Jake Mammen
5/6/22
Research Paper

Understanding the Influence of Socioeconomic and Environmental Characteristics on the Development of New Wind Farms.

Abstract

Wind energy has become one of the leading producers in renewable energy. There will be a never-ending demand for energy and being able to extract clean renewable energy is a very important strategy to combat climate change. Research suggests fossil fuels have harmful impacts on the environment, and many in opposition of wind farm development believe wind energy contributes as well. For example, habitat loss, disruption to migratory patterns, and simply being unaesthetically pleasing are some of the dislikes those in opposition have. There have been several case studies that focus more on public perception of wind farms, which analyze the attitudes of the public based off multiple social, environmental, and economic variables. This study, however, solely aims to understand how certain characteristics may influence the development of new wind farms and compare the results across the study regions. The objective of this study is to analyze twelve different socioeconomic variables and one environmental dataset across Iowa, Oklahoma, and Texas to determine if there are any influences on wind farm development. Additionally, this study will determine if there is spatial clustering among wind farms and whether it's due to a random process. Lastly, the results of this study will show how socioeconomic and environmental characteristics alone don't provide enough evidence to predict the likelihood of future wind farm development. While there may be numerous studies addressing the impacts of common factors, these studies tend to only focus on each factor individually. Through a widely used mixed methods approach of geospatial and statistical analysis, this study effectively analyzes combined qualitative and quantitative data

pertaining to wind farms and is utilized to evaluate and organize the results (Leech et al., 2010). This type of research will be important in fully understanding what may impact or influence wind farm development apart from public perception.

Introduction

According to the Energy Information Administration (EIA), fossil fuels accounted for approximately 68% of greenhouse gas emissions in the United States in 2020, with approximately 32% of emissions from electricity generation (EIA, 2021). To combat climate change, wind power development can be a vital source of renewable electricity generation and contribute to reducing global greenhouse gas emissions (Peri and Tal, 2020). Thus, adopting non-carbon-emitting energy sources is essential to minimize the impacts of climate change around the world (Pavlowsky and Gliedt, 2021). Wind energy accounts for 8.4% of the total electricity supply in the United States and is expected to grow continuously due to its low cost (Hamilton et al., 2020). However, while the development of wind energy receives broad support, the ongoing controversy over the benefits and uncertainty of how it affects landowners continues to create opposition in wind producing communities (Pavlowsky and Gliedt, 2021). As of January 14, 2022, there are 70,808 wind turbines located throughout the United States, according to the U.S. Wind Turbine Database from the United States Geological Survey. Wind power has been around for many centuries and was developed to generate electrical power over 130 years ago (Leung and Yang, 2012). Throughout those years, wind power has performed well contributing to the United States total electricity generation, but opponents of wind power believed that environmental impacts include noise, visual, or climate impacts (Leung and Yang, 2012). Such an environmental impact is possible, as roads and transmission lines associated with wind development represent a potential threat and to the turbines themselves (Kuvlesky Jr. et al., 2007). However, this study focuses on perceptions, socioeconomic, and physical impacts of existing wind turbines, and the possible effects on development of new wind farms. Additionally, there are concerns that wind turbines negatively impact property values, though, research suggests that the sales price of residential properties was not significantly impacted by turbine adjacency (McCarthy and Balli, 2014; Vyn and McCullough, 2014).

Several studies have investigated the planning and placement of wind farm development in multiple countries (Peri and Tal, 2020; Santos-Alamillos et al., 2014; Stefanakou et al., 2019). Similar to other countries, the United States faces obstacles pertaining to wind turbine placement relative to land suitability meaning a set of comprehensive factors (Peri and Tal, 2020), such as demographics, economics, policies, and topography shape the way engineers and policy makers think about where to place large wind turbines (Bennui et al., 2007). Researchers have attempted to provide useful analysis on wind farm development via the use of Geographic Information Systems (GIS) which can be used to develop a framework on how to evaluate site suitability and establish feasible land that may be available for potential wind turbine development (Rodman and Meentemeyer, 2006). However, providing an objective, data-driven analysis may prove to be inefficient to decision makers. There remains a correlation between wind turbine acceptance and wind turbine development. A common issue with respect to wind turbine placement and wind farm development is the perception of the public. New technologies often spur public reactions, therefore it is imperative to understand the public's response to these new ideas (Boudet, 2019). While public perception can potentially influence decision making, research on wind energy and its contribution to cutting greenhouse gas emissions has the potential to mitigate opposition over time (Pasqualetti, 2001). Therefore, through a geospatial and statistical analysis of quantitative and qualitative data, communities across the country may become more receptive to ideas of wind farm development (Greene and Geisken, 2013). Community engagement will ultimately be a key factor to a sustainable future of wind-generated electricity (Peri and Tal, 2020).

Much of the research conducted suggests an analysis that consists of meaningful results, “can be helpful for permitting agencies, local planners, and engineers engaged in permitting processes, zoning ordinances, and the development of regulations for the wind farms” (Kumar and Sinha, 2016). While there is plenty of research on wind energy and wind farm development, many are perception-based case studies and don’t focus specifically on other potential factors that could be used to compare similar wind producing communities across the United States. Additionally, despite research on wind energy and farms in select states, there remains a need for extensive analysis on wind turbine development that could be used to address the obstacles policy makers and engineers face, across the United States more broadly. Furthermore, there may be limitations to the analysis that differ across multiple landscapes and communities effecting the outcomes because those ideas may not be fully considered (Greene and Geisken, 2013; Pavlowsky and Gliedt, 2021). With such a diverse scope of research and variables that go into suitable land for wind farm development, a mixed methods approach provides a unifying framework designed to validate information for all types of data and verify that the results are significant and meaningful.

Data and Methods

This study focuses on three states: Iowa, Oklahoma, and Texas. These three states are among the leading wind producers across the country. Overall, most wind turbines are in clusters of approximately 70-93 turbines throughout the central United States (Table 4). However, in certain areas there can be a maximum of approximately 193 wind turbines per cluster. In western Oklahoma, the Weatherford wind farm is located on about 5,000 acres of land which include 98

GE 1.5 MW turbines with a rated capacity of 147 MW of electricity and generates enough electricity to power approximately 44,000 homes. Each wind turbine is approximately 262 feet (80 meters) tall from ground to the hub center of the blades. On average, the distribution of wind turbine height across this study region ranges from 80 meters to 120 meters high. Most wind turbines located in Texas are also GE wind turbines and are similar in height compared to those in Oklahoma. In Iowa, you will find wind turbines manufactured by GE and other such companies. Broadly, turbines differ by manufacturer across different regions of the United States. A review of the metadata in the United States Wind Turbine Database dataset (USGS 01/14/2022), indicates a difference in the height of turbines across regions. This is important because wind turbines are generally placed in locations of higher elevation to increase the daily experience of consistently strong winds. The central plains are geographically significant given the winds that come off the Rocky Mountains as the jet stream moves from west to east. In states like Oklahoma and Texas there are generally less trees given the environment. Furthermore, the map generated by the National Renewable Energy Laboratory (NREL 2017; Figure 4) combined with a favorable wind environment, may contribute to promising energy production making this region ideal due to its overall flat and rural terrain (Woody, 2020).

There are multiple quantitative and qualitative datasets analyzed in this study. The United States Wind Turbine Database (USWTDB) dataset (United States Geological Survey, 1/13/2022), in collaboration with the Lawrence Berkley National Laboratory (LBNL) and the American Wind Energy Association United States Wind Turbine Database. The latest release on January 14, 2022, of data includes 70,808 turbines covering 44 states (plus Guam and Puerto Rico). The most recent turbines added to the USWTDB became operational as recently as the second quarter of 2021, with approximately 1,097 new turbines from the third quarter of 2021.

The oldest turbines in the data set were installed prior to 1990, as this dataset ranges from 1982 to 2021. The data are available as a shapefile and in vector data format. A shapefile stores non-topological geometry and attribute information for the spatial features in a data set. The geometry for a feature is stored as a shape comprising a set of vector coordinates. The USWTD shapefile contains point data with multiple attributes such as coordinates, state, county, turbine manufacturer, turbine height in meters, and date the turbine was built/became operational. The wind turbine dataset is used to map existing wind turbines, to analyze the clustering and point intensity of wind turbines geospatially and statistically. Additionally, it is used to perform a geospatial analysis in relation to nearby communities and to measure adjacency in meters. Socioeconomic data comes from the US Census Bureau. In this study, there are twelve variables which include: Population, Total Housing Units, Educational Attainment, Degree Status (Bachelor's or Higher), Employment, Employment in Agriculture, Total Houses Built, House Built 2014 to Later, Houses Built, 2010 to 2013, Houses Built 2000 to 2009, House Value 2010 (Median Dollars), and House Value 2020 (Median Dollars). To analyze land cover change, National Land Cover datasets ranging from 2001 to 2019 from the Multi-Land Characteristics Consortium (MRLC) were used. Furthermore, TIGER/Line Shapefiles from the U.S. Census Bureau were used to map and perform analysis at the census tract level which useful for better sample sizes.

A mixed-methods approach is applied, consisting of two parts: a geospatial and statistical analysis of socioeconomic and environmental data from within the study regions. Using this approach, I will analyze the clustering of existing wind farms and the possible relationship between wind farm development and community adjacency. I adopted a mixed approach to 1) facilitate comparison with previous studies followed (Arun, 2017; Greene and Geisken, 2013;

Woody, 2020), and 2) because in research a mixed methods approache enhances the scope and improves the analytical power of a study (Sandelowski, 2000). In research that requires more than one approach, the mixed methods approach proves to be more adequate in gauging the logic than would a one method approach (Palinkas et al., 2015).

Given the high density of wind turbines in western Texas, northwestern Oklahoma, and northern Iowa, I expect new development of wind turbines to expand outwards into less dense areas. Therefore, certain criteria such as economical (distance to community, houses built, house value), social (residential density or population), and environmental (land cover change) can be considered as a Multi Criteria Decision Making (MCDM) problem and can be used to determine wind farm land suitability (Al-Yahyai et al., 2012). Land suitability is defined here as the applicability of a specific type of land use. While similar research uses a criterion classification index to analyze wind farm suitability, this study will use a geospatial approach to address commonly researched environmental, and socioeconomic factors. In addition to the geospatial approach, a statistical analysis of wind turbine locations (Figure 1) and US census variables (Table 1,2, and 3) will be used to address the clustering of wind farms, distance between wind turbines, distance from adjacent communities, and to test for spatial autocorrelation of population and total houses-built variables. This study builds upon (Fast and Mabee, 2015; Greene and Geisken, 2013; Groth and Vogt, 2014; Hoen et al., n.d.; Jacquet, 2012; Rodman and Meentemeyer, 2006; Slattery et al., 2012) to test the assumption that communities that have similar characteristics as the ones with nearby wind farms, should be able to gain information and apply it towards future wind farm development.

