GC13I-0860: An Assessment of Surface Water Detection Methods for the Tahoua Region, Niger

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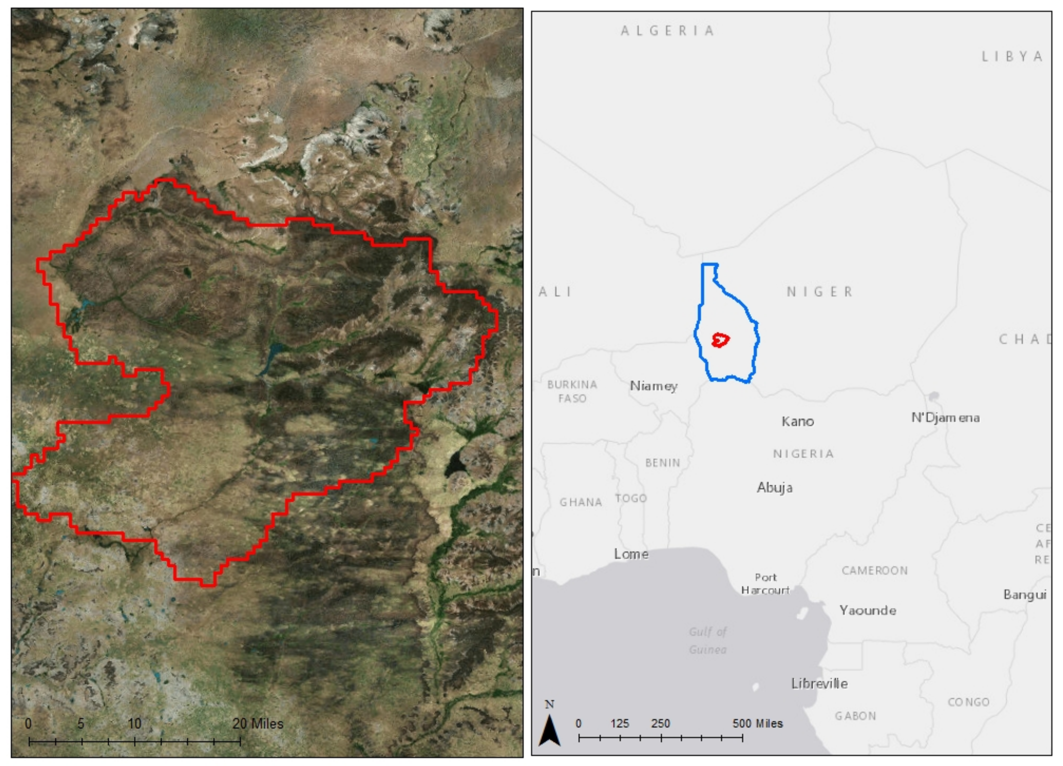
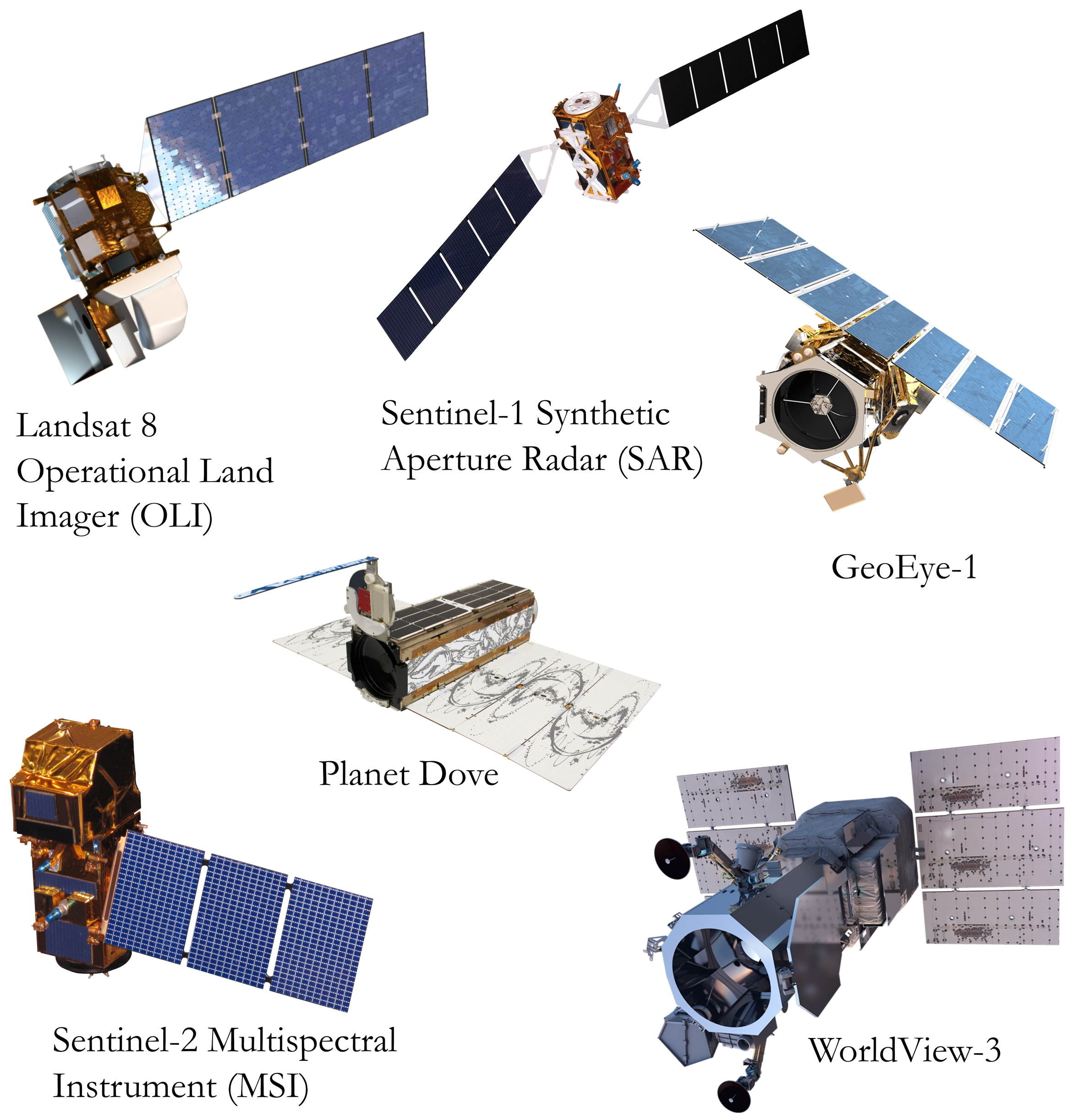
Abstract

