Intermediate Spatial Data Science Lab Report

Title: Final Project: Restorable Wetland MCDA, Equal Weight Assessment
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Google Drive Link: n/a
Time Spent: > 20 hours

Abstract
Wetlands have been significantly converted to urbanized and agricultural land uses over the past 150 years, with much of the conversion taking place in the past 50 years due to field tiling. This project aims to use MCDA to use land use classification (developed, agricultural, wetland) and hydrologic properties (TWI, slope, soil class) to identify the highest quality sites for potential wetland restoration projects. Previous research on wetland restoration has been used to establish the key site characteristics, and is the basis for equal weighting of all the characteristics (Widis et al. 2015, Galatowitsch et al. 1996, Galatowitsch et al. 1998). Results of the MCDA analysis are compared to a set of randomly weighted scenarios. Results suggest that equal weighting does affect the location and rating of restorability significantly. MCDA outcomes were compared to a recent Minnesota Department of Natural Resources (DNR) and Natural Resources Research Institute (NRRI, UMN) study that used machine learning algorithms along with additional data layers. The DNR and NRRI results show significant differences in restorability within the study area.

Problem Statement
This project aims to use multi-criteria data analysis (MCDA) to identify restorable wetland areas in Minnesota. The projects has specific task goals including:

1. Download DEM data to establish local slope values and total water index (TWI) values for the watershed, then use restricted values for valuation within a cost layer [*Slope, TWI*].
2. Download national land cover data (NCLD) and reclassify it from 16 to 5 categories, then use specific categories for valuation within a cost layer [*agricultural, not-developed*].
3. Download hydric soils data and use specific hydric soil percentages for valuation within a cost layer [*hydric soils > 50%*].
4. Download National Wetlands Inventory (NWI) data and create a wetlands buffer to identify connective wetland areas [*<500 meters*].
5. Establish a single cost surface layer using the input cost layers and equal weights.
6. Analyze the effects of random weighting schemes on the model output histograms to establish whether equal weighting is as effective at identifying the sites.
7. Compare results to current MN restorable wetlands layer (Johnson et al. 2024)

Data for each task were obtained from publicly available websites and downloaded using API interactions. Data was initially processed so that it was accessible, e.g. files unzipped, data fields created, etc. The general data processing is shown below in Figure 1, where blue is the initial dataset, yellow is the processed data, and green is the final data used in the products.

Figure 1. Table showing the transformation of data for each of the tasks.

#	Requirement	Defined As	(Spatial) Data	Attribute Data	Dataset	Preparation
1	**MN DEM API**	Download data via an API, then unzip the data, project coordinates	Raster Data	Elevation data by grid location	MN Lidar County DEM	API request for DEMs; unzip file; reproject and clip to boundary
2	**MRLC Land Cover API**	Download data via an API, set .bil files into mosaic layer	Raster Data	Location, Land Cover Type (16 categories)	MRLC	API request for NCLD file; unzip file; reproject and clip to boundary
3	**SSURGO Hydric Soils**	Download data directly and then transform	Raster Data	Location, Hydric Soil Percentage	SSURGO US Hydric Soils	Direct Download, Save to File, Reproject and Clip
4	**DNR NWI API**	Download data via an API, then unzip the data, project coordinates.	Polygon	Location, Wetland Type	MN DNR, NWI	API request for NWI file, unzip file; reproject and clip to boundary
5	**DEM to Slope**	Create slope layer from DEM	Raster Data	Location, Slope Degrees	to “slope_reclass”	DEM to slope, then reclass by ideal slope (<10*)
6	**DEM and Slope to TWI**	Create TWI layer using slope and DEM	Raster Data	Location, TWI index value	to “TWI_reclass”	DEM/Slope to TWI, then reclass by ideal TWI (>7)
7	**NCLD Layers**	Create NCLD layer with reclassified categories, as well as a buffer from developed land	Raster Data, Polygon Data	Location, Land Cover Type	to “NCLD_reclass”, to “NCLD_buffer”	Reclass 16 Categories to 5; Raster to Polygon, ID 4s, Buffer from 4 (100m)
8	**Hydric Soils**	Create soils with hydric soil percentages	Raster Data	Location, Hydric Soil Percentage	to “hydric_soils_reclass”	Reclass Hydric Percentages by ideal values (>50%)
9	**Cost Surface Layer**	Weighted overlay of cost surfaces	Raster Data	Location, Weighted Sum from Layers	to “Cost Surface”	Use equal weighting to perform overlay
10	**DNR Restorable Wetlands**	Finished Data Layer for Comparison	Raster Data	Restorable Wetlands, (5-Class values)	Restorable_DNR	Direct Download, Save to File, Reproject and Clip

Input Data

Figure 2. Data layer(s) used to perform the described processes.

#	Title	Purpose in Analysis	Link to Source
1	**MN County DEM Data**	Used to establish a .las database pointcloud for creating a DEM layer and a TIN layer.	LIDAR Data
2	**MRLC Land Cover Data**	Used to derived cost service rasters based on land cover in the DEM area: No Ag, No Water	MRCL (NCLD)
3	**USDA Soil Survey**	Used to determine hydric soil percentages for creating a cost layer: > 50 % hydric soils	Soil Survey
4	**NWI Data (MN DNR)**	Used to determine the location of existing wetland areas for establishing hydrological connectivity: < 500 m	NWI Data
5	**DNR Restorable Wetlands, NRRI (DRUM)**	Used to do a final comparison of restorable land valuation between machine learning and standard MCDA	UMN DRUM

Methods

Figures 3 and 4 (below) show the generalized ETL used in the project. All data layers were extracted or downloaded, unzipped (if necessary), and then reprojected into NAD 1983 UTM 15N before being clipped to the outside bounds of the watershed boundary bounding box.

