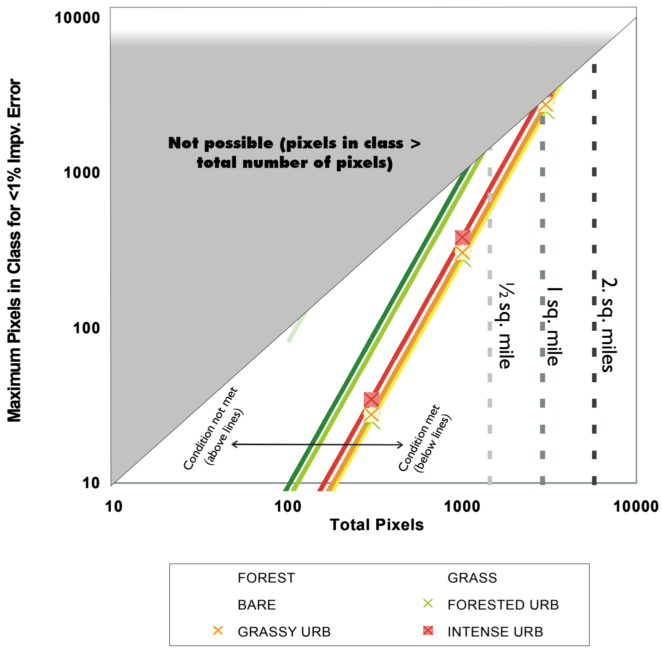

Figure 2. Graph showing the minimum number of pixels (and corresponding land area) required to limit errors in total impervious-area percentages to one percentage point in each of the six listed land-cover classes (water is excluded). This condition is met below and to the right of each of the lines, which needs to be evaluated for each class individually.

APPLICATION TO WATERSHED-BASED EVALUATIONS OF LAND COVER

Although multiple land-cover categories have great utility, there is particular appeal in a single "index" variable that characterizes the magnitude of urban development in a watershed. Patterns can be readily displayed, correlations are simplified, and communication between scientists and planners is enhanced. Yet urban development comes in many styles, occurs on many different types of landscapes, and is accompanied by a variety of mitigation measures designed to reduce its negative consequences on downstream watercourses. So any simple correlation between any single measure of urbanization and aquatic-system condition are unlikely to be precise.

Past efforts to quantify the degree of urban development have not been consistent. Recent and historical use of the most widely accepted parameter, percent impervious area in the contributing watershed, has been carefully documented in a recent review article (Schueler, 1995) but several issues remain ambiguous. Most significant of these is the distinction between ***total impervious area*** (TIA) and ***effective impervious area*** (EIA).

TIA is the “intuitive” definition of imperviousness: that fraction of the watershed covered by constructed, non-infiltrating surfaces such as concrete, asphalt, and buildings. Hydrologically this definition is incomplete for two reasons. First, it ignores nominally “pervious” surfaces that are sufficiently compacted or otherwise so low in permeability that the rate of runoff from them are similar or indistinguishable from pavement. For example, Wigmosta and others (1994) found that the impervious unit-area runoff was only 20 percent greater than that from pervious areas, primarily thin sodded lawns over glacial till, in a western Washington residential subdivision. Clearly, this hydrologic contribution cannot be ignored entirely.

The second limitation of TIA is that it includes some paved surfaces that may contribute nothing to the storm-runoff response of the downstream channel. A gazebo in the middle of parkland, for example, probably will impose no hydrologic changes into the watershed except a very localized elevation of soil moisture at the drip line of its roof. Less obvious, but still relevant, will be the different downstream consequences of rooftops that drain alternatively into a piped storm-drain system, with direct discharge into a natural stream, or onto splashblocks that disperse the runoff onto the garden at each corner of the building.

