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The Effects of Spatial Resolution on Impervious Cover Classification in Watersheds and Riparian Zones in Vermont

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THE EFFECTS OF SPATIAL RESOLUTION ON
IMPERVIOUS COVER CLASSIFICATIONS IN
WATERSHEDS AND RIPARIAN ZONES IN VERMONT

BY

JESSICA N. MORGAN

A DISSERTATION SUBMITTED IN PARTIAL FULFILLMENT OF THE
REQUIREMENTS FOR THE DEGREE OF
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2016

DOCTOR OF PHILOSOPHY DISSERTATION
OF
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ABSTRACT

Impervious cover (roads, rooftops, etc.) is a known stressor on stream biota and habitat and is often used as an indicator for assessing the effects of urbanization on stream health. Understanding how spatial data resolution impacts estimates of impervious cover is important for effective modeling and management of water resources at multiple scales. However, broad scale classifications of high spatial resolution data can be time consuming and expensive. High spatial resolution data classifications in Vermont, USA were compared to nationally available impervious cover classifications in order to understand the impact of scale on impervious cover estimates. I used National Agriculture Imagery Program (NAIP) imagery, a Normalized Difference Vegetation Index, ancillary road data, and a supervised evolutionary algorithm classification program to extract and quantify impervious cover for 888 catchments in Vermont, USA. Post-classification accuracy assessments were conducted to quantify the accuracy of the data set. Impervious cover characterized from NAIP imagery ranged from 1.83-48.31% in the study catchments. Overall accuracy for the NAIP impervious cover classifications was consistently high, ranging from 93-99%. National Land Cover Database (NLCD) data showed a bias towards overestimating impervious cover in more developed catchments and underestimating impervious cover in less developed catchments. The high spatial resolution dataset characterized from NAIP data was used to develop a Bayesian classification and regression tree model to predict where the NLCD may be adequate for classifying impervious cover and where higher spatial resolution data may be needed. Data inputs included NLCD land use/land cover classifications and U.S.

Census Bureau housing data. High spatial resolution impervious cover was best predicted in catchments with less than 55-65% NLCD forested land cover. For catchments with greater than 55-65% NLCD forested land cover, impervious cover was best predicted where higher levels of NLCD open space development land cover existed. In areas where a full watershed analysis may not be feasible, the condition of the riparian zone along stream channels can provide information on water quality. Impervious cover in the riparian zone was calculated using both fixed-width and elevation based buffer metrics. Percent impervious cover was obtained from the National Land Cover Database (NLCD) and compared to the high resolution imagery analysis from National Agriculture Imagery Program data within the buffer zones. Percent impervious cover ranged from 1.58-8.67% within both types of buffers. The spatial resolution of impervious cover data had less of an effect in the riparian zone than in the full catchments within the same HUC 10 and HUC 12 units. Buffer type had minimal impact on percent impervious cover, except in areas of unconfined valleys, where there were notable differences between fixed-width and elevation based buffers. The results suggest that although there is a trend toward the NLCD underestimating impervious cover at lower levels of development, it may be adequate for mapping impervious cover in the riparian zone, depending on the land use/land cover characteristics of the catchments being studied.

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And finally, I dedicate this work to my two boys, Logan Tucker and Finnian James. You are my heart. While at times it seemed like parenthood was at odds with finishing my program, you provided the motivation and dedication required to get it done and provide a great life for all of us. I love you both with all of my heart and I am forever grateful to have you in my life.

PREFACE

This dissertation is written in manuscript format consisting of three main chapters, each an individual manuscript. The first two chapters, Comparison of Catchment Impervious Cover Estimates Using National Agriculture Imagery Program (NAIP) Data and the National Land Cover Database (NLCD), and Using Bayesian Classification and Regression Trees to Predict High Spatial Resolution Impervious Cover Data Requirements for Watershed Management follow the manuscript formatting requirements of the journal Environmental Management and were submitted for publication in September and August 2016 respectively. The third chapter, Impervious Cover in the Riparian Zone – An Analysis of Method and Scale, follows the manuscript formatting requirements of Northeastern Naturalist.

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Chapter 1

“Comparison of Catchment Impervious Cover Estimates Using National Agriculture Imagery Program (NAIP) Data and the National Land Cover Database (NLCD)”

by

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Introduction

Nonpoint source pollution is one of the leading causes of water pollution in the United States (US EPA 2002) and the relationship between land use/land cover, water pollution, and stream ecosystem health is well documented (Harding et al 1998; Allan 2004; Walsh et al 2005; Johnson and Host 2010; Zhang et al 2013). The extent of impervious cover (IC) in a catchment is a known stressor on stream biota and habitat and has been used as a metric for estimating the effects of urbanization on stream health (Schueler 1994, 2003; Arnold and Gibbons 1996; Brabec 2002; Morse et al 2003; Roy and Shuster 2009; Schueler et al 2009; Arnold et al 2010). Urban development drastically alters the landscape and affects stream ecosystem health by changing the magnitude and timing of stormwater runoff, leading to: higher peak stream discharges, less infiltration of stormwater, changes in channel morphology, increases in nutrient and pollutant inputs, decreases in biotic richness and subsequent increases in pollutant tolerant species, and altered thermal regimes (Wang and Kanehl 2003; Walsh et al 2005; Nelson and Palmer 2007).

The effects of combined anthropogenic stressors from urbanization on freshwater streams can be difficult to quantify. IC as an indicator metric can help to quantify these effects on stream biota and habitat (Schueler 1994; Arnold and Gibbons 1996; Schueler and Claytor 1997; Brabec 2002; Schueler et al 2009). The extent of IC in a catchment has been used to guide stormwater management practices, to develop stormwater management utility rates and credits, and to develop an impervious cover Total Maximum Daily Load (TMDL) for mitigating water quality impacts as

mandated by the U.S. Clean Water Act (Parikh et al 2005; Schueler et al 2009; Arnold et al 2010; Wickham et al 2016).

Towns and municipalities, already restricted by tight budgets, are increasingly being tasked with addressing stormwater management and water quality issues. The U.S. Municipal Separate Storm Sewer System (MS4) stormwater rule requires publicly owned agencies, such as cities, towns, counties, or states, to implement six minimum control measures within a stormwater management plan. These measures include public education and outreach, public participation or involvement (community clean-ups, citizen water quality monitoring, etc.), detection and elimination of illicit discharges, controls for stormwater runoff both pre- and post-construction, and pollution prevention measures for municipal operations (US EPA 2016).

Increasingly, stormwater management utility districts are being established to fund stormwater projects. These utilities charge a user fee for stormwater management, similar to a sewer service charge for wastewater. The fees are often based on the extent of IC on each property in the district (van der Tak et al 2014). The shared fees provide a dedicated funding source for stormwater improvement projects including flood mitigation, water quality impairment remediation, and replacement of aging stormwater infrastructure (NH DES 2014). Higher spatial resolution estimates of IC are required for accurate fee structures and more effective decisions in the context of integrated water resources management.

Fine-scale mapping of IC at broad spatial extents presents unique challenges. Site-specific estimates of IC are often derived from digitized aerial imagery and the

use of Light Detection and Ranging (LIDAR) technology. Object-oriented classification methodologies, using programs such as eCognition and the ArcGIS Feature Analyst extension, have yielded impressive results for classifying IC and other land use/land cover classes (O'Neil-Dunne 2013; Stueve et al 2015). Multiple Agent Segmentation and Classification (MASC) using submodels of segmentation, shadow-effect, MANOVA-based classification, and post-classification have been successfully utilized to classify IC over broad spatial extents (Zhou and Wang 2008). However, these methodologies can be costly and time-intensive. For broad-scale studies, estimates of IC are commonly obtained from the National Land Cover Database (NLCD). This 30m resolution dataset, produced by the Multi-Resolution Land Characteristics Consortium, classifies land surface data into thematic classes (e.g. high intensity developed, open space developed, agriculture), and estimates percent IC and percent tree canopy cover from Landsat imagery (Homer et al 2015).

A 10-12% IC threshold historically has been associated with quantifiable impacts to water quality at the catchment scale (Schueler 2003, Schueler et al 2009). High spatial resolution IC data have also been shown to improve hydrologic simulation models (Zhou et al 2010; Zhou et al 2014). However, recent analyses suggest that macroinvertebrate communities are being impacted at much lower levels of IC (Baker and King 2010; Detenbeck et al 2013; Smucker et al 2013). It has been suggested that the 30m resolution NLCD data are underestimating IC, particularly in suburban areas where impervious surfaces may be masked by vegetation and trees (Roy et al 2003; Jones and Jarnagin 2009; Claggett et al 2013). Stueve et al (2015) found that the NLCD underestimated tree cover and overestimated water classes in a 25 km²

Minnesota catchment. An assessment of the 2001 NLCD demonstrated that the NLCD underestimated both canopy cover and IC when compared to photographic interpreted imagery (Nowak and Greenfield 2010). Recent studies have found that the NLCD underestimates impervious cover in less developed watersheds and overestimates impervious cover in more developed watersheds (Smucker et al 2016). A timely, cost-effective method for accurately mapping IC from high spatial resolution data over broad scales is needed to accurately depict the impact of urbanization on stream response variables.

Using readily available 1m National Agriculture Imagery Program (NAIP) data (USDA 2013), we developed a method for characterizing IC from high spatial resolution data over broad spatial extents. IC was extracted and quantified at the Hydrologic Unit Code (HUC) 10 and HUC 12 levels (USGS and USDA 2013) as well as at the National Hydrography Dataset (NHDPlus) catchment level (USGS and US EPA 2010) for select catchments in Vermont, using an inexpensive supervised classification program and genetic algorithms. Post-classification accuracy assessments were conducted on the 1m NAIP classifications to quantify the accuracy of the data set. The 1m NAIP estimates were then compared to the 30m NLCD estimates and validated against established high spatial resolution IC estimates from the University of Vermont. The data and methodologies described will benefit both water quality modelers and decision makers in meeting challenging water resource and policy goals, particularly at the urban-rural interface.

Methods

Study area and site selection

The study area focused on four HUC 10 catchments and eighteen HUC 12 catchments in the state of Vermont and their surrounding Municipal Separate Storm Sewer System areas (MS4s) (Figure 1-1). MS4 areas were included in the classifications because improved estimates of IC will be useful in meeting or setting regulatory requirements at this scale but were not included in the analysis because they are administrative boundaries that cross catchment boundaries and lack ecological significance. HUCs are defined as drainage areas that are delineated into nested, hierarchical classifications of surface areas draining to a specific point, based on hydrologic principles (USGS and USDA 2013). HUCs range in size from HUC 2 to HUC 16, with HUC 2s representing the broadest regional scale and HUC 16s representing the finest local scale. The HUC 10 units ranged in size from 190.3-578.4 km². HUC 12 units ranged in size from 55.1-165.4 km². The HUC 12 catchments were selected because they were determined to contain the highest number of stormwater best management practices in the state of Vermont, over a range of IC. Results will be utilized in future studies to assess the effectiveness of green infrastructure practices at the catchment scale by comparing predicted aquatic community and habitat condition with observed condition in catchments with high densities of stormwater best management practices. All HUC 10 and HUC 12 units contained less than 13.15% IC, making comparisons at higher levels of IC impossible (Table 1-1).

In order to increase the number of samples over a wider range of IC and catchment size, IC was calculated for 902 NHDPlus catchments within the study area

for both the high spatial-resolution and NLCD data. There are 5,982 NHDPlus catchments fully or partially contained in Vermont, thus approximately 15% of the catchments in Vermont were analyzed, primarily within urbanized areas. Selected NHDPlus catchments ranged in size from 0.001 to 55.2 km². A comparison of NAIP and NLCD classifications of NHDPlus catchments with low (<10%), intermediate (10-25%), and high (>25%) levels of IC showed various levels of accuracy across different landscape types (Figure 1-2).

Data Preparation

We acquired 1m resolution digital imagery from 2011 NAIP data, which served as the base data for mapping IC. NAIP imagery was selected for use because it is readily available at a national scale at frequent temporal intervals, has a fine spatial resolution, supports red, green, blue (RGB), and near-infrared (NIR) spectral bands, is low or no-cost, and it has been acquired using consistent standardized United States Department of Agriculture (USDA) Farm Service Association protocols (USDA 2013). One challenge of working with NAIP data is that it is recorded during the growing season and tree canopy cover can complicate characterization of IC. Road networks were added from the Vermont E911 dataset (VGCI 2015) to compensate for forest and tree overhang inherent in data collected during the growing season. Normalized Difference Vegetation Index (NDVI) bands were created and added to the five-band NAIP data in ArcGIS 10.1 (ESRI, Redlands, CA). Recent studies have suggested that adding an NDVI band to NAIP imagery greatly improves mapping of water/wetland areas as well as identifying impervious surfaces (O'Neil-Dunne 2013).

NDVI is traditionally used for estimating vegetation properties from remote sensing data and is calculated using the equation:

$$NDVI = \frac{(NIR - VIR)}{(NIR + VIR)}$$

where NIR = the value of the near-infrared band and VIR= the value of the visible infrared band.

Impervious Cover Classifications

IC data were extracted utilizing GeniePro2.4 (Observera, Inc. Los Alamos, NM). GeniePro uses genetic algorithms and supervised classification to analyze multispectral remote sensing imagery. In addition to spectral input vectors, GeniePro also incorporates spatial relationships (texture, shape, proximity) and evolutionary algorithms to classify imagery (Harvey et al 2002). IC classifications were validated against a high-resolution dataset from the University of Vermont (UVM) Spatial Analysis Laboratory, which was based on a vector classification of 2011 NAIP imagery using eCognition software (O’Neil-Dunne 2013; VGCI 2013). For this study, the UVM data were converted to raster format and then clipped to individual catchments for comparison to our data, where the two datasets overlapped. IC classifications were then compared to previously established estimates based on 30m NLCD 2011 IC data (MRLC 2014).

