Greening Local Energy

Explaining the Geographic Distribution of Household Solar Energy Use in the United States

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Problem: Solar energy has potential to solve many types of planning problems. Knowing where existing household solar energy users are located and what factors explain this distribution can help craft appropriate local policies.

Purpose: This study analyzes the spatial distribution of households who heat their homes with solar energy across the contiguous United States.

Methods: We use geographic information systems (GIS) and zero-inflated negative binomial statistical techniques to test three sets of geographic predictors at the scale of the county: environmental, economic, and sociopolitical.

Results and conclusions: Descriptive, GIS, and regression results indicate that the expected number of households using solar energy to heat their homes increases significantly with the amount of solar radiation received, but that other environmental, socioeconomic, and political factors are also significant predictors. The number of solar households in a county is a positive function of wealth (operationalized as median home value), urbanization, and the percentage of residents in the peak period of the lifecycle-consumption curve. Having a solar energy technology provider in the county did not appear to be significant. Finally, we confirmed that households heating with solar energy increase with the percentage of persons who vote for the Democratic Party in presidential elections and with local government involvement in the International Council for Local Environmental Initiatives.

Takeaway for practice: Our model can be used to enhance adoption of solar technologies by showing which localities possess most of the attributes that predict solar use, but adoption lags expectations. This can help design efficient and effective local plans and incentives calibrated to local environmental, economic, and sociopolitical conditions.

Keywords: household solar energy use, solar heating, GIS, green communities

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On July 15, 1979, President Jimmy Carter delivered his infamous "Crisis of confidence" speech (Carter, 1979) to the American public, arguing that "excessive dependence on OPEC" caused economic paralysis and drift, and constituted a "clear and present danger" to the "very security" of the United States. This "dependence on foreign oil," Carter declared, necessitated a "war on energy." To prosecute this war and to achieve "energy security," Carter proposed the "most massive peacetime commitment of funds and resources . . . to develop America's own alternative sources of fuel." Carter's commitment of funds and resources involved a mix of planning instruments, including import quotas on foreign oil, the issuance of energy bonds, energy conservation and efficiency credits, a tax on "windfall profits," and the establishment of an "energy mobilization board" to enable the switch to alternative fuel sources.

The sun was a cornerstone of Carter's energy security plan. By the year 2000, Carter envisioned that solar power would supply one fifth of domestic energy needs, with a substantial percentage of American households heating their homes with solar power. This solar energy vision was supported by a two-volume report issued by the Office of Technology Assessment (OTA; 1978) on the *Application of Solar Technology to Today's Energy Needs.* The report claimed that with proper financial incentives, compensating subsidies, and government investment in research and development, "onsite solar devices could be made competitive in markets representing over 40% of U.S. energy demand by the mid-1980s" (p. 3). Moreover, the OTA report noted that with the diffusion of onsite solar energy devices, considerable environmental, economic, and social benefits would flow to the country, including reductions in consumption of electricity and conventional pollutants like suspended particulates. Not to be outdone, the Department of Energy forecasted a 12-fold increase from 1980 to 2000 in the amount of energy U.S. households would derive from active solar installations (Dukert, 1985, p. 271).

But according to data from the 2000 Census, only about 47,000 out of 105.5 million American households (fewer than half of 1%) had adopted solar home heating by the year 2000, far below Carter's plan. There may be many reasons for actual use falling short of Carter's expectations, including poor solar technology performance[1] (Sawyer & Wirtshafter, 1985), the high cost and long payback period associated with installing solar heating systems (Hausman, 1979; Sidiras & Koukios, 2004), resistance to change in the energy industry, and Reagan Administration decisions to cut the solar budget by 70% and to allow solar tax credits to lapse.[2]

Interest in renewable sources of energy, like solar power, and Carter administration rhetoric and planning tools promoting energy independence have revived in recent years. For example, in 1997 the U.S. Department of Energy (DOE) established the Million Solar Roofs Initiative (MSRI) with the goal of achieving cost-competitiveness for solar technologies across all market sectors by 2015. Between 1997 and 2005, 94 coalitions across the country signed on with the DOE as official MSRI partners. These voluntary partnerships consist of 971 private sector firms, electric utilities, builder-developers, nonprofit organizations, and governmental entities. The MSRI (now called the America Solar Initiative) aims to provide 5 gigawatts of electric capacity (equivalent to the amount of electricity needed to power 1.25 million homes), and avoid 7 million metric tons per year of CO_2 emissions[3] (DOE, 2006).

