LAND COVER CLASSIFICATION: A COMPARISON BETWEEN U.S. NATIONAL LAND COVER DATASET (NLCD) AND INTERMAP'S NEXTMAP® USA DERIVED LAND COVER MAPS

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ABSTRACT

Land cover classification is a valuable tool for professionals in a diverse range of fields, ranging from environmental and ecosystem management, to land use planning and fire management, these applications play an important role in both the public and private sectors. The most thorough and recent of the datasets used for land cover classification have been the 1992 and 2001 30-meter-posted National Land Cover Database (NLCD) datasets created by the United States Geological Survey (USGS). While these datasets provide a good medium-scale land cover dataset, there are limitations to the NLCD's accuracy and use in finer-scale applications. Under the NEXTMap® USA program, Intermap Technologies™ is assembling a nationwide dataset of high-resolution 1.25-m orthorectified radar imagery (ORI) and 5 m elevation datasets for the entire conterminous United States. NLCD data and NEXTMap® Land Cover Data were compared in five different study areas across the United States (California, Colorado, Montana, and two locations in Minnesota), and verified with field measurements. Nine land cover classes (water, barren, grassland, urban, shrub, mixed forest, deciduous forest, evergreen forest, and wetlands) constituted the majority of the study areas. Overall, the result of using NEXTMap radar and elevation data for classification of land cover yielded very favorable results. The majority of the land cover classes were delineated with an overall accuracy ranging between 86.30% - 86.91% on the order of 90%, versus 59.16% - 63.93% for the NLCD. The NLCD map often confusing deciduous and wetland, underestimating evergreen, and overestimating shrub vegetation classes.

Key words: NLCD, Radar, Land Cover, Intermap, Classification

INTRODUCTION

Land cover data is a valuable and often necessary product when performing studies and analysis in a number of fields. To accurately access trends of change across the surface of the earth, the data in use must fully meet the project manager's need in regards to scale, data frequency, consistency, and accuracy. While the NLCD is excellent in intermediate to large scale mapping projects, it can run into issues when being applied in projects at finer scales. In applications such as large scale change detection, environmental impact analysis, and ecosystem management, intermediate scale land cover data is often sufficient to the users needs. However, in finer scale applications such as calculation of surface roughness within a potential wind energy project, finer scale land cover data can be an extremely valuable asset. To map land cover at the finer scales necessary for some of these applications, high quality imagery is the first important component. Imagery with a finer resolution, seamless transition between tiles/scenes, and no cloud cover is the ideal solution to this problem. There are a number of high resolution optical satellites currently in operation; however it is difficult to provide entirely cloud free and seamless data on a country-wide basis. A solution to this problem would be to use primarily radar imagery, such as that offered by the Intermap NEXTMap data program, which provides a highly accurate, cloud-free source of imagery for the potential creation of a nationwide 5-meter land cover dataset. While this data is not free of problems (it is greyscale, has shadows in high relief areas, etc.) it provides a viable solution for the creation of a land cover dataset on a nationwide basis.

Over the past decade, the use of IFSAR data to derive two-dimensional land cover has matured considerably (Zebker *et al.,* 1991; Madsen *et al.,* 1993; Zebker *et al.,* 1994; Wegmuller and Werner, 1995; Hagberg *et al.,* 1995; Luckman *et al.,* 2000; Weydahl *et al.,* 2001; Corr, 2003; Stilla *et al.,* 2003; Yan *et al.,* 2006; Huang *et al,* 2007; Santoro *et al.,* 2007). This source of data was used in this paper to determine its feasibility in the production of land cover maps. The derived land cover maps were tested in several areas of varying land cover, climate, and scale.

