Estimating and Mapping Impervious Surface Area by Regression Analysis of Landsat Imagery

Marvin E. Bauer and Brian C. Loffelholz
University of Minnesota

Bruce Wilson
Minnesota Pollution Control Agency

Contact Information

Marvin Bauer
University of Minnesota
Department of Forest Resources
1530 Cleveland Avenue North
St. Paul, MN 55108-6112

Phone: 612-624-3703
Fax: 612-625-5212
E-mail: mbauer@umn.edu

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1. INTRODUCTION

Impervious surfaces are defined as any surface which water cannot infiltrate. These surfaces are primarily associated with transportation (streets, highways, parking lots, sidewalks) and buildings. Expansion of impervious surfaces increases water runoff, and is a primary determinant of stormwater runoff volumes, water quality of lakes of lakes and streams, and stream habitat quality in urbanized areas. Increases in impervious surfaces, and accompanying phosphorous, sediment and thermal loads, can have profound negative impacts to lakes and streams and habitat for fisheries. Percent impervious surface area has emerged as a key factor to explain and generally predict the degree of impact severity to streams and watersheds. It has been generally found that most stream health indicators decline when the impervious area of a watershed exceeds 10 percent (Schueler, 1994). Arnold and Gibbons (1996) suggest that impervious surface area provides a measure of land use that is closely correlated with these impacts, and more generally that the amount of impervious surface in a landscape is an important indicator of environmental and habitat quality in urban areas. In the area of urban climate, Yuan and Bauer (2006) have recently documented a strong relationship between amount of impervious surface area and land surface temperatures or the urban heat island effect. It follows that impervious surface information is fundamental for watershed planning and management and for urban planning and policy.

Continued urban growth, expected to occur over the next three decades, should be accompanied by carefully designed and maintained stormwater runoff controls as required by new federal and state stormwater permits and Total Maximum Daily Load (TMDL) allocations for municipal stormwater sources. In Minnesota, there are more than 200 Municipal Separate Storm Sewer System (MS4) communities that are required by the Stormwater Program to begin stormwater pollution prevention planning and implementing urban best management practices. The MS4 cities must identify best management practices and measurable goals associated with each minimum control measure. Quantifying impervious cover should be one of the first steps for these areas. Given the number and size of the areas of interest, an economical and consistent method for mapping impervious surface area is needed.

Since the formulation by Ridd (1995) of a conceptual model of urban landscapes as a spectral mixture of vegetation, impervious surfaces and soil, a growing number of researchers have used Landsat data to map impervious surface area. A variety of approaches, including spectral mixture analysis (Wu and Murray, 2003; Wu, 2004, Lu and Weng, 2006), regression tree modeling (Yang et al., 2003a, b; Xian and Crane, 2005), decision tree classification Doughtery et al., 2004), subpixel classification (Civco et al., 2002), neural network classification (Civco and Hurd, 1997), and regression (Bauer et al., 2004, 2005) have shown that Landsat remote sensing has the potential for mapping and monitoring impervious surface area. Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) data have several advantages for this application: synoptic view of multi-county areas, digital, GIS compatible data, availability of data since 1984, and economical costs.

In an urban area where most pixels of Landsat data are mixed pixels with mixtures of vegetation (particularly grass and trees), water, and impervious surfaces, we believe the best approach is to consider impervious as a continuous variable. By treating impervious as a continuous variable, the errors associated with assigning a mixed pixel to a single nominal class with a range of impervious amounts or in assigning an average impervious value to each land cover/use class are avoided. Our approach has been to use a regression model to estimate the percent of impervious for each pixel. The theoretical basis for the approach is illustrated in Figure 1. The greenness component of the tasselled cap transformation of Landsat TM/ETM+ data is sensitive to the amount of green vegetation and inversely related to the amount of impervious surface area. The resulting classification provides a continuous range of impervious area from 0 to 100%.

This chapter describes the methods and results for estimation and mapping of impervious surface area, using multiple regression modeling, for the state of Minnesota for two time periods, 1990 and 2000. Minnesota has a wide variety of rural and urban landscapes, making it a near ideal setting to implement and evaluate the use of Landsat remote sensing for land cover and impervious surface mapping. The rural areas include agricultural cropland, forests and wetlands cover types, interspersed with towns. The urban areas range from low to high intensity development and from small towns in rural areas to regional center cites to the Twin Cities metropolitan area. Although the primary impetus for our work has been to quantify and map impervious surface area in support of watershed management and planning, imperviousness is also important in relation to aesthetics, habitat and urban climate.

2. METHODS

Landsat TM/ETM+ digital imagery were acquired and analyzed for two time periods, 1990 and 2000. The key steps in the procedures were image acquisition; rectification, land cover classification, development and application of a regression model relating percent impervious to Landsat TM tasselled cap greenness, and accuracy assessment (Figure 2). Image processing was performed in ERDAS Imagine, GIS operations in ArcGIS, and statistical analyses in SAS.

2.1 Landsat Image Acquisition, Rectification and Land Cover Classification

Nineteen images Landsat images are required to cover the state of Minnesota. Selection of clear, cloud and haze-free, imagery was a high priority and the selected images had only a few areas with clouds. In those areas, the clouds and cloud shadows were manually digitized to create a cloud mask that was overlaid on the impervious classification and all pixels within it were assigned a value of zero. It should be noted, however, that there were very few areas where clouds and urban overlapped.

The 19 images were rectified to the Universal Transverse Mercator (UTM) coordinate and projection system using approximately 35 ground control points per image and nearest neighbor resampling to a 30-meter pixel size with an RMS error of 1/4 pixel (7.5-meters) or less. The coordinates of the final images were adjusted to values evenly divisible by 30. Following rectification the imagery was transformed to unsigned 8-bit Landsat TM/ETM+ tasselled cap values (Crist and Cicone, 1984; Huang et al., 2002).