Solar energy is one of the most promising climate-friendly energy sources, and an important component of sustainable or green communities (Gordon, 1990; Grant, Manuel, & Joudrey, 1996). Solar energy can be passive or active. Passive solar uses architectural design to convert sunlight directly into heat by orienting buildings and locating windows to take advantage of the sun. In contrast, active solar heating systems use mechanical equipment such as pumps, fans, and most commonly photovoltaic cells to convert sunlight into other forms of energy. While passive solar systems have zero operating costs, active systems can generate significantly greater savings because they are more able to transfer and transport heat (Kreider & Kreith, 1982).

Solar energy could help planners address many social dilemmas, possibly including national security, economic growth, climate stewardship, sustainable land use, and economic development (Beatley, 2000; Beatley & Manning, 1997; Haughton & Hunter, 2003; James & Lahti, 2004; Pimentel, et al., 2002; Thomas, 2003). Solar technologies offer the potential to reduce our reliance on fossil fuels and resulting CO_2 emissions. Solar heating and photovoltaic power generation can make communities more self-reliant and resilient because they are less dependent on central power grids, can reduce air and water pollution, and can address global climate change.

In this article, we use environmental, economic, and sociopolitical predictors to investigate the spatial distribution of U.S. households using solar technologies to heat their homes. We use geographic information systems (GIS) analytical techniques and zero-inflated negative binomial (ZINB) regression to study mechanisms that encourage or discourage the spread of solar technology at the county scale. By analyzing what predicts conditional expectations of solar energy use, we hope to make it possible to design incentives and plans suited to specific communities.

Our investigation is organized into four sections. First, we review relevant literature on the adoption and diffusion of solar technology to derive testable claims on the spatial distribution of solar energy use. Second, we detail our secondary data collection, variable operations, and analytic procedures. Third, we present descriptive, geographic, and regression results. In the final section we discuss the local planning implications of the results and suggest how future research could inform policy encouraging the adoption and spread of solar technologies.

Environmental, Economic, and Social Predictors of Solar Energy Use

Household willingness to install solar thermal technologies is a question of environmental, economic, and social geography (Gadsden et al., 2003). The amount of solar radiation a locality receives is crucial (Feder, 2004) for determining whether solar product installation will make economic sense (Durham et al., 1988). All else equal, the cost of a solar heating system is inversely related to the availability of solar radiation. Areas with less solar radiation need more collector space for equivalent energy output (Durham et al., 1988), which increases the cost of installation. The benefits from a given amount of collector surface area are also lower in areas with less abundant sunshine. Both factors reduce the net present value of switching from conventional to solar energy in less sunny locations (McDaniel, 1983).

Active solar heating units are about 33% cheaper to install in the southern United States than in the north (Pimentel et al., 1994). However, in a rare U.S. empirical study probing the geographic link between solar radiation and household solar energy use, Durham et al. (1988) found a negligible connection between solar radiation and adoption of solar energy systems. This may be because their econometric model used state level data, camouflaging important variance within individual states. For example, in California, average daily solar radiation ranges from 7.19 kWh/m^2 (kilowatt hours per square meter) in San Bernardino County to 4.03 kWh/m^2 in Humboldt County. This demonstrates why it is important to model the relationship between solar radiation and solar energy use at a scale small enough to get valid and reliable results. McDaniel (1983) studied tax credits' effects on the competitiveness of solar energy, and found cities in Colorado (Boulder and Denver) and Kansas (Kansas City and Manhattan) to be ideal because of high solar radiation values. McDaniel's study was limited by the small number of cities examined, but the spatial scale was sufficiently precise.

Outside the United States, studies confirm the relationship between solar radiation and use of active solar heating (Kablan, 2006; Ridao, García, Escobar, & Toro, 2007). China is the world's largest market for solar water heating systems (Wallace & Wang, 2006), and active solar thermal technologies are spreading fastest in the southern province of Yunnan, where solar radiation values are highest (Lin, Lu, Gao, Pu, & Liu, 1996).