The NHDPlus hydrologic framework includes attributes of the National Hydrography Dataset, the National Elevation Dataset, and the Watershed Boundary Dataset (USGS and US EPA 2010). NHDPlus flowlines are based on medium-resolution 1:100,000 scale stream networks and have associated local catchments as well as full upstream drainage basins (USGS 2007). To compare NAIP and NLCD IC

classifications within NHDPlus V1 catchments, landscape attributes (% 2011 NLCD IC) were allocated to the catchments using the NHDPlus Ca3T program (Horizon Systems, Herndon, VA). Mean percent IC was calculated for both the NAIP and UVM datasets using the zonal statistics tool in ArcGIS 10.1. The USGS cautions against using NLCD data in catchments less than tens of square kilometers (USGS 2012). However, a multiple extents accuracy assessment of NLCD land use and land cover suggests that NLCD may be accurate for spatial extents as small as 10km², particularly for predominant land use classes or those with unique spectral signatures (Hollister et al 2004). Fourteen NHDPlus catchments were eliminated from the analysis due to very small catchments for which characterization was limited by the resolution of the 30m NLCD data (i.e. one or two pixels caused a large variation in the percent IC), for a total of 888 catchments (Figure 1-3). These fourteen outlier catchments were less than 1 km², well below the recommended threshold for analysis of 30m NLCD data (USGS 2012).

Post-Classification Accuracy Assessment

IC characterization was checked at various stages. Initial IC characterization of preliminary data sets in GeniePro was checked visually to confirm that mapping methods were accurately delineating separate land cover features. A post-classification accuracy assessment was performed for the 1m NAIP data utilizing the methods of Stehman and Czaplewski (1998). Post-classification accuracy assessments were conducted at the HUC 10 and HUC 12 scales. Reference data included the original NAIP imagery and Google Earth historical imagery. Stratified random sampling of the reference data was performed with 100 points per class and compared to the mapped

land cover classifications. Overall, user's and producer's accuracies were calculated to describe the accuracies of the IC classifications. Overall accuracy describes the number of correctly identified pixels divided by the total number of classified pixels. Producer's accuracy measures the ratio between the number of correctly classified pixels and the total number of reference pixels for that category (probability that IC on the ground is correctly classified). User's accuracy measures the ratio of correctly classified pixels to the total number of pixels in that category (probability that a pixel labeled as IC is actually IC).

Statistical Analysis

A regression analysis was run to identify the relationship between NLCD and NAIP data. The ratio of NLCD to NAIP IC was then compared to the NAIP data within the NHDPlus catchments to identify where the NLCD data are adequate and where they may be over- or underestimating IC. Classification and Regression Tree (CART) analyses were run using Systat 13.1 (Systat Software, Inc. San Jose, CA) to quantitatively assess the level at which the NLCD under- or overestimates IC. CART analysis compares independent and dependent variables through a series of binary splits (Breiman et al 1998). CART was run for all NHD catchments in the study area using the least absolute deviation option for choosing splits with bootstrapping (sample of 800 repeated 1000 times, maximum=2 splits, p=0.05 stopping rule). CART was rerun for the 41 catchments larger than 10km² in the study area using the least absolute deviation option for choosing splits with bootstrapping (sample of 38 repeated 1000 times, maximum=2 splits, p=0.05 stopping rule)

Results

Post-Classification Accuracy Assessment

Overall accuracies of HUC 10 and HUC 12 IC classifications for the NAIP data ranged from 93.0-99.0% with an average accuracy of 95.3% for HUC 10s and 96.2% for HUC12s (Table 1-1). These accuracies exceed the recommended United States Geological Survey (USGS) minimum accuracy of 85% for land use/land cover classifications (Anderson 1976). Producer's accuracies were close to 100% for all catchments and user's accuracies ranged from 85.0-98.0%. Accuracy assessments were not conducted for individual NHDPlus catchments because all catchments were contained within the HUC 12 and HUC 10 study areas. Accuracy assessment results did not vary by catchment size or by level of urban development.

Impervious Cover Classification Comparison

IC characterized from NAIP imagery ranged from 1.83-10.95% in the HUC 12 units and from 1.66-5.06% in HUC 10 units (Table 1-1). The NAIP data at the HUC 10 and HUC 12 level predicted NLCD classifications well but with a bias shown by the regression equation (Figure 1-4):

$$NLCD = -1.55 + 1.30(NAIP), r^2 = 0.98 \text{ (n=22, } p < 0.001).$$

The ratio of NLCD IC to NAIP IC was plotted against NAIP IC (Figure 1-5). An idealized relationship would yield a slope of 0 across all levels of IC (ratio=1), indicating no difference between the two classifications. The regression equation for the NLCD to NAIP ratio resulted in a non-linear relationship, with NLCD

underestimating at low levels of IC and overestimating at higher levels of IC (Figure 1-5):

$$NLCD/NAIP = 0.33 + 0.39\ln(NAIP) \quad r^2 = 0.71 \quad (n=22, p<0.001).$$

A comparison of the ratio of the UVM to NAIP data shows a ratio closer to 1 across all levels of IC, resulting in a slope closer to 0, with 95% confidence intervals between -0.01 and 0.03 (Figure 1-5):

$$UVM/NAIP = 0.97 + 0.01(NAIP) \quad r^2 = 0.08 \quad (n=13, p=0.34).$$

A pattern emerged of NLCD underestimating at low levels of IC (<5%) by up to 50% and overestimating by up to 20% at higher levels of IC (>6%), although there are fewer data points at the upper end of the scale (Figure 1-5).

Statistical Analysis

To further elucidate the relationship between the high resolution estimates and the NLCD data across a range of IC at a finer scale, IC classifications were compared across NHDPlus catchments. IC in NHDPlus catchments ranged from 0 - 48.31% (Figure 1-3). With more sample points, it is clear that the NLCD is underestimating IC at low levels of development, although there is a wider range of NLCD to NAIP ratios at lower levels of IC, suggesting greater uncertainty in the data. Across all NHDPlus catchments, the subset of classification trees with a single split had a median cut value of 0.77 for high resolution IC (95% confidence interval 0.18 – 3.59), with average node medians of 0.10 and 0.61 for the ratio of NLCD to NAIP IC and an average 16.2% reduction in error (Figure 1-3). The median cut value shows that the data

shifted at 0.77% IC, with an average NLCD to NAIP ratio of 0.10 below that level of IC and an average ratio of 0.61 above that level.

For NHDPlus catchments larger than 10km², the subset of classification trees with a single split had a median cut value of 2.09 for high spatial resolution IC (95% confidence interval 1.36-7.40), with average node medians of 0.41 and 0.83 for the ratio of NLCD to NAIP IC and an average 25.3% reduction in error (Figure 1-6). The median cut value shows that the data shifted at 2.09% IC, with an average NLCD to NAIP ratio of 0.41 below 2.09% IC and 0.83 above. Even with the smaller sample size, the data follow a similar trend of underestimating IC by 20-80% at low levels of development, with less noise in the data than in the sample containing all NHD catchments (Figure 1-6). There were too few samples with greater than 10% IC to identify trends in the data at higher levels of development.

Discussion

Classification of IC from high resolution NAIP data produced a highly accurate data set for 18 HUC 12 units and 4 HUC 10 units in Vermont. Accuracy levels were quite high in all catchments and supported by a comparison to the UVM high spatial resolution dataset from the same 2011 NAIP data. Producer's accuracy was expected to be very high due to the fact that most pixels within the catchments are not impervious, thus the chance of correctly identifying a pixel as not impervious is somewhat biased. The user's accuracies were expected to be somewhat lower than the producer's accuracies but were still high, and met or exceeded the USGS standard for accuracy assessment. Key areas with higher levels of IC included the MS4 areas in Burlington, Rutland, and St. Albans as well as isolated resort areas. Calculating IC by

NHDPlus catchment provided a broader gradient of urbanization to compare differences between highly developed catchments and catchments with low levels of IC. The data clearly indicate that NLCD is underestimating IC at low levels of development and overestimating at higher levels of development.

High resolution classifications of IC are needed for effective modeling and management of water resources at the catchment scale. Medium resolution data, such as the NLCD, have traditionally been utilized for regional analyses. However, recent regional analyses have shown impacts to stream macroinvertebrate and periphyton populations at very low levels of IC. Baker and King (2010) found taxon-specific change points of declining macroinvertebrates at 0.81-3.3% developed land. Declines in macroinvertebrate community metrics have been found at 1-2% IC and as low as 0.6% IC for diatom communities (Detenbeck et al 2013; Smucker et al 2013). Data from the current study suggest that the NLCD data are underestimating IC in this range of low levels of IC. Corrected values using the regression equation for Figure 1-4 would suggest that macroinvertebrate community metrics would be affected at 2.2-2.70% IC and diatom communities would be affected at as low as 1.65% IC. This bias would be magnified in areas where community metrics are affected at even slightly higher levels of IC (i.e. 3-10% NLCD IC = 3.5-8.9% NAIP IC). Further research is needed to identify the impact of the spatial resolution of IC data on regional analyses of stream response to urbanization.

Municipalities across United States are increasingly exploring the concept of stormwater utilities to fund stormwater infrastructure implementation, repair, and maintenance. The IC TMDL developed by the Connecticut Department of Energy and

Environmental Protection identifies a target level of 11% IC for both regulated and unregulated sources of stormwater (12% IC target – 1% margin of safety) for the Eagleville Brook catchment in Mansfield, CT (CT DEEP 2007; Arnold et al 2010). Both stormwater utilities and IC TMDLs require high spatial resolution estimates of IC for accurate rate setting and target levels of IC. A difference of even 1% accuracy, as shown in this study, could potentially result in significant legal and policy ramifications.

While the data suggest that NLCD is underestimating IC at the catchment scale for low levels of IC and overestimating at higher levels of IC, there are many catchments where there is minimal difference between the two data sets. A predictive model of where the NLCD data are adequate for analyses and where higher resolution estimates are required may be of particular interest to watershed organizations and communities attempting to find effective stormwater management solutions with limited budgets and resources. Residential and commercial properties developed from agricultural and non-forested landscapes may yield more accurate catchment IC estimates than those developed from forested landscapes, due to the lack of overhanging tree cover that can impede classification accuracy. Evaluating the age of housing developments may identify areas of urban fringe and expansion, which may differ in classification accuracies than older, more established neighborhoods with more plentiful canopy cover. The data from this study will be utilized to create a predictive model of high resolution IC values, utilizing readily available land cover and U.S Census data.

There are several possible sources of error in the data. First, differences in spatial resolution and methodologies may impact the classification of IC based on the format

of the source data and not misclassification (Hollister et al 2004; Loveland et al 2005). NLCD IC was characterized from 30m spatial resolution raster data while the NAIP data were characterized as rasters from 1m digital orthophotographs. The UVM dataset was classified as a vector and then rasterized for the purposes of this study. All raster data exhibit some degree of “stair stepping” effects and the comparison and conversion of data from different formats may introduce some error. Second, the reference data used in the accuracy assessments included the source data as well as historical imagery from Google Earth. Congalton and Green (2008) do not recommend using the source data as reference data as it may introduce additional error. However, the imagery was not analyzed until several years after it was taken, thus it was impossible to set up an accurate system for ground referencing in the field. Last, the analysis of the NHDPlus catchment data includes catchments that are smaller than the spatial extent recommended by the USGS (USGS 2012). However, removal of catchments less than 10km² results in a similar trend of underestimating IC at low levels of development by 20-80%.

We developed a cost-effective method for characterizing IC that is comparable to other high spatial resolution datasets produced with object-oriented classification and is easily reproducible with minimal GIS resources. While other methodologies require expensive and specialized software to delineate IC over broad scales, this method utilizes readily available NAIP imagery, E911 road data, GIS software, and a relatively inexpensive supervised classification program to produce highly accurate results. Through a comparison of NLCD and high spatial resolution NAIP IC classifications, we determined that NLCD data are underestimating IC in less

developed catchments and overestimating IC in more urbanized catchments. The implications of this study for modeling stream response to urbanization may be significant. Future research will explore the landscape patterns and processes contributing to the discrepancy of classification accuracies across the urbanization gradient.

Table 1-1. HUC 10 and HUC 12 Accuracy Assessments and % IC Comparison

Catchment Number	HUC 12 Catchment	^a NAIP (%IC)	^b NLCD (%IC)	^c UVM (%IC)	NAIP Overall Accuracy (%)	NAIP Producer's Accuracy (IC)	NAIP User's Accuracy (IC)
1	Ball Mountain Brook	2.33	1.20	^d	98.5	100.0	97.0
2	Bloody Brook	2.88	2.71	^d	96.5	100.0	93.0
3	Branch Brook	3.05	1.90	^d	98.5	100.0	97.0
4	Calendar Brook	1.83	0.91	^d	95.0	100.0	90.0
5	East Creek	3.35	3.08	3.17	98.0	100.0	96.0
6	HW Ottauquechee	2.40	1.72	^d	96.5	100.0	93.0
7	Jay Branch	1.88	1.00	1.77	95.0	100.0	90.0
8	Jewett Brook	6.96	7.19	6.94	94.0	98.9	89.0
9	Lulls Brook	3.45	3.68	^d	95.5	100.0	91.0
10	Mallets Bay	3.92	3.87	4.19	99.0	100.0	98.0
11	Mallets Creek	2.80	1.97	2.77	93.0	96.7	89.0
12	Mill Brook	2.30	1.05	2.01	97.0	100.0	94.0
13	Mill River	4.15	3.63	4.10	96.5	99.0	94.0
14	Moon Brook	6.81	7.56	6.61	95.5	98.9	92.0
15	Muddy Brook	6.89	7.34	7.22	96.5	100.0	93.0
16	N Branch Deerfield	3.28	1.78	^d	94.0	100.0	88.0
17	Snipe Island	2.25	1.58	2.47	96.0	98.9	93.0
18	Winooski	10.95	13.15	11.69	97.0	99.0	95.0

Catchment Number	HUC 10 Catchment	NAIP (%IC)	NLCD (%IC)	UVM (%IC)	NAIP Overall Accuracy (%)	NAIP Producer's Accuracy (IC)	NAIP User's Accuracy (IC)
1	Black River	2.16	1.56	^d	96.5	98.9	92.0
2	Mallets	3.58	3.27	3.75	93.8	98.8	85.0
3	Ottawaquechee	1.66	1.03	^d	94.9	98.9	88.0
4	Shelburne	5.06	5.45	6.12	96.1	98.9	91.0

^aNAIP = National Agriculture Imagery Program, ^bNLCD = National Land Cover Database, ^cUVM = University of Vermont, ^dData not available.

