Wind Turbine Siting In Maine

Blaise Foley ‘19 Introduction to GIS and Remote Sensing

Environment Studies Program, Colby College, Waterville, ME

Introduction

The State of Maine has considerable potential for renewable wind energy, and represents the greatest amount of current wind power in New England (U.S Wind Industry, 2017). Creating a statewide wind turbine siting map could help government officials, private landowners, and land surveyors better understand wind turbine potential, and allow further analysis of particular areas. In this study, I use ArcGIS to locate future wind turbine locations through logistic regression models using economic, social and physical variables within the state of Maine.

Methods

I used ArcGIS to display four raster layers of initial variables that were researched for the creation of a wind turbine potential model. These variables were: wind power class, elevation, average household income and population density. The wind power class layer was provided from the National Renewable Energy Laboratory (Wind Data, 2009). Current and proposed wind turbines locations were provided by the Federal Aviation Administration Wind Turbine Location Data (FAA, 2018). The average income per household and population density layers were created using data from Social Explorer and Tiger Census data (Social Explorer, 2016). All data was then projected using the North American Datum 1983 Universal Transverse Mercator Zone 19N coordinate system.

The next step was to create 100 random points throughout the state to compare with the current 469 wind turbine locations. Using the extract values to point tool in ArcGIS all random points and current wind turbines locations were assigned specific values from the raster layers of the four variables. Using Microsoft Excel and R studio the data was then used to create Mann-Whitney U tests comparing mean values associated with the random points and current wind turbine points for all four variables. All variables with a significantly low P-value which included wind power class, elevation and average household income were then used to create an initial logistic regression model (Model A). After analysis of Model A, a second logistic regression model was created for comparison only including elevation and wind power class as variables (Model B). These equations were used in ARCGIS to display wind turbine potential throughout the state.

Results

The results of the Mann-Whitney U Test allowed three of the variables to continue to the logistic regression model. Wind turbine locations had a significantly lower mean average household income ($59041) compared to random points ($67,110), $P < .001$. Wind turbine locations had a significantly higher mean elevation (405m) compared to random points (217.1m), $P < .001$. Wind turbine locations had a significantly higher mean wind power class (2.708) compared to random points (1.32), $P < .001$. Wind turbine locations did not have a significant mean population density (12.095) compared to random points (34.465), $P > .001$. Significant variables were computed into the initial logistic regression, Model A (Figure 7). Model A had an r-squared value of .2121, meaning that roughly 20 percent of the probability model can be explained by the three variables used in the model. Model B, the secondary logistic regression only used elevation and wind power class data (Figure 7). Model B had an r squared value of .1802, showing that the model accounted for slightly less than 20 percent of the probability model.

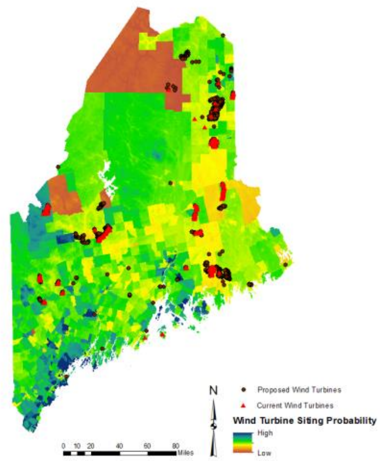

Figure 1: Probability of future wind turbine sites using Model A, depicting current and proposed wind turbine locations

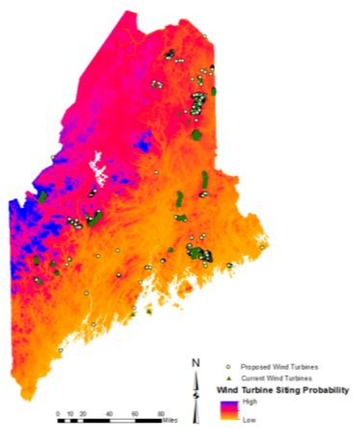

Figure 2: Probability of future wind turbine sites using Model B depicting current and proposed wind turbine locations

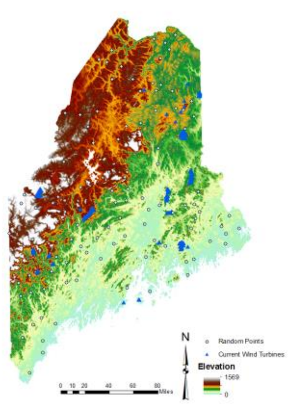

Figure 3: Elevation variable showing random points and current wind turbine locations. This variable had a significantly low p value (p=2.2e-16) and was used in both logistic regression models.