The data was further transformed into cost layers that were integrated into an equal weighted overlay. Cost surface layer data parameters include:

1) **Hydrological Connectivity:** Areas near other wetlands, water bodies, or landscape features allow water movement between areas [< 500 meters of wetlands, NWI].
2) **Hydrological Potential (Geographic):** Areas with topology that allows a) water collection and b) water retention during precipitation and thawing events [Slope < 3.5; TWI > 0.7, DEM and slope derived].
3) **Hydrological Potential (Geological):** Areas with soils that retain moisture and/or have evidence of prolonged moisture in the past [Hydric Soils > 50% , SSURGO/USDA]
4) **Distance from Infrastructure:** Areas that are less likely to be influenced by tiling and drainage structures, as well as impervious surfaces that can increase pollutant runoff amounts [Distance > 100 meter from Development, NLCD].
5) **Availability of Land:** Areas that are located on agricultural or vegetated lands more likely to be purchasable and not in competition with other development activities [Class == Agriculture, NLCD].

Figure 3. Data flow diagram showing the API interactions, data transformations used in the ETL to create cost surface layers for restorable wetland sites.

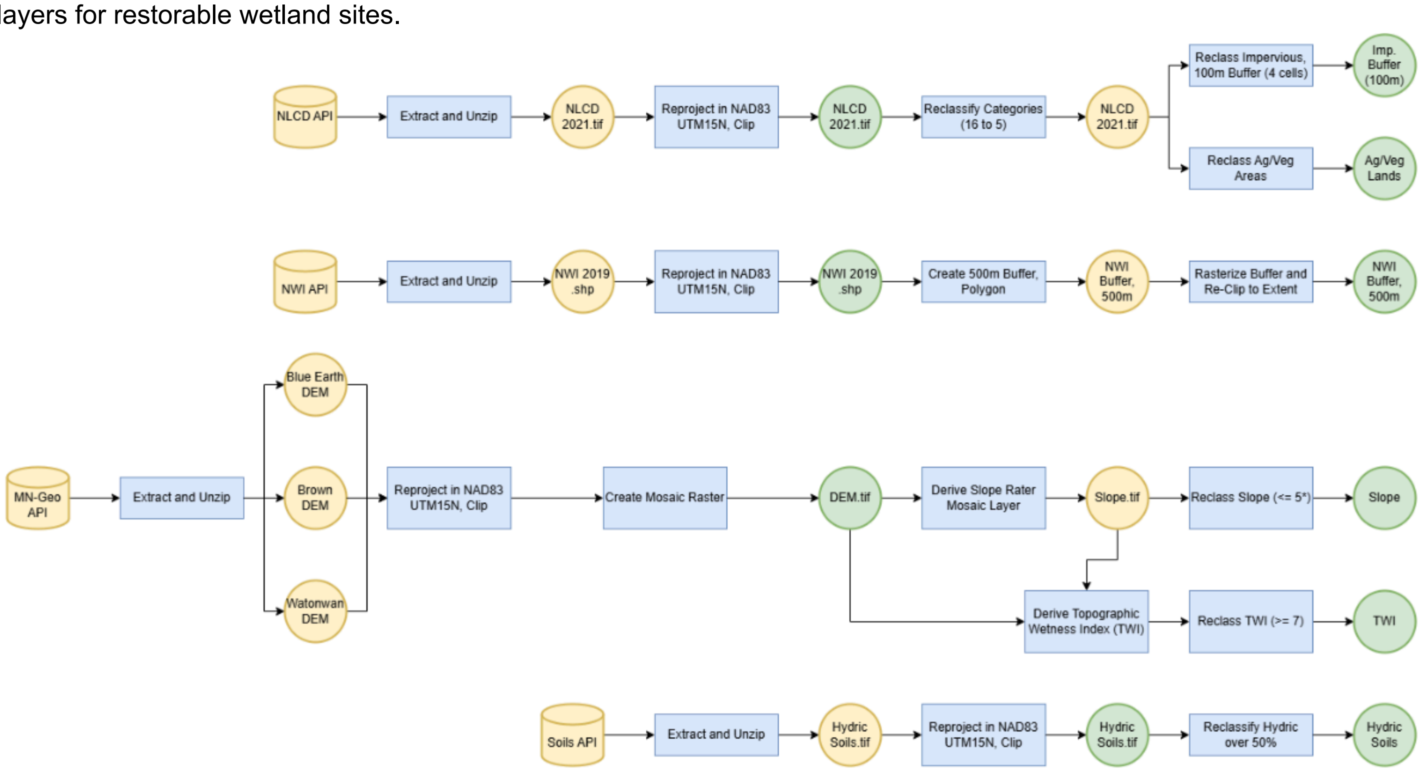
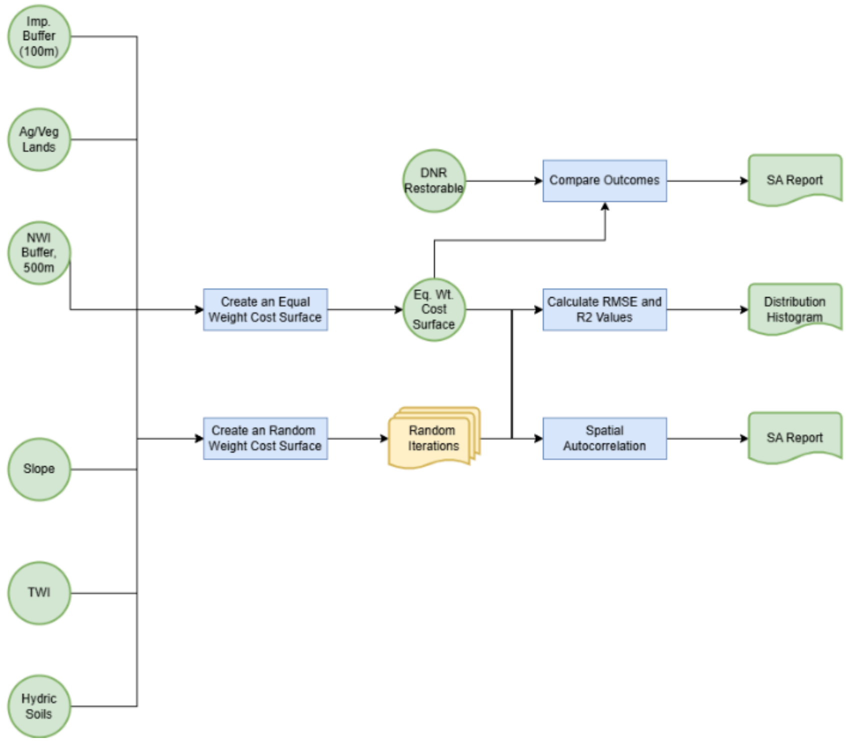


Figure 4. Data flow diagram showing the application of the data layers to create a final cost surface layer and then perform equal and random weighting to the individual layer values before comparing the results.



