Legacy and shockwaves: A Spatial Analysis of strengthen resilience of the power grid in Connecticut.

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Abstract

Grid resilience and reliability are pivotal in the transition to low and zero carbon energy systems. Tree-trimming operations (TTOs) have become a pivotal tool for increasing the resilience power grids, especially in highly forested regions. Building on recent literature, we aim at assessing the temporal and spatial extents of the benefits that TTOs produce on the grid from three perspectives: the frequency, extent, and duration of outages. We use a unique dataset provided by Eversource Energy, New England's largest utility company, with outage events from 2009-2015. We employ both quasi-experimental approaches and spatial econometrics to investigate both the legacy and spatial extent of TTOs. Our results show TTOs benefits occur for all three metrics for at least 4 years, and benefits spillover to up to 2km throughout the treated areas.

Keywords: Spatial modeling, electricity, vegetation management, trimming, outages, energy transitions.

1. Introduction

The reliability of power grids is often seen as a pivotal element for energy transitions (Verbong and Geels, 2007), especially as more and more economic sectors electrify (Scholten et al., 2020), and the frequency of extreme events increases because of climate change (Bartos and Chester, 2015; Cohen et al., 2018; Jenkins, 2021). The increased frequency of these events has led to costly losses for all types of customers across the economy of a region (Graziano et al., 2020; Küfeoğlu and Lehtonen, 2015). For example, Campbell (2012) reported that storms due to changing climate patterns result in outages costing \$20 to \$55 billion annually to the U.S. economy. The interaction between extreme events and the vegetation surrounding the powerlines is particularly problematic: overgrown tree-branches have been found to be responsible for a large proportion of outages (Guikema et al., 2006). The effects of poor vegetation management and extreme events became very tangible on August 14th, 2003, which led to one of the largest blackouts ever experienced in North America (Andersson et al., 2005). In the U.S., several utility companies maintain tree-trimming operations (TTOs) to manage the growth of vegetation around power lines (Executive Office of the President, 2013): these operations are costly, and often incur several limiting factors, whether in relation to cost-reduction strategies or property rights issues (Short, 2016). Literature on the exact effects of TTOs on reducing vegetation-related outages, is quite scarce, and focuses primarily on prediction models or have worked using aggregated data, (Guikema et al., 2006; Radmer et al., 2002; Cerrai et al., 2019; Most and Weissman, 2012; Ou et al., 2016; Simpson and Bossuyt, 1996) mostly due to limitations in accessing point-level data from utility companies. Recently, Graziano et al. (2020) combined disaggregated data with a quasi-CGE to estimate the benefits of reducing power outages in Connecticut.

Their work serves as the basis for this paper: their work did not focus only on vegetation-related outages, nor did it investigate the spatial effects of TTOs. The latter are particularly relevant as the grid is a network of interrelated 'regions', thus benefits (or costs) propagate throughout the state. To fill those gaps, in this study we aim at using a unique dataset provided by New England's largest utility company and the largest owner of power lines in Connecticut, Eversource Energy.

Stated explicitly, our objectives are:

1) *To investigate whether spatial spillovers throughout the grid increase the spatial extent of TTOs benefits previously found by Parent et al. (2019) and Graziano et al. (2020);*

2) *To assess if these benefits are pervasive in time;*

3) *To investigate the extent to which the benefits from TTOs in Connecticut have so far equitably impacted communities throughout the state.*

To fulfill these objectives, we build upon an initial assessment of the link between TTOs and power outages developed by Graziano et al. (2020) by taking a spatial perspective, and by focusing only on tree-induced outages, which are defined as those lasting more than 5 minutes. The element of 'justice' within sustainable energy transitions processes has become central in recent years, both in developed and developing country (McCauley and Heffron, 2018; Newell and Mulvaney, 2013). By looking at the spatially distributive effects of these benefits, we aim to understand if transitioning towards a more resilient power grid - a requirement for the electrification of the economy – may incur in socially unbalanced outcomes, and if these benefits may be redistributed via a publicly funded program for sustaining the expansion of TTOs.

Our findings show that TTOs indeed have spatially and temporally pervasive benefits in reducing the occurrence, duration, and number of customers affected by tree-related outages in

Connecticut. In addition, trimming has focused on highly populated areas, and more can be done to incorporate elements of social justice and the emerging issues related to changes in work modes in a post-2020 world.

The remainder of this paper is organized as follows: section two walks through the historical literature of grid resiliency through TTOs; section three describes the study area and data we used; section four describes the methods used to ascertain the spatiotemporal effects of TTOs; section five presents our results. Finally, section six draws policy conclusions based on our findings.

2. Grid resiliency through TTOs

Among the studies focusing on understanding how to improve the grid infrastructure for accommodating both climate change events and the addition of new electricity uses and efficiency standards, those focusing on the role of vegetation management are limited. This lack of studies is due primarily to the difficulty to gather grid data, which are often seen as proprietary by utility companies (Guikema et al., 2006). Grid resiliency though TTOs can be classified into three disparate yet linked categories; observational, econometric/statistical, and predictive. Initially, a few studies used observational approaches for investigating the relationship between TTOs and outages (see e.g., Simpson and Bossuyt, 1996; Simpson, 1999). Following, Radmer et al. (2002) and Guikema et al. (2006) used econometric approaches for investigating this relationship, although they incurred in severe data and methodological limitations. Further, Cerrai et al. (2019), Doostan et al. (2020), Hughes et al. (2021), and Alpay et al. (2020) have employed predictive modeling in their assessments of the interlink between TTOs, extreme weather events, and localized storm events. Most recently, Parent et al. (2019) contributed to the understanding of TTOs (in the form of enhanced tree trimming, ETT) and reduction of power outages. They found that ETT reduced the outage rates compared to standard TTOs, although not for significant causes, and only for minor storm-related outages. Although an improvement, their work still did not consider spatial effect of trimming, nor the distributions of benefits throughout their study area. However, both their work and that by Graziano et al. (2020) serve as the basis for further investigating how TTOs-related resiliency benefits spread through time and space.