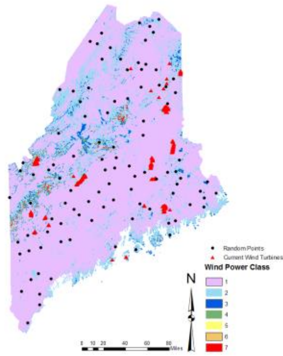

Figure 4: Wind Power Class variable showing random points and current wind turbine locations. This variable had a significantly low p value (p=2.2e-16) and was used in both logistic regression models.

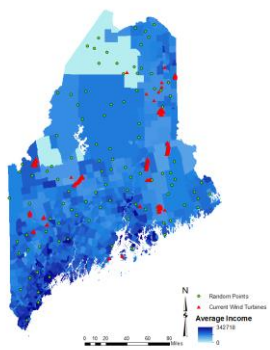

Figure 5: Average income per household variable showing random points and current wind turbine locations. This variable had a significantly low p value (p=1.243e-07) and was used in Model A but was excluded from Model B

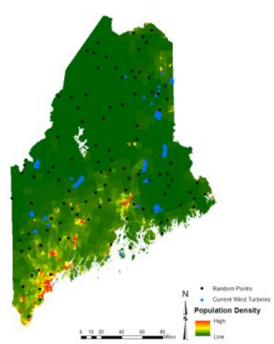

Figure 6: Population Density variable showing random points and current wind turbine locations. This variable did not have a significantly low p value (p=.5134) and was not used in any logistic regression models.

Model A Equation:

$$\frac{1}{1 + e^{(.749 - .0002114(\mathit{Elevation}) + .01756(\text{Wind Power Class}) + .000004703(\text{Average Income}))}}$$

Model B Equation:

$$\frac{1}{1+e^{(.6499891 - .0009314(\mathit{Elevation}) + ..008591(\text{Wind Power Class}))}}$$

Figure 7: Logistic regression equations for Model A & Model B

Table 1: Results of Mann- Whitney U tests

Variable	Mean Actual	Mean Random	S.D Actual	S.D Random	Mann-Whitney U test P value
Average Household Income	$59,041	$67,110	10,695.62	28,007.15	1.243e-07
Elevation	405m	217.1m	206.175	171.2267	2.2e-16
Wind Power Class	2.708	1.32	1.206	.6798	2.2e-16
Population Density	12.095	34.465	16.9	68.843	.5134

Discussion

Model A overemphasizes the importance of average household income. This is visibly represented by the well-defined census block areas (Figure 1), and the similarities to the average household income raster layer (Figure 5). This is most likely because current wind turbines are constructed in bunches, many in close proximity to each other. This would mean wind turbines would likely be in the same census block, creating identical average household income values. Wind turbines would have more similar average household incomes when compared to the 100 random points scattered throughout the state, falsely creating a high correlation between average household income and wind turbine siting locations. This overemphasize was corrected in model B, which looks only at variables associated with wind. Model B has a slightly smaller r squared value (.1802) when compared to Model A (.2121) but is more accurate in representing future wind turbine sites. This is because Model B only incorporates wind power class and elevation raster values which were much more precise and could have different values for wind turbines in similar clusters, which could not be achieved by values for average household income.

Conclusion

Variables associated with wind, elevation and wind power class showed to be the greatest indicators of predicting future wind turbine sites. Average household income was statistically relevant for the logistic regression model but proved to have too broad of census blocks to be accurately displayed on ArcGIS. Population density was proven to not be statistically significant in predicting future wind turbine sites. In the future, more detailed census data could prove useful to this model, allowing more accurate detail to better predict social and economic variables.

Acknowledgments

I would like to thank Philip Nyhus, Associate Professor of Environmental Studies and Manny Gimond, Geographic Information System and Quantitative Analysis Specialist for their immense help and time dedicated towards my project.

References

Average Income per Household. (n.d.). Retrieved from https://www.socialexplorer.com/

Carollynn Hammersmith, SSD, Web Services Staff. (2010). United States Census Bureau. Retrieved May 1, 2018, from https://www.census.gov/cgi-bin/geo/shapefiles2010/main

Federal Aviation Administration (FAA) Wind Turbine Location Data. (2018, April). Retrieved May 1, 2018, from https://www.fws.gov/southwest/es/Energy_Wind_FAA.html

Population Density Table. (2016). Retrieved May 1, 2018, from https://www.socialexplorer.com/

U.S. Wind Industry Third Quarter 2017 Market Report. (2017). *American Wind Energy Association*. Retrieved May 1, 2018, from http://awea.files.cms-plus.com/3Q 2017 AWEA Market Report Public Version.pdf

Wind Data. (2009). Retrieved May 1, 2018, from https://www.nrel.gov/gis/data-wind.html

Wind Power Classification. (n.d.). Retrieved from http://rredc.nrel.gov/wind/pubs/atlas/tables/1-1T.html