DATA

National Land Cover Database (NLCD)

The USGS has produced several sets of land cover data covering the United States, with the most recent and comprehensive datasets being released in 2001. This dataset consisted of three different layers: the NLCD 2001 land cover dataset, the NLCD 2001 impervious surface, and the NLCD 2001 canopy density set. The NLCD land cover dataset consists of 16 primary classes (with additional classes in coastal areas), while the impervious surface layer classifies pixels on a scale of 0 – 101, with increasing numbers signifying increases in impervious percentage. The canopy density is also based on a scale of 0 – 101, however this only applies to forest and measures forest canopy density on a pixel-by-pixel basis. The entire NLCD dataset is derived from optical satellite imagery, which has many favorable attributes for land cover classification, but also some drawbacks. For one, this type of data is widely available in both the public and private sector. There are many optical satellites operating both currently and throughout the past couple of decades. This current imagery, combined with legacy data, provides mapping professionals with a broad range of optical products. Another advantage of using optical is its ease-of-use. The majority of the population can easily interpret an optical image, as these images are sensed in the same portion of the electromagnetic spectrum as the human eye. Finally, satellites can capture large amounts of data in less time than terrestrial systems. While this dataset is an excellent resource for those working on intermediate to large scale projects, it can be less useful when applied to finer scale mappings. With the 30m posting of this product, mapping in scales below 1:100,000 can become more difficult due to this pixel size. This pixel size was derived from the source data, in the case of the NLCD, this source data is Landsat 30 imagery.

NEXTMap Orthorectified Radar Imagery

The primary source of data that we used in our study is 1.25m posted ORI. This data is derived from an airborne X-band sensor, which operates in the microwave portion of the electromagnetic spectrum versus the visible portion for optical imagery. The radar pulse in an X-band system has a wavelength anywhere from 2.4-3.75cm and a frequency of 8000 – 12500 MHz. The ORI is orthorectified utilizing the elevation model captured by this system during acquisition, in order to remove errors associated with terrain displacement. This orthorectified radar imagery is a greyscale image with a range in values from 0-250. Radar imagery appears similar to a greyscale optical image, however is differs in several ways. For one, radar sensors are an active system and can operate independent of energy from the sun. This enables radar operators to collect imagery and elevation data both at night and in poor weather conditions when optical image acquisition would not be possible. Radar images are created by measuring the intensity of the radar backscatter, and assigning it with a value on the scale of 0-250. The amount of energy contained in this backscatter is highly dependent on the surface from which it is being reflected. The dielectric constant of a surface is a major determining factor of the amount of energy that will either be reflected or absorbed by the surface. For example, agricultural fields will return different amounts of backscatter depending on the amount of water in the soil. Thus, a field with very similar structural properties but differing levels of soil moisture may appear slightly different in a radar image. Surface structure is another major factor in determining the amount of backscatter a sensor will receive over a certain area. This is one of the primary differences between radar and optical systems, as radar is dependent more on structure and composition versus surface reflection in optical systems. Areas that have a rough surface generally return a stronger signal than areas with a smooth surface. For example, a forest will return a stronger signal than a smooth road will, assuming the radar frequency remains the same. This surface roughness creates a valuable "texture" component within the image, providing the user with valuable information on the makeup of the land cover in a given area. In order to derive this land cover information from a radar image, this texture must be a major component of the analysis. While different classes of land cover may have a similar tone in a radar image (shrub, grass, and forest could have similar tones) they will all have different textures due to the diffuse reflection within a patch of vegetation, thus providing a valuable parameter for deriving land cover.

In order to help with the validation of the land cover derived from the radar imagery, as well as the NLCD, field measurements were collected at all of the study areas. These measurements were taken at various verification checkpoints (VCP) throughout each study site, as a way to validate both datasets.

STUDY AREAS

In order to observe a wide variety of land cover classes, analysis for this study was performed in a number of different locations throughout the United States. There were three locations within the western U.S. and two in the Upper Midwest/Great Lakes region (Figure 1). These locations give a good analysis of the varying climate and land cover types throughout the U.S., as well as to provide insight into the feasibility of using radar imagery as a base for a nationwide land cover dataset.