Our approach for mapping impervious surfaces applies an impervious estimation model to developed and urban areas, thereby requiring a concurrent land cover map to separate rural areas from developed/urban areas. We used a multitemporal, multispectral image classification with a combination of spring, summer and fall Landsat TM images acquired in ~2000 to classify land cover. The images were stratified into spectrally consistent classification units (SCCU) based on the Landsat image acquisition dates and paths, ecoregions, and vegetation phenology (Figure 3). The tasselled cap features of greenness, brightness, and wetness features for the three-date multitemporal images were used with a k-nearest (kNN) classifier to generate a land cover classification of the state with seven classes: agriculture, grassland, forest, wetland, water, extraction, and urban. The kNN classifier assigns each unknown pixel of the satellite image the attributes of the most similar reference pixels for which field data exists. The similarity is defined by the Mahalanobis distances between classes. The kNN method has proven to be an accurate and cost-efficient method for extending field inventory data to landscape scales (McRoberts et al., 2002). The average statewide overall accuracy for the level 1 cover type classifications was 84.5% with a Kappa statistic of 0.81. The average producer and user accuracies for the urban class were 91.7 and 95.4%, respectively.

2.2 Development of Impervious Surface Regression Models

Model calibration sites were selected separately for each Landsat image with approximately 50 sites for each Landsat image. The selection of sites was stratified by the range of amounts and types of impervious cover (e.g., parks, residential housing with varying densities, commercial, and industrial land uses), as well as by variations in amounts and kinds of vegetative cover (e.g., grass, forest, shrub). Stratification by vegetation cover type was done to account for seasonal variability in greenness between vegetative cover types.

The calibrations sites were typically 40 to 100 Landsat pixels, or approximately 2.5 to 10 ha in size. Further, the boundaries of the calibration sites were “snapped” to the 30-meter Landsat grid to ensure that the calibration sites in the high resolution images matched the Landsat images. The impervious surface area of each site digitized from 1991-92 1-meter panchromatic digital orthophoto quadrangles (DOQs) for 1990 and from 2003 1-meter color DOQs for 2000 to determine the percent impervious surface area within each site. Sites where the land cover or impervious area might have changed between acquisition of the aerial and Landsat imagery were not included.

The measurements of impervious surface area from the calibration sites were used to develop a least squares regression model relating percent impervious to the Landsat tasselled cap greenness responses for each SCCU image. Greenness is sensitive to the amount of green vegetation and therefore is inversely related to the amount of impervious surface area. The summer images provide the greatest contrast between impervious and vegetation responses. The images used for the impervious classifications are listed in Table 1.

2.3 Impervious Surface Classification

Classification of impervious surface was performed using an ERDAS Imagine Spatial Model with the Landsat tasseled cap greenness values for the calibration sites used as the input values for the impervious estimation models. Values generated represented the percent of impervious surface within the area of each pixel.

To remove estimation bias an inverse calibration was computed from the linear fit of measured vs. Landsat-estimated plots and applied to the impervious surface classification (Walsh and Burk, 1993). Following the inverse calibration, the accuracy of the Landsat-derived impervious surface estimates was reassessed. The inverse calibration process did not significantly affect the R^2 or standard error values, but decreased the intercept and increased the slope of the regression equations, reducing the overall bias of the models and improving the final classification accuracy.

The land cover classification was used to mask and reclassify the non-urban areas to zero percent impervious surface values. The 2000 land cover classification map was utilized as the primary identifier of urban in order to have consistent comparisons of the urban areas between the two years. We assumed that areas identified as urban in 2000, but not developed in 1990, would have a high greenness value (due to vegetative cover) in the 1990 imagery and would be modeled as having low to no impervious surface in the 1990 images. However, areas of bare soil in agricultural fields in 1990 that changed to urban by 2000 would have low greenness values in each date causing errors in the modeling of impervious surface for 1990. A land cover map for the early 1990's, the Minnesota GAP land cover classification (Lillesand, et al., 1998; Minnesota Department of Natural Resources (DNR), 2002), was used to remove the cropland and grassland areas from the areas considered as urban for 1990 to minimize this error.

Mines (gravel and sand quarries and iron ore open pit mines), considered as developed or urban in the 2000 land cover classifications, were identified for further processing in the impervious surface classification. Bare soil is classified in the impervious models as having a high degree of impervious surface due to its low greenness value. Much of the area of mines is bare soil, gravel and related materials, making separation of the impervious surface from bare soil difficult. Data identifying the location and extent of all mines in the state does not exist, however, there were data produced by the Minnesota DNR–Division of Lands and Minerals that identified the locations of active mining areas in the Mesabi Iron Range where the majority of open pit mines are located. This dataset was used to force the pixel values that fell within the iron mines data to an impervious value of zero.

The last processing procedure established a minimum and maximum for the modeled impervious values. Although the regression modeled estimate of percent impervious for a pixel might be less than 0% or more than 100% that is not physically possible. Therefore, pixels with estimated impervious surface values greater than 100% were reclassified to 100% impervious and those with less then 0% were reclassified as 0% impervious.

2.4 Accuracy Assessment

An independent random sample of approximately 25 accuracy assessment sites was selected from each of the Landsat images. The impervious surface values for these sites were determined in the same manner as the calibration sites described above. These sites were used for performing inverse calibration to remove estimation bias and to measure the accuracy of the final Landsat-derived impervious surface estimates. Accuracy was evaluated by regression analyses of measured vs. predicted amounts of impervious area.

3. RESULTS AND DISCUSSION

We have found a strong relationship between Landsat tasselled cap greenness and percent impervious surface area. An example of the relationship of greenness to percent impervious surface is shown in Figure 4. The second order regression model has an R^2 of 0.91 and standard error of 10.7. By considering greenness and percent impervious area as continuous variables we can use a regression model to estimate the percent impervious area of each Landsat pixel. The resulting classification provides a continuous range of impervious surface area from 0 – 100%. Figure 5 evaluates the agreement between the measured and Landsat-estimated percent impervious area for the same image as in Figure 4 following the inverse calibration. Similar results were obtained for the other 1990 and 2000 images. Figure 6 compares part of a DOQ image and the Landsat classification of percent impervious at the pixel level for an urban area. Although the Landsat classification is at a coarse resolution compared to the DOQ, the correspondence of features, particularly the pattern of streets and other urban features such as parks, residential areas and commercial and industrial areas, is readily apparent in the two images.

