Lidar Pilot Study

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Introduction

This section of the report describes a pilot study that investigates the potential benefits of light detection and ranging (lidar) data for wetland analysis in Virginia.

Light detection and ranging (lidar) data

Lidar sensors are described as active sensors, where high energy laser pulses transmitted in short intervals are directed toward the ground and the time of pulse return is measured. Since the velocity of light is constant (i.e., 3×10^8 m s^{-1}), the elapsed time between transmitting and receiving the pulse can be used to determine the distance between the sensor and object or the ground, through a process known as pulse ranging (Wehr and Lohr, 1999). Using this concept, x, y, and z measures can be obtained in the form of a point cloud, with horizontal accuracies of 50 cm and vertical accuracies of 10 cm (Baltsavias, 1999; Wehr and Lohr, 1999; Lim *et al.*, 2003, Thomas, 2006).

Modern airborne lidar sensors are described as either "discrete" (i.e., time-of-flight) or "full waveform", depending on how they sample the vertical and horizontal structure of the canopy. Lim *et al.* (2003) describe discrete systems as having the capability of recording one, two, or a few returns for each transmitted laser pulse (i.e., because each pulse consists of multiple photons). The horizontal sampling is determined by the ground area of the footprint which is a function of the divergence of the laser pulse and flying height, and the number of footprints per unit area. In contrast, full waveform systems record the amount of energy returned to the sensor over equal time intervals. The number of these time intervals determines the level of detail of the canopy profile within the laser footprint. This study utilizes discrete airborne lidar systems which record two or more returns for each laser pulse.

In general, discrete lidar data can be described as a three-dimensional point cloud, subsets of which can be easily viewed in a 3-D scatterplot (Figure 1a, for the pilot study site). Profiles along transects provide an alternative view showing the detailed depiction of the ground, vegetation, and understory (Figure 1b, for the pilot study site). Many authors have used the vegetation returns to assess biomass, understory, and forest biophysical parameters. In fact, lidar is becoming so "mainstream" that is being widely considered as the principle technology for forest inventory mapping. Research conducted over small areas has illustrated successful modeling of forest biophysical variables to a high degree of accuracy and precision (Næsset 1997; Magnussen and Boudewyn 1998; Means et al. 2000; Lim and Treitz 2004; Hopkinson et al. 2005). Transition of this success to larger scales has been limited in North America, but is

being actively researched in Norway and Sweden (Næsset and Bjerknes 2001; Næsset 2002; Holmgren 2004). In Norway, there are at least six large-scale commercial projects in operation that use high-density airborne lidar. Naesset (2004) validated the findings of one of these projects to confirm the accuracy of models of mean height, dominant height, basal area, and volume over the entire area. Large swaths of northern Ontario, Canada have had data acquisitions by forest companies and the provincial government for inventory purposes.

While the adoption of lidar data for forest inventory purposes is being closely examined by many interested parties, the use of lidar for wetland studies is in its infancy. Wetland studies are typically more interested in the detailed micro-topography that can be derived from digital elevation models (DEMs) with vegetation removed. Removal of vegetation is a somewhat divergent goal between wetland studies and most vegetation/forestry studies. Hence, lidar data collected for wetland studies is often a winter activity, with the goal of removing as much of 'confounding vegetation' as possible prior to the development analysis of the DEM. **In practical terms, this means that it is generally not optimal to use the same lidar acquisition for forestry and wetlands applications** (unless wetland vegetation is the primary interest). Rather, if agencies interested in wetlands studies wish to reduce lidar acquisition costs by collaborating with other groups, they are likely better off collaborating with those parties more interested in the DEMs with vegetation removed, such as groups interested in transportation, geology, landforms, mining, etc.

Recent work using lidar for wetland studies

Lidar data can provide detailed and accurate ground elevation information for the identification of micro-topographic features that indicate the presence of wetlands, which would otherwise be undetected. Fine-scale elevation data is particularly helpful in flat, wetland-rich areas where complex interspersion of uplands and lowlands may cause mapping confusion and inaccuracy (Maxa and Bolstad 2007). Lidar is a relatively new technology and its full potential in wetland related studies is yet to be realized. Hogg and Holland (2008) compared the use of digital elevation model (DEM) derived from lidar, 1:20,000 point elevation data source and 1:50,000 National Topographic Series-based DEMs to detect wetlands at Turkey Lakes region of Ontario. Wetland classification results with lidar were significantly high compared to other methods and 35% of the wetland mapped by lidar was not detected by other methods. Richardson et al. (2009) used DEM derived from lidar to not only classify wetlands but also to delineate wetland boundaries using various topographic indices and edge detection procedures. Various information derived from lidar data in combination with optical data have the potential for improving wetland mapping. Specifically, studies have utilized lidar derived DEM for calculating wetness index (Murphy et al. 2009; Richardson et al. 2009; Sorensen and Seiber 2007) which

