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Half-Length and the FACT Framework: Distance-Decay and Citizen Opposition to Energy Facilities

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Half-Length and the FACT Framework: Distance-Decay and Citizen Opposition to Energy Facilities.

I. *Introduction*

What factors drive citizen opposition to new energy facilities? This question is important to study because new renewable energy projects are being built around the world to mitigate the climate crisis, improve energy security and reduce air pollution. Studies show that the deployment of clean energy technologies will need to surge to meet the 2-degree Celsius Paris Targets. IRENA (2018). estimates that between 2015 and 2050 an incremental US$120 trillion of investment will be required to achieve this energy transition. This includes new renewable energy facilities, electricity substations, as well as high voltage transmission lines. The new renewables and accompanying infrastructure are required to replace decommissioned fossil fuel plants. In addition, there will be a need for increased renewable energy facilities for the electrification of buildings (E3, 2019; Keramidas et al, 2020) and transportation energy (Oeko-Institut, 2016) Renewable electricity will also be required to increase carbon free renewable hydrogen for building heating and industrial purposes (Simon, 2020).

Yet, at the same time as the huge need for increased supply of clean energy, citizen political and legal actions are creating significant barriers to getting new infrastructure built due to strong citizen opposition. Citizens have been shown to oppose land uses that are perceived as impinging on their quality of life. Given these considerations, a better scientific understanding of the dynamics of citizen opposition could be beneficial to all relevant stakeholders. The main goal of this paper is to develop a spatially-enabled theoretical framework to explain the effect of distance on citizen opposition to Locally Unwanted Land Uses (LULUs). To operationalize the spatial framework, two metrics of how opposition decays over distance are developed. These distance-decay indicators can likely help future researchers explain and predict the effects of space on citizen attitudes and behavior.

II. *Citizen Opposition & the FACT Siting Framework*

Much has been written on the Not-In-My-Backyard (NIMBY) and LULU phenomena (Schively, 2007). The most influential explanation for NIMBYism has come from Bell et al (2007) who posit that individual self-interest in opposing wind energy facilities explains only a part of citizen opposition. Social psychologists such as Devine-Wright (2009) argue that NIMBY-opposition stems largely from place protective actions. Citizen opposition to LULUs can possibly be muted with community ownership of the land use (Warren & McFadyen, 2010). In addition, there is consistent support for the claim that the attributes of the LULU (Wustenhagen, et al, 2007), the existing land-use (Wolsink, 2000), as well as the demographics of the community, can all affect citizen opposition (Cain & Nelson, 2013; Devine-Wright, 2013). Interested readers can find a survey of the factors contributing to citizen opposition in Carlisle et al (2015).

However, there is an important empirical and theoretical question that remains hotly debated: *Does a household's proximity to a LULU increase their level of opposition to it?* While most research has examined citizen opposition to wind farms, there is no consensus regarding the effect of proximity. Devine-Wright's (2005) review showed no consistent relationship for wind farms and citizen distance. Rather, attitudes from the residents closest to wind farms can be extremely positive or negative (Braunholtz, 2003; Swofford & Slattery, 2010). Other technologies also show inconsistent results. Residents living up to 270 meters away have expressed concerns about safety and health problems from high voltage transmission lines (HVTLs) —much further than what scientists posit for externalities (Priestly, 1988). Van der Horst (2007) finds that citizen opposition levels are related to proximity, but “vary according” to local context and the perceived value of the land. Gravelle & Lachapelle (2014) find a non-linear relationship between attitudes towards the Keystone XL pipeline in the US and citizen proximity.

In contrast, some empirical research has shown a consistent, if complicated, negative relationship between proximity and citizen attitudes and behavior. Mueller (2018) finds that proximity increases citizen opposition to HVTLs, as does Nelson et al (2018), who also discover that the effects of proximity are moderated by trust in the project sponsor. Gravelle & Lachapelle (2014) find that ideology moderates the negative relationship between proximity and attitudes, but only for liberal survey respondents. These two studies’ regression results, along with Van der Horst’s qualitative results, highlight that the lack of consensus regarding the effects of proximity on citizen opposition. This “spatial heterogeneity” is likely to be due to multiple factors that vary across energy technologies and project context (Walker, 2011). The field has yet to develop a generalizable spatial framework to integrate into local social movement theories.

Geographers have been grappling with The First Law of Geography (Tobler, 1970) for five decades. This truism posits that near things are more related to each other than distant things, based on the concept of the “friction of distance”. This concept is the foundation of spatial dependence and spatial statistics. Proximity is a powerful indicator of other factors that are prominent in the LULU literature. Because of the complexity of modern life, most citizens are rationally ignorant of LULU’s that are not relevant to their quality of life. Rational ignorance is the foundation of the economic voting that explains why voting turnout is so low (Downs, 1957). In contrast to rational ignorance from distant citizens, residents proximate to a LULU have clear self-interests in being informed. Perceptions about a LULU are shaped by local news media, who have economic incentives to report on nearby phenomena frequently. The media coverage influences perceptions of residents (Dunaway et al, 2010). Proximity also measures the risk communications distributed by local governments that have institutional incentives to respond to demands for citizens’ place protective actions (Cain & Nelson, 2013).

This paper’s first extension to the literature is the hypothesis that *ceteris paribus*, citizen oppositional attitudes and behaviors regarding LULU’s should show a negative relationship (decline) with distance. This “distance-decay” hypothesis is close to a truism for anyone who has looked at a map of the addresses of citizens who commented on an energy facility proposal clustered around the project. Distance-decay is widely used in ecological economics (Bateman et al, 2006; Leon et al, 2016) which is the most similar application to facilities siting. The concept is foundational to urban planning (Halas et al, 2014), transportation research (Schaafsma et al, 2013), and bio-geography (Harte et al, 2005) among others. In geography, Hammond (1994) called distance-decay geographic discounting which leverages concepts from time discounting. He notes that like time discounting includes both and impatience component as well as a risk component, geographic discounting arises from psychological and aesthetic issues as well as perceived risks from a LULU (p.162).