Other environmental indicators that vary with geography, like temperature and precipitation, may also predict the spatial distribution of household solar energy use. Gadsden et al. (2003) modeled the suitability of sites for domestic solar hot water and photovoltaic panel systems in the United Kingdom as a function of annual mean daytime air temperature, among other variables. Areas that are neither extremely warm nor extremely cold appear to have the greatest potential for solar. In warmer parts of the United States, the demand for home heating is low, lengthening the payback period for solar energy systems, while experience in colder climates (like Syracuse, New York, or Burlington, Vermont), shows that active solar thermal systems perform unreliably, needing more antifreeze protection (Fry & Gene, 1986). Studies show that active solar thermal users in cold climates are more likely than those in warmer climates to encounter problems like leakage, snow and rain damage to collector surfaces, and damage to pipes from freezing during cold spells (Sidiras & Koukios, 2004). Assuming that potential adopters know these things, we expect fewer households to use solar energy in cold climates with high rates of precipitation.

Because solar energy systems are costly to install, it is not surprising that several studies noted the role of economic variables in predicting household solar energy adoption (Labay & Kinnear, 1981). In addition to installation, maintenance costs are also high, and energy efficiency gains and resulting savings modest, making for long payback periods (Sidiras & Koukios, 2004). As with other forms of green consumption (Olli, Grendstad, & Wollebark, 2001), scholars find positive associations between measures of household income and wealth and solar energy adoption (Labay & Kinnear, 1981; Sidiras & Koukios, 2004), presumably because wealthier households can more easily absorb these costs and can wait longer for return on their investment.

Economists and demographers also note that the consumption of expensive durable goods is a function of consumer age, peaking somewhere between 40 and 49, and declining sharply with the onset of retirement. This relationship between age and consumption persists even when controls are added for family size, age cohort, time period, education, and occupation (Gourinchas & Parker, 2002). We expect to find higher numbers of solar energy users in localities that are wealthier and whose residents are more concentrated in the age range with the greatest consumption.

In addition to demand-side measures like wealth and age structure, estimates of market supply may assist prediction of the spatial distribution of household solar energy use. To our knowledge, no study has examined the spatial relationship of solar energy users and solar energy retailers. We expect local access to a solar energy retailer to increase the probability that a household will act on a preference to purchase an active solar energy system. It is likely also true that providers of solar energy products and services gravitate to areas where expected demand for services is higher. Thus, we expect the number of households using solar energy in a locality to be positively associated with the presence of one or more solar energy retailers.

Research also indicates that household solar energy users concentrate in urbanized areas, where access to solar technologies and the probabilities of social contact with existing solar users are higher (Wallace & Wang, 2006). Contact with other solar energy users reduces information costs, proving the concept to potential users. Information spreads more readily in urban areas. Several studies have shown that solar technologies spread through dense social networks by way of role modeling and information transmission processes (Lutzenhiser, 1993; Warkov & Monnier, 1985). Moreover, urban areas have greater percentages of politically left-of-center residents with higher than average annual incomes. To the extent that solar energy use is a function of contact likelihoods and metropolitan culture, we expect to find higher numbers of solar energy users in more urbanized localities.

Past studies also suggest that the spatial distribution of household solar energy use may depend on more than the availability of solar resources and financial capability. People derive important status and environmental benefits from installing and using active solar thermal technologies (Sidiras & Koukios, 2004; Tsoutsos, Frantzeskaki, & Gekas, 2005; Tsoutsos & Stamboulis, 2005), which may motivate them to adopt these technologies. When solar energy is substituted for conventional fuels, the public benefits from reduced emissions of sulfur dioxide (SO_2), nitrogen oxides (NO_x), carbon dioxide (CO_2), and particulate matter. These reductions can lead to better air quality, lower morbidity and mortality rates, and improvements to agriculture, forests, and ecosystems (Diakoulaki, Zervos, Sarafidis, & Mirasgedis, 2001; Rabl & Spadaro, 2000). Studies suggest that solar energy users are motivated by environmental concerns and perhaps by status that others confer on people who reduce their consumption of nonrenewable energy. Insofar as adopters of solar heating systems are motivated by environmental interests (see Sawyer & Wirtshafter, 1985), we should find higher numbers of solar users where environmentalist values and activities are stronger.

Overall, the research on solar energy use suggests that a blend of environmental, economic, and social causes may explain the spatial distribution of solar energy use in the United States.

Research Design

In this section, we detail our research design, including how we chose and measured our model variables, and the analytic procedures we used.

Dependent Variable

Data for our dependent variable, *households heating their residences with solar energy*, measured for counties, come from item H40 on the long form of the 2000 Census of Population and Housing. Thus, it reflects responses from a sample of all persons living in housing units in the United States in 2000. The question asked "Which fuel is used most for heating this house, apartment, or mobile home?"[4] As explained previously, we are interested in active solar technologies, which require mechanical equipment, most commonly air flat-plate solar collectors affixed to residential rooftops, to transform and transfer solar energy throughout the home. The census question does not distinguish between active and passive solar heating systems, but the word "fuel" does imply a heating system powered by some external source of energy. Thus, we interpret those saying that solar energy is the fuel they use most to be referring to active solar heating systems, although a few might be describing passive solar heating systems.