can be used as indicator of wetland distribution. Forested wetlands are one of the most difficult wetlands type to detect as their associated canopy layers prevent detection of underlying hydrology, and relatively small variations in topography can form these types of wetland. Based on these preliminary findings, the general feeling is that high resolution DEM as provided by lidar coupled with optical data can improve mapping of forested wetlands.

Pilot Study Objectives/Questions

Before the expense of lidar acquisition for large areas is incurred, it is necessary to ask if the benefits of acquiring lidar data are worth the expense, particularly if the full cost of lidar data is incurred by a single entity (company, government agency, academic institution, or other). From a wetlands perspective, there has been speculation about the benefits of DEMs that provide information on micro-topography but specific benefits, as well as the robustness of analyses techniques, are unknown at this time. Our pilot study begins to investigate several questions of interest for Virginia wetlands such as:

1.) Can DEMs derived from lidar data provide information on depression features that would improve the identification of wetlands in agricultural fields, forested wetlands, or other areas that have large omission errors in the National Wetland Inventory?
2.) Can we use simple indices of wetness, such as the topographic wetness index, to map the potential of the landscape to be a wetland, that provides either an improvement over NWI, or that identifies previously unknown wetlands?
3.) Can detailed micro-topography derived from lidar help us to identify man-made features in wetlands that might be indicative of wetland restoration or disturbance activities?

Study Area

The pilot study area consists of the Cedar Run Watershed and surrounding landscape in Prince William and Fauquier counties, Virginia (Figure 2). This region was selected for a number of reasons. First, the Cedar Run wetlands bank consists of 715 acres of created wetland, constructed in former cattle pasture and cultivated land. This provides a good test for the identification of restoration activities (i.e., non-natural wetland forms).

The Cedar Run wetlands were created in different phases in different tracts of land:

- Phase 2: 63–acre completed in September 2000
- Phase 3 and 4: 245-acre completed in October 2001
- Phase 2A, 6, and 8: 230-acre completed in October 2002

- Phase 1B and 9: 67-acre completed in October 2004
- Phase 10: 106-acre completed in September 2005