The recent release of several global surface water datasets derived from remotely sensed data has allowed for unprecedented analysis of the earth's hydrologic processes at a global scale. However, some of these datasets fail to identify important sources of surface water, especially small ponds, in the Sahel, an arid region of Africa that forms a border zone between the Sahara Desert to the north, and the savannah to the south. These ponds may seem insignificant in the context of wider, global-scale hydrologic processes, but these smaller sources of water are important for local and regional hydrologic assessments. Particularly, these smaller water bodies are significant sources of hydration and irrigation for nomadic pastoralists and smallholder farmers throughout the Sahel. For this study, several methods of identifying surface water from Landsat 8 OLI, Sentinel 1 SAR, Sentinel 2 MSI, and Planet Dove data were compared to determine the most effective means of delineating these features in the Tahoua Region of Niger. The Automated Water Extraction Index (AWEInsh) had the best performance when validated against very high resolution Digital Globe imagery, with an overall accuracy of 98.6%. This study reiterates the importance of region-specific algorithms and suggests that the AWEInsh method may be the best for delineating surface water in the Sahelian ecozone, likely due to the nature of the exposed geology and lack of dense green vegetation.

Study Area



Earth Observations



Methodology

Landsat 8 OLI Surface Reflectance → **Calculate Indices**
MNDWI (SWIR 1), MNDWI (SWIR 2), AWEInsh, AWEIsh, NIR, SWIR 1, SWIR1, NDWI, NDMI, NDPI (SWIR 1), NDPI (SWIR 2), TCW

Sentinel 1 SAR → **Calculate Backscatter**

Sentinel 2 MSI → **Calculate Indices**
MNDWI (SWIR 1), MNDWI (SWIR 2), AWEInsh, AWEIsh, NIR, SWIR 1, SWIR1, NDWI, NDMI, NDPI (SWIR 1), NDPI (SWIR 2

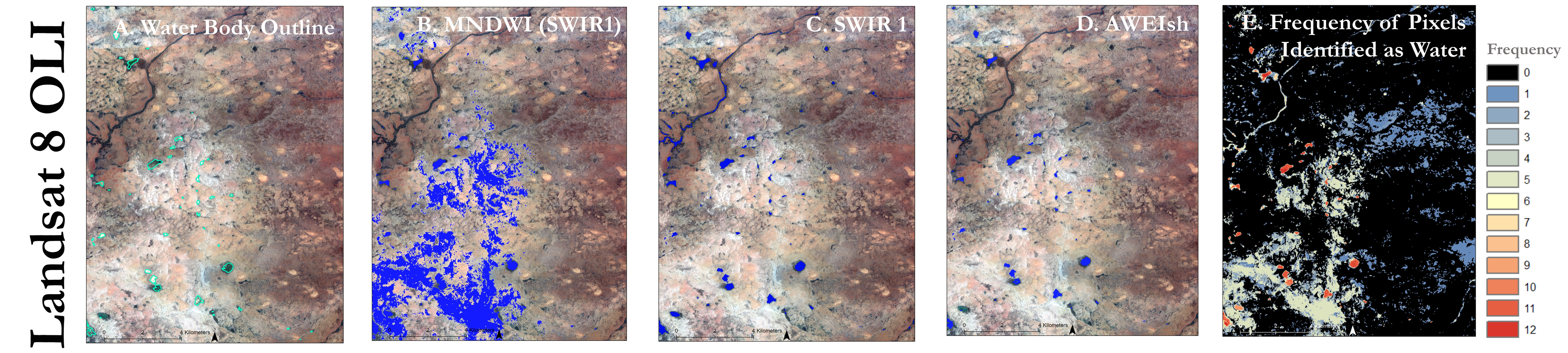
Planet Dove Surface Reflectance → **Calculate Indices**
NIR, NDWI

Accuracy Assessment
The accuracy assessment was conducted using a second, separate set of sample points. An error matrix was created and the overall accuracy of each index was calculated

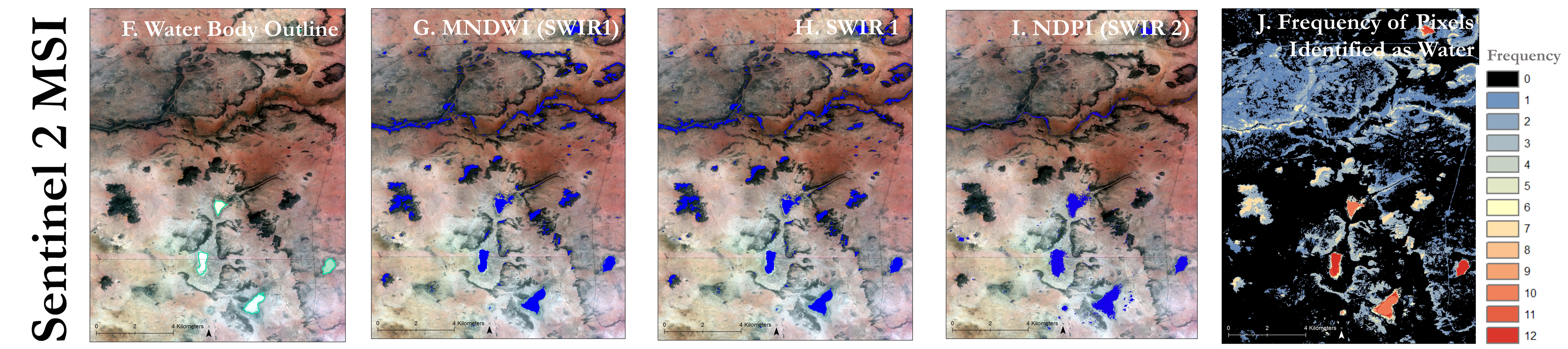
Optimize Thresholds
Thresholds were optimized by calculating the sensitivity and specificity, constructing a ROC curve, and selecting the point that minimized the distance to (0,1).

