AUTOMATING WIND TURBINE SITE ANALYSIS

AUTHORS

Gautam Mathur is an environmental scientist interested in natural resource management, remote sensing, and spatial analytics, who is currently a masters student at the University of Michigan's school for Environment and Sustainability, specializing in Geospatial Data Science. Gautam aims to consult governments of all levels, and other organizations on managing and tracking the use and health of their natural resources.

Lawson Schultz is an artist, researcher, and planning student focused on land use, environmental justice, and criminalization and resistance. Lawson aims to collaborate with communities as a planner and researcher to empower visions of sustainability, safety, and joy.

INTRODUCTION

Climate change demands urgent action necessitating a shift towards green energy. Wind power stands out as a crucial element in this transition due to its sustainability and wide applicability. Currently, 23 states have passed legislation committing to 100% renewable energy by a specific year (1). To encourage similar commitments in other states, it is vital to provide data demonstrating the benefits and feasibility of such initiatives. Our project focuses on creating an automated GIS process to identify suitable locations for land-based wind turbines. We apply this process to Ohio, a purple state that has yet to commit to 100% renewable energy, in hopes of showcasing the potential for clean energy adoption (2). Additionally, we provide analysis of feasible locations in relation to the state as a whole and per county, bearing in mind political considerations.

Wind energy, or wind power, is the most abundant source of renewable energy in the United States, accounting for over 10% of total electricity (3). Wind energy is generated by wind turbines. After the wind turbines are constructed, they produce electricity without producing carbon dioxide. Large and medium sized wind turbines in groups are most cost effective for wind projects connected to power grids. Medium-sized land-based wind turbines are about 250 feet tall and can generate up to 1.8 megawatts of power (4,5). For this project, we are accessing locations for horizontal-axis turbine land-based wind energy rather than distributed wind energy that is associated directly with small scale locations they are serving (6).

METHODOLOGY

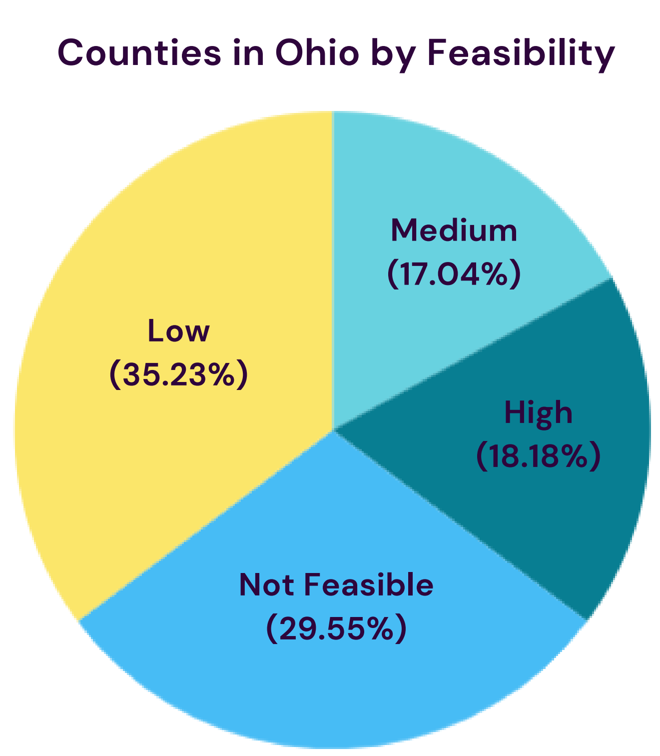
We accessed hourly wind speed data from Iowa State University for the calendar year of 2023 (7). Using Pandas in python, we then aggravated the wind speed data to obtain the annual average wind speed for 61 airport stations across Ohio. Additionally, we used geopandas to convert the latitude and longitude values into points. We created a raster of estimated wind speed values by interpolating the annual average wind speed station data points using the IDW method to estimate wind speed across Ohio. Next, we eliminated areas with slow wind speeds with the con tool to convert any pixels below an estimated wind speed of 7 mph to 0. The resulting raster was then rescaled to a range of 1 to 0.