Environmental Variables

We use two measures of environmental context to predict household solar energy use at the county level: solar radiation and maximum temperature. The data we use to measure direct normal *solar radiation* are from the National Renewable Energy Laboratory (NREL). NREL scientists model average total solar radiation (expressed in $kWh/m^2/day$) for grid cells that are 40 km square, using inputs that include: satellite and/or surface observations of cloud cover, aerosol optical depth, precipitable water vapor, albedo, atmospheric pressure, and ozone. We employed a GIS to join solar radiation grid values with county shape files for the entire continental United States, so that county averages are computed by weighting grid cell radiation values based on the area of each grid cell within each county. As suggested in the literature, we expect to find higher numbers of households heating with solar energy in counties with higher solar radiation.

Our *maximum temperature* measure is from the Hadley Center for Climate Prediction and Research in the United Kingdom. We calculated annual averages using monthly maximum temperature data from global circulation models that the Hadley Center calibrated regionally for the United States, at a spatial resolution 0.5 degrees latitude by 0.5 degrees longitude, or grid cells of about 80 square miles each.

Again, county averages weight cell maximum temperatures based on the area of each grid cell within each county. We expect to find a positive relationship between maximum temperature and the count of solar households in county.

We also include a squared version of the maximum temperature variable in the model to test whether the relationship between temperature and solar adoption might resemble a bell curve. Such a relationship could exist if neither counties with high maximum temperatures nor counties with low maximum temperatures were ideal for operating solar heating systems.

Economic Variables

We measure four economic variables that may increase the expected number of households heating with solar energy in a county: median home value, the presence of solar energy service providers, urbanization, and the percentage of county residents aged 40 to 49. We use the 2000 Census question asking owner occupants to estimate the market values of their housing units rounded to the nearest hundred dollars, to measure *median home value* for counties. We expect households heating with solar energy to increase with a county's median home value because this represents a source of capital to finance solar system installation.

We also assign counties a score of 1 if they have at least one *solar energy provider* as inventoried by the Solar Energy Industries Association (SEIA; http://www.seia.org/), and a score of 0 if they do not have such a provider. We expect households heating with solar energy to increase with the presence of one or more SEIA member companies.

We measure a county's *urbanization* as the number of persons residing in portions of that county which the 2000 census defines as urban,[5] divided by the total population of that county. Literature indicates that household solar energy users concentrate in urban areas (Wallace & Wang, 2006).

Finally, our *consumption age* variable measures the share of county residents who are aged 40 to 49. We expect to find higher numbers of households using solar energy to heat their homes in counties with a higher percentage of residents in peak consumption ages.

Sociopolitical Variables

We also use three sociopolitical variables in our model predicting household solar energy use at the county scale: a measure of whether county residents voted for Democrat Albert Gore in the 2000 presidential election, the number of environmental nonprofit organizations, and whether or not a locality is party to the International Council for Local Environmental Initiatives (ICLEI). The first of these, *Democrat*, we measured as the total percentage of county votes cast in the 2000 presidential election for Albert Gore minus the percentage of county votes cast for George W. Bush. Research shows that in 2000, self-identified Democrats manifested greater concern for the environment. Zahran, Brody, Grover, and Vedlitz (2006) find that Democratic voters are significantly more likely to adopt behaviors that conserve and preserve environmental assets, and are more likely to support government policies that mitigate human sources of environmental degradation.

We also included the total number of *nonprofit environmental organizations* in a county as a variable. The National Center for Charitable Statistics (NCCS) defines nonprofits as organizations of tax-exempt status, with at least $25,000 dollars in gross receipts, that are required to file Form 990 with the Internal Revenue Service (IRS). We obtained our data on environmentally focused nonprofits from the NCCS 2001 core file and category codes.[6] Insofar as environmental organizations provide local residents with opportunities for involvement in environmental causes and educate them in environmentally sound behavior, we expect higher numbers of households heating with solar energy in areas with more environmental nonprofits.

