Analyzing Urbanization of Northern Menomonie through Supervised and Unsupervised Classification

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INTRODUCTION

Urbanization refers to concentrations of human populations. Urban expansion is monitored through the alteration of landscapes into residential, commercial, and industrial uses. Continually tracking the movement of urbanization allows for the assessment of climate vulnerability within an urban system.

Image classification is an image scanning technique that analyzes the individual pixels of the image to classify objects within a picture. Pixels themselves do not reflect patterns but the grouping of pixels relays spatial trends.

There are two main types of Image Classification:

- Supervised classification: Requires user input to key in multiple examples of the object of interest within the imagery.
- Unsupervised classification: Automatic clustering of similar pixels by a pre-trained model.

Purpose: The purpose of this study is to analyze the urbanization of Northern Menomonie over the previous two decades.

- Study this change through supervised and unsupervised classification models.
- Analyze the change in land usage over time.

We're interested in determining if unsupervised classification—the automated and more time-efficient method—can produce a classified map as accurate and detailed as the user-intensive supervised method.

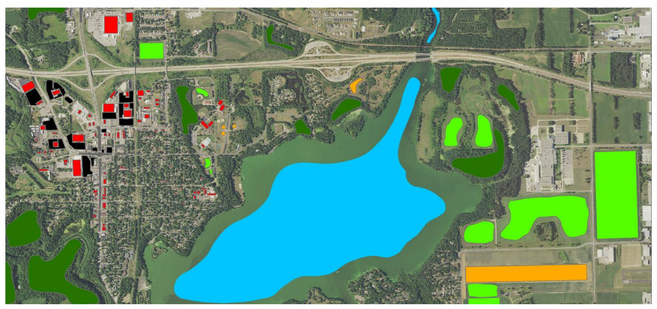

Figure 1. Menomonie, WI (2022) with supervised classification training sample

METHODS

Aerial images for analysis were obtained from the U.S. Department of Agriculture's National Agriculture Imagery Program (NAIP) (Geospatial Enterprise Operations, Salt Lake, Utah). The aerial data for Dunn County, WI was accessed for the year 2004 at ground-sample distance (GSD) of 3 meters, 2010 at 1m GSD, 2017 at 0.6m GSD, and 2022 at 0.3m GSD.

- Supervised: Obtain high resolution imagery of target area, make samples of the different objects, run classification program, color code the different classes, and get a pixel count of each classification.
- Unsupervised: ESRI pre-trained High Resolution Land Cover Classification – USA Deep Learning model

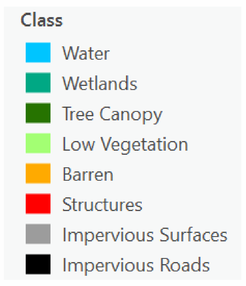

Figure 2. Unsupervised legend (left column)

Figure 3. Supervised legend (right column)