Figure 1-1. Map of Study Area – Watershed labels correspond to catchment and catchment number in Table1-1.

Figure 1-2. Comparison of NAIP and NLCD IC classifications in select NHDPlus catchments.

	NAIP	NLCD
<p>NHD Catchment: 4578214</p> <p>1.2% IC NAIP 0.24% IC NLCD</p> <p><10% IC</p>
<p>NHD Catchment: 22220891</p> <p>22.5% IC NAIP 31.6% IC NLCD</p> <p>10-25% IC</p>
<p>NHD Catchment: 6090067</p> <p>28.3% IC NAIP 48.9% IC NLCD</p> <p>>25% IC</p>

Figure 1-3. Ratio of medium to high spatial resolution IC classifications at the NHDPlus catchment scale over a range of % IC classified from NAIP data. Outliers removed from analysis are shown on the secondary y-axis. Solid line represents a perfect ratio of NLCD to NAIP data with slope = 0. Dashed lines represent CART average node medians of 0.10 and 0.61 for the ratio of NLCD to NAIP IC. Median cut value = 0.77% IC

Figure 1-4. Relationship of NLCD to NAIP data at the HUC 10 and HUC 12 scale. Shaded area shows 95% confidence interval. Solid line through origin shows 1:1 ratio.

Figure 1-5. Ratio of medium to high spatial resolution IC classifications at the HUC 10 and HUC 12 scale over a range of % IC classified from NAIP data.

Figure 1-6. Ratio of medium to high spatial resolution IC classifications in NHDPlus catchments greater than 10 km². Solid line represents a perfect ratio of NLCD to NAIP data with slope = 0. Dashed lines represent CART average node medians of 0.41 and 0.83 for the ratio of NLCD to NAIP IC.

Chapter 2

“Using Bayesian Classification and Regression Trees to Predict High Spatial Resolution Impervious Cover Data Requirements for Watershed Management”

by

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Introduction

Impervious cover (IC) is a known stressor on stream biota and habitat and has been used as a metric for measuring the effects of urbanization on stream health (Arnold et al. 2010; Arnold and Gibbons 1996; Brabec 2002; Morse et al. 2003; Roy and Shuster 2009; Schueler 1994; Schueler 2003; Schueler et al. 2009). As IC in a watershed increases, streams produce higher peak discharges, less infiltration of stormwater occurs, channel morphology changes, pollutant inputs increase, biotic richness decreases, pollutant tolerant species increase, and thermal regimes are altered (Nelson and Palmer 2007; Walsh et al. 2005; Wang and Kanehl 2003). Biological monitoring and assessment are often used by water quality programs to monitor changes in stream systems (Johnson and Host 2010). Indicator metrics including species richness, species composition, relative abundance, feeding relationships, body size, and others have been utilized by state agencies to assess goals set by the Federal Clean Water Act (Bellucci et al. 2013; Karr 1993). Changes to these metrics, combined with landscape information from Geographic Information Systems (GIS), can provide a detailed response of biota to urbanization impacts, track environmental changes through time, and be used to forecast the effects of future land use scenarios (Richards et al. 1997).

Accurate predictions of ecological response to urbanization and subsequent remediation efforts are required for adaptive watershed management. Recent analyses have suggested that macroinvertebrate and periphyton communities are impacted at lower thresholds than the 10-12% IC in a watershed typically described in the literature (Baker and King 2010; Detenbeck et al. 2013; Smucker et al. 2013). Baker

and King (2010) found taxon-specific change points of declining macroinvertebrates at 0.81-3.3% developed land. Declines in community metrics have been found at 1-2% IC for macroinvertebrates and as low as 0.6% IC for diatom communities (Detenbeck et al. 2013; Smucker et al. 2013). Others have suggested that landscape patterns may explain varying levels of water quality in catchments with similar amounts of IC (Beck et al. 2016).

Medium resolution spatial data such as the National Land Cover Database (NLCD) have traditionally been used for regional analyses. Thirty-meter resolution land use/land cover, percent IC, and percent canopy cover are available for national coverage of the United States (Coulston et al 2012; Coulston et al 2013; Homer et al. 2015; Xian et al. 2011). However, the NLCD data may underestimate IC, particularly in suburban areas where IC can be masked by vegetation and trees (Claggett et al. 2013; Roy et al. 2003). Recent studies support this hypothesis and suggest that the NLCD data are underestimating IC at low levels of development and overestimating IC in more developed areas (Morgan et al. in review-a; Smucker et al. 2016). NLCD underestimated tree cover and overestimated water classes in a 25 km² Minnesota watershed when compared to high spatial resolution land use data (Stueve et al. 2015). A national assessment of the 2001 NLCD canopy cover and IC data sets demonstrated that the NLCD underestimated both canopy cover and IC when compared to photographic interpreted imagery (Nowak and Greenfield 2010).

High spatial resolution predictions of IC are needed for effective modeling and management of water resources at the watershed scale (Zhou et al. 2010; Zhou et al. 2014). However, broad scale classifications of high spatial resolution data can be time

consuming and expensive. In addition to errors due to coarse spatial resolution, errors relating landscape characteristics to biotic responses in streams also occur due to the inability to match the temporal scale of landscape change with responses. The NCLD is updated every 5-10 years, so an exact match with the year of response measurements is rarely possible. Some responses to land-use change have built-in lags, so that simply matching the year of land-use with the year of response variables will be insufficient to describe the most precise relationship possible (Harding et al. 1998). Thus, new estimates of high spatial resolution data are needed, as well as the ability to evaluate time series data.

The ability to predict where high spatial resolution data are required based on derived relationships from readily available medium resolution data would decrease the cost and resources required for broad scale classifications of IC estimates. While many values match for both NLCD and high spatial resolution IC classifications, there are many points where there is considerable scatter along the best fit line (Figure 2-1). A methodology is needed to enable decision makers to prioritize which areas require high spatial resolution estimates and identify areas where the NLCD are adequate for analysis. Communities would realize a cost-savings by eliminating the purchase and classification of high spatial resolution data in areas where NLCD are already adequate.

Here, we propose a Bayesian classification and regression tree (BCART) model to predict where the high spatial resolution value of IC can be predicted by NLCD data, based on the readily available medium resolution data available from the NLCD and U.S. Census Bureau. We demonstrate that high spatial resolution IC data will be

more easily predicted from the NLCD estimates in less forested areas, as trees and vegetation can mask houses and roads (Claggett et al. 2013; Roy et al. 2003). Previous and current land use/land cover also influence the ability to predict high resolution IC estimates, as neighborhoods developed from farmland generally contain fewer trees than those developed from forested areas. Finally, housing age negatively affects IC classifications, as older subdivisions generally have more established vegetation and canopy cover than newer developments. Using NLCD land use/land cover data and U.S. Census Bureau housing data, a BCART model was developed to predict where NLCD data are sufficient and where higher spatial resolution data are needed. Cross validation of the model was performed to assess the robustness of results and recommendations are made for evaluating which landscape characteristics result in the need for higher spatial resolution IC data.

Methods

Study Area

The study focused on 902 National Hydrography Dataset Plus (NHDPlus) catchments in Vermont in areas where high spatial resolution IC data were characterized from 1m National Agriculture Imagery Program imagery (Morgan et al. in review-a) (Figure 2-2). There are 5,982 NHDPlus catchments fully or partially contained in Vermont, thus approximately 15% of the catchments in Vermont were analyzed, primarily within urbanized areas. The NHDPlus hydrologic framework includes attributes of the National Hydrography Dataset, the National Elevation Dataset, and the Watershed Boundary Dataset (USGS and EPA 2010). NHDPlus

flowlines are based on medium-resolution 1:100,000 scale stream networks and have associated local catchments as well as full upstream drainage basins (USGS 2007). The USGS cautions against using NLCD data in watersheds of less than tens of square miles (USGS 2012). However, a multiple extents accuracy assessment of NLCD land use and land cover suggests that NLCD may be accurate for spatial extents as small as 10km², particularly for predominant land use classes or those with unique spectral signatures (Hollister et al. 2004). Fourteen NHDPlus catchments (Appendix 1) were eliminated from the analysis due to very small catchments for which characterization was limited by the resolution of the 30m NLCD data (i.e. one or two pixels caused a large variation in the percent imperviousness). All outlier catchments were less than 1 km², well below the recommended threshold for analysis of 30m NLCD data (USGS 2012). The remaining 888 NHDPlus catchments ranged in size from 0.001 to 55.2 km².

Bayesian Classification and Regression Tree (BCART) Methods for Assessing NLCD Adequacy

Classification trees can be useful in identifying the predictive structure of a problem by determining which variables drive a phenomenon or process and have previously been utilized in characterizing urban environments (Torbick and Corbiere 2015). As data sets increase in complexity, the relationships between variables can vary across measurement space, resulting in non-homogeneity (Breiman et al. 1984). Classification and regression trees compare independent and dependent variables through a series of binary splits and then fit a separate model within subsets of the data to identify relationships that may vary across a dataset (Chipman et al. 2002). Thus,

the model structure itself, rather than just the data, is homogenous at each terminal node split (Chipman et al. 2002). Previous classification trees relied on growing large classification trees and then “pruning” them back to identify terminal node means or class probabilities. More recent Bayesian approaches utilize a prior distribution to produce smaller trees at the outset, with linear regression models at each terminal node. Prior probability distributions for a variety of models have been evaluated and default choices suggested to avoid the overfitting of models and to shrink bottom node parameters, thus stabilizing the estimation (Chipman and McCulloch 2000; Chipman et al. 2002). Chipman et al. (2002) developed an algorithm for estimating the posterior distribution that prevents the model from getting stuck on a local solution, incorporates both grow/prune steps and swap/change steps to improve tree structure, and utilizes multiple restarts to create a more diverse set of trees. The final nodes of the BCART analysis are assumed to be parametric, thus the data must meet assumptions of homoscedasticity, a linear relationship between the variables (for a linear model only), and normality of the error distribution.

Modeling differences between NLCD and NAIP data

A Bayesian CART model was developed to predict where differences are likely to occur between high spatial resolution IC data and NLCD data. The ultimate goal was to predict where NLCD data are sufficient and where higher spatial resolution data are needed. End node regression models were constructed to identify variables with good predictive ability for high spatial resolution IC data in specific landscapes determined by the classification portion of the analysis. Landscape patterns with poorer fitting end node models may require higher resolution IC data than those with

well-fitting end node models. It is possible that a single predictor (or more) with a robust enough relationship with the dependent variable could yield sufficient predictive power. Factors considered in the model included the effects of historical land use/land cover, housing unit age, and current land use/land cover including measurements of canopy cover, agriculture, development intensity, and catchment size.

Effects of historical land use/land cover

To explore the effects of historical land use/land cover on the accuracy of IC data, land use/land cover data were allocated to the NHDPlusV1 catchments, using the NHDPlus Ca3T Version 1.017 program (Horizon Systems, Herndon, VA). The attributes allocated and accumulated included the 30m Coastal Change Analysis Program (CCAP) 1996-2010 land use change “to developed” category and the NLCD 2001-2011 land use change “to developed” category (NOAA 2010; MRLC 2014). The “to developed” class represents land use change from a prior land use to a developed state (i.e. from agriculture to high intensity developed). Both datasets were evaluated for use because the CCAP data allowed for a longer time series comparison while the NLCD is readily available for the entire United States, not just coastal areas. The accumulate function within Ca3T was used to build, for each NHDPlus flowline, the total upstream accumulated values for landscape attributes that were allocated to the NHDPlus catchments. The accumulated attributes were imported into a Microsoft Access Database and further broken down into developed from forested and developed from non-forested landscapes. These values were summed and divided by the 2011 total developed area and joined with NHDPlus catchments in ArcGIS 10.1 (ESRI,

Redlands, CA) to identify NHDPlus catchments that transitioned to developed from either forested or non-forested landscapes.

While the total developed for the two datasets matched, the developed “from-to” categories did not match in total developed from forested and agricultural patches in extent or spatial distribution, above and beyond what might be expected from the six year difference in the data sets. A NLCD 1992/2001 retrofit land cover change program is available for comparison to the 1992 NLCD classifications, but it is only recommended for use at a regional scale, thus it was not included in the analysis (Fry et al. 2009). Due to such a major inconsistency between the NLCD and CCAP datasets, we decided to use the background NLCD landscape as a classification variable instead, assuming that in areas of agriculture, development was from agricultural parcels and in areas of forest, development was from a forested landscape.