To allow for a clean analysis, the data must be managed properly so that none of the data gets lost or ingested wrongly. Most of the shapefiles used in this study were ingested into ESRI's

ArcMap, which allowed for manipulation and proper reprojection. A projected coordinate system was used to print maps and successfully calculate measurements in the statistical analysis. For the geospatial portion of this study, data was projected and then mapped in Arcmap. There were additional figures that were produced using R Studio. The statistical analysis of this study was performed in R Studio in which each dataset was carefully ingested into R Studio and organized in a way that made working with the data clear and concise. Beginning with the statistical analysis, a general analysis which included looking at the five number summaries of each of the variables provided insight of how this data initially varied spatially. The wind turbine dataset was filtered into three separate categories that corresponded with each of the three study regions. Simple functions were used to group, summarize, and omit any null values in each of the three divided up wind turbine data tables. All the twelve socioeconomic variables were mapped using ggplot in R Studio. To analyze the spatial clustering of wind turbines and test the hypothesis of Complete Spatial Randomness (CSR), a point pattern analysis method was used. The F function can be used to see how clustered a point pattern or dataset is clustered. However, to understand if the patterns being analyzed are statistically significant, a Monte Carlo Simulation on the F function can be used. This method draws boundaries around the top and bottom functions and forms a Monte Carlo envelope with "acceptance intervals" which mean the range of values that are not statistically different from the null hypothesis or completely random. Furthermore, this type of simulation allows for a point pattern to be modeled and calculates the probability a point pattern was generated by some random process.

Point process models were fitted to each of the divided-up wind turbine data tables. Additionally, another data table was joined to the three wind turbine data tables to create one data table containing wind turbines and population data per study region. This was done to explore the relationship that population, more specifically urban vs rural, has on wind farms. The fitted point process models show that a particular point pattern may vary spatially due to some covariate influence. The model then suggests that some other process may be at work leading to the analysis of spatial autocorrelation between the variables. Lastly, the national land cover datasets ranging from 2001 to 2009 were put through a raster analysis in R Studio which analyzed land cover change across each of the study regions in comparison to wind turbine locations.

Results

The results of this study were very useful in understanding the influences that certain socioeconomic and environmental characteristics have on wind farm placement. The results seen in (Table 1,2, and 3) provide statistical information about the characteristics in each study region. The population means were interesting because they compared similarly with an average of 3,000 or more people per census tract, with Texas having the higher average of the two. This should be assumed since this state is larger in area than the two other study regions. This is useful because according to the U.S. Census Bureau in 2010 an area is identified as “urban” if there are more than 2,500 people in an urban cluster or urbanized area. This alone shows that population is one variable that drives this spatial process. Additionally, from (Table 1,2, and 3) the House Value from 2010 to 2020 increases. However, this could be due to a multitude of factors, the housing market increases in value, the price for materials, or maybe some other process that this study does not dive into. Similar to (Hoen et al., 2009), there is no statistically significant evidence to show that wind farm development has a significant impact on nearby house prices.

On average there are approximately 60-90 wind turbines per project across the study regions, with the minimum being one and the maximum being about 140 turbines (Table 4). In Iowa and Oklahoma there are approximately 4,000-6,000 total turbines, whereas, in Texas there are approximately 17,000 turbines. Texas has a larger surface area than the other two study regions, so again this is to be expected. In Figures 6, 10, and 14 we see the U.S. wind turbine dataset overlayed with the joined total houses-built variable. This variable in addition to population appeared to be the most significant in terms of a geospatial analysis. In Iowa, we see that most of the houses built, surround the urban areas or cities given the relatively low values not near the wind turbines. Similarly in Texas we see the same thing as most of the wind turbines are out west in which the census tract shows lower corresponding population values. However, in Oklahoma this is not the case as higher values of total houses built appear denser throughout and specifically around some of the wind farm locations. The average distance from wind farm to adjacent community was approximately 12,000 meters or 7.8 miles (Table 5). Lastly, the geospatial analysis of wind turbines and wind farms across the study regions showed high point intensities and small mean nearest neighbor distances (Figures 1 and 2, & Table 6). It was obvious that the wind farms and wind turbines across the study regions were showed spatial clustering.

Figures 5, 9, and 13 indicate that the mean number of wind turbines per project appear to be increasing overtime, especially in the last ten years. Given the increasing number of wind turbines per project and the visually significant patterns that both population and total houses built indicate, a possible process may be at work. The Monte Carlo Simulation on the F function provided a statistically significant result. The wind farms in each of the study regions are clustered and by testing for complete spatial randomness (CSR), the null hypothesis was rejected given the observed value nowhere near the expected value (Figures 8, 12, and 16 & Table 6). This can also be proven by looking at the mean nearest neighbor distances for all the study regions and compare against the simulated mean nearest neighbor distances. The mean nearest neighbor distances and simulated mean nearest neighbor distances are nowhere near each other, therefore, some other spatial process is at work. The fitted point process models (Table 7) show the point intensities at the census tract for the "rural" and "urban" classification given by the criteria from the US Census (2010). These point intensities aim to help identify what spatial process may be at play. After fitting these models, the results indicate the full model is the best model to go with (Table 7, highlighted in yellow). The AIC scores were calculated and given that the full model had the lowest AIC scores, we indicate that the full model is best fit because the AIC is measure of how well a statistical model fits a data set. This allows for the two variables, population and total houses built, to be tested for spatial autocorrelation. The results for all three study regions show a similar statistically significant p-value of less than 0.05 (Table 8 and 9). However, the R-squared values for all three are very small and would indicate that there is no linear relationship as it pertains to spatial variance across the study regions.

Lastly, in Figures 7, 11, and 15 the land cover gain and loss for each of the study regions show that from 2001 to 2019 there have been changes to the land use overtime. In Figure 11 we see that Oklahoma experiences the most change over that time. However, in Iowa and Oklahoma, there isn't much change in land use and there are no visually significant observations in relation to the wind farms, to confidently say there is a process at work.

Discussion

Overall, before this study was conducted it seemed plausible to be able to perform an analysis of a broad region of wind farms with a variety of socioeconomic and environmental variables. However, as the study progressed, I realized the amount of data that this study was previously going to include just wasn't possible given the time constraints for this research. Thus, the study region was narrowed down from eight total states down to three, Iowa, Oklahoma, and Texas. For this purpose of this study, I believe these three study regions were the best given their history in the wind industry and being the lead producers. Even still, the amount of data that was used in this study was to much as most of the variables were thrown out. There were several obstacles along the way as the initial idea for this research quickly evolved as the data was being analyzed. Initially, the goal was to provide an idea of how certain socioeconomic and environmental characteristics influence wind farm development. Additionally, given the expected results, was hopeful to be able to create a model that predicted the likelihood of wind farm development based off certain variables in the USWTB dataset. This wasn't possible due to the dataset being updated frequently and the changes being made, therefore, this study aimed more towards understanding the potential influences certain characteristics have on wind farm development.

Unlike other research, this study was focused on the physical factors themselves rather than the ideas and attitudes of the public. Even though an argument can be made that most of the barriers engineers and policy makers face stem from the public. This study, however, was able to piece together some statistically significant results that show that there is some sort of physical process at work and for reasons that may not be as obvious than by looking at a map. There is significant proof that the number of wind farms per project are increasing, whether it be wind farms in general or that the intensity of wind turbines is increasing. There is also reason to believe that wind farms will continue to be developed in mostly rural areas, away from highly densely populated areas. While this study, couldn't provide a prediction it certainly gave an opportunity to be studied more harshly and frequently. Additionally, this study compared the results across all three study regions and though there are still more answers to be had it demonstrates the ability to study each region individually and understand how this work varies across the landscape.

There were several limitations in this study. The opportunity to have more time could've perhaps allowed the variables to be studied more deeply. During the analysis process there were several errors that were brought up in the code used to analyze the data. More knowledge and practice on the statistical analysis would've allowed for a more technical approach. Lastly, obtaining more statistically significant results, I believe would have enhanced the overall conclusions in this study. I think for anyone wanting to continue with this study, should consider the type of data they want to pull, limit the amount of data they are working with, and maybe conduct the analysis at a smaller level to achieve more statistically significant results this study aimed for.

Conclusion

A mixed methods approach consisting of two parts, a geospatial and statistical analysis was utilized to understand the influence socioeconomic and environmental characteristics has on wind farm development. This study revealed that there is spatial clustering of wind farms in each of the study regions. In fact, there is more spatial clustering than expected under the null hypothesis for complete spatial randomness. The Monte Carlo simulation on the F function showed that the wind turbines are not clustered randomly and rather there is another spatial process at work. While population and total houses built are two socioeconomic variables that may have had a significant visual pattern as it relates to wind farm clustering, there was no linear relationship across the study regions. It is clear that a better understanding of the types of socioeconomic variables may prove to be more statistically significant than those analyzed in this study. Land use change over time also didn't prove to be statistically significant as there were no visual patterns in relation to the wind farms to indicate they had an impact on wind farm development. Additionally, while there has been an increase in House Value in median dollars over time, there is no evidence that shows wind farms have an impact on house prices. Overall, this study obtained clear and concise results that can be used by adjacent communities to better understand the influencing factors on future wind farm development.

References:

Al-Yahyai, S., Charabi, Y., Gastli, A., Al-Badi, A., 2012. Wind farm land suitability indexing using multi-criteria analysis. Renew. Energy 44, 80–87. https://doi.org/10.1016/j.renene.2012.01.004

Arun, K., 2017. Geospatial approach for wind farm site selection — A Kerala scenario, in: 2017 International Conference on Technological Advancements in Power and Energy (TAP Energy). Presented at the 2017 International Conference on Technological Advancements in Power and Energy (TAP Energy), pp. 1–5. https://doi.org/10.1109/TAPENERGY.2017.8397360

Bennui, A., Rattanamanee, P., Puetpaiboon, U., Phukpattaranont, P., Chetpattananondh, K., 2007. Site selection for large wind turbine using GIS. PSU-UNS International Conference on Engineering and Environment 561–566.

Boudet, H.S., 2019. Public perceptions of and responses to new energy technologies. Nat Energy 4, 446–455. https://doi.org/10.1038/s41560-019-0399-x

Fast, S., Mabee, W., 2015. Place-making and trust-building: The influence of policy on host community responses to wind farms. Energy Policy 81, 27–37. https://doi.org/10.1016/j.enpol.2015.02.008

Greene, J.S., Geisken, M., 2013. Socioeconomic impacts of wind farm development: a case study of Weatherford, Oklahoma. Energ Sustain Soc 3, 1–9. https://doi.org/10.1186/2192-0567-3-2

Groth, T.M., Vogt, C.A., 2014. Rural wind farm development: Social, environmental and economic features important to local residents. Renewable Energy 63, 1–8. https://doi.org/10.1016/j.renene.2013.08.035

Hamilton, S.D., Millstein, D., Bolinger, M., Wiser, R., Jeong, S., 2020. How Does Wind Project Performance Change with Age in the United States? Joule 4, 1004–1020. https://doi.org/10.1016/j.joule.2020.04.005

Hoen, B., Wiser, R., Cappers, P., Thayer, M., Sethi, G., n.d. The Impact of Wind Power Projects on Residential Property Values in the United States: A Multi-Site Hedonic Analysis 164.