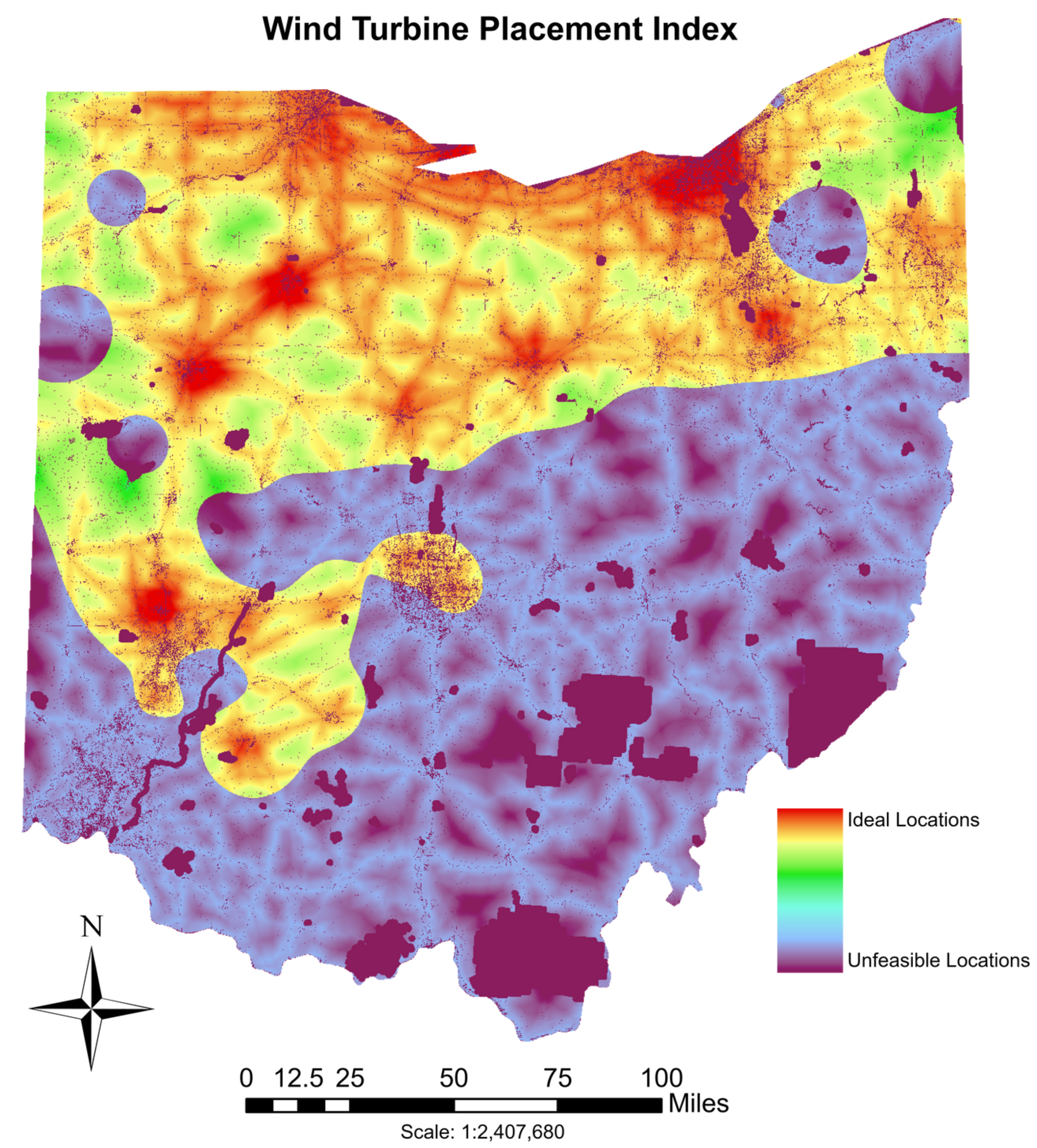
We acquired road data from the Bureau of Transportation Statistics' North American Roads dataset (8). This dataset contains major roads and highways across North America. Roads were important to include in our analysis since wind turbine infrastructure is extremely large and heavy, and therefore, sites near a major road or highway are more ideal. Additionally, due to the importance of large-scale wind turbines being connected to the power grid, we also included power line data in our analysis. We acquired power line data from a US Electrical Powerline Transmission dataset (9). Next, we applied a euclidean distance function on the road and powerline distance line shapefiles. These rasters were then rescaled to a scale of 1 to 0, where the pixel closest to the roads or powerlines had a value of 1. The wind speed, powerline distance, and road distance rasters were added together, along with their allocated weights, to an index raster with values between 0 and 1. Wind speed was given a weight of 70%, whereas powerline and road distances were given a weight of 15% each.