The statistics for all of the images for both the 1990 and 2000 classifications were consistent with R^2 values ranging from 0.80 – 0.94 and standard errors of 7.7 to 15.9 (Table 2). Figure 7 combines the data from all classifications for 1990 and 2000 to assess the overall accuracy of the Landsat estimates. The overall agreement between measured and Landsat estimates of percent impervious was high for both time periods with R^2 values of 0.86 and standard errors of 11.8 and 11.7.

The statistics, as well as the image comparisons, of Landsat estimates and DOQ measurements of impervious area indicate strong agreement; however, there are several known sources of error. These include: (1) Land cover classification errors in urban / developed vs. rural / non-urban areas. Our approach estimates impervious for only the urban class so errors in classification of urban vs. non-urban will lead to errors in the location and amount of impervious area. (2) Bare soil is spectrally similar to impervious surfaces. Although we used summer Landsat images when there is relatively little bare soil, some still is present and likely is misclassified as impervious. (3) Tree cover that obscures impervious areas. Although tree-covered areas are included in the calibration models, they are still a likely source of error. However, the error was less than 6% in a preliminary evaluation of this affect in an urban area with varying amounts of tree cover. (4) Differences in image acquisition dates and vegetation condition and phenology within images. We used mostly August images, but several are early September that likely had somewhat less greenness for grass that was not irrigated than for irrigated lawns. Similarly early senescing trees would have less greenness. Both these conditions may cause an overestimate of imperviousness.

Examples of the impervious classifications and change maps for two areas, St. Cloud and Rochester, in east central and southeast Minnesota that are experiencing significant growth, are shown in Figure 8. The growth of urban area and accompanying increases in amount of impervious surface area are readily apparent with a 40% increase for St. Cloud and 28% for Rochester. The large area covered by the classifications makes it impossible to show here their relevant spatial detail, especially at county to state scales. However, maps of the entire state with capability to roam and zoom can be viewed at: http://land.umn.edu/, along with statistics on amounts and changes in impervious area. The maps and statistics can be viewed, printed and/or downloaded for county, city/township, ecoregion, watershed, and lakeshed units.

Table 3 lists the amount of impervious surface area for several representative cities, ecoregions, watersheds, and the state. Between 1990 and 2000 the amount of impervious area for the entire state increased 118,464 ha from 1.31 to 1.88% of the total land area, a 44% increase. However, it is the increases at the local, city and watershed scales that are most critical to the water quality and other environmental effects. At the major watershed level, 20 of 81 watersheds had increases in total impervious area of more than 100% between 1990 and 2000, with 23 experiencing increases of 50-99% and 22 with 10-49%. Only 16 had increases of less than 10% or a small decrease. At the city scale, many cities, especially in the suburbs surrounding Minneapolis-St. Paul, as well as in regional center cities, had increases of 50% or more.

However, increases are not restricted to the larger urban centers. The area and degree of imperviousness also increased in and around many of the smaller towns. Of particular concern is the lake rich areas of northern Minnesota, where, for example, in the Northern Lakes and Forest Ecoregion, the impervious area increased more than 13,000 hectares, 32.5% increase. Impervious cover increased about 56% in 25 lake watersheds in north central Minnesota with about 1-4 % of the watersheds being impervious. In the Crow River Watershed (the Crow River is an impaired water body for one to three parameters) west of the Twin Cities, 23 cities and towns and seven associated townships had impervious area increases of 48% for the municipal areas and 129% for the townships. In 71 non-Twin Cities metro area cities and associated townships, the amount of imperviousness increased 69%. These examples illustrate that relatively large percentage increases in impervious cover have been occurring over the past decade and that watershed management efforts may need more rapid updating of land cover information than on 10 or 20 year cycles.

4. CONCLUSIONS

A strong relationship between impervious surface area and greenness enables percent impervious area on a pixel basis to be mapped with Landsat TM/ETM+ data. Classification of the Landsat data provides a means to map and quantify the degree of impervious surface area, an indicator of environmental quality, over large geographic areas and over time at modest cost. This chapter has described work concentrated on mapping imperviousness over large areas using Landsat data; however, we have previously reported (Sawaya et al., 2003) that the same methods can be successfully applied to high resolution IKONOS satellite imagery of local areas.

Although we are at an early stage in analysis of spatial and temporal patterns of urban growth and imperviousness, the Minnesota Pollution Control Agency is incorporating the impervious cover data, obtained from Landsat satellite remote sensing, into watershed management efforts and stormwater best management practice planning and monitoring efforts. An increasing number of future community stormwater management efforts are expected to have phosphorus and sediment loading rates determined by formal TMDL allocation processes in order to restore and/or protect receiving water quality and habitat – based on impervious cover and associated stormwater management practices. The consistent impervious surface data provided by the Landsat classifications for over 200 MS4 communities, covered by the phase II stormwater regulations, is a new foundational data layer needed for refining watershed management strategies for protection as well as for rehabilitation.

Increasing population, new development in lake and river recreation areas, and growing cities and towns all translate into increasing impervious surface areas across Minnesota. The Landsat classifications provide critically important, consistent and multi-date, impervious surface area maps and statistics for any area of Minnesota. It is envisioned that these data and updates, will be an important foundation of Minnesota's stormwater management efforts. As urban stormwater runoff from impervious areas can have profound negative impacts to receiving waters, it is a critical new component of statewide stormwater education and management efforts.