Specific Layer Functions

DEM layers were mosaiced and clipped to the Lower Watonwan Watershed (HUC 8) boundary. The DEM data was used to calculate a slope raster, and both the DEM and slope rasters were used to calculate the topographic water index (TWI) raster using the following equation:

$TWI = Ln(ContributingArea\,/\,Tan(slope_{rad}))$, where $ContributingArea = flow\_accumulation * cell\_size$

Flow accumulation is calculated from the DEM directly, by determining the number of cells that flow into each cell, based on the slope and direction.

NLCD land cover data was reclassified from its original 16 categories to 5 categories (wetlands, vegetation, agricultural, development, and water) in order to simplify the cost layer transformations. A 100 m buffer layer was created using the development category as the identifier. An agricultural and vegetation layer was also created by remapping the values that were not agriculture or vegetation as 0.

The national wetlands inventory (NWI) data from 2019 was used as a ground-truthed data set for establishing proximity (<500m) from existing wetlands.

Cost Weighting and Analysis

Equal weighting was used to establish an effectively binary cost surface layer for restorable wetland areas. This was performed based on data provided by a longitudinal assessment of wetland restoration papers, which identified the limited information used to determine weighting values (Widis et al. 2015). Widis et al. determined that the six cost surface categories in this project (slope, TWI, hydric soils, wetland proximity, development distance, and agricultural land) were identified in all of the studies examined as factors of successful wetland restoration projects.

It was important to determine what the effect of randomized weighting was on the cost surface outcome, and whether the distribution of values varied significantly from the equal weighting scheme. One hundred different randomized weighting schemes were created for the cost surface layers, using a total weighting amount of 1.

The distribution of cell values across the randomly weighting layers was compared using a histogram analysis.

Comparison to DNR Restorable Wetland Areas

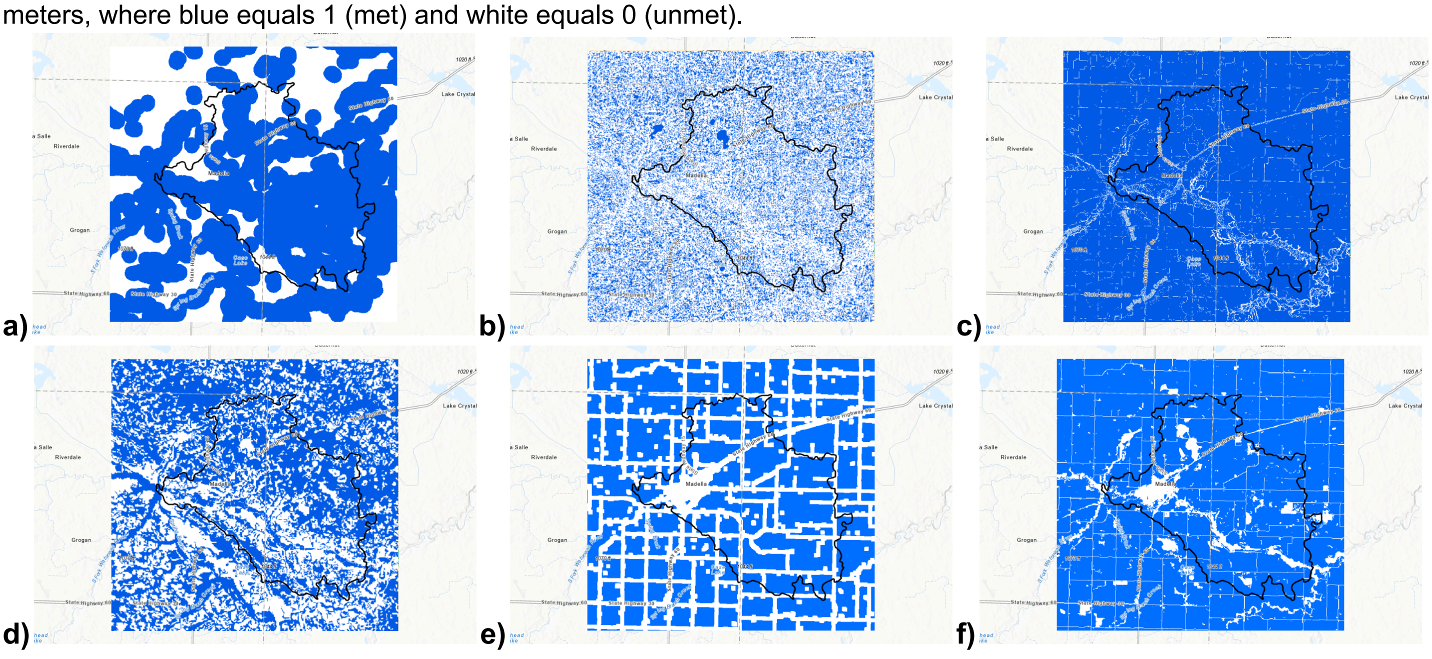
The DNR worked in conjunction with the NRRI at the University of Minnesota (Johnson et al. 2024) to create a cost surface layer showing the percentage likelihood of a parcel being restorable. This layer was generated using the same general data sets as this project, but also included normalized difference vegetation index (NDVI), normalized difference water index (NDWI), and compound topographic index (CTI) values. This surface layer was generated using a two-way random forest model to generate the most likely value.

Though it was not the direct goal of this study, the wetland restoration values generated by this project were compared to the DNR values. A 250 acre stacked grid was applied to the watershed boundary since parcel data was not publicly available for Brown, Blue Earth, or Watonwan counties. Zonal statistics were run to determine the mean cell value within each grid area. Spatial autocorrelation and RMSE (r^2) values calculated and compared.

Results

The six base cost surface layers were successfully created using the parameters described in the methods and can be seen in Figure 4. The initial setup of this project was to examine an equally weighted criteria analysis for the key features of successful wetland restoration sites. Because of the equal weighting scheme, fuzzy logic was not applied to the input data, and raster values were deemed meeting conditions (1, blue) or not meeting conditions (0, white).