3. Study area and data sources

Connecticut offers an interesting opportunity as a study area for two reasons: the state is located in a region that is undergoing both a rapid change in the way in which electricity is used, and its power grid is routinely and negatively affected by tree-related outages, whether during clear skies (Graziano et al., 2020) or storm events (Parent et al., 2019). As extreme events increase their frequency due to changing climate patterns (Kirshen et al., 2008; Moser et al., 2008), this lack of reliability is becoming a pressing issue for the state, and, more broadly, for the electricity region it belongs to, Independent System Operator-New England (ISO-NE) (Parent et al., 2019). With most of its territory covered by forests (Vogt and Smith, 2016) (Figure 1), TTOs are seen by the state's largest energy utility company, Eversource, as a pivotal tool for reducing outage occurrences (Eversource, *personal communication)*.

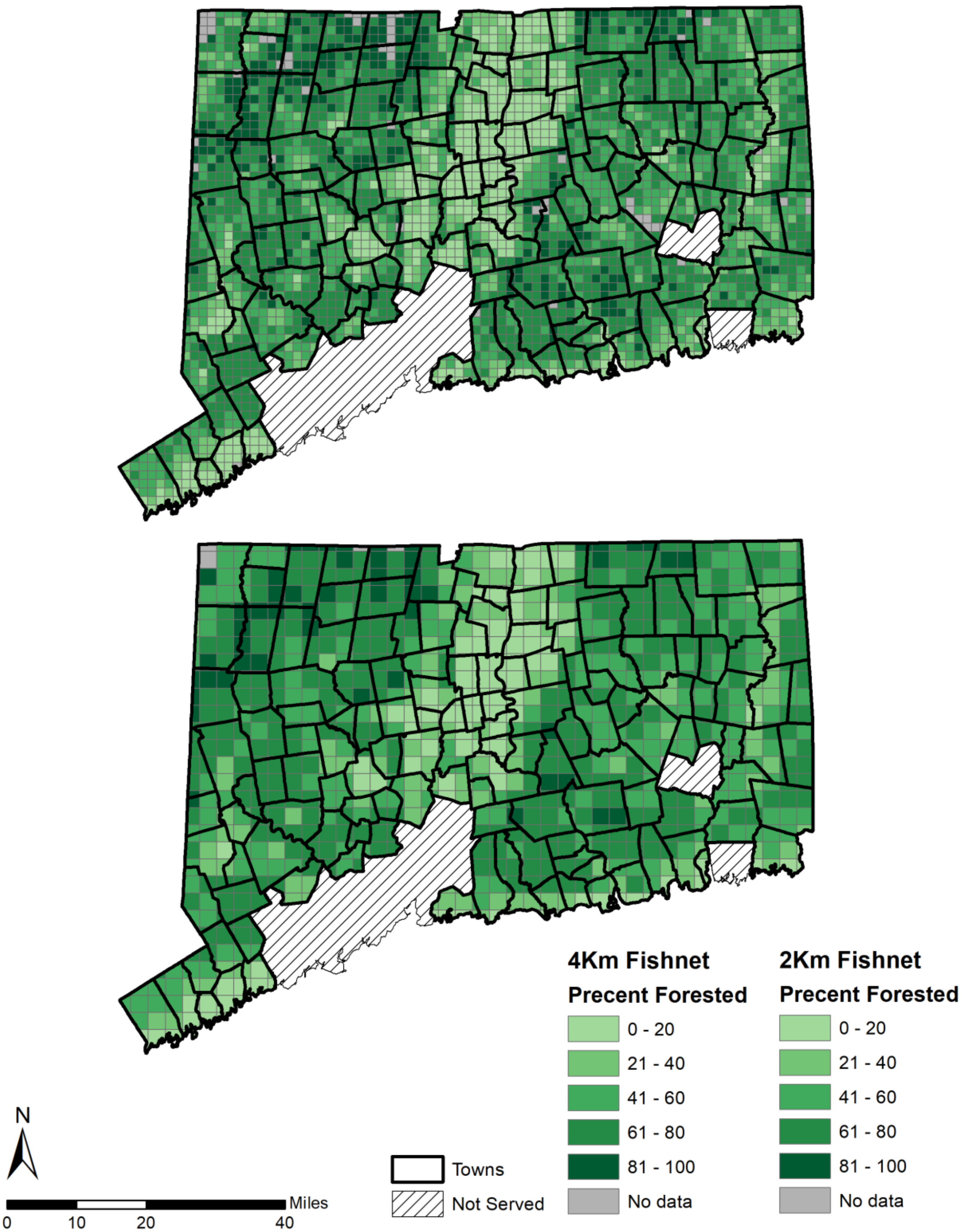


Figure 1: Map of Connecticut showing author derived percent forested for each fishnet areal size.

These operations are conducted throughout the towns controlled by Eversource Energy (Figure 2), which cover 1.2 million customers in 149 of Connecticut's 169 towns.[1] Although costly operations, their immediate economic benefits have been found to outweigh them, in part due to the effects of outages on the broader economic state system, which already copes with rates higher than the national average (Graziano et al., 2020).