5. ACKNOWLEDGEMENTS

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Table 1. Landsat image acquisition dates and paths and rows. Strata refer to the maps in Figure 3.

Strata	***~1990***		***~2000***	
	Date	**Path / Row**	**Date**	**Path / Row**
1	30 August 1990	29 / 28-29	07 August 2001	26 / 27
2	30 August 1990	29 / 27	12 September 2000	27 / 26-28
3	30 August 1990	29 / 26	26 August 2000	28 / 26
4	04 September 1991	27 / 30	28 August 2001	29 / 26-28
5	04 September 1991	27 / 29	24 August 2000	30 / 27
6	26 August 1991	28 / 29	24 August 2000	30 / 26
7	07 August 1990	28 / 30	10 August 2000	28 / 30
8	07 August 1990	28 / 27	10 August 2000	28 / 29
9	10 August 1991	28 / 26	28 August 2001	29 / 29
10	04 September 1991	27 / 26-28	10 August 2000	28 / 28
11	07 August 1990	28 / 28	26 August 2000	28 / 27
12	09 August 1990	26 / 27	12 September 2000	27 / 29-30
13	25 August 1990	26 / 29-30	11 September 1999	26 / 30
14	23 July 1991	30 / 26-27	11 September 1999	26 / 29

Table 2. Accuracy of impervious surface classifications by strata and year. The locations of strata are shown in Figure 2.

Strata	1990		2000	
	R^2	Std. Error	R^2	Std. Error
1	0.86	11.2	0.94	7.7
2	0.89	11.2	0.87	8.9
3	0.90	10.3	0.87	11.7
4	0.83	12.8	0.82	13.4
5	0.82	12.9	0.94	7.8
6	0.89	10.2	0.92	8.9
7	0.94	7.8	0.90	10.1
8	0.85	12.9	0.85	12.8
9	0.87	12.8	0.89	9.6
10	0.86	9.4	0.91	9.4
11	0.84	12.0	0.89	10.8
12	0.81	15.2	0.81	13.1
13	0.82	14.7	0.80	13.9
14	0.90	9.7	0.80	15.9

Table 3. Impervious surface area (ISA) statistics for selected cities, counties, ecoregions, watersheds, and state of Minnesota for 1990 and 2000.

Area	Total Area (ha)	1990 ISA (ha)	2000 ISA (ha)	Change (ha)	1990 % ISA	2000 % ISA	Percent Change
St. Cloud	10,405	2,045	2,862	817	20.25	28.09	39.95
Rochester	11,932	2,285	2,921	636	20.16	24.74	27.83
Alexandria	2,562	377	667	290	15.58	27.41	76.92
Bemidji	3,448	607	676	69	19.21	21.27	11.37
Brainerd	2,936	514	568	54	18.47	20.24	10.51
Fergus Falls	3,878	399	625	226	11.14	17.39	56.64
Elk River	11,343	793	1,278	485	7.25	11.55	61.16
Sauk Rapids	1,409	316	483	167	23.67	36.06	52.85
Duluth	22,600	3,047	3,032	-15	17.33	17.23	-0.49
Mankato	4,290	929	1,389	460	21.81	32.69	49.52
Owatonna	3,436	746	973	227	21.83	28.44	30.43
Northern Lakes & Forest Ecoregion	6,823,378	41,308	54,738	13,430	0.67	0.88	32.51
N. Central Hardwoods Ecoregion	4,332,968	109,779	158,808	49,029	2.70	3.89	44.66
Western Corn Belt Ecoregion	4,152,960	50,195	88,895	38,700	1.22	2.16	77.10
Mississippi River – St. Cloud Watershed	290,477	7,330	15,671	8,341	2.64	5.58	113.79
St. Croix River - Stillwater Watershed	238,997	4,774	9,107	4,333	2.12	4.03	90.76
Canon River Watershed	380,867	5,530	9,821	4,291	1.49	2.64	77.59
Crow Wing River Watershed	503,935	3,925	6,596	2,671	0.84	1.40	68.05
State	21,852,928	269,649	388,700	119,051	1.31	1.88	44.15

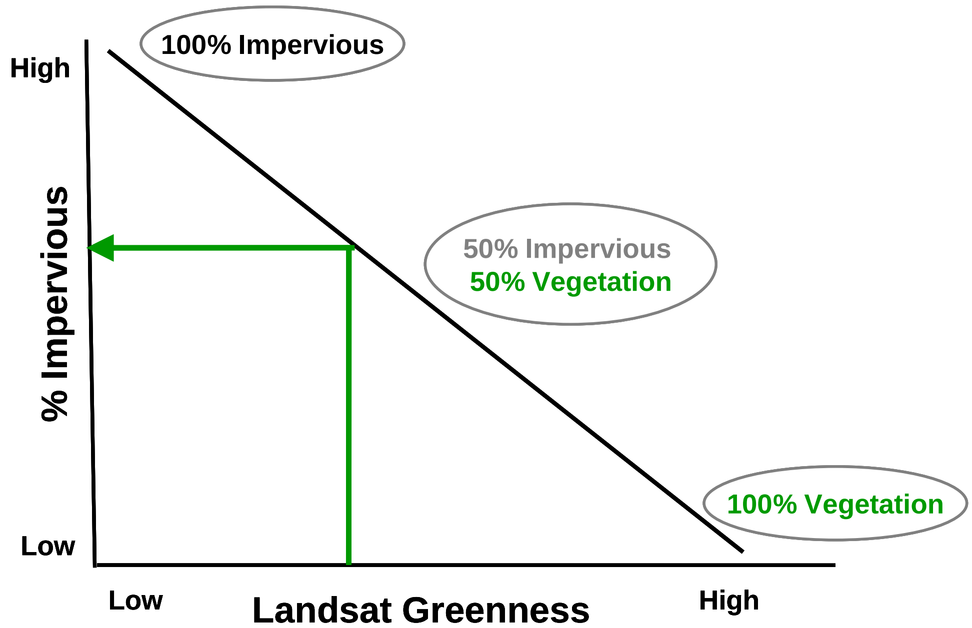

Figure 1. Conceptual model for estimating percent impervious surface area at the pixel level.