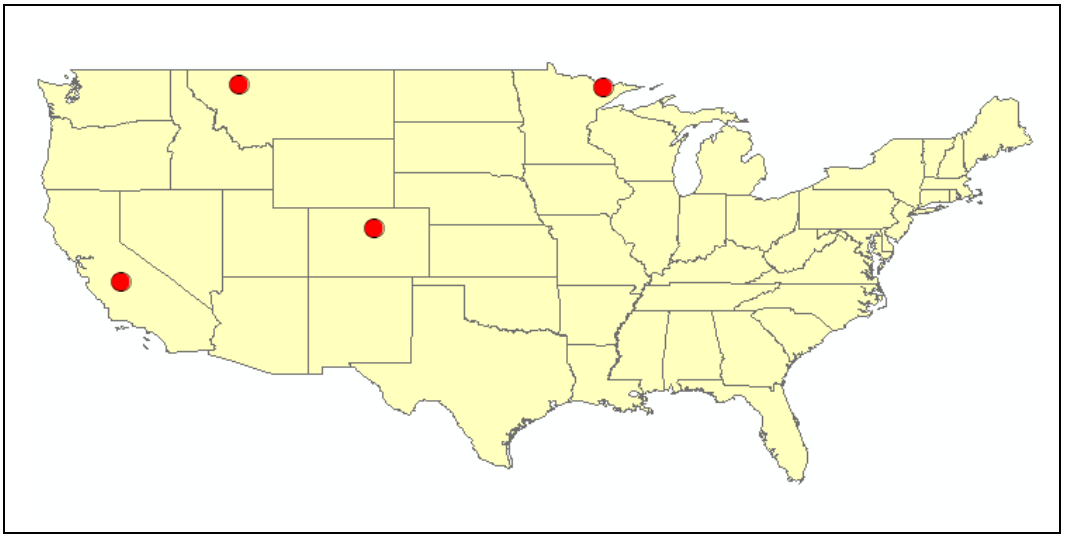

Figure 1. Location of the study sites.

Western Study Sites

All of the western study areas had very similar land cover types, as they all were in relatively similar climatic conditions. The primary classes of land cover that were identified throughout these locations include grass, shrub, wetlands, evergreen forest, deciduous forest, urban, water, and rock/barren. The Colorado and Montana locations contain fairly similar vegetation types, with evergreen forest prominent in both. Terrain relief is significant in both as well, as the Colorado study area is located along the Front Range of the Rocky Mountains, while the Montana location lies within the Bob Marshall Wilderness in north central Montana. The primary difference between these locations is the amount of urban development within the Colorado study area. Almost the entire eastern half of the Colorado site is urbanized, with several western sections of the Denver metro area present in the image. There are also several small to medium sized water bodies located in the Colorado study site, while only a couple of small ponds lie within the Montana tile. The California study area has a much drier and more sparsely vegetated landscape, with the primary land cover classes being shrub, barren, or grass. There is, however, a significant portion of irrigated agricultural land within eastern sections of this location, which provide a stark contrast to the rest of the study area. Urbanization is also very sparse in this area of interest.

Eastern Study Sites

The two locations in Minnesota, provided a landscape more indicative of the eastern United States. The first of the study areas is located along the eastern edge of International Falls, Minnesota, and lies on the U.S. border with Canada. There is a significant amount of urban development throughout the eastern portions of the study area, while the rest of the tile primarily consists of dense evergreen, deciduous, and mixed forest. There are also areas of wetlands, open water, shrub, and grassland. The second Minnesota location has sparse urban development, with few roads and houses widely scattered throughout the area. There are also significant water bodies, deciduous and evergreen forest, as well as grassland and shrub classes.

METHODS

Pixel-Based Classification Process

Given the different tendencies and characteristics of radar data versus optical data, a non-traditional method of classification was needed in order to play into the strengths that radar data possesses in this application. In the case of the NLCD, a pixel based analysis was employed. Analyzing a scene on a pixel-by-pixel basic can be effective in the case of optical data, but this method can be less effective when applied to radar data. The primary issue we run into when attempting to classify radar data pixel-by-pixel is associated with the texture of the image. Radar images generally have some noise within the image known as coherent speckle. This speckle can cause problems with a pixel based classification, as pixels of varying tones lie within every class of data. These varying tones give the image its roughness and texture, which combine to provide the useful information necessary to derive land cover. When radar imagery is processed through a pixel based image classification workflow, the result can often be a "salt and pepper" like classification. (Mansor, Date last observed 9/9/09) In this study an object-based classification system was utilized.