Effects of Housing Unit Age

The age of housing units was calculated using the 2013 American Community Survey (ACS) five year estimates for the year of structure built. We tested the assumption that older neighborhoods would contain more established canopy cover, leading to more difficulty in identifying IC. The ACS data were joined with the 2010 block group shapefile and intersected with the NLCD catchment boundaries. A weighted average age of housing (WtAvgHouseAge) was calculated by averaging the midpoint of the housing statistics for each decade and dividing by the total number of houses built. A separate variable was calculated for the proportion of houses built prior to 1940 (WtAvgPre40), as those data are aggregated in the ACS. The housing age and the proportion of houses built before 1940 were then weighted by the

proportion of each variable within the watershed boundaries divided by the total watershed area and dissolved by the NHDPlus common identifier field (COMID).

Selection of Classification and Regression Variables

BCART can incorporate either continuous or categorical variables and classification tree variables can overlap with predictor variables for the final regression models. A changepoint analysis can also be simulated by including a predictor variable in the classification tree variables (Chipman et al. 2002). Potential variables considered for the model included measurements of canopy cover, agricultural land use, development intensity, housing age, and catchment area (Table 2-1).

The dependent variable was the high resolution IC data (HRImp) developed for the 888 NHDPlus catchments in Vermont (Morgan et al. in review-a). Forward and backward stepwise regression was conducted in R to identify significant independent variables for the regression portion of BCART. Stepwise regression has been criticized for bias in parameter estimation, inconsistencies in model selection, multiple hypothesis testing, and reliance on a single best model (Freckleton 2011; Whittingham et al. 2006). To reduce the level of multiple hypothesis testing, multicollinearity between variables was identified using a variance inflation factor, with a factor of less than 10 indicating independence (Philippi 1993). Three canopy variables (NLCD 2011 Analytical Canopy Cover (PtCanAnaly), NLCD 2011 Canopy Cover Edited (PtCanEdit), and NLCD 2011 Forested (NLCD11Forest)) performed equally well in the stepwise regression and were highly collinear (VIF= 68.39, 78.38, 14.48 respectively). As all three are measurements of the same ecological phenomena,

PtCanAnaly was chosen for the regression equations because it was developed by the U.S. Forest Service as a more analytically rigorous data set than the cartographic canopy cover data set (MRLC 2014).

The NLCD 2011 IC (NLCD11IMP) was correlated with the NLCD 2011 High Intensity Developed (HID), Medium Intensity Developed (MID), Low Intensity Developed (LID), and Open Space Developed (OSD) land use classes (VIF=146.17, 16.46, 39.82, 15.24, 3.23 respectively) and performed best in the stepwise regression, thus the separate developed land use classes were removed from the regression equation but kept for the tree splitting classification process. Catchment area (CatchArea) was included as a classification variable and NLCD 2011 Agricultural land use (NLCD11Ag) was included as both a classification and regression variable. BCART was used to estimate parameters for the model selection process. The final variables input into the model were:

Classification variables: PtCanAnaly, NLCD11Ag, NLCD11Forest, CatchArea, OSD, LID, MID, HID, PtCanEdit, NLCD11Imp, WtAvgHouseAge, WtAvgPre40

Regression variables: NLCD11Ag, PtCanAnaly, NCLD11Imp, WtAvgHouseAge, WtAvgPre40

Transformation of raw data

While running regression diagnostics for the data, plots of the residuals versus predicted values of IC showed possible signs of heteroscedasticity, particularly at lower levels of predicted IC. The plots of residuals vs. predictor variables also showed signs of heteroscedasticity. In an effort to correct the violation of these regression assumptions, percentage data were divided by 100 to generate proportion data. There

is some debate in the literature whether arcsine square root transformations or logit transformations best transform proportional data (Warton and Hui 2011; Wilson et al. 2010). It has been recommended that the residuals of untransformed data be evaluated first and if they fail to meet the assumptions of homoscedasticity, normality, and equal variance, then both the arcsine and logistic regression transformations be applied to see which better fits the data (Wilson et al. 2010).

Both logit and arcsine square root transformations were applied to the data. The arcsine transformation was first performed only on the HRImp data but this introduced non-linearity into the NLCD11Imp vs. HRImp residuals plot and the subsequent HR residuals vs. HR predicted. Therefore, all proportional regression input variables were also transformed. This improved the issues of heteroscedasticity, non-linearity, and normality. The residual deviance of the logit transformation was poor (1,816,042 on 883 degrees of freedom). In such cases, a quasibinomial distribution can be used, which includes an extra parameter to account for more variance in the data. However, the BCART program cannot accommodate a quasibinomial fit, so the arcsine transformed data was used for the BCART analysis (Chipman and McCulloch 2002).

BCART Analysis

Data analyses were run for both the full data set (n=888 catchments) and the catchments greater than 10 km² (n=41). BCART was first run for the full data set with 100,000 iterations and one restart to identify the s^2 of the initial pooled estimate of the model ($s^2=0.001903$) and where the log likelihood stabilized (8,000 iterations).

BCART was then run once each with the prior probabilities suggested by Chipman and McCulloch (2000) with 20 restarts to make the convergence more efficient and to

prevent the model from getting stuck at a local solution (Chipman et al. 2002). The tree size with the largest log likelihood (least negative) value for the most visited solution was chosen (Chipman and McCulloch 2000). All features were standardized to have zero mean and unit variance. The procedure was repeated for the catchments greater than 10km², resulting in an s^2 of 0.002562 and a stabilized log likelihood at 1,000 iterations. Cross validations were performed ten times with a random sampling of 10% of the observed data. Residuals were plotted against the predicted data to check for homogeneous variance and against original predictors to check for potential non-linearities. The residuals were homogeneous, suggesting that the assumption of homoscedasticity was met and there were no non-linearities with the original predictors, indicating that second and third order terms were not necessary. Final regression models for each node were re-run using the MASS package in R (Venables and Ripley 2002) to determine the significant regression coefficients. The R code for all analyses is listed in Appendix 2.

Results

Study Area Catchments

The best BCART model for the full data set was found with prior probability parameters of 0.5, 2, 1, and $0.404*s^2=0.000769$, with a stabilized log likelihood at 8,000 iterations and 20 restarts. The classification variables that best partitioned the data included NLCD11Forest (split point between 55-65% throughout the cross-validations) and open space development (OSD) (split point of ~1.2%) (Figure 2-3). These classification variables were consistent through the ten cross-validation runs,

with catchment size (split point 0.005-0.01 km²) occasionally occurring as an additional classification variable. A generalized best fit model for the full data set is shown in Figure 2-3 and the specific model for cross validation number 5 is shown in Figure 2-4. A generalized description of each node and example catchments are shown in Figure 2-5.

Geographic distribution of nodes varied by region (Figure 2-6). As expected, with low levels of forested land cover, the majority of catchments in Node 1 occurred in more urbanized areas, such as Burlington. The catchments in Node 2 were mainly in less developed areas, such as those in the Black River and Ottauquechee watersheds in central Vermont. Catchments in Node 3 were found in forested areas with moderate development and comprised most of the study area, particularly in northeastern and southern Vermont and the majority of central Vermont.

Final regression models explained 92% of the variance for Node 1, 69% of the variance for Node 2, and 79% of the variance for Node 3 (Table 2-2). Because the data were standardized, the magnitude of regression coefficients can be compared to determine the relative importance of each (Chipman et al. 2002). The most important predictor for all three nodes was the NLCD11 Imp (Figure 2-7). For Node 1, other moderating variables, in descending order of magnitude, included PtCanAnaly and NLCD11Ag. Node 2 had one moderating variable - NLCD11Ag. Moderating variables for Node 3 included PtCanAnaly, WtAvgPre40, and WtAvgHouseAge in descending order of importance. Test data for each cross validation run showed a good fit with the model with an r^2 of 0.93 for 890 test fits (Figure 2-8).

The root mean square error (RMSE) provides a measure of the predictive power of a model, with smaller numbers reflecting a better model fit. The RMSE for Nodes 1-3 was 1.01, 1.02, and 1.01 respectively. While it appears that all three nodes performed equally well, the RMSE represents a much larger proportion of the predicted value for Node 2 ($<1.2\%$ OSD), suggesting that it has less predictive power than the other two nodes.

Catchments Larger than Minimum Recommended Areas

The best BCART model for the 41 larger catchments was with prior probability parameters of 0.5, 2, 1, and $0.404*s^2=0.001035$, with a stabilized log likelihood at 1,000 iterations and 20 restarts. One classification variable (NLCD11Ag) best partitioned the data with a split point of 58.24%, splitting off only 1 catchment from the rest (Figure 2-9). This was consistent through the ten cross-validation runs. A generalized description of Node 1 and an example catchment is shown in Figure 2-10. The final regression model explained 95% of the variance for Node 1 (Table 2-3). The most important predictor for Node 1 was NLCD11Imp, followed in descending order of magnitude by NLCD11Ag, WtAvgHouseAge, and WtAvgPre40 (Figure 2-11). Node 2 could not be evaluated due to the small sample size. Test data for each cross validation run showed a moderate fit with the model with an r^2 of 0.79 for 40 test fits (Figure 2-12).

Discussion

Study Area Catchments

Urbanized areas generally have less canopy cover than suburban or rural areas. Thus, it was suspected that high spatial resolution IC data should be more easily

predicted from the NLCD estimates in urban areas than in less developed areas, where trees and vegetation can mask houses and roads (Claggett et al. 2013; Roy et al. 2003). Previous land use/land cover may also influence the ability to predict high resolution IC estimates, as neighborhoods developed from farmland generally contain fewer trees than those developed from forested areas. The full BCART model supported the urbanization effect, identifying canopy cover as the major classifier that split the data into homogenous sets for the final terminal node models. Agricultural land use influenced the final regression models in less forested catchments and forested catchments with low levels of open space development but was not identified as a classifier that split the data into homogeneous sets. Housing age influenced the final regression model for Node 3 (>55% forested and >1.2% OSD) supporting the generalization that older neighborhoods complicate high resolution data predictions due to more established canopy cover.

As expected, NLCD IC values had the strongest relationship with the predicted high resolution data, although the relationship can be biased in areas of very low or very high IC (Morgan et al. in review-a). Further, the BCART model results showed that while the NLCD IC data adequately predicts high spatial resolution IC data in less forested catchments, it over predicts the high resolution data in heavily forested catchments with low levels of open space development and under predicts the high resolution data in heavily forested catchments with higher levels of open space development (Figure 2-7). This is further supported by the adjusted r^2 values for the end node regressions (Table 2-2). Node 1 (less forested) with an adjusted $r^2 = 0.92$, suggests a well-fit model. Node 2 (more forested, low OSD) shows much less

predictive power ($r^2=0.69$) and Node 3 (more forested, higher OSD) shows moderate predictive power ($r^2=0.79$). It is likely that NLCD best predicts the high resolution impervious data in less forested watersheds because there is less canopy cover to complicate the classification process. In forested watersheds with low levels of OSD, it may be that since NLCD “burns in” road networks, which account for the majority of IC in rural areas, 30m pixels may over-represent smaller rural roads, leading to poor predictive power for the model. Medium and larger roads may be adequately represented by the 30m NLCD, leading to better predictive power for the model. Overall, the data suggest that NLCD IC data may be adequate in catchments with less than 55-65% forested land cover but may require moderating variables in more heavily forested catchments, and likely requires higher resolution IC estimates in heavily forested catchments with low levels of development.

The catchments with less than 55-65% forested cover best predicted high resolution IC values using canopy cover, agricultural land use, and percent medium resolution IC (Node 1, Figure 2-4). Canopy cover, agriculture, and NLCD IC all had positive predictive relationships with high spatial resolution IC estimates in Node 1 (Figure 2-7). This further supports the hypothesis that the high resolution IC classifications are more easily predicted in catchments with less forested land cover.

In contrast, catchments with greater than 55-65% forested cover were further split by the amount of open space development. Open space development includes areas with less than 20% IC and is generally dominated by large lot single family homes, recreation areas, golf courses, or vegetation planted in developed settings (MRLC 2014). Catchments with very low levels of open space development (<1.2%) best

predicted the high resolution IC values using agricultural land use and percent medium resolution IC (Node 2, Figure 2-4). So, in heavily forested catchments with low levels of development, proximity to agriculture had a positive relationship with predicting high spatial resolution IC values (Figure 2-7). This makes sense as developments from agricultural land use are less likely to contain canopy cover that can obscure IC. However, as noted above, overall the end node model for Node 2 had less predictive power ($r^2=0.69$), thus it is likely that higher resolution estimates of IC would be required in these catchments.

Catchments with greater than 1.2% open space development best predicted the high spatial resolution IC values using canopy cover, medium resolution IC data, and housing age (Node 3, Figure 2-4). Both heavily forested areas and residential development age had a negative relationship with the ability to predict high spatial resolution IC data, with the proportion of developments built before 1940 being slightly more important than the average housing age (Figure 2-7). Heavily forested catchments with higher levels of open space development were the only catchments in which prediction of the dependent variable was influenced by housing age. Predicting IC classifications in areas of dense forest depends on the age of the housing developments. Newer developments are easier to delineate than older developments. This is likely because older housing developments tend to have more established vegetation and canopy cover, making delineation of impervious surfaces more difficult. The end node model for Node 3 showed moderate predictive power ($r^2=0.79$) thus it may provide adequate IC estimates from NLCD data, particularly in areas of newer developments.

Catchments Larger than Minimum Recommended Area

The 41 catchments larger than the minimum recommended area for analysis (Hollister et al. 2004; USGS 2012) were split by the NLCD11Ag variable. However, only one catchment, consisting of 85.43% agriculture, was split from the rest of the catchments. The majority of catchments were forested, moderately developed, with a range of agriculture from 1.5-50%, and an average housing age of 23.1 years. All of the catchments fell within nodes 1 and 3 of the original BCART analysis; none were categorized into Node 2. It is possible that Node 2 for the full data set has less predictive power because the catchments border on the minimum recommended size for analysis.