Jacquet, J.B., 2012. Landowner attitudes toward natural gas and wind farm development in northern Pennsylvania. Energy Policy 50, 677–688. https://doi.org/10.1016/j.enpol.2012.08.011

Kumar, I., Sinha, K.C., 2016. Regional Land Suitability Framework for Utility-Scale Wind Farm Development. J. Infrastruct. Syst. 22, 04016018. https://doi.org/10.1061/(ASCE)IS.1943-555X.0000301

Kuvlesky Jr., W.P., Brennan, L.A., Morrison, M.L., Boydston, K.K., Ballard, B.M., Bryant, F.C., 2007. Wind Energy Development and Wildlife Conservation: Challenges and Opportunities. The Journal of Wildlife Management 71, 2487–2498. https://doi.org/10.2193/2007-248

Leung, D.Y.C., Yang, Y., 2012. Wind energy development and its environmental impact: A review. Renewable and Sustainable Energy Reviews 16, 1031–1039. https://doi.org/10.1016/j.rser.2011.09.024

McCarthy, I., Balli, H.O., 2014. Windfarms and residential property values. International Journal of Strategic Property Management 18, 116–124. http://dx.doi.org/10.3846/1648715X.2014.889770

Palinkas, L.A., Horwitz, S.M., Green, C.A., Wisdom, J.P., Duan, N., Hoagwood, K., 2015. Purposeful Sampling for Qualitative Data Collection and Analysis in Mixed Method Implementation Research. Adm Policy Ment Health 42, 533–544. https://doi.org/10.1007/s10488-013-0528-y

Pasqualetti, M.J., 2001. Wind Energy Landscapes: Society and Technology in the California Desert. Society & Natural Resources 14, 689–699. https://doi.org/10.1080/08941920117490

Pavlowsky, C.E., Gliedt, T., 2021. Individual and local scale interactions and adaptations to wind energy development: A case study of Oklahoma, USA. Geography and Sustainability 2, 175–181. https://doi.org/10.1016/j.geosus.2021.08.003

Peri, E., Tal, A., 2020. A sustainable way forward for wind power: Assessing turbines' environmental impacts using a holistic GIS analysis. Appl. Energy 279, 115829. https://doi.org/10.1016/j.apenergy.2020.115829

Rodman, L.C., Meentemeyer, R.K., 2006. A geographic analysis of wind turbine placement in Northern California. Energy Policy 34, 2137–2149. https://doi.org/10.1016/j.enpol.2005.03.004

Sandelowski, M., 2000. Combining Qualitative and Quantitative Sampling, Data Collection, and Analysis Techniques in Mixed-Method Studies. Research in Nursing & Health 23, 246–255. https://doi.org/10.1002/1098-240X(200006)23:3<246::AID-NUR9>3.0.CO;2-H

Santos-Alamillos, F.J., Pozo-Vazquez, D., Ruiz-Arias, J.A., Lara-Fanego, V., Tovar-Pescador, J., 2014. A methodology for evaluating the spatial variability of wind energy resources: Application to assess the potential contribution of wind energy to baseload power. Renew. Energy 69, 147–156. https://doi.org/10.1016/j.renene.2014.03.006

Slattery, M.C., Johnson, B.L., Swofford, J.A., Pasqualetti, M.J., 2012. The predominance of economic development in the support for large-scale wind farms in the U.S. Great Plains. Renewable and Sustainable Energy Reviews 16, 3690–3701. https://doi.org/10.1016/j.rser.2012.03.016

Stefanakou, A.A., Nikitakos, N., Lilas, T., Pavlogeorgatos, G., 2019. A GIS-based decision support model for offshore floating wind turbine installation. Int. J. Sustain. Energy 38, 673–691. https://doi.org/10.1080/14786451.2019.1579814

Vyn, R.J., McCullough, R.M., 2014. The Effects of Wind Turbines on Property Values in Ontario: Does Public Perception Match Empirical Evidence? Canadian Journal of Agricultural Economics 62, 365. http://dx.doi.org/10.1111/cjag.12030

Woody, T., 2020. 'When the wind comes right behind the' … sales pitch: alternative views to wind energy development in a rural Oklahoma host community.

Tables:

Summary Statistics of Socioeconomic and Environmental Characteristics			
	Min	Mean	Max
Population	0	3516	15301
Housing Units	0	1571	6346
Education Attn.	0	1749	7880
Bachelor's Degree or Higher	0	550.5	5136
Employed	0	1799	8642
Employed in Agriculture	0	67.46	603
Houses Built	0	1571	6346
Houses Built 2014 - Later	0	56.75	2237
Houses Built 2010 - 2013	0	46.19	869
House Built 2000 - 2009	0	170.83	2520
House Value 2010 (Median Dollars)	227700	117299	412500
House Value 2020 (Median Dollars)	51400	152084	750000

Table 1: Five number summary of socioeconomic variables in Iowa. Data: US Census Bureau.

Summary Statistics of Socioeconomic and Environmental Characteristics			
	Min	Mean	Max
Population	0	3277	9906
Housing Units	0	1445	3494
Education Attn.	0	1654	5146
Bachelor's Degree or Higher	0	437.6	3739
Employed	0	1476	5096
Employed in Agriculture	0	64.2	741
Houses Built	0	1445	3494
Houses Built 2014 - Later	0	56.89	881
Houses Built 2010 - 2013	0	56.3	1177
House Built 2000 - 2009	0	191.3	1537
House Value 2010 (Median Dollars)	17700	105254	415600
House Value 2020 (Median Dollars)	31500	142721	769400

Table 2: Five number summary of socioeconomic variables in Oklahoma. Data: US Census Bureau.

Summary Statistics of Socioeconomic and Environmental Characteristics			
	Min	**Mean**	**Max**
Population	0	4152	19704
Housing Units	0	1612	8846
Education Attn.	0	2154	10541
Bachelor's Degree or Higher	0	678.7	5905
Employed	0	1952	9196
Employed in Agriculture	0	55.42	1461
Houses Built	0	1612	8846
Houses Built 2014 - Later	0	113.9	3667
Houses Built 2010 - 2013	0	82.97	1822
House Built 2000 - 2009	0	300.9	2187
House Value 2010 (Median Dollars)	15400	133383	981800
House Value 2020 (Median Dollars)	16500	204986	1951500

Table 3: Five number summary of socioeconomic variables in Texas. Data: US Census Bureau.

Study Area Turbine Statistics				
	Years Constructed (Historical)	**Mean # of Turbines per project**	**Std. dev. # of Turbines per project**	**Total # of Turbines**
Iowa	1992-2021	69.79	51.15	6,148
Oklahoma	1983-2021	65.45	31.01	4,905
Texas	1999-2021	93.93	29.96	17,439

Table 4: History of Wind Turbines. Data: USWTDB from USGS.

Wind Farm Distances from Urban Areas				
	Min (meters)	**Mean (meters)**	**Max (meters)**	**Mean (Miles)**
Iowa	12,222	12,335	15,999	~7.67
Oklahoma	2,970	12,690	15,990	~7.88
Texas	1,202	11,398	15,999	~7.08

Table 5: Community adjacency, distance to wind turbines (meters). Data: USWTDB from USGS.

Point Pattern Statistics		
	Mean Nearest Neighbor Distance (m)	Simulated MNND (m)
Iowa	558.0749	82615.87
Oklahoma	425.5609	150212.1
Texas	398.3438	122614.2

Table 6: Nearest neighbor distances. Data: USWTDB from USGS.

Point Process Model Statistics			
	Iowa	Oklahoma	Texas
Point Intensity (Rural)	**0.000771167**	6.84E-05	9.36E-05
Point Intensity (Urban)	**0.001568015**	0.001084027	0.000411496
AIC - Null Model (Rural)	**51996.98**	1823.617	141144.8
AIC - Null Model (Urban)	**96537.64**	25032.98	231487.5
AIC - Grad Model (Rural)	**51689.24**	1728.3	137502.7
AIC - Grad Model (Urban)	**96505.89**	24696.95	224144.6
AIC - Full model (Rural)	**51110.34**	1458.975	135213.3
AIC - Full model (Urban)	**90931.75**	21104.85	222790.6

Table 7: Fitted Point Process models. Data: USWTDB from USGS.

Regression Model Statistical Analysis - Population			
	Iowa	Oklahoma	Texas
R-squared	0.2485	0.1011	0.1806
p-value	< 2.2e-16	< 2.2e-16	< 2.2e-16

Regression Model Statistical Analysis - Houses Built			
	Iowa	Oklahoma	Texas
R-squared	0.1211	0.07803	0.09497
p-value	< 2.2e-16	< 2.2e-16	< 2.2e-16

Table 8: Linear Regression model for Population Data: USWTDB from USGS.

Table 9: Linear Regression Model Houses Built. Data: USWTDB from USGS.