Object-Based Classification Process

Object-based classification identifies pixels with similar characteristics, and aggregates them into meaningful objects, referred to as segments. This is accomplished by taking the average value (tone, brightness, saturation, etc.) of the multiple pixels in close proximity of each other, and assigning these pixels the average value. These averaged pixels are then grouped onto small objects termed "segments". Segments can then be grouped together with other similar segments, and finally classified. Object-based classification is particularly useful when applied to radar data, as there is generally a wide variety in pixel tones throughout the image. In vegetated areas such as forest or shrub, the wide range in pixel values is particularly troublesome, as the diffuse reflection caused when a radar signal interacts with a vegetated canopy, leads to a wide distribution of returns to the sensor. Each return can have a image tone ranging from 0 to 255 (for 8-bit imagery). Given the variation of tone within a vegetation canopy, a pixel based classification would classify a forest area into a number of different classes based primarily on image tone, even though only a single class is present. Another potential benefit of object-based classification is that it allows for the analysis on not only tone, but texture and spatial attributes as well. The added information of texture and spatial attributes results in a more robust classification of land cover. In particular, texture characteristic is the most valuable trait for land cover classification within a radar image.

Classification Methodology

The software used to perform this analysis is the ENVI feature extraction module from ITT. This software allows the user to conduct analysis on tone, texture, and spatial attributes simultaneously. These attributes combine to give the user a group of objects within an image that can then be classified. After object classification, either manually or by creating an unsupervised rule set, the results are exported to land cover layers. The workflow employed within ENVI consists of three basic steps, filtering, segmentation and classification. The airborne X-band NEXTMap data will be classified to land cover classes consisting of water, bare earth, urban development, grassland, shrub, deciduous forest, evergreen forest, mixed forest and wetlands, as defined in Table 1.

Table 1. Land Cover Classes and Description modified after Homer et al., 2007.

Land Cover Class	Description
Open Water	All areas of open water, generally with <25% cover of vegetation or soil.
Barren Land	Areas of earth material with <15% vegetation cover.
Urban-Developed	Highly developed areas such as apartment complexes, row houses, and commercial/industrial. Impervious surfaces account for >50% of the total cover.
Hay Grass Pasture	Areas dominated by grasslike plants, sedges and forbs or herbaceous vegetation, generally >80% of the total vegetation.
Shrub Crop	Areas dominated by shrubs <5 m tall with shrub canopy typically >20% of the the total vegetation.
Deciduous Forest	Areas dominated by trees generally >5 m tall and >20% total vegetation cover. More than 75% of the trees species shed foliage simultaneously in response to seasonal change.
Evergreen Forest	Areas dominated by trees generally >5 m tall and >20% total vegetation cover. More than 75% of the trees species maintain their leaves all year.
Wetland	Areas where forest, shrubland vegetation accounts for >20% of vegetation cover or where perennial herbaceous vegetation accounts for >80% of vegetation cover and the soil or substrate is periodically saturated with or covered with water.

Step1: Data Filtering. The use of SAR imagery in forest/non-forest separation has proven feasible and is widely reported in the literature (Baltzer et al., 2000; Hoekman et al., 2002; Engdahl et al., 2003). SAR imagery is however, dominated by speckle. Therefore, for land cover classification and extraction of land cover from these data to be successful, speckle suppression was performed before vegetation classification. From amongst many commercially available speckle filters, for land cover classification, Quegan et al. (2000) concluded that the most appropriate form of filter is simple adaptive averaging. A gamma filter (two iterations of a 3 by 3 boxcar) was applied to generate an ORI with reduced speckle. NEXTMap® data for all study sites were collected during leaf-off conditions and where wetlands were more dried out. Within ENVI there are a number of radar filters, each with benefits and drawbacks. When the filter is run, it averages like pixels so their attributes more closely match its neighboring pixels. This process makes the later steps within ENVI run more accurately, as pixels which have more similar attributes will be classified more accurately. The filter employed herein was a gamma filter, which is optimized for radar imagery and effective at reducing speckle, while still preserving borders and lines. One of the major benefits of a gamma filter is its tendency to preserve stark boundaries, such as a barren field next to a road. The primary reason for filtering the data is to make analysis more accurate, as well as reduce coherent speckle and noise. One consideration is to “not” over-average values (or over filter) between contrasting land cover types since the accuracy and effectiveness of the analysis could be diminished. On small scale land cover projects, the preservation of natural and artificial boundaries is critical in the preservation of accuracy. This is accomplished employing small size (3X3 or 5X5) boxcar filters.

