Modeling How Widespread Soft Energy Can Help Avoid Catastrophe: A Texas Hurricane Case Study

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ABSTRACT

Anthropogenic emissions have impacted global climate and weather regimes, leading to the increase in frequency and severity of natural disasters. The current centralized energy infrastructure is highly vulnerable to natural disasters. It is quantitatively uncertain if a soft energy framework is less vulnerable and more resilient. I conducted a case study of Texas hurricanes and examined the relationship between resilience to these natural disasters and increasing soft energy deployment. A dataset on past hurricanes and electricity generation statistics was collected. I used a multivariate linear regression to test the relationship between selected proxies for resilience and key explanatory variables of a soft energy framework. Cost, death toll, and recovery time were chosen as proxies for resilience and key explanatory variables for soft energy framework were increasing electricity generation from renewables and distributed sources. From the regression models, no statistically significant relationship was found between my proxies for resilience and key explanatory variables. However, when plotting the proxies for resilience against changing electricity generation from renewables and distributed energy, downward trends were observed for all expect cost and changing renewables. These trends are promising and could lead to key insights about how to structure future electricity infrastructure in the face of climate change, but more research is needed.

KEYWORDS

resilience, renewable energy, linear regression, natural disasters, energy infrastructure

INTRODUCTION

Decades of burning oil and other fossil fuels has resulted in the emission of greenhouse gasses, higher radiative forcings, and ultimately global climate change (Forster et al. 2021). A positive feedback loop of cloud coverage continues the warming effect and causes our global weather patterns to become more unpredictable (Forster et al. 2021). The frequency of natural disasters, defined as an ecological phenomenon affecting the ability to recover by disrupting an area socially, economically, and ecologically, are increasing, and with them the severity and costs of damages (Kamara et al. 2018). In 2012, there were 357 natural disasters recorded globally, affecting 125 million people, killing 9,655, and costing US $157 billion in damages (Brown et al. 2016). Additionally, from 2014 to 2017 the Asian and Pacific regions alone experienced 453 cases of severe storms, cyclones, and flooding (Ko et al. 2019). It is apparent that the natural systems have been thrown out of balance and that a certain degree of damage from climate change is unavoidable. There is now a challenge to find management practices that reduce the frequency of these natural disasters and furthermore, help become more resilient to them.

Global temperature rise and the severe weather it causes largely results from CO2 emissions from the energy sector (Stern 2007). The United States power infrastructure has traditionally followed a hard energy path characterized by technology and policy choices that aim to increase energy supply through centralized, complex, capital-intensive energy systems (Schelly et al. 2016). Unfortunately, by using these energy and power systems, extreme weather has been generated which in turn, is inducing a greater stress on these infrastructures (Krausmann et al. 2019). The impacts of natural disasters on the energy systems can lead to: partial or total failure, reduced source of power (i.e. less water available for hydropower during a drought), increased service demand during heat waves or cold spells, and even pollution of hazardous chemicals into the environment (Brown et al. 2016). Introduced by Amory Lovins in 1976, a soft energy path, defined by technology and policy choices that aim to reduce energy demands, with an emphasis on distributed, simple, modular, energy generation systems, could increase resilience to natural disasters (Lovins 1976). In the Maldives, it was found that soft technology increases resilience to disasters by involving stakeholders at all levels of the community and by combining modern and traditional knowledge (Sovacool 2011). To endure the increased frequency of natural disasters, there must be an effort to reduce emissions from the energy sector while simultaneously increasing resilience.

Resilience is the ability to adapt to survive future events and in the case of natural disasters to withstand damage and learn how to build a societal structure that will sustain minimum damage in possible future disasters (McLellan et al. 2012). Resilience includes an adaptive capacity by analyzing potential events *and* the recovery process of the whole system (Gasser et al. 2019). Following the events of the 2021 Hurricane Ida, it is evident more resilient energy systems are needed. Damages to the grid caused power outages for days on end; however, homes with rooftop solar panels survived the storm and still had electricity (Parker 2021). These homes had less of a reliance on gridded electricity and weren't as affected when the power lines were cut off, vastly reducing the stress of the Hurricane's effects on these victims (Weir and Kumar 2020). With an economic cost of Hurricane Ida estimated at US$95 billion and a death toll of 82, it is unknown if it could have been lower with widespread soft energy (Stevens 2021). There is much qualitative research on the topic of resilience within the energy sector, but substantial quantitative data aimed at numerically estimating increased resilience seems to be lacking.