Figures:

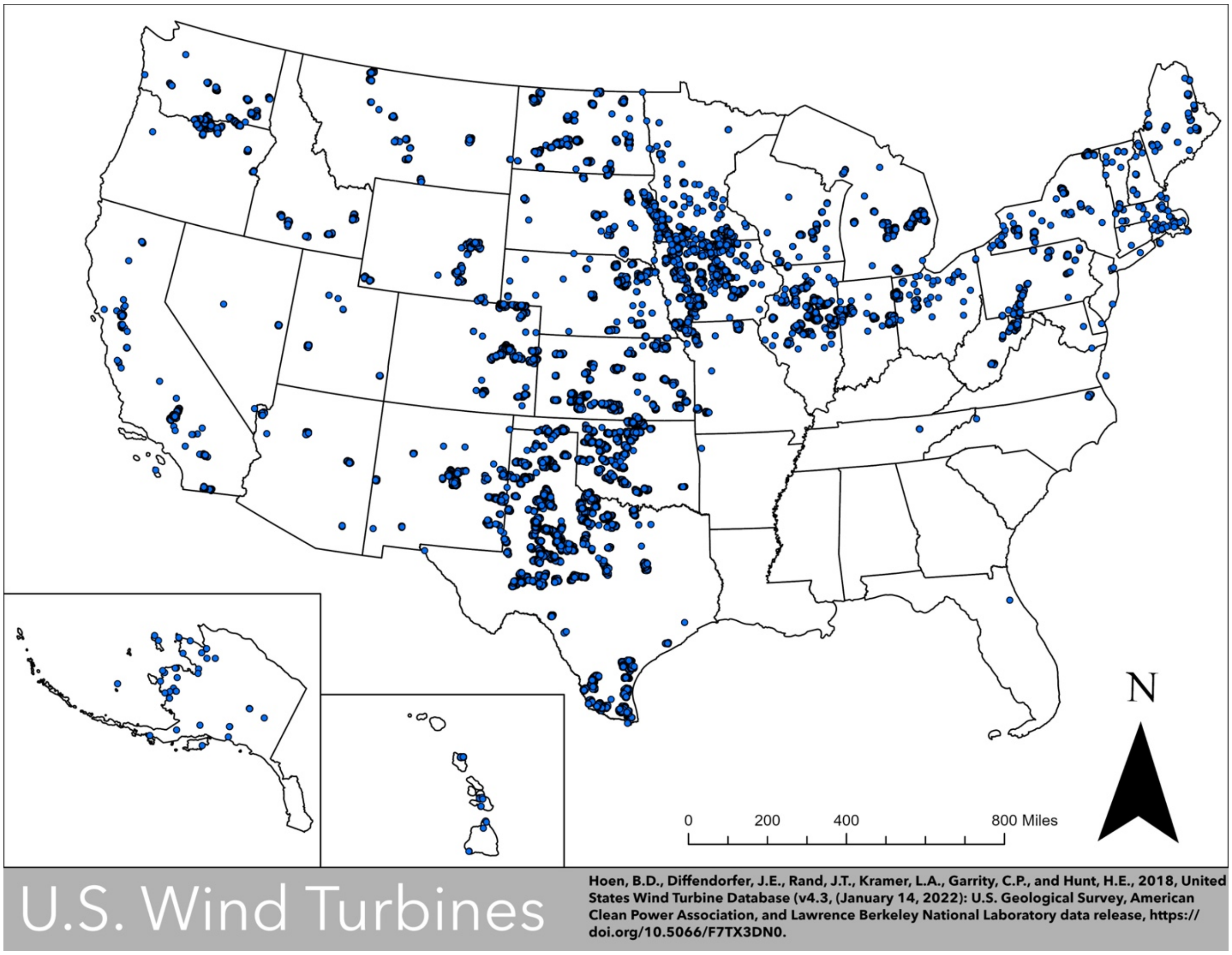

Figure 1: US Wind Turbines. Data: USWTDB from USGS.

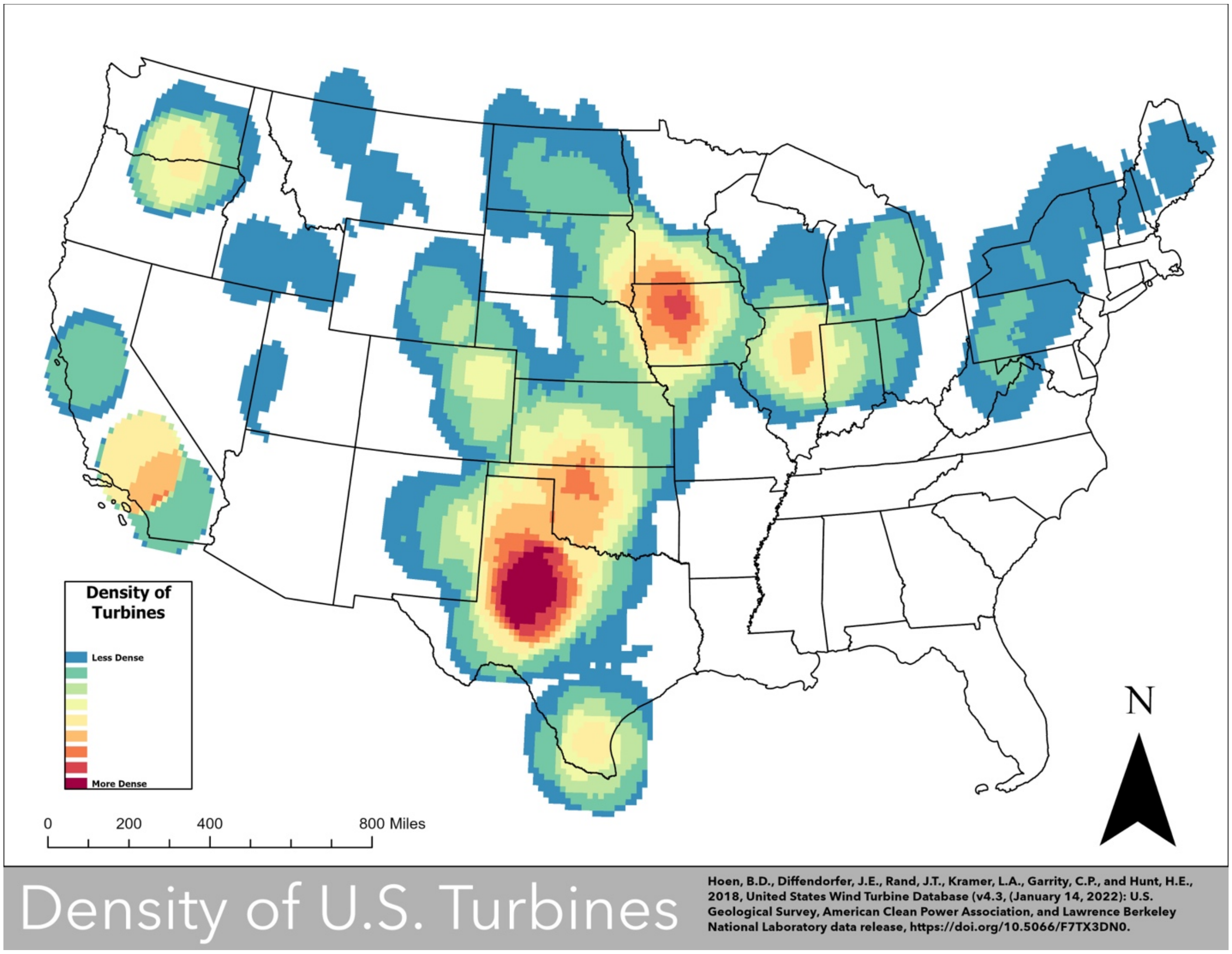

Figure 2: US Wind Turbines Density. Data: USWTDB from USGS.

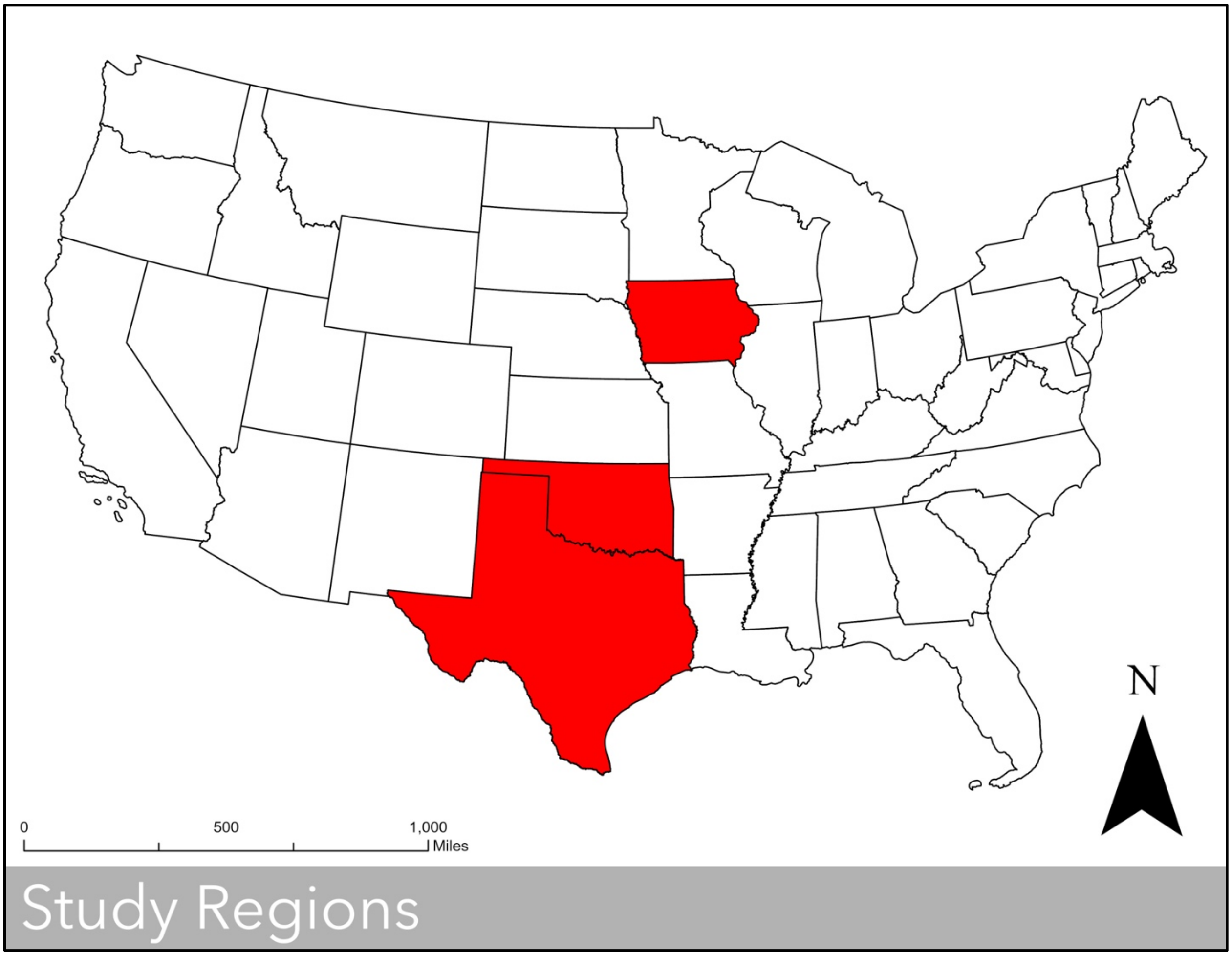

Figure 3: Study Regions. Data: USWTDB from USGS.