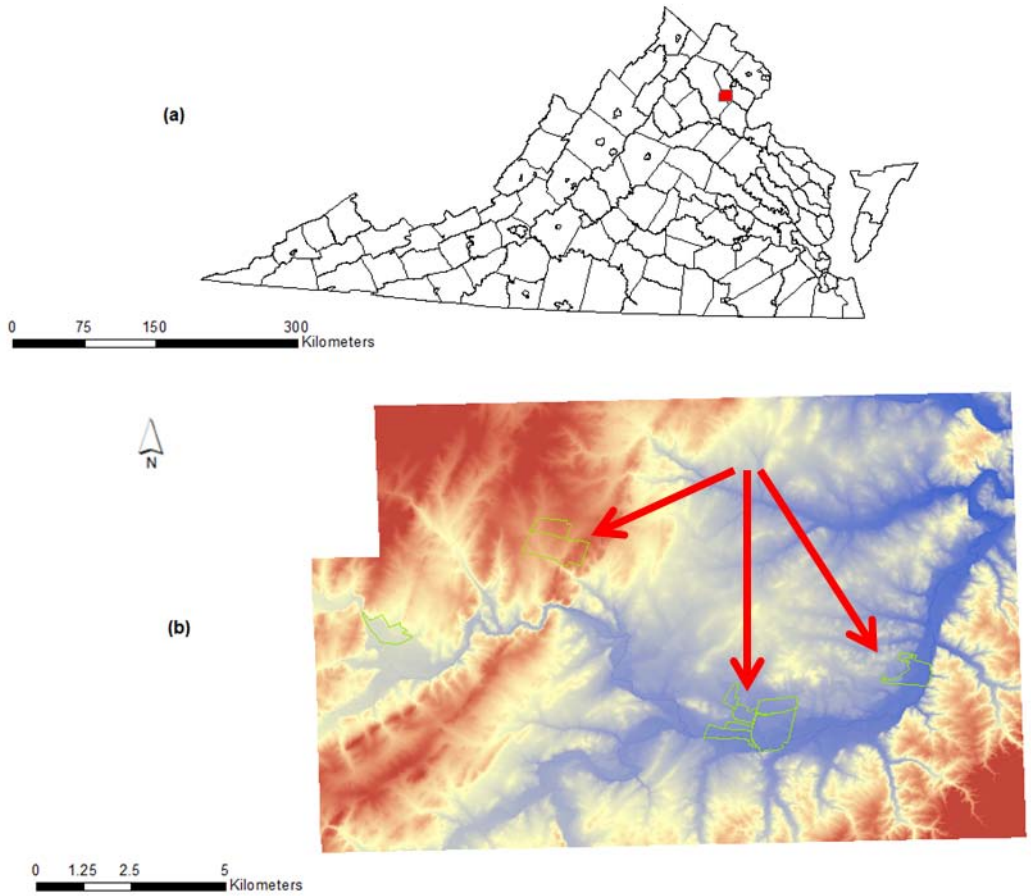

Figure 1. Pilot Study Area. a) Location of the Cedar Run Watershed in Virginia. b) Location of created watersheds within Cedar Run (green outlines, indicated by red arrows), overlaid on the lidar-derived digital elevation model.

The Cedar Run wetlands and the surrounding landscape are fairly typical of this region in Virginia, and have mixed land cover, including agriculture, forest, forested wetlands, roads, etc. (Figure 3).

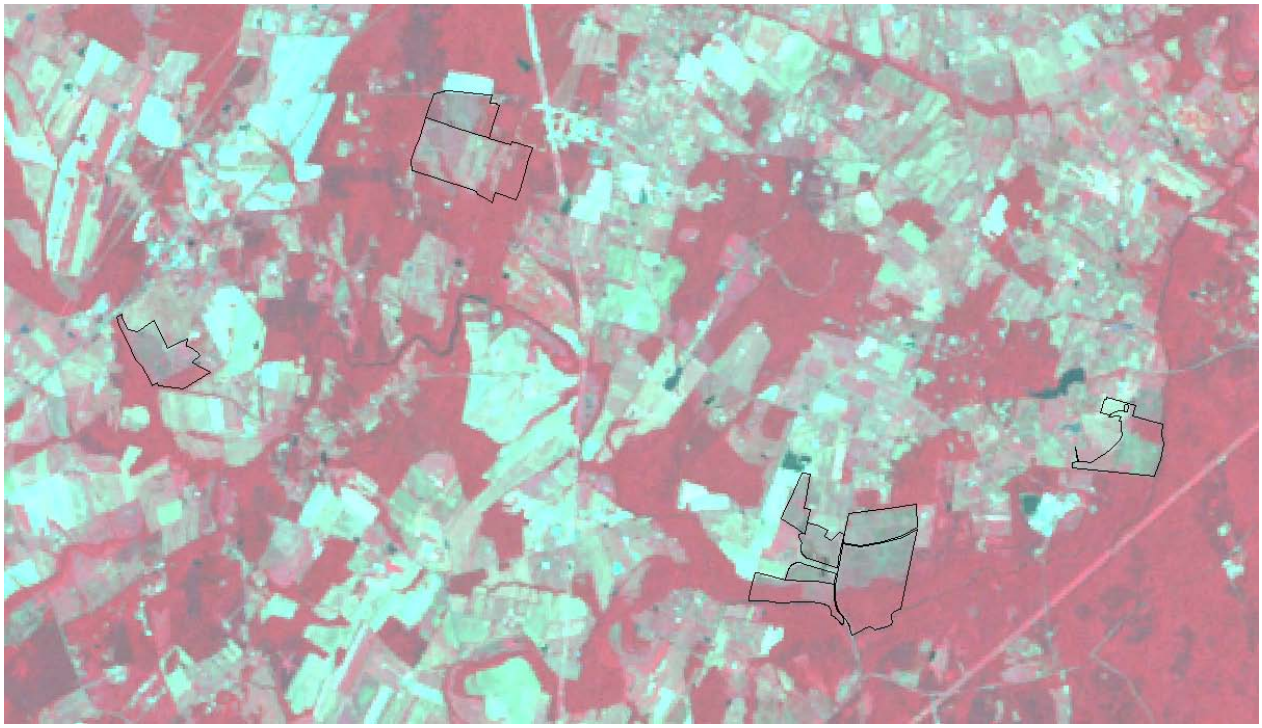

Figure 2. False color Landsat Image of Cedar Run Wetlands and surrounding landscape. Mixed land cover classes are evident, where cyan represents cleared, non vegetated areas, pink indicates crops, and red is forest cover. The Cedar Run wetlands are outlined in black.