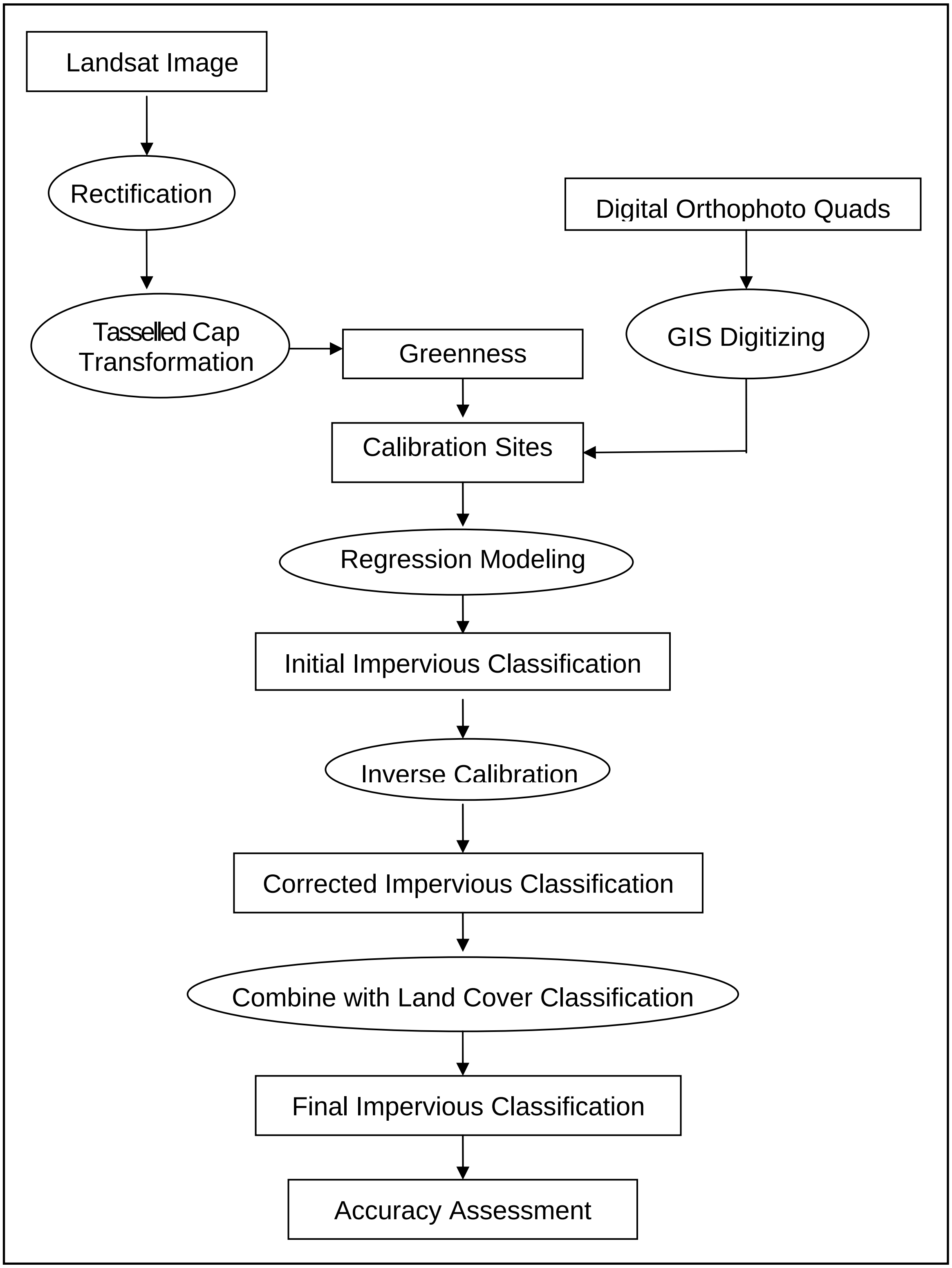

Figure 2. Flowchart of image processing and classification procedures for mapping impervious surface area.