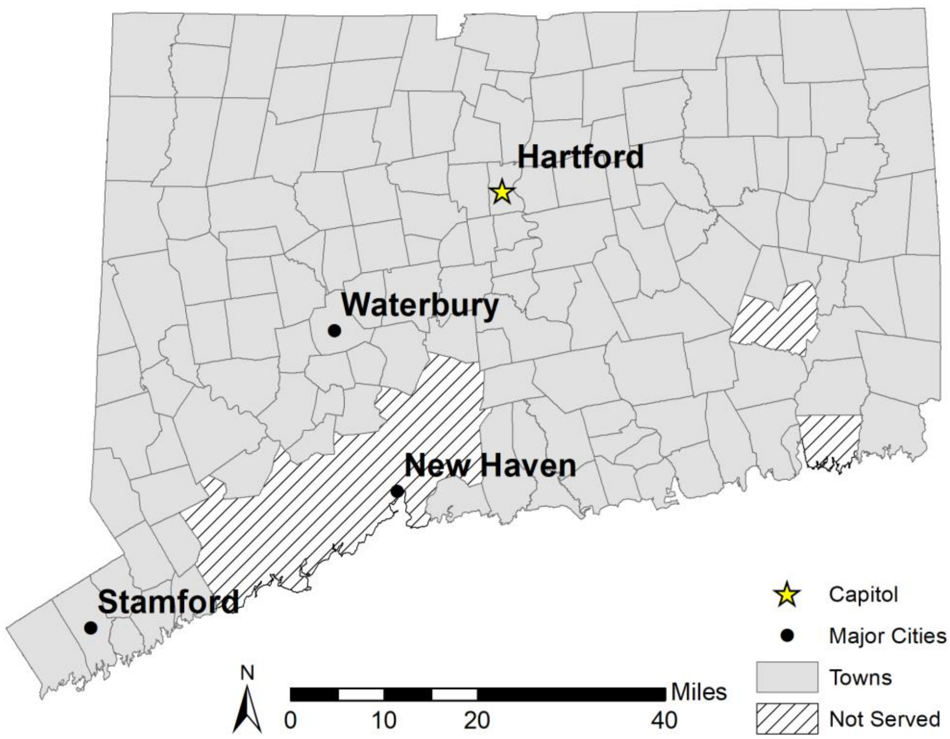


Figure 2: Map of Connecticut showing towns served by Eversource and those which are not.

Eversource operates within the broader ISO-NE, one of the seven independent, non-profit Regional Transmission Organization (RTO) overseeing the operation of the U.S. bulk electric power system. Connecticut's electrical profile relies primarily on nuclear energy for its baseload, and has shifted most of its capacity towards natural gas, although plans exist for

[1] https://www.eversource.com/content/general/about/about-us/about-us/customer-profile

developing the State's and region's offshore wind potential (Graziano et al., 2020). Socioeconomically, Connecticut is one of the most unequal states in the U.S., with Gini index of 0.4963 in 2019, equivalent to that recorded in upper-middle and lower-middle income nations like Colombia or Guatemala (World Bank, 2020; U.N., 2014). The second highest among all states (excluding D.C.) (U.S. Census). In addition, the state suffers from income segregation through a system of public services, planning, and infrastructures managed at the town level, which contributes to retain these vast inequalities (Bischoff and Owens, 2019; Boggs, 2017).

3.1 Data sources

We created two uniquely rich datasets which can be broken down into three sets: *i) power outage and distribution line characteristics; ii) climatic data describing the average and extreme values; and iii) land cover/land use (LCLU) data*. Each dataset uses the same structure, although data are collected at two different fishnet sizes (Table 1).

Table 1: Summary statistics and sources for 2 km fishnet

Variable	Observations	Mean	Std. Dev.	Min	Max	Source
Distribution Lines (m)	21,623	8,842.60	6,536.00	3.00	43,710	Eversource Energy
Four-year legacy of TTOs	21,623	0.29	0.45	0.00	1	Eversource Energy
Number of tree outages	21,623	4.84	9.28	0.00	142	Eversource Energy
Log duration of tree outages (min)	21,623	5.49	3.69	0.00	13.54	Eversource Energy
Customers affected by tree outages	21,623	210.62	622.77	0.00	17,356	Eversource Energy
Sum of squared average precipitations (mm/day)	21,623	86.78	36.89	0.00	243.72	Thornton[2] (2017)
Sum of squared average maximum temperature (degrees C)	21,623	340.01	32.83	0.00	425.32	Thornton (2017)
Sum of squared average minimum temperature (degrees C)	21,623	117.13	11.39	0.00	154.12	Thornton (2017)
Sum of squared average snow water equivalent (kg/m2)	21,623	1,351.33	1,834.61	0.00	34,682.65	Thornton (2017)
Cooling degree days	21,623	24,684.57	3,498.14	0.00	34,478.10	Author derived

[2] Thornton, P. E., Thornton, M. M., Mayer, B. W., Wei, Y., Devarkonda, R., Vose, R. S., & Cook, R. B. (2017). Daymet: Daily Surface Weather Data on a 1-km Grid for North America, Version 3. ORNL Distributed Active Archive Center. https://doi.org/10.3334/ORNLDAAC/1328.

