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Operational Remote Sensing Solutions for Estimating Total Impervious Surface Areas

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16. ABSTRACT

The Washington State Department of Transportation (WSDOT) commissioned this research, conducted by the Urban Ecology Research Laboratory (UERL) at the University of Washington, to assist in effectively designing and managing operational, maintenance, and improvement activities within the context of the many growth management and clean water regulations and ordinances in Washington State. The goals of this study were to 1) implement a classification scheme for mapping the percentage of total impervious surfaces due to different types of transportation infrastructure based on satellite imagery, 2) develop and assess a remote sensing methodology for detection of road impervious surface area (RISA) and the fraction of RISA compared to the total impervious surface area (TISA) and 3) make recommendations on the imagery best suited for identifying impervious surfaces related to transportation infrastructure.

The results of this analysis have important implications regarding the use of remote sensing to determine the contribution of impervious surface from transportation infrastructure at regional scales. Higher resolution satellites, while more visually appealing, do not necessarily provide a net benefit in terms of accuracy that may justify their added expense. Our results indicate that, in most cases, Landsat performed as well if not better than the higher resolution SPOT imagery for determining regional scale roadway impervious surface area. The problem with using high resolution data for extracting road footprints at regional scales lies in the difficulty and cost of gathering a comprehensive set of imagery for the entire area of interest. Furthermore, extracting road footprints from high resolution imagery is a difficult proposition.

Our findings recommend using digital imagery with other GIS data that can serve as a proxy for road footprints. Transportation rights-of-ways taken from vector parcel data were highly effective at limiting the area that could be considered as road. Using this in combination with Landsat impervious surface data proved to be an accurate and relatively simple way to estimate road impervious surface area. We recognize that not all areas are covered by the detailed parcel datasets used in this analysis. To fill these gaps, a simple predictive road impervious surface area model was developed using a combination of data developed and gathered for this project. Linear regression was used to build the model and road impervious surface area extracted from test sites was used as the independent, or predicted, variable. The predictors, or independent variables, used in the model were total impervious surface (as measured by Landsat or SPOT), urban area background, and total road length measured using readily available GIS transportation data. All three independent variables were significant with a 95% confidence interval and the model as a whole was significant at the 99% level.

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Introduction

Study Objectives

The Washington State Department of Transportation (WSDOT) commissioned this research, conducted by the Urban Ecology Research Laboratory (UERL) at the University of Washington, to assist in effectively designing and managing operational, maintenance, and improvement activities within the context of the many growth management and clean water regulations and ordinances in Washington State. The goals of this study were to 1) implement a classification scheme for mapping the percentage of total impervious surfaces due to different types of transportation infrastructure based on satellite imagery, 2) develop and assess a remote sensing methodology for detection of road impervious surface area (RISA) and the fraction of RISA compared to the total impervious surface area (TISA) and 3) make recommendations on the imagery best suited for identifying impervious surfaces related to transportation infrastructure. Specifically, the objectives of this project were as follows:

1. Develop a typology of transportation infrastructure-related impervious surfaces based on a feasibility assessment of identifying transportation mode features from remote sensing data.
2. Develop and implement rules for detection and classifying percent impervious surfaces specifically attributable to mode of transportation.
3. Conduct classification accuracy assessment and sensitivity analysis of transportation infrastructure impervious surface classification.
4. Provide WSDOT an initial dataset describing the contribution of transportation infrastructure to statewide total impervious surface area.

To meet the study objectives, we developed a predictive model to determine the contribution of RISA for a given area using readily available data such as total impervious area and total road length. The model will enable WSDOT to estimate the amount of RISA for a given area without having to digitize or classify road footprints. Additionally, we devised a strategy for comparison of optimal data sources for extracting the impervious surface contribution to road infrastructure.

Spatial Scale

The spatial scale of this project was determined by the objective to identify transportation networks at a regional scale, which dictated that imagery used for classification must have a relatively large spatial extent. There is a significant trade-off between spatial extent and spatial resolution within remote sensing products. Spatial resolution dictates what objects can be resolved (seen) in the image and is a major limiting factor in the level of detail in any resulting classification. Imagery with very high spatial resolution typically has a fairly small spatial extent. For example, Ikonos imagery has a spatial resolution of 4 m with a spatial extent of only 7 km^2. Imagery with a larger spatial footprint typically has lower spatial resolution. The trade-off between extent and resolution presents numerous challenges when trying to identify features, such as roads, which, because of their narrow width, can only be resolved with relatively high resolution instruments. Lower resolution results in pixels that may be composed of several different types of material resulting in a spectral signature that is the composite of the different objects. For example, a 30 m Landsat pixel in a residential area might include part of a house, a driveway, and a backyard. This composite pixel is said to have a mixed spectral signature and adds to the difficulty when trying to classify discrete land cover types. Developing a spatiotemporally contiguous dataset for a region from such instruments presents numerous difficulties, including cost, temporal synchronicity, and computer processing capabilities.

Road Impervious Surface Area (RISA) Classification

The classification or extraction of road footprints from remotely sensed images, whether from satellite or air photos, is fraught with difficulties. Even with high resolution imagery, spectral similarities and spatial heterogeneity makes it impossible to completely separate roads from other urban surfaces using traditional classification techniques. Even newer algorithms that use textural information to extract linear features have trouble separating roads from sidewalks, driveways, and even houses. Recent progression in feature segmentation and extraction software, such as Feature Analyst® 4.0 and eCognition™, have enhanced remote sensing capabilities with the promise of being able to automate tasks that were once only possible using time consuming on-screen digitizing. While this latest generation of remote sensing software offers greater functionality, they are not a panacea for the automatic and accurate extraction of features from either high resolution air photos or medium resolution satellite imagery. Feature extraction algorithms work quite well in areas where features of interest are highly contrasted with the background landscape. For example, feature extraction applied to an aerial photo of a highway splitting a dense forest will work quite well. On the other hand, road extraction in a heavy or even medium density urban area will yield less than optimal results. In such cases, unwanted features such as driveways and even buildings are impossible to completely exclude during feature extraction. Therefore, in order to extract a specific type of feature, such as a road, ancillary data sources are needed to help remove unwanted features.

Given the issues stated in the preceding paragraphs, it quickly became apparent that classifying regional road footprints, let alone transportation typologies, from imagery alone was not feasible. Instead, we focused on methods that combined readily available vector datasets, such as county parcel and street data, with medium resolution satellite imagery to determine the impervious surface contribution of roads for a given area. In addition, we estimated a predictive model that may be utilized in areas where vector data is not existent or inadequate. With just two inputs, total impervious surface and total road length, the impervious surface contribution from roads may be estimated quickly and accurately for a given area.

Methodology

Spatial Scale

After researching image availability from various sensors, we chose the Seattle and Yakima metropolitan areas as the test sites. These sites were representative of the two main eco-regions in Washington: Pacific Lowland Mixed Forest on the west side of the Cascades range and Intermountain Semi-desert on the east side. A strategy to extract transportation networks for these areas will be transferable to the majority of landscapes found in Washington State.

The conflict between spatial extent and resolution was a key factor in determining the direction of the analysis. In order to maximize spatial extent and resolution, we used SPOT imagery as the regional data source with the finest resolution at 10m, while still maintaining a relatively large spatial extent. We also used Landsat imagery for both the Yakima and Seattle test sites. The analysis comparing SPOT and Landsat classifications provided information as to the net benefits of higher resolution imagery such as SPOT. The increased spatial resolution of commercial satellites such as SPOT comes with a cost, both financially and functionally (SPOT is significantly more expensive and has a lower spectral resolution and lower spatial extent compared to Landsat). The results of this analysis provided valuable information as to the type of imagery that is best suited for road extraction at regional scales.

Total Impervious Surface Area (TISA) Classification

The first step in our classification was to create an impervious surface data set that could be used to determine TISA. We used a hybrid approach that combined sub-pixel classification techniques, such as linear spectral unmixing, with an object oriented classification approach using the software eCognition™ (4.0). The goal of using object oriented classification was to delineate objects and then classify them as urban or non-urban. eCognition™ segmented images using a region growing type algorithm (clusters of contiguous pixels were grouped together based upon a spectral heterogeneity). The resulting segments or objects (polygons) were based upon band values (spectra) and a user-defined scale parameter that dictated the size of the objects. The user may create several levels of segmentation in which finer-level objects are nested within larger-level objects, creating a hierarchy of image objects. For example, a given object in Level C can be related not only to its immediate neighbors within Level C, but also to the superior object(s) that it belongs to (e.g., Levels A and B), as well as the subordinate objects that it is composed of (e.g., Levels D, E, F, etc.). This object-oriented approach allowed for the development of a knowledge base whereby semantic rules may be used, in addition to the traditional classification techniques, to classify remotely sensed images.