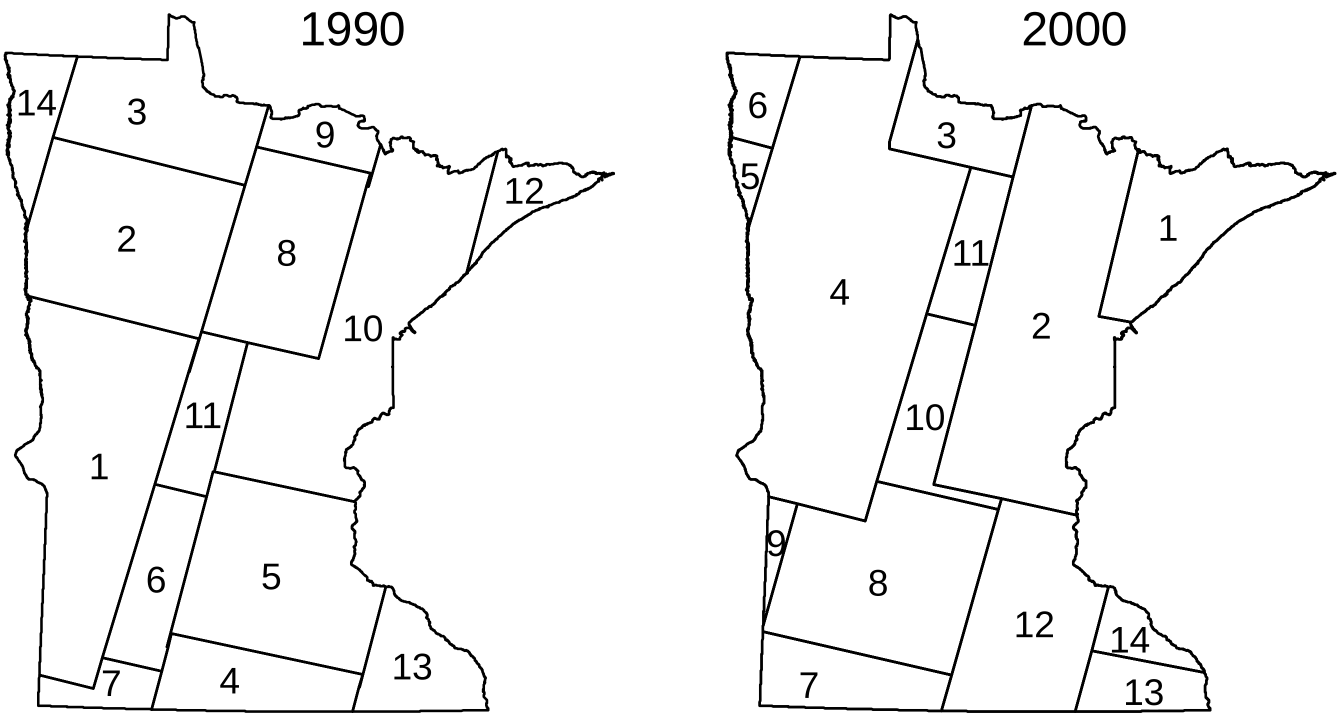

Figure 3. Strata, based on Landsat image acquisition dates, ecoregions and vegetation phenology, used for land cover and impervious classifications. The Landsat image paths and rows and acquisition dates are listed in Table 1.

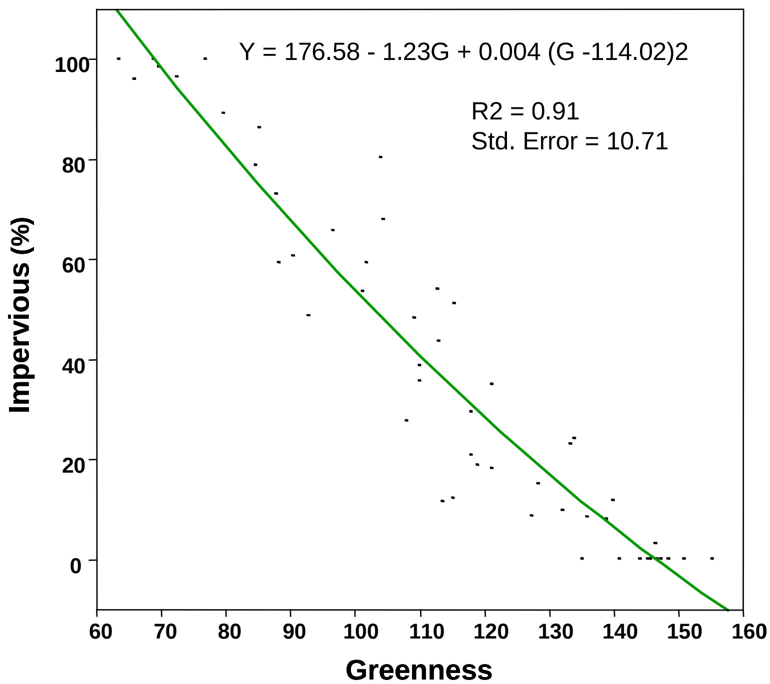

Figure 4. Example of relationship of Landsat greenness to percent impervious surface area (ETM+ data, path 28/row 28, August 10, 2000).

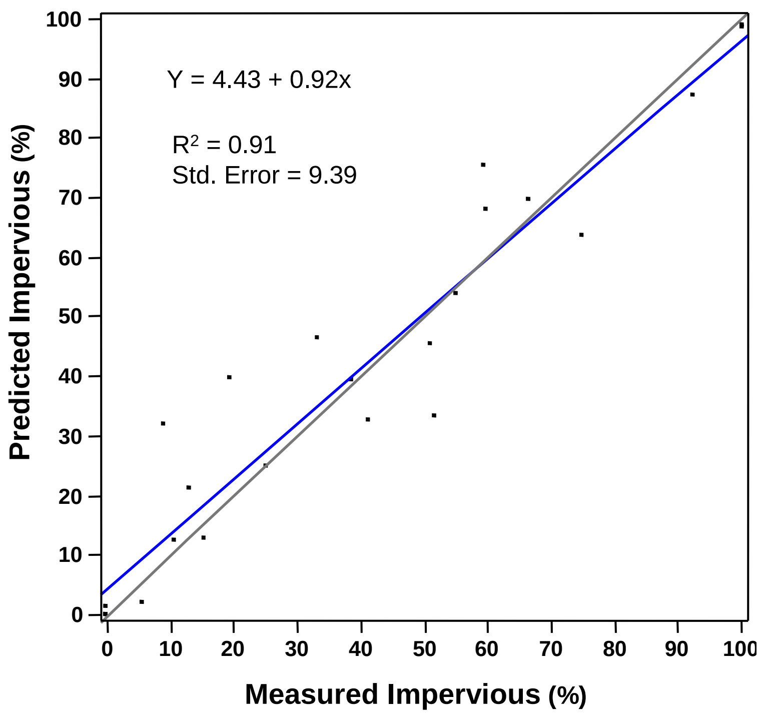

Figure 5. Comparison of measured to Landsat estimated impervious surface area (ETM+ data, path 28/row 28, August 10, 2000).