The second reason to select the Cedar Run Watershed that is that lidar data flown at a "typical" density were available for this area. These data were acquired using Leica Systems ALS50 II on December of 2008 by [1]Science Applications International Corporation. The sensor was flown at 6500 feet with a field of view of 44 degrees and scan frequency of 41.3 Hz. First and last returns were collected for each pulse. The bare earth model was calculated by identifying the ground returns and interpolating a surface between these points with a resolution of 1 meter. Based on 45 control points, the average error between bare earth and control points was 0.004 meter with a root mean square error of 0.107 meter.

Pilot Study Analysis: Question 1.

Can DEMs derived from lidar data provide information on depression features that would improve the identification of wetlands in agricultural fields, forested wetlands, or other areas that have large omission errors in the National Wetland Inventory?

[1] http://www.saic.com/tools/contact.html

In many cases, localized depressions within agricultural fields and woody areas are characteristic of wetlands. These areas are not typically classified as wetlands in the NWI but could potentially be identified through the analysis of high quality lidar DEMs. To examine this, we utilized tools developed for hydrologic analysis within a geographic information system (GIS). We specifically used the hydrologic analysis tools in ArcMap Spatial Analyst, but point out that several GIS packages perform similar analyses, including the freeware "GRASS". There are several tools for hydrologic analysis that are designed to delineate watersheds and create stream networks. We specifically used "sink" analysis, which identifies sinks, or areas that have lower elevations than the surrounding areas. In most applications, sinks are considered to be erroneous elevations that skew hydrologic analysis because during waterflow simulations, water that flows into them cannot flow out. The normal procedure is to identify sinks and fill them to remove the erroneous depressions. We performed an additional step, and subtracted the original DEM from the "sink filled DEM" to identify depressed areas. In this fashion, spurious depressions can be ignored, but larger depressed areas (still smaller than a watershed) can be identified. We noted several instances of depressed areas that are currently not classified as wetland areas in the NWI, but may very well be wetlands. Some examples are illustrated below, with probable wetland areas outlined in red over NAIP aerial photography.

Figure 3. Probably wetland depression example in agricultural fields.

Figure 3 illustrates two depressed areas in agricultural fields that likely have wetland characteristics. The upper left area is particularly note worthy, with evident drainage and vegetation patterns.

Figure 4. Probable woody wetland areas, based on significant depressions.

Figure 4 highlights 4 possible woody wetland areas. Again, the uppermost area has linear patterns in the vegetation that may be indicative of wet areas. The other areas are less obvious. If indeed they are wetlands, the relatively simple depression filling technique is very promising for the improved identification of woody wetlands.

Figure 5. Probable woody wetland areas, based on depressions.

Figure 5 illustrates two probable woody wetland areas north of the road. The lower left area is evergreen forest, while the right hand area is deciduous forest broken by a cleared area.

This preliminary analysis suggests that the relatively simple depression filling techniques, which could be done in most GIS packages, have high promise for the improved identification of isolated wetlands in woody areas and in agricultural fields. The work suggests that there would be value in additional study, particularly in a highly target field validation. The next stages in research would be to quantify the accuracy in the detection previously unidentified wetland areas and the shape of their boundaries.

Pilot Study Analysis: Question 2

Can we use simple indices of wetness, such as the topographic wetness index, to map the potential of the landscape to be a wetland, that provides either an improvement over NWI, or that identifies previously unknown wetlands?

The topographic wetness index (TWI) uses the upslope contributing areas and slope to determine an index of moisture for each cell (Moore et al. 1993). The TWI is defined as

$$\ln\left(\frac{A}{\tan\beta}\right)$$

Where:

A is the upslope catchment area, and

β is the local slope.

This TWI is a compound topographic index (i.e. it is derived from more than one topographic attribute) and reflects the tendency of water to accumulate in the soil at a point in the landscape (accumulated drainage), countered by the tendency of the soil to transmit this water i.e. slope (Murphy et al., 2008). We calculated TWI using the lidar derived DEM at multiple spatial resolutions, including 1, 3, 5 and 10 m.