The first of these TIA limitations, the production of significant runoff from nominally pervious surfaces, is typically ignored in the characterization of urban development. The reason for such an approach lies in the difficulty in identifying such areas and estimating their contribution, although site-specific studies demonstrate that these tasks can be accomplished with simple field methods and the resulting hydrologic insights are often valuable (Burges and others, 1989). Furthermore, the degree to which pervious areas shed water as overland flow should be related, albeit imperfectly, with the amount of impervious area: where construction and development is more intense and covers progressively greater fractions of the watershed, the more likely that the intervening green spaces have been stripped and compacted during construction and only imperfectly rehabilitated for their hydrologic functions during subsequent “landscaping.”

The second of these TIA limitations, inclusion of non-contributing impervious areas, is formally addressed through the concept of effective impervious areas, defined as the impervious surfaces with direct hydraulic connection to the downstream drainage (or stream) system. Thus any part of the TIA that drains onto pervious (i.e. “green”) ground is excluded from the measurement of EIA.

This parameter, at least conceptually, captures the hydrologic significance of imperviousness. EIA is the parameter normally used to characterize urban development in hydrologic models.

Yet the direct measurement of EIA is complicated. Studies designed specifically to quantify this parameter must make direct, independent measurements of both TIA and EIA (Alley and Veenhuis, 1983; Laenen, 1983; Prysch and Ebbert, 1986). The results can then be generalized either as either a correlation between the two parameters or as a “typical” value for a given land use. Alley and Veenhuis found that [EIA] = 0.15 $[TIA]^{1.41}$ in their highly urbanized watersheds in Denver, Colorado (r^2 = 0.98). Using the other approach (*i.e.* typical land-use values), Dinicola (1989) compiled the findings of these earlier studies to recommend a single set of impervious-area values based on five land-use categories for use in studies of western Washington watersheds (Table 6).

LAND USE	**TIA (%)**	**EIA (%)**
Low density residential (1 unit per 2-5 acres)	10	4
Medium density residential (1 unit per acre)	20	10
“Suburban” density (4 units per acre)	35	24
High density (multi-family or 8+ units per acre)	60	48
Commercial and industrial	90	86

Table 6. Presumed Relationship between Imperviousness and Land Use (from Dinicola, 1989).

Because our analysis is being conducted at a much finer scale (30-m pixels) and detects only land-cover differences, we can evaluate only *total* imperviousness. Land-use categories, and thus EIA, might be inferred from larger clusters and patterns of individual pixels, but this lies outside the scope of this present effort.