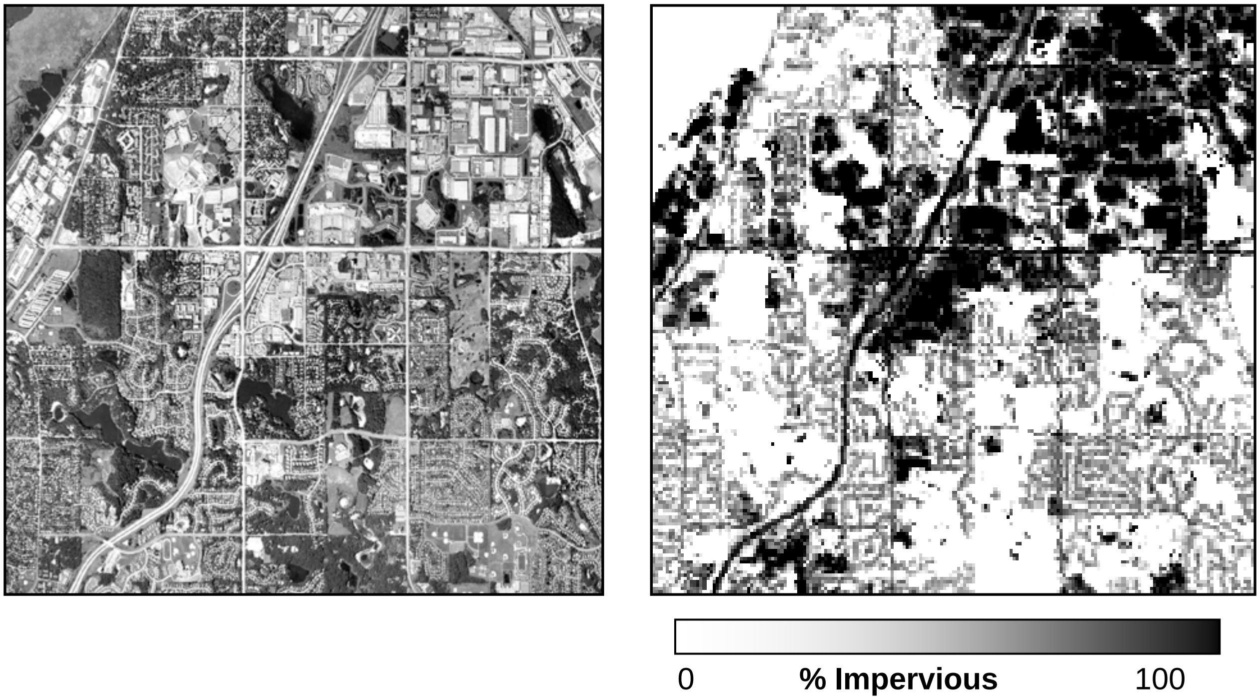

Figure 6. Comparison of a high resolution DOQ of a local area in Eagan (left) to the Landsat-derived classification of intensity of impervious surface area.

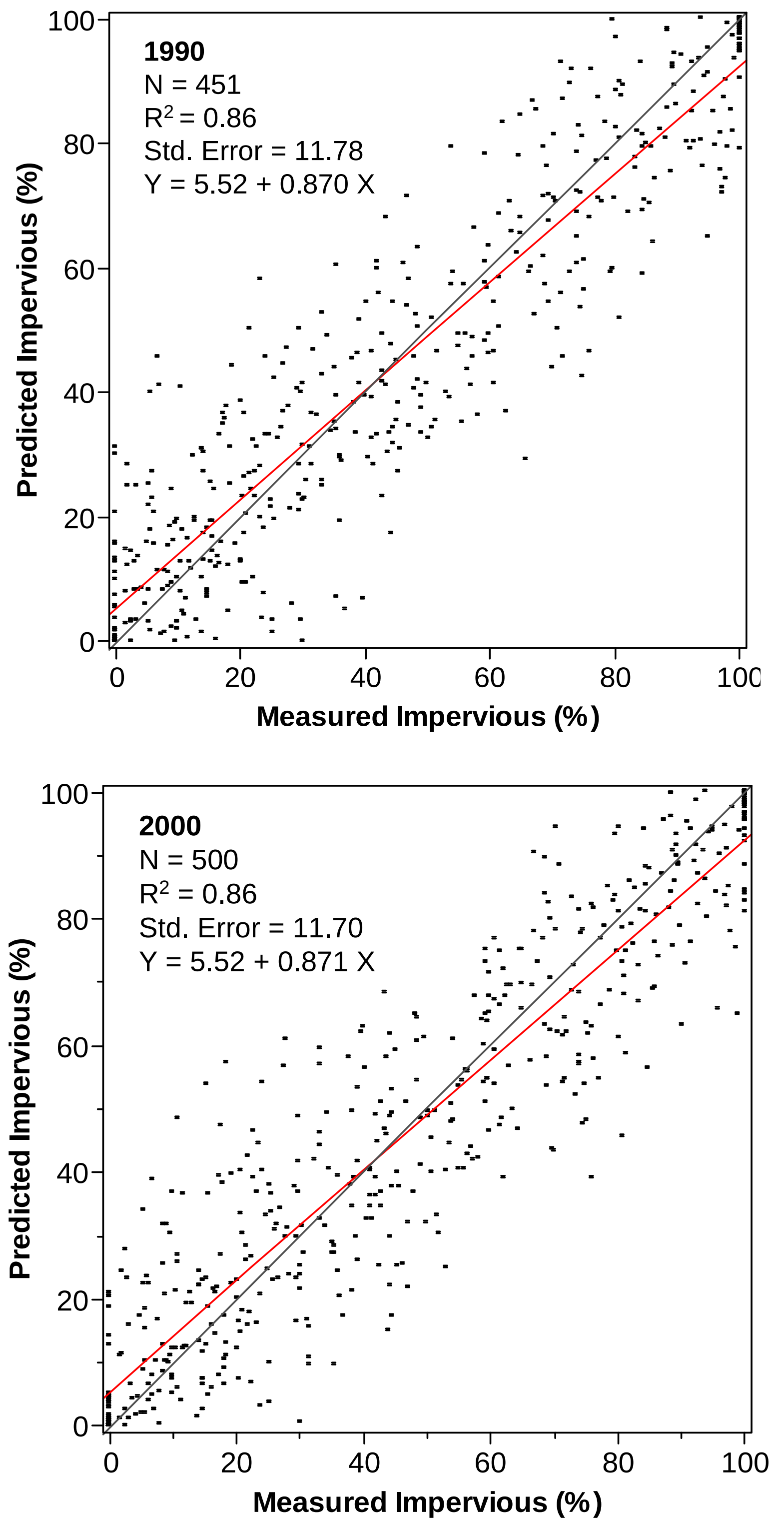

Figure 7. Evaluation of accuracy assessment statistics for 1990 (top) and 2000 (bottom) for the entire state.

