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Detecting Surface Water Over Diverse Mississippi Landscapes Using Uncrewed Aerial System Imagery and the Normalized Difference Water Index

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Background

This research addresses challenges in surface water detection for flood mapping and emergency response using uncrewed aerial systems (UAS) imagery, specifically the limitations of conventional methods like the Normalized Difference Water Index (NDWI). Despite NDWI's widespread use, its accuracy is hindered by similar reflectance patterns between water and impervious surfaces. To improve precision of surface water detection over rural and urban landscapes, RGB and near-infrared (NIR, hereafter RGBN) imagery captured from UAS over select sites in Mississippi are analyzed.

Data and Methods

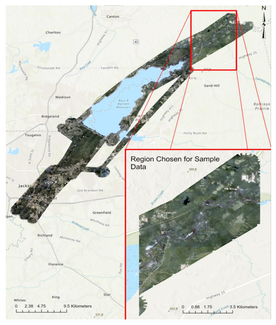
Drone:
Group 3 Tigershark XP3

Sensor Package:
Firewatch TK-5

Location:
Jackson, MS

Date:
July 31, 2023

Spatial Resolution:
14.7 cm



Indices:
NDWI is calculated using (1). Average RGBN pixel values where NDWI = 1 are subtracted from their respective bands. An adjusted NDWI is calculated using Equation 1 with these normalized bands.

$$NDWI = \frac{G - NIR}{G + NIR} \quad (1)$$

Classification:
Support vector machine (SVM) classification is trained using ArcGIS Pro with 500 manually chosen sample points across 8 classes. The classified image using this model is compared to NDWI and the adjusted NDWI.

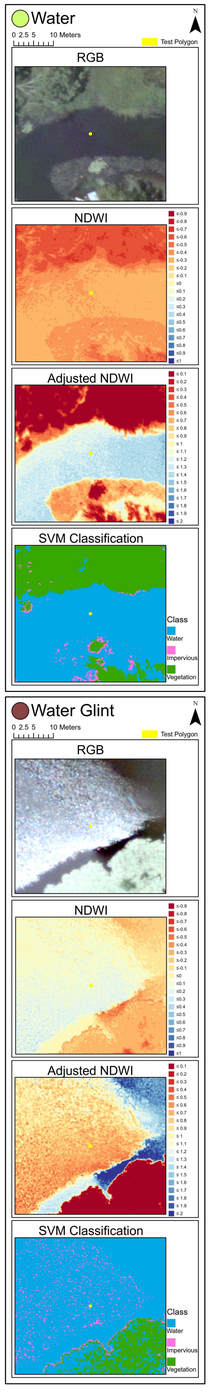
Performance Evaluation:
Both indices and SVM classification performance are analyzed using contingency tables (right) and associated statistics including Critical Success Index (2) and Cohen's kappa coefficient (3).

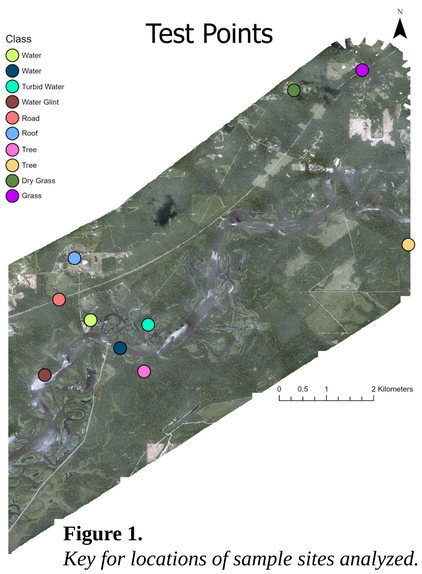
Predicted \ Observed	Water	Non-water
Water	a	b
Non-water	c	d

$$CSI = \frac{a}{a+b+c} \quad (2)$$

$$\kappa = \frac{2(ad-bc)}{[(a+c)(c+d)+(a+b)(b+d)]} \quad (3)$$

Results





Scan for more information:

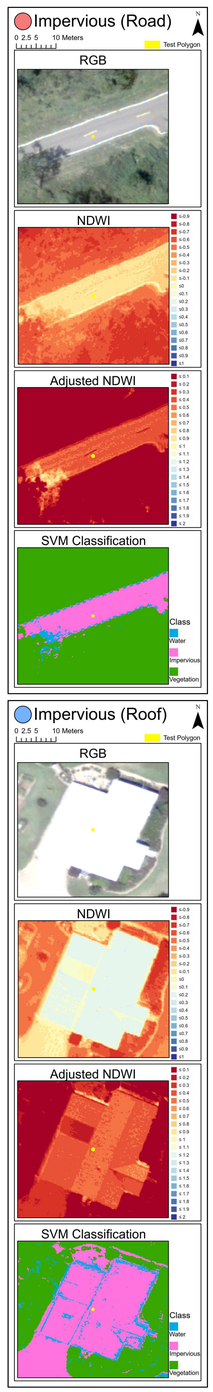


Figure 1.
Key for locations of sample sites analyzed.

Table 1. *Contingency tables of index and classification performance. (a) NDWI, (b) Adjusted NDWI, and (c) SVM Classification. Highest skill index threshold is shown. Performance statistics: Critical Success Index (CSI), Cohen's Kappa Coefficient (κ)*

(a) NDWI

	Reference: Water	Reference: Non-water	Total
Water	115	70	185
Non-water	13	122	135
Total	128	192	320

CSI: 0.5808
κ: 0.4970

(b) Adjusted NDWI

	Reference: Water	Reference: Non-water	Total
Water	103	0	103
Non-water	25	192	217
Total	128	192	320

CSI: 0.8047
κ: 0.8318

(c) SVM Classification

	Reference: Water	Reference: Non-water	Total
Water	128	0	128
Non-water	0	192	192
Total	128	192	320

CSI: 1
κ: 1

Figure 2. *Comparison of various methods over water (Smooth water – top, Turbulent water – bottom).* Notice the vegetation floating atop the water at the south of both images, and how each method performs.

Figure 3. *Comparison of various methods made over impervious surfaces (Road – top; Roof – bottom).*

Conclusions

- Adjusted NDWI has higher skill in detecting surface water (>80%) compared to NDWI (>58%).
  - Adjusted NDWI kappa values indicate skill beyond random chance ($\kappa = 0.8313$).
- SVM Classification performance statistics indicates a perfect skill (CSI = 1, $\kappa = 1$).
  - Fig. 2 and 3 show inaccuracies beyond sample boundary.
- Visual inspection determines all methods struggle with shadows and algae on the surface.

Discussion

The adjustments made to the NDWI improved the ability to discriminate water from impervious surfaces. However, it struggles with highly reflective (turbulent) water (Fig. 2). To overcome this, masking of positive NDWI values over the adjusted NDWI output is considered. Despite these improvements, all methods still struggle to classify vegetation over water, such as algae (Fig. 2).

Although SVM classification performance statistics indicate a perfect performance, it struggles to accurately, consistently differentiate vegetation and impervious surfaces from water especially at class boundaries (Fig. 3). This is due to sample selection bias. Closer inspection of the SVM classification model, including consideration of hyperplane equations between water and non-water classes, can allow for further adjustments to an index-based approach. Adding an NDWI and/or Adjusted NDWI value to classification training may aid in SVMs accuracy.

Acknowledgements

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