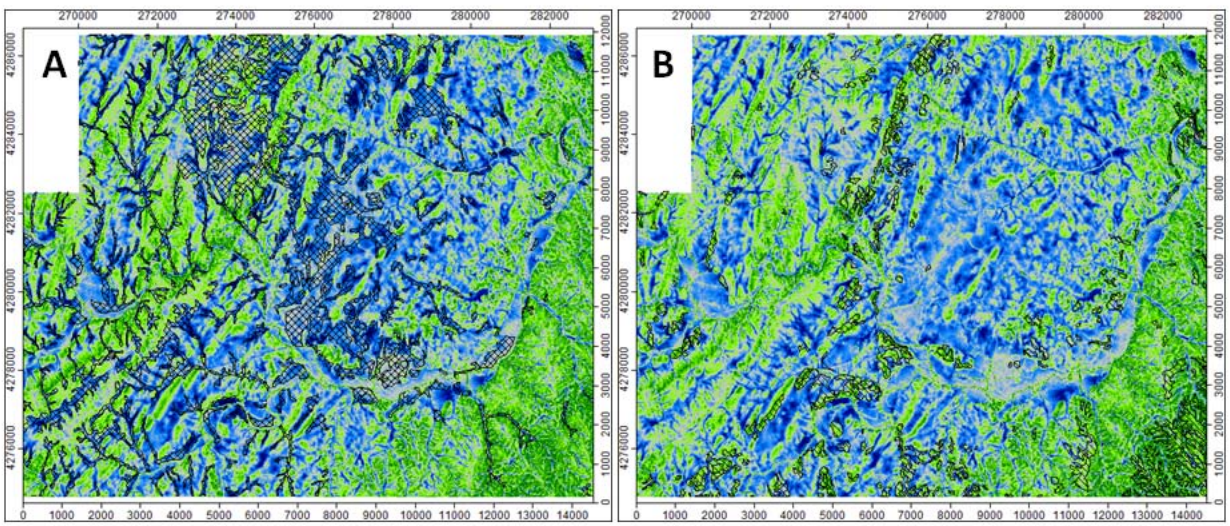

Figure 6. TWI calculated on a 3 m DEM. A) Hydric soil layer shown as crosshatches. B) Non-hydric layer shown as crosshatches. Color scheme ranges from dry green to wet blue.

With limited ability for extensive field validation for this pilot study, we used the hydric soil layer from the SSURGO database as a rough validation for this assessment. Hydric soil is a soil that is formed under conditions of saturation, flooding, or ponding long enough during the growing season to develop anaerobic conditions in the upper part. This is a part of the legal definition of a wetland. It should be kept in mind, however, that there are likely to be inaccuracies in the SSURGO hydric soil layer itself, as it is significantly older than the lidar dataset. However, it serves as a good estimate of potential wetland areas. Figure 6a demonstrates a high correlation between the hydric soil layer and the blue “wet” TWI values. The non-hydric layers shown in 6b correlate very well to the green “dry” TWI values. Note that

there are considerable "blue" areas on the TWI map that are omitted from the hydric soil layer that could, in fact, be wetlands. Further field validation would be required to assess this adequately.

To further this assessment, we performed a regression tree classification of hydric and non-hydric soils. Specifically, we used RandomForest, which is a CART-based analysis. We used a number of topographic variables derived from the lidar DEM in this classification, including the TWI dataset above, slope, plan and profile curvature, and the topographic position index. We validated our classification using the SSURGO hydric and non-hydric soil layers. Overall classification accuracy was 81% (Table 1).

Random Forests Prediction Success.

Actual Class	Total Class	Percent Correct	H N=373	NH N=529
H	291	85.91	250	41
NH	611	79.87	123	488

The classification results suggest 2 things. First, lidar derived DEMs can be used to identify hydric soils through robust classification techniques. Second, it may be possible to further investigate the < 20% discrepancy between the SSURGO hydric layer and the RandomForest classification to see if any previously unidentified hydric soils can be identified. This could also be compared to the NWI directly. In other words, we could assess areas that are classified as hydric in the RandomForest, but that are not classified as wetland in NWI to determine the % unclassified "true" wetlands. Obviously additional field validation would be necessary to confirm these results.

Pilot Study Analysis: Question 3

Can detailed micro-topography derived from lidar help us to identify man-made features in wetlands that might be indicative of wetland restoration or disturbance activities?