In this study I aim to determine if widespread deployment of soft energy technologies can help communities and regions become more resilient to natural disasters that have been worsened by climate change. I focus my study within Texas as it is vulnerable to disasters such as hurricanes and flooding. To quantitatively define resilience to natural disasters I compare the relationship that three different proxies of resilience cost, death toll, and recovery time have to key explanatory variables, percent of electricity generated from renewable sources and percent of electricity generated at the distributed level. In other words, I am comparing how the proxies for resilience change as there is an increasing use of a soft energy framework. I expect that the soft energy scenario will lead to greater resilience in the form of less economic costs, smaller death toll, and decreased recovery time compared to a centralized and fossil fuel reliant energy model, i.e., the business as usual (BAU) scenario. Additionally, in a soft energy scenario, the reduced emissions will start to decrease the frequency and severity of natural disasters in the long term.

Texas: vulnerability and history of natural disasters

With its coast lining the Gulf of Mexico, Texas's geographical location makes it prone to being struck by multiple hurricanes per year. Every year the hurricane season produces around 100 tropical disturbances, with about 15 of them developing into tropical depressions, 10 into tropical storms, and 6 into hurricanes (Roth 2010). Every five years or so one of these hurricanes can reach a category 5 status, which has catastrophic outcomes if it strikes the land. Since the 1850's, 64 hurricanes and 56 tropical storms have struck Texas (Roth 2010). Recently, Texas has been in a hurricane-rich period. Unfortunately, as global temperatures continue to rise from anthropogenic activities, this hurricane-rich period will be exacerbated. Warmer temperatures of the sea and air increase the total amount of energy available for hurricanes, as well as the amount of moisture the air can hold (Deng et al. 2019). As a result, NOAA's Geophysical Fluid Dynamics Laboratory predicts that a higher number of hurricanes globally will reach a disastrous category 4 or 5 level with higher rainfall and storm surge averages (NOAA 2019).

Texas has been reliant on a centralized, fossil fuel powered grid with a majority of the electricity coming from coal and natural gas. These extreme weather events will continue to affect the centralized power grid's ability to provide electricity. The reliance on a large, complicated structure of overhead power lines makes centralized grids vulnerable to high winds and flooding (Bennett et al. 2021). Outages will only become more frequent as hurricanes become more severe. For instance, in Texas from 1992 to 2009, outages due to severe storms affected approximately 500,000 electricity customers per year; between the years of 2008 to 2013, this number jumped to 1.4 million affected customers per year (DOE 2015). A more decentralized grid may be able to lessen the impact and decrease the amount of people affected by extreme weather events.

Soft energy framework

Soft energy is defined by its technical and sociopolitical structure. The five characteristics of soft energy are: (1) Reliance on renewable energy sources such as wind or solar, (2) diversity of generation sources, being derived from multiple sources to combat the intermittency of renewables, (3) easy to understand, flexible, and low technology, (4) the generation of energy is matched to the geographic scale of end-use needs and takes advantage of the free distribution of natural energy flows, and (5) the energy quality is matched to end-use needs (Lovins 1976).

The simplicity and diversity of soft technologies has a lower risk of technical failure. An example of this are microgrids, defined as a form of aggregation where multiple systems are treated as a single pool of electricity that is interconnected but can function independently from the grid (O'Shaughnessy et al. 2019). Connection of multiple small, dispersed power sources allows for those reliant on it to be directly involved in their power generation and to not be affected by a failing grid (Lovins 1978). Therefore, microgrids have the ability to continue to provide power in the event of a natural disaster when the central grid may be down (Zhou et al. 2015). These features enhance resilience and diminish the potential for environmental cost inequities of soft energy.

Centralized energy is built and distributed on a large scale with complicated technologies that do not match the end-use power needs. This type of delivery requires specially trained technicians to operate the technology, making repairs harder, lengthening downtime, and increasing cost for training and equipment (Lovins 1978). As a result, there is decreased reliability and increased vulnerability of centralized technology because both are limited by technician expertise and availability. Community based or soft technologies rarely require high level skills, they are smaller, simpler, and more comprehensible because these technologies are often installed directly by the people using them (Lovins 1978). While this seems true in theory, the town, Toro Negro, Puerto Rico seems to suggest otherwise. A series of installed microgrids, indeed has the opportunity for higher resilience and engaged participation from decision makers, but it has been found that it is difficult for the community to easily understand, monitor, and fix technical problems without external aid (Deng et al. 2019). The nature of microgrids makes communities increasingly independent from an overarching governance and while Toro Negro is a particularly remote community, this factor may lead to communities inadequately equipped to deal with the task of operating a microgrid. Soft energy is not without its drawbacks.

METHODS

Data collection methods

Data was collected from the National Weather Service (Roth 2010), the Energy Information Administration (EIA 2019), and ERCOT Fuel Mix Reports (ERCOT 2022), to gather statistics on past hurricanes and energy generation at the time of the hurricane. All data was input into a Microsoft Excel spreadsheet to be saved as a CSV file and uploaded to RStudio Version 2021.9.2.382 (RStudio Team 2022). Metrics collected are included in table 1:

Table 1. Independent variables of study.

