Estimating Impervious Surface Cover in Flathead County, Montana

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(ABSTRACT)

Northwest Montana has seen a significant increase in its population in the past twenty years. The increase in population, and associated development, has resulted in significant changes in man-made impervious surface cover in the area. Impervious surfaces can serve as a suitable proxy for tracking the spread of various anthropogenic influences on an ecosystem; it impacts groundwater recharge, increases overall surface runoff as well as pollution and sediment load, and fragments landscapes. In this study, an Artificial Neural Network model was developed to update NLCD impervious surface product (2011) in Flathead County, Montana. Four Landsat 8 images from 2015 and 2016 were used to characterize imperviousness. This multi-temporal analytical method was designed to reduce the spectral confusion between impervious surface and soil/agricultural lands. We compared the neural network-predicted impervious surface maps with 2011 NLCD. When all four neural network prediction images agreed with a change of 50% or more from the 2011 NLCD map, the average of those four images replaced that pixel from the 2011 imperviousness map. Compared to the ground truth, the method used showed significant promise, with an R^2 of 0.73 and RMSE of 0.123. A comparison of the artificial neural network model results and the 2011 NLCD data showed a continuation of urbanization trends; the urban cores of towns in the study remain static while the majority of impervious surface development takes place along the perimeter of urban areas.

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(GENERAL AUDIENCE ABSTRACT)

Remotely sensed Landsat data can be used to rapidly detect and estimate changes in impervious surface cover. This study used artificial neural networks in conjunction with the National Landcover Database's 2011 Percent Developed Imperviousness layer and Landsat 8 data from four dates between the summer of 2015 and fall of 2016 to predict impervious surface cover in 2016, by deriving spectral relationships between Landsat data and impervious surfaces. We found that by requiring agreement between the four dates' neural networks outputs, we eliminated many of the false positives that arose from exposed soil. Using this method, we achieved an R^2 of 0.73 and RMSE of .123, sampling only the areas along a rural-urban gradient, in an area with significant seasonal spectral variability.

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1.0 Introduction

By mid-2017, the United Nations expects almost 55% of the world's nearly 7,500,000,000 people to live in urban areas (United Nations 2014). Since 2000, urban areas have gained almost 1.3 billion people, while estimates for rural populations have actually dropped slightly, signifying a mass migration to the world's cities (United Nations 2014). To accommodate this massive population influx, urban areas have expanded, creating significant changes in sizes, distributions and densities of associated physical structures.

This urbanization trend is only expected to increase (United Nations 2014). In the United States, city planners and land managers are required to balance between expansion to meet this increased demand, and preservation of natural assets and attractions that bring people to certain areas. One of key tasks for city planners and land managers is to assess and understand where, when, and how land has been developed in the past, where it is currently being developed, and how they can balance the demands of the future with responsible land use practices. Several studies have concluded that areas most impacted by increasing urbanization are most often those along the urban-rural gradient (Theobald 2001, Clark et al. 2009). The motivations for this migration are subject to speculation, but authors have noted that when people move to a scenic area to enjoy its natural bounty, this results in unintended consequences: in order to enjoy solitude offered by the area, people feel it is necessary to push further afield into previously undeveloped areas, bringing with them roads, infrastructure and private enterprise (Glorioso and Moss 2007, Hansen et al 2002, McGranahan 2008, Price et al 1997).

Impervious surface cover can serve as an efficient metric for estimating and gaining an understanding of a wide variety of anthropogenic problems associated with this in-migration (Hansen et al 2005). For example, roads can be associated with human encroachment on formerly unsettled or sparsely populated areas (Forman and Alexander 1998). Several studies have shown that impervious surface construction, particularly when it intrudes into relatively undisturbed areas, results in landscape fragmentation with important biological and hydrological consequences (Heilman et al. 2002, McGarigal et al 2001, Tinker et al 1998). While almost all fragmentation (landslides, clear cuts, wild fires, blow downs, road construction) impacts ecosystem health, fragmentation introduced from the growth and spread of impervious surfaces may have the most profound implications (Barnes et al., 2001). McGarigal et al. (2001) stated that roads are permanent, static and unnatural additions that present greater and often times unique ecological impacts. Spatial distribution of impervious surface is also important, for example, road systems are actually less impactful when they are densely distributed as compared to evenly distributed across an area, because of impacts upon biodiversity in a given area for various wildlife species, and through decreased mobility and increased competition for resources (Tinker et al 1998, Forman and Deblinger 2000). Roads also serve as effective conduits for invasive and non-native plant species (Gelbard and Belnap 2003, Hansen and Clevenger 2005). Additionally, an increase in impervious surfaces corresponds to a reduction in pervious surfaces of the same area; this results in both an increase in stormwater runoff, as well as an increased pollutant and sediment load being carried by that runoff to local bodies of water (Brabec et al 2002, Lee and Lathrop 2005).

Until advent of more advanced remote sensing technologies, the best way to understand the spread of any land cover type was to manually trace and calculate the area of objects using aerial photographs (Jensen 1981). As technology has progressed, remotely sensed imagery is now routinely used for land cover mapping and change detection, greatly increasing cost-effectiveness, and decreasing the amount of time used in data/image analysis (Campbell and

Wynne 2011). Various image classification algorithms, such as a Maximum Likelihood Classification and Classification and Regression Tree, have been widely used in characterization of land cover at local, regional, and national scales (e.g., Friedl et al., 2002). Most image classification algorithms focus on per-pixel mapping where each pixel (e.g., 30m spatial resolution) is assumed to have a single homogenous land cover (Richards & Richards 1999). Such per-pixel mapping method may not be appropriate in dealing with suburban areas where houses, roads, neighborhoods and other complex forms of infrastructure very rarely align well, if at all, with the simple geometry of a 30m x 30m pixel (Wu and Murray 2003; Shao et al., 2015).