The second contribution to the literature is to develop two indicators of distance-decay. The first is the concept of *half-length*, the distance from the LULU that encompasses half of the number of citizen comments, and is measured as the median distance for any LULU. This is equivalent to temporal half-life associated with radioactive substances and pharmacology (Kocher, 1981; Boxenbaum and Battle, 1995). The smaller the half-length (median distance), the more localized is the citizen opposition. Half-length is an important first step in systematically including spatial considerations in siting theories.

The second indicator of distance-decay comes from the slope coefficient of a discrete event (count) regression model described below. The slope coefficient predicts the rate at which comments are expected to occur over space.

II.A. The FACT Siting Framework

This paper's second extension builds on Cain & Nelson's (2013) multi-level framework to explain the causal factors driving distance-decay. To better understand citizen opposition to LULUs, proven functional forms for analyzing distance-decay from other fields are employed. As described below, the first is the negative exponential function, that also is the basis of radioactive half-life dynamics (Kocher, 1981) and used in pharmacology (Boxenbaum and Battle, 1995). The second functional form is the reciprocal of distance squared, which also explains radar waves, gravitational force, and light intensity (Smith, 2003).

While distance-decay may consistently be negative in the natural sciences, social scientists have found significant heterogeneity in distance-decay at the individual and community level (Schafsma et al, 2013; Martinez and Viegas, 2013). Differences are a function of citizen demographics, the extent of natural areas, the built environment, and social ties. These factors explain why some communities have more actively opposed energy facilities than others (Devine-Wright, 2013). In other words, each backyard is different, and each project is perceived differently by citizens.

Ecologists are interested in explaining the reproduction and survival of unique species across geographies (Nekola and White, 1999). Similarly, siting theorists attempt to explain the reproduction and survival of citizen opposition attitudes and behavior across space. Two spatial and two context factors are explicated in the following FACT siting framework:

1. *Favorability* of the project attributes (F) to generate opposition behaviors. This context element includes history of interactions of the project sponsor with communities, and their trust in the sponsor (Nelson, Cain Swanson, 2018). The perceived risks of the energy technology also fit into this element, including the perceived scale of its associated externalities (Wustenhagen et al, 2007) . The perceived disruption of the project relative to the existing project right-of-way status (brownfield or greenfield) is included here as well (Wolsink, 2000).
2. Citizen attributes related to the oppositiona*l ability* (A) of each community. The context includes demographics such as owner-occupied vs renter-occupied housing, education, income, and citizen place attachment (Carlisle et al, 2016; Devine-Wright, 2013).
3. *Corridors* for transmission of opposition *(C)*. Opposition attitudes and behaviors are spread along road corridors because the friction of distance decreases as travel times decrease. Roads also increase citizen exposure to the unwanted land-use when they pass by it or the proposed location. Electronic corridors of transmission include citizen communication networks and community-based organizations (Hestres, 2015). Non-governmental organizations (NGOs) utilize member advocacy information technology infrastructure such as websites, email, and, increasingly, social media platforms, are another electronic corridor for opposition to energy facilities (Wang et al, 2019).
4. The spatial *template (T)*. This includes geographical barriers to the transmission of opposition behaviors including rivers, forests, mountains, and other features that reduce face-to-face communication of citizens. Olsen et al (2019) find that bridges predict a discontinuity in resident willingness-to-pay to move an unwanted landfill. The template also includes the population density, and the type of zoning of neighborhoods adjacent to the project.

The FACT siting framework is not an exhaustive list, but rather illustrative of how existing siting theory can be re-conceptualized using a distance-decay framework for citizen opposition. These elements interact across space and time and result in nonlinear outcomes associated with complex adaptive systems (Abdollahian et al, 2013; Nikolo & Brown, 2007).

III. Research Methods

To explore the FACT siting framework and to develop the distance-decay metrics requires historical siting data. Figure 1 explicates the research process used to collect and analyze historical siting data. After citizens had commented on completed projects, the sample was selected based on the level of citizen opposition to the energy facility, not on the project outcome, to mitigate any potential bias in inferences caused from the sample selection (Freedman, 2003). The initial sampling methodology included randomly selecting projects from the pool of energy projects that generated significant citizen opposition with more than 300 citizen comments as part of the formal Environmental Impact Assessment process. The projects needed to be concluded no earlier than 2010 in order to obtain current addresses for survey research for another part of the research effort.

Six of the energy projects were located in California and the Pacific Northwest (the main sample frame), and were identified using news searches. Google news searches were formed with the terms using “citizen opposition” “wind turbines” “energy” and other terms for the sample frame. The Chokecherry wind project in the state of Wyoming was initially chosen, but the US Bureau of Land Management did not respond to the Freedom of Information Act request for citizen comment data. The takeaway from the sampling process is that these projects are not likely to introduce selection bias, as they are mostly the entire population of high-profile LULUs in the energy sector in California and the Pacific Northwest.

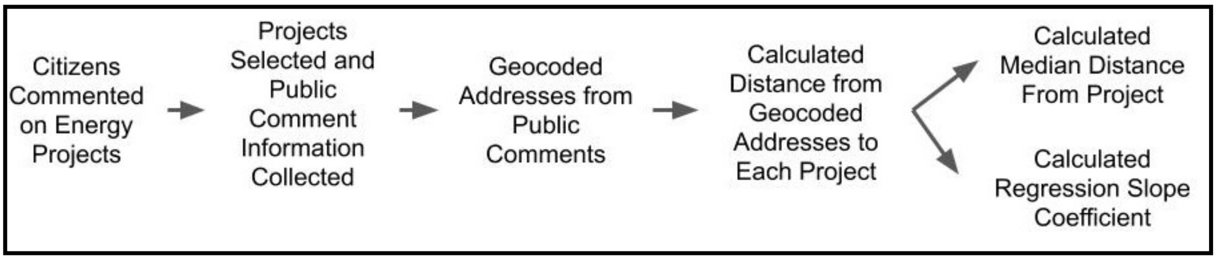

Figure 1: Research Process

No gas or oil pipelines in the western area were found to have generated the minimum level of 300 citizen comments, so the sample frame was expanded to the rest of the US in order to include a pipeline in the sample. One natural gas pipeline in New York/New Jersey was randomly chosen from Federal Energy Regulatory Commission’s database of the top 10 pipeline projects that generated significant (more than 1,300) citizen comments.