Node 1 for the 41 catchments had good predictive power ($r^2=0.95$) overall and the test validations showed a moderate fit ($r^2=0.79$). Cross validations were conducted with 10% of the data, thus only four catchments in each set were used as test fits, for a total of 40 test points. It is possible that with a larger sample size, the model fit could be improved. NLCD11Imp best predicted the HRImp, with a regression coefficient of 0.99, suggesting that NLCD11Imp alone might be a sufficient predictor for larger catchments in areas with low levels of forest as well as highly developed forested catchments. (Figure 2-11). HRImp was also weakly negatively correlated with both housing variables and NLCD11Ag. Thus, as percent agriculture and housing age increased, predictive power for the model decreased. This is consistent with the full data set for the housing metrics, but the opposite of the results for agriculture. This may be because there were only 9 catchments with less than 55% NLCD forested in the 41 catchment data set, which is the primary classification variable for the full data

set analysis. This essentially eliminated the sample size for less forested areas in the 41 catchment analysis. It may be that the negative relationship to agriculture is simply a response to a lack of less forested catchments available for analysis.

Limitations of the Approach

There are several limitations to the approach utilized in this study. First, the high resolution data were classified from NAIP imagery taken during the growing season. While the benefits to NAIP imagery include that it is free/low cost, available at regular intervals, and contains a near-infrared band for improving IC classifications, the cost is that it is “leaf on” imagery can make classifying IC more difficult in forested areas. This may have contributed to the importance of the NLCD forested land use class in the classification portion of the analysis. However, the cost-effective benefits of using NAIP imagery, combined with using ancillary data such as road datasets, likely outweigh the cost of using a “leaf on” data set.

Second, the analysis included catchments smaller than those recommended by the USGS (Hollister et al. 2004; USGS 2012). However, out of 888 catchments available for analysis, only 41 catchments were greater than the 10km² recommended by Hollister et al. (2004) and only 1 was larger than the “tens of square miles” (20mi²=51.8km²) threshold suggested by the USGS (2012). Further, tools such as the NHDPlus Ca3T were developed for allocating land use attributes to NHDPlus Catchments and are routinely used for regional analyses, even when the majority of catchments do not meet the minimum mapping unit. The USGS recommends that any use of the data in watersheds of less than tens of square miles should be examined at the local extent to determine its appropriateness for analysis. Our BCART model

provides a method for determining where the NLCD may be adequate and where higher resolution data may be needed.

Last, the small sample size for 41 catchments that met the minimum mapping unit essentially removed NLCD11 Forest from the analysis. This, combined with using only 10% (4 catchments) per cross-validation analysis, may have impacted the accuracy of the minimum mapping unit analysis. Further study is required to determine the impact of catchment size on the adequacy of NLCD IC classifications.

Management Implications

The ability to determine where NLCD data are adequate and where higher resolution estimates are needed is important for municipalities and watershed managers, who often have limited resources for geospatial mapping. With recent analyses suggesting that the NLCD data are underestimating IC (Morgan et al. in review-a; Nowak and Greenfield 2010), accurate classifications of IC on the landscape are required for watershed modeling. Changes to taxon-specific and community metrics of macroinvertebrate populations occur at as low as 0.81% and 1-2% IC (Baker and King 2010; Detenbeck et al. 2013). If NLCD data are underestimating IC, minor errors in classification accuracy could potentially lead to magnified errors in watershed modeling efforts.

Our BCART model successfully predicted high resolution IC values for 799 test fits using readily available 30m land use/land cover data and U.S. Census housing data. NLCD data can best predict higher spatial resolution IC in less forested catchments, in the absence of older housing developments. Moderating factors such as increased canopy cover and older housing developments negatively impact the

classification process. It is likely that higher spatial resolution estimates of IC are required in highly forested areas with older housing developments.

Our model provides a quick and cost-effective method for assessing the utility of NLCD IC data over broad spatial extents. The data and methodologies described will benefit municipalities and watershed managers by providing information on where NLCD predicts high resolution IC data accurately and where higher resolution data may be needed. This information can then be used to determine where limited monetary and geospatial resources can be spent to best mitigate the impacts of urbanization on water quality.

Table 2-1. Potential Regression and Classification Variables.

Variable	Unit	Description	Source
PtCanAnaly	%	NLCD 2011 U.S. Forest Service Tree Canopy Cover Analytical	NLCD
PtCanEdit	%	NLCD 2011 U.S. Forest Service Tree Canopy Cover Cartographic	NLCD
NLCD11Forest	%	NLCD 2011 Deciduous, Evergreen, Mixed, and Woody Wetlands Land use/Land cover Classes	NLCD
NLCD11Ag	%	NLCD 2011 Shrub/Scrub, Grassland/Herbaceous, Pasture/Hay, Cultivated Crops, and Emergent Herbaceous Wetlands Land use/Land cover Classes	NLCD
NLCD11IMP	%	NLCD 2011 Percent Developed Imperviousness	NLCD
HID	%	NLCD 2011 Developed, High Intensity (apartments, row houses, commercial/industrial - 80-100% impervious cover)	NLCD
MID	%	NLCD 2011 Developed, Medium Intensity (single family housing - 50-79% impervious cover)	NLCD
LID	%	NLCD 2011 Developed, Low Intensity (single family housing - 20-49% impervious cover)	NLCD
OSD	%	NLCD 2011 Developed, Open Space (large lot single family housing, parks, golf courses, vegetation - <20% impervious cover)	NLCD
CatchArea	km ²	NHDPlus Catchment Area	NHDPlus
WtAvgHouseAge	years	Weighted average housing age (see methods)	American Community Survey, U.S. Census
WtAvgPre40	%	Weighted average of houses built before 1940 (see methods)	American Community Survey, U.S. Census
HRImp	%	NAIP 2011 Percent Impervious Cover	Morgan et al.

NLCD= National Landcover Dataset, NAIP=National Agriculture Imagery program, NHDPlus=National Hydrography Dataset Plus - Version 1

Table 2-2. Regression variable significance for final BCART nodes for full data set based on generalized linear model. Nodes correspond to Figures2-3-2-7

Node	n	Variable	p	r²adj
1	217	PtCanAnaly	0.003	0.92
1	217	NLCD11Ag	0.004	0.92
1	217	NLCD11Imp	<.001	0.92
2	150	NLCD11Ag	0.001	0.69
2	150	NLCD11Imp	<.001	0.69
3	432	PtCanAnaly	<.001	0.79
3	432	NLCD11Imp	<.001	0.79
3	432	WtAvgHouseAge	<.001	0.79
3	432	WtAvgPre40	<.001	0.79

Table 2-3. Regression variable significance for final BCART nodes for catchments greater than 10 km² based on generalized linear model. Node corresponds to Figures 9-11

Node	n	Variable	p	r²adj
1	40	NLCD11Ag	0.04	0.95
1	40	NLCD11Imp	<.001	0.95
1	40	WtAvgHouseAge	0.02	0.95
1	40	WtAvgPre40	0.04	0.95

Figure 2-1. Relationship of NLCD to NAIP data at the NHDPlus catchment scale.
Solid line through origin shows 1:1 ratio

Figure 2-2. Map of study area. NHDPlus catchments analyzed are shown in gray and NLCD 2011 % impervious cover is shown in red

Figure 2-3. BCART generalized best fit model output. Classification variables are shown at each split and significant regression variables for each node are shown within the circles. Node numbers correspond to Figures 4-7 and Table 2-2. Variables are defined in Table 2-1

Figure 2-4. BCART example best fit model output. Numbers indicate number of catchments, listed with significant regression variables for each node and adjusted r^2 for node final regressions. Variables are defined in Table 2-1

Figure 2-5. Description of each node and example catchments for full data set

<p>Node 1</p> <ul style="list-style-type: none"> • Catchments characterized by <55-65% forested land cover. • High resolution spatial data can be predicted by NLCD11 Imp, PtCanAnaly, and NLCD11 Ag. • Mixed forested-agricultural-developed landscape.
<p>Node 2</p> <ul style="list-style-type: none"> • Catchments characterized by >55-65% forested land cover and <1.2% open space development. • High spatial resolution data can be predicted by NLCD11 Imp and NLCD11 Ag. • Heavily forested landscape interspersed with agricultural land use and open space development.
<p>Node 3</p> <ul style="list-style-type: none"> • Catchments characterized by > 55-65% forested land cover and > 1.2% open space development. • High spatial resolution data can be predicted by NLCD11 Imp, WtAvgHouseAge, WtAvgPre40, and PtCanAnaly. • Forested landscape with older residential housing developments and open space development.

Figure 2-6. Geographic Distribution of Nodes for cross-validation 5. Bolded region names correspond with Figure 2-1

Figure 2-7. BCART regression coefficients for best fit model of full data set. Error bars show standard error and * indicates significance at the $p < .05$ level. Dashed line shows 1:1 relationship for regression coefficients

Figure 2-8. Cross validation for full data set (arcsine transformed data). Black dotted line shows 1:1 comparison

Figure 2-9. BCART example best fit model output for catchments greater than 10 km². Numbers indicate number of catchments, listed with significant regression variables for each node and adjusted r² for node final regressions. Node numbers correspond to Figures 10-11 and Table 2-3. Variables are defined in Table 2-1

Figure 2-10. Generalized description of each node and example catchment for Node 1 of the greater than 10km² data set

Figure 2-11. Regression Coefficients for best fit model of catchments greater than 10 km². Error bars show standard error and * indicates significance at the p<.05 level. Dashed line shows 1:1 relationship for regression coefficients

Figure 2-12. Cross validation for catchments greater than 10 km² (arcsine transformed data). Black dotted line shows 1:1 comparison

Chapter 3

“Impervious Cover in the Riparian Zone – An Analysis of Method and Scale”

by

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Introduction

Riparian areas provide a number of functions for maintaining the integrity of stream ecosystems threatened by encroaching urbanization, including: water temperature regulation, bank stability, sources of organic and inorganic material, energy dissipation, and nutrient, sediment, and contaminant retention (Allan 2004, Chen et al. 1998, Gregory et al. 1991, Naiman and Decamps 1997, Naiman et al. 2005). Further, forested and wetland riparian areas have been shown to help to mitigate the effects of urbanization, even when the natural functions of these zones are altered by stormwater drainage infrastructure (Smucker et al. 2013). Recognizing the key role that buffer areas play in preserving water quality, municipalities across the Northeast have enacted regulations to protect and restore riparian areas using a variety of methods for determining optimal buffer widths.

Riparian buffer zone regulations vary by state and municipality and many analyses for informing stormwater regulations utilize fixed-width buffers. Most commonly, these analyses create 30m-120m wide buffers, based on the 30m pixel width of the National Land Cover Database (NLCD) (Goetz 2006). Previous analyses have defined 120m fixed-width buffer distances along flow paths and summarized land use types (urban, agriculture, etc.) at the riparian and catchment scale (Detenbeck et al. 2013, Smucker et al. 2013). Several studies have found that buffer distances smaller than 100m were not accurate predictors of fish or macroinvertebrate populations (Lammert and Allan 1999, Roth et al. 1996, Van Sickle et al. 2004, Vølstad et al. 2003). In another study, a 30m buffer was found to be a weak secondary predictor of stream health, with regional land use undermining the ability of vegetation to maintain high quality habitat (Roth et al. 1996). Fixed-width buffers may

underestimate the actual riparian boundary by up to 2.5 times the distance from the stream (Skally and Sagor 2001). Further, it has been suggested that medium spatial resolution data such as the NLCD may not be adequate for mapping riparian zone features (Baker et al. 2007, Fernández et al. 2014, Hollenhorst et al. 2006).

Accurate mapping of riparian zone condition from remote sensing data presents several challenges, including the determination of functional buffer width (Baker et al. 2006) and the spatial resolution of elevation (Abood et al. 2012), land use/land cover (Hollenhorst et al. 2006), and stream map data (Baker et al. 2007). Fixed-width buffers may not correspond to relevant ecotones and can include areas that are irrelevant to the functions of buffers, causing the misinterpretation of landscape patterns (Baker et al. 2006). Functional riparian metrics have been developed based on the connectivity of source land cover area to the stream channel (Baker et al. 2006) and distance weighting has been used to examine land use/land cover influence on stream health (Van Sickle and Johnson 2008). More recent studies have used elevation and flood height data to delineate riparian buffer zones based on readily available digital elevation models (DEMs) and the 50 year flood plain (Abood et al. 2012, Fernández et al. 2012).

Urban expansion increasingly affects riparian zones, causing hydrologic changes, which then cause changes to soil, vegetation, and the ability to filter pollutants (Groffman et al. 2003). While urbanization and increasing amounts of IC are known stressors on stream ecosystem health (Schueler et al., 2009 Walsh et al. 2005), proximal IC, i.e., IC that is adjacent to streams, may disproportionately affect water quality compared to IC distributed throughout the watershed (Wickham et al.

2016). While 27% of streams in the United States have proximally distributed IC, in watersheds that had spatial changes over time, most had increases in IC across the entire watershed compared to increases near surface waters (Wickham et al. 2016). This may have important implications for IC Total Maximum Daily Load (TMDL) allocations that are increasingly being developed to restore water quality (Wickham et al. 2016). Further, NLCD data have been shown to underestimate IC in less developed catchments and overestimate IC in more developed catchments (Claggett et al. 2013, Morgan et al. in review-a, Roy and Shuster 2009, Smucker et al. 2016) while others have found that NLCD underestimates IC regardless of development intensity (Jones and Jarnagin 2009). Higher resolution estimates of IC in the riparian zone are needed for more accurate estimates of in-stream response to urbanization.