This question can most easily be examined by identifying features of interest on the landscape, either through personal knowledge or through aerial photography, and determining the visibility of these features on the high quality lidar DEM. We discuss several examples below.

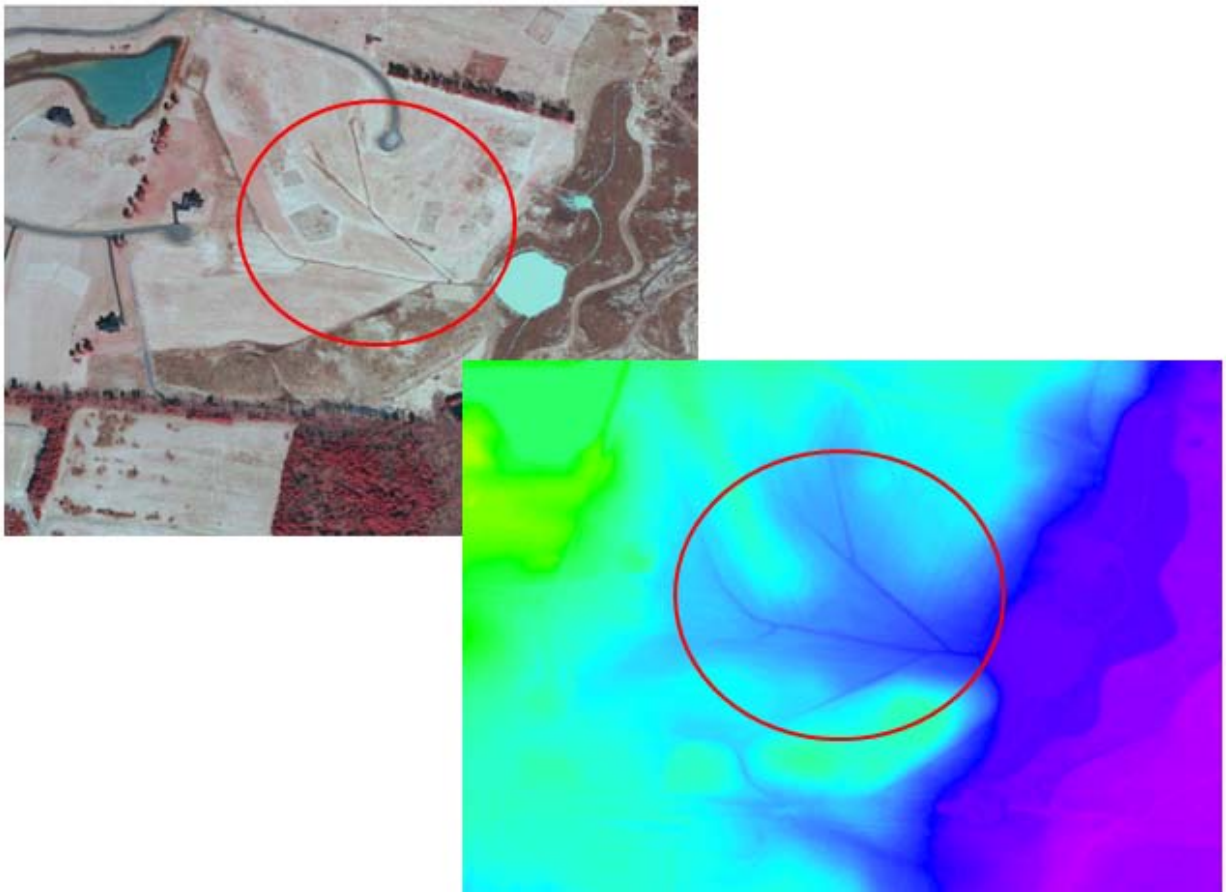

Figure 7. Linear man-made drainage feature.

The first example, Figure 7, illustrates a linear man-made drainage feature that is clearly evident on an air photo, but that is not visible at all in a regular, non-lidar derived DEM. The feature and its details is clearly visible in the 1 m lidar DEM, and would be evident in the streamflow hydrologic analysis discussed above, if that analysis were performed locally. Note that in Figure 7, details to the east of the man-made drainage feature are not very distinct. However, it is possible, through contrast stretching, to magnify the amount of detail, to clearly depict the drainage pond and unique elevation patterns to the east of the pond (Figure 8).