Next, given the sample, the research team collected historical citizen comment data. Public records from the Environmental Impact Assessment (EIA) or other process provided the citizen comments about each project. It is important to note that not all projects required citizens to provide addresses at each opportunity for public comments (public scoping, draft EIA report, final EIA report, etc.), so the comments are not necessarily reflective of citizen opposition at all stages of the project. Also, the analyses below include only opposition comments. This is because not all projects were coded with a field for supportive comments versus opposition comments. However, supportive comments were only about 1.6 percent of the total, and were from citizens who typically resided far away from the project they commented on.

III.A. Data

The projects included in the final sample are:

- Alberhill Substation (California Public Utilities Commission, 2019);
- Boardman to Hemmingway high voltage transmission line (Bureau of Land Management, 2017);
- The Carty II natural gas generation station (Oregon Department of Energy, 2019);
- The Constitution natural gas pipeline (Federal Energy Regulatory Commission, 2014);
- The Ocotillo wind project (Bureau of Land Management, 2011);
- The Tesoro crude-by-rail project (Washington Energy Facilities Siting Council, 2014);
- The Tule wind project (US Bureau of Land Management, 2010).

Figure 2 shows a heat map of the project locations and technology types. The size of the bubbles in the heat maps reflect the number of comments in each region. The large bubble in Washington and Oregon reflect the large number of publicly available comments for the fossil fuel projects that caused significant opposition. The two wind farms and one electricity substation in Southern California did not receive as many comments.

Figure 2: Heat Map of Projects & Locations

Table 1 shows key attributes of the sample projects and their location. The number of comments per project ranged from 35 (Tule) to 2,875 (Carty II) that were able to be geocoded was always less than the total number of citizen comments because not all contained valid addresses, or addresses were not required at the time of submission.

Project	Type	Location	Population density	Number of Comments	Outcome
Alberhill	Substation	Southern California	Suburban	60	On Hold
Boardman to Hemmingway (B2H)	High voltage transmission line	Idaho & E. Oregon	Rural	85	Approved (Federal) Pending (Oregon)
Carty II	Natural gas electricity generation	E. Oregon	Rural	2875	Denied
Constitution	Natural gas pipeline	New York	Mixed	661	Denied (NY)

Ocotillo	Wind farm	Southern California	Suburban	127	Approved with modifications
Tesoro	Oil-by-rail	Washington	Mixed	456	Denied
Tule	Wind farm	Southern California	Suburban	35	Approved with modifications
				4299	

Table 1: Energy Facilities Overview

The sample selected contained an appropriate mix of suburban and rural locations, as well as variation in other demographics that have been shown to affect citizen opposition. Data was collected on household income as well as percent owner occupied housing for the counties that the

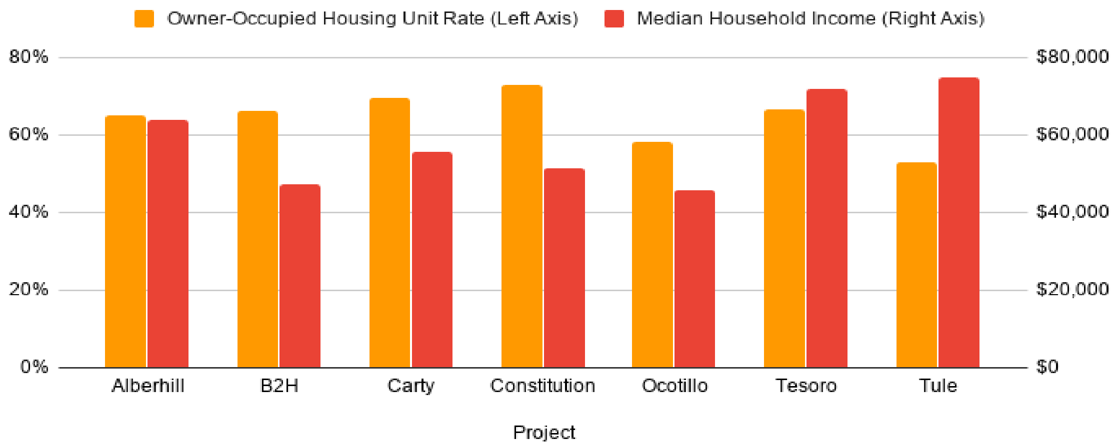

Figure 3: County Demographics

projects were sited in (US Census, 2018). For projects that spanned multiple counties (pipeline, crude-by-rail), the mean value of the relevant counties was calculated. Figure 3 shows higher household income for the Tule wind project, Tesoro crude-by-rail, and Alberhill substation. Tule was also notable for its lower share of owner-occupied housing.

III. B. Methods

Once the citizen comments had been collected (typically from PDF files), the research team geocoded the longitude and latitude of each valid street address submitted as part of the facility siting process. For the few P.O. Box addresses that were submitted, the centroid of the zip code was geocoded. The near distance function in ArcGIS was used to estimate the Euclidean distance between the citizen and the project. Each project's attributes determined its exact location: For polygons such as the Alberhill substation, the distance to the project centroid was used. For wind projects, the nearest wind turbine to each citizen was used to generate each citizen distance. For a linear project such as a pipeline, transmission line, and the oil-by-rail project, the nearest section of the line to each citizen was used to estimate distance.

Next, the first of two measures of distance-decay was estimated. The first is the median distance of opposition comments for each project, described as the *half-length* as described above. The second measure is based on the outcome variable of the sum of citizen comments at each distance from the project. This measure of opposition distance-decay is the regression slope coefficient, which measures the rate at which comments occur across space.

A zero-truncated, negative binomial (NB) regression was used to fit the cumulative number of comments at each distance (km) for each event (siting project). The negative bionomial is a class of

Poisson count models that includes the alpha parameter (α) to model the dispersion of discrete events (y) given an independent variable (x) using a Gamma distribution (Γ).