Because of this sub-pixel land cover complexity, other image classification methods have been developed in order to derive proportional land cover from the relative strengths of spectral signals within a pixel. One of the most well-known of these techniques is linear spectral unmixing (LSU), a strategy that makes a basic assumption: all pixels are composed of some combination of known materials (Kauth and Thomas 1976, Richardson and Wiegand 1977). Further, by masking out water and clouds, each pixel is often simplified to main components of vegetation, impervious surfaces, and soil, or V-I-S (Ridd 1995). By associating "pure" pixels of given materials with their spectral signature, an analyst, with the assistance of a linear unmixing computer program, can tease out the approximate composition of the pixels in an area (Ridd 1995). However, LSU has well known accuracy problems in certain conditions; it overestimates in areas with little impervious cover while underestimating in areas with a high density of impervious surfaces (Weng and Hu 2008). Additionally, LSU requires expert analysis as well as access to highly specialized, advanced, software packages that might exceed budgets of small municipalities. In a locale with significant forested and agricultural area, LSU would not be the best fit, as it would tend to over-estimate the percentage of impervious surface cover in those land cover types.

Other advanced image classification techniques, such as Classification and Regression Tree (CART), are increasing used for estimating imperviousness (Vogelmann et al., 2011). For example, the US National Land Cover Database (NLCD) provides ready-to-use sub-pixel impervious surface map (30 m resolution) every 5-6 years. The foundation for this approach is to analyze high-resolution imagery (e.g., National Agriculture Imagery Program photographs) to build proportional sub-pixel impervious cover as training data, then apply CART to establish relationships between Landsat signals and impervious surfaces (Homer et al., 2007). Additional popular algorithms include artificial neural networks (ANNs). For example, Weng and Hu demonstrated that artificial neural networks can outperform linear spectral unmixing assessments across different geographical areas (Weng and Hu 2008). Currently, many researchers and practitioners in the USA are using NLCD impervious surface products directly for local applications, mainly because the products are readily available and have overall acceptable accuracy (Cooper et al., 2017). However, NLCD products may have high variation in image classification accuracy across space (Wickham et al., 2013), thus accuracy assessment of NLCD is often needed for local applications. More importantly, NLCD products are released very 5-6 years, so there might be significant delay between data collection and product availability (Homer et al., 2015).

Ideally, locally-updated NLCD products with high accuracy and timely delivery are preferred for environmental assessment. Specifically, after defining a study area, an image analyst may use samples of available NLCD impervious products (e.g., NLCD 2011) and the most recent Landsat data (e.g, 2016) as inputs to generate near-real time impervious surface map.

The purpose of this study was to develop an artificial neural network approach to update NLCD impervious products and assess the change of impervious cover over time. For characterizing change of impervious surface, the authors sought to assess changes happening not in the urban core of cities or surrounded by sparsely settled areas, but along a gradient between urban areas and the rural areas surrounding them. Several authors have noted that these populated but low housing density areas, with between 6 and 25 housing units per $1km^2$, called the "ex-urban fringe", are the fastest growing areas in the United States (Brown, et al. 2005). In this study, the authors seek to determine if this trend is applicable to the Crown of the Continent Ecosystem, and Flathead County in particular. Two main objectives of this study are:

1) Develop an artificial neural network model to rapidly detect and display changes in impervious surface cover of a relatively quickly developing urban area.

2) Quantify and display the extent of impervious surface cover across a subset of the Crown of the Continent Ecosystem.

2.0 Study Area

The Crown of the Continent Ecosystem (CCE) is a region of the Rocky Mountains in North America, occupying almost $44,000km^2$ in northwestern Montana, southeastern British Columbia and southwestern Alberta (Prato and Fagre 2007). The region is prized for its sightseeing, skiing, hiking, hunting, mountain biking, fly fishing and myriad other outdoor pursuits. It is an excellent example of this recent surge in urbanization, and associated impervious surface cover in the United States, and a prime study area for its impacts on healthy ecosystems. This area is remarkably diverse, from prairies and farm fields to glaciers, forested wilderness areas to high alpine tundra (Prato and Fagre 2007). Since 1980, Flathead County, the most populous county within the CCE, has seen its population almost double, and the rate of increase is predicted to remain steady or go even higher in coming years (American Fact Finder). Because of its location, Flathead County effectively serves as a gateway to Glacier National Park (GNP), characterized by growing popularity as a destination that attracts not only tourists but permanent residents. In 2016, GNP had 2,946,681 visitors, which represents a 50% increase from 2006 and a 70% increase from 2000 (National Park Service). Visitor statistics from year to year can be impacted by weather or economic events, and a sudden increase or decrease from one year to the next is not necessarily indicative of an overall pattern, but in the case of GNP (and many other National Parks), the trend is clear: people are visiting and moving to these wild areas in ever-increasing numbers, and the infrastructure to house, feed, and support those people must expand accordingly.

Hansen (2005) noted that population movements to this area are not random; quite the opposite. They are almost entirely correlated with access to public lands, in the form of National Forests, National Parks, or areas under the stewardship of the Bureau of Land Management. Additionally, research has shown the value of recreational pursuits as a vehicle for economic development in previously sparsely settled areas (Price et al 1997, Rasker and Hansen 2000). With increasing numbers of people interested in extracting value from this natural landscape comes an ironic conflict, as they must tear down a portion of what they covet in order to gain permanent access to it in the forms of housing, roads, supermarkets, schools, etc. (Hansen et al 2002, Glorioso and Moss 2007). As a result, the landscape sees significant changes as the population increases. Per Brown et al. (2005) these new “exurban” communities, those areas with between 6 and 25 residences per square kilometer, are the fastest growing form of development within the United States.