We also measured the willingness of local governments to adopt policies and regulations that encourage environmentally sound behavior among their residents, thinking this would foster the adoption of solar heating technologies. The International Council for Local Environmental Initiatives (ICLEI) promotes global environmental sustainability by coordinating the activities of hundreds of local governments in 43 countries. ICLEI provides technical assistance, information, and capacity-building services to help local governments achieve measurable targets on issues ranging from air quality to energy efficiency that are linked programmatically to international goals like Agenda 21, the Rio Conventions, the Habitat Agenda, and the United Nations Millennium Development Goals. We assume that U.S. localities that are members of ICLEI are more likely to provide residents with incentives to adopt practices like heating their homes with solar energy.

Statistical Procedure

The distribution of household solar energy use in the contiguous United States is non-Gaussian. Counties with no households heating with solar energy significantly skew the distribution, with 1,736 of the 3,108 counties observed to have zero households using solar energy to heat their homes. Mathematical transformation (logarithm, square root, or reciprocal) cannot address the problems this creates for statistical analysis. A standard Poisson count model assumes that the conditional variance of the distribution of solar households is equal to the expected value. The variance for our dependent variable is 15,669 and the arithmetic mean is 13; dispersion is 1206 times greater than the mean, violating Poisson assumptions (Long, 1997; Long & Freese, 2006).

The observed number of households heating with solar energy (y) has more zero observations than predicted by a Poisson process (Long, 1997). Vuong model selection tests and Bayesian information criterion tests indicate evidence of significant overdispersion and strongly favor a zero-inflated negative binomial regression approach to analyzing the data.

ZINB regression assumes that the data are a combination of two data generation processes. One process is binary, in this case determining whether or not a county will have any households at all that use solar heat. The second determines, for counties likely to have at least a few households using solar heat, how many of them there will be. Thus, ZINB regression estimates two separate models simultaneously. The first is a logistic model (also called the inflated model) to derive a conditional expectation of the probability that y will be zero. The second is a negative binomial model (also called the count model) to derive a conditional expectation that y will assume a positive value.

Results

We begin by ranking counties in the United States by the percentage of resident households heating with solar energy. Table 1 reveals that half of the top 30 counties are located in Colorado, with Hinsdale County having the

Table 1. Counties in the contiguous United States with the highest percentage of households heating their homes primarily with solar energy in 2000.

Rank	County	State	Households	Households heating with solar energy	% solar households
1	Taos County	NM	12,675	360	2.84
2	Hinsdale County	CO	359	10	2.79
3	Gilpin County	CO	2,043	38	1.86
4	Saguache County	CO	2,300	37	1.61
5	San Juan County	CO	269	4	1.49
6	Santa Fe County	NM	52,482	774	1.47
7	Camas County	ID	396	5	1.26
8	San Miguel County	CO	3,015	36	1.19
9	Esmeralda County	NV	455	5	1.10
10	Grant County	NM	12,146	130	1.07
11	Ouray County	CO	1,576	16	1.02
12	Gunnison County	CO	5,649	57	1.01
13	Teller County	CO	7,993	77	0.96
14	Archuleta County	CO	3,980	36	0.90
15	Park County	CO	5,894	51	0.87
16	Golden Valley County	MT	365	3	0.82
17	Catron County	NM	1,584	13	0.82
18	Custer County	CO	1,480	12	0.81
19	Jeff Davis County	TX	896	7	0.78
20	Huerfano County	CO	3,082	24	0.78
21	Chaffee County	CO	6,584	50	0.76
22	Hamilton County	KS	1,054	8	0.76
23	Torrance County	NM	6,024	45	0.75
24	Baker County	GA	1,514	11	0.73
25	San Juan County	UT	4,089	29	0.71
26	Perkins County	NE	1,275	9	0.71
27	La Plata County	CO	17,342	114	0.66
28	Storey County	NV	1,462	9	0.62
29	Costilla County	CO	1,503	9	0.60
30	Luna County	NM	9,397	54	0.57
	National average		33,736	13.17	0.04

highest percentage (2.79%) of households with solar heat among Colorado counties. In only 12 out of 3,108 counties in the entire country do more than 1% of households heat with solar energy. Santa Fe County, New Mexico has the highest count, with 774 households heating with solar energy. Santa Fe County appears to have ideal environmental, sociopolitical, and economic characteristics for fostering the adoption and spread of solar thermal technologies. It is in the ninety-fifth percentile on solar radiation, it is among the most Democratic counties in the country with 64.7% of residents voting for Albert Gore in the 2000 presidential election, and its median home value of $189,400 in 2000 placed it in the top 100 counties in the country on this measure.