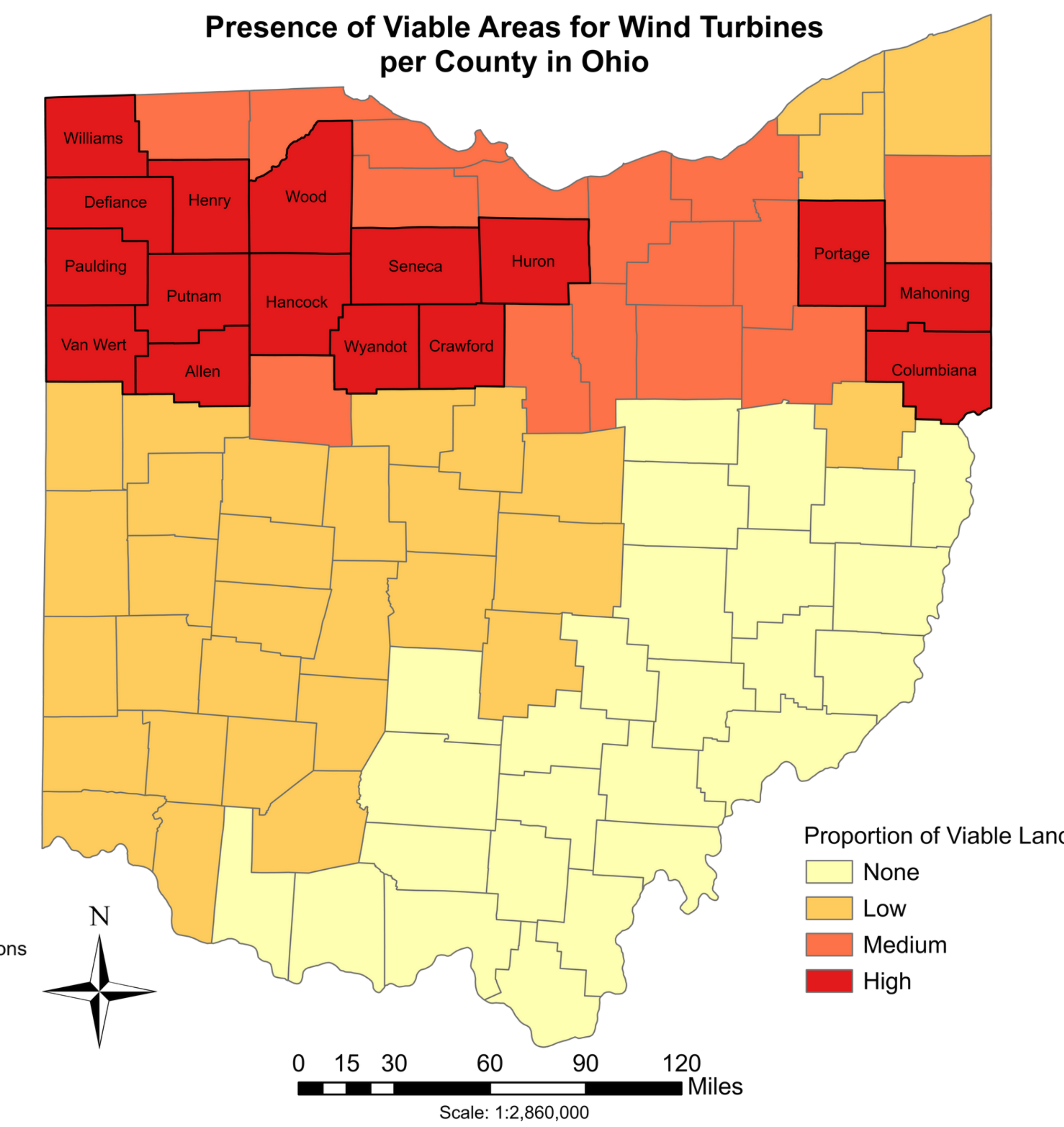
From this initial raster, we also excluded areas of land where wind turbines would not be feasible including protected parks and inappropriate land cover. We used USGS' "PAD(Protected Areas Dataset) 3" to obtain geometries of natural areas protected by state and federal bodies (. A 1 km buffer was added on all sides of geometries to prevent areas on the boundaries of these geometries to be classified as viable) (10). We also applied a euclidean distance function to the buffered boundaries, followed by the con tool, using which areas within the buffers were classified as 0, and areas outside were classified as 1. Moreover, we obtained land cover data for the area from the ESA WorldCover dataset (11), and applied the con tool to convert this to a binary raster, with viable land covers obtaining a value of 1 (trees, shrubs, grasslands, croplands, and sparse vegetation), and unviable land covers obtaining a value of 0. Lastly, we used raster calculator to multiply the land cover and protected areas binary rasters with the index rasters, so that unviable areas would have a value of 0 in the index raster, and the index values for viable areas would stay the same.