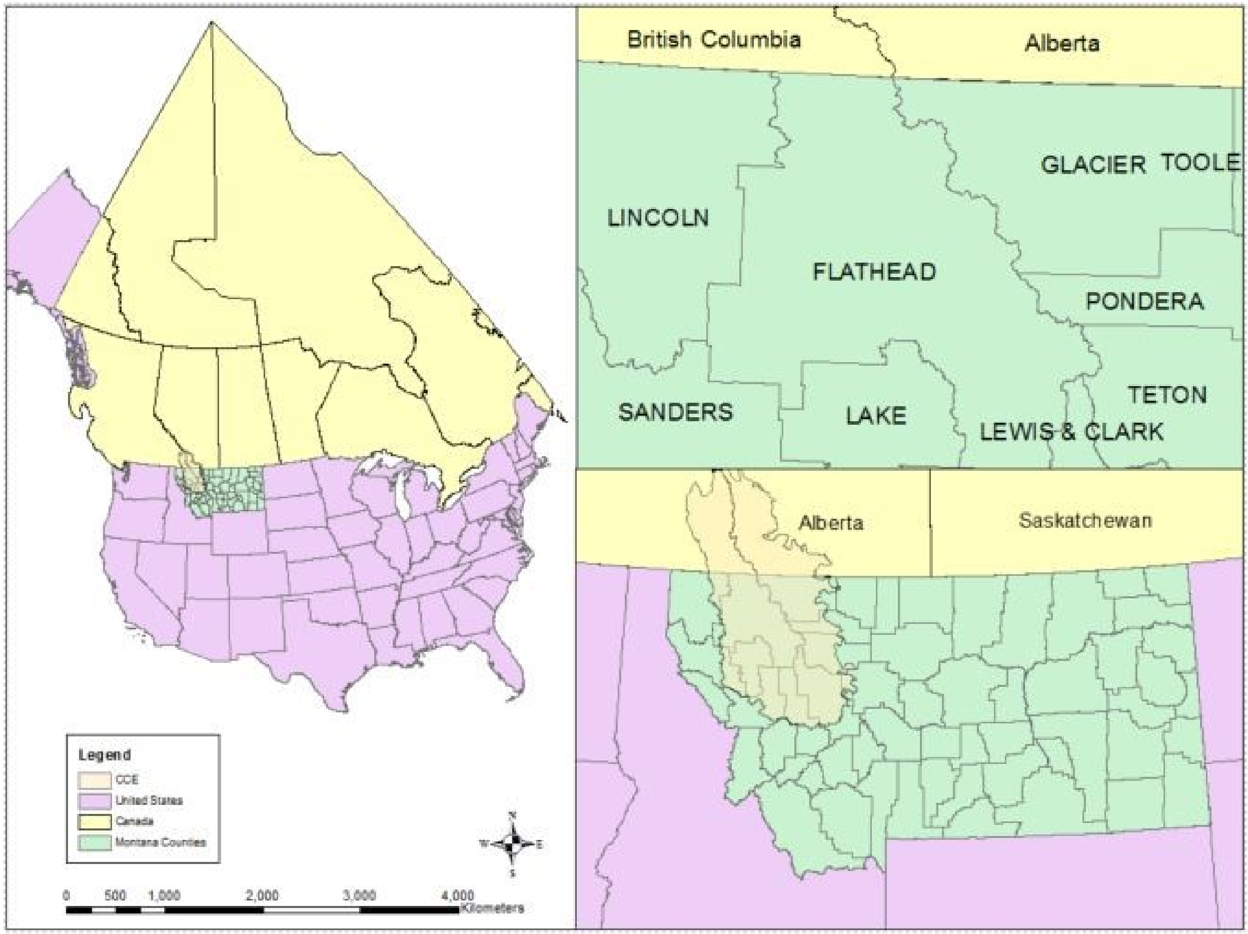


Figure 1. Study Area: Flathead County, MT.

3.0 Data and Image Acquisition

Landsat 8 scenes from Path 41, Rows 26 and 27 from July 2015, April 2016, July 2016 and October 2016 were used in this assessment. Summer imagery was used to reduce impacts of spectral confusion between bright soils and impervious surface cover, as well as decrease the likelihood of cloud or snow cover (Kauth and Thomas 1976). Additionally, National Land Cover Database (NLCD) Percent Developed Imperviousness (PDI) data was used as an initial input in the neural network modeling process, and also used for the purpose of change detection. For the purposes of model calibration and accuracy assessments, aerial imagery from 2011 and 2015 was collected from both public (National Agricultural Inventory Program) and private sources (Pleiades 1 satellite).

4.0 Methods

The first step in this assessment was determining whether or not NLCD PDI from 2011 would be an appropriate input in a machine learning algorithm designed for locally updating impervious surface map products. So, gaining a measure of the relative accuracy of the 2011 NLCD PDI data was essential before using it as an input in any predictive model. In order to obtain a ground truth estimation of impervious surface cover, a random stratified sampling technique was used to select areas for assessment. A one kilometer × one kilometer grid was created and overlaid on the study area using ArcMap 10.3. Using the 2001 and 2011 NLCD PDI layers, the authors used an image change detection analysis to assess locations, concentrations and relative abundance of impervious surface cover as it pertained to built-up areas, and by doing so, noted that the majority of town centers remained relatively stable over time, and that the majority of change took place on the periphery of urbanized areas. Additionally, this helped define the zones for sampling. If any $1km^2$ square contained more than 2% change from 2001 to 2011, it was categorized as “urban/urbanizing”, and added to a pool of potential sampling target polygons.