We divided counties in the contiguous United States into equal quintiles according to how many of their households used solar energy for heating. Figure 1 maps this, with darker colors reflecting higher numbers of solar energy users. The most striking feature of the map is the large number of counties with zero solar users (1,736). These counties cluster vertically from western Texas through Kansas, Nebraska, and South Dakota, up to a stretch of counties that border Canada in Montana and North Dakota.

Counties with many solar users also display geographic patterns. A cluster of such counties can be found stretching from California through Arizona and New Mexico and up through Colorado, encircling Nevada. Another set of such counties in southern Florida surround the Everglades, and another is observable in the Northeast between southern Maine and eastern Pennsylvania. In addition to these clusters, we observe a peppering of counties with high numbers of solar households around the Great Lakes, on the coast in the Southeast, and in metropolitan centers in the Midwest. This geographic distribution of households using solar energy cannot be explained by number of housing units alone.

Again, because our dependent variable is a nonnegative integer exhibiting significant overdispersion with a disproportionate number of zero counts, we used a ZINB regression model to assess the net effects of independent predictors on the number of household solar energy users at the county scale (Hausman, Hall, & Griliches, 1984). We loaded independent variables incrementally, beginning with a baseline model that predicts the number of households heating with solar energy in a county using only the number of housing units in that county. We followed this

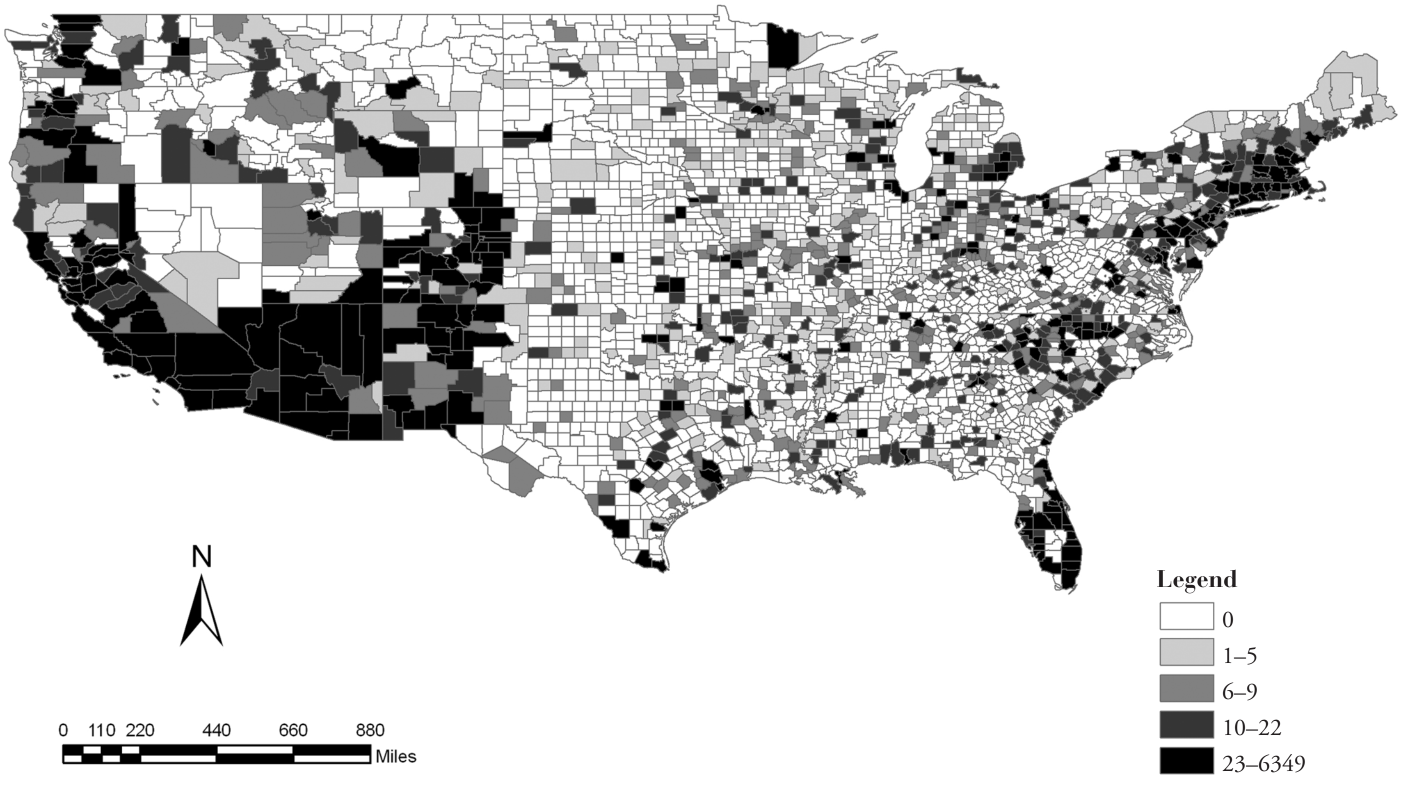

Figure 1. Observed households heating with solar energy by county quintiles.