NB is preferred over Poisson count models as it relaxes the restrictive assumption of discrete event models that the variance must be equal to the mean (μ). All the historical comment data demonstrated overdispersion of variance which was mitigated by the α parameter. The NB equation is:

$$\Pr(y \mid x) = \frac{\Gamma(y+\alpha^{-1})}{y!\Gamma(\alpha^{-1})}\left(\frac{\alpha^{-1}}{\alpha^{-1}+\mu}\right)^{\alpha^{-1}}\left(\frac{\mu}{\alpha^{-1}+\mu}\right)^{y} \qquad \text{Eq. 1}$$

Since none of the citizen comments originated from 0.00 km from the project, a zero-truncated specification was used. This is appropriate in this case as 0's are not included in the data collection (Long and Freese, 2006, pg. 382). Zero truncated models estimate the conditional probability of the discrete event (y_i) occurring given the zero truncation:

$$\Pr(y_i \mid y_i > 0, x_i) = \frac{\Pr(y_i \mid x_i)}{1-(1+\alpha\mu_i)^{-1/\alpha}} \qquad \text{Eq. 2}$$

Discrete event models, of which the zero-inflated, negative binomial is a best-in-class example, are typically used to account for the effect of time on a discrete event. However, innovative researchers in public health have employed them for mapping the incidence of disease burdens (Thurston et al, 2000). The regressions use Sandwich variance estimators which account for heteroskedasticity and reduce the chances of underestimating regression coefficients' variance and standard errors due to spatial autocorrelation (Bertanha & Moser, 2016). The risks of spatial autocorrelation is lowered due to the reduced likelihood of neighborhood effects from a regression model being developed for each energy project (rather than pooling all the data together).

IV. *Results*

The descriptive statistics for geocoded distances of each citizen opposition comment to the energy facility are presented in Table 2.

Project	Type	N	Min	Max	Mean	Half-length (median)	Standard Deviation	Primary comment type
Alberhill	Substation	60	1	23.7	5	**3.2**	4.2	Local
B2H	High voltage transmission line	85	0.1	446.4	53.3	**5.1**	96.9	Local
Carty II	Natural gas electricity generation	2875	38.4	3621	268.6	**227.9**	144.1	NGO
Constitution	Natural gas pipeline	661	0	7782.5	348.4	**16.9**	1314.3	Mixed
Ocotillo	Wind farm	127	0.8	3766.6	276.1	**100.4**	505	Local
Tesoro	Oil-by-rail	456	0	5604.9	383.9	**15.4**	921.4	NGO
Tule	Wind farm	35	1.2	83	13.8	**5.9**	20.2	Local
Total		4299	0	7783	283	**222**	618	

Table 2: Descriptive Statistics for Comment Distances

Half-Length

The first measure of distance-decay is the half-length, which gives the distance within which half of the geocoded comments fall. Alberhill, B2H, and Tule all have half-lengths of less than 6 kilometers (km), showing the local nature of opposition as half of all comments in the sample originated from within this short distance. B2H has a much higher standard deviation, likely because the power line runs 500 km through sparsely populated Eastern Oregon.

Table 2 also indicates that the half-length measure is less susceptible to skewness from long-distance outliers than mean values. A comparison of the two measures in Table 2 shows the Carty, Constitution, and Tesoro fossil-fuel projects received a large number of geocoded citizen comments, but many of them were submitted from long-distances. The most localized opposition in the sample came from Alberhill, with a maximum distance of only 24 km and a difference between mean and median of less than 2 km.

The half-length calculations revealed two underlying types of citizen comments. The first type was from citizens who had connections to the impacted community. The second type of comment came from citizens who were members of NGOs such as the Sierra Club or Physicians Social Responsibility. NGO comments came primarily on the fossil-fuel projects.

Discrete-Event Regression Results

The second measure of distance-decay is derived from the slope coefficient of regression models. The slope coefficient literally represents the slope of the cumulative count of opposition comments over distance in km. Four models were fit for each of the seven projects to identify the optimal functional form to measure the slope of distance-decay. The historical count data was decidedly non-linear over distance so additional distance-decay terms were included to improve the models' fit:

1. M1 is the bivariate negative binomial model that includes raw distance. A positive sign for the distance coefficient is expected in the bivariate models as cumulative comments increase as distance increases.
2. M2 also includes the natural log of the reciprocal of distance (1/distance) squared (in thousands of km). A negative sign is expected for the coefficient as distance is transformed by its reciprocal. A negative sign is expected for the coefficient as distance is transformed by its reciprocal.
3. M3 is a bivariate model which substitutes for M1 using the reciprocal of exponentiated distance (in thousands of km) rather than raw distance in M1. A negative sign is expected for the coefficient as exponentiated distance is transformed by its reciprocal.
4. M4 adds the same reciprocal of distance squared in M2 to exponentiated distance in M3.

Table 3 shows the zero-truncated negative binomial regression results where the outcome is the log of the cumulative count of citizen comments. All models converged with Chi Square $p < .05$, indicating that the full models were significantly different from the intercept-only model (not shown). The ln alpha statistic shows $p < .05$ in all models indicating variance in the data is greater than the mean and the appropriateness of the NB model over Poisson estimator.

The Distance regression coefficients in M1 of Table 3 are the most intuitive models and show the bivariate relationship between Distance and the log of the expected count of comments. For example, for M1 for Alberhill substation, a one km increase in Distance predicts a .137 increase in the log of expected count of citizen opposition comments. At .137, Alberhill has the steepest slope coefficient for distance for any of the seven projects (in M1), followed by the Tule wind project at .0154. As indicated in Table 2 above, Alberhill and Tule are two of the projects with the most local, as opposed to NGO-driven, citizen comments.

The regression results show insights from the different functional forms for distance. The Akaike Information Criteria (AIC) is used to compare models with different numbers of predictors. The AIC results for the two bivariate models indicate that the negative exponential distance form (M3) generally outperforms the raw distance form (M1). However, the improvement in AIC associated with the negative exponential term is more modest in the projects with local opposition (Alberhill, B2H, Tule) as compared to the NGO-driven opposition projects (Carty, Constitution, Tesoro). This indicates that distance-decay tends to follow an exponential pattern over space where the cumulative number of comments is lower at any given distance for NGO-driven projects as opposed to locally-driven opposition.