Sub-pixel analysis is any technique used to determine the relative portions of different materials within a pixel. In this study, we used linear spectral unmixing and matched tuned filtering to determine the amounts of impervious surface in pixels that have been identified as containing ‘urban” materials. .Sub-pixel techniques cannot always accurately differentiate between impervious surfaces and soil so it was essential that urban pixels were identified before sub-pixel impervious surface estimates were associated with those pixels. Non-urban pixels were assigned the value of zero percent impervious surface while urban pixels were given the value of the percent impervious surface derived from sub-pixel unmixing. While non-urban surfaces may behave like an impervious surface, this behavior was not able to be determined from these digital images. In this capacity, we were limited to determining the amount of impervious cover for a particular pixel and could not determine the level of porosity for a given material.

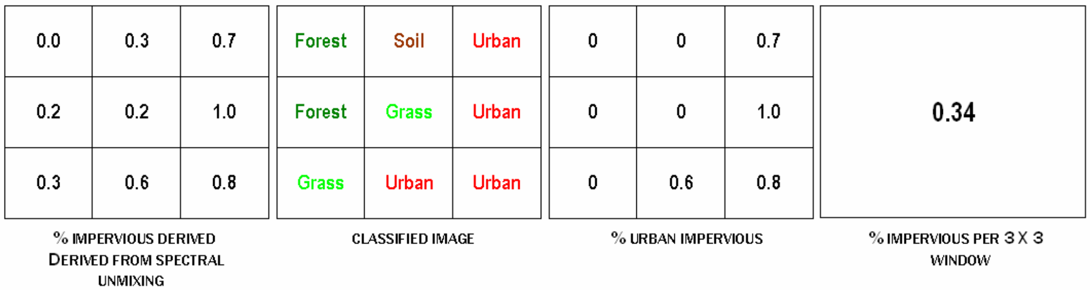


Figure 1. Example of how Landsat classification and sub-pixel impervious surface estimates are combined to produce a final impervious surface grid.

Landsat & SPOT Object Oriented Classification
A rules-based classification was developed using the object oriented classification software eCognition™ using SPOT and Landsat spectral bands and calculations from these bands such as NDVI and texture. Image segmentation was performed using a scale parameter of eight, which yielded small image objects. These objects were then classified using a set of hierarchical rules derived from the various data layers. The final result was a binary image representing urban and non-urban objects. This was exported as a grid and used to mask the impervious surface data so that only urban pixels received impervious surface values.

For Landsat imagery, a pixel-based classification was performed using Erdas Imagine software using the same rule set as described above, once the class rules were fine-tuned and produced a robust classification. The object based classification using Landsat imagery resulted in objects that over-generalized the imagery and which may have lost important detail. A pixel based classification was needed to preserve the already low level of detail that was inherent in the 30 m Landsat pixel. This step was unnecessary for the SPOT imagery where the higher resolution made it a better candidate for a truly object oriented classification. It should be noted that eCogntion™ was a great tool to facilitate the development of classification rules because it was so easy to develop, run, evaluate, and modify a hierarchical rules-based classification.

Impervious surface data were developed using linear spectral unmixing applied to Landsat imagery that were normalized for brightness. This brightness normalization method, proposed by Wu (2004), helped to reduce the within-band spectral variability of similar land cover types. The brightness normalization process reduced variability while preserving the spectral shape of similar land cover types and provided more consistent results when used for both end member selection (pure pixels whose spectral values are used in the unmixing models) and the unmixing process itself.

For the Puget Sound region, a two-end member model was developed using urban and vegetation spectral end-members. The unmixing process produced a fraction image for each end-member indicating the relative percent of each end-member in each pixel. A percent impervious layer was created by dividing the urban end-member layer from the sum of the urban and vegetation end-members.

The arid Yakima landscape had far greater amounts of exposed soil than the Puget Sound region and presented an important consideration for spectral unmixing. In previous work in the Puget Sound, it was found that urban and soil end-members were not particularly unique and could not be included within the same mixing models. This was acceptable since bare soil exists mostly as large homogenous patches and could be classified as such using other techniques. Except for sites in the process of being developed, soil was not a dominant sub-pixel component in the urban fabric in the Puget Sound area. This was not the case for the Yakima area and exposed soil was a dominant land cover type even in urban areas. Fortunately, it was found that the spectral signature for soil in Yakima is fairly unique and represented a distinct end-member in mixing space. Not only did this model yield accurate impervious surface amounts, but the soil fraction images were used as a layer in the object oriented classification to help separate urban from non-urban (e.g. soil) objects. Final impervious surface layers derived from spectral unmixing were masked using the urban/non-urban classification created during the TISA classification.

Road Impervious Surface Area (RISA) Classification

Vector data for roads offered little assistance in terms of determining the actual physical footprint of a road. Most often, roads were depicted in GIS using polylines to represent road centerlines. Moreover, the width of the road segments was often unavailable in the attribute tables for most road data, at least in Washington. Thus, it was impossible to extrapolate road footprints based upon road attribute data. One way to derive the road footprint from road center-lines was to buffer the data by assigning a particular road type a certain buffer width. The results of this method were greatly generalized and inaccurate.

County-wide parcel datasets offered a great deal of potential to increase the accuracy of road extraction. Parcel datasets typically included polygons for areas allocated to transportation right-of-ways, if not the road themselves. Using this data to mask or limit the area that can be considered “road” was very helpful for both road extractions from high resolution air photos and to determine road impervious surface area from classifications from medium resolution satellite imagery.

In this study, polygon right-of-ways from parcel data were used successfully in both Seattle and Yakima to isolate roads from other urban surfaces. It was best to use this in conjunction with remote sensing as opposed to assuming the right-of-ways themselves represented RISA because parcel right-of ways can contain areas that are not impervious, such as grassy medians.

Reference Site Development

In order to test the accuracy of our SPOT and Landsat classifications, sample sites for both the Puget Sound and Yakima regions were digitized from high resolution aerial photos. As mentioned earlier, more homogenous landscapes were, in general, easier to classify. In order to prevent any biases associated with heterogeneity within our sample sites, we used a stratified random sample to sample the accuracy of sites from a series of different types of backgrounds or dominant land cover types as described in Table 1. This stratification ensured that the dominant landscapes in each region were represented in our samples. These samples served two main purposes: 1) to create a series of reference sites to test the accuracy of our regional, lower resolution classification and 2) to test the effectiveness of the feature extraction software called Feature Analyst® 4.0 for extracting roads using high resolution color imagery. Figure 2 shows a series of maps of one test site depicting the overall methodology.

Table 1: Reference sites selection results in Seattle and Yakima

Land Cover	# of sites in Seattle	# of sites in Yakima	Total
High Urban	5	5	10
Forest	5	5	10
Low Urban	5	6	11
Grassland and Non-forest Wetland	5	0	5
Forest	5	0	5
Agriculture	5	6	5
Water	4	1	5
Bare Soil	0	2	2
Forest Wetland	0	2	2

Site Selection

A 1x1km vector grid was overlaid on the roads layer for both the Seattle and Yakima sites. Cells with no roads present were flagged and excluded from the selection process. Next, land cover data was used to assign the dominant land cover for each 1km grid cell. Nine land cover types (Figure 2) were examined in this project and five sites were selected for each land cover type. The selection was based on the major land cover percentile and the number of road types contained per study site. Priority was given to those sites with a majority of a specific land cover type and second priority was given to the sites containing a variety of road types. A visual evaluation followed to confirm site selection. The results from the above steps are represented in Table 1, which shows the number of sites being selected for each land cover category. A total of 64 reference sites were selected and used to test the accuracy of the regional Landsat and SPOT TISA/RISA classifications (Figure 3).

Figure 2. Example images of the land cover categories for the reference sites.