Figure 4. Maps showing each of the cost layers produced: **a)** wetland < 500 meters, **b)** TWI value > 0.7, **c)** slope angle < 3.5, **d)** hydric soil percentage > 50%, **e)** distance from development > 100 meters, and **f)** proximity to wetlands < 500 meters, where blue equals 1 (met) and white equals 0 (unmet).



An equal weighted cost surface layer was created using all six base restorable wetlands data layers using a 1 to 10 scale, where 1 is low restorability and 10 is high restorability. Figure 5 shows the distribution of highly restorable land areas within the Lower Watonwan River watershed area, near Madelia, Minnesota. Purple and blues represent areas that are low restorability and oranges and red represent high restorability.

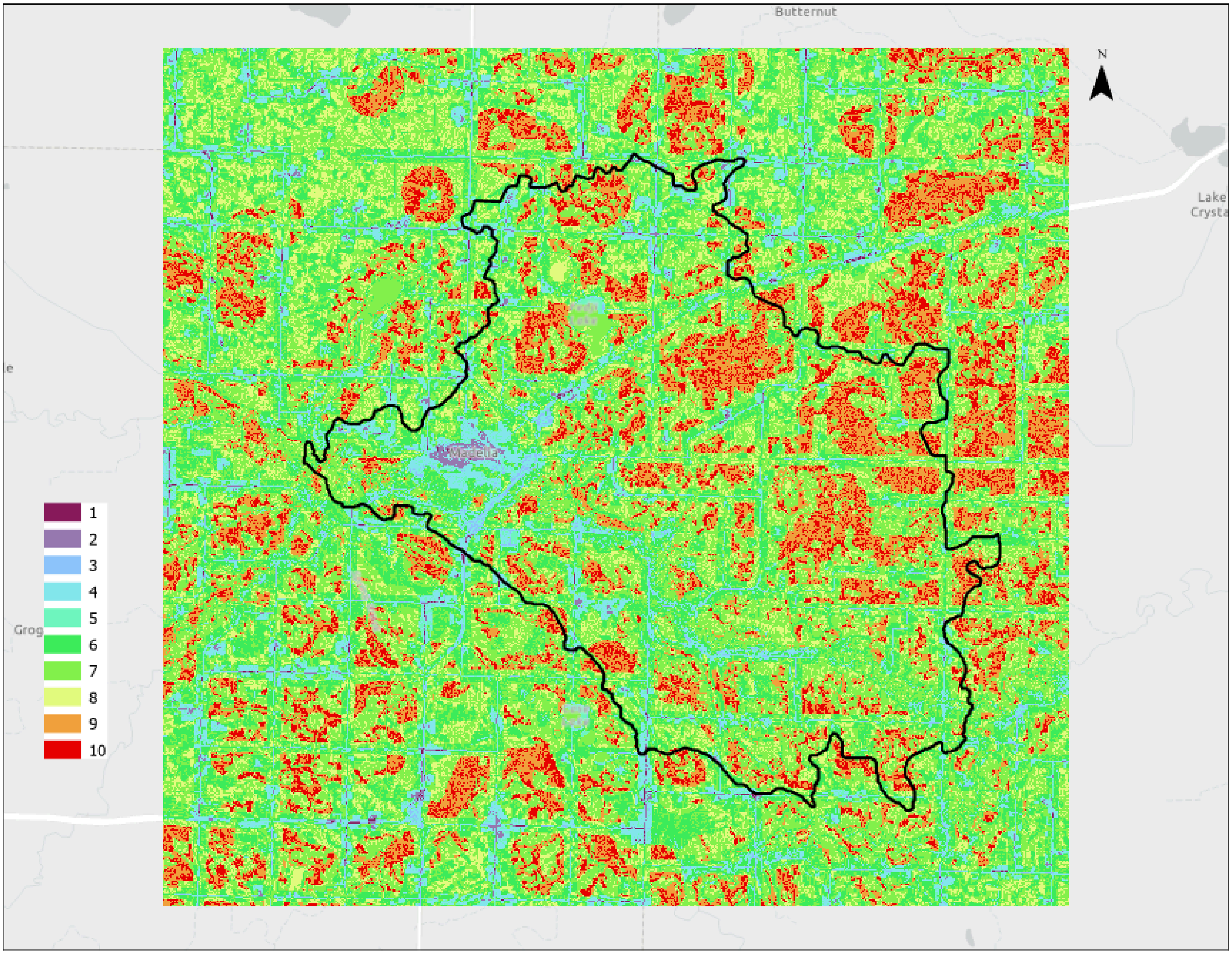


Figure 5. Map of showing the equal weight values of the wetland restorability cost surface layer, 1 = low restorability (purple and blue) and 10 = high restorability (orange and red).

As would be expected, the city of Madelia is purple and blue, and does not have land that is suitable for wetland restoration projects. The northeastern half of the watershed has significant amounts of land deemed highly suitable for wetland restoration projects. These areas are agricultural lands near existing wetland areas. It is notable that this cost surface shows extreme influence due to the infrastructure (e.g. roads) proximity.

A set of 100 cost surface layers were produced using a randomized weighting scheme. All of the weights were set to equal 1, to compare the effect of emphasizing some datasets over others. Figure 6 (below) shows six examples of the randomized cost surface layers using the same 1 to 10 scale and color ramp.

The randomized map examples show the general effect of the limited data layers and the use of binary decision making. The road layer data is visible in nearly all of the cost surfaces. The impact of wetland proximity and hydric soils seems to also have a significant impact on the distribution limits of high value restoration areas, regardless of weighting value. Figure 5 and 6 seem to have few areas of low restorability (purple and blue) outside of the city proper, and have a large area of mid-range values (greens). Compared to the equal weighted cost surface layer, the randomly weighted cost surface layers appear to have much less maximum value restoration areas (red).