The objectives of this study were to 1) determine the effects of spatial resolution on IC estimates in the riparian zone and 2) to compare IC derived from fixed-width and elevation based buffers. Given the smaller spatial area of delineated riparian buffers, it was expected that the NLCD would underestimate proximally distributed IC. Based on the literature, it was expected that fixed-width buffers would underestimate IC when compared to elevation based buffers. Both spatial resolution of IC data and delineation method are critical considerations for accurate modeling of water resources.

Methods

Study area

The study area included riparian buffer areas of four Hydrologic Unit Code (HUC) 10 catchments and eighteen HUC 12 catchments in the state of Vermont

(Figure 3-1). HUCs are defined as drainage areas that are delineated into nested, hierarchical classifications of surface areas draining to a specific point, based on hydrologic principles (USGS and USDA 2013). HUCs range in size from HUC 2 to HUC 16, with HUC 2s representing the broadest national scale and HUC 16s representing the finest local scale. The HUC 10 units ranged in size from 190.3-578.4 km². HUC 12 units ranged in size from 55.1-165.4 km². The HUC 12 catchments were selected because they contained the highest number of stormwater best management practices in the state of Vermont, over a range of IC. Results can be utilized in future studies to assess the effectiveness of green infrastructure practices at the catchment and riparian scale by comparing predicted aquatic community and habitat condition with observed condition in catchments with high densities of stormwater best management practices.

Defining the riparian zone

Definitions of the riparian zone are many, varied, and dependent on the resource being evaluated. Some definitions include the aquatic environment while others exclude it, some definitions incorporate soils and hydrology, while others focus on landscape characteristics and geomorphology (Ilhardt et al. 2000). Functional definitions of riparian areas focus on the ecosystem services provided by riparian zones rather than their individual components (Ilhardt et al. 2000, Verry et al. 2004). For the purposes of this study, a functional riparian zone is defined as “a three dimensional space of interaction that includes terrestrial and aquatic ecosystems that extend down into the groundwater, up above the canopy, outward across the floodplain, up the near-slopes that drain to the water, laterally into the terrestrial ecosystem, and along the water

course at a variable width.” (Verry et al 2004). This study focuses on the riparian zone up to the 50-year flood height.

Delineating riparian zones

Fixed-width buffers. Fixed-width buffers were generated along flow paths from the National Hydrography Dataset Plus (NHDPlus) Version 1 stream network (USGS 2007). The NHDPlus hydrologic framework includes attributes of the National Hydrography Dataset, the National Elevation Dataset, and the Watershed Boundary Dataset (USGS and US EPA 2010). NHDPlus flowlines are based on medium-resolution 1:100,000 scale stream networks and have associated local catchments as well as full upstream drainage basins (USGS 2007). 120m fixed-width buffers were generated using the ArcGIS FLOWPATH tool based on the distance along the flow path rather than perpendicular to the flow path (Detenbeck et al. 2013, Detenbeck et al. 2016). This generated a distance from the NHDPlus flowline, which was then classified into two categories: buffer and non-buffer areas. The raster was then reclassified so that the cells in the buffer were equal to one and the remaining cells were equal to zero. This resulted in a buffer along the flow path of 120m on each side. A null conditional was set in ArcGIS Spatial Analyst to make the buffer area =1 and the non-buffered areas=NoData.

Elevation based buffers. Elevation buffers were created with the Riparian Buffer Delineation Model (RBDM) ArcGIS Toolbox (Abood et al. 2012) using ArcGIS 10.4.1(ESRI, Redlands, CA). The toolbox allows delineation of riparian

buffers using DEMs and flood height data. Required inputs include a vector catchment boundary, the NHDPlus stream lines, NHDPlus waterbodies, either a 10m or 30m DEM, and optionally, classified land use/land cover data. The stream map requires the Strahler stream order (Strahler 1957) from the NHDPlus Flowline Value Added Attributes table and a specified flood depth for the 50-year floodplain. The 50-year floodplain was calculated as twice the bankfull depth, as that elevation is most commonly associated with the first stream terrace and likely to extend to areas of steep slopes (Bent and Waite 2013, Fernández et al. 2012). Bankfull depth was estimated by the equation:

$$\text{Bankfull mean depth (ft)} = 0.9502 [\text{Drainage area (mi}^2)]^{0.2960}$$

The bankfull mean depths and associated 50-year floodplain elevations for each HUC 10 and HUC 12 unit are shown in Table 3-1. Bankfull depth was held constant over each HUC 10 and HUC 12.

Ten meter DEMs were chosen for processing as 30m DEMs have been shown to have too coarse a resolution to effectively map riparian zones (Abood et al. 2012, Fernández et al. 2012). DEMs were obtained from the 3D Elevation Program (3DEP) (formerly the National Elevation Dataset) 1/3 arc second (10m) continuous dataset (Gesch et al. 2014). Data were projected into NAD83 Albers using nearest neighbor interpolation because bilinear interpolation altered the scale of the raster and also included more errors than those in the cells calculated by nearest neighbor as determined by visual inspection of the original dataset. Most likely, this is due to bilinear interpolation using a weighted average across the four nearest cells, thus introducing smoothing error in areas with steep elevation gradients. Nearest neighbor,

although not recommended for continuous data, calculates each cell value using the nearest cell in the input and does not change the values of cells from the input raster (ESRI 2016). It was necessary to reproject the data prior to processing because the RBDM automatically extracts percent IC by area based on a classified land use land cover dataset. Two HUC 12 units overlapped into New Hampshire. In these cases, the NED data from each state were downloaded and mosaicked together with the mosaic operator set to take the values of the VT raster, where data overlapped. One HUC 12 unit overlapped into Canada so the catchment boundary was clipped at the Canadian border, as the NLCD does not extend into Canada.

The RBDM calculates 360° radial transects from sample points along the stream to calculate elevation data, based on a user specified maximum transect length. Abood et al. (2012) suggest setting a maximum transect length of 250m-500m, while balancing floodplain characteristics and processing time. Preliminary analysis showed setting a 500m transect length had minimal improvement in riparian buffer delineation, resulting in a 0.1% change in IC calculations but greatly increased processing time, so the maximum transect length was set at 250m.

Impervious cover mapping

Percent IC for both the fixed-width and elevation based buffers were extracted from the 30m NLCD 2011 IC data (MRLC 2014) and 1m 2011 high spatial resolution data derived from the National Agriculture Imagery Program (NAIP) for the selected HUCs in Vermont (Morgan et al. in review-a). The extract by mask function of Spatial Analyst was used to extract the NLCD 2011 IC in the buffer layer for both the fixed-

width and elevation based buffers. The resulting raster was used to calculate the percent IC within the buffer. Zonal statistics in the Spatial Analyst toolbox were used to calculate NLCD 2011 IC within the buffer area for each HUC 10 and HUC 12. Because the high resolution data were not contiguous, extract by mask was used to extract only the buffer regions of the high resolution data. Zonal statistics were then run to calculate the mean percent IC for each buffer zone in the HUC 12 and HUC 10 units for the fixed-width buffers. The RBDM tool automatically calculated percent IC from the high spatial resolution data as an optional input. To maintain consistency with the RBDM tool, which removes waterbodies (e.g., lakes) from the final output, waterbodies were removed from the fixed-width buffers as well.

Statistical analysis

A regression analysis was run to identify the relationship between NLCD and NAIP data among HUC 10 and HUC 12 units for both fixed-width and elevation based buffers. The ratio of NLCD to NAIP IC was then compared to the NAIP data within the buffer types to identify where the NLCD data are adequate and where they may be over- or underestimating IC. Last, high spatial resolution IC data were compared among buffer types to identify differences in the total percent IC.

Results

Riparian buffer zones

Elevation buffers generally had greater spatial extents than those generated by the fixed-width method (Figure 3-2). IC characterized from NAIP imagery by both

methods ranged from 1.58-8.67% in the buffer zone of HUC 12 units and from 3.79-5.42% in HUC 10 units (Table 3-2). IC characterized from NLCD imagery by both methods ranged from 1.40-8.81% in the HUC 12 units and from 3.07-5.48% in HUC 10 units (Table 3-2). As expected, greater percentages of IC in both types of buffer zones were found in the more urbanized catchments such as those located in Burlington, Rutland, and St. Albans.

Statistical analysis

The NAIP data at the HUC 10 and HUC 12 level predicted NLCD classifications well for both types of buffers, with some noise in the data (Figures 3-3 and 3-4). The fixed-width buffer percent IC classifications trended toward NLCD underestimating the amount of IC in the buffer area at the lowest levels of IC but the difference was not significant (95% CI of slope 0.77-1.41, intercept $p=0.295$). The elevation based buffers showed an opposite trend of overestimating at lower levels of IC but again, the difference was not significant (95% CI 0.57-1.03 of slope, intercept $p=0.254$). The regression equations for each buffer type are shown below.

Fixed-width (Figure 3-3): $NLCD = -0.80 + 1.09(NAIP)$

$$r^2=0.72, n=22, p < 0.001, 95\% \text{ CI for slope} = 0.77-1.41$$

Elevation based (Figure 3-4): $NLCD = 0.68 + 0.80(NAIP)$

$$r^2=0.72, n=22, p < 0.001, 95\% \text{ CI for slope} = 0.57-1.03$$

The ratio of NLCD IC to NAIP IC was plotted against NAIP IC for both buffer types (Figures 3-5 and 3-6). An idealized relationship would yield a slope of 0 across

all levels of IC (ratio=1), indicating no difference between the two image classification products. The relationship between IC classifications in both the fixed-width and elevation buffers were not significantly different from zero (95% CI -0.02-0.11 for fixed-width and -0.11-0.02 for elevation based), suggesting that there was little difference in the percent IC based on spatial resolution. However, there is a trend of NLCD underestimating the percent IC in the fixed-width buffers and less of a trend of NLCD overestimating IC at low levels of IC (Figures 3-5 and 3-6). The regression equations for both buffer types are shown below:

Fixed-width (Figure 3-5): $NLCD = 0.66 + 0.05(NAIP)$

$$r^2=0.11, n=22, p=0.13, 95\% \text{ CI}=-0.02-0.11$$

Elevation based (Figure 3-6): $NLCD = 1.19 - 0.04(NAIP)$

$$r^2=0.09, n=22, p=0.19, 95\% \text{ CI}=-0.11-0.02$$

The elevation based buffers showed an outlier (Muddy Brook) that severely overestimated the amount of IC in the buffer area, with a ratio 2. This outlier is not indicated in the fixed-width buffer analysis. With the exception of the Muddy Brook outlier, the NAIP percent IC was comparable between buffer types at lower levels of IC (<5.5%) but showed more scatter at higher levels of IC (Figure 3-7).

Discussion

Choosing the appropriate spatial scale and methodology for delineating riparian buffer zones is critical for defining ecologically relevant riparian buffer regulations. Many municipalities create regulations based on fixed-width buffers

because they are easy to define and enforce. Recent advances in delineating riparian zones have moved toward functional definitions and methodologies (Abood et al. 2012, Ilhardt et al. 2000). Although conceptually, it is more difficult to gain public support for functional riparian zones, recent studies suggest that functional riparian zones may be more cost-effective than fixed-width buffers (Tiwari et al. 2016). This is particularly true in areas of wetlands and low production forest.

Surprisingly, spatial resolution had less of an effect on IC estimates in the riparian zone than in full catchments at the same locations (Morgan et al. in review-a). The NLCD IC estimates still showed a trend of underestimating IC at low levels of development but it was not as strong as at the catchment level. It is possible that with more data points, the relationship would be significant. We expected that there would be more variation at the riparian scale due to the limited spatial extent and more opportunities for small inaccuracies to create large differences between the NLCD and NAIP data. This was not the case as there was no major change to the ratio for either NLCD or NAIP data.

As land use/land cover type can vary across a watershed, it is possible that differential use within the watershed impacted IC classifications more than the spatial resolution of the data, as the type of land use/land cover may influence the accuracy of the NLCD percent IC classifications (Morgan et al. in review-b). Historically, development has occurred near streams and waterbodies, although recent analyses of proximal impervious cover change suggest that development has shifted away from near surface waters towards the rest of the catchment (Wickham et al 2016). Roads and industrial development are common along waterways and less common further

away. Forested land cover may be more predominant in upland areas as riparian areas have historically been cleared for development. Thus, IC and land use/land cover type may influence IC characterization in the riparian zone more than at the catchment level.

Estimates for high spatial resolution NAIP IC data were comparable at lower levels of IC for both buffer types. However, one prominent outlier, Muddy Brook, had a drastic difference in the amount of NAIP IC for the elevation based buffers (Figure 3-7). Upon closer examination, Muddy Brook appears to be an outlier due to differences in valley confinement. Although it is one of the smaller catchments (55km^2), percent IC in other small catchments such as Calendar Brook (60km^2) were similar between buffer types. However, the two catchments have very different terrain. Muddy Brook has a less confined valley than Calendar Brook. It is likely that less confined valleys have more variation in the elevation based buffer. Moon Brook, a much larger catchment (100km^2) similarly had a less confined valley and more variation between the buffer types (Figure 3-7). These findings are consistent with previous studies that suggest deep vee valleys and gorges require higher bankfull depths for accurate modeling of riparian areas than less confined valleys (Fernández et al. 2012).

Limitations of the approach include a limited number of sample catchments and no buffers with greater than 8.81% IC. Future work could include a larger sample size and varying landscapes. Bankfull depth was estimated from regression equations throughout the Northeast, (Bent and Waite 2013) not specific to Vermont and held constant across HUC 10 and HUC 12 units. More accurate bankfull depths calculated

by individual stream reach would result in a more accurate 50-year flood plain characterization and delineation of more accurate elevation based buffers. Further, evaluating bankfull depths in relation to valley confinement could help to improve the accuracy of mapped elevation based buffers.