Variable	Definition	Data Type
Year	Year the hurricane or tropical storm occurred	Integer, years 1983-2021
Category	Category of hurricane	Integer 0 = tropical storm, 1-5
Name	Name of hurricane or tropical storm	Character Descriptive
Winds	Maximum speed of winds recorded, sustained for 1 minute	Integer MPH
Rainfall	Largest recorded inches of rainfall	Integer Inches
Peak Outages	Reported peak number of customers with a outage	Integer
Generation from Utility Level Coal	How much electricity was generated from coal at a utility level for a given year	Integer MWh
Generation from Utility Level Natural Gas	How much electricity was generated from natural gas at a utility level for a given year	Integer MWh

Generation from Utility Level Wind	How much electricity was generated from wind at a utility level for a given year	Integer MWh
Generation from Utility Level Solar	How much electricity was generated from solar at a utility level for a given year	Integer MWh
Generation from Distributed Level Fossil Fuels	How much electricity was generated from fossil fuels at a distributed level for a given year	Integer MWh
Generation from Distributed Level Wind	How much electricity was generated from wind at a distributed level for a given year	Integer MWh
Generation from Distributed Level Solar	How much electricity was generated from solar at a distributed level for a given year	Integer MWh
Total Generation	How much electricity was generated in total for a given year	Integer MWh
% Fossil Fuel	What percentage of electricity was generated from fossil fuels, utility, and distributed level (natural gas and coal sources)	Integer %
% Renewable	What percentage of electricity was generated from renewables, utility, and distributed level (wind and solar sources)	Integer %
% Utility	What percentage of electricity was generated from utility level	Integer %
% Distributed	What percentage of electricity was generated from distributed level	Integer %

Table 2. Dependent variables of study.

Variable	Definition	Data Type
Cost	Reported economic cost of damage to property and infrastructure in Texas from hurricane	Integer Millions of $USD
Deaths	Deaths reported in Texas from hurricane	Integer
Recovery Time	How long it took to get power back on after outages caused by hurricane	Integer Days

Key variables include cost, deaths, recovery time, percent of generation from renewable energy, and percent of generation from distributed energy sources. Costs considered from hurricanes included insurance reports, damage to households, businesses, energy infrastructure, and loss of agricultural production. Costs were gathered from numerous news articles and Roth 2010. Deaths considered from each hurricane were only deaths that occurred in Texas. Recovery time is the number of days it took responders to fully restore power due to outages from the hurricanes, collected from the Quanta technology report (Quanta Technology 2009), various news articles, and hurricane situation reports from the Department of Energy (Department of Energy 2022).

From the generation data collected, percentages of generation from fossil fuels and renewables were calculated, as well as percentages from utility scale and distributed generation. Distributed generations were gathered from ERCOT distributed generation reports (ERCOT MIS 2022). Report metrics were given in installed capacity (MW). To convert to MWh, capacity factors for each technology were taken from the 2021 NREL Annual Technology Baseline report (NREL 2021) and multiplied by the yearly installed capacity to find an estimated annual generation in MWh.

Key variables are used to determine if there is a relationship between the dependent variables (cost, deaths, and recovery time) and increasing electricity generation from renewables and distributed energy.

Linear regression methods

Data analysis was performed in RStudio using packages: tidyverse (Hayes et al. 2019), Hmisc (Harrell Jr 2021), corrtable (Wei and Smiko 2021), xtable (Dahl et al. 2019), ggthemes (Arnold 2021), stargazer (Marek 2022), and vtable (Huntington-Klein 2021). In order to discover if a relationship exists between renewable generation, distributed generation, and the dependent variables a multivariate linear regression model was used to compare each variable. Linear regressions are used to conclude whether there is a linear model for the effect of one variable on another, and how well that model describes that data. Assumptions for linear regression were checked according to Williams et al. 2013. Equations for each model are:

$$[\ \text{Cost} = \alpha + \boldsymbol{\beta}_1 * \%\text{Renewable} + \boldsymbol{\beta}_2 * \text{Wind} + \boldsymbol{\beta}_3 * \text{Rainfall} + \varepsilon\ ] \tag{1}$$

$$[\ \text{Deaths} = \alpha + \boldsymbol{\beta}_1 * \%\text{Renewable} + \boldsymbol{\beta}_2 * \text{Wind} + \boldsymbol{\beta}_3 * \text{Rainfall} + \varepsilon] \quad (2)$$

$$[\ \text{Recovery Time} = \alpha + \boldsymbol{\beta}_1 * \%\text{Renewable} + \boldsymbol{\beta}_2 * \text{Wind} + \boldsymbol{\beta}_3 * \text{Rainfall} + \varepsilon] \quad (3)$$