Heating degree days	21,623	36,973.24	12,535.94	0.00	73,446	Author derived
Percent forested	21,623	52.43	24.01	0.00	96	USGS GAP[3]

We built our estimation dataset as a partial sub-set of Graziano et al. (2020). Power outage data, the number of customers affected[4], and duration (in minutes) of outages is contained within GIS points spatially distributed throughout Connecticut at locations near where the outage occurred. We selected those outages whose cause was recorded as "vegetation". Power distribution and TTO GIS polyline data contained selected characteristics, such as length of distribution line and length and year of TTOs along distribution lines. Building upon the geospatial approach used by Parent et al. (2019), we constructed a unique climate dataset derived from Daymet daily climatological summaries. We included the following attributes: average minimum and maximum temperature, precipitation, snow water equivalent, and author derived Heating Degree Day and Cooling Degree Day, a measure related to regional climate and energy interactions. Each of the four Daymet variables were squared and summed to better accentuate extreme events that might occur during the study period. Lastly, we utilized a USGS GAP land use/land cover (LULC) dataset for the purpose of quantifying the percent of forest cover per 2km cell as a means of estimating the relative risk of tree-related power outages. The final results were two unique harmonized datasets for Connecticut at a 2 (and 4 km, see the Appendix) spatial resolution suitable for analysis of the effects that TTOs have on tree-related power outages.

[3] USGS GAP. https://www.usgs.gov/core-science-systems/science-analytics-and-synthesis/gap
[4] The number of customers affected is recorded at the household, business, or commercial level and not the individual (e.g., one household customer might comprise four individuals residing within that household).

4. Methods

In our analysis, we focus on the temporal (by using both a negative binomial specification), and spatial spillovers of TTOs (by using a spatial autoregressive and spatial Durbin model). As pointed out by Graziano et al. (2020), fishnetting may be sensitive modifiable areal unit problems (MAUP). To reduce MAPU-related issues, we use two levels of aggregation: 2 and 4 kilometers (Svoray et al., 2005) (see Figure 3) for the years 2008-2015. The use of a standardized areal unit ranging from smaller than a Census Tract to smaller than a Town provides us with the opportunity to leave the data untransformed (see Graziano et al., 2020).

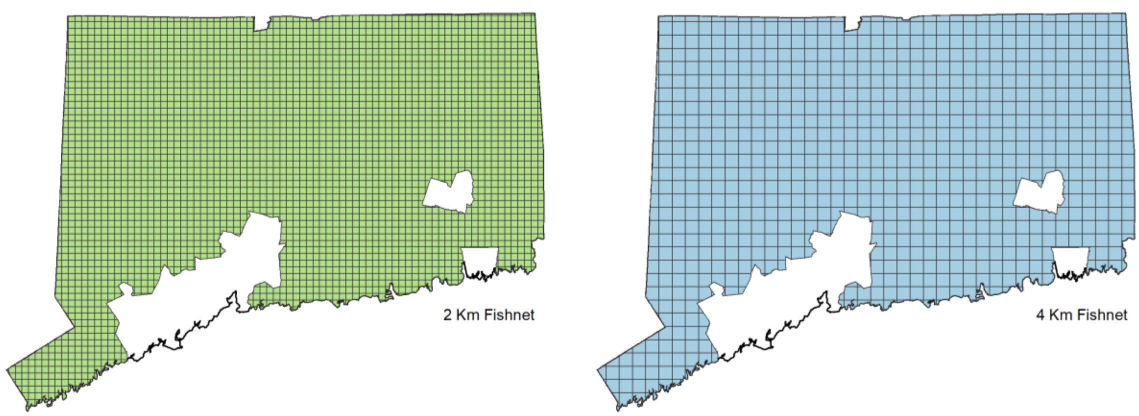


Figure 3: Map of the fishnets used in analysis

Our modelling strategy is focused on the analysis of the spatial-temporal relationship of TTOs and tree-related power outages, utilizing Spatial Autoregressive (SAR) and Spatial Durbin (SDM) models. To this aim, as per the standard procedures of the spatial analysis, we run an ordinary linear regression and a Poisson model and, once, assessed the spatial correlation of the residuals, we proceed with the spatial econometric analysis.

4.1 Temporal spill-overs

Our model for estimating the influence that TTOs exhibit on the number of tree-related power outages, can be parsimoniously stated as:

$$Tree\_Outage\_Count_{i,t} = \alpha + \mathcal{X}_i \beta_i + \mathcal{L}_{i,t} \delta_{i,t} + \psi_{i,t+4} + \varepsilon_{i,t}$$

(Eq. 1)

Where: $Tree\_Outage\_Count_{i,t}$ is the number of tree-related outages, with duration longer than 5 minutes, occurring in cell i in year t; α is our intercept; $\mathcal{X}_{i,t}$ is a vector containing percent forested calculations; $\mathcal{L}_{i,t}$ is a matrix containing climate data (i.e., precipitation, max and min temperature, and snow water equivalent); and $\psi_{i,t+4}$ is a four-year legacy variable; and $\varepsilon_{i,t}$ is zero-mean error term. Given the annual characteristics of our data, and to minimize issue with simultaneity (Brock and Durlauf, 2010), trimming variables are modeled as time-lagged (t-1), following the assumption that effects from TTOs will not be present until the following year. In our preferred specification, a dummy time-lagged variable is created, where 1 indicates a cell has received TTOs at t and it remains 1 up to t+4. If additional treatment is received in t to t+3, the lead effect is further lagged. This strategy accounts for Eversource expectation that trimming effects last up to 4 years (Eversource, *personal communication*; Louit et al., 2009). See table one for source and summary statistics of above variables.