FINDINGS

Our analysis created an index of the viable locations for wind turbines in Michigan. This index raster highlights the regions of the state that are most likely to support wind turbines. Upon initial inspection, the index highlights the northern and western regions of Ohio as having particularly high presence of viable areas. Through our additional analysis, we identified the proportion of viable areas of land for wind turbines per county. We classified viable land for wind turbines as those in the 75th percentile of our index. We classified the counties into 4 classes (High, Medium, Low, Not Feasible), based on the Natural Breaks (Jenks) classification in ArcGIS Pro. Twenty six of the eighty eight total counties in Ohio did not have any areas with an index value above the 75th percentile. Sixteen out of the remaining sixty-two counties were prioritized as "High", and fifteen were prioritized as "Medium".







CONCLUSION

Our automation of feasible locations of wind turbines produced an index highlighting the most feasible areas of Ohio. The parameter that can be changed in this automation is the input data. Therefore, it can be re-run with data from another state to produce additional indexes. In addition to the overall trends indicated with the index, we did additional analysis to highlight patterns by county. This is significant as state level policies for renewable energy can have implications that impact each county. For instance, in Michigan, policy makers and rural residents have come in conflict over arguments over which communities should face the burden of hosting renewable energy infrastructure (12). Within the state of Ohio, distribution of feasible areas of land for wind turbine location is highly clustered. We argue that these findings suggest policies that aim to encourage increased production of renewable energy will need to prioritize efficiency of wind turbines over proportional distribution across all counties. That said, more detailed wind speed data, additional analysis of zoning and property ownership, and analysis of bird migration would all drive more conclusive results.

LIMITATIONS

Our first limitation is the resolution of our wind speed data. We used data from 62 wind stations to interpolate wind speed for the whole state. More dense station data would help increase the accuracy of this process. Secondly, while we account for protected areas, wind turbines can be dangerous to protected bird species, and migratory paths of protected avian species should be included in further analysis. Lastly, To make sure that areas are viable wind farm sites, properties of land such as ownership, soil type, county-level zoning and laws etc. also need to be looked into. While these properties will be different for different areas, this process is an automated first step that can help lawmakers and planners prioritize where to further investigate viability.

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