These equations are designed to predict the cost (millions of $USD), the death toll, and the recovery time (days) of a hurricane as the electricity generation from renewables changes. The category of a hurricane event is determined by the wind speed. As such, the wind speed is used as a control variable to see the impact of %Renewable on cost, death toll, and recovery time, holding the strength of the hurricane constant. Likewise, rainfall is also included as a control variable to isolate the impact of the key explanatory variable, holding the level of rainfall constant. I am interested in whether the key explanatory variable of interest associates negatively with a set of proxy variables for resilience - cost, death toll, and recovery time.

$$[\ \text{Cost} = \alpha + \boldsymbol{\beta}_1 * \%\text{Distributed} + \boldsymbol{\beta}_2 * \text{Wind} + \boldsymbol{\beta}_3 * \text{Rainfall} + \varepsilon] \quad (4)$$

$$[\ \text{Deaths} = \alpha + \boldsymbol{\beta}_1 * \%\text{Distributed} + \boldsymbol{\beta}_2 * \text{Wind} + \boldsymbol{\beta}_3 * \text{Rainfall} + \varepsilon] \quad (5)$$

$$[\ \text{Recovery Time} = \alpha + \boldsymbol{\beta}_1 * \%\text{Distributed} + \boldsymbol{\beta}_2 * \text{Wind} + \boldsymbol{\beta}_3 * \text{Rainfall} + \varepsilon] \quad (6)$$

These equations are designed to predict the cost (millions of $USD), the death toll, and the recovery time (days) of a hurricane as the electricity generation from distributed sources changes. I am interested in whether the key explanatory variable of interest associates negatively with costs, death toll, and recovery time.

$\boldsymbol{\beta}$ is the regression coefficient for each variable. ε is the error term or the difference between values and observed observations.

A null hypothesis: there is no difference in cost, death toll, or recovery time with changing electrical generation, was used and the linear regression was fit using function lm(). Summary statistics and p-values were produced with summary() function and were visually displayed into tables using stargazer() and sumtable(). Relationships were then graphed using ggplot().

RESULTS

Data collection results

17 hurricane occurrences in Texas were collected from 1983 to 2021, ranging from tropical storm, recorded as a 0 in my dataset, to category 4. A majority of Texas's energy comes from natural gas and coal however the percentage from renewable energy has been on the rise with 20% of its fuel mix coming from wind in recent years. Utility scale energy dominates the market, reported energy generated from distributed sources is still less than 1% of total generation. A summary of key variables is listed below:

Table 3. Summary of study variables.

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Year	17	2009.588	10.013	1983	2005	2019	2021
Category	17	1.647	1.412	0	1	3	4
Wind	17	90.588	30.867	45	65	115	150
Rainfall	17	17.794	15.457	4	11	15	61
Peak Outages	17	435382.412	807986.317	5000	45000	306058	3200000
% Fossil Fuel	17	0.775	0.112	0.607	0.675	0.867	1
% Renewable	17	0.108	0.108	0	0.012	0.214	0.289
% Utility	17	0.998	0.003	0.992	0.995	1	1
% Distributed	17	0.002	0.003	0	0	0.005	0.008
Cost	17	11198.824	29988.675	30	180	5000	125000
Deaths	17	18.824	31.221	0	1	13	103
Recovery Time	17	7.941	5.573	2	4	9	21

Linear regression results

A correlation analysis was performed to determine which variables could be viable independent variables:

Table 4. Correlation between variables.

	Year	Category	Wind	Rainfall	Peak Outages	% Fossil Fuel	% Renewable	% Utility	% Distributed	Cost	Deaths
Year											
Category	-0.27										
Wind	-0.18	0.92****									
Rainfall	0.23	0.11	-0.06								
Peak Outages	-0.16	0.45	0.40	-0.24							
% Fossil Fuel	-0.96****	0.23	0.14	-0.22	0.17						
% Renewable	0.85****	-0.15	-0.06	0.24	-0.19	-0.95****					
% Utility	-0.68**	0.18	0.09	-0.01	0.16	0.83****	-0.90****				
% Distributed	0.68**	-0.18	-0.09	0.01	-0.16	-0.83****	0.90****	-1.00****			
Cost	0.21	0.54*	0.44	0.70**	0.11	-0.17	0.19	0.13	-0.13		
Deaths	0.00	0.61**	0.48*	0.42	0.65**	0.06	-0.09	0.31	-0.31	0.79***	
Recovery Time	-0.14	0.55*	0.50*	0.23	0.69**	0.19	-0.22	0.26	-0.26	0.41	0.80***

Generation percentages from fossil fuel, renewable, utility, and distributed energy are all highly correlated therefore, only one can be used at time as an independent variable. Wind, rainfall, and peak outages are not highly correlated with each other, generation percentages, or the dependent variables so they were used as independent variables in the models as they may factor into the relationships observed.