Step 2: Image Segmentation. Image segmentation is the process of taking homogenous pixels, and converting them into recognizable, real world objects to help with recognition of a particular land cover class. A moderate segment size was chosen so that details about structures, small patches of vegetation, and water bodies were preserved, without making them so small that speckle and processing time would become issues. This step results in all of the pixels within the image being analyzed merged into segments, which is the precursor step to segment definition.

Step 3: Segment Definitions and Classification. Segments are next defined prior to the classification process. There are two primary methods of performing segment definition using ENVI software. First, is manual segmentation definition, which may be performed by selecting several segments which possess characteristics representative of a particular land cover class. Once segment definition is completed, classification in performed on the segments, rather than pixels. Second, segments are defined using a user defined rule set. This is suited for any size area of interest, as it allows the user to automate your workflow. Rule set segmentation definition diminishes the amount of manual work required to classify an area; however the development of these rules sets can be time consuming. Rule set segmentation definition allows for automation as it may be applied to large geographic extents. The rule sets can be developed to classify segments based on several variables, such as texture, tone, size, and shape. In the case of radar imagery, the textural and spatial attributes tend to be the primary variables under consideration.

The rule set method was not employed in this study because supervised classification was employed. In the future however, this will most likely be the more suitable method of classification. The NLCD were used as a guide to help with the definition of segments. In addition, the NEXTMap elevation data were also utilized to help define segments. Of particular use were the subtraction of the digital terrain model from the digital surface model to create an above the ground feature height model. This allowed for better separation of open, grass, shrub, urban and forested land cover classes. Once steps 1-3 were completed, each of the nine land cover classes (were applicable) were exported in shape file format. The results were compared to fielding-situ measurements at these locations to validate the results of the classification from both the ORI, as well as the NLCD dataset (Tighe et al., 2009).

Accuracy Assessment of Land Cover

Accuracy for the NEXTMap® USA and NLCD derived land cover maps was assessed against the field observations in detail using error matrices and their associated statistics, namely: overall accuracy, class Producer's Accuracy (PA), class User's Accuracy (UA), the average UA and PA (Foody, 2004).

DISCUSSION/RESULTS

Western Study Area Results

Tables 2 and 3 present the accuracy assessment for the western study sites for the NEXTMap land cover maps and the NLCD maps, respectively. The diagonal elements contain the number of samples correctly identified for each class. Results indicate that the NEXTMap® derived land cover maps achieved an overall accuracy 86.30% with the primary confusion was between barren and shrub and between deciduous and mixed forests. The NLCD map had an overall accuracy of approximately 63.93%, often confusing deciduous and mixed, underestimating evergreen and overestimating shrub vegetation classes. The Colorado location was dominated by the grass, urban, and evergreen classes. Both the NLCD and the ORI had good results identifying the urban areas within the eastern urban areas, however there ORI derived urban layer had significantly more coverage due possibly to temporal change. (NLCD data is older, while NEXTMap data was collected in the 2005 – 2008 range). Within the higher elevations in the western portion of the tile, there was also significantly more evergreen coverage within the ORI versus the NLCD. As was the case within many areas, the NLCD seemed to be overly biased towards the shrub class, while this class was not prevalent at all within the ORI derived land cover. Water bodies were also underrepresented within the NLCD class, but there could be multiple causes for this issue. One issue the ORI land cover had within this location was the over classification of urban classes within the mountain areas. While the urban was well represented within the eastern portions of the tile, the classification seemed to struggle more with classifying this class in areas where forest and structures are mixed. The NLCD showed no urban classes within this area; however this is most likely due to the larger post spacing of the dataset. Also, some small areas of shadow or bright returns within the evergreen forests were occasionally classified as urban, as were some small areas of rock. One solution to this issue would be to increase the size of the segments within this area, as this could merge some of the speckle into objects and alleviate this issue. Some of the ancillary datasets used in this area were the 1.0m NAIP imagery, Intermap Digital Surface Model (DSM), and several types of optical satellite imagery. Within the Montana study area, there were fewer land cover classes than the Colorado area due to the remoteness of this site. The primary class was evergreen, which dominated most of the tile. This class was well represented by both the NLCD as well as the ORI, while some of the less prominent classes were limited or missing in the NLCD. Grassland classes were largely missing in the NLCD, while being relatively prominent in the ORI derived land cover. This was especially the case on the edges of the forest, as well as within several large burn areas spread throughout the study area. Another problem within the NLCD was water bodies. While there were only a few small lakes in this area, they were underrepresented in the NLCD. Rock and barren classes prominent in the higher elevations above the tree line were also underrepresented in the NLCD. Some of the problems associated with the ORI land cover, included a small area of wetlands which was present within the NLCD but missing in the ORI class. This was confirmed by viewing this area within a set of NAIP images, as well as the ORI, which both confirmed the presence of the wetlands. The wetlands were classified as grass, as the texture was similar to tall grasses; however had a higher dielectric constant due to the presence of water. This could be corrected by the use of ancillary data, such as optical data or elevation data. Another issue the ORI derived land cover had was several large shadows within areas of high terrain relief. As the radar sensor received no return signals in this area, it has the same tone and texture as water, and therefore was classified as such. This could also be corrected by use of ancillary data. The California area was relatively different from the rest of the western locations as it was not only a more arid climate, but it featured significant areas of agricultural coverage. The NLCD and ORI both had very positive results delineating the agricultural classes, as well as some of the evergreen dominated areas in the higher elevations. The issues for the NLCD were primarily focused around differentiating between evergreen and shrub classes, as there was some confusion between the two. The NLCD overestimated shrub and underestimated evergreen in the higher elevations, while also missing many of the irrigation canals surrounding the agricultural areas. The missing canals are most likely due to the pixel size of 30m, as this is much larger than the canals themselves. In many cases, even the 5m pixel of the ORI land cover was too large to detect the canals. Urban was primarily missing within this area.