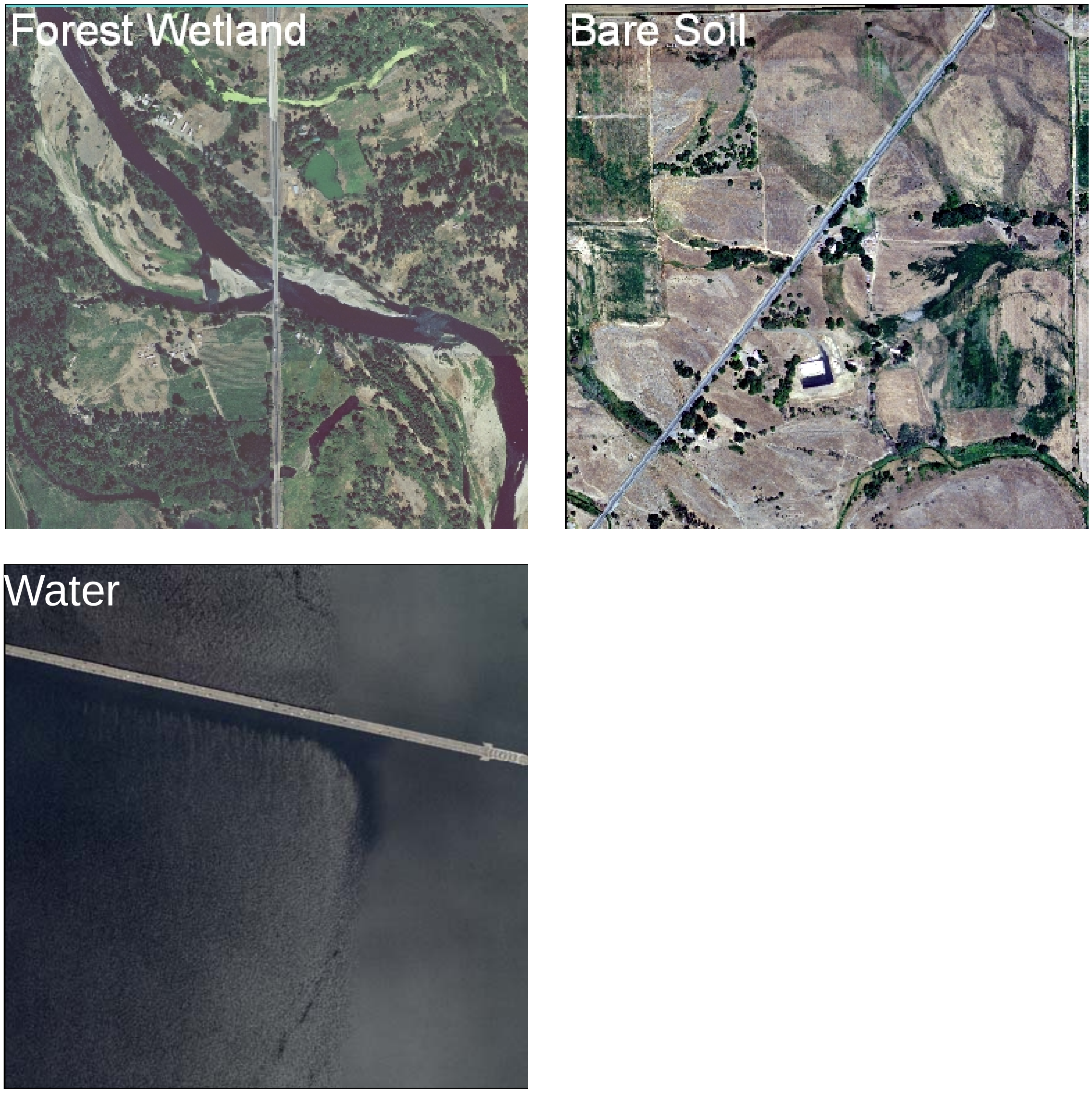


Figure 2. con’t. Example images of the land cover categories for the reference sites

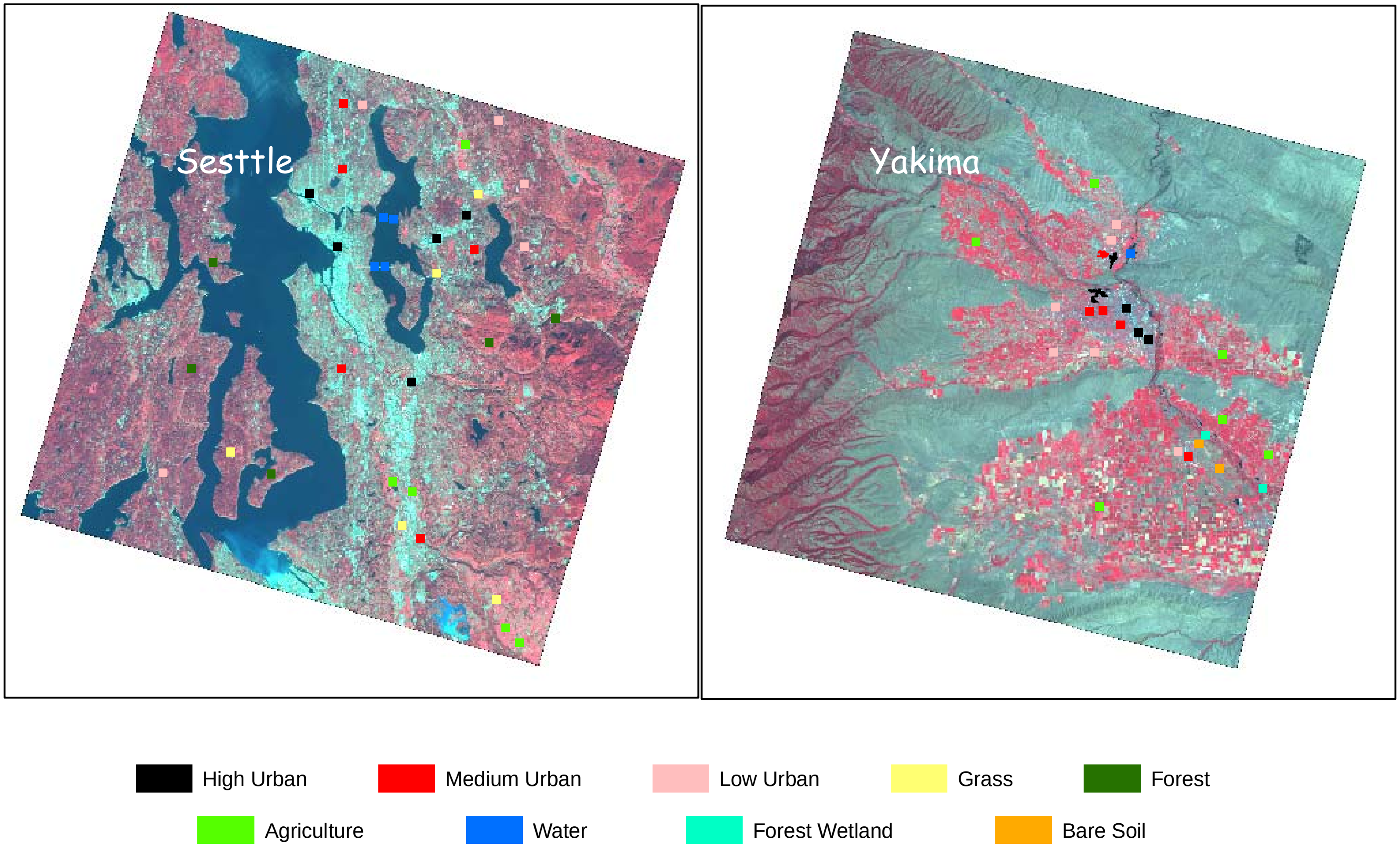


Figure 3. Reference sites distributions in Seattle and Yakima

Road Extraction in Reference Sites

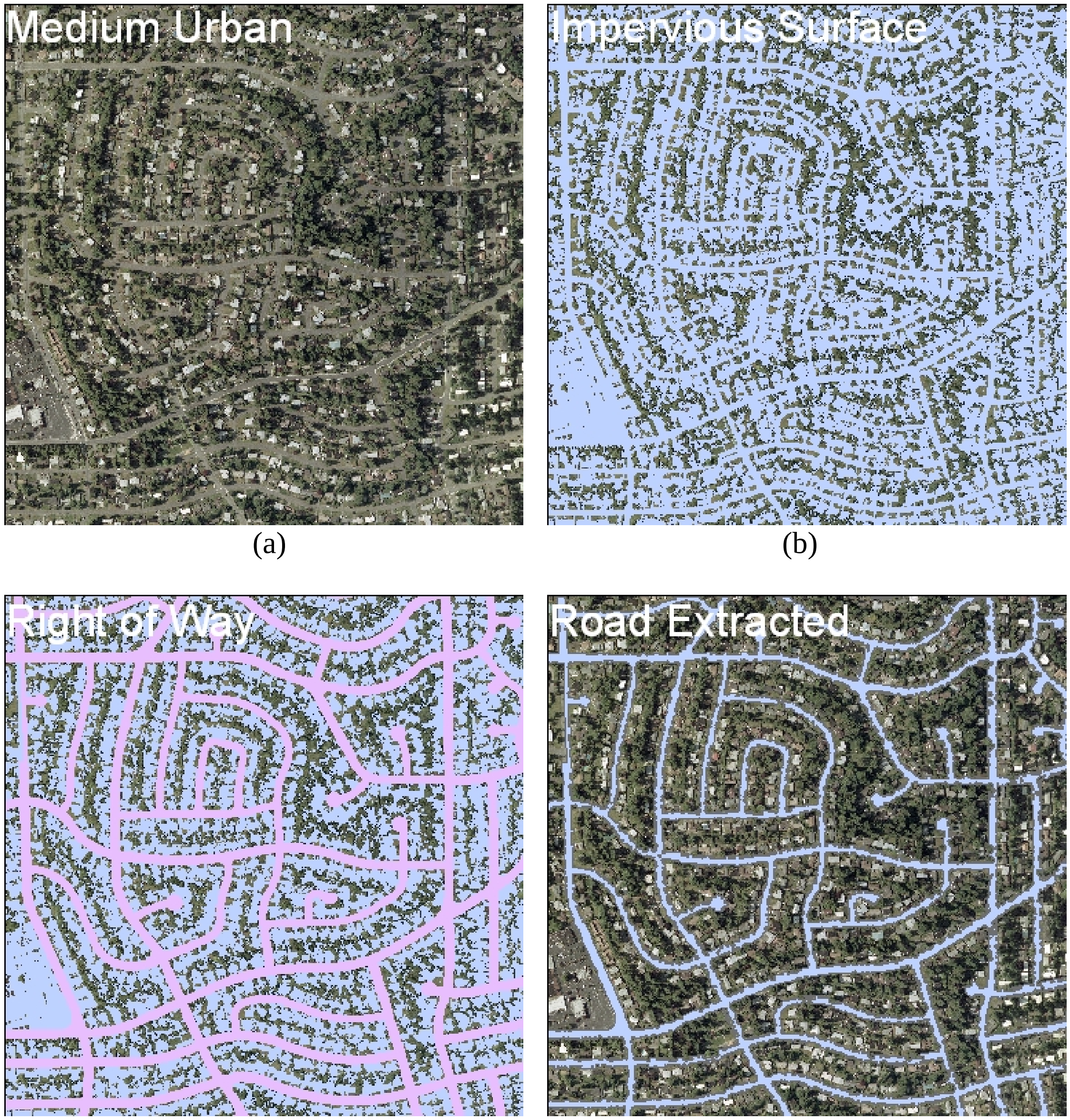
Reference data for road area was extracted from 2 sq ft USGS aerial photos of the test sites to evaluate the accuracy of road extraction from the Landsat and SPOT classifications. Instead of hand-digitizing road footprints, Feature Analyst® 4.0 for ArcGIS® was employed to automate road extraction from aerial photos of the test sites. The initial attempt to use this software to extract just roads from the aerial photos had mixed results. For example, results were good in areas where roads have strong spectral contrast with a homogenous background such as water scene (Figure 4). Extraction quality was quite poor in heavy urban areas, where the building, parking, drive ways and roads were highly interconnected and all gave similar spectral information (Figure 5). These results did not match our expectations so we used Feature Analyst® 4.0 primarily to digitize impervious surfaces in the photos and then used the parcel right of ways to extract the roads from the impervious surface.