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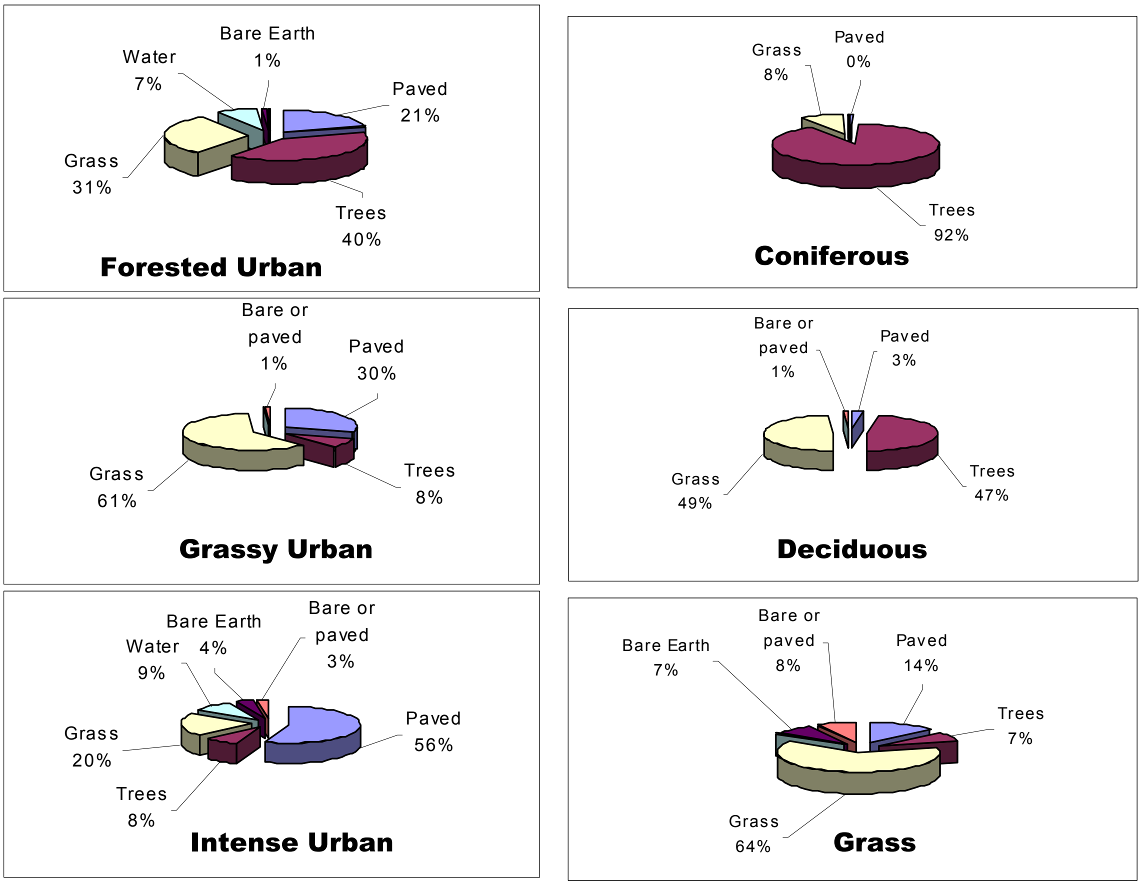
APPENDIX—"PHOTO-TRUTHING" THE CLASSIFIED IMAGES

After classifying the entire Landsat images, randomly selected classified pixels were compared with low-elevation orthophotos to determine the actual land cover that corresponds to each category in the classified image. The categories, and their corresponding average land cover percentages, are as follows for the 1991 and 1998 images:

1991 IMAGE	**Actual Land Cover from Orthophotos (percentages, averaged for 100 pixels)**			
	Open water	Trees	Shrubs/ grass	Pavement or bare earth
Categories from the classified Landsat image:				
"UNDEVELOPED"				
Open water	100	0	0	0
Coniferous vegetation		91	8	1
Deciduous vegetation		47	49	4
"DEVELOPED"				
Grassy/shrubby vegetation		8	63	29
Forested urban	7	39	31	23
Grassy urban		8	61	31
Intense urban	9	8	21	62