4.2 Spatial Temporal Models

When regressing geographic variables, spatial autocorrelation, or the presence of systematic spatial variation within variables may occur (Tobler, 1970). Testing for spatial autocorrelation (Moran's I) within a variable of interests serves as the motivation for utilizing spatial models. We found that, tree-related outages are spatially autocorrelated with a Moran's I of 0.217 and a z-score of 170.17 indicating that there is less than a one percent chance that clustering of tree-related outages is by random chance. To investigate the spatial spillovers of TTOs, we utilized two model variants of the spatial autoregressive framework, the spatial autoregressive model (SAR; Cliff and Ord, 1973).and the Spatial Durbin Model (SDM; Durbin, 1960; Anselin, 1980; Dubin, 2003). As described in LeSage (2014), SAR is motivated based on time-dependency (i.e., modeling the space-time lagged values of the dependent variable using the spatial autoregressive process), and the SDM is motivated on the basis of spatial heterogeneity (i.e., specifying models to have individual effects). While both models have slightly different motivations, they share in common a weighting matrix, an element essential in the construction of spatial autocorrelation models. When spatial units resemble that of a grid, like the fishnet used in this analysis, the utilization of a queen's weighting matrix is advantageous, as it results in the greatest number of spatial interactions. Both the SAR and SDM are proven models and will accommodate the analysis of spatial relationships within the panel dataset (see e.g., Elhorst, 2010 for more insights; and Balta-Ozkan et al., 2015; Dharshing, 2017; Graziano et al., 2019; Müller and Trunevyte, 2020 for examples of applications).

The addition of the queen's case weight's matrix allows us to control for spatial interactions within our temporal model so as to better estimate the effect TTOs have on reducing tree-related power outages.

The spatial panel specification can be parsimoniously stated as:

$$Log\_Tree\_Outage\_Rate_{i,t}\rho\mathcal{W}_{i,t} = \alpha + \mathcal{X}_i\beta_i + \mathcal{K}_{i,t-1}\gamma_{i,t} + \mathcal{L}_{i,t}\delta_{i,t} + \psi_{i,t+4} + \varepsilon_{i,t} \quad \text{(Eq. 2)}$$

$$Log\_Tree\_Outage\_Rate_{i,t}\rho\mathcal{W}_{i,t} = \alpha + \mathcal{X}_i\beta_i + \mathcal{K}_{i,t-1}\gamma_{i,t} + \mathcal{L}_{i,t}\delta_{i,t} + \psi_{i,t+4}\rho\mathcal{W}_{i,t} + \varepsilon_{i,t}\rho\mathcal{W}_{i,t}$$

(Eq. 3)

Where each of our variables of interest are the same as those found in section 4.1 above. The important difference between, our temporal model and spatial models, is the transformation of our dependent variable into the log of tree-related outages per kilometer of distribution lines, a common approach to handling count data within the spatial autoregressive framework (LeSage, 2008). The main difference between these two models is the placement of the weight's matrix. The SAR assumes that tree-related outages in cell i have an effect on the tree-related outages of neighboring cells through the weight's matrix. Expanding on this, the SDM assumes that those same effects, from the SAR are in place, in addition to the effects that TTOs (four-year legacy) have on tree-related outages in neighboring cells, along with the inclusion of autoregressive errors.

5. Results and discussion

Following section 4 above, our results are twofold: temporal and spatial-temporal. Overall, the results of each model consistently show that TTOs produce a reduction across each tree-related variable of interests; outages, customers affected, and duration. The following results described in this section refer to our preferred 2 km fishnet study size. Section 5.1 reports the temporal results and 5.2 the spatial-temporal ones. Additionally, in an effort to model TTOs in accordance with practices implemented by Eversource the variable of interest is a four-year legacy of trimming (i.e., trimming will have a four-year effect). For robustness, a 4km cell size specification was included.

As a way of visualizing the percent change in tree-related power outages over time, five maps were created, ranging from 2010 to 2015, see Figure 4. Cells that are shades of red are indicating increases in tree related power outages at various magnitudes and cells that are shades of blue are the opposite (i.e., decrease in tree-related power outages). It is important to note that for each year all cells with TTOs were included regardless of the amount treated per cell (i.e., if a cell has one meter of TTOs or 1,000 meters of TTOs it is all included). The visualization of this data can provide important insights into which areas have been treated with TTOs, and if they are producing acceptable results. Additionally, by informing Eversource if these maps they can better direct their efforts to provide more effective and efficient use of TTOs.