Figure 4. Road extraction from aerial photo using Feature Analyst® 4.0 in a water scene.

Figure 5. Roads extraction from aerial photo using Feature Analyst® 4.0 in a urban scene.

A large body of literature provided methods on automatic road extraction from high resolution images (Dell'Acqua and Gamba 2001a 2001b, Hinz and Baumgartner 2003, Mena 2003, He et al. 2004, Stoica et al. 2004, Mena and Malpica. 2005). Most of these methods are applied to extract roads from rural or low density urban areas within a simple image scene, while road extraction in dense urban areas with complicated image scenes are rarely documented and no published papers have provided a creditable road extraction method for multiple types of image scenes. In response to the universally unresolved obstacles for automatic road extraction, we integrated image processing and GIS data for road extraction. The process is illustrated in Figure 6 using a medium urban site in Bellevue, WA as an example. First, the 1 x 1km aerial photo (Figure 6a) was digitized into two classes, impervious surface (Figure 6b) and vegetation, using Feature Analyst R 4.0. Parcel right-of-way was then used to extract roads from impervious surfaces (Figure 6c). There were two obstacles associated with parcel right of ways that could lead to inaccurate extraction results. First, the parcel right-of-ways include highway medians. In our method, highway medians do not cause errors because highway medians, as non-impervious surface, are not included in the classified impervious surface. Second, parcel right-of-ways are usually wider than the actual roads, so the extracted roads (Figure 6d) may still contain a small portion of drive way, but for the scale, 1 x 1km, that we are looking at this type of error was considered acceptable.

The thresholds of TISA and RISA in each land cover category were derived using the extraction results of impervious surface and roads in the 64 reference sites (Figures 7-8). The three urban classes (high urban, medium urban and low urban) had a higher percentage of TISA and RISA than the five non-urban classes (agriculture, forest, forest wetland, bare soil and water). This was consistent with our empirical knowledge. Grass was the only land cover category whose TISA and RISA threshold was confusing as it may include both urban parks and rural pastures. In contrast, the ratios of RISA to TISA in the three urban classes were lower than those in the five non-urban classes (Figure 9).



(a) (b)

(c) (d)

Figure 6. Roads extraction from aerial photo using Feature Analyst® 4.0 and right-of-ways.

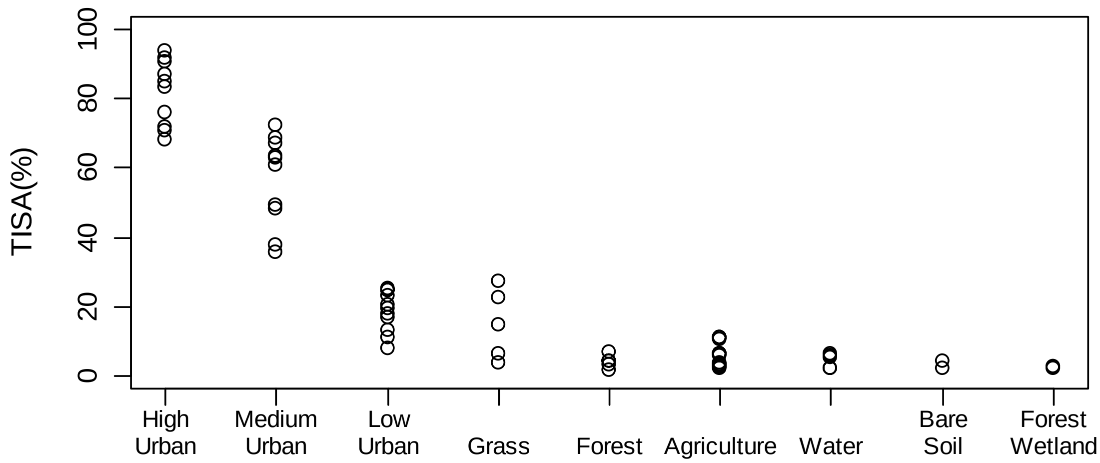


Figure 7. Percentage of total impervious surface area (TISA)

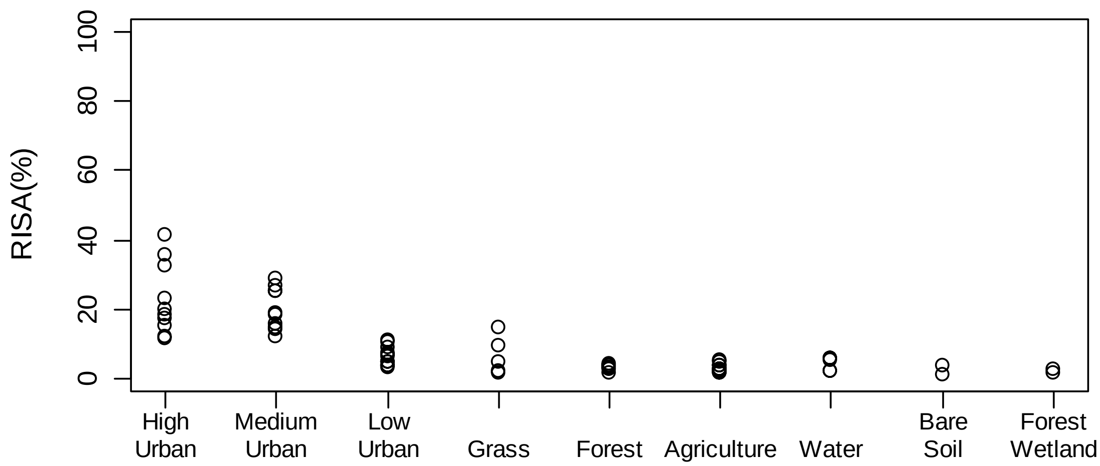


Figure 8. Percentage of road impervious surface area (RISA)

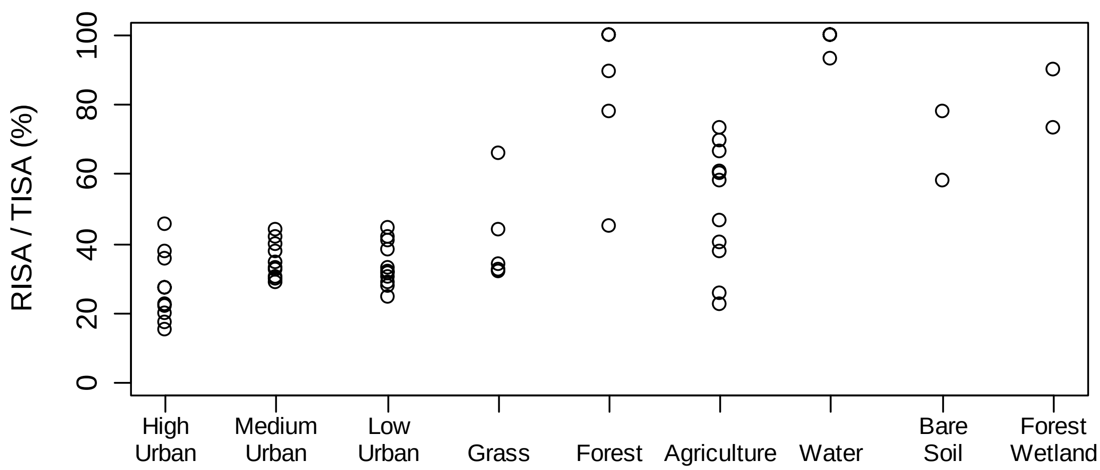


Figure 9. Percentage of road impervious surface area (RISA) in total impervious surface area (TISA)