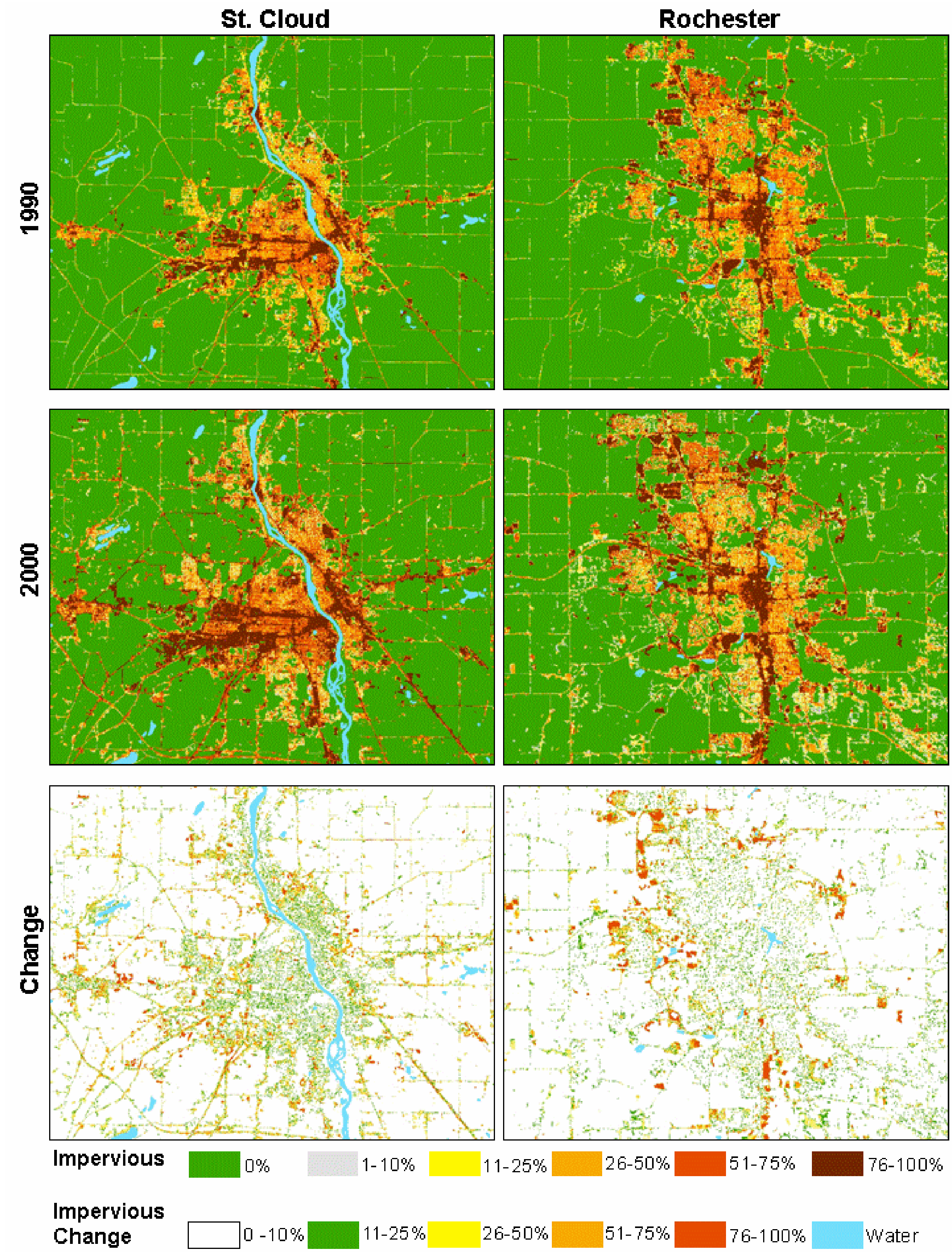

Figure 8. Impervious classifications of St. Cloud and Rochester for 1990 and 2000 and change maps.

Biosketches

Marvin Bauer is professor of remote sensing in the Department of Forest Resources, College of Agricultural, Food and Natural Resource Sciences at the University of Minnesota. His current research is focused on development and applications of digital satellite remote sensing for mapping and monitoring land and water resources in Minnesota. He also teaches classes on remote sensing of natural resources and environment and digital remote sensing, and serves as editor of the journal, Remote Sensing of Environment. He is a Fellow of the American Society of Photogrammetry and has received the NASA Distinguished Service Award and the Minnesota GIS/LIS Lifetime Achievement Award.

Brian Loeffelholz was a research fellow with Department of Forest Resources and Remote Sensing and Geospatial Analysis Laboratory, University of Minnesota, where his work focused on analysis and classification of Landsat, IKONOS and QuickBird imagery for mapping land cover and forests. He is now a GIS analyst with the Wisconsin Department of Agriculture, Trade and Consumer Protection.

Bruce Wilson is a limnologist and research scientist with the Minnesota Pollution Control Agency. He has led several water quality assessment efforts of major lake and river systems in Minnesota and has provided technical assistance to over 30 locally led watershed management projects. His current work includes satellite remote sensing of lake and river water quality, impervious mapping, and monitoring the effectiveness of stormwater Best Management Practices. He is a past president of the North American Lake Management Society.