The AIC also shows the inclusion of the reciprocal of distance squared term (M2 & M4) improves the fit over the bivariate models (M1 & M3) in all cases. M4 with exponentiated distance and the reciprocal of distance squared is the preferred specification across all seven projects. Again, the exponentiated distance form (M4) adds very little explanatory power compared to the raw form (M2) for the Alberhill substation and Tule wind projects.

The McFadden's Pseudo-R^2 also provides insights for model evaluation. The inclusion of the reciprocal of the log of distance squared (M2 & M4) increases R^2 by up to 10x over the bivariate models (M1 & M3). The McFadden's Pseudo-R^2 for the M4 models ranges from 5% for the Carty natural gas plant to over 32% for the Ocotillo wind project. Recall that McFadden's R^2 does not represent the percent of variation explained by the models for the count data. Rather it is defined as 1- the ratio of the fitted model with covariates to the intercept-only model, and thus should interpreted cautiously. However, it is useful for comparing models with different numbers of covariates, akin to Adjusted R^2 as it penalizes models for additional covariates.

Figure 3 shows the predicted (squares) and historical (circles) cumulative number of comments at each distance for each project using M4, the best fitting specification, for all projects. The Y-axis is the sum of citizen opposition comments. Figure 3 shows that the NB specification fits the historical data well rather well. Figure 3 is consistent with the McFadden's Pseudo-R^2 results that also indicate that the models' explanatory power is better for projects with localized rather than regional opposition (Alberhill and Ocotillo).

The fits in Figure 3 are better in areas with a high density of comments. When distance approaches its edge points, the models fit the data less well as predictions are driven by the functional specifications. The discrete event data increases monotonically in this data, but the NB models allow for decreases in the expected count which is contrary to the data generating process for this application.

	M1-Alb	M2-Alb	M3-Alb	M4-Alb	M1-B2H	M2-B2H	M3-B2H	M4-B2H	M1-Carty	M2-Carty	M3-Carty	M4-Carty	M1-Const	M2-Const	M3-Const	M4-Const
Distance	0.137***	-0.0815***			0.00371***	-0.00544***			0.00526***	-0.00254***			0.000147***	-0.000197***		
	-4.72	(-5.29)			-8.54	(-4.34)			-9.32	(-17.93)			-11.9	(-23.43)		
1/ln(Distance/1000)^2		-0.601***		-0.604***		-0.290***		-0.307***		-1.578***		-5.254***		-0.178***		-0.204***
		(-12.71)		(-12.67)		(-8.98)		(-9.65)		(-33.96)		(-18.37)		(-46.86)		(-58.09)
1/exp(Distance/1000)			-137.8***	83.24***			-4.304***	7.016***			-8.755***	36.08***			-1.623***	1.724***
			(-4.77)	-5.3			(-9.57)	-5.27			(-23.54)	-14.26			(-11.06)	-31.07
Constant	2.602***	2.058***	140.3***	-81.19***	3.496***	2.576***	7.790***	-4.477**	5.783***	-9.675***	13.90***	-78.92***	5.731***	4.639***	7.197***	2.878***
	-15.83	-23.75	-4.88	(-5.15)	-49.62	-22.52	-19.79	(-3.14)	-38.03	(-19.83)	-48.82	(-15.42)	-249.97	-186.94	-54.38	-40.27
lnalpha	-1.847***	-18.25***	-1.855***	-18.30***	-1.122***	-2.956***	-1.137***	-3.160***	-0.857***	-1.151***	-0.970***	-1.383***	-0.678***	-3.048***	-0.812***	-3.798***
	(-4.50)	(-72.08)	(-4.50)	(-93.28)	(-4.97)	(-7.42)	(-4.99)	(-7.53)	(-15.46)	(-34.98)	(-25.11)	(-38.28)	(-9.91)	(-37.25)	(-11.14)	(-44.03)
Observations	60	60	60	60	85	85	85	85	2875	2875	2875	2875	661	661	661	661
Pseudo R^2	0.0966	0.317	0.0972	0.317	0.0353	0.181	0.0367	0.193	0.0189	0.0387	0.0265	0.054	0.00555	0.173	0.0166	0.217
AIC	471.5	360	471.2	**359.8**	768.1	655.2	767	**645.7**	46184.6	45251.4	45823.1	**44531.1**	8830.3	7349.2	8732	**6954.2**

	M1-Oco	M2-Oco	M3-Oco	M4-Oco	M1-Tesoro	M2-Tesoro	M3-Tesoro	M4-Tesoro	M1-Tule	M2-Tule	M3-Tule	M4-Tule
Distance	0.000840**	-0.000507***			0.000317***	-0.000492***			0.0154***	-0.0476***		
	-2.94	(-5.71)			-16.93	(-11.13)			-5.31	(-3.75)		
1/ln(Distance/1000)^2		-0.306***		-0.472***		-0.238***		-0.304***		-0.767***		-0.784***
		(-20.75)		(-18.59)		(-23.73)		(-34.94)		(-5.11)		(-5.17)
1/exp(Distance/1000)			-2.164***	2.984***			-1.234***	2.526***			-16.09***	50.96***
			(-9.11)	-12.8			(-21.37)	-23.72			(-5.35)	-3.83
Constant	3.867***	1.260***	5.828***	-2.910***	5.264***	3.761***	6.403***	0.975***	2.625***	0.248	18.71***	-50.75***
	-42.94	-9.62	-31.97	(-6.57)	-184.59	-61.46	-151.21	-6.56	-22.18	-0.51	-6.42	(-3.69)
lnalpha	-0.984***	-3.510***	-1.238***	-20.49	-0.791***	-2.274***	-0.883***	-2.849***	-1.351***	-2.636***	-1.355***	-2.661***
	(-5.63)	(-18.17)	(-6.66)	(.)	(-9.09)	(-35.40)	(-9.68)	(-62.41)	(-3.56)	(-7.73)	(-3.57)	(-7.73)
Observations	127	127	127	127	456	456	456	456	35	35	35	35
Pseudo R^2	0.0269	0.234	0.0499	0.321	0.0144	0.131	0.0222	0.175	0.0377	0.167	0.0381	0.169
AIC	1254.9	990.4	1225.3	**877.8**	5704.2	5034.1	5659.1	**4777.9**	258.4	226.4	258.3	**225.8**

