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

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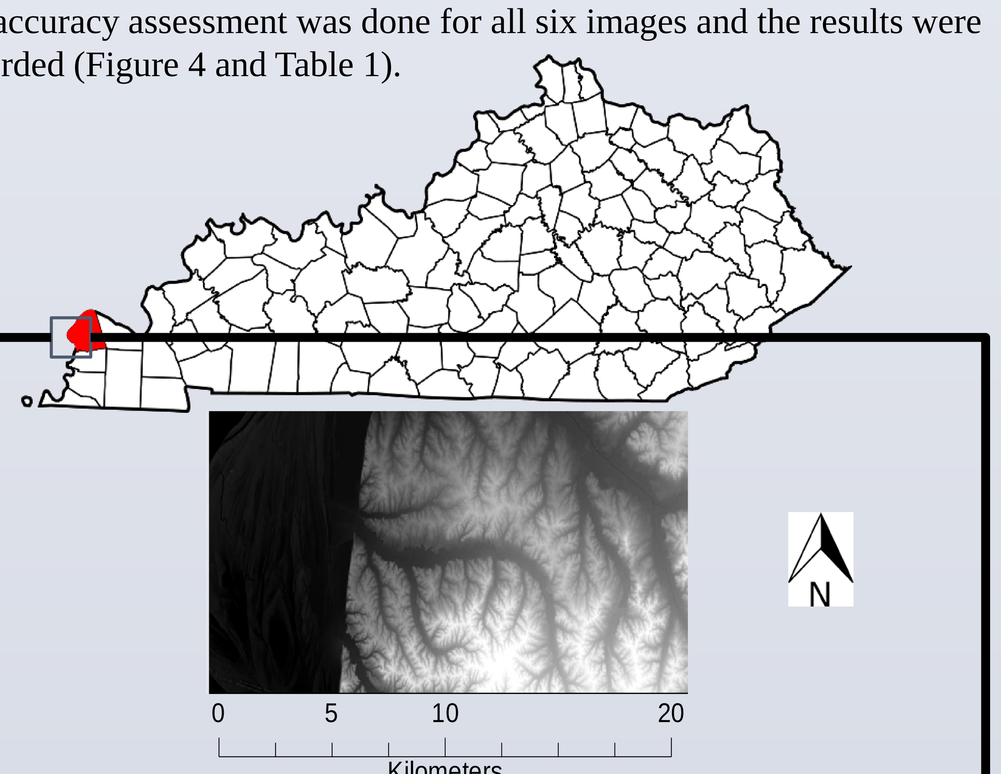
Introduction

Imagery-based classifications of inland water bodies for separate years allow us to observe the change in fresh water concentrations (Canaz, 2015). 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 (**Li**ght **D**etection **A**nd **R**anging) 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 and contrast to 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 were 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).



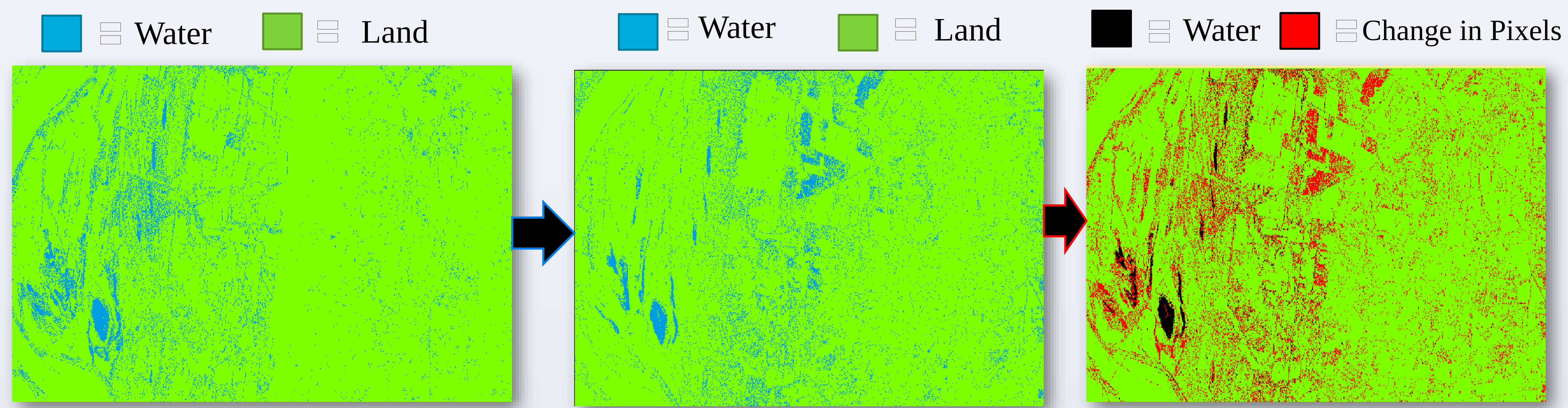
Low-pass filtered LiDAR data (11X11 kernel)