These urban/urbanizing $1km^2$ grid squares were then merged to create a single polygon per urban area (e.g., Kalispell, Whitefish, and Columbia Falls). For every $5km^2$ in the urban areas, one random point was placed within the polygon, with only one point per $1km^2$ grid square. Then, these $1km^2$ grid squares had three points randomly placed inside them, with a minimum separation of 130m, in order to prevent overlap during random distribution. Additionally, the heavily farmed corridor east of Kalispell was sampled at a rate of $1km^2$ per 20

km^2, for a total of three $1km^2$ sample areas and nine sample points. A single, $1km^2$ cell along the U.S. Route 2 was randomly selected from ten total cells, for an additional three sample points.

Using this random, stratified sampling technique, a total of 87 points were then converted into 90m * 90m polygons, or 3 * 3 30m pixel squares, aligned with the pixels of the 2011 NLCD PDI layer. Then, impervious surfaces and pervious surfaces were delineated within these 87 polygons, for the purposes of serving as a ground truth layer. It should be noted that the authors used both 4-band 2011 NAIP imagery and Google Earth to help determine the correct composition of any 90m * 90m polygon. The use of color infrared and natural color NAIP imagery, plus Google Earth imagery, helped reduce the impact of particularly bright or dark areas, shadows, extremely dry vegetation, and other impacts of seasonality when performing the digitization by helping confirm or deny the presence of materials through multiple viewing options.

Then, the total area of the digitized polygons was calculated. The percent imperviousness of the digitized polygons was compared against the 2011 NLCD PDI data contained within the corresponding 87, 90m * 90m squares, and it was determined that the PDI was very accurate, with an R^2 of 0.86. Thus, at least for the urbanized/urbanizing areas of Flathead County, the NLCD PDI data was a close approximation of the ground truth, and was deemed a suitable input for the neural network model to update impervious surface map products to the most recent year.

4.1 Image Processing and Preparation

Landsat data from Path 41, Row 26 and Path 41, Row 27 were combined as mosaic files using ArcMap 10.3, with each individual band (Bands 2-7 for Landsat 8) comprising a single input file. Mosaic files were produced for July 2015, 19 April 2016, July 2016, and October 2016, for a total of 24 single band mosaic files across the four dates. The images were selected with two reasons in mind: all four were during the leaf-on season, approximately mid-April to mid-October. This was done to maximize the spectral differences between impervious surface cover and green vegetation, and also to reduce the likelihood of snow or cloud cover in the mountainous portions of the study area. Also, the dates selected resulted in an array of differing ground conditions under which to observe the study area: the early part of the leaf-on season, the peak of plant productivity during the height of summer, and senescence or reduction in productivity during the fall. All data were projected to NAD 1983 UTM Zone 12N, and clipped to the boundary of Flathead County, MT, such that all Landsat and NLCD PDI pixels were aligned.

All images were processed through FMask, an automated cloud, cloud shadow and snow masking algorithm in Matlab (Zhu and Woodcock 2012, Zhu and Woodcock 2014). With some images from the shoulder seasons, this greatly reduced the spectral influence of snow, clouds and cloud shadow in the respective images. The post-processing, and reclassified cloud mask image for April 2016 is shown below in Figure 2, and the reclassified mask image is shown below in Figure 3. This mask was used to select pixels for analysis for all of the input files; only pixels shown as “clear land” or “clear water” after processing were included in this assessment. Table 1 shows the path/row, image date, and percent cloud cover for each image used in this study.

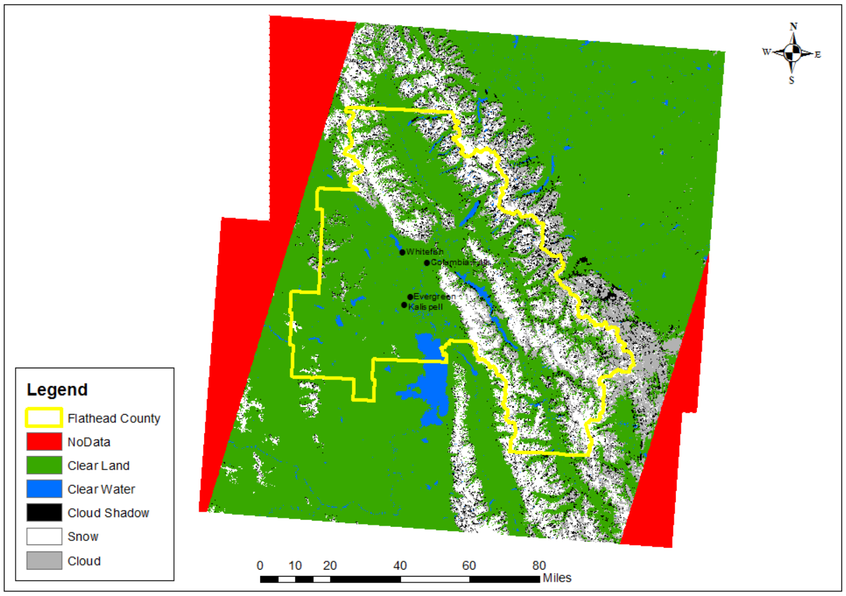


Figure 2. Post-FMask Processing Mosaic Image.