Regression results yielded no significant statistical evidence for a relationship between the dependent variables and renewable, or distributed energy.

Cost ~ Renewable Regression

	Dependent variable:
	Cost
`% Renewable`	13,459.160
	(42,105.110)
Wind	469.189***
	(143.766)
Rainfall	1,382.634***
	(294.943)
Constant	-57,355.460***
	(15,393.000)
Observations	17
R^2	0.717
Adjusted R^2	0.652
Residual Std. Error	17,698.770 (df = 13)
F Statistic	10.978*** (df = 3; 13)
Note:	*p<0.1;* ***p<0.05;*** p<0.01

Deaths ~ Renewable Regression

	Dependent variable:
	Deaths
`% Renewable`	-51.666
	(60.042)
Wind	0.506**
	(0.205)
Rainfall	1.003**
	(0.421)
Constant	-39.308*
	(21.951)
Observations	17
R^2	0.469
Adjusted R^2	0.347
Residual Std. Error	25.239 (df = 13)
F Statistic	3.828** (df = 3; 13)
Note:	*p<0.1;* ***p<0.05;*** p<0.01

Recovery Time ~ Renewable Regression

	Dependent variable:
	`Recovery Time`
`% Renewable`	-13.416
	(11.551)
Wind	0.091**
	(0.039)
Rainfall	0.116
	(0.081)
Constant	-0.924
	(4.223)
Observations	17
R^2	0.383
Adjusted R^2	0.241
Residual Std. Error	4.855 (df = 13)
F Statistic	2.693* (df = 3; 13)
Note:	*p<0.1;* ***p<0.05;*** p<0.01

Figure 1-3. Regression tables: dependent variables with % Renewable.

Cost ~ Distributed Regression

	Dependent variable:
	Cost
`% Distributed`	-1,025,005.000
	(1,452,479.000)
Wind	458.315***
	(141.993)
Rainfall	1,406.498***
	(282.524)
Constant	-53,459.910***
	(15,126.030)
Observations	17
R^2	0.725
Adjusted R^2	0.662
Residual Std. Error	17,437.340 (df = 13)
F Statistic	11.441*** (df = 3; 13)
Note:	*p<0.1; **p<0.05;*** p<0.01

Deaths ~ Distributed Regression

	Dependent variable:
	Deaths
`% Distributed`	-2,850.780
	(2,011.529)
Wind	0.491**
	(0.197)
Rainfall	0.923**
	(0.391)
Constant	-36.828
	(20.948)
Observations	17
R^2	0.514
Adjusted R^2	0.402
Residual Std. Error	24.149 (df = 13)
F Statistic	4.581** (df = 3; 13)
Note:	*p<0.1; **p<0.05;*** p<0.01

Recovery Time ~ Distributed Regression

	Dependent variable:
	`Recovery Time`
`% Distributed`	-404.812
	(409.810)
Wind	0.090**
	(0.040)
Rainfall	0.095
	(0.080)
Constant	-1.142
	(4.268)
Observations	17
R^2	0.367
Adjusted R^2	0.221
Residual Std. Error	4.920 (df = 13)
F Statistic	2.510 (df = 3; 13)
Note:	*p<0.1; **p<0.05;*** p<0.01

Figure 3-6. Regression tables: dependent variables with % Distributed.

However, when plotted against each other, noteworthy trends were observed. When the dependent variables were plotted against increasing renewable energy percentage, cost appeared to increase, death toll decreased, and recovery time decreased. When plotted with increasing distributed energy generation, all dependent variables appeared to decrease.