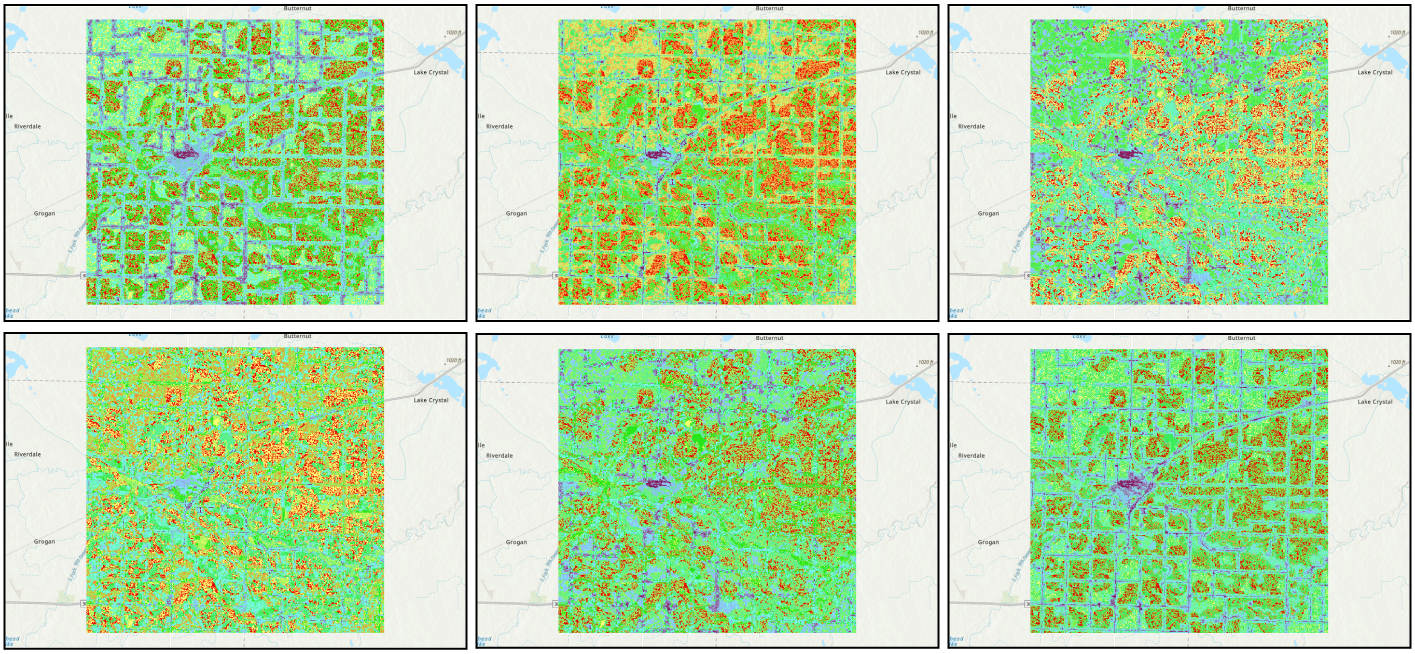
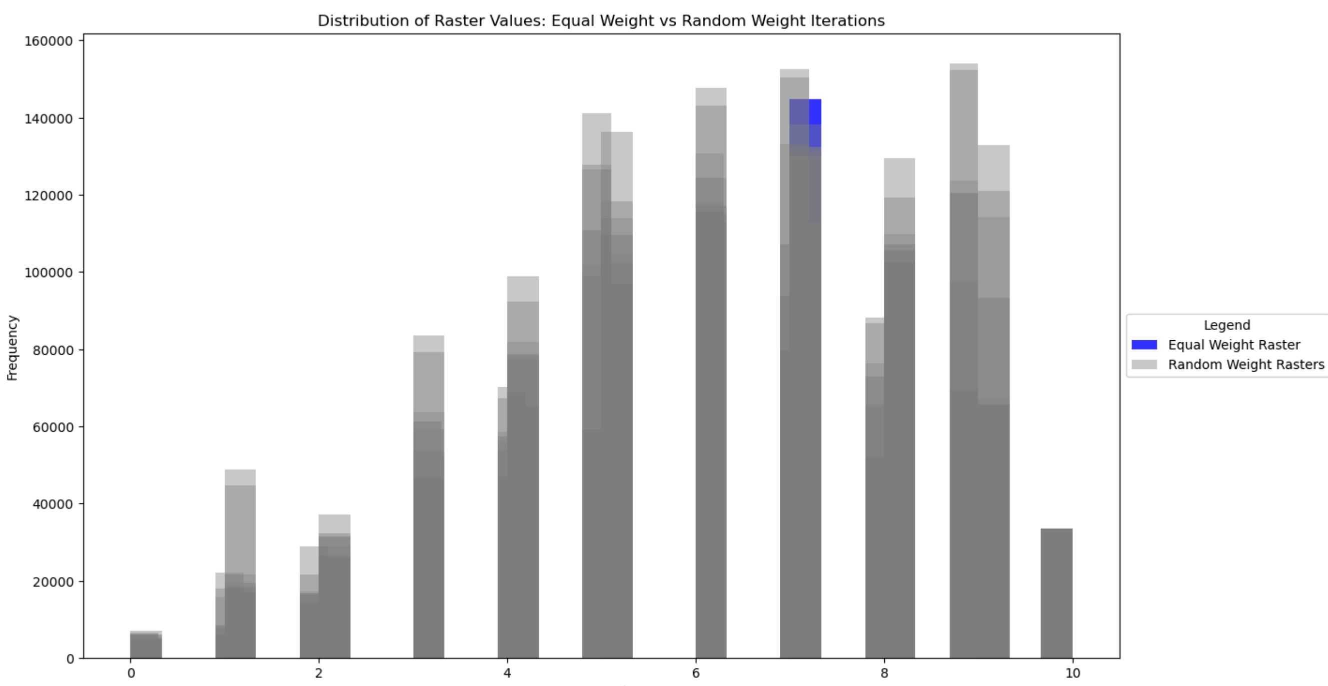


Figure 6. Maps showing six examples of random weighting values of the wetland restorability cost surface layer, 1 = low restorability (purple and blue) and 10 = high restorability (orange and red).

Results Verification

To determine whether these observations were valid, the distribution of the values from within the randomly weighted layers was compared to the equally weighted mean value, figure 7. The mean value within the equally weighted cost surface layer was about 7. Histogram values skew towards the right for values 5-9 but drop significantly at 10. This suggests that the data layers might not discriminate enough between low and high value areas. These data obtained a T-statistic of 20.4, p-value 4.7×10^{-37}, suggesting a significant and non-random difference between the randomly weighted values and the equally weighted values.