with a model that included housing units and our environmental variables, then a model that included housing units with both environmental and economic variables, and ending with a full model that included housing units, environmental, economic, and sociopolitical predictors (see Tables 2 and 3). Table 2 shows that alpha, a measure of overdispersion in the data, suggests a greater resemblance to a negative binomial than a Poisson distribution. For ease of interpretation, Table 3 expresses each model coefficient as the percentage change in the expected numbers of household solar energy users for a one-unit change in the independent variable and for a one-standard-deviation change in the independent variable. Table 3 also reports fit statistics for all models.

In our baseline control model, where the number households heating with solar energy is solely a function of the number of households, we find that the expected count of households with solar heat increases by 98.9% for every one-standard-deviation increase in number of households (where $p < .01$). The inflated (or binary) portion of Model 1 is a mirror image of the count model, with the odds of having zero households in a county using solar heat

Table 2. Zero-inflated negative binomial regression models predicting households per county heating with solar energy.

	Model 1		Model 2		Model 3		Model 4	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Negative binomial (count) portions of the models								
Constant	2.280**	.041	−.208	.358	−2.420**	.466	−2.326**	.450
Housing units	6.57×10^{-06}**	3.65×10^{-07}	6.55×10^{-06}**	3.32×10^{-07}	3.19×10^{-06}**	2.74×10^{-07}	2.60×10^{-06}**	2.76×10^{-07}
Solar radiation			.462**	.031	.337**	.027	.343**	.028
Temperature maximum			.053	.037	.071*	.033	.078*	.032
Temperature maximum squared			−.002	.001	−.001	.001	−.001$^{\psi}$	.001
Median home value					6.49×10^{-06}**	7.98×10^{-07}	5.69×10^{-06}**	7.99×10^{-07}
Solar providers					.119	.098	.143	.097
Urbanization					.010**	.001	.009**	.001
Consumption age					.087**	.021	.091**	.020
Democrat							.007**	.001
Environmental groups							.027	.070
ICLEI participation							.465**	.173
Logistic (binary) portions of the models								
Constant	1.107**	.074	2.640**	.585	2.713**	.816	3.541**	.834
Housing units	-7.08×10^{-05}**	6.05×10^{-06}	-8.06×10^{-05}**	6.63×10^{-06}	-5.61×10^{-05}**	5.92×10^{-06}	-5.69×10^{-05}**	6.04×10^{-06}
Solar radiation			−.312**	.064	−.311**	.062	−.447**	.069
Temperature maximum			−.076	.059	−.057	.059	−.083	.059
Temperature maximum squared			.004*	.002	.003$^{\psi}$	.002	.004*	.002
Median home value					-1.06×10^{-05}**	1.84×10^{-06}	-1.10×10^{-05}**	1.91×10^{-06}
Solar providers					−1.026	.720	−.915	.707
Urbanization					.005*	.002	.006**	.002
Consumption age					.024	.036	.007	.036
Democrat							−.011**	.002
Environmental groups							−.313	.324
ICLEI participation							3.065*	1.199
lnalpha	.266**	.055	.037	.054	−.298**	.054	−.357**	.054
alpha	1.308	.072	1.038	.056	.742	.040	.700	.038

$^{\psi}p < .10$ $\quad$ $^{*}p < .05$ $\quad$ $^{**}p < .01$

Table 3. Percentage of change in households heating with solar energy[a] per unit increase in the dependent variable, and per one-standard-deviation increase in the dependent variable.