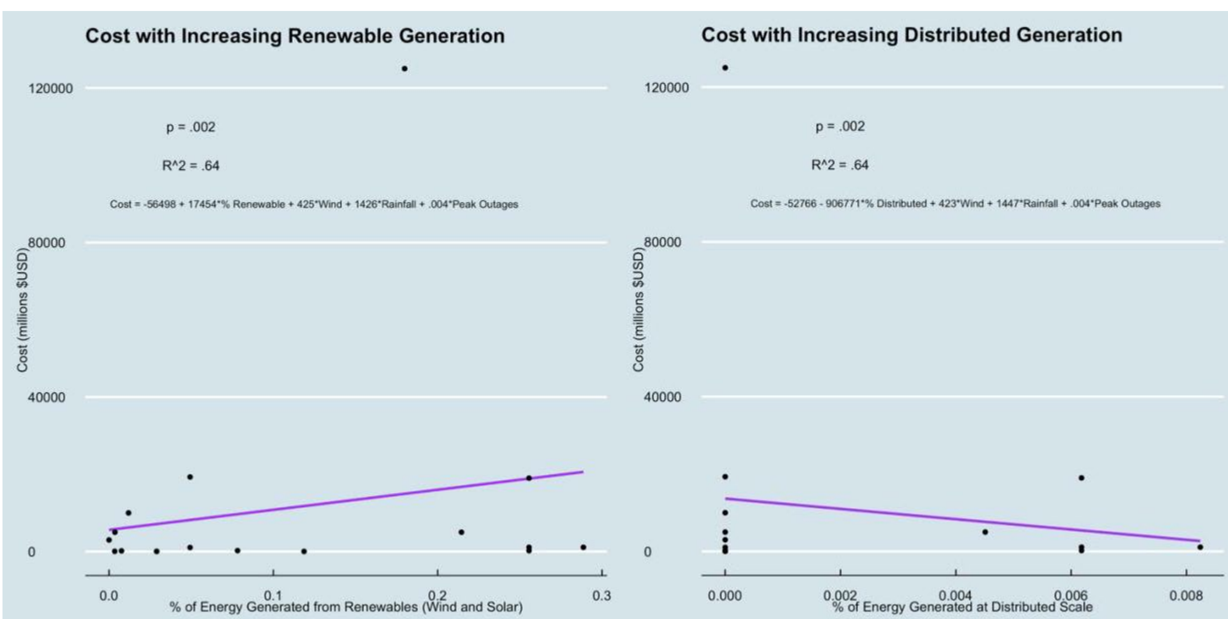

Figure 7-8. Cost with key variables. Cost of hurricane in millions $USD on the y-axis and percentage of total electricity generation from renewables (left figure) and distributed sources (right figure).

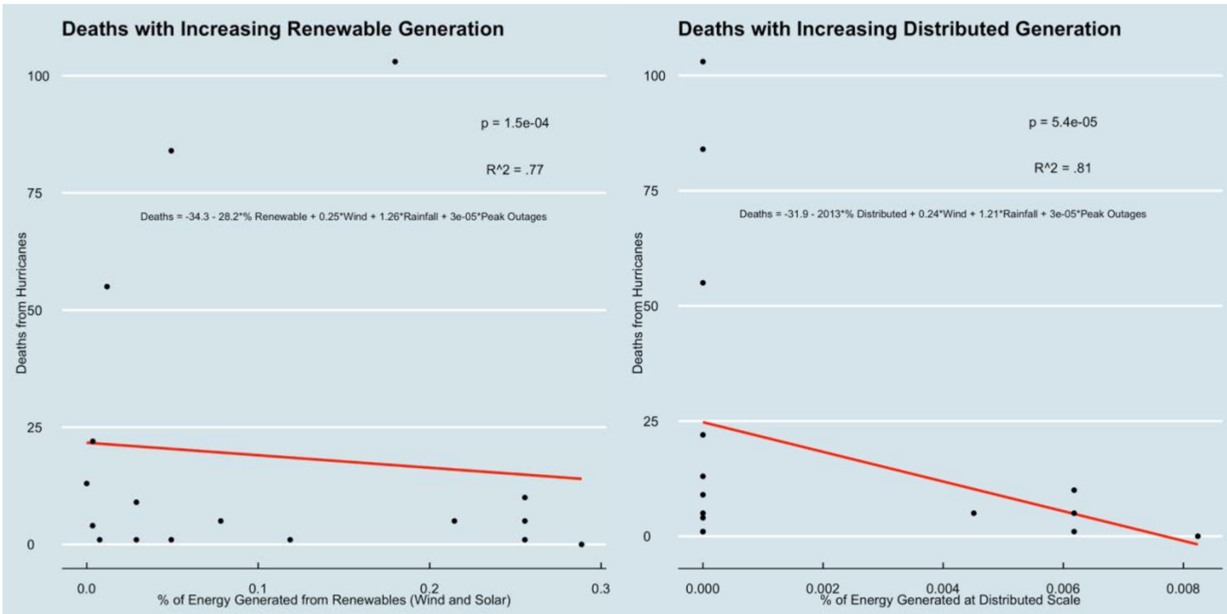

Figure 9-10. Death toll with key variables. Death toll from hurricanes on the y-axis and percentage of total electricity generation from renewables (left figure) and distributed sources (right figure).