* p<0.05 ** p<0.01 *** p<0.001

Table 3: Truncated Negative Binomial Count Regression Results for the Seven Siting Projects

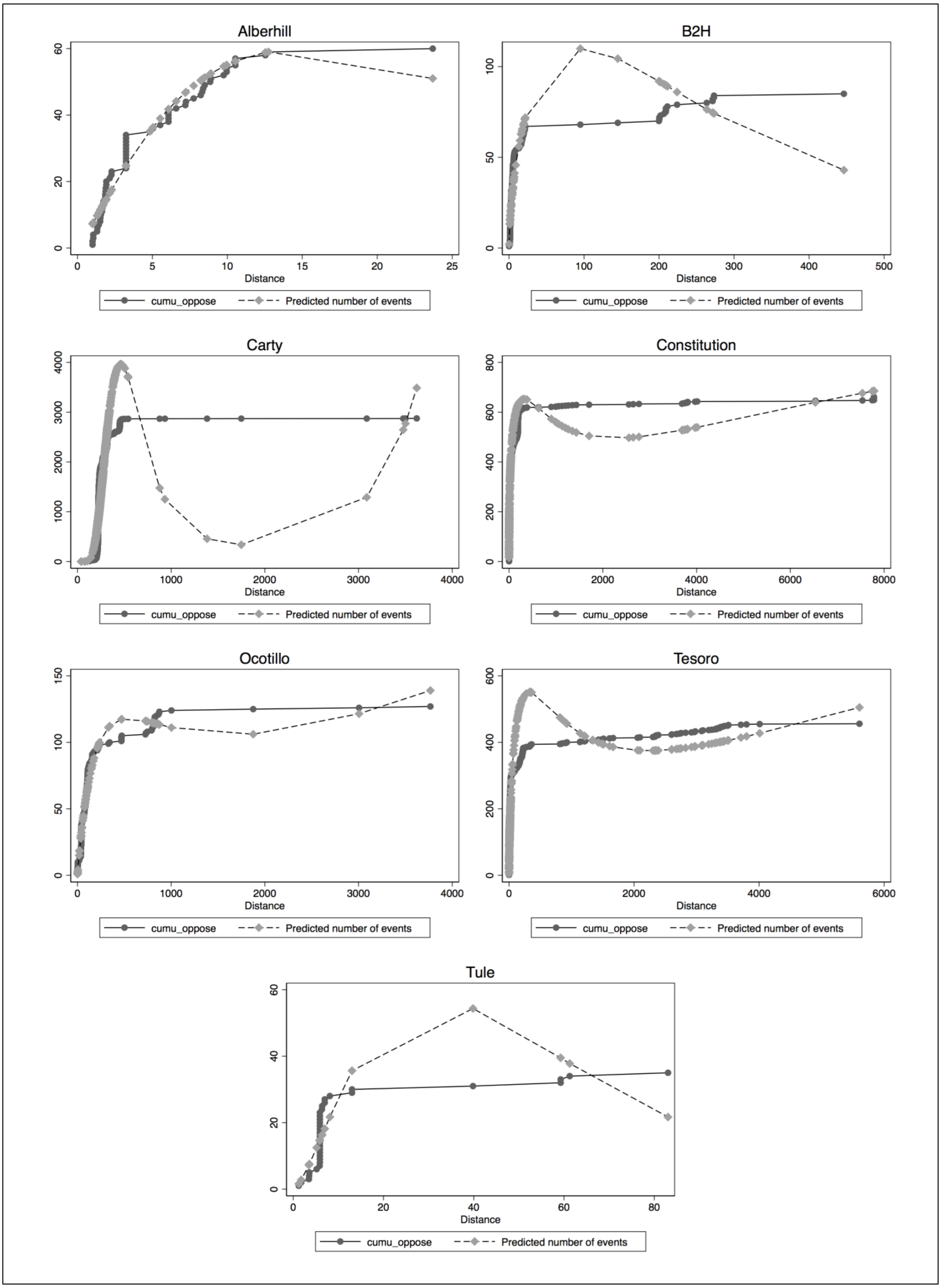

Figure 4: Predicted and Actual Citizen Comment Counts

V. *Discussion*

The two measures of citizen distance-decay different provide insights into how citizen proximity affects opposition to a LULU. The half-length is an intuitive measure for distance-decay that can easily be communicated to researchers and project stakeholders, with smaller values indicating more localized opposition. One benefit of the half-length indicator is that it can quickly identify NGO vs community-driven opposition.

While they also file comments on projects as stakeholders, membership-based NGOs such as the Sierra Club, manufacture citizen opposition utilizing their information technology platforms. It's hard to get Sierra Club members to drive 250 km for a public scoping meeting on a LULU, but they happily forward an email template to the project's administrator. In contrast, citizen opposition on projects with small half-lengths tends to be much more place-based; driven by municipal outreach tools and existing citizen communication networks (Nelson, Swanson & Cain, 2018).

For at least one of the projects in the sample (Carty), citizen opposition was entirely outside the hosting community as the minimum comment distance was 38 km. Most of the opposition to Carty came from far-away Portland, Oregon entirely through electronic corridors of opposition by environmental NGOs concerned about air quality and climate change. The lack of local opposition can partially be explained by the favorability of the project to the local community. There is an existing natural gas generation plant in Boardman, Oregon where the Carty expansion project was proposed. Rural Boardman is also a "company town" where the project sponsor has developed a high level of trust with the community.