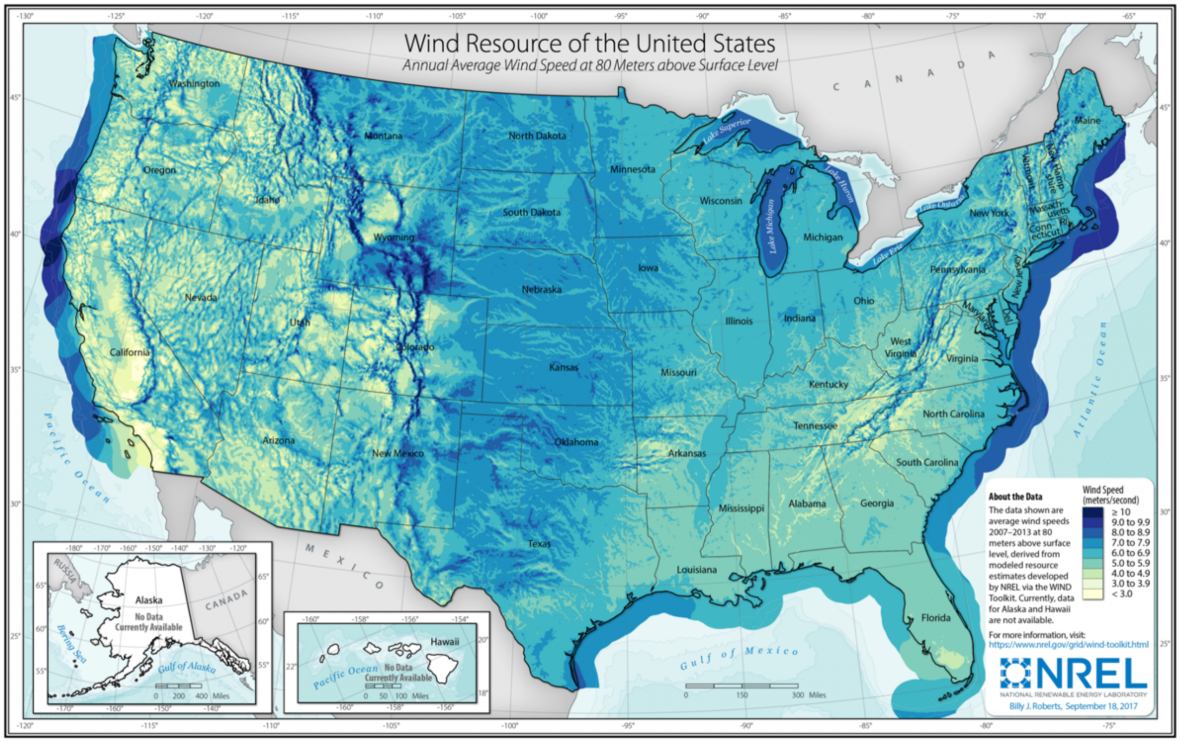

Figure 4: Wind speed. Data from NREL.

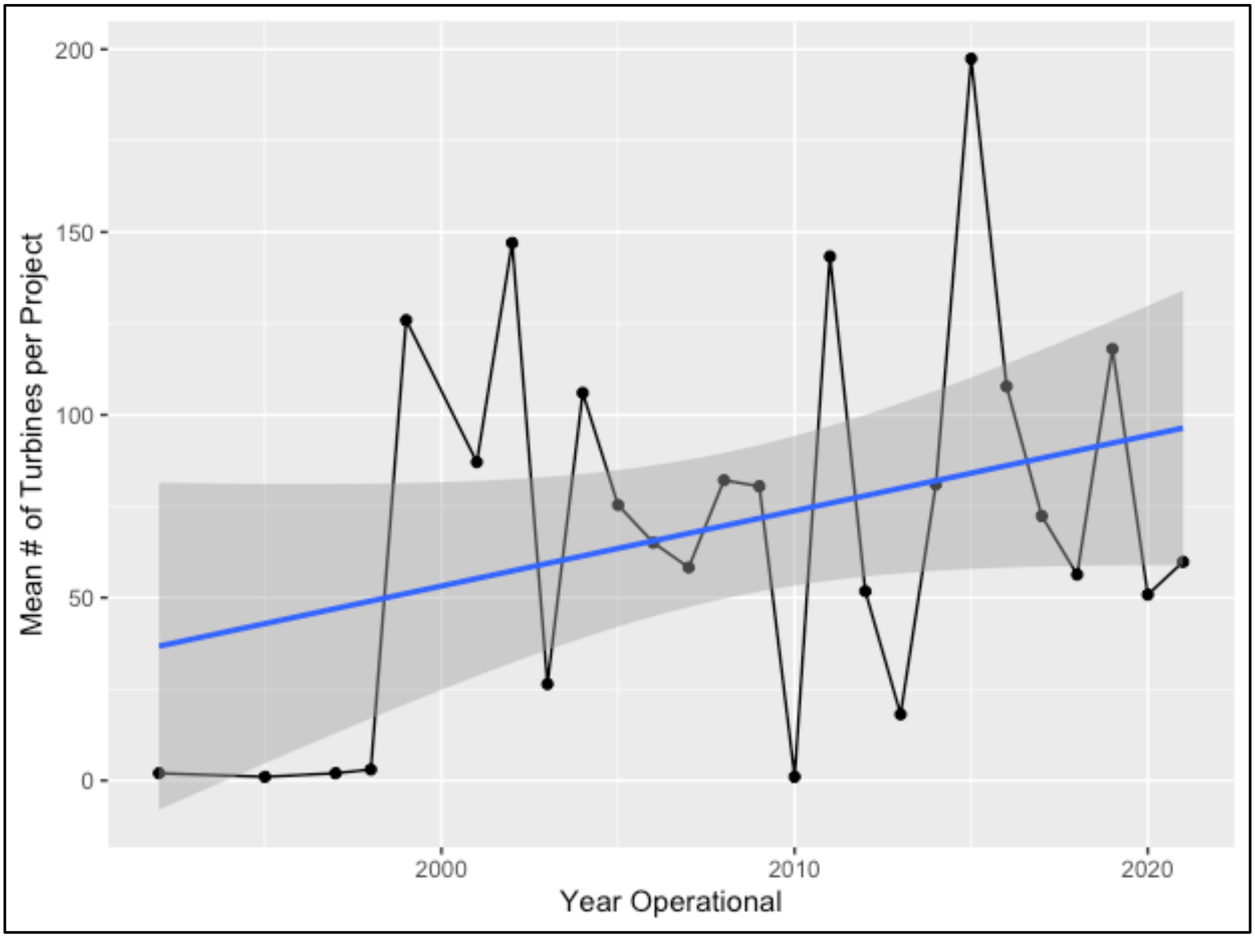

Figure 5: Mean number of wind turbines per project in Iowa. Data: from USWTDB from USGS.

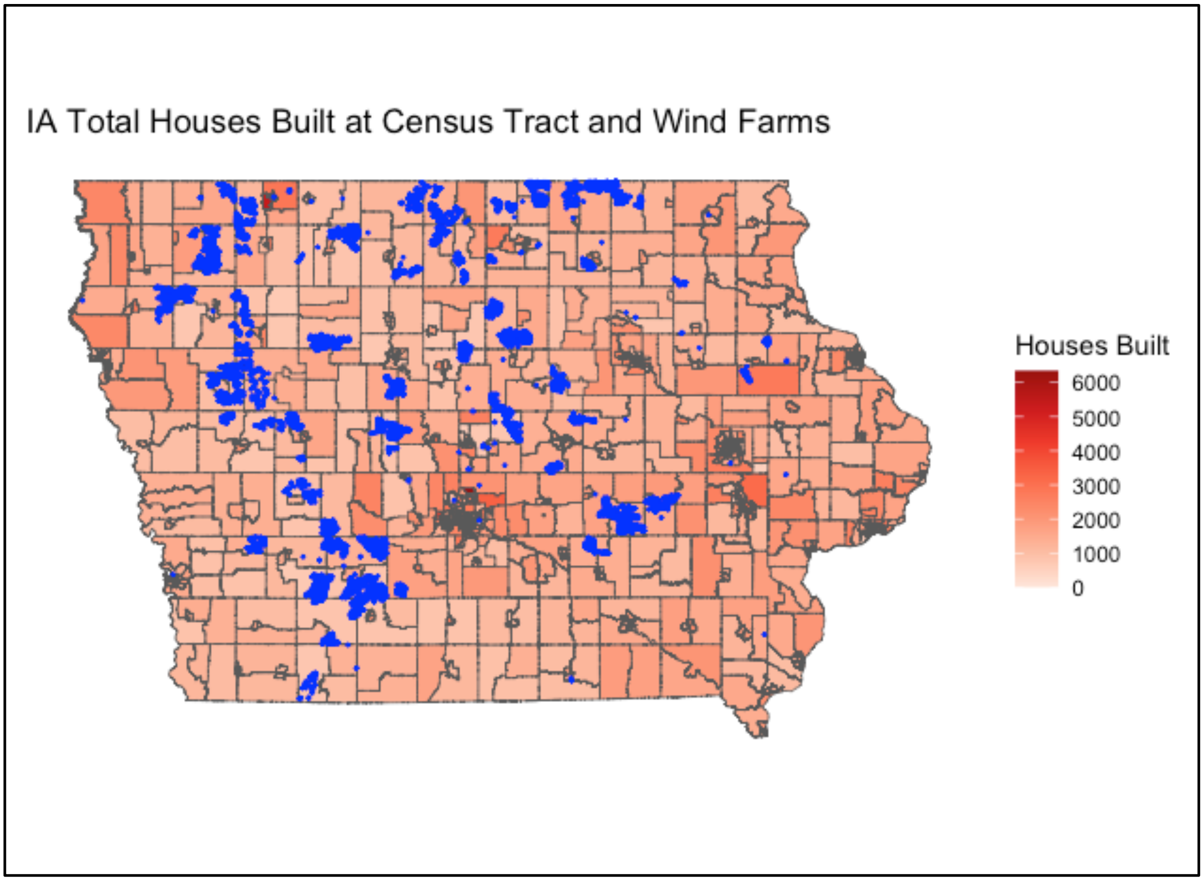

Figure 6: Houses Built and Wind farms in Iowa. Data: USWTDB from USGS and US Census Bureau.