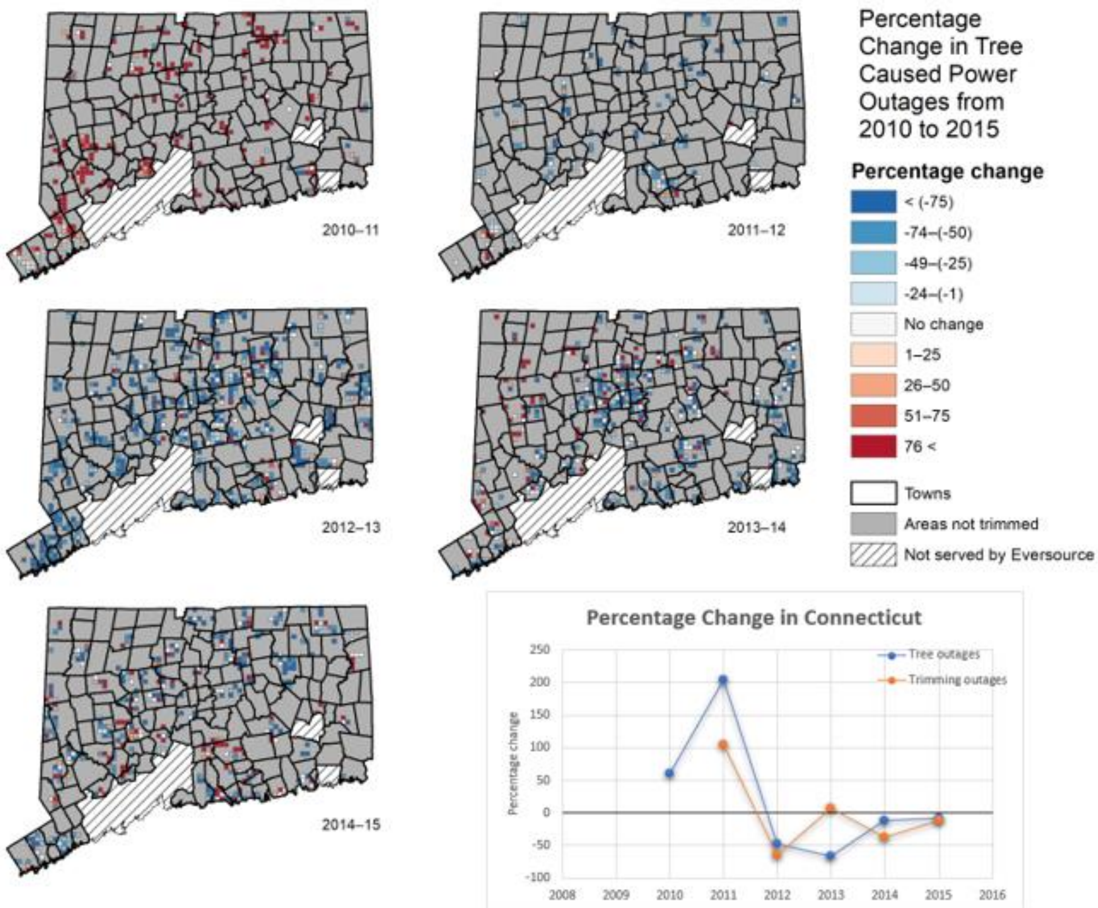


Figure 4: Maps displayed here show the percent change in power outages from the Eversource distribution in Connecticut. The outages are ones which were reported to be caused by trees. Each cell has an area of 2Km and represents the areas that Eversource treated with TTOs. Each map contains the TTOs cells from the previous year, showing the effect that TTOs have tree caused outages in the following year. The graph to the left shows the percent change in tree caused power outages year over year along with percent change in tree caused power outages where TTOs were.

5.1 2km Temporal Model Results

Results for the total number of tree-related power outages at the 2km fishnet cell size can be found in table 2, these are the preferred specifications for each set of dependent variables. Initial results indicate that there is an inverse relationship between TTOs and tree-related power outages across all three metrics used in assessing power outages. Beginning with the preferred specification, results show that our trimming variable (four-year legacy trimming) has a β

coefficient of -0.100 tree-related power outages, see model 1. Following traditional regression workflows of count data, a Poisson was also modeled and can be found in appendix c.

For the total number of customers affected, results show that having a four-year legacy produced a β of -0.121 customers affected by outages caused by trees at the 99% confidence interval, see model 2. The third and final dependent variable of interests for the 2km fishnet is the log duration (in minutes) of tree-related power outages. It is important to note that due to the highly skewed nature of the duration of outages the log was taken as a transformation to produce a normal distribution. As with both the total number of tree-related power outages and the number of tree-related customers affected, the log of duration used the same predictor variables. Results show that TTOs and log of duration also exhibit an inverse relationship as was shown with tree-related power outages and customers affected by those outages. The β for log of duration is -0.247 and is significant at the 99% confidence interval, see model 3.

Table 2: Results for 2 km temporal specification

	1	2	3
Model Type	Negative Binomial	Negative Binomial	OLS
Dependent Variable*	Tree Outages	Tree Customers Affected	Log Tree Duration
Independent Variable			
Four-year trimming legacy	-0.100***	-0.121***	-0.247***
	(-0.0169)	(-0.0196)	(-0.0531)
Percent forested	0.0100***	0.00138**	0
	(-0.00117)	-0.000483	(.)
Cooling degree days	0.0000023	0.00000794*	0.000114***
	(-0.00000656)	(-0.00000376)	(-0.0000271)
Heating degree days	0.0000154***	-0.0000390***	0.0000769***
	(-0.00000382)	(-0.00000126)	(-0.0000201)
Snow water equivalent squared	-0.0000109*	0.0000114	0.0000165
	(-0.00000535)	(0.00000612)	(-0.0000194)
Precipitation squared	0.00108***	0.00847***	-0.00531***
	(-0.000299)	(0.000247)	(-0.00108)
Minimum temperature squared	0.0391***	0.00869***	0.0763***
	(-0.00194)	(0.00128)	(-0.00751)
Maximum temperature squared	-0.0160***	-0.00579***	-0.0361***
	(-0.00108)	(-0.000456)	(-0.00489)
Constant	0.644	0.378*	1.786
	(-0.445)	(0.160)	(-1.871)
N	20,622	20,587	21,623
R-sq			0.406
AIC	65,732.40	156,150	94,986.50

Standard errors in parentheses
* p<0.05 ** p<0.01 *** p<0.001

Notes: Dependent variables are referring to outages that are reported by Eversource to have been caused by a tree.

These results translate to 468 fewer outages per year, and, for those occurring outages, a reduction of 2,626,953 minutes, or roughly 24% of the total. Finally, TTOs contribute in reducing the number of customers affected by 20,461/year on average.