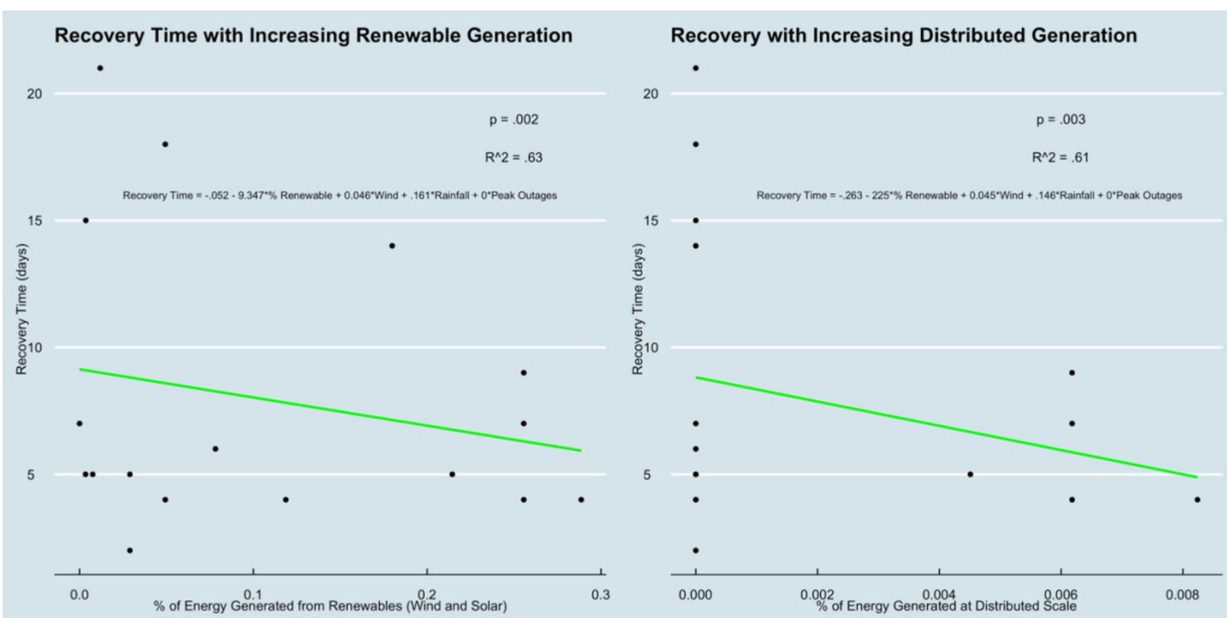

Figure 11-12. Recovery time with key variables. Recovery time of hurricane in days on the y-axis and percentage of total electricity generation from renewables (left figure) and distributed sources (right figure).

DISCUSSION

My linear regression models have found no statistical significance for the relationship between my proxies for resilience and the key variables, percent of energy generated from renewables and percent of energy generated from distributed. Therefore, within this study, I cannot say for certain that an increasing soft energy framework enhances resilience to hurricanes and further research is needed. The statistical insignificance could be due to a small sample size, as there were only 17 data points. By expanding the study to include nearby states and countries, the sample size could be increased and perhaps a more meaningful relationship could be established. However, the trends seen in the plots are promising and may lead to further insights about the relationship resilience and soft energy.

Cost and soft energy

When plotting the cost of hurricanes against increasing electricity generation from renewables an upward trend is observed. This could be due to higher replacement, installation, and storage costs for renewable energy technology. For example, if a homeowner with rooftop solar wants to be independent of the grid and not be affected by a centralized power outage, they need solar batteries to store energy. The average cost of a battery is around $9,000 USD, not to mention the installation costs, which could increase the price to as much as $20,000 USD (EnergySage 2022). Furthermore, with an average cost to replace or fix a solar panel being $850 (Watson 2018), most of the costs associated with renewable, distributed energy are borne onto the individuals or communities utilizing them (Deng et al. 2019). These factors can make microgrids more expensive than traditional centralized grids. However, as the technology is improved and made into modular systems, the price of PV systems has been falling over the past decade (Weir and Kumar 2020). Additionally, for remote island communities, having a community microgrid lowers the cost of electricity due to a decreased reliance on erratic gas imports and the ease of setting up the technology (Weir and Kumar 2020). This can also explain the downward trend in cost seen when plotting against increasing electricity generation from distributed sources. Centralized grids rely on the complicated architecture of transmission lines that are very vulnerable to high winds and flooding, which are the main risks in the event of a hurricane. The average cost to replace transmission structures is $90,000 USD (Watson 2018). Moving towards more distributed energy there becomes less of a need for a large network of overhead transmission lines and can reduce that cost. A recent study that modeled the fragility of Puerto Rico's energy systems in hurricane events concluded that a centralized fossil fuel grid will always result in the highest cost due to its vulnerability (Bennett et al. 2021). This contradicts my findings for the trend in renewable energy but makes sense when considering the cost of replacing fossil fuel power plants. The average cost to replace a gas or coal power plant is $5 million USD, with the substation replacement and repair costs at $1 million USD (Watson 2018). The study by Bennett et al. also modeled the costs under an increased storm frequency scenario based off of existing fragility curves and found that the cost of rebuilding distributed renewables will be cheaper, inferring that within this proxy of resilience, soft energy is more resilient (Bennett et al. 2021).