The discrete event regression slopes give a more nuanced version of distance-decay, and can include other citizen information, if available (demographics, NGO membership, main objection to the project, etc.) that can increase our understanding of citizen opposition dynamics. The differences in slope coefficient across energy technologies indicate that each has very different perceived externalities, project contexts, and spatial templates. Localized and renewable energy projects have the best predicted fit along the project distances compared to projects that have a high perceived risks, more dispersed impacts, and higher NGO involvement.

One key finding for siting theory from the regression results is finding that distance-decay is most decidedly non-linear–in this sample at least. This is supported by two observations. First, the improvement in model fit with the coefficient for 1/exponentiated distance (M3) is always preferred to linear distance (M1). Secondly, the inclusion of distance squared term (M2 & M4) is always preferred to models without it (M1 & M3). The squared term is consistently negative. The intuition here is that opposition distance-decay effect is concave (∩-shaped). This indicates that the effect of distance decreases as distance increases. This again reaffirms the importance of local factors as drivers of opposition. The concave shape of the distance square term also implies that context and project factors can moderate distance, providing support for the findings in Gravelle & Lachapelle (2015) as well as Nelson, Swanson & Cain (2018).

This supports theorists that argue for place-based explanations of citizen opposition (Devine-Wright, 2009). It also reinforces the logic of rational ignorance of land-use conflict for those citizen's not impacted by the LULU (Downs, 1957). It also supports Mueller's (2020) claim that physical exposure to externalities is required for wind opposition. In sum, the regression results reinforce that "Backyards" are *local*.

However, how should we define local? One of the contributions of this study is its attention to multiple energy technologies. Much of the research on LULUs has been single case studies of citizen opposition to wind farms. These regression results hopefully show generalizable insights on how to define local. Van der Horst (2007) and others have argued that citizen "use value" is a key to citizen concern. Projects with large negative exponentiated coefficients for the show higher local use values, as opposed to projects where opposition was more spread out. The use-values for the citizens in this sample are more likely to be avoided damages rather than heritage values ascribed to the land. The Tesoro crude-by-rail project received many comments from locals concerned about oil spills in the Scenic Columbia River Gorge as well as from NGO members concerned about climate change (Washington Energy Facilities Siting Council, 2014). Due to strong opposition, this project was denied a permit by Washington's Governor. Non-proximate opposition fits into Wolsink's (2000) category of opposition to the technology (wind) rather than selfish NIMBY behavior.

V.A. Implications for the FACT Siting Framework

The half-length and NB regression coefficients provide empirical support and measurement tools for opposition distance-decay, and give headline metrics for the "localness" of opposition. These parsimonious headline measures, by definition, include causal variables from existing siting theories. FACT's two context components of Project favorability (F) and citizen oppositional ability (A) have been widely studied by scholars and practitioners:

- <u>F</u>avorability includes the type of perceived risk of the project such as health and safety (Elliot & Wadley, 2012), property values (Mueller et al, 2017), existing land-uses (Wolsink, 2000) that have been shown to drive citizen opposition. Risks of climate change for fossil fuel plants are clearly a risk from citizens in this sample. The fossil fuel projects had the largest number of opposition comments, most from distant citizens. These projects are perhaps better described GULU's: globally unwanted land-uses.
- Oppositional <u>A</u>bility can include demographics (Firestone & Kempton, 2007) well as place attachment (Devine-Wright, 2009). Institutional and psycho-social factors such as citizen efficacy, process fairness, and trust are also embedded in the distance-decay measures (Nelson, Cain & Swanson, 2018).

The FACT framework makes the above existing siting theories spatially-enabled with the addition of corridors for transmission (C) and the spatial template (T) categories. An illustration of these factors for the Alberhill substation circled in red in Figure 4. Citizen comments are blue comment shapes.

- The impacts of <u>C</u>orridors for transmission: Recall that Alberhill experienced entirely local opposition as the maximum distance of an opposition comment was 24 km. The citizen comment locations in Figure 4 shows that citizen opposition was not randomly distributed, but rather clustered in certain areas. The location driver was corridors of opposition.
    - Comments were distributed along the corridor of Corona Freeway (Interstate 15) that cuts through the valley between the Santa Ana mountains on the west and the Gavilan Plateau to the northeast. The substation was salient to residents as it would be visible while driving on the interstate (CPUC, 2019)
    - Corridors of transmission are both physical and social (Lewicka, 2005). Schools are often a focal point of citizen communication networks as students, teachers, staff and parents gather to talk about local issues.
- The spatial <u>T</u>emplate also explains the location of citizen comments. Proximity matters. The highest density of comments came from the planned community surrounding Luiseno

Elementary school, which is located directly across the valley from the substation, and not from the more heavily populated Lake Elsinore to the southeast.