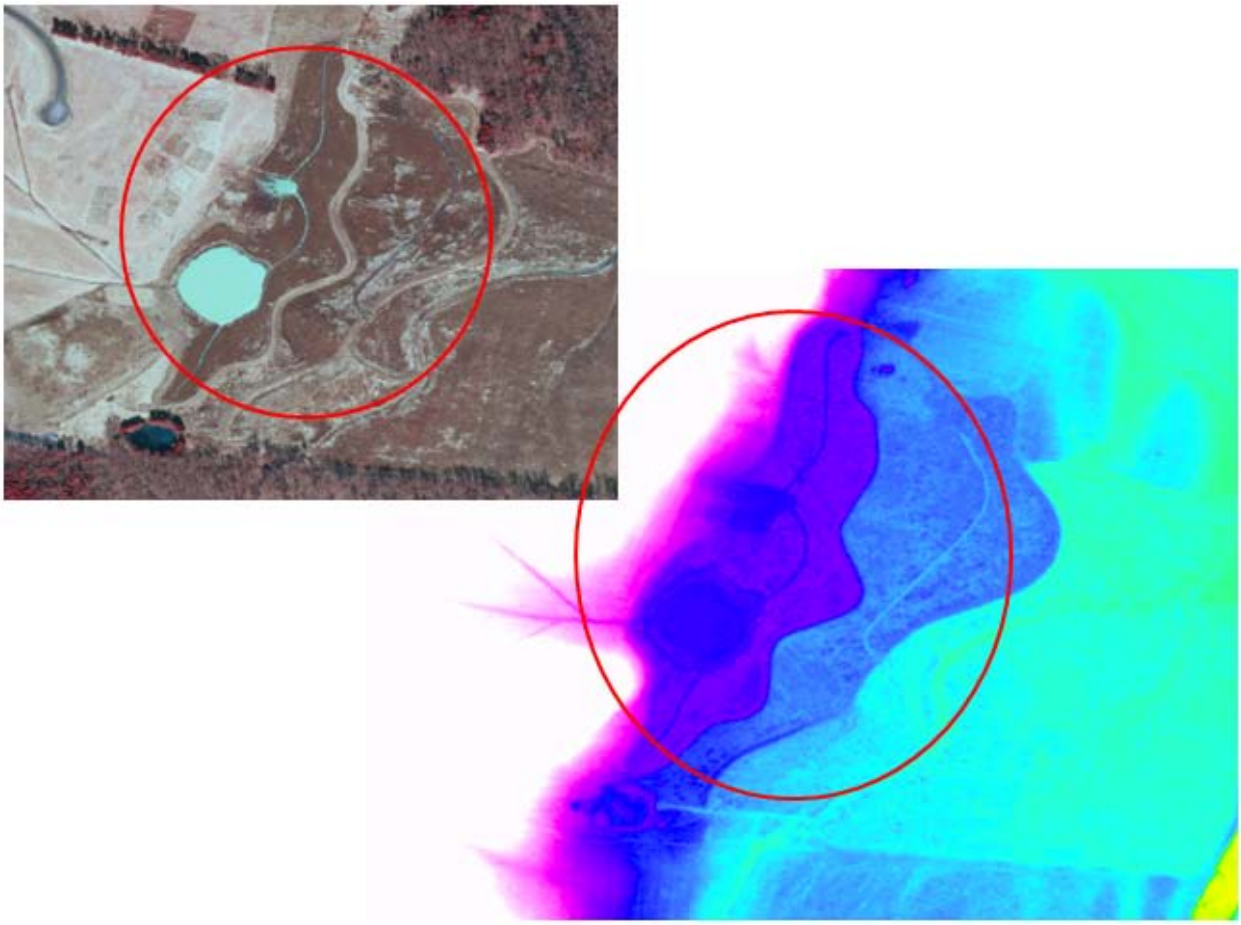

Figure 8. Drainage pond and other elevation features to the east of the linear, man-made drainage feature.

The final example micro-topographic features that are not visible in non-lidar DEMs is shown in Figure 9. The 4 Cedar Run Wetland banks are shown, with the man-made elevation patterns clearly evident in each. In Figure 9a and 9d, the location and shape of the berms, as well as each phase of restoration, can clearly be seen, particularly north of the road.

Further investigation is required to determine if the delineation of these man-made features can be accomplished in an automated fashion that would distinguish them from natural features. At the very least, the DEM itself can provide a very clear view of the pattern an extent of human restoration activities.