Figure 7. Histogram showing the distribution of values within each of the 100 randomly weighted cost surface layers (grey) compared to the mean value of the equally weighted cost surface layer (blue).



The RMSE and R^2 values further support these findings, showing that the randomly weighted values have a moderate fit compared to the equally weighted values, but a poor overall prediction performance (figure 8). While the RMSE values are relatively low, the variability of the values indicate that value assignment varies significantly across the cost surface layers (figure 7). R^2 values are near zero, while some are negative, suggesting that the equally weighted values are significantly different than a randomly weighted scheme.

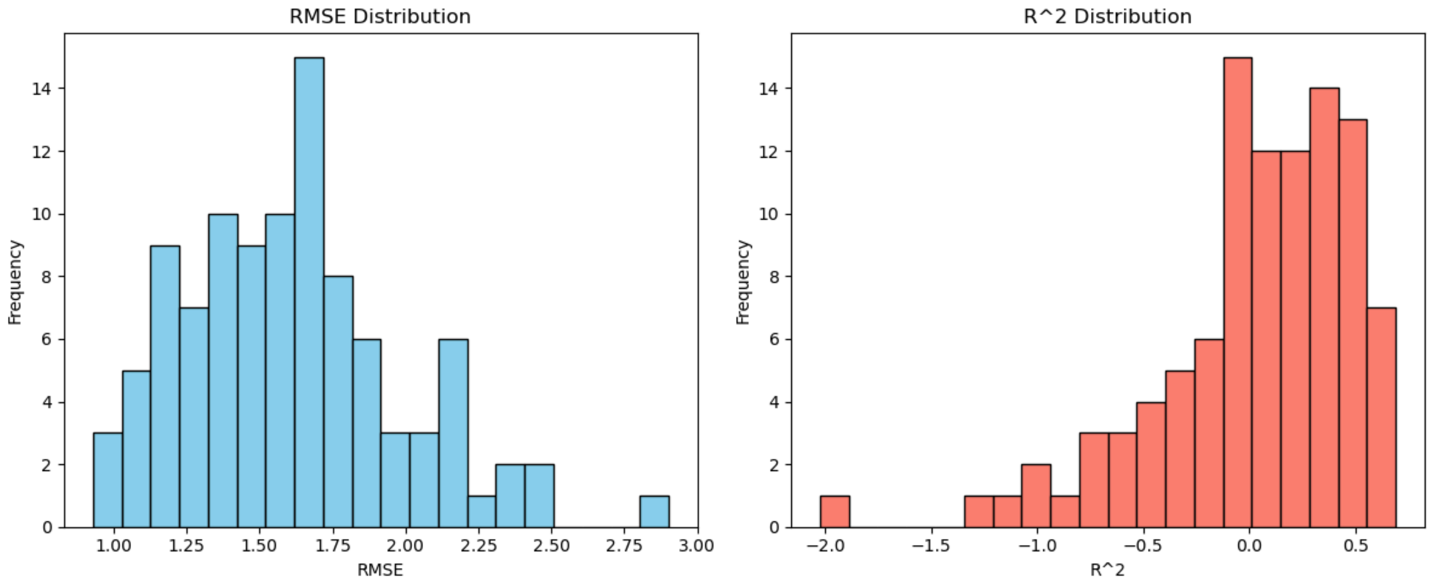


Figure 8. Histograms showing the distribution of RMSE and R^2 values for each of the 100 randomly weighted cost surface layers compared to the mean value of the equally weighted cost surface layer (RMSE: min=0.9285, max=2.9021, mean=1.6053, R^2: min=-2.0226, max=0.6906, mean=0.0244).

Comparison to DNR Restorable Wetland Areas

The DNR (UMN, NRRI) restorable wetland area layer used a two-way random forest algorithm to examine the connections between a larger set of data in both spatial and temporal patterns. Comparing this dataset to the MCDA cost surface layer was not originally part of the project, but seemed reasonable given the similar sets of data and the common goal of the cost surface layer.

Initial comparison was challenging because the DNR cost surface layer has a cell resolution of 3 meters, while the MCDA cost surface has a cell resolution of 30 meters. This made doing a histogram distribution comparison difficult and is not included in this project. Visual inspection of the DNR cost surface layer (Figure 9) shows that there are few highly restorable areas within the watershed boundary area (5, red). The DNR cost surface shows much more left-hand skewing, towards 1 (purple), with fewer mid-range values present (green).

Comparison was attempted by creating a 250 acre stacked grid within the watershed boundary. This was done to mimic land parcel distribution within the boundary area more accurately than TIGER file census tract boundaries were able. Figure 10 shows the equally weighted cost surface layer (left) next to the DNR cost surface layer (right) with zonal mean values provided for each of the grid parcels.

The color ramps in figure 10 are set to reflect the natural breaks distribution of values, in order to visualize higher priority and lower priority areas with similar colors. There are similar higher value distributions in the northeastern half of the watershed area and lower value distributions in the southwestern half of the watershed area, with the lowest values both showing up over the city of Madelia.

The data appear to be statistically significantly different from each other visually, and the RMSE and R^2 values confirm this trend. Even after adjustment for scale differences, the RMSE was 4.6, with an R^2 value of -26.04. The moderately high RMSE value combined with an extremely negative R^2 value show that the data are very different and non-related. When normalized, the RMSE became 0.46, but the R^2 value remained highly negative at -8.73.