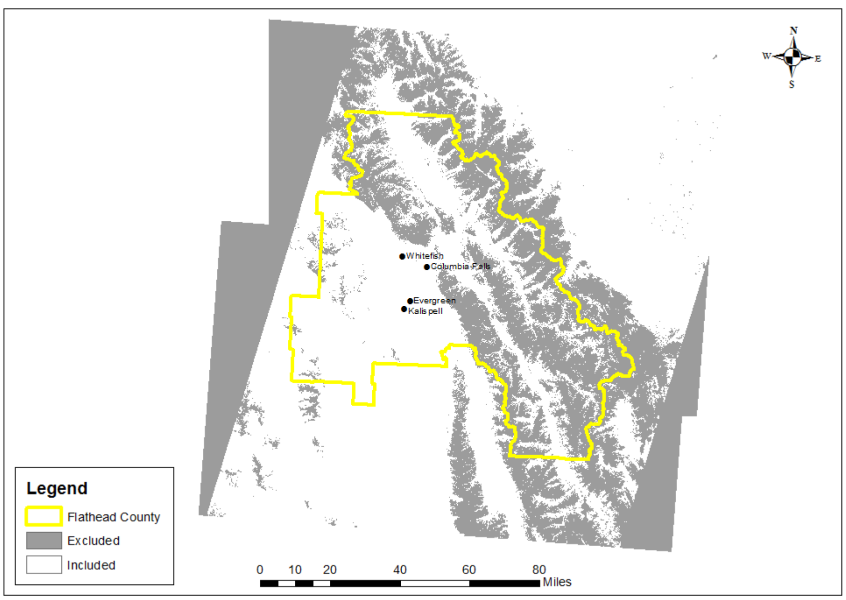


Figure 3. Reclassified Post Processing Image Showing Included and Excluded Pixels.

4.2 Neural Network

In a Matlab environment, we developed four neural network models to establish relationships between Landsat signals and 2011 impervious surfaces. For each neural network model, we used one Landsat image as input (i.e., one of four 2015/2016 Landsat images). The 2011 NLCD PDI layer was used as the predictive target. A total of over 10000 training pixels were selected by stratification of percent impervious surface map. Our assumption was that only small amount of impervious/urban change occurred within a relatively short 5 year interval (2011-2015/2016), thus the 2011 NLCD could still serve as a valid target layer that allows a neural network to develop the general relationship between Landsat signals and impervious surface targets.

We used a three-layer Multi-layer perceptron (MLP) neural network for the training. MLP neural network has been widely used for general land cover mapping applications (Atkinson et al., 1997; Bruzzone et al., 1999). Given a moderate-large number of training data points, MLP neural network often generates good image classification results. Upon completion of the neural network training and prediction, the output pixels were compared to the NLCD PDI 2011 pixels. Any pixel predicted to have 50% or more impervious surface cover change, when compared to the NLCD PDI pixel at the same location, would be labeled as potential change pixel. If all four neural network prediction models showed a 50% change or higher, the average of the four models was computed and used as the new output for that pixel. In the case of pixels when 3 or fewer models showed 50% or greater change, the 2011 NLCD PDI data was used. By requiring this multi-temporal agreement, false positives were reduced, and processing time was significantly improved. This process is shown below in Figure 4.

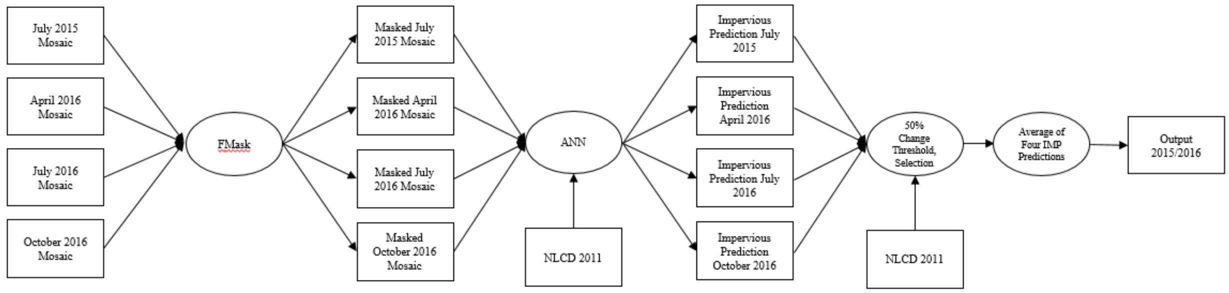


Figure 4. Overall Modeling Process.

4.3 Accuracy Assessment

The results of the 2015 models were compared to 60 random, stratified samples from the Kalispell and Evergreen areas. Due to a fire burning in the Flathead National Forest on the schedule flight date, and smoke obscuring the area around Kalispell, the 2015 National Agriculture Imagery Program photography for the study area were not collected. As such, the 2015 model results were assessed using Pleiades 1 imagery, taken 26 June 2015.

Using the 1km x 1km grid described previously, 28 individual 1km^2 polygons in this area were identified as having 2% or more change in imperviousness from 2001 to 2011, and existing entirely within available Plieades 1 imagery of the Kalispell-Evergreen area. 20 of these 1km^2 polygons were randomly chosen to serve as sample area boundaries for the accuracy assessment. The imagery was selected with the knowledge that the urban core of the city would remain mostly unchanged, based on the 2001 to 2011 change detection analysis, as well as determining that significant areas southeast of Kalispell were within Federal Emergency Management Agency floodplain areas along the Flathead River, and as such, unlikely to be developed (FEMA).

Within each of these 20 1km^2 polygons, 3 random points were distributed in ArcMap 10.3, for a total of 60 sample locations. 3 * 3 pixel, or 90m * 90m squares, aligned with the 2011 NLCD PDI layer, were digitized at these 60 sample locations, with all road, building, parking lot or other impervious surfaces digitized, and the average percent imperviousness of each 90m * 90m squares was calculated.