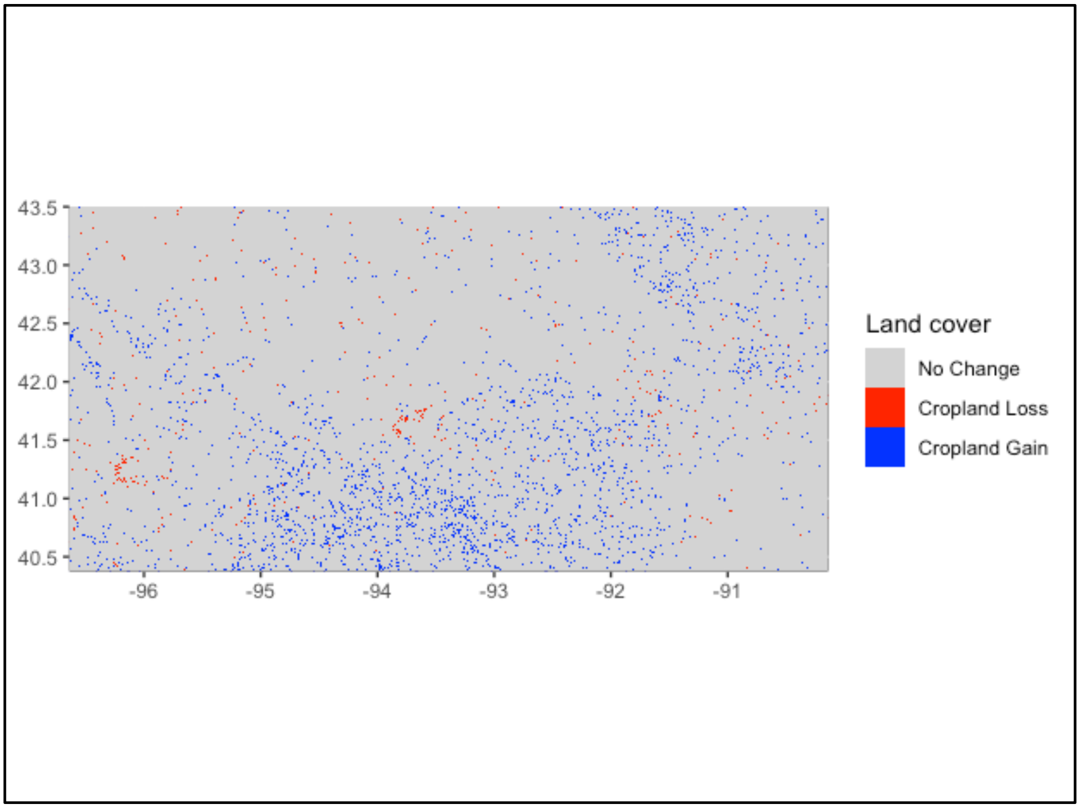

Figure 7: Cropland gain and loss (land cover change) in Iowa. Data: from USWTDB from USGS.

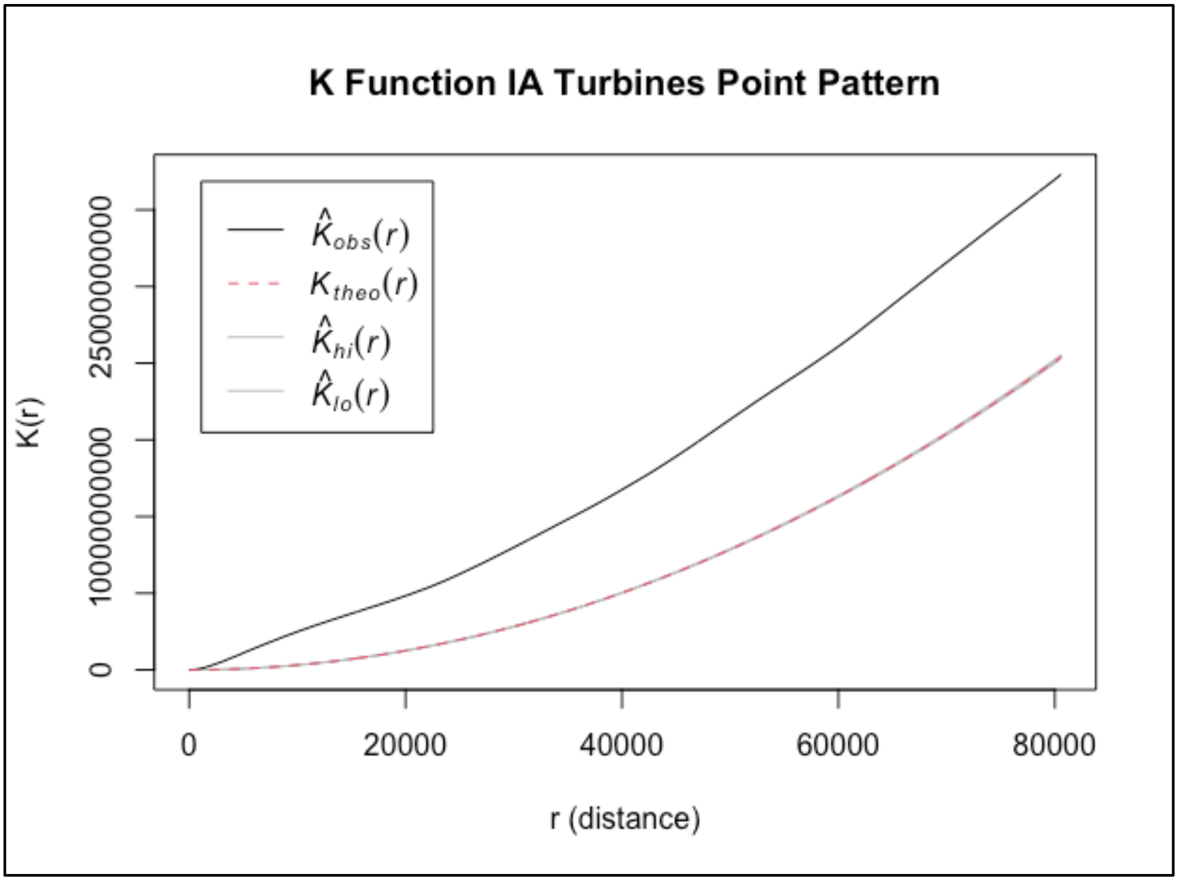

Figure 8: Monte Carlo Simulation on F function in Iowa. Data: USWTDB from USGS.

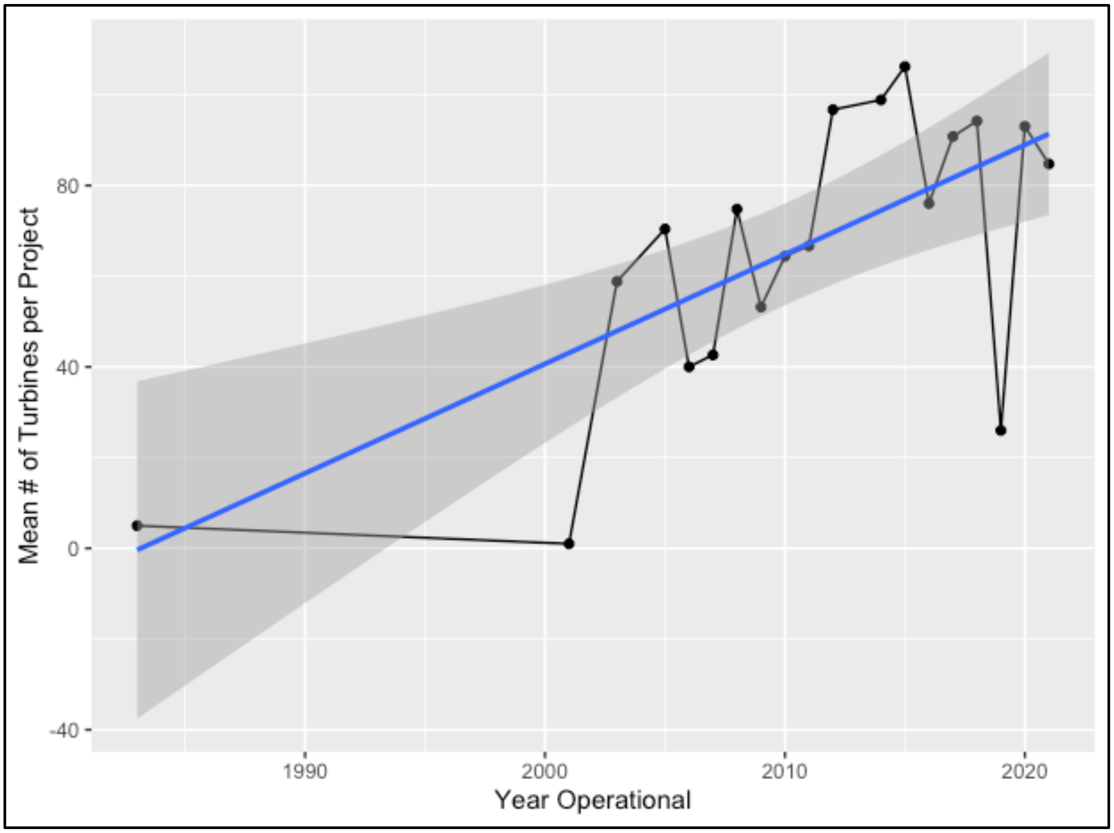

Figure 9: Mean Number of wind turbines per project in Oklahoma. Data: USWTDB from USGS.

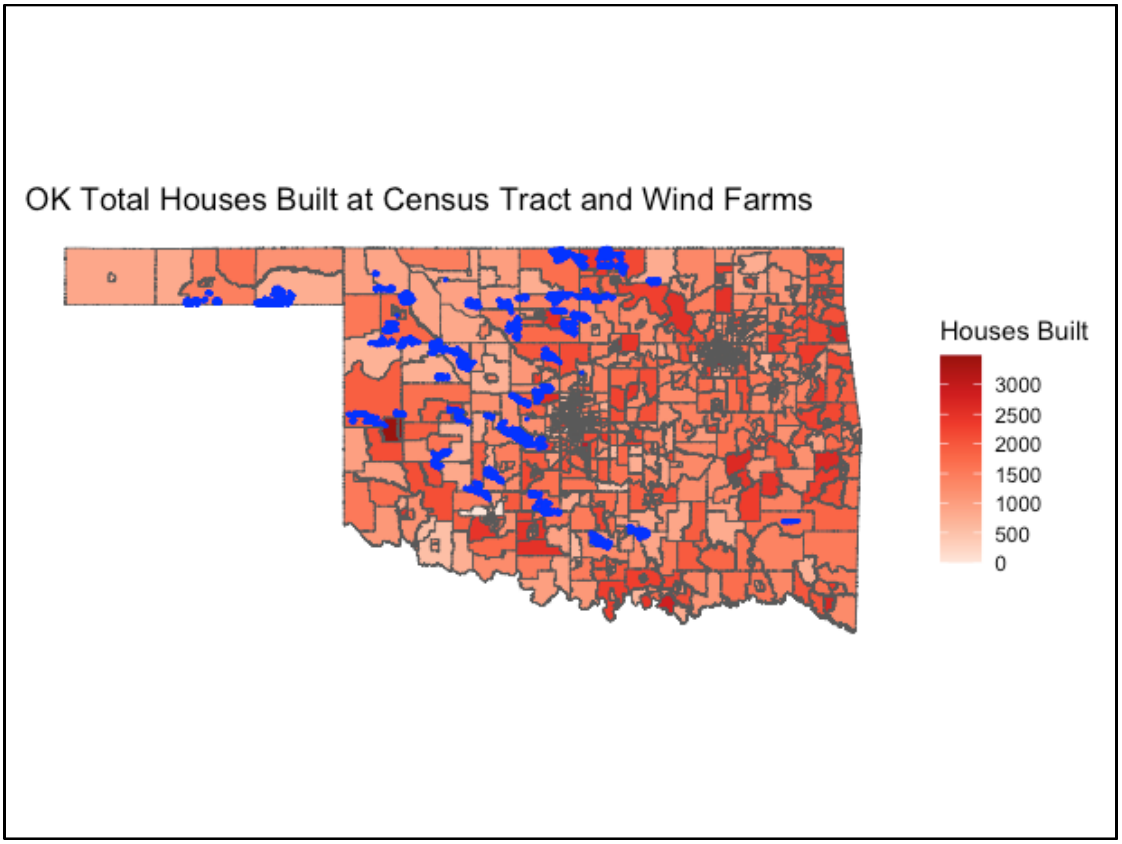

Figure 10: Houses built and wind farms in Oklahoma. Data: USWTDB from USGS.