5.2 2km Spatial-Temporal Model Results

Geography presents interactions within data which can be modeled using extensions of existing models, such as SAR and SDM. Presented here are the results of the same analysis presented above with the inclusion of spatial interactions. As referenced in section 4.2 the SAR is an extension of an OLS and should be treated as such (Cliff and Ord, 1973). Because of this, as one of the key assumptions in an OLS, the dependent variable should follow a normal distribution. To account for this each dependent variable was transformed into a rate based on the density of distribution lines per cell, following this the log of that rate was taken to transform the variable towards a more normally distributed curve. The tree outage rate approximates population density by means of distribution lines (i.e., the more distribution lines, the higher the population density): it is represented as the number of tree-related outages per km of distribution lines. Following, the second model quantifies a rate equivalent to the total number of customer's affected per km of distribution lines, and the third model quantifies a rate equivalent to the log duration of tree-related power outages per km of distribution lines. Results for the SAR model of tree-related power outages per km of distribution lines show a β of -0.0139. When looking at a four-year trimming effect on the rate of tree-related power outages, see appendix table C.2. When there is a change in a single observation for example, tree-related outage, and its association with any given explanatory variable will affect that tree-related outage in that cell (direct impact) additionally, it can potentially affect other cells indirectly (indirect impact)

(LeSage and Pace, 2009). The direct impact has a β of -0.0144 and the indirect impacts of -0.0119. Comparing these results to those of the SDM which adds additional lags on the error term and the dependent variable, it emerges that SDM has a β of -0.0193 (appendix table C.2), which is slightly larger than that of the SAR. Direct impacts of a four-year trimming on the rate of tree-related outages is -0.0184 (appendix table C.3). Interestingly, the indirect impacts are the opposite as the direct impacts, there is a change of the signs from negative to positive, the β is 0.0187 (appendix table C.3), however these results for indirect impacts are shown to not be statistically significant.

Beginning with the SAR model, the β for customers affected by tree-related outages is -0.2134 (appendix table C.2) and was significant at the 99% confidence interval. Both the direct and indirect impacts were significant at the 99% confidence interval as well with a β of -0.2166 and -0.0823 respectively. The SDM shows slightly less impressive results as the SAR, a four-year legacy of trimming has a β of -0.1264, direct and indirect impacts of -0.1455 and -0.3668, all results were significant at the 99% confidence interval (appendix table C.3).

Results for log of tree-related outage duration show that as with the non-spatial models a four-year trimming effect is reducing the duration of said outages. When considering the SAR model, it can be seen that the β coefficient is -0.111 and direct and indirect impacts are -0.1145 and -0.0846 respectively, all results are significant at the 99% confidence interval. Slight changes can be found when considering the SDM, results for the global effect of a four-year trimming are no longer significant, however, direct and indirect impacts are. The β for four-year trimming is -0.1065, direct and indirect impacts it is -0.1279 and -0.4294 respectively (appendix table C.3).

As a general remark, we are able show consistent and statistically significant results for the spatial analysis with highest values for direct effects in the rate of customer affected, with respect to the outages and duration rate. This is clearly framing the importance of TTOs for the power grid end-users and thus pointing at potentially interesting drivers of competition as well as policy measures. A generalized significance of the indirect effects of TTOs for the rates of outages, customer affected, and duration shows, persistence in their spatial dependence calling for policy coordination and a deeper reflection on the optimal planning size.

Table 3: Results for 2 km spatial-temporal specification

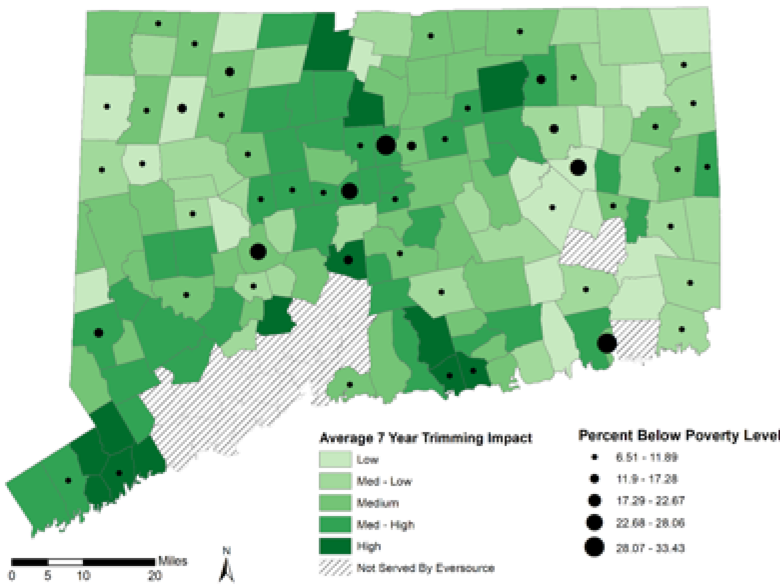
	1	2	3
Model Type	SAR	SAR	SAR
Dependent Variable	Log Tree Outages Rate	Log Customers Affected Rate	Log Duration Rate
Direct Effects	-0.0144*	-0.2166***	-0.1145***
	(-0.0057)	(-0.0246)	(-0.0392)
Indirect Effects	-0.0119*	-0.0823***	-0.0846***
	(-0.0047)	(-0.0101)	(-0.0291)
Total Effects	-0.0263*	-0.2990***	-0.1992***
	(-0.0105)	(-0.0339)	(-0.0683)
N	21,623	21,623	21,623

Standard errors in parentheses
*p<0.05 **p<0.01 ***p<0.001
Notes: Dependent variables are referring to outages that are reported by Eversource to have been caused by a tree. Additionally, distribution line density was calculated along with the log of each dependent variable. Effects are calculated based on a four-year trimming effect

These results translate to 66 fewer outages within a cell (direct) and 102 fewer outages spilling over to neighbor cells (indirect) per year, and, for those occurring outages, a reduction of 342.66 minutes (direct) and 8,094.74 (indirect) per year. Finally, TTOs contribute in reducing the number of customers affected by 3,139 (direct) and 3,216 (indirect) per year. Absolute values for spillovers are larger than for direct effects due to the nature of the queen's connectivity matrix.

