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Integration of LiDAR and Imagery to Delineate Water Bodies for Change Detection

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Imagery-based classifications of inland water bodies for separate years allow us to observe the change in fresh water concentrations (Canaa, 2013). Surrounding lakes, ponds, and even puddles are various ecosystems that depend on the constant supply of water for agricultural and ecological practices. Through the classifications and integration with LiDAR (Light Detection And Ranging) data, the bodies of water can hopefully be delineated. However, with classifications, issues, such as shadows and flat, non-water areas need to be addressed (Chen, 2009). LiDAR data provides better vertical accuracy and spatial resolution (Gesch, 2009), thus making it ideal to compare to and contrast the other classification approaches.

The purpose of this study was to monitor changes of inland water in Ballard County using unsupervised classifications of Landsat and airborne imagery. The hypothesis is that integration of LiDAR slope data with the classifications of Landsat and airborne imagery will improve the accuracy of mapping.

Methods
- All images were subsetted (Figure 1).
  - Landsat-5, Landsat-8 (obtained from USGS)
  - NAIP 2010, NAIP 2014 (obtained from USDA)
  - LiDAR data was mosaicked together: a low-pass filter with 11X11 Kernel size was used. Then a slope map was created (Figure 3).
  - 2010 Landsat/NAIP and 2014 Landsat/NAIP images were combined using Ehler’s merge. All images underwent an unsupervised classification using 64 clusters to delineate the inland water bodies from the surrounding areas (Figure 2).
  - The classification results were coded as water and non-water
  - Water and non-water classes were created for simplicity
  - An accuracy assessment was done for all six images and the results were recorded (Figure 4 and Table 1).

Table 1: Accuracy percentage and Kappa values.

<table>
<thead>
<tr>
<th>Classification</th>
<th>Overall Accuracy %</th>
<th>Kappa Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>2010 USGS</td>
<td>76.67%</td>
<td>0.8889</td>
</tr>
<tr>
<td>2010 NAIP</td>
<td>95.00%</td>
<td>0.9362</td>
</tr>
<tr>
<td>2014 USGS</td>
<td>96.67%</td>
<td>0.9325</td>
</tr>
<tr>
<td>2014 NAIP</td>
<td>95.00%</td>
<td>0.9231</td>
</tr>
<tr>
<td>2014 Landsat</td>
<td>70.94%</td>
<td>0.5290</td>
</tr>
<tr>
<td>2014 NAIP</td>
<td>98.33%</td>
<td>0.9620</td>
</tr>
<tr>
<td>Slope Map</td>
<td>76.67%</td>
<td>0.7144</td>
</tr>
</tbody>
</table>

Discussion
- LiDAR data helped differentiate the water pixels from other flat areas, shadows, and previously misclassified pixels. The shadows and rooftops often were incorrectly labeled as water in the classifications.
- Overall, 2014 Ehler’s merge and 2014 Landsat were closely tied for accuracy. The 2014 Landsat image actually has the cleanest distinction of the inland water bodies to the surrounding area even though it lacked the spatial resolution of NAIP images.
- The NAIP unsupervised classifications were insufficient. There needed to be more than 64 clusters to differentiate the classes.
- The change in pixels (Table 2) more often indicated the amount of error, than the actual change in water concentrations because there were not enough classes to properly classify the images.

Table 2: Histogram and area of change in Inland Water

<table>
<thead>
<tr>
<th>Classification</th>
<th>Histogram (Red Pixels)</th>
<th>Area [m²]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ehler’s Change</td>
<td>18912</td>
<td>18912</td>
</tr>
<tr>
<td>USGS Change</td>
<td>7632</td>
<td>688880</td>
</tr>
<tr>
<td>NAIP Change</td>
<td>3556565</td>
<td>3556565</td>
</tr>
<tr>
<td>Slope Map/Ehler’s</td>
<td>57404235</td>
<td>5227854</td>
</tr>
</tbody>
</table>

Conclusion
On its own, image-based classification was not adequate to monitor the change in water concentrations. Integration of LiDAR data was crucial to differentiate several misclassified pixels. The Ehler’s fused image provided the best results and when it was integrated with the slope map, it helped indicate the sources of error. Gathering more images and LiDAR data from separate years would be necessary to continue the monitoring of fresh water in Ballard County. Increasing the number of classes and diverse data supply will also enhance the accuracy before completing change detections.

Acknowledgement
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References

Figure 1: Landsat and NAIP images of the study area.

Figure 2: Classification of 2010 and 2014 NAIP/Landsat images and their corresponding change maps.

Figure 3: Visual comparison of Swan Pond with the 2014 Ehler’s image and slope map, and their change detection map: Red pixels were actually shadows, which were incorrectly classified as water. Purple pixels were slope pixels, which were incorrectly classified as water due to their apparent surfaces, such as buildings.

Figure 4: Accuracy assessment and Kappa values.

Table 1: Accuracy percentage and Kappa values.