NAIP 2010 (top-left) and NAIP 2014 (top-right)

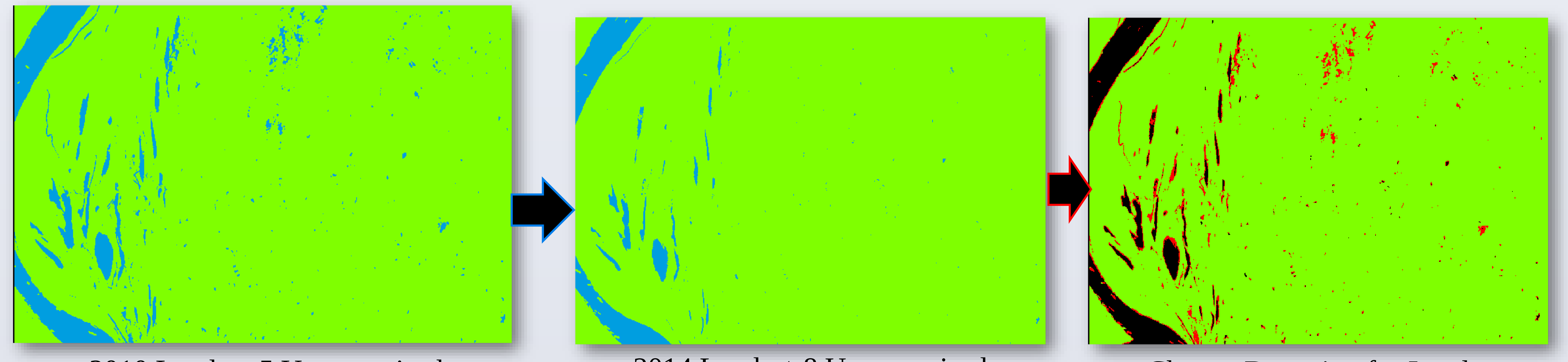
2010 Landsat-5 (left) and 2014 Landsat-8 (right): True color composite