This study examined the effects of spatial resolution of IC data in the riparian zone and evaluated the impact of buffer type on IC estimates. Percent IC ranged from 1.58-8.67% within both types of buffers. The spatial resolution of IC data had less of an effect in the riparian zone than it did on the full catchments within the same HUC 10 and HUC 12 units. Buffer type had minimal impact on percent IC, except in areas of unconfined valleys where there were notable differences between fixed-width and elevation based buffers. These results suggest that the NLCD may be adequate for mapping IC in the riparian zone for water quality studies. Future research should address other types of land use/land cover data and the impact of unconfined valleys on elevation based buffers.

Table 3-1. Bankfull Depth by HUC 10 and HUC 12 Catchment

Catchment Number	HUC 12 Catchment	Area (km ²)	Bankfull Depth (ft)	2x Bankfull Depth (m)
1	Ball Mountain Brook	87.18	2.79	1.70
2	Bloody Brook	165.43	3.37	2.05
3	Branch Brook	114.13	3.02	1.84
4	Calendar Brook	60.01	2.50	1.52
5	East Creek	159.06	3.33	2.03
6	HW Ottauquechee	114.96	3.03	1.84
7	Jay Branch	136.69	3.19	1.94
8	Jewett Brook	59.96	2.50	1.52
9	Lulls Brook	139.51	3.20	1.95
10	Mallets Bay	136.55	3.19	1.94
11	Mallets Creek	61.45	2.51	1.53
12	Mill Brook	98.69	2.89	1.76
13	Mill River	60.01	2.50	1.52
14	Moon Brook	100.49	2.91	1.77
15	Muddy Brook	55.14	2.43	1.48
16	N Branch Deerfield	144.93	3.24	1.98
17	Snipe Island	152.20	3.29	2.00
18	Winooski	127.87	3.12	1.90

Catchment Number	HUC 10 Catchment	Area (km ²)	Bankfull Depth (ft)	2x Bankfull Depth (m)
1	Black River	528.94	4.76	2.90
2	Mallets	197.99	3.56	2.17
3	Ottauquechee	578.36	4.88	2.98
4	Shelburne	190.34	3.51	2.14

Table 3-2. HUC 10 and HUC 12 Percent Impervious Cover (IC) Comparison by Buffer Type.

Catchment Number	HUC 12 Catchment	^a NAIP (%IC) Fixed Width	NAIP (%IC) Elevation Based	^b NLCD (%IC) Fixed Width	NLCD (%IC) Elevation Based
1	Ball Mountain Brook	3.00	3.83	1.40	1.80
2	Bloody Brook	2.84	3.21	2.13	2.71
3	Branch Brook	5.80	7.86	4.42	6.22
4	Calendar Brook	2.56	2.83	1.76	2.12
5	East Creek	3.94	4.72	3.77	4.78
6	HW Ottauquechee	6.04	8.67	5.69	7.89
7	Jay Branch	2.48	2.30	1.89	2.31
8	Jewett Brook	8.16	7.92	8.56	8.81
9	Lulls Brook	3.52	4.50	3.68	4.87
10	Mallets Bay	6.15	6.88	7.06	8.09
11	Mallets Creek	2.88	2.31	1.57	1.58
12	Mill Brook	6.55	8.15	3.95	5.37
13	Mill River	3.86	3.87	3.80	3.89
14	Moon Brook	7.13	5.14	8.72	6.09
15	Muddy Brook	5.32	1.58	7.60	3.21
16	N Branch Deerfield	7.24	7.74	5.20	5.74
17	Snipe Island	2.35	2.00	1.75	1.97
18	Winooski	3.55	2.95	4.65	4.08

Catchment Number	HUC 10 Catchment	^a NAIP (%IC) Fixed Width	NAIP (%IC) Elevation Based	^b NLCD (%IC) Fixed Width	NLCD (%IC) Elevation Based
1	Black River	3.79	4.50	3.15	3.72
2	Mallets	4.58	4.20	3.07	4.63
3	Ottawaquechee	4.21	5.42	3.28	4.10
4	Shelburne	4.83	4.50	5.48	5.21

^aNAIP = National Agriculture Imagery Program, ^bNLCD = National Land Cover Database

Figure 3-1. Map of Study Area – Watershed labels correspond to catchment and catchment number in Tables 3-1 and 3-2.

Figure 3-2. Comparison of delineated riparian buffer zone by data (NAIP, NLCD) and buffer type (Elevation Based, Fixed Width).

Figure 3-3. Relationship of NLCD to NAIP data at the HUC 10 and HUC 12 scale for fixed width riparian buffers. Solid line through origin shows 1:1 ratio.

Figure 3-4. Relationship of NLCD to NAIP data at the HUC 10 and HUC 12 scale for elevation based riparian buffers. Solid line through origin shows 1:1 ratio.

Figure 3-5. Ratio of medium to high spatial resolution IC classifications for fixed width riparian buffers. Solid line represents a perfect ratio of NLCD to NAIP data with slope=0.

Figure 3-6. Ratio of medium to high spatial resolution IC classifications for elevation based riparian buffers. Solid line represents a perfect ratio of NLCD to NAIP data with slope=0.

Figure 3-7. Comparison of fixed width and elevation based buffer IC classifications for high spatial resolution NAIP data. Solid line through origin shows 1:1 ratio. Outliers are labeled by catchment name.

APPENDICES

Appendix 1. Table of outliers removed from Chapter 2 analysis.

NHDPplus COMID	NLCD %IC	NAIP % IC	NLCD/NAIP Ratio	Comment
<i>HUC12s</i>				
4578754	29.760	2.490	11.95	.04 km2 watershed - NLCD overestimating IC; NAIP accurate
6088969	0.120	0.000	-	.03 km2 watershed - 1 pixel difference
6089107	2.500	0.050	50.00	.002 km2 watershed - 2 pixel difference (2 pixel watershed)
6089771	16.600	0.000	-	.01 km2 watershed - NLCD overestimating; NAIP slightly underestimating trails in golf course
6090249	0.007	0.001	7.21	.49 km2 watershed - 1 pixel difference
9327084	0.330	0.002	177.42	.32 km2 watershed - difference of 6 pixels; NLCD overestimating
9327920	16.640	2.380	6.99	.06 km2 watershed - NLCD overestimating; NAIP slightly underestimating
9328070	0.080	0.000	-	0.9 km2 watershed - NLCD accurate; NAIP missing road; 29 pixels
22220899	5.190	0.000	-	.01 km2 watershed - NLCD overestimating (only 9 pixels); NAIP missing 2 houses
22221047	0.150	0.010	15.00	.66 km2 watershed - NLCD accurate; NAIP underestimating road;
<i>HUC10s</i>				
6089073	0.000	5.020	0.00	.65 km2 watershed - NLCD underestimating
6090307	0.000	41.000	0.00	.001 km2 watershed - 1 pixel difference
9327962	0.000	5.060	0.00	.01 km2 watershed - slightly underestimating - 15 pixels (NAIP pixels take up less than 1 NLCD pixel)
9327840	0.000	12.400	0.00	.02 km2 watershed - NLCD underestimating - 19 pixels (NAIP takes up about 2 NLCD pixels total)

Appendix 2. R code Used in Analysis for Chapter 2.

Stepwise Regression and VIF code:

```
##Install libraries and call data##
library("MASS")
mydf <- read.csv("Data.csv")
summary(mydf)
pairs(mydf)

##Stepwise AIC on model using PtCanAnlay as canopy variable##
model1<-
lm(HRImp~PtCanAnlay+NLCD11Ag+PctOSD+PCTLID+PCTMID+PCTHID+NLCD11Imp+
WtAvgHouseAge+WtAvgPre40,data=mydf)
step <- stepAIC(model1, direction="both")
summary(model1)
summary(step)

##Stepwise AIC on model using NLCD11Forest as canopy variable##
model2<-
lm(HRImp~NLCD11Ag+NLCD11Forest+PctOSD+PCTLID+PCTMID+PCTHID+NLCD11Imp
+WtAvgHouseAge+WtAvgPre40,data=mydf)
summary(model2)
step2 <- stepAIC(model2, direction="both")
summary(step2)

##Stepwise AIC on model using PtCanEdit as canopy variable##
model3<-
lm(HRImp~NLCD11Ag+PctOSD+PCTLID+PCTMID+PCTHID+PtCanEdit+NLCD11Imp+Wt
AvgHouseAge+WtAvgPre40,data=mydf)
summary(model3)
step3 <- stepAIC(model3, direction="both")
summary(step3)

stepfinal <- stepAIC(model3, direction="both")

##Calculate VIF for all variables##
modelvif <-
vif(lm(HRImp~PtCanAnlay+NLCD11Ag+NLCD11Forest+PctOSD+PCTLID+PCTMID+PCT
HID+PtCanEdit+NLCD11Imp+WtAvgHouseAge+WtAvgPre40,data=mydf))
modelvif

##Calculate VIF using PtCanEdit as canopy variable##
```

```

modelvif3<-
vif(lm(HRImp~NLCD11Ag+PctOSD+PCTLID+PCTMID+PCTHID+PtCanEdit+NLCD11Imp+
WtAvgHouseAge+WtAvgPre40,data=mydf))
modelvif3

##Calculate VIF using PtCanEdit as canopy variable and removing NLCD11Imp##
modelvif4<-
vif(lm(HRImp~NLCD11Ag+PctOSD+PCTLID+PCTMID+PCTHID+PtCanEdit+WtAvgHouse
Age+WtAvgPre40,data=mydf))
modelvif4

##Calculate VIF using NLCD11Forest as canopy variable and removing NLCD11Imp##
modelvif5<-
vif(lm(HRImp~NLCD11Ag+PctOSD+PCTLID+PCTMID+PCTHID+NLCD11Forest+WtAvgH
ouseAge+WtAvgPre40,data=mydf))
modelvif5

#Calculate VIF using PtCanAnlay as canopy variable and removing NLCD11Imp##
modelvif6<-
vif(lm(HRImp~NLCD11Ag+PctOSD+PCTLID+PCTMID+PCTHID+PtCanAnlay+WtAvgHous
eAge+WtAvgPre40,data=mydf))
modelvif6

#Calculate VIF using PtCanAnlay as canopy variable and using NLCD11Imp instead of
developed classes##
modelvif7<-
vif(lm(HRImp~NLCD11Ag+PtCanAnlay+NLCD11Imp+WtAvgHouseAge+WtAvgPre40,da
ta=mydf))
modelvif7

##Run final model##
finalmodel<-
lm(HRImp~NLCD11Ag+PtCanAnlay+NLCD11Imp+WtAvgHouseAge+WtAvgPre40,data
=mydf)
finalmodel

summary(finalmodel)

stepfinal <- stepAIC(finalmodel, direction="both")

```

Residual Script and Data transformations:

```
install.packages("dplyr")
install.packages("leaps")
install.packages("car")
library("MASS")
library("dplyr")
library("leaps")
library("car")

##Model untransformed data##
mydf2<-read.csv("Data.csv")
model2.lm<-
lm(HRImp~PtCanAnlay+NLCD11Ag+NLCD11Imp+WtAvgHouseAge+WtAvgPre40,
data=mydf2)
summary(model2.lm)

## Normality of Residuals for untransformed data##
# #qq plot for studentized resid##
qqPlot(model2.lm, main="Untransformed QQ Plot")

# #Distribution of studentized residuals for untransformed data##
sresid <- studres(model2.lm)
hist(sresid, freq=FALSE,
     main="Untransformed Distribution of Studentized Residuals")
xfit<-seq(min(sresid),max(sresid),length=40)
yfit<-dnorm(xfit)
lines(xfit, yfit)

##Plot residuals vs. predictors for untransformed data##
model2.lm.res = resid(model2.lm)
plot(mydf2$NLCD11Imp, model2.lm.res, ylab="Residuals", xlab="NLCDImp",
main="Untransformed HR Residuals vs. NLCDImp")
plot(mydf2$PtCanAnlay, model2.lm.res, ylab="Residuals", xlab="PtCanAnaly",
main="Untransformed HR Residuals vs. PtCanAnaly")
plot(mydf2$NLCD11Ag, model2.lm.res, ylab="Residuals", xlab="NLCDAg",
main="Untransformed HR Residuals vs. NLCDAg")
plot(mydf2$WtAvgHouseAge, model2.lm.res, ylab="Residuals",
xlab="WtAvgHouseAge", main="Untransformed HR Residuals vs. WtAvgHouseAge")
plot(mydf2$WtAvgPre40, model2.lm.res, ylab="Residuals",
xlab="WtAvgHousePre40", main="Untransformed HR Residuals vs.
WtAvgHousePre40")
```

```

##Plot residuals vs. predicted (fitted) for untransformed data##
model2.lm.res = resid(model2.lm)
model2.lm.pred = fitted(model2.lm)
plot(model2.lm.pred, model2.lm.res, ylab="HR Residuals", xlab="Predicted HR",
main="Untransformed HR Residuals vs. HR Predicted")
##Read Proportion Data for Arcsin transformation##
mydf<-read.csv("Data.csv")

##Transform data with ArcSin##
asinTransform <- function(p) { asin(sqrt(p)) }
p <- (mydf$HRImpP)
head(p)
pAsin <- asinTransform(p)
plot(p, pAsin, type='l', lwd=2, col='blue', las=1, xlab='p', ylab='arcsine(p)')

p <- (mydf$PtCanAnalyP)
head(p)
PtCanAnalyAsin <- asinTransform(p)

p <- (mydf$NLCD11AgP)
head(p)
NLCD11AgAsin <- asinTransform(p)

p <- (mydf$NLCD11ImpP)
head(p)
NLCD11ImpAsin <- asinTransform(p)

p <- (mydf$WtAvgPre40P)
head(p)
WtAvgPre40Asin <- asinTransform(p)

##Model Arcsin transformation##
modelAsin <-
lm(pAsin~PtCanAnalyAsin+NLCD11AgAsin+NLCD11ImpAsin+WtAvgHouseAge+WtAvg
Pre40Asin, data=mydf)
summary(modelAsin)

## Normality of Residuals for Arcsin transformation##
##qq plot for studentized resid##
qqPlot(modelAsin, main="ArcSin Transformed QQ Plot")