Table 2. Western Study Sites NEXTMap Classification Results – 86.30% Overall Accuracy.

Western Study Sites		NEXTMap® Land Cover Map							
		Evergreen	Deciduous	Mixed	Wetland	Shrub/Scrub	Barren	Urban	
Field	Data: Evergreen - 36	34	0	2	0	0	0	0	36
	Deciduous - 66	0	55	11	0	0	0	0	66
	Mixed - 36	0	9	27	0	0	0	0	36
	Wetland - 0	0	0	0	0	0	0	0	0
	Shrub/Scrub - 66	0	2	0	0	59	5	0	66
	Barren - 8	0	0	0	0	0	7	1	8
	Urban - 7	0	0	0	0	0	0	7	7
		34	66	40	0	59	12	8	86.30%

Table 3. Western Study Sites NCLD Classification Results – 63.93% Overall Accuracy.

Western Study Sites		National Land Cover Data (NLCD)							
		Evergreen	Deciduous	Mixed	Wetland	Shrub/Scrub	Barren	Urban	
Field	Data: Evergreen - 36	23	9	2	2	0	0	0	36
	Deciduous - 66	3	42	0	2	0	19	0	66
	Mixed - 36	2	12	22	0	0	0	0	36
	Wetland - 0	0	0	0	0	0	0	0	0
	Shrub/Scrub - 66	0	12	0	0	43	11	0	66
	Barren - 8	0	0	0	0	0	5	3	8
	Urban - 7	0	0	0	0	0	2	5	7
		28	75	24	4	43	37	8	63.93%

Eastern Study Area Results

Tables 4 and 5 present the accuracy assessment for the Eastern study sites for the NEXTMap and the NCLD land cover maps, respectively. Results indicate that the NEXTMap® derived land cover maps achieved an overall accuracy 86.91% with the primary confusion was between barren and urban and between deciduous and mixed forests. The NLCD map had an overall accuracy of approximately 59.16%, often confusing deciduous and shrub with wetlands, underestimating evergreen vegetation classes. The NLCD and ORI land cover within the two Minnesota tiles showed many of the same errors that were present in the western study areas. Urban was actually well represented in both land cover products; however roads were a problem in both the NLCD and ORI products. Within the NLCD, some of the roads were present while others were missing, most likely depending on the size/area of the roads. Within the ORI land cover, some of these roads were misclassified. As the roads within the ORI have very similar characteristics to water, some were classified as such. Also, some roads within the ORI land cover lied under shadows from the surrounding forest, and were either obscured or classified incorrectly. As far and the vegetation, both products performed fairly well, however the ORI classified many of the vegetations correctly when the NLCD did not. One notable exception would be a significant area of wetlands in the Southern reaches of the International Falls tile, which the ORI land cover has classified as deciduous or evergreen forest. These issues could be corrected with more extensive use of ancillary data during classification of segments. Water was also classified incorrectly or underrepresented by the NLCD in several areas, including some small ponds, water treatment ponds, and rivers/river inlets.