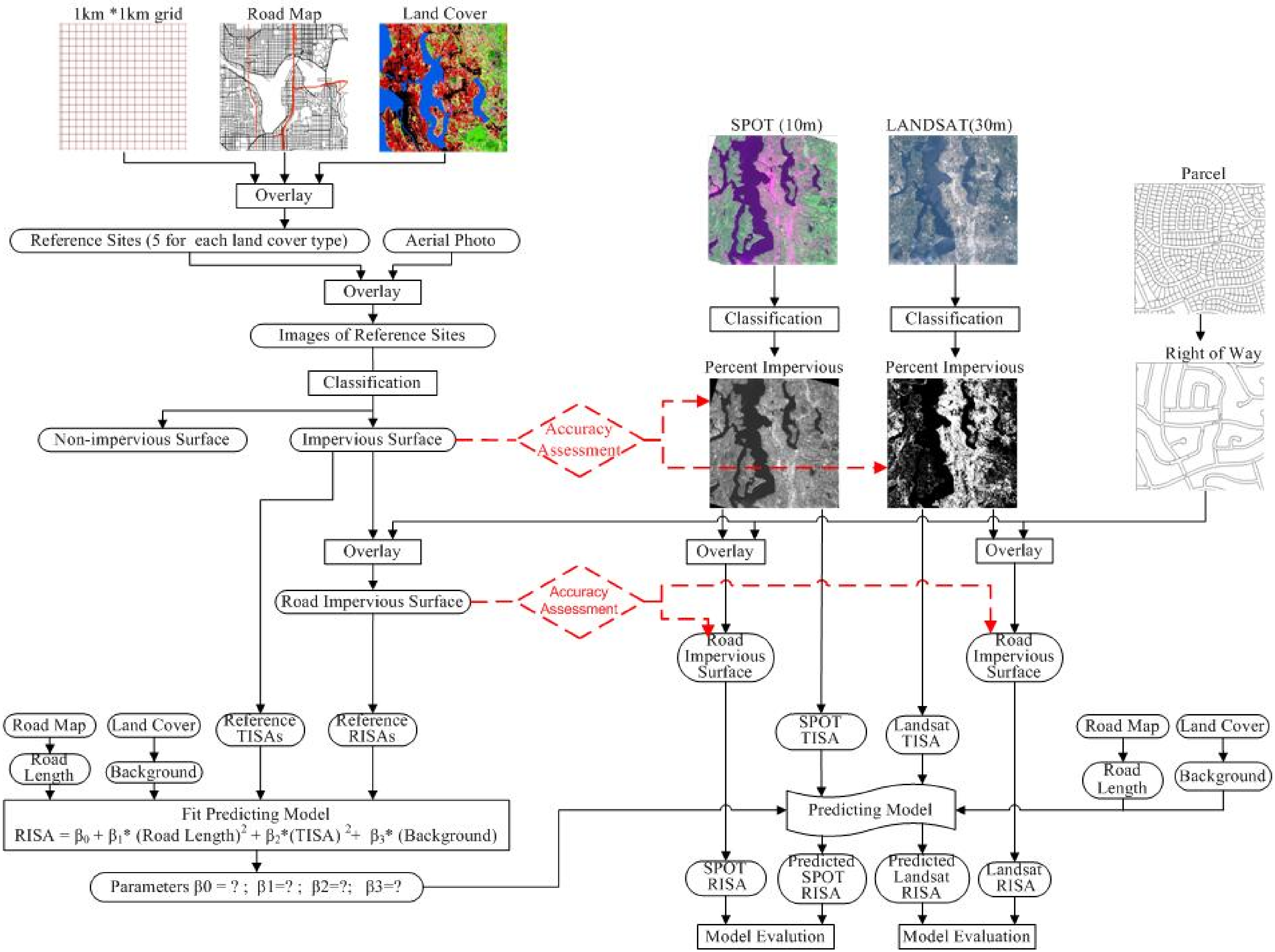


Figure 10. The process of creating reference sites, establishing TISA, and modeling RISA

Results

RISA & TISA Analysis

TISA and RISA were calculated from SPOT and Landsat for each study site. RISA was extracted from TISA using the parcel right-of-ways. The amount of TISA and RISA from both Landsat and SPOT was then compared to the test sites to assess agreement. We compared each to the reference data using scatter plots and the r^2 statistic to assess agreement. The r^2 statistic is a good tool to measure the degree of variability that may be explained by one or more independent variables. For example, as Figures 12 and 13 indicate, 95.9 percent of the variance of the reference data in the Puget Sound TISA may be explained by the Landsat TISA while 89.3 percent of its variance may be explained by SPOT TISA. For RISA in the Puget Sound region, Landsat has an r^2 of 0.967 and SPOT has an r^2 of 0.9561. These results were very good and indicate that both Spot and Landsat may be used to estimate TISA and RISA with high a degree of confidence.

While the Yakima test sites showed strong agreement, the results were not as good as the Puget Sound Region test sites. Landsat data performed as well, if not better, in all cases. Except for the detailed visual characteristics of SPOT imagery due to its higher spatial resolution, there was not a distinct advantage of SPOT data over Landsat for regional impervious surface analysis.

(a) (b) (c)

Figure 11. RISA extracted from SPOT TISA using parcel right-of-ways: a) aerial photo; b) SPOT with right-of-ways; c) SPOT RISA..