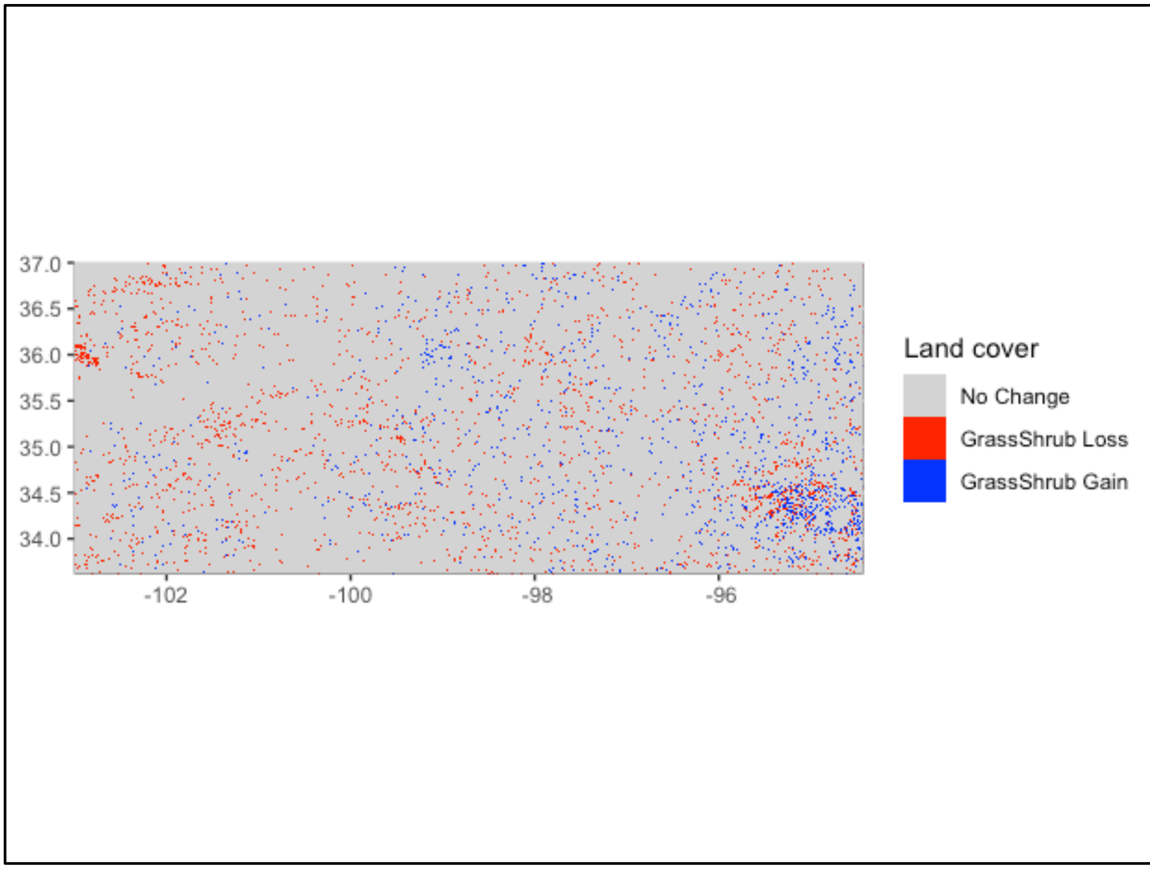

Figure 11: Grass Shrub loss and gain (land cover change) in Oklahoma. Data: USGS and MLCR.

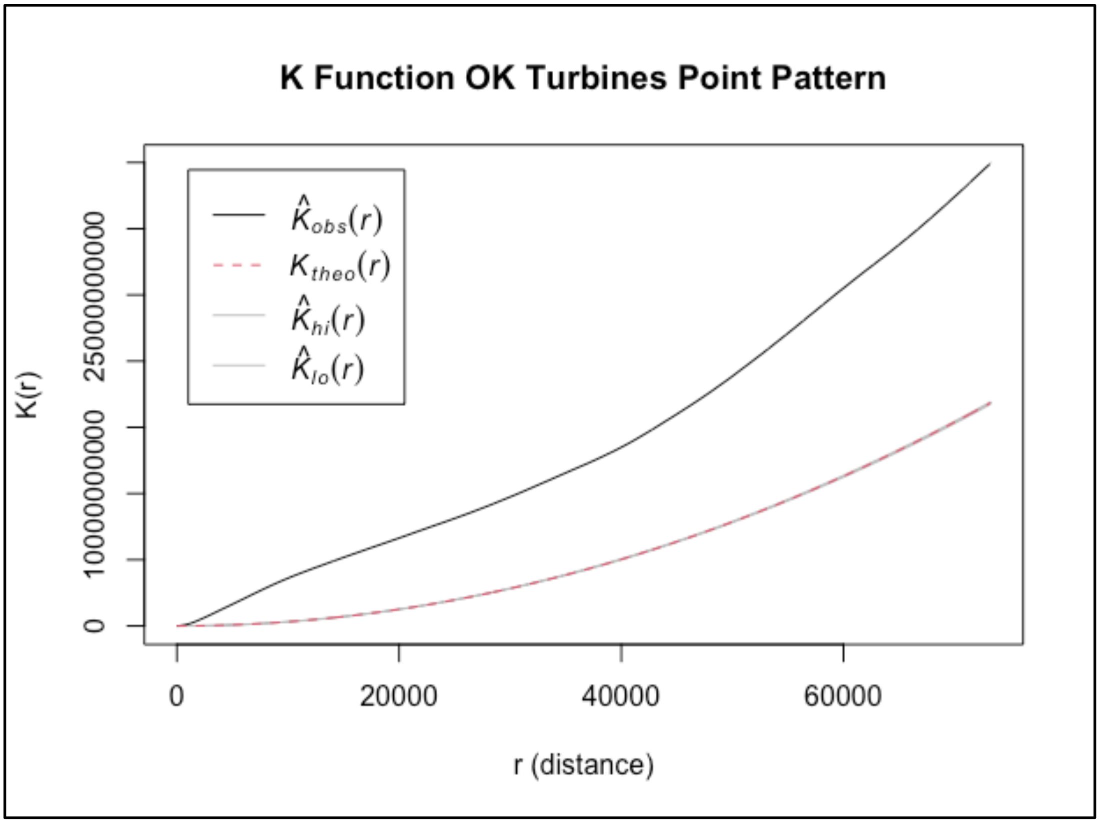

Figure 12: Monte Carlo Simulation on F function in Oklahoma. Data: USWTDB from USGS

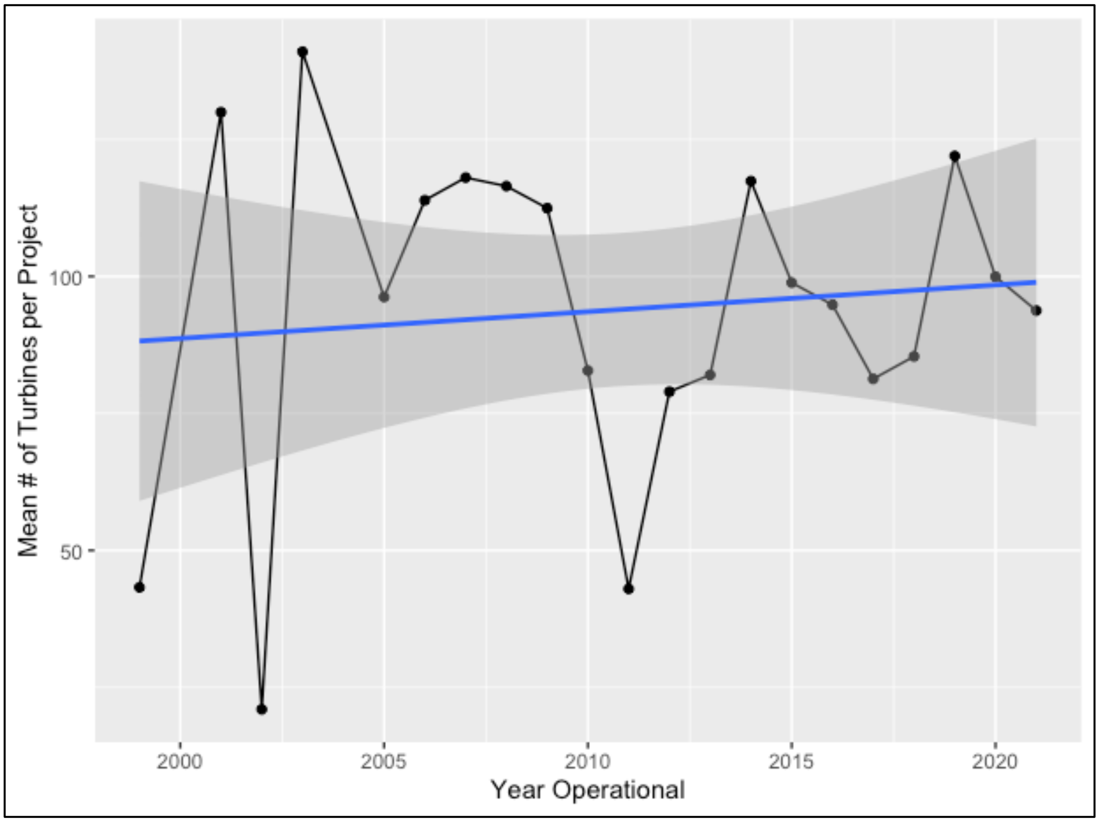

Figure 13: Mean number of wind turbines per project in Texas. Data: USWTDB from USGS