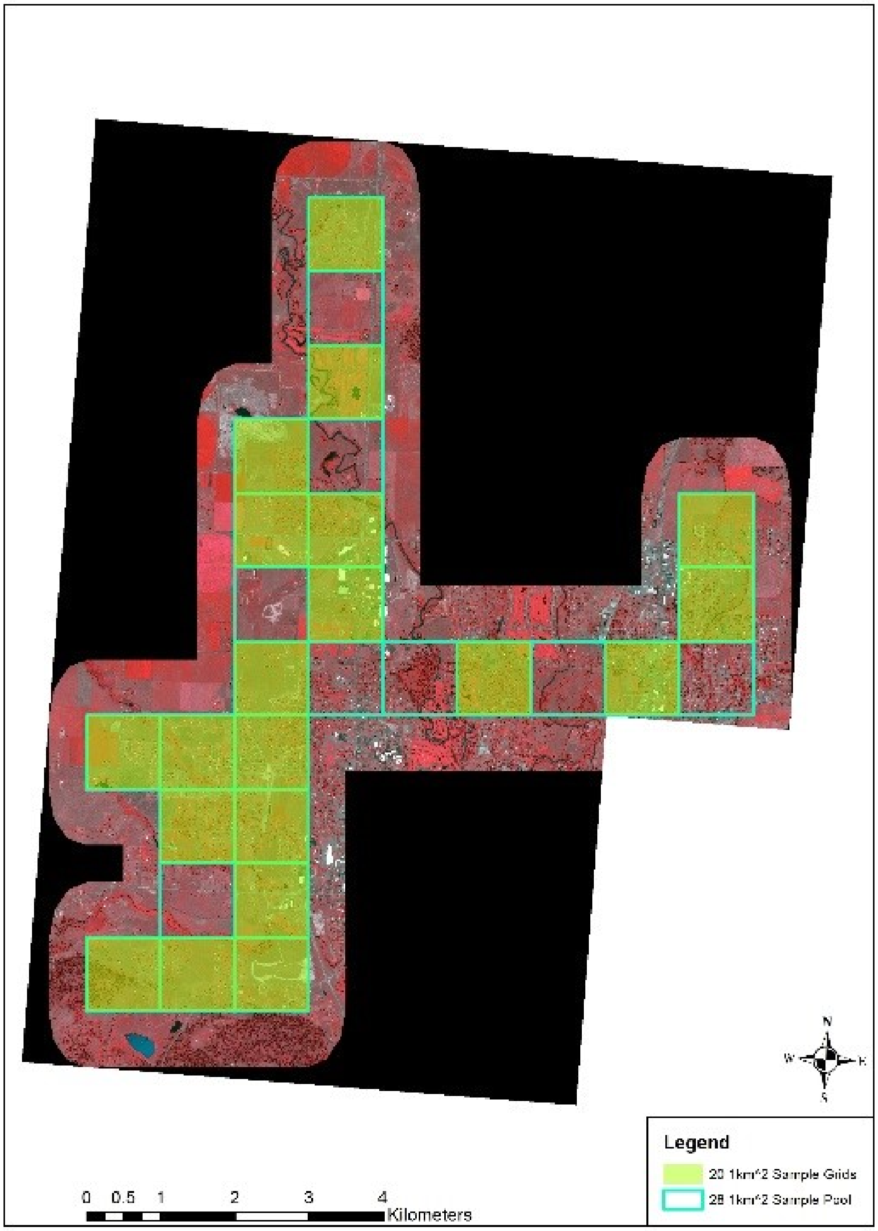
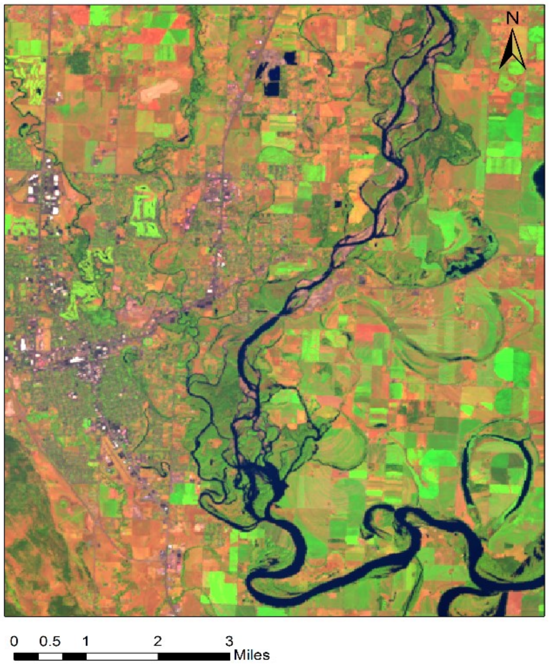


Figure 5. Random Distribution of Sample Areas within Sample Area Pool

Figure 6. Random Distribution of Ground Truth Polygons within Sample Areas

5.0 Results

Figure 7 shows neural network-predicted impervious surface using the July 2015 image as input. Urban core area, suburban residential area, and road network were clearly identified. However, some of the agricultural lands were falsely labeled with moderate to high level of impervious surface. These agricultural lands did not have vegetation cover in July 2015 and spectral confusion between bare soil and impervious surface led to large uncertainties in impervious surface mapping. Figure 8 showed neural network-predicted impervious surface using the Oct 2016 image as input. Similar to the July 2015 image, there were significant overestimation of impervious surface for agricultural fields. However, the comparison of these two predicted impervious surface maps showed that error distributions were quite different, largely due to different phenological development in agricultural lands. If two or more neural network-predicted impervious surface were combined through a voting or averaging method, a significant amount of falsely classified impervious surface areas could be removed.