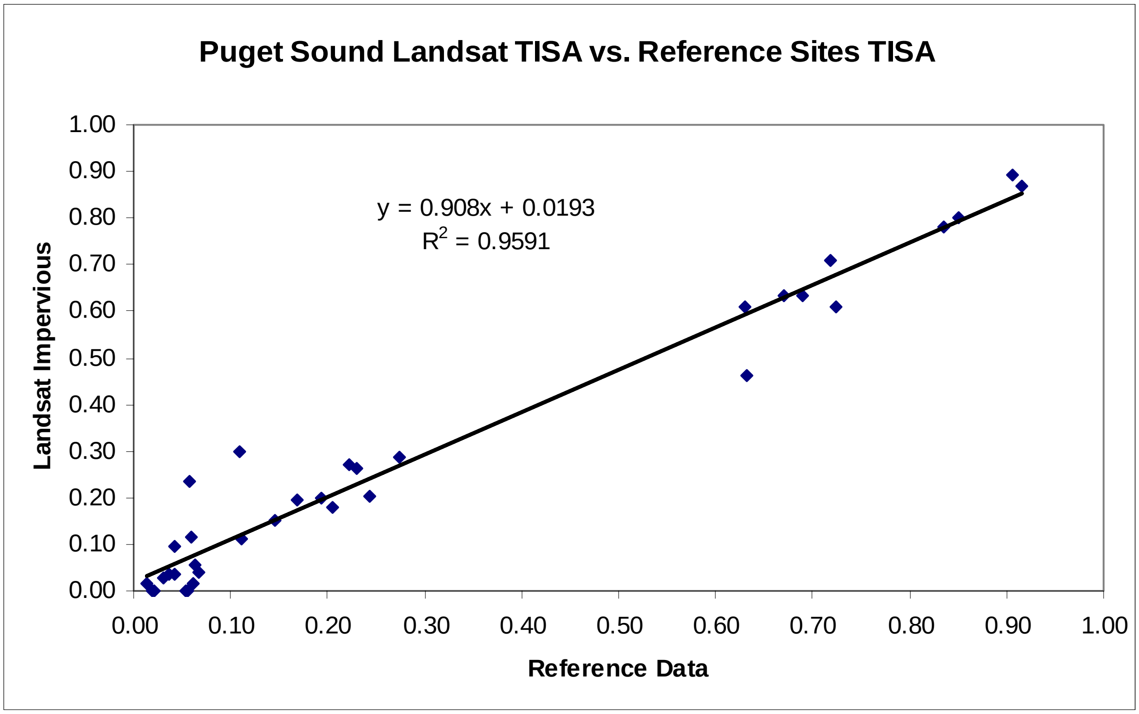


Figure 12. Puget Sound Landsat TISA versus reference site TISA

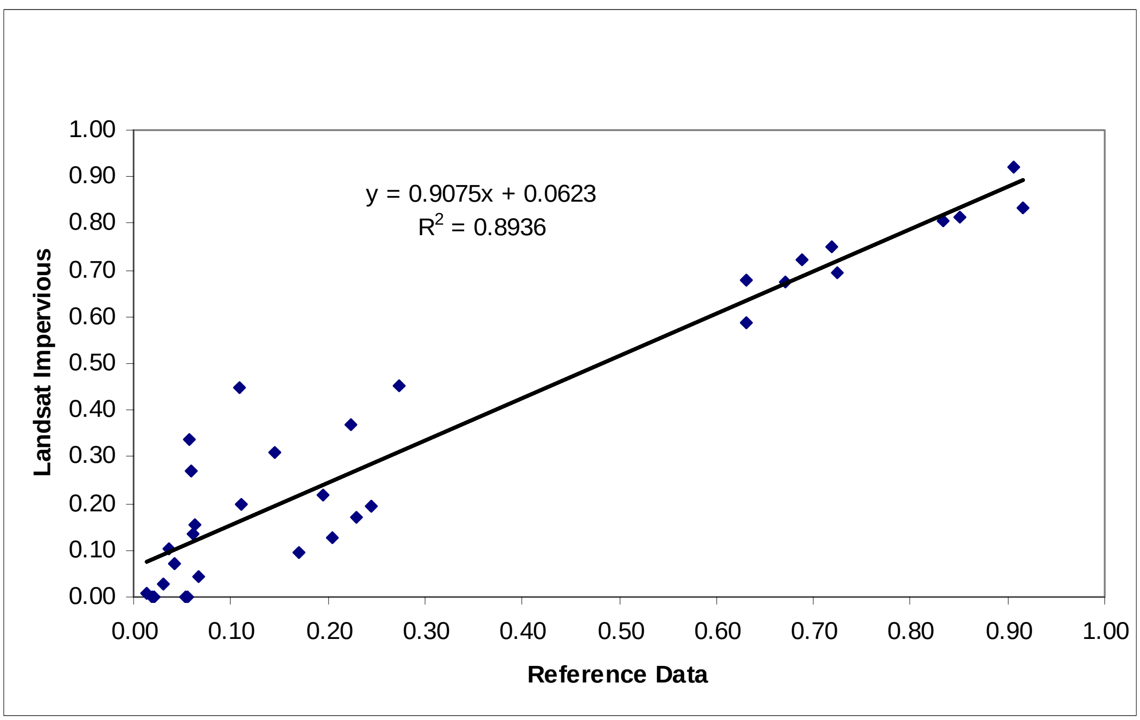


Figure 13. Puget Sound SPOT TISA versus reference site TISA

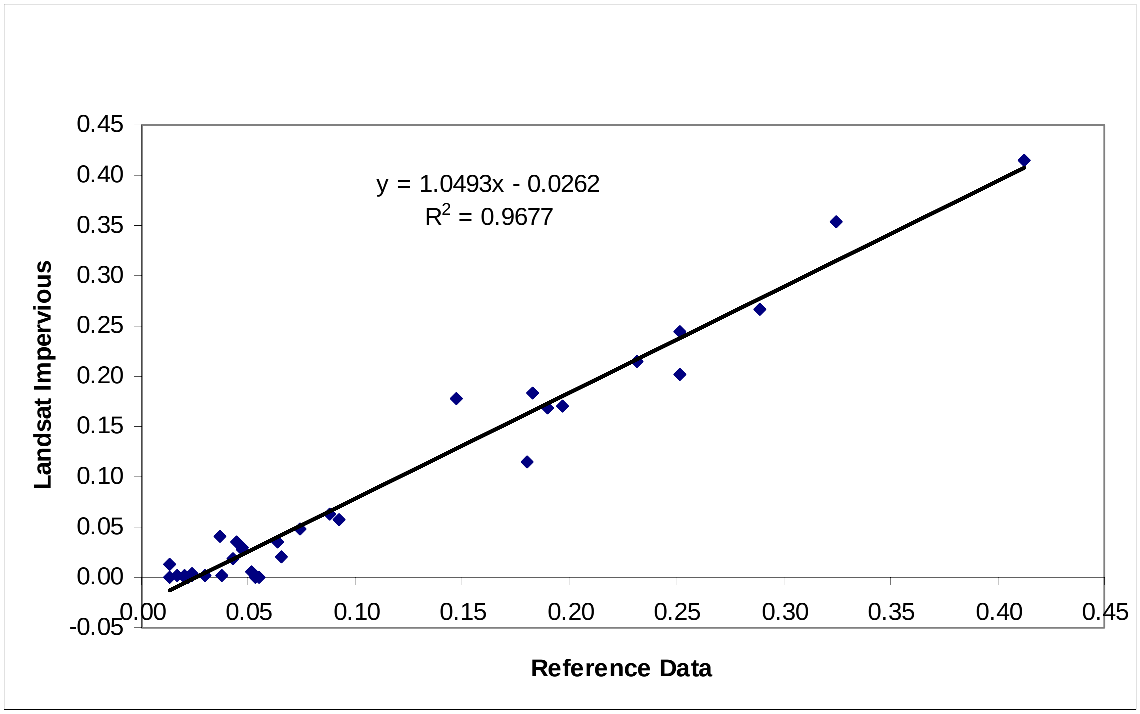


Figure 14. Puget Sound Landsat RISA versus reference site RISA

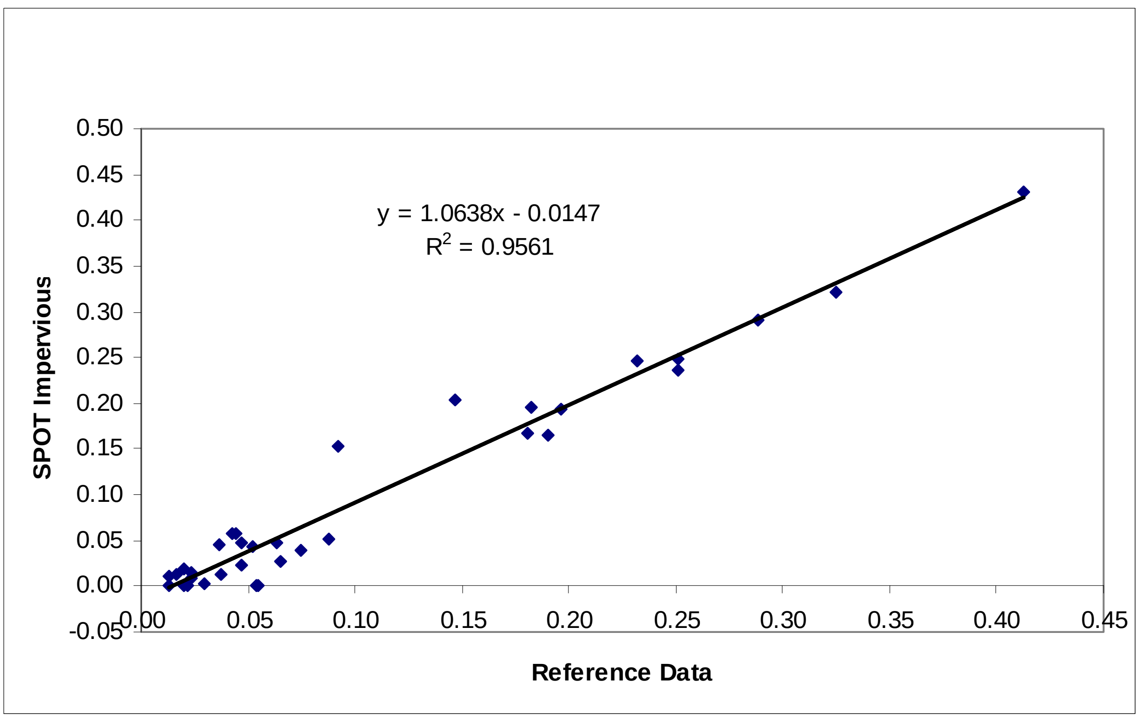


Figure 15. Puget Sound SPOT RISA versus reference site RISA

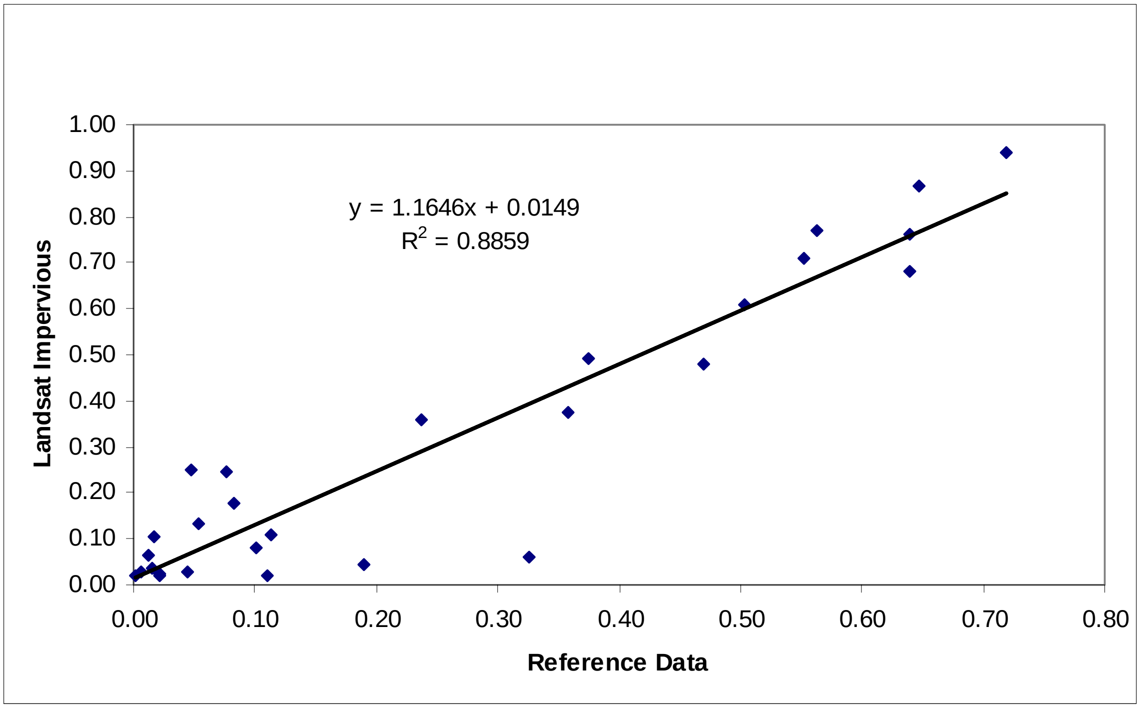


Figure 16. Yakima Landsat TISA versus reference site TISA

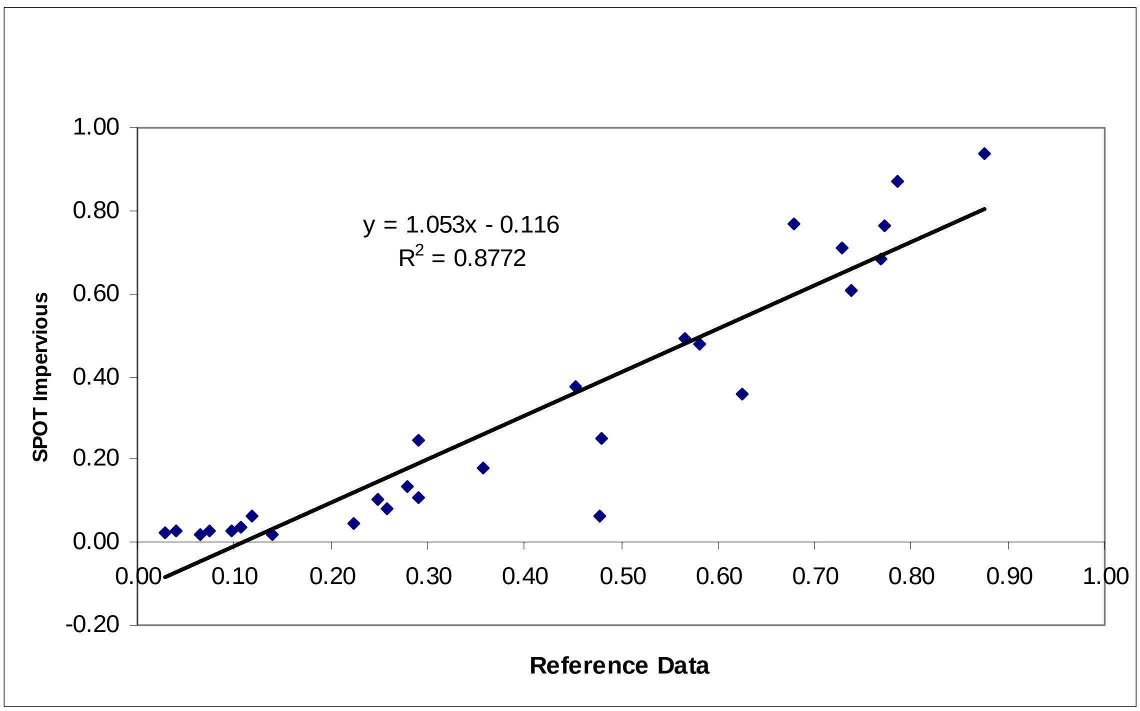


Figure 17. Yakima SPOT TISA versus reference site TISA

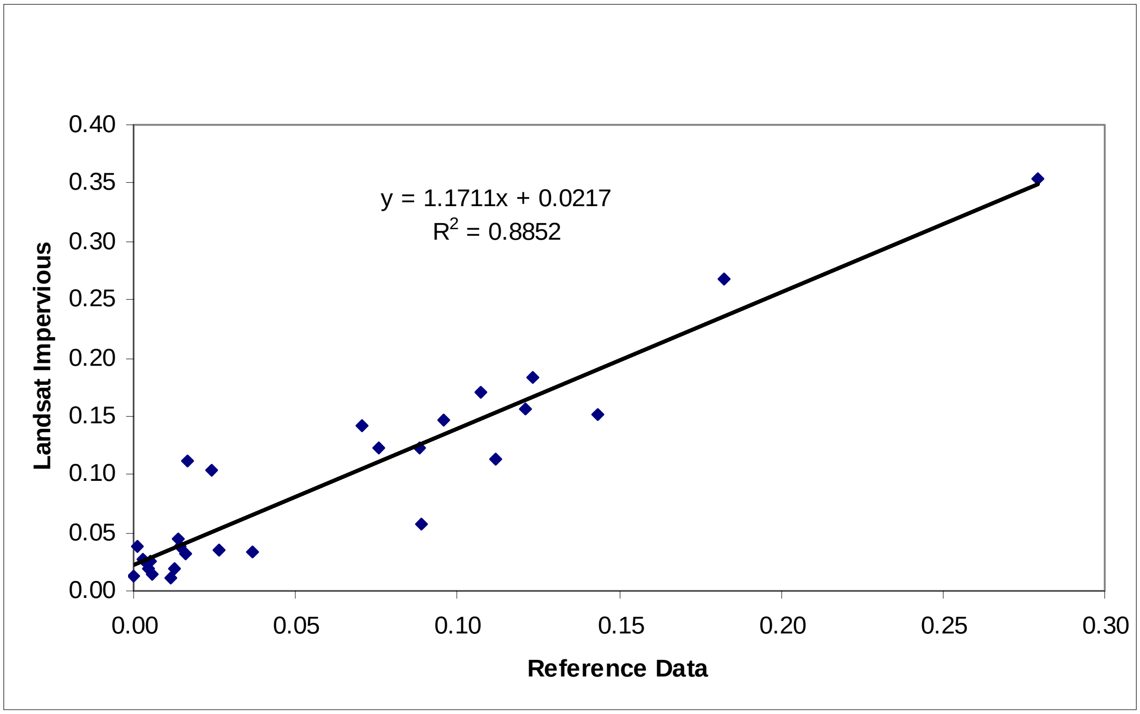


Figure 18. Yakima Landsat RISA versus reference site RISA