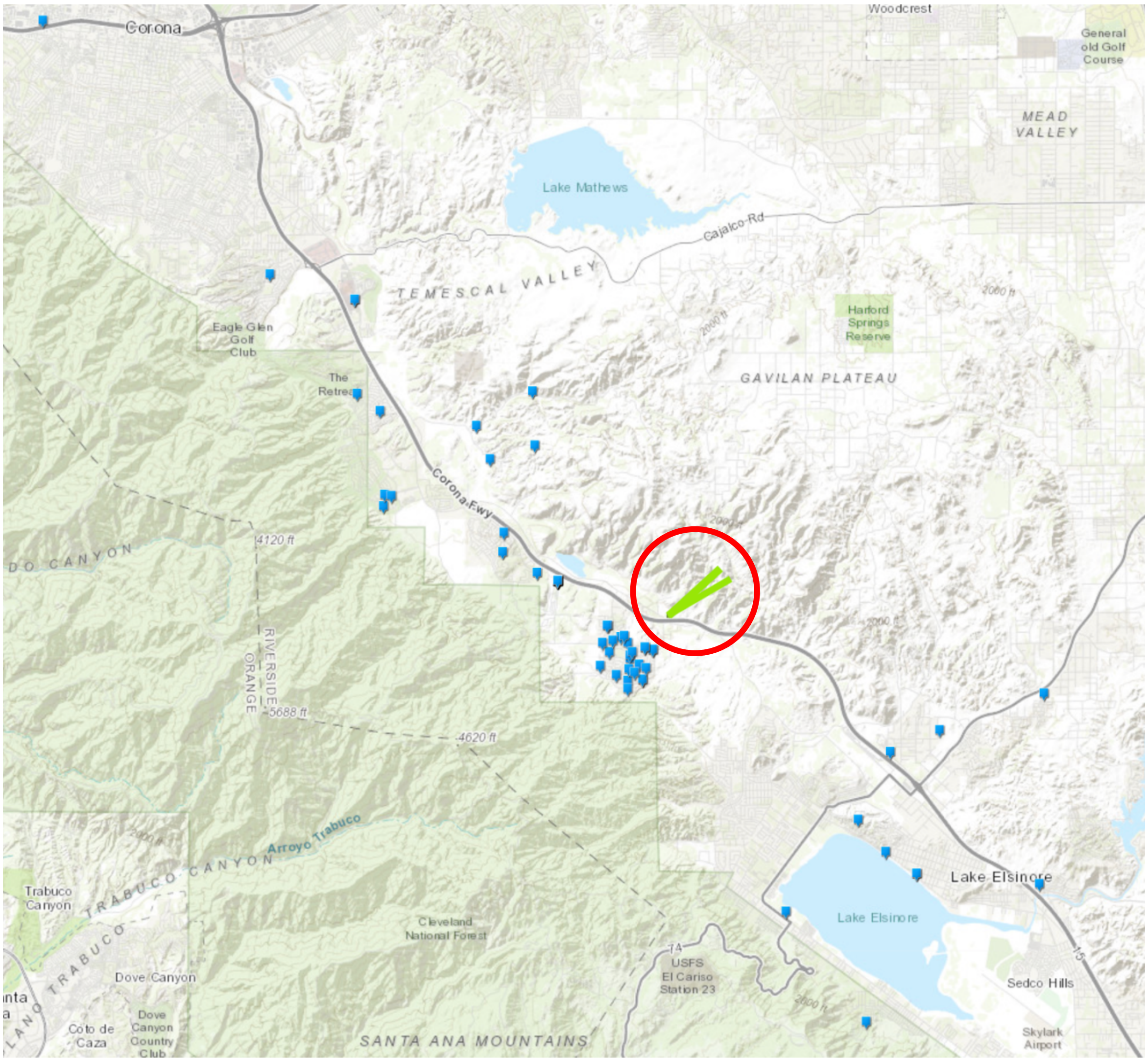

Figure 5: Alberhill Substation Spatial Template and Corridors for Transmission

VI. Conclusion & Recommendations

The FACT siting framework and the two indicators of distance-decay were developed in response to repeated calls for more holistic approaches to siting theory (Devine-Wright, 2005; McAdam et al, 2010; Cain & Nelson, 2013). Energy facilities siting occurs within a complex set of technical, social, political and economic systems which partially explains the lack of consensus on the effect of distance-decay of citizen opposition behavior. The empirical tools and theoretical framework develop here can be used in other LULU domains including waste management and transportation to better understand public engagement.

The six energy technologies analyzed in this paper provide a wider range of energy technologies than in most siting studies. The sample of 4,300 citizen comments across the United States cuts a wide geographical scope. The geocoded distances between the citizen comments and their corresponding LULU project enabled the calculation of the half-length (median distance) of the half-way point between the minimum and maximum distance. Half-length is the spatial equivalent of half-life from pharmacology and radioactivity. The half-length was the smallest for projects with strictly place-based opposition. Half-length is a parsimonious, and easily calculated metric for the spatial scale of opposition. Half-length is complemented by another metric; a spatial discrete-event regression model. The modeling showed pronounced non-linear dynamics for distance-decay. These two metrics provide indicators for the spatially-enable FACT siting framework. The FACT framework can subsume existing siting theories including, demographics, place attachment, social ties, and institutional frameworks.

The contributions from this research are in part due to its holistic research process. The spatially-enabled FACT theoretical framework was developed from a range of relevant interdisciplinary domains across the natural and social sciences. This paper applies the FACT framework to six of the most prevalent energy technologies that have very different perceived risks, including: wind farms, a gas pipeline, a gas-fired electricity generation facility, a high voltage powerline, a crude oil terminal, and an electricity substation. The methodology geocodes data from actual citizen behavior, without the social desirability bias that can be associated with survey research. The research design is easily replicable to other locations and temporal frames.

The FACT siting framework and half-length concepts can potentially provide scholars and practitioners new tools to incorporate spatial variables into their analyses. Social scientists routinely incorporate temporal dimensions into their work using well-developed methodologies; this research proposes a theoretical framework and empirical tools to allow the systematic inclusion of spatial dimensions in the consideration of project planning. Social scientists routinely include time discounting as well as explicitly model temporal effects in their quantitative and qualitative analyses. Consider the shelves of books on time series statistics (the 5^{th} edition of Box et al, (2015) as an example), and effects of history in research and decision making (Neustadt and May, 2011).

VI.A. Recommendations

The modest advances from this research to the study of LULUs can be extended from future analyses. Environmental Impact Assessment and other processes can facilitate the further development of spatially-enabled siting theory by requiring valid addresses to be submitted as part of comments. A significant number of comments were excluded from this research because project sponsors did not require citizens to submit their home addresses in the siting process. For these cases, distance-decay calculations are impossible. For the above projects, recall that the geocoded citizen comments do not reflect all the citizen comments for each of the LULUs. For example, some projects allowed comments to be emailed without requiring the commenter's address to be included. Citizen address requirements tend to be required during public meetings and for web-based forms dedicated to collecting citizen comments. Researchers and practitioners can enhance the transparency and accountability of siting processes by advocating for address data.

This, and other research referenced herein on distance-decay and proximity in siting research is a modest start. Siting theorists that systematically integrate distance-decay measures in their research can learn from our colleagues in the natural and social sciences to advance spatial theories and metrics. Citizen opposition to unwanted renewable energy and electricity infrastructure is a major potential barrier to the clean energy transition the planet and its inhabitants require. Spatial insights on the subject are likely to increase the range of choices available to decisionmakers attempting to implement the transition.

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