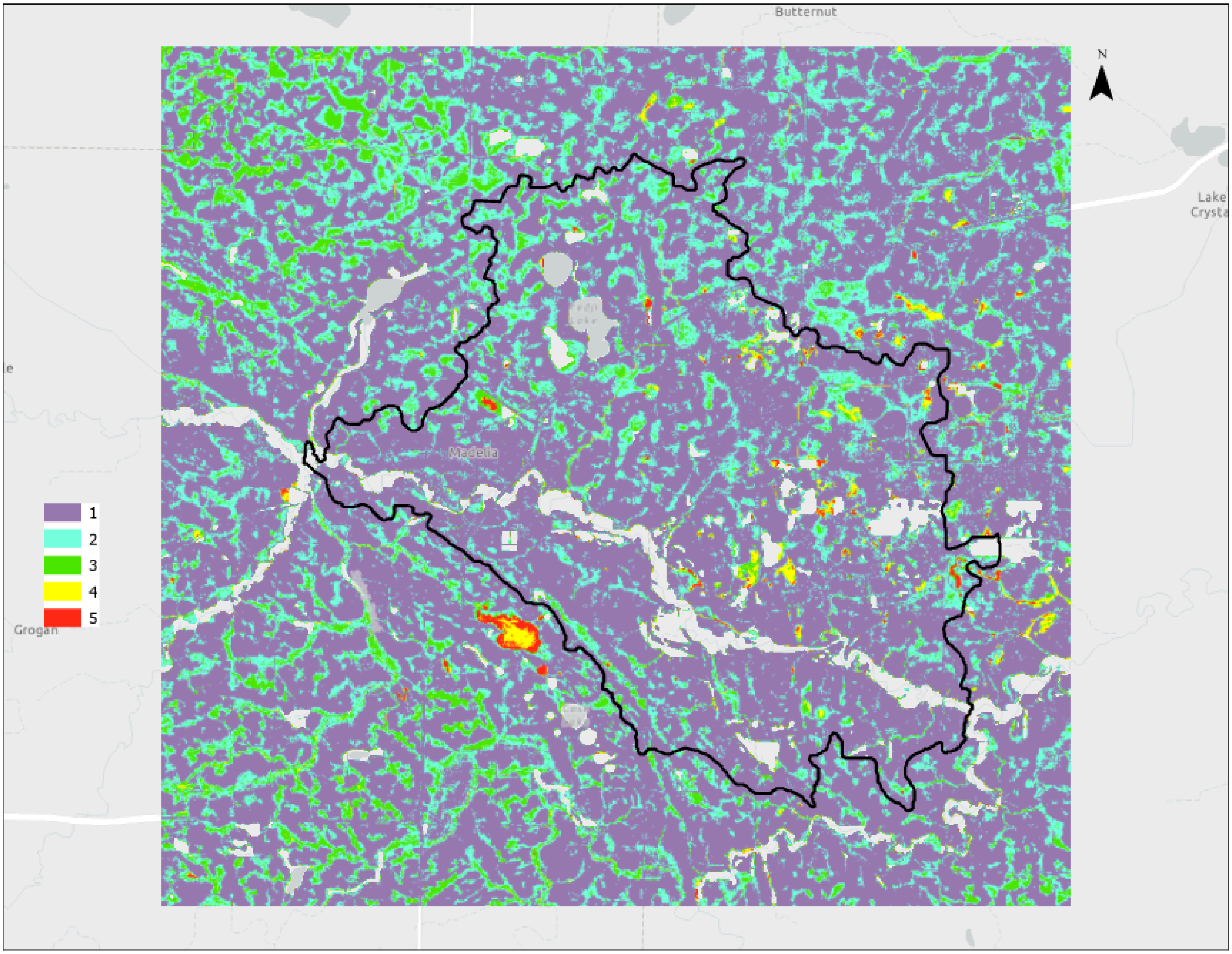
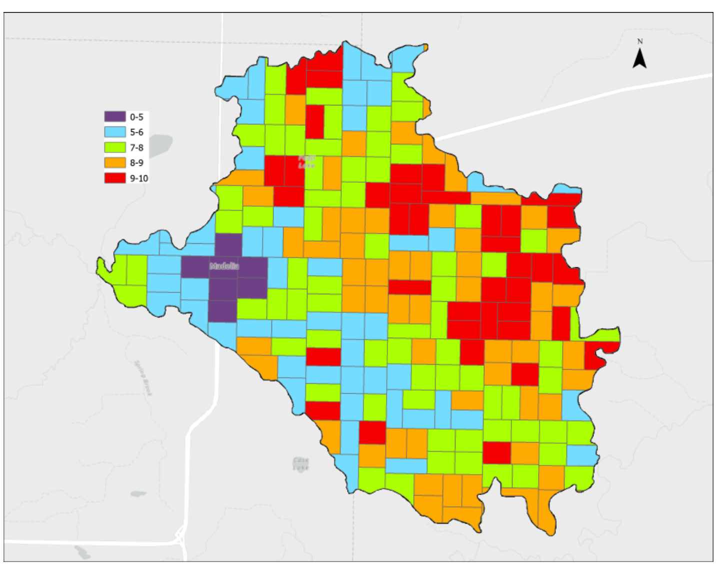


Figure 9. Map showing the DNR/UMN values of the wetland restorability cost surface layer, 1 = low restorability (purple and blue) and 5 = high restorability (red).



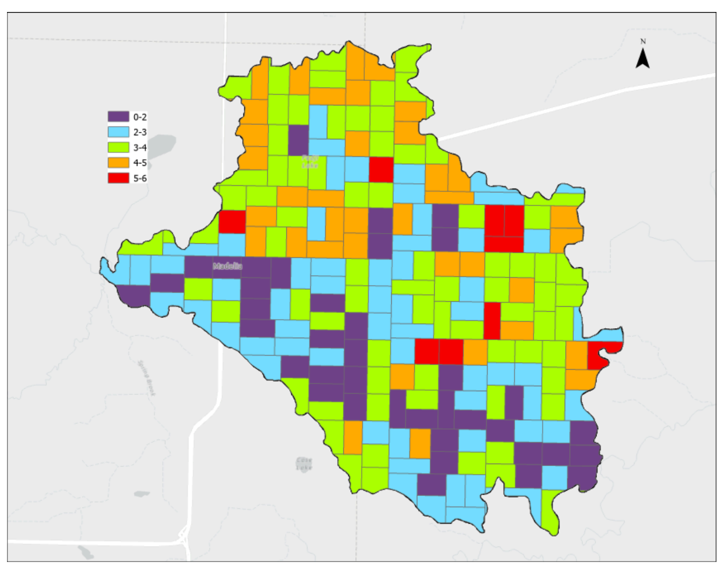


Figure 10. Map showing zonal mean values for each 250 acre watershed parcel with the equal weight values (left) and the DNR/UMN values (right); DNR values have been doubled to reflect the 1-10 scale in this project.

Table 1. Table showing the descriptive statistics comparing the distribution of cell values for the equal weight cost surface layer and the DNR (doubled) cost surface layer.