WorldView 3 / **GeoEye-1** → **Water Observations**
The very high resolution WorldView-3 and GeoEye-1 data were pansharpened using the Brovey method. All visible surface water was then traced by hand as a polygon in ArcMap 10.4. The resulting polygons were converted to a raster dataset in the resolution of the sensor being tested. These values served as the "in situ" data values to optimize the index thresholds and conduct the accuracy assessment.

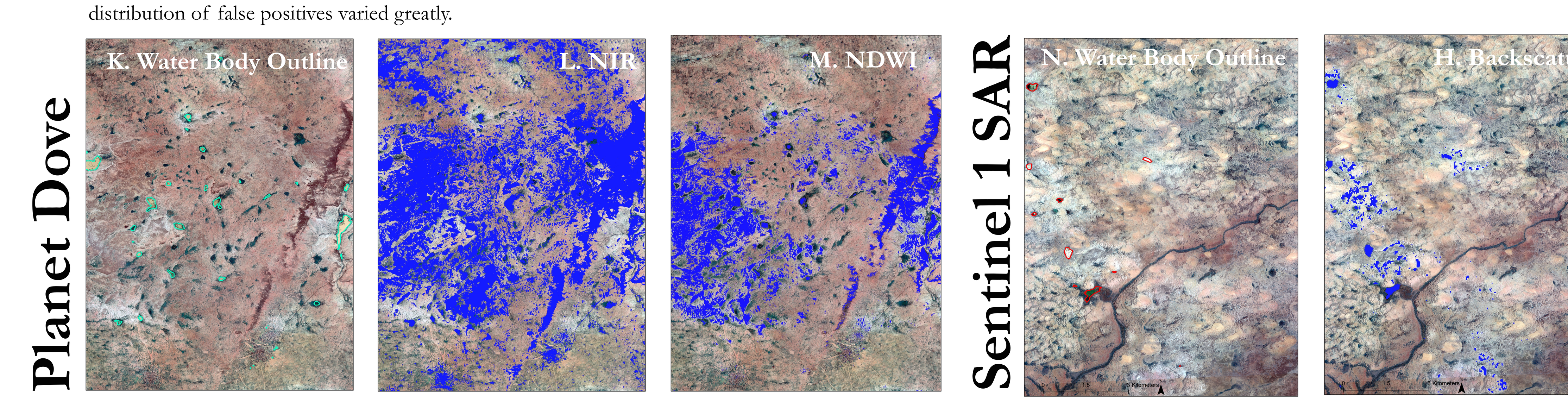
Results



Figures B through D represent the water masks created from a small selection of the indices, ratios, and band thresholds tested for Landsat 8. Figure E. shows the number of indices that identified a given pixel as water. Areas where surface water is present were accurately identified across all methods, indicated by the red areas in Figure E.; the distribution of false positives varied greatly.



Figures H through I represent the water masks created from a small selection of the indices, ratios, and band thresholds tested for Sentinel 2. Figure J shows the number of indices that identified a given pixel as water. Areas where surface water is present were accurately identified across all methods, indicated by the red areas in Figure E.; the distribution of false positives varied greatly.



Figures L and M represent the results of the two methods tested for the Planet Dove Data. Performance was poor for both the NDWI and NIR threshold. Figure H shows the results of surface water identification using backscatter calculated from the Sentinel 1 Synthetic Aperture Radar.

Conclusions

- This project calculated the optimal threshold and assessed the accuracy of 12 different water detection indices across four satellite sensors.
- For Landsat 8 OLI, the AWEInsh index developed by Feyisa et al. (2014) had the best performance with an overall accuracy of 0.97. The simple SWIR 1 band threshold and Tasseled Cap Wetness (TCW) methods also performed well. Other indices were inconsistent in separating water from land cover with high albedo, dense green vegetation, shadow, and other areas with very low albedo, including MNDWI, one of the most commonly cited methods of surface water identification.
- The poorest performing index for Landsat 8 was the NDWI with an overall accuracy of 0.73.
- This project did not allow for a comparison across sensors due to limitations on the availability of very high resolution data. Data from each sensor represent a different date.
- Future work will be looking at how stable the optimal threshold is over space and time. Additionally, a sub-pixel accuracy assessment will be conducted to determine the under- or over-estimation of surface water area due to mixed pixels.
- Water quality varied greatly across each image. Future work will examine the impact of turbidity on surface water detection.

Acknowledgements

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