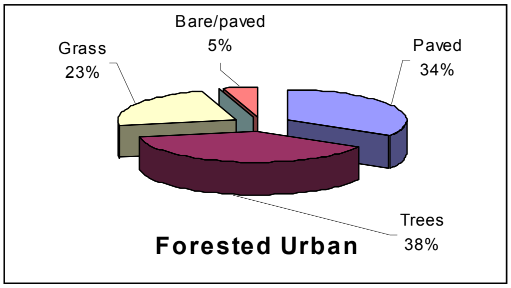
1991 LAND COVER CATEGORIES

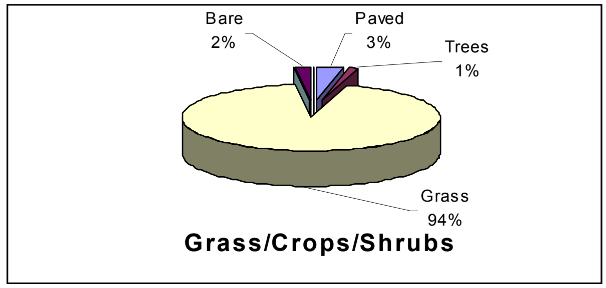


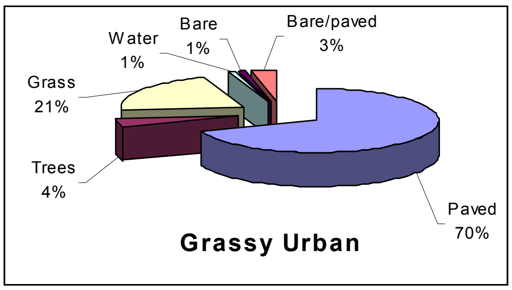
Note: See the associated spreadsheet for the percentage of land-cover values for *each* of the 100 pixels evaluated for each classification category. The category "Water" had 100% observed water coverage and so is not graphed here.

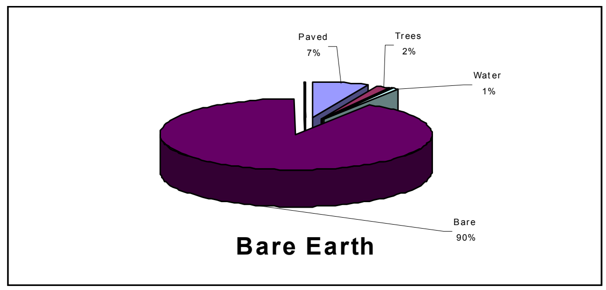
1998 IMAGE	**Actual Land Cover from Orthophotos (percentages, averaged for 56 pixels; Standard deviation shown in brackets)**						
	Open Water	Trees	Shrubs/ grass	Pave-ment	Bare earth	Pave-ment or bare earth	Shadows
Categories from the classified Landsat image:							
"UNDEVELOPED"							
Open water	100 [0]	0 [0]	0 [0]	0 [0]	0 [0]	0 [0]	0 [0]
Forested	0 [1]	96 [15]	1 [6]	1 [2]	2 [14]	0 [0]	0 [0]
Grassy/shrubby vegetation	0 [0]	1 [5]	94 [16]	3 [14]	2 [8]	0 [0]	1 [5]
"DEVELOPED"							
Bare earth	1 [4]	2 [4]	0 [1]	7 [17]	91 [20]	0 [2]	0 [0]
Forested urban	0 [0]	39 [27]	23 [34]	34 [25]	0 [0]	5 [9]	3 [7]
Grassy urban	1 [6]	4 [4]	21 [25]	70 [28]	1 [6]	3 [7]	0 [1]
Intense urban	1 [5]	5 [19]	2 [12]	92 [23]	0 [0]	0 [0]	0 [1]

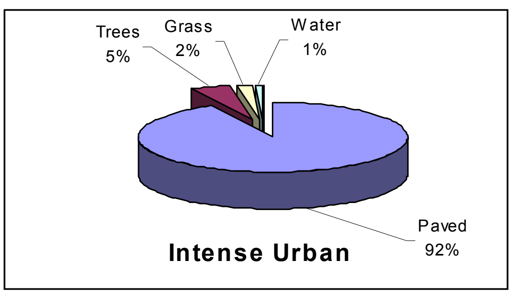
1998 LAND COVER CATEGORIES

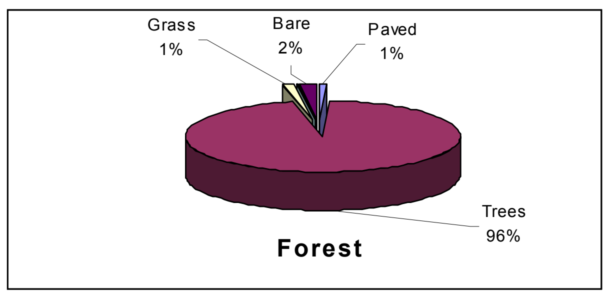












Note: See the associated 1998 spreadsheet for the percentage of land-cover values for *each* of the 50 pixels evaluated for each classification category; the category "shadows" is not included in the graphs, which is why some category values are not identical between the pie charts and the spreadsheet. The category "Water" had 100% observed water coverage and so is not graphed here.