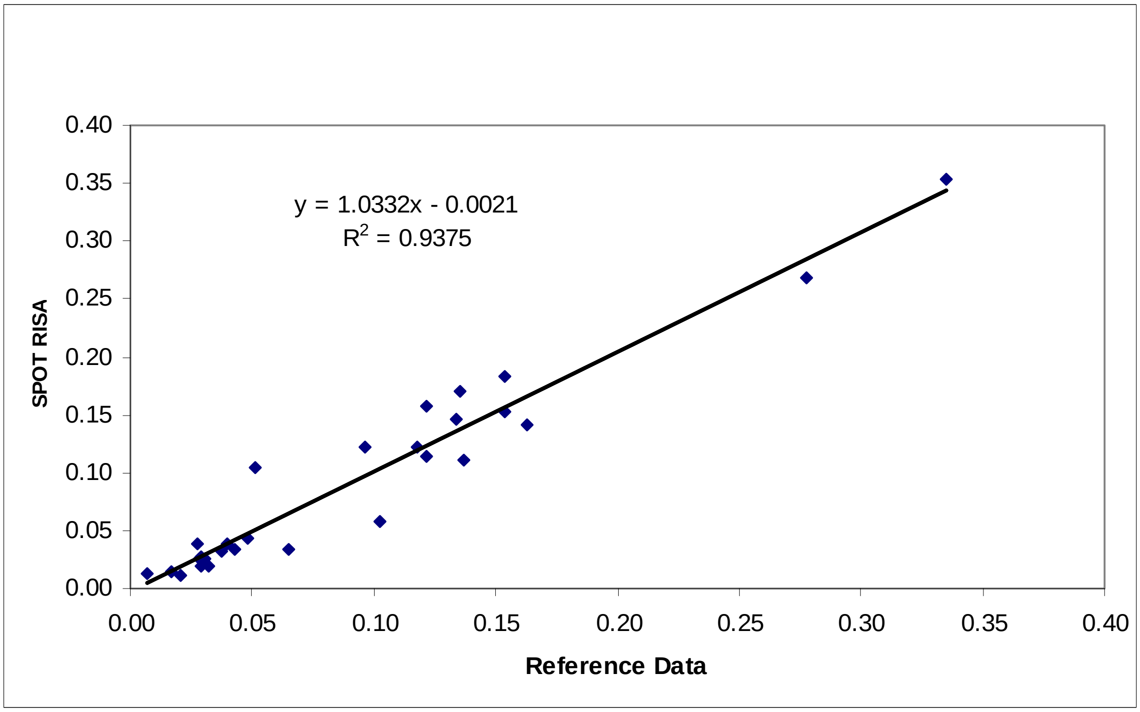


Figure 19. Yakima SPOT RISA versus reference site RISA

RISA Predictive Model
A simple predictive RISA model was developed using a combination of data developed and gathered for this project. Linear regression was used to build the model and RISA extracted from our test sites was used as the independent, or predicted, variable. The predictors, or independent variables, used in the model were total impervious surface (as measured by Landsat or SPOT) and total road length measured using readily available GIS transportation data. Sixty percent of the test sites were used to estimate the model and the remaining sites were used as hold out data to test the validity of the model.