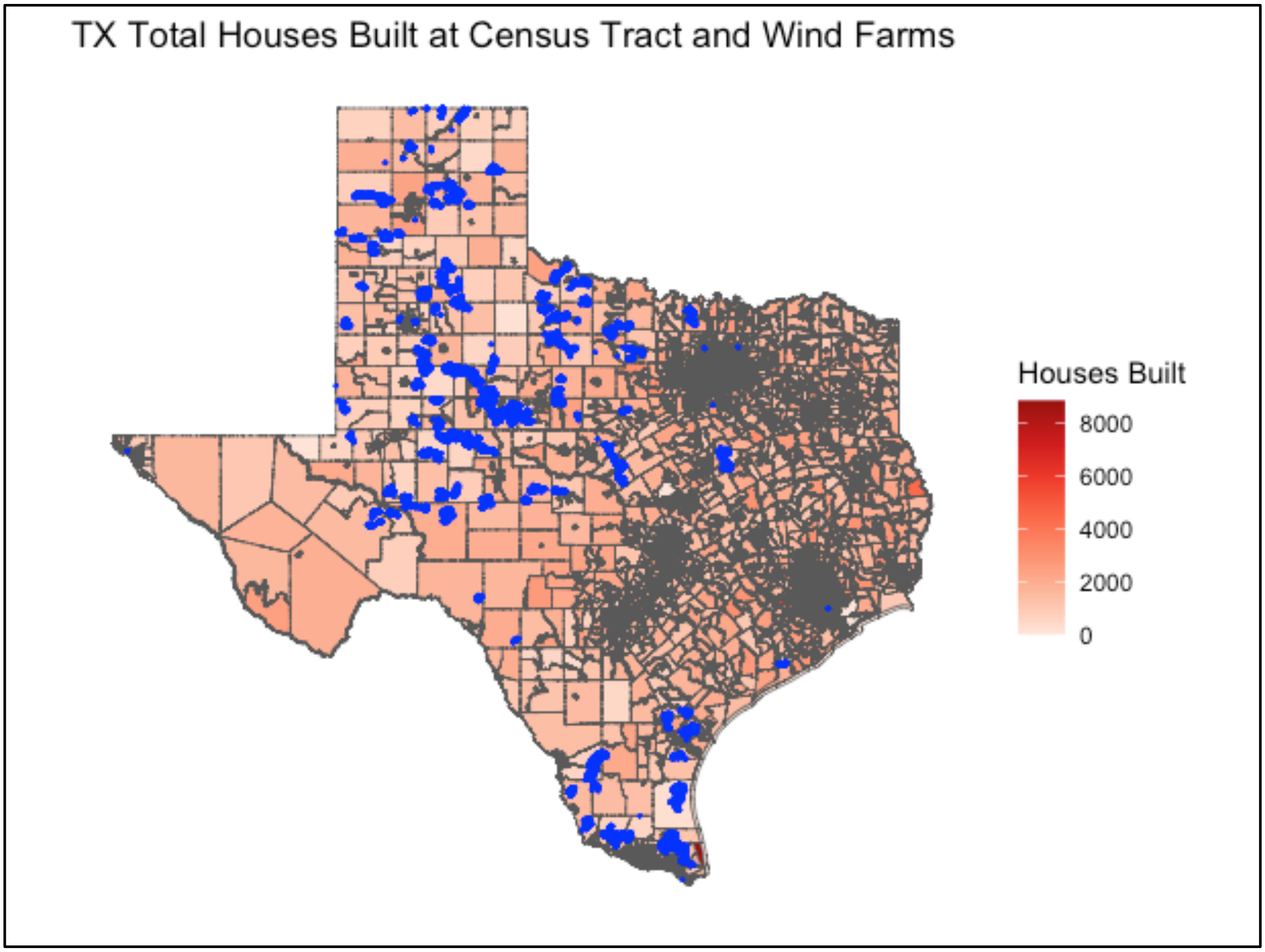

Figure 14: Houses Built and Wind Farms in Texas. Data: USWTDB from USGS

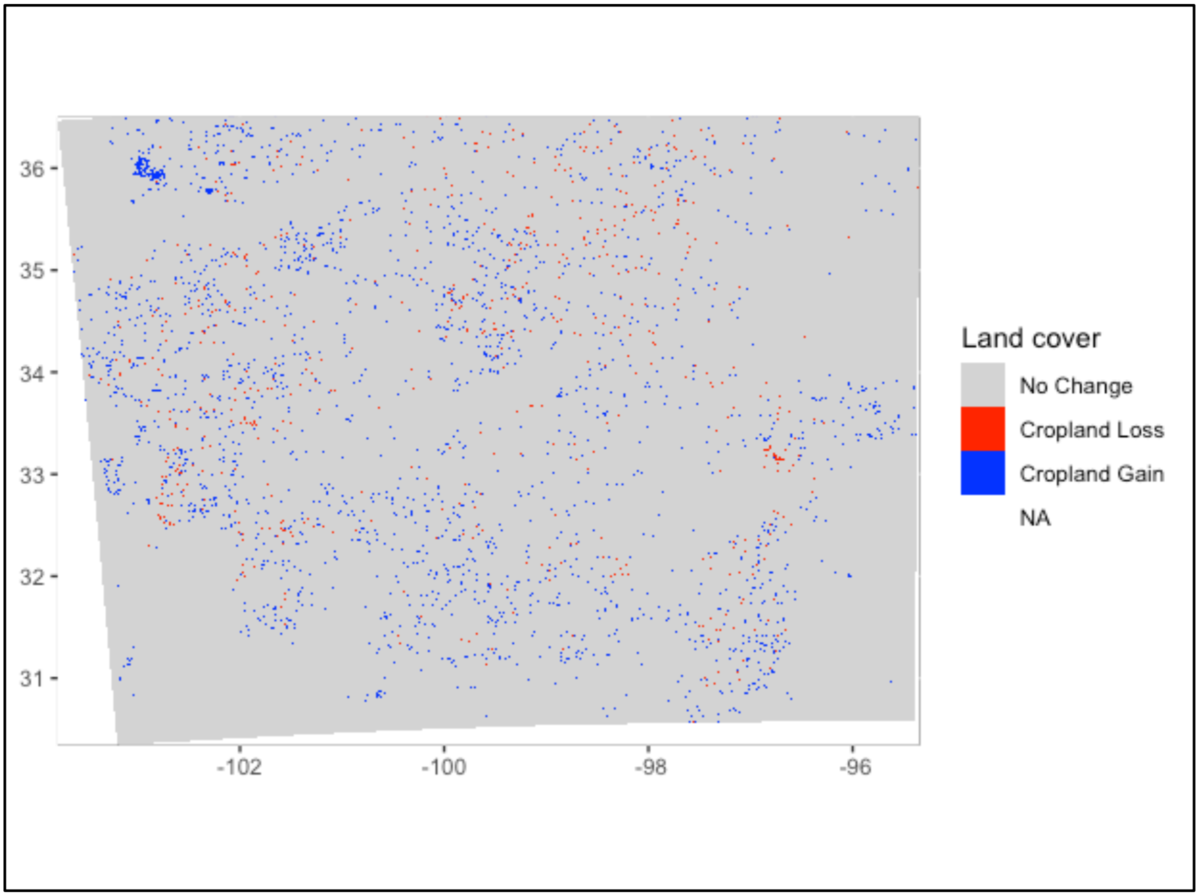

Figure 15: Cropland gain and loss (land cover change) in Texas. Data: USWTDB from USGS

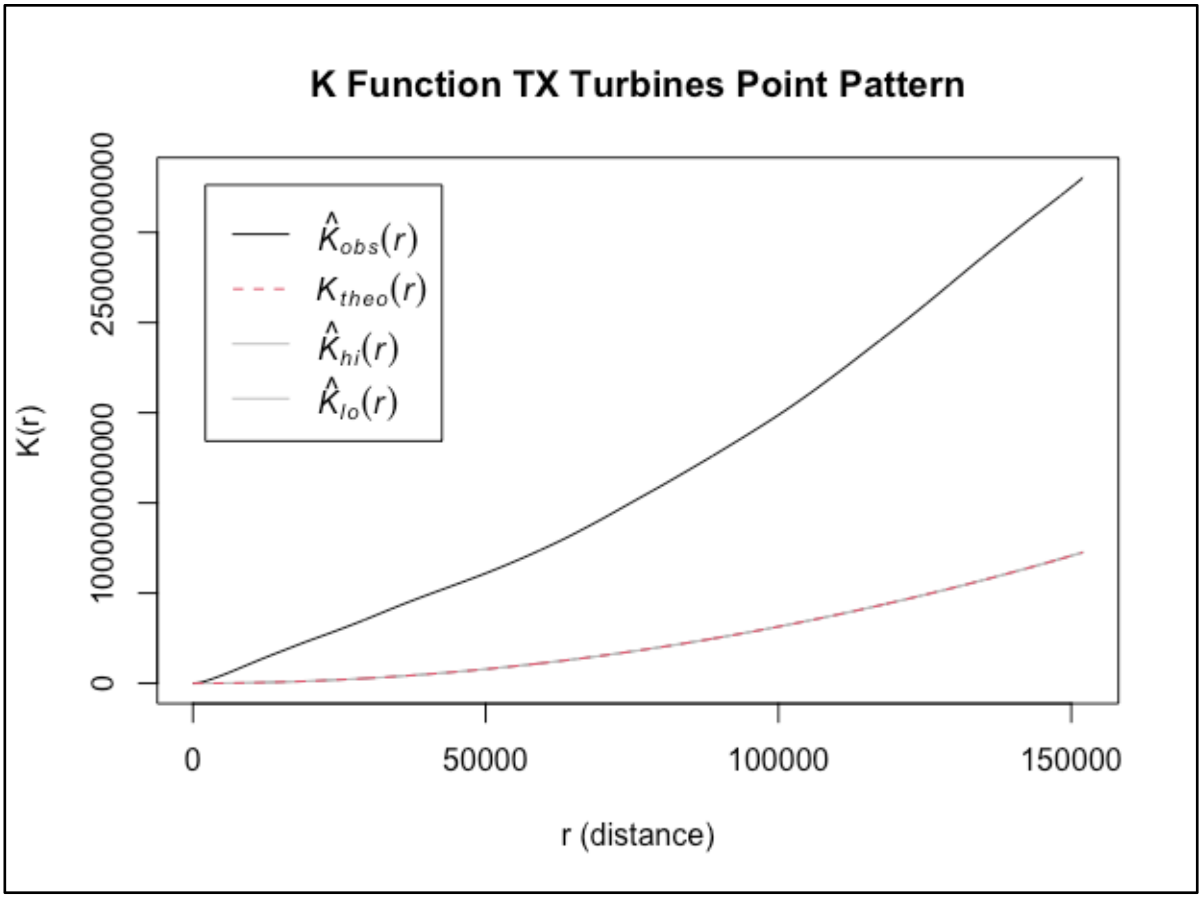

Figure 16: Monte Carlo Simulation on F function in Texas. Data: USWTDB from USGS