Landsat 8 image: July 2015

Neural network-predicted percent impervious surface

Figure 7: Neural network-predicted percent impervious surface using July 2015 image as input

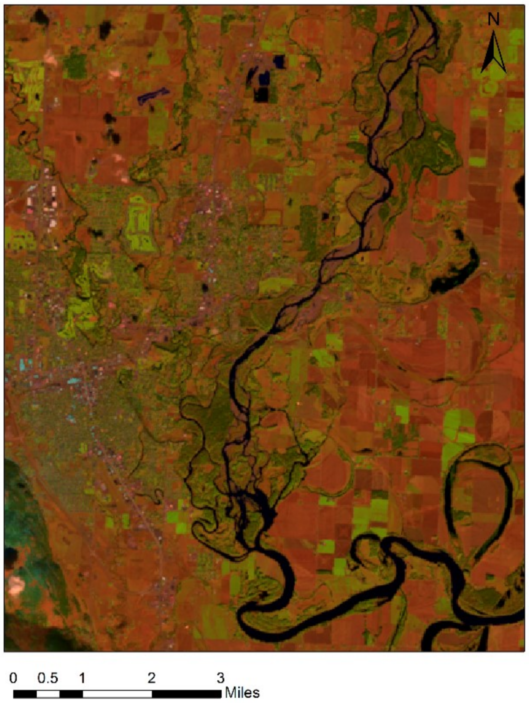
	
Landsat 8 image: October 2016	Neural network-predicted percent impervious surface

Figure 8: Neural network-predicted percent impervious surface using October image as input

For this study, the final impervious surface map was derived from four neural network-predicted impervious surface maps using a voting/averaging method. If all four neural network prediction models showed a 50% change or higher compared to the 2011 NLCD PDI data, the average of the four models was computed and used as the new impervious surface estimation. The calculated percent imperviousness from the digitized polygons were compared against the results of the predictive artificial neural network model. The RMSE of the neural network-predicted impervious surface map, when compared to the digitized ground truth polygons, was 0.128. The R^2 of the assessed polygons was 0.73. These numbers and scatter plots, shown below in Figure 9, suggest that this method produced moderately accurate predictive results for the 2015/2016 timeframe, based solely on the urban-rural fringe sampling area. However, it should be noted that, due to design construction of the model, R^2 would likely increase significantly if the stable, urban, core of the study area was sampled as well. As shown below in Figure 10, the neural network-derived impervious surface, when compared to the 2011 NLCD PDI, shows that most of the change between 2011 and 2015/2016 occurred in northern and western outskirts of the Kalispell/Evergreen area, or on highways between Kalispell and Whitefish. Additionally, results of the model, and resultant change detection map (Figure 10) validated one argument for the sampling procedure devised by the authors: that the presence of the Flathead River, and its associated floodplain, serve as a geographic barrier to prevent further southeastward expansion of the cities of Kalispell and Evergreen.

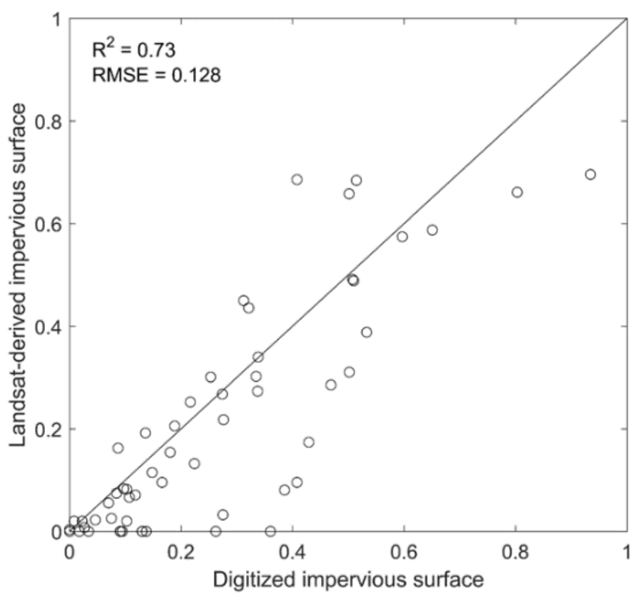


Figure 9. Scatter plot of accuracy assessment results from Landsat-derived model vs. digitized satellite imagery.