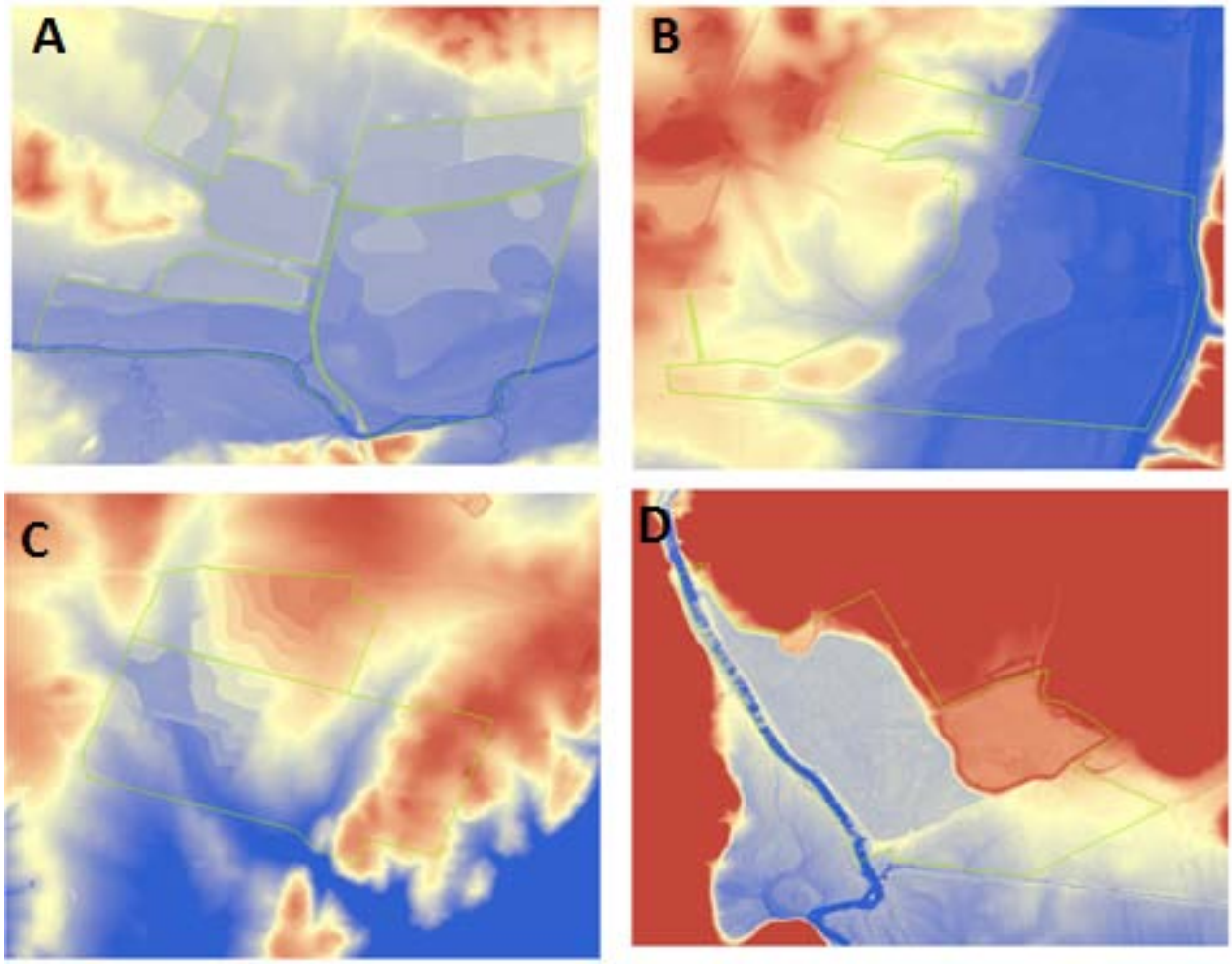

Figure 9. Drainage features in the Cedar Run Wetland Banks

Conclusions

It is evident that lidar-derived DEMs and their by-products can provide considerable detail on micro-topographic features indicative of wetland restoration activities. Our preliminary analysis also suggests that it is likely that lidar can be used to identify previously unknown wetlands using relatively straight forward analysis techniques. Further work is needed to validate these findings. We recommend field validation to quantify the accuracy of wetland identification as discussed for Questions 1 & 2.

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