6. Access to a reliable grid

Connecticut consistently ranks among the most unequal states in the U.S. by income (Sommeiller and Price, 2018; U.S. Census, 2019). The state is also organized with a highly income-segregated structure which governs the provision and access to multiple services, including school access and infrastructure management (Owens, 2019), thus impairing social mobility (Bischoff and Owens, 2019). Even before the COVID-19 pandemic, the economy was undergoing a rapid electrification (Blonsky et al., 2019; Jenkins et al., 2018), thus making its reliability a key element for economic development (Cohen et al., 2018). Several works have either pointed out (Küfeoğlu and Lehtonen, 2015; Lineweber and McNulty, 2001) or quantified (e.g., Graziano et al., 2020) of the wider economic benefits of vegetation management, additionally remarking the existence industrial establishments that may be particularly susceptible to long and short outages (*lato sensu*). In this section, we want to explore and highlight the issue related to access to a resilient grid based on the TTOs done so far by Eversource.



Top Five Towns by Poverty Level

Rank	Town	Percent Poverty Level	Ratio to State Average (6.5)	TTO Benefits
1	Hartford	33.43	5.14	Med-High
2	New London	28.62	4.40	Medium
3	Waterbury	25.13	3.87	Medium
4	Windham	24.32	3.74	Low
5	New Britain	23.35	3.59	Med-High

Top Five Towns by Population

Rank	Town	Percent Poverty Level	Ratio to State Average (6.5)	TTO Benefits
1	Stamford	9.41	1.45	Med-High
2	Hartford	33.43	5.14	Med-High
3	Waterbury	25.13	3.87	Medium
4	Norwalk	8.36	1.29	High
5	Danbury	12.01	1.85	Med-High

Figure 5: Map of impact level of 7 years of trimming on outage reductions and share of population living in poverty as per ACS 2019 (Census, 2019). The two rankings show the top 5 towns in terms of poverty level and by population.

In Figure 5, the average seven-year impacts of TTOs on reducing tree-related power outages by town are derived using the spatial interactions built by the queen spatial weights matrix. Each cell in our fishnet could take on one of three categorical values; a 1 if there were TTOs in neighboring cells that spilled over, a 2 if there were direct TTO activities within the cell, and a 3 if there were direct and spillover TTOs within a cell.[5] These values were summed up and averaged, so that we may have one value per cell, which was aggregated up to the town level. Finally, each group of values was categorized as ('low', 'mid-low', 'medium', mid-high, and 'high') to represent the cumulative level of benefits received directly or indirectly through TTOs over 7 years.

Along with the trimming impacts, we added the level of poverty for those towns above the state's average (6.5%). We found that majority of TTOs occurred within population centers. Additionally, the top five most populous towns under Eversource service received more TTOs compared to the top five towns with the highest poverty levels. Windham in Particular received the lowest TTOs while ranking fourth in poverty: in comparison to Norwalk which received the highest TTOs and is only 1.86 percentage points away from the state average poverty level.

7. Discussion Policy Implications: building the backbone of an electrified future

This paper quantifies the relationship in both, temporal and spatial-temporal variations in TTOs across Connecticut from 2009 through 2015, focusing on three attributes of power outages: power outages in their entirety, the number of customers affected, and the duration of those outages. Our panel results are consistent even when using a quasi-experimental approach;

[5] These values can be replaced or used with the coefficients of our analysis.

meanwhile, meanwhile, spatial effects are found to be significant, meaning that benefits diffuse throughout the network. Finally, we find that TTOs in the period analyzed benefitted primarily populated areas, although several high-poverty communities received overall limited benefits.

The results of our work have relevance to policies and practices related to managing the Connecticut grid as its decarbonization proceeds along with the electrification of the state's economy, within a changing, and often more extreme climate. The spatial character of the TTOs is good news for utility companies: they will propagate the benefits of vegetation management throughout the grid, beyond the trimmed area, and for at least 4 years. This also means that planning for TTOs should be thought as a spatiotemporal process, with optimization of TTO practices aimed at maximizing these spillovers across the grid. The spatial character of TTOs benefits should also be considered in relation to work and educational practices emerging in the current (March 2021) and post Severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) pandemic. The pace at which the electrification of the economy has increased after 2020: remote work, education, and entertainment have become pivotal issues affecting most households, beyond the initial concerns about electrification and reliability identified by Graziano et al. (2020). In this sense, spatial justice and equity in TTOs, and, more broadly, grid reliability, must be introduced as part of how these operations are carried out by the utility companies, and how many resources should be allocated for improving the overall reliability by policymakers in semi- and regulated markets. In other words, the SARS-CoV-2 pandemic has likely increased the value of the increasing the reliability of the grid beyond the levels previously ascertained in literature (see e.g., Cohen et al., 2018; Graziano et al., 2020) because of the new role that residential units have come to play. Although at the time of this work the pandemic is, alas, still ongoing, evidences suggest that, at least in the U.S., this pattern merges from the increased demand of electricity from residential units (see e.g., Gillingham et al., 2020). Along with the rapid changes in the role of electricity, the increased frequency of extreme climate events across New England and the U.S. have made resiliency one of the main issues faced by utilities and policymakers alike. In this sense, our work shows the lasting and widespread benefits of investing in a labor-intensive practice, TTOs, which delivers increased levels of resilience from extreme events and 'clear sky' days alike. Consequently, in regulated markets like Connecticut, efforts should be made to expand these programs, even via increasing base tariffs, and to plan for TTOs including the new role that electricity play in our society.

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