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

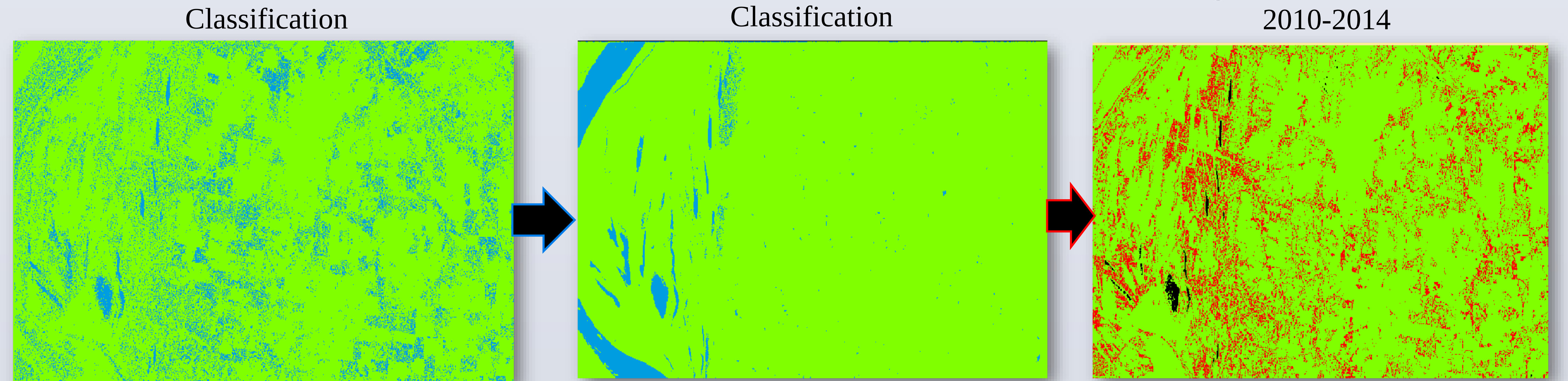
Results



2010 NAIP Unsupervised Classification | 2014 NAIP Unsupervised Classification | Change Detection for NAIP 2010-2014



2010 Landsat-5 Unsupervised Classification | 2014 Landsat-8 Unsupervised Classification | Change Detection for Landsat 2010-2014



2010 Ehler's Merged Image | 2014 Ehler's Merged Image | Change Detection for Ehler's Merge 2010-2014

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

LiDAR Slope Map: Swan Pond | 2014 Ehler's Image: Swan Pond | Change Detection Slope/Ehler 2014: Swan Pond

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.

Results Cont.

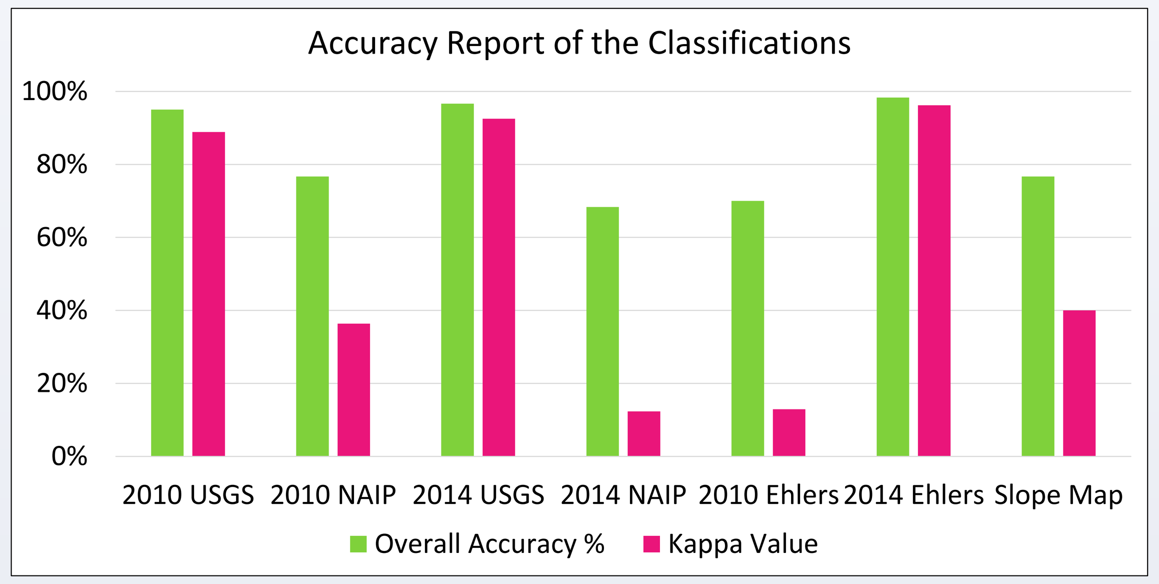


Figure 4: Accuracy assessment and Kappa values.

Table 1: Accuracy percentage and Kappa values.

Classifications	Overall Accuracy %	Kappa Value
2010 USGS	95%	0.8889
2010 NAIP	76.67%	0.3636
2014 USGS	96.67%	0.925
2014 NAIP	68.33%	0.1231
2010 Ehlers	70%	0.129
2014 Ehlers	98.33%	0.962
Slope Map	76.67%	.4

Table 2: Histogram and area of change in Inland Water

	Histogram (Red Pixels)	Area (m^2)
Ehler's Change	18912	18912
USGS Change	7632	6868800
NAIP Change	35565655	35565655
Slope Map/Ehler's 2014 Change	57404235	52237854

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 data were closely tied for accuracy. The 2014 Landsat image actually has the clearest 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.

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

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