RMSE:	4.61	R^2 Value:	-26.04

Descriptive Statistics:	Equal Weights Project	DNR Random Forest
Count	219	219
Mean	7.176009	2.642489
Standard Deviation	0.888548	0.361384
Minimum	3.036585	2.101930
25%	6.616361	2.385215
50%	7.187826	2.598541
75%	7.771302	2.813125
Maximum	9.001736	4.091886

Table 2. Table showing the results of Moran's I spatial autocorrelation analysis for both the equal weight cost surface layer and the DNR (doubled) cost surface layer.

Moran's I Analysis:	Equal Weights Project	DNR Random Forest
Moran's Index	0.4505	0.2276
Expected Indix	-0.00459	-0.00459
Variance	0.001028	0.001025
Z-Score	14.19	7.25
p-Value	0.000000	0.000000

Final comparison between the two dataset was done by determining the effects of spatial autocorrelation on the results. Moran's I was calculated for both the equal weight raster and the DNR random forest raster, using the gridded parcel data for distribution comparison. Table 2 shows the Moran's I output scores, along with z-scores and p-values for both datasets. Both datasets were found to have significant spatial autocorrelation and clustering patterns.

Discussion and Conclusion

Researchers have been attempting to identify a "best" cost surface layer for wetland restoration potential for a long time (Anaya et al. 2017, Galatowitsch et al. 1996, Galatowitsch et al. 1998, Horvath 2017, Johnson et al. 2024, Tang et al. 2012, Widis et al. 2015). The challenge comes in interpreting which variables are most important for successful wetland restoration, and assumes that wetland restoration requirements are unified for all areas and all types of wetlands.

Comparison to Randomly Weighted Cost Surfaces

This project utilized six specific data layers with parameters that are required for Minnesota wetlands in the prairie pothole region. Equal weighting was applied to the individual cost layers based on research suggesting that weighting systems have been haphazardly applied to previous wetland identification research (Widis et al. 2015). The results of the equal weighting produced a reasonable distribution of high and low priority areas in the wetland study area (Figure 5). While there are a large number of mid-range values (near 7), prioritization using this particular map should be focused on areas with values of at least 9 if not 10. This should make sense since each cost layer is treated as a boolean trait (yes or no), and any value less than 10 represents an area that may not be hydrologically active or connected, and may be on land that is developed or unobtainable.

Randomized weighting schemes were used to help determine whether or not there was any difference in the outcomes of the cost surface layer. If the equal weighted cost surface layer was similar to randomly weighted cost surface layers, it may suggest that the data is inherently limiting and weighting is irrelevant or that the data itself is as good as randomly selected data values. The equal weighting was significantly different from the randomly weighted cost surface layers, which rarely produced areas with values of 10.

Comparison to DNR Restorable Wetland Areas

The DNR (NRRI) restorable wetland cost surface layer was used as a general comparison of method and cost value outcome. The original goal of the project was to simply compare the type of weighting scheme and how it would impact the value distribution. But it seemed relevant to compare the DNR cost surface values to those of the much simpler MCDA cost surface. These surfaces were produced using relatively similar data sets, with the exception of the NDVI, NDWI, and CTI data included in the DNR model. The MCDA cost surface does not use any form of machine learning to determine the results, while the DNR model uses a two-way random forest model.

These models produced significantly different results in their value distributions. The DNR model had a much lower distribution of values throughout the entire surface, with only a few areas of high restorability identified around some existing wetland areas. This model does not take developed land into consideration and does not seem to use land cover type as a direct method of valuation at all. The DNR model appears to be much less generous to land potential than research suggests it could be, though specifics on the methodology used was not publicly available except a small description in the layer metadata.

In order to attempt some kind of comparison of the DNR model and the equal weight model, false parcels (of about 250 acres) were created to view the land value distribution at a broader scale. At the parcel scale we can see relatively similar distributions of higher and lower restorability values. But if we look at the value scales within each model output it becomes clear how much lower the DNR model valued land restorability compared to the equal weight model. The DNR model had no land parcel mean values greater than 5 even after being adjusted to a common value scale. Seven of the parcels were identified in the highest value category across both models.

Takeaways and Next Steps

It seems easy to determine that the DNR model is inherently better because it uses a more complex model structure with more data layers. But the output suggests that there are essentially no areas worth restoring wetlands, even in an area that was covered by nearly 50 percent wetlands. The equal weight model shows a much more extensive set of areas that would likely have successful wetland restoration potential. It is hard to determine whether the DNR model is more realistic or more pessimistic, or if the equal weight model is more realistic or more optimistic.

Ultimately these data would need to be ground-truthed using “success rates” of wetland restoration projects. The DNR model was ground-truthed based on correctly identifying wetland areas. This is a standard method for remote-sensing object-based identification, but does not account for the amount of wetland loss that occurred before aerial imagery data were collected. In many areas the actual extent of wetlands was never recorded or mapped (Galatowitsch et al. 1996). Wetland potential is challenging to quantify, and the DNR model is not able to explain why areas received higher or lower values. The transparency of the equal weight model may make it more reliable and reasonable for conservation scientists.

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Self-Score

Category	Description	Points Possible	Score
Structural Elements	All elements of a lab report are included **(2 points each)**: Title, Notice: Dr. Bryan Runck, Author, Project Repository, Date, Abstract, Problem Statement, Input Data w/ tables, Methods w/ Data, Flow Diagrams, Results, Results Verification, Discussion and Conclusion, References in common format, Self-score	28	**28**
Clarity of Content	Each element above is executed at a professional level so that someone can understand the goal, data, methods, results, and their validity and implications in a 5 minute reading at a cursory-level, and in a 30 minute meeting at a deep level **(12 points)**. There is a clear connection from data to results to discussion and conclusion **(12 points)**.	24	**24**
Reproducibility	Results are completely reproducible by someone with basic GIS training. There is no ambiguity in data flow or rationale for data operations. Every step is documented and justified.	28	**28**
Verification	Results are correct in that they have been verified in comparison to some standard. The standard is clearly stated **(10 points)**, the method of comparison is clearly stated **(5 points)**, and the result of verification is clearly stated **(5 points)**.	20	**20**
		100	**100**