Table 4. Eastern Study Sites NEXTMap Classification Results – 86.91% Overall Accuracy.

Eastern Study Sites		NEXTMap® Land Cover Map							
		Evergreen	Deciduous	Mixed	Wetland	Shrub/Scrub	Barren	Urban	
Field Data	Evergreen - 36	30	3	3	0	0	0	0	36
	Deciduous - 66	0	60	6	0	0	0	0	66
	Mixed - 36	0	7	29	0	0	0	0	36
	Wetland - 18	0	2	0	16	0	0	0	18
	Shrub/Scrub - 24	0	0	0	2	22	0	0	24
	Barren - 8	0	0	0	0	0	6	2	8
	Urban - 3	0	0	0	0	0	0	3	3
		30	72	38	18	22	6	5	86.91%

Table 5. Eastern Study Sites NCLD Classification Results – 59.16% Overall Accuracy.

Eastern Study Sites		National Land Cover Data (NLCD)							
		Evergreen	Deciduous	Mixed	Wetland	Shrub/Scrub	Barren	Urban	
Field Data	Evergreen - 36	16	10	2	8	0	0	0	36
	Deciduous - 66	4	41	0	18	0	3	0	66
	Mixed - 36	3	4	19	6	4	0	0	36
	Wetland - 18	3	0	0	15	0	0	0	18
	Shrub/Scrub - 24	0	1	0	8	14	1	0	24
	Barren - 8	0	0	0	0	0	5	3	8
	Urban - 3	0	0	0	0	0	0	3	3
		26	56	21	55	18	9	6	59.16%

Overall Results

Some of the primary issues encountered with the NLCD are due partly to the larger post spacing. For one, small features such as roads, thin water bodies, and some urban development are missing in the NLCD due to its pixel size. Also, shrub was overestimated in almost every location tested, specifically the western study areas. Also, many of the NLCD's issues can be attributed to temporal change, cloud cover, and pixel based classification. While the NEXTMap ORI yielded a much higher accuracy for many of the land cover classes that it can be used to classify, it is not without issues. For one, shadow is a significant problem in areas of high relief, as well as highly vegetated areas. The shadows within the ORI possess the same attributes as water bodies, and must be corrected for using ancillary data. This adds some significant time and work to creating this product, but is necessary especially in areas of high terrain relief. Also, there is some confusion within the ORI with objects/classes that appear similar. Many roads resemble rivers, and are occasionally classified as such. Also, some forested areas can be confused with urban classes, as the two have similar tone and texture characteristics.

CONCLUSIONS

Derivation of land cover from NEXTMap radar imagery as an alternative to optical data is a viable option, once some of the challenges in its implementation can be addressed. There are many positive attributes of radar imagery which can make it valuable in the creation of nation wide land cover datasets. For one, this data is collected from an active sensor; therefore any issues associated with lighting and weather becomes a non-factor. There is no cloud cover in radar data, and it can be collected at night, in any lighting condition. Additionally, the ORI we used in this research has significantly higher resolution than the Landsat data (1.25m versus 30m). Finally, certain areas which may not be distinguished in an optical image can be delineated within a radar image. (For example, shrub and grass classes which may appear similar in an optical image, but have contrasting textures in a radar image.) This data combined with the utility of object-based classification software holds great promise in the creation of a higher resolution land cover dataset on a nationwide basis. Given all of the positive attitudes of this data, there are several challenges that must be addressed in order for higher accuracies to be accomplished on a nationwide basis.

FUTURE WORK

Intermap's ORI is seamless and consistent throughout the entire U.S., which provides the capability to create consistent land cover data on a nationwide basis. Manual editing by different operators would most likely lead to slight differences from region to region, as different editors will have different tendencies when classifying land cover. Going forward, an extensive set of classification rule sets are planned for development in order to reduce manual work, as well as processing time. This will also work to create a homogenous dataset throughout the country. The development of this rule set will also help to correct some of the issues associated with urban and forested areas. Finally, a solution must be developed to deal with radar shadow. This will most likely involve use of an ancillary dataset to infill and properly classify these areas.

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