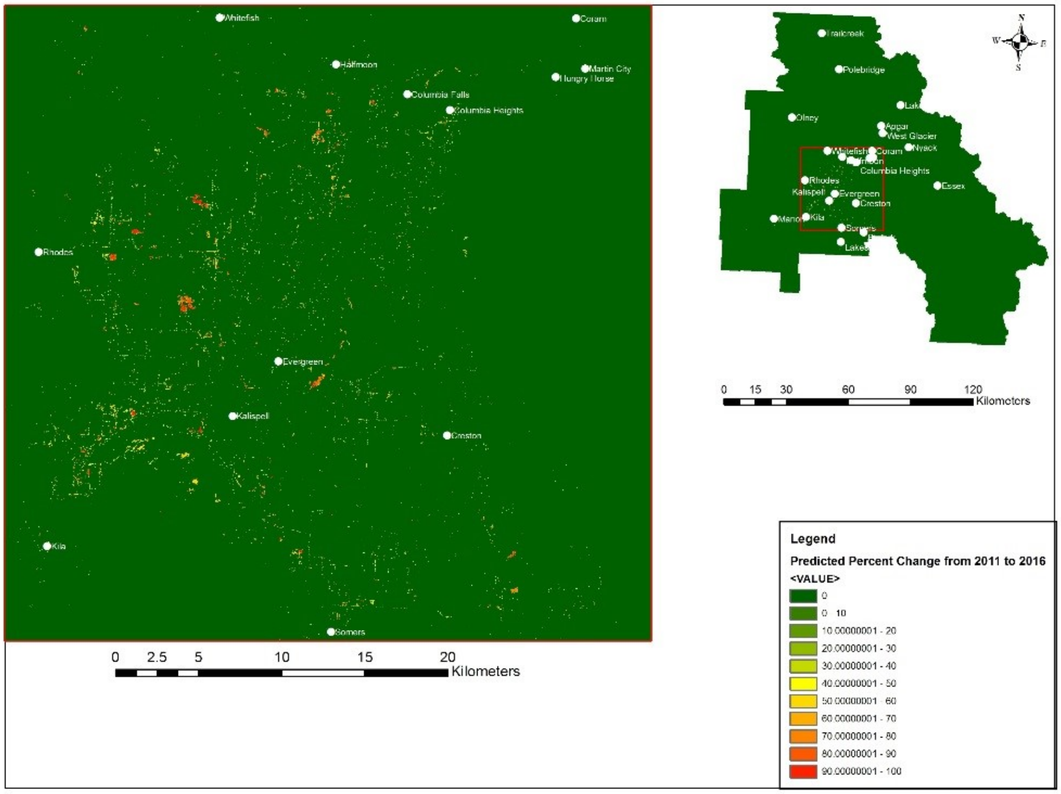


Figure 10. Distribution of Impervious Surface Cover Change, Flathead County, MT, 2011-2015

	Impervious 2001	Impervious 2011	Impervious 2016
Total area	20.16km^2	56.64 km^2	66.10 km^2

Table 1. Estimated Total Impervious Surface Cover, Flathead County, MT, USA, 2001-2016.

Change patterns displayed by Figure 10 indicate that the majority of change in the physical environment is taking place on the outskirts of the incorporated Kalispell and Evergreen metropolitan areas-- generally in what was formerly agricultural land. In some cases, the built up areas are not housing developments, but infrastructure or service providers to local communities. Upon closer inspection, three of the largest contributors to the change from 2001 to 2016 are large, open-pit material excavation operations, operated by concrete or asphalt companies that have expanded dramatically within a relatively short interval. Additionally, the Flathead County Landfill is a significant source of impervious surface reflectance.

However, it should also be noted that increases in impervious surface cover from 2001 to 2011 might also be due to improved accuracy of the NLCD PDI data from 2011 to 2011. While this study did not assess the relative accuracy of the 2001 NLCD PDI layer, there are instances where a visual analysis of the two layers, in conjunction with aerial imagery, shows that the 2011 layer detects and correctly labels impervious surfaces that were omitted by the 2001 NLCD layer.

Overall, the numbers presented in Table 1 are not surprising-- significant growth in impervious surfaces from 2001 to 2011 accompanied population increases, and a corresponding increase in the physical footprint of companies expanding their operations to meet a rise in demand for materials and services. From 2011 to 2016, growth slowed down compared to 2011 to 2011, perhaps reflective of both a more stable economy, and associated housing and infrastructure growth, as well as a more accurate detection method.

6.0 Discussion

One of the more difficult and problematic portions of any ground validation assessment involves the highly subjective analysis of surfaces that do not fit neatly into traditional groupings of impervious and pervious surfaces. Under normal conditions, soils differ spectrally and materially from vegetation, as well as impervious surfaces like asphalt, concrete, or roofing materials. However, under other conditions, particularly those involving the right amount of moisture and compaction, for example, from construction equipment or normal passenger vehicles, soil and gravel surfaces not only no longer absorb water, but their spectral properties also change. For the purposes of runoff calculations, many engineering manuals assign compacted soil, oiled compacted soil and gravel surfaces runoff curve numbers approaching those of pavement (Montana Department of Transportation). In some recently developed areas, soil near newly constructed buildings appears so highly compacted and/or amended that it does not resemble normal soil when viewed in either color infrared and natural color. In this instance, this portion of the study area was within one of the ground truth polygons, and the authors designated the soil around this house an impervious surface.

When assessing a more mature, older area with a longer history of development, like central Kalispell, assessments like this become less critical, or unnecessary. As demonstrated in Figure 10, city centers remain relatively stable over time, with the exception of tear-down construction projects that generally replace impervious surfaces with other impervious surfaces. At the perimeter of an urban area, where most development takes place, and at a higher rate, this subjective assessment by an analyst becomes much more critical.

In a more phenologically stable study area, perhaps with less agricultural operations, our image analytical methods might be more accurate in predicting impervious surface cover change. Or, it might not need as many inputs to achieve a high level of accuracy. In an area without significant exposed surface soil or limited agriculture, and thus fewer false positives, two or three Landsat images and subsequent change agreement results might be enough to achieve accuracy results that surpass those demonstrated with the four image method for Flathead County. In areas with higher amounts of exposed soils, the number of images required to produce similar results could be higher, as the number of false positives due to spectral confusion could be higher.

7.0 Conclusions

This study demonstrates the high potential of a multi-temporal image analytical method for a rapid update to the NLCD PDI layer. It represents a way to reproduce impervious surface cover maps annually for a given study area once a neural network design has been established. Some thought must be given to the inputs; too wide an array of dates will result in some detail being lost at the newer end of the date spectrum. And, with too narrow a timeframe, or without a wide array of data, the input imagery used may not capture the spectral variability of an area in different portions of the phenological cycle. For developing agricultural areas, this method represents a viable way to supplement the NLCD PDI product before its release.

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