Death toll, recovery time, and soft energy

The plots for death toll and recovery time against increasing electricity generation from both renewables and distributed energy show a downward trend. These two proxies for resilience are inherently linked when considering the role access to electricity plays in evaluating these metrics. Following a natural disaster that damages the electricity network and results in the reduced ability to produce energy, many deaths can occur. Long power outages cause the service of basic needs to be interrupted, favoring the increase in morbidity rates (Gargani 2022). Hospitals and businesses can lose access to life support technology, communication transportation, and water facilities (Lempriere 2017). The downward trend in deaths and recovery time could be explained by the addition of more microgrids to the energy supply, which are inherently a soft energy infrastructure (Zhou et al. 2015). A microgrid connects multiple electricity generating components, including control, energy storage, and load devices, powered from a multitude of sources such as solar PVs, wind turbines, thermal, hydroelectric, and even fossil fuels (Deng et al. 2019). This can increase the local grid reliability and sustain a constant electricity supply. For example, following Hurricane Allison, Katrina, and Sandy, Texas set out to modernize their grid. When Hurricane Harvey hit Houston, a series of microgrids prevented outages to multiple gas stations and hospitals, such as the Texas Medical Center (Lempriere 2017). This was an extraordinary feat when comparing the effects of Hurricane Harvey to Hurricane Allison. Allison dropped more than 40 inches of rain over the span of 15 days, causing detrimental damage to the grid and shutting down 22 hospitals, while Harvey dropped 61 inches of rain in just 5 days, yet the Texas Medical Center remained fully operational through the disaster (Lempriere 2017). Having access to a continued power supply ensures that basic services can be accessed, and death rates will decrease. Additionally, never losing power means that recovery time also decreases, as there was no outage to recover from.

Limitations and future directions

Since my linear regressions models produced non-significant relationships, I cannot answer whether increasing generation from renewables and distributed enhances resilience in this study. To effectively determine if widespread soft energy deployment increases resilience to natural disasters, this study would need to be expanded to increase the sample size. I would need to include a larger geographic area and the consideration of other natural disaster types. Furthermore, this study did not consider a carbon tax or other climate change policies which might set a baseline requirement for the amount of energy produced from renewables play as a confounding variable affecting both the explanatory and dependent variables. Nevertheless, the trends observed in the plots are interesting and seem to indicate a relationship between resilience and soft energy exists, but more research is needed.

Broader implications and conclusions

The idea of resilience emphasizes a community's ability to cope in the immediate aftermath of a disaster event (Weir and Kumar 2020). The short-term resilience needs to focus on providing food, water, shelter, and medical aid. For energy, resilience calls to have strong energy infrastructure already in place, rather than waiting and depending on the sporadic aid from central governments (Weir and Kumar 2020). The National Renewable Energy Laboratory has some suggestions for how to establish and design renewable energy infrastructure. Among many things, the NREL recommends establishing design standards and specifications for materials used in building (Hotchkiss, 2018). Furthermore, they advise that a verification of proper installation is conducted, along with regular maintenance (Hotchkiss, 2018). NREL also emphasizes the importance of site-specific infrastructure and that this be modified over time, especially adjusting equipment before a storm (Hotchkiss, 2018). These steps will increase the durability of equipment and lead to less damage. Microgrids and community level electricity production also requires local governance. Microgrids can be seen as a common resource pool meaning there needs to be active participation from decision makers and well outlined boundaries and consumers (Deng et al. 2019). This can create tighter knit communities and an environment that supports a shared sense of responsibility. However, due to the nature of microgrids there is less external involvement, which can be a threat. For instance, Texas has an electricity grid independent from the rest of the nation and federal oversight. When multiple severe winter storms hit the state, it resulted in 2021 with the Texas Power Crisis. Due to the unwinterized infrastructure and the disconnected grid, electricity imports were made very difficult (Krauss et al. 2021) and millions were left without power for days (Stelloh et al. 2021). While this disaster could have very well been avoided with increased distributed energy, the lack of external involvement factor is still something to consider. Policy options to support small renewable projects include net metering (SEIA 2022), renewable energy certificates (US EPA 2022), and direct subsidies (Taylor 2020). Data indicating how to build energy infrastructure and disseminate information about increasing resilience from natural disasters will only become more important in the face of climate change. The trends observed in this study lay a strong foundation for further research on structural solutions to promote greater resilience and provide support for soft energy as a critical component to ensuring these solutions are sustainable and effective.

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