```

```

## distribution of studentized residuals for ArcSin transformation##
sresid <- studres(modelAsin)
hist(sresid, freq=FALSE,
     main="ArcSin Transformed Distribution of Studentized Residuals")
xfit<-seq(min(sresid),max(sresid),length=40)
yfit<-dnorm(xfit)
lines(xfit, yfit)

##Plot residuals vs. predictors for Arcsin transformed data##
modelAsin.res = resid(modelAsin)
plot(mydf$NLCD11ImpP, modelAsin.res, ylab="Residuals", xlab="NLCDImp",
     main="ArcSin Transformed HR Residuals vs. ArcSin Transformed NLCD11Imp")
abline(h=0)
plot(mydf$PtCanAnalyP, modelAsin.res, ylab="Residuals", xlab="PtCanAnaly",
     main="ArcSin Transformed HR Residuals vs. ArcSin Transformed PtCanAnaly")
plot(mydf$NLCD11AgP, modelAsin.res, ylab="Residuals", xlab="NLCDAg",
     main="ArcSin Transformed HR Residuals vs. ArcSin Transformed NLCD11Ag")
plot(mydf$WtAvgHouseAge, modelAsin.res, ylab="Residuals",
     xlab="WtAvgHouseAge", main="ArcSin Transformed HR Residuals vs. Untransformed
WtAvgHouseAge")
plot(mydf$WtAvgHousePre40P, modelAsin.res, ylab="Residuals",
     xlab="WtAvgHousePre40", main="ArcSin Transformed HR Residuals vs. ArcSin
Transformed WtAvgHousePre40")

##Plot residuals vs. predicted (fitted) for ArcSin transformed data##
modelAsin.res = resid(modelAsin)
modelAsin.pred = fitted(modelAsin)
plot(modelAsin.pred, modelAsin.res, ylab="HR Residuals", xlab="Predicted HR",
     main="ArcSin transformed HR Residuals vs. HR Predicted")
abline(h=0)

##Read True/False for Logit transformation##
mydf3<-read.csv("Data.csv")

install.packages("HSAUR")
library("HSAUR")

##Model Logit transformed data - binomial distribution##
data("mydf3", package="HSAUR")
fm1<- cbind(Imp, NonImp)~PtCanAnlay+NLCD11Ag+NLCD11Imp+WtAvgPre40
LogitGlm<-glm(fm1, data=mydf3, family = binomial())
summary(LogitGlm)

```



```

##Model Logit transformed data - quasibinomial distribution##
data("mydf3", package="HSAUR")
fm1<- cbind(Imp, NonImp)~PtCanAnlay+NLCD11Ag+NLCD11Imp+WtAvgPre40
LogitGlmQuasi<-glm(fm1, data=mydf3, family = quasibinomial())
summary(LogitGlmQuasi)

##Plot residuals vs. predicted (fitted) for logit transformed data##
LogitGlm.res = resid(LogitGlm, "pearson")
LogitGlm.pred = fitted(LogitGlm)
plot(LogitGlm.pred, LogitGlm.res, ylab="HR Residuals", xlab="Predicted HR",
main="Logit transformed HR Residuals vs. HR Predicted")

##Plot residuals vs. predictors for logit transformed data##
plot(mydf3$NLCD11Imp, LogitGlm.res, ylab="Residuals", xlab="NLCDImp",
main="Logit transformed HR Residuals vs. NLCDImp")
plot(mydf3$PtCanAnlay, LogitGlm.res, ylab="Residuals", xlab="PtCanAnaly",
main="Logit transformed HR Residuals vs. PtCanAnaly")
plot(mydf3$NLCD11Ag, LogitGlm.res, ylab="Residuals", xlab="NLCDAg", main="Logit
transformed HR Residuals vs. NLCDAg")
plot(mydf3$WtAvgHouseAge, LogitGlm.res, ylab="Residuals",
xlab="WtAvgHouseAge", main="Logit transformed HR Residuals vs.
WtAvgHouseAge")
plot(mydf3$WtAvgPre40, LogitGlm.res, ylab="Residuals", xlab="WtAvgHousePre40",
main="Logit transformed HR Residuals vs. WtAvgHousePre40")

## Normality of Residuals##
##qq plot for studentized resid##
qqPlot(LogitGlm, main="Logit Transformed QQ Plot")

## distribution of studentized residuals##
sresid <- studres(LogitGlm)
hist(sresid, freq=FALSE,
main="Logit Transformed Distribution of Pearson Residuals")
xfit<-seq(min(sresid),max(sresid),length=40)
yfit<-dnorm(xfit)
lines(xfit, yfit)

```

Final End Node Regressions:

```

##Read data and install packages##

```

```

mydf<-read.csv("Data.csv")
model1<-
lm(HRImpPAsin~PtCanAnalyAsin+NLCD11AgAsin+NLCD11ImpAsin+WtAvgHouseAge+
WtAvgPre40Asin, data=mydf)
summary(model1)
install.packages("dplyr")
install.packages("leaps")
install.packages("car")
library("MASS")
library("dplyr")
library("leaps")
library("car")

attach(mydf)

##Select Node 1 - CV5 and Regression on NLCDForest Split (n=217), Stepwise
Regression on Node1##
node1<-select(mydf,
HRImpPAsin,PtCanAnalyAsin,NLCD11AgAsin,NLCD11ImpAsin,WtAvgHouseAge,WtAvg
Pre40Asin, Node) %>% filter(Node==1)
head(node1)
node1Regression<-
lm(HRImpPAsin~PtCanAnalyAsin+NLCD11AgAsin+NLCD11ImpAsin+WtAvgHouseAge+
WtAvgPre40Asin, data=node1)
step1<-stepAIC(node1Regression, direction="both")
summary(node1Regression)
summary(step1)

## Normality of Residuals for CV5 data##
# qq plot for studentized resid
qqPlot(node1Regression, main="Node 1 QQ Plot")

## Distribution of studentized residuals for Node 1##
sresid <- studres(node1Regression)
hist(sresid, freq=FALSE,
     main="Node 1 Distribution of Studentized Residuals")
xfit<-seq(min(sresid),max(sresid),length=40)
yfit<-dnorm(xfit)
lines(xfit, yfit)

##Calculate Root Mean Squared Error##
rmse <- function(error1)

```

```
{
  sqrt(mean(error1^2))
}
```

```
error1 <- sresid
```

```
rmse(error1)
```

```
##Plot residuals vs. predictors for Node 1##
```

```
node1Regression.res = resid(node1Regression)
```

```
plot(node1$NLCD11ImpAsin, node1Regression.res, ylab="Residuals",
xlab="NLCDImp", main="Node 1 HR Residuals vs. NLCDImp")
```

```
plot(node1$PtCanAnalyAsin, node1Regression.res, ylab="Residuals",
xlab="PtCanAnaly", main="Node 1 HR Residuals vs. PtCanAnaly")
```

```
plot(node1$NLCD11AgAsin, node1Regression.res, ylab="Residuals", xlab="NLCDAg",
main="Node 1 HR Residuals vs. NLCDAg")
```

```
plot(node1$WtAvgHouseAge, node1Regression.res, ylab="Residuals",
xlab="WtAvgHouseAge", main="Node 1 HR Residuals vs. WtAvgHouseAge")
```

```
plot(node1$WtAvgPre40Asin, node1Regression.res, ylab="Residuals",
xlab="WtAvgHousePre40", main="Node 1 HR Residuals vs. WtAvgHousePre40")
```

```
##Plot residuals vs. predicted (fitted) for Node 1##
```

```
node1Regression.res = resid(node1Regression)
```

```
node1Regression.pred = fitted(node1Regression)
```

```
plot(node1Regression.pred, node1Regression.res, ylab="HR Residuals",
xlab="Predicted HR", main="Node 1 HR Residuals vs. HR Predicted")
```

```
##Select Node 2 and Regression on OSD Split (n=150), Stepwise Regression on
Node2##
```

```
node2<-select(mydf,
```

```
HRImpPAsin,PtCanAnalyAsin,NLCD11AgAsin,NLCD11ImpAsin,WtAvgHouseAge,WtAvg
Pre40Asin, Node) %>% filter(Node==2)
```

```
head(node2)
```

```
node2Regression<-
```

```
lm(HRImpPAsin~PtCanAnalyAsin+NLCD11AgAsin+NLCD11ImpAsin+WtAvgHouseAge+
WtAvgPre40Asin, data=node2)
```

```
step2<-stepAIC(node2Regression, direction="both")
```

```
summary(node2Regression)
```

```
summary(step2)
```

```

## Normality of Residuals for Node 2##
# qq plot for studentized resid
qqPlot(node2Regression, main="Node 2 QQ Plot")

## Distribution of studentized residuals for Node 2##
sresid <- studres(node2Regression)
hist(sresid, freq=FALSE,
     main="Node 2 Distribution of Studentized Residuals")
xfit<-seq(min(sresid),max(sresid),length=40)
yfit<-dnorm(xfit)
lines(xfit, yfit)

##Calculate Root Mean Squared Error##
rmse <- function(error2)
{
  sqrt(mean(error2^2))
}

error2 <- sresid

rmse(error2)

##Plot residuals vs. predictors for Node 2##
node2Regression.res = resid(node2Regression)
plot(node2$NLCD11ImpAsin, node2Regression.res, ylab="Residuals",
     xlab="NLCDImp", main="Node 2 HR Residuals vs. NLCDImp")
plot(node2$PtCanAnalyAsin, node2Regression.res, ylab="Residuals",
     xlab="PtCanAnaly", main="Node 2 HR Residuals vs. PtCanAnaly")
plot(node2$NLCD11AgAsin, node2Regression.res, ylab="Residuals", xlab="NLCDAg",
     main="Node 2 HR Residuals vs. NLCDAg")
plot(node2$WtAvgHouseAge, node2Regression.res, ylab="Residuals",
     xlab="WtAvgHouseAge", main="Node 2 HR Residuals vs. WtAvgHouseAge")
plot(node2$WtAvgPre40Asin, node2Regression.res, ylab="Residuals",
     xlab="WtAvgHousePre40", main="Node 2 HR Residuals vs. WtAvgHousePre40")

##Plot residuals vs. predicted (fitted) for Node 2##
node2Regression.res = resid(node2Regression)
node2Regression.pred = fitted(node2Regression)
plot(node2Regression.pred, node2Regression.res, ylab="HR Residuals",
     xlab="Predicted HR", main="Node 2 HR Residuals vs. HR Predicted")

```

```
##Select Node 3 and Regression on OSD Split (n=432), Stepwise Regression on
Nodes2&3##
node3<-select(mydf,
HRImpPAsin,PtCanAnalyAsin,NLCD11AgAsin,NLCD11ImpAsin,WtAvgHouseAge,WtAvg
Pre40Asin, Node) %>% filter(Node==3)
head(node3)
node3Regression<-
lm(HRImpPAsin~PtCanAnalyAsin+NLCD11AgAsin+NLCD11ImpAsin+WtAvgHouseAge+
WtAvgPre40Asin, data=node3)
step3<-stepAIC(node3Regression, direction="both")
summary(node3Regression)
summary(step3)
```

```
## Normality of Residuals for node 3##
# qq plot for studentized resid
qqPlot(node3Regression, main="node 3 QQ Plot")
```

```
## Distribution of studentized residuals for node 3##
sresid <- studres(node3Regression)
hist(sresid, freq=FALSE,
     main="node 3 Distribution of Studentized Residuals")
xfit<-seq(min(sresid),max(sresid),length=40)
yfit<-dnorm(xfit)
lines(xfit, yfit)
```

```
##Calculate Root Mean Squared Error##
rmse <- function(error3)
{
  sqrt(mean(error3^2))
}
```

```
error3 <- sresid
```

```
rmse(error3)
```

```
##Plot residuals vs. predictors for node 3##
node3Regression.res = resid(node3Regression)
plot(node3$NLCD11ImpAsin, node3Regression.res, ylab="Residuals",
     xlab="NLCDImp", main="node 3 HR Residuals vs. NLCDImp")
```

```

plot(node3$PtCanAnalyAsin, node3Regression.res, ylab="Residuals",
xlab="PtCanAnaly", main="node 3 HR Residuals vs. PtCanAnaly")
plot(node3$NLCD11AgAsin, node3Regression.res, ylab="Residuals", xlab="NLCDAg",
main="node 3 HR Residuals vs. NLCDAg")
plot(node3$WtAvgHouseAge, node3Regression.res, ylab="Residuals",
xlab="WtAvgHouseAge", main="node 3 HR Residuals vs. WtAvgHouseAge")
plot(node3$WtAvgPre40Asin, node3Regression.res, ylab="Residuals",
xlab="WtAvgHousePre40", main="node 3 HR Residuals vs. WtAvgHousePre40")

##Plot residuals vs. predicted (fitted) for node 3##
node3Regression.res = resid(node3Regression)
node3Regression.pred = fitted(node3Regression)
plot(node3Regression.pred, node3Regression.res, ylab="HR Residuals",
xlab="Predicted HR", main="node 3 HR Residuals vs. HR Predicted")

```

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