RESULTS

Unsupervised Classification

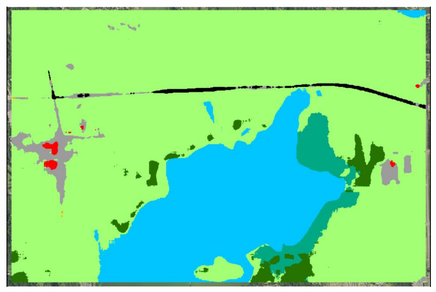

Figure 4. Unsupervised LULC 2004

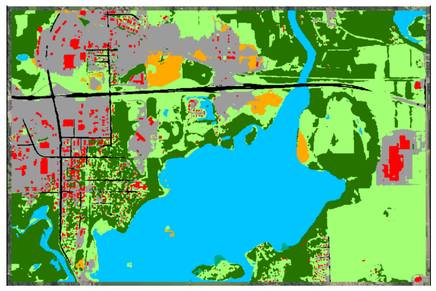

Figure 6. Unsupervised LULC 2010

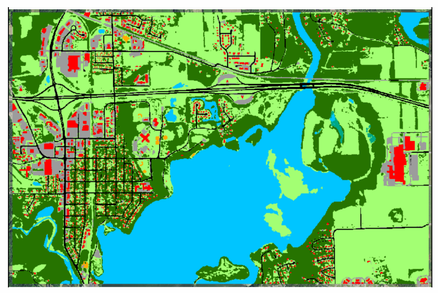

Figure 8. Unsupervised LULC 2017

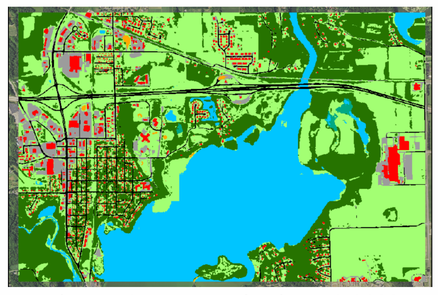

Figure 10. Unsupervised LULC 2022

Supervised Classification

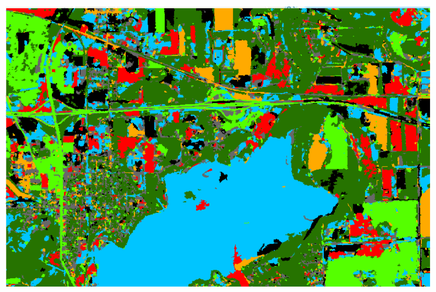

Figure 5. Supervised LULC 2004

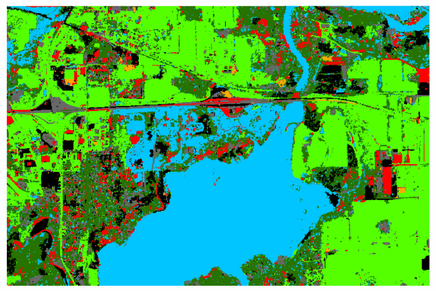

Figure 7. Supervised LULC 2010

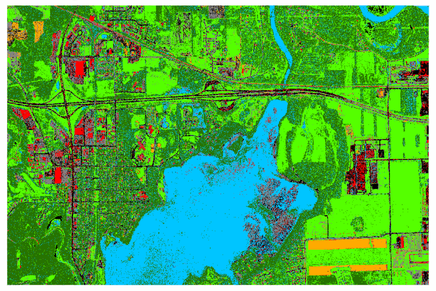

Figure 9. Supervised LULC 2017

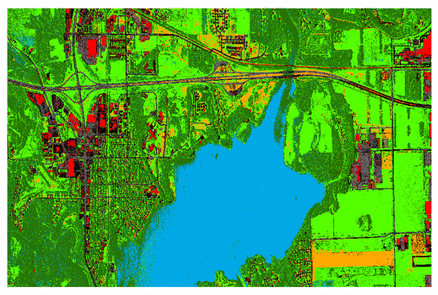

Figure 11. Supervised LULC 2022

Both unsupervised and supervised classification struggled to analyze the 2004 NAIP imagery due to low image resolution. As the GSD increased with each year, the quality of the classification increased in both detail and accuracy.

- Unsupervised classification succeeded at being a more time-efficient method of image classification but failed at being as precise as supervised and relayed more generalized results.
- Supervised classification succeeded at being more detailed in its analysis of low-resolution imagery but failed in accurately identifying the classes.

The reduction in GSD throughout the years yielded higher resolution imagery. The increase in the number of pixels allowed for greater detail and increased accuracy from both types of classification. Because of technological advancements, 2017 and 2022 was most precise and accurate for both supervised and unsupervised classification.

DISCUSSION

The ability to monitor the spread of urbanization greatly increased as technology in GIS and remotely sensed imagery increased. Technological advancements allowed NAIP imagery to be captured at a higher resolution which allotted more pixels per area and more contrast of captured colors.

Overall technology advancements permitted both supervised and unsupervised classifications to yield more accurate LULC classified maps. As the quality of the images improved, the model could better differentiate between impervious and pervious structures and their different types of terrain.

Strengths of unsupervised classification:

- More homogenous areas of segmentation and classification
- More time-efficient
- Ability to identify more complex LULC types

Strengths of supervised classification:

- Better ability to distinguish objects at lower resolutions
- Increased ability to capture details

CONCLUSIONS

Supervised classification was more detailed in its image analysis than unsupervised. However, unsupervised classification yielded higher accuracy by generalizing the image into homogenous segments.

Both classifications struggled with detail and accuracy at lower resolutions. In addition, the variation in object appearance (size, color, etc.) was another source of error in proper classification.

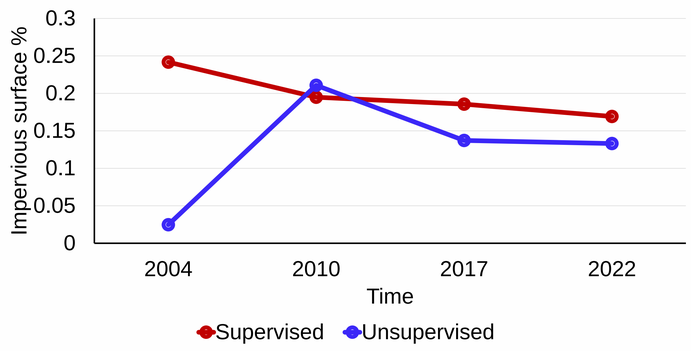

Figure 12. Graph showing the percent of impervious surfaces detected for supervised and unsupervised classification throughout the years analyzed.

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ACKNOWLEDGEMENTS

We want to acknowledge and thank Dr. Nicole Hayes and Dr. Innisfree McKinnon for their guidance and support. We also want to mention the UW-Stout Archives for allowing us to access their many stored documents.