Several tests and diagnostics were used to evaluate the model during its estimation. Although both road length and total percent impervious were strong linear predictors of RISA, it was determined from the scatter plots that the relationship of these independent variables to the dependent variable could be better represented in a non-linear fashion. Several types of curves were estimated for both road length and total impervious surface and it was determined that both were better represented as polynomial curves. To do this, these two terms were squared as shown in the following equation:

$$\mathrm{Y} = 0.022 + 0.174 * (total\ \_\ impervious\ \_\ area)2 + 0.00002 * (road\ \_\ lenght)2 + 0.025(is\ \_\ urban\ \_\ backround)$$

As indicated in Table 2, the model showed strong predicative power with an adjusted r^2 of 0.897. All three independent variables were significant with a 95% confidence interval and the model as a whole was significant at the 99% level.

Table 2. Model Summary

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.952(a)	.905	.897	.02678901

a Predictors: (Constant), dum_urban, sqrd_km, sq_spot

Table 3. Model Coefficients

Coefficients(a)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.022	.007		3.403	.002
	sq_spot	.174	.031	.489	5.587	.000
	sqrd_km	.00002	.000	.441	6.084	.000
	dum_urban	.025	.012	.151	2.149	.039

a Dependent Variable: rd_p_imp

The model was applied to the 21 test sites that were left out during model estimation to see how well the model worked as a predictive tool. Figure 20 shows the predicted values of the hold out data against their observed values. The model does a good job at predicting RISA for the hold out as indicated by the r^2 of 0.827 for the observed versus predicted values. The model may be used to calculate RISA for a given area with just a few input variables that are easy to calculate with readily available data.

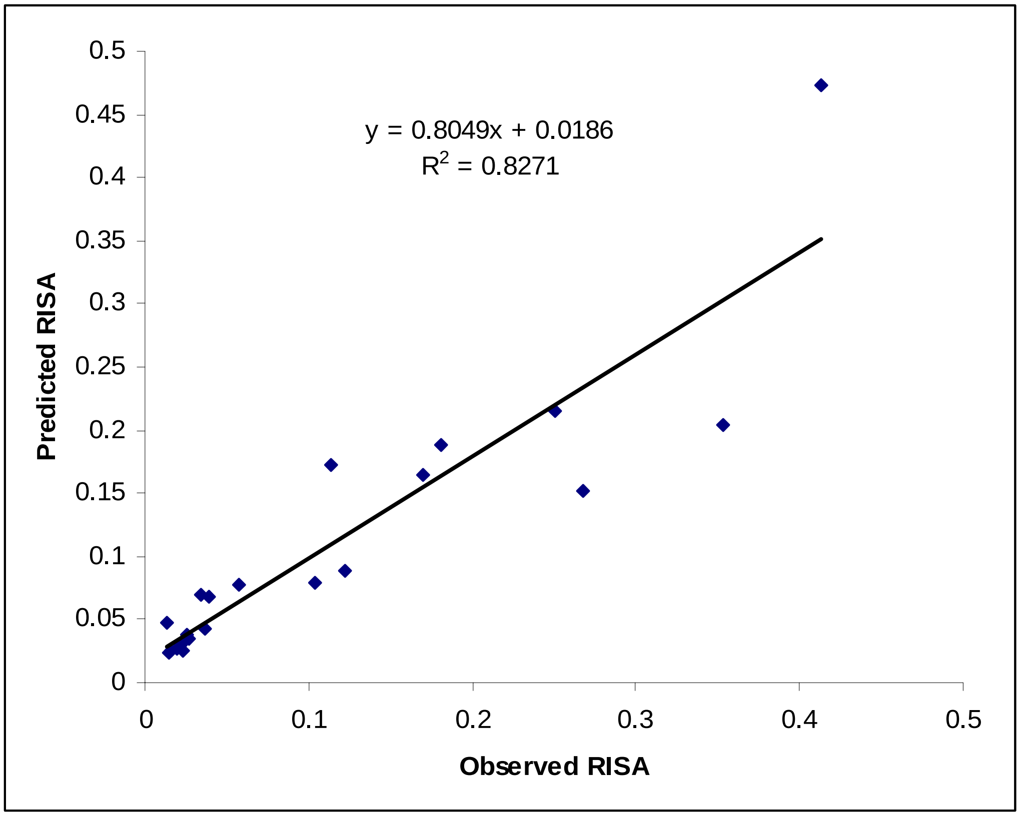


Figure 20. Predicted RISA vs. observed RISA

Discussion

The results of this analysis have important implications regarding the use of remote sensing to determine the contribution of impervious surface from transportation infrastructure at regional scales. Higher resolution satellites, while more visually appealing, do not necessarily provide a net benefit in terms of accuracy that may justify their added expense. Our results indicate that, in most cases, Landsat performed as well if not better than the higher resolution SPOT imagery for determining regional scale RISA . At any spatial scale, neither 10m nor 30m pixel resolution may be used by itself to extract road footprints as the pixel size is too big to capture the narrow width associated with transportation infrastructure. The problem with using high resolution data for extracting road footprints at regional scales lies in the difficulty and cost of gathering a comprehensive set of imagery for the entire area of interest. Furthermore, extracting road footprints from high resolution imagery is a difficult proposition. On-screen digitizing of a small geographic region such as a city is a timely and costly process, let alone for an entire region (i.e. several counties). Feature extraction software provides an attractive alternative to on-screen digitizing, but at the present time these tools are not sophisticated enough to provide a completely seamless, automated extraction.

Since extracting RISA from satellite or aerial imagery alone is difficult, our findings recommend using digital imagery with other GIS data that can serve as a proxy for road footprints. Transportation rights-of-ways taken from vector parcel data were highly effective at limiting the area that could be considered as road. Using this in combination with Landsat impervious surface data proved to be an accurate and relatively simple way to estimate RISA. We recognize that not all areas are covered by the detailed parcel datasets used in this analysis. For those areas we recommend using the predictive model as outlined in this paper. RISA may be easily estimated by calculating the total impervious surface and the total length of roads for a given area. Since these two inputs exist for the entire State of Washington, a rapid estimate of RISA using the predictive model should be very straightforward.

References

Dell'Acqua, F., P. Gamba. 2001a. Detection of Urban Structures in SAR Images by Robust Fuzzy Clustering Algorithms: The Example of Street Tracking. IEEE Transactions On GeoScience and Remote Sensing 39(10): 2287-2297.

Dell'Acqua, F., P. Gamba. 2001b. Improvements to Urban Area Characterization Using Multitemporal and Multiangle SAR images. IEEE Transactions On GeoScience and Remote Sensing 41(9): 1996-2004.

He, Y., Wang, H., B. Zhang. 2004: Color-Based Road Detection in Urban Traffic Scenes. IEEE Transactions On Intelligent Transportation Systems 5(4): 309-318.

Hinz, S., A. Baumgartner. 2003: Automatic Extraction of Urban Road Networks from Multi-view Ariel Imagery. Journal of Photogrammetry & Remote Sensing 58: 83-98.

Mena, J. B. 2003. State of the Art on Automatic Road Extraction for GIS Update: A Novel Classification. Pattern Recognition Letters 24: 3037-3058.

Mena, J.B., J. A. Malpica. 2005: An Automatic Method for Road Extraction in Rural and Semi-urban areas starting from High Resolution Satellite Imagery. Pattern Recognition Letters 26: 1201-1220.

Wu, J., and J. David. 2002. A spatially explicit hierarchical approach to modeling complex ecological systems: theory and applications. Ecological Modelling 153:7-26.

Stoica, R., Descombes, X., J. Zerubia. 2004. A Gibbs Point Process for Road Extraction from Remotely Sensed Images. International Journal of Computer Vision 57(2): 121-136.