	% change in households using solar							
	Model 1		Model 2		Model 3		Model 4	
	per unit change	per SD change	per unit change	per SD change	per unit change	per SD change	per unit change	per SD change
Negative binomial (count) portions of the models								
Housing units	0.0	98.9	0.0	98.4	0.0	39.6	0.0	31.2
Solar radiation			58.7	44.2	40.0	30.5	40.9	31.2
Temperature maximum			5.5	32.9	7.4	46.4	8.1	51.8
Temperature maximum squared			−0.2	−25.8	−0.1	−21.9	−0.1	−24.0
Median home value					0.0	35.2	0.0	30.2
Solar providers					12.6	2.3	15.4	2.7
Urbanization					1.0	35.3	0.9	31.8
Consumption age					9.1	13.6	9.5	14.3
Democrat							0.7	18.0
Environmental groups							2.7	0.7
ICLEI participation							59.2	4.9
Logistic (binary) portions of the models								
Housing units	−0.0	−99.9	−0.0	−100.0	−0.0	−99.7	−0.0	−99.7
Solar radiation			−26.7	−21.8	−26.8	−21.9	−36.1	−29.8
Temperature maximum			−7.3	−33.4	−5.6	−26.4	−8.0	−35.9
Temperature maximum squared			0.4	113.8	0.3	76.9	0.4	108.7
Median home value					−0.0	−38.8	−0.0	−39.9
Solar providers					−64.1	−17.6	−60.0	−15.8
Urbanization					0.5	18.1	0.6	21.9
Consumption age					2.4	3.5	0.7	1.0
Democrat							−1.1	−22.5
Environmental groups							−26.9	−8.3
ICLEI participation							2,042.4	37.0
Nonzero observations	1,372		1,368		1,368		1,366	
Zero observations	1,736		1,730		1,730		1,729	
Vuong z	16.11		17.23		18.67		18.42	
Prob. > z	0.000		0.000		0.000		0.000	
Log-likelihood full model	−6,957.07		−6,779.22		−6,606.05		−6,552.66	
D	13,914.13		13,558.44		13,212.10		13,105.31	
LR	1,560.60		1,201.26		1,491.99		2,292.33	
Prob. > LR	0.000		0.000		0.000		0.000	
Maximum likelihood R^2	0.395		0.452		0.510		0.523	
Cragg and Uhler's R^2	0.397		0.455		0.514		0.527	
AIC	4.480		4.384		4.277		4.251	
AIC * n	13,924.13		13,580.44		13,250.10		13,155.31	
BIC	−11,039.37		−11,256.45		−11,538.48		−11,569.95	
BIC′	−1,536.47		−1,800.68		−2,082.718		−2,115.50	
N	3,108		3,098		3,098		3,095	

Note:
a. From the zero-inflated negative binomial regression models shown in Table 2.

decreasing by 99.9% for every one-standard-deviation increase in the number of households. With our baseline control established, we load more theoretically meaningful variables.

As expected, results for Model 2 show that for every additional kilowatt hour per day[7] of solar radiation a county receives, the expected count of households heating with solar energy increases by 58.7% (where $p < .01$), where the number of housing units, precipitation, maximum temperature, and maximum temperature squared are controlled for. Both temperature coefficients have the expected sign, but are statistically insignificant. The inflated portion of the ZINB model indicates that the odds of a county having zero solar households decreases significantly with an increase in solar radiation ($B = -0.311$, $p < .01$). Also, the odds of a county having zero solar households increase significantly when maximum temperature squared increases by one unit ($B = .004$, $p < .05$).

In Model 3, which adds economic variables to Model 2, solar radiation remains significant, and increasing solar radiation by 1 kWh/day increases the expected count of solar households by 40.0%. Maximum temperature is positively associated with solar households ($B = .071$, $p < .05$) after the other environmental and economic variables are controlled for. As expected, median home value is positively associated with the number of households heating with solar energy in a county. We find that a one-standard-deviation increase in median home value increases the expected count of solar households by 35.2%. Somewhat surprisingly, the presence of a solar energy provider in a county area does not significantly boost the count of household solar energy users (where $p < .05$). As predicted, a one-standard-deviation increase in the proportion of county residents between the ages of 40 and 49 increases the expected total of households heating with solar energy by 9.1%. All else equal, our results also show that urbanization is positively associated with households heating with solar energy ($B = .010$, $p < .01$). In the inflated model, a one-standard-deviation change in median home value reduces the odds of falling into the group of counties with no solar users at all by 38.8% (where $p < .01$).

As indicated by the Bayesian Information Criterion (BIC′) statistic (−2,115.5), Model 4 provides the best fit among the models we considered. Also, the Cragg and Uhler's R^2 statistic on the proportion of explained variance is .527 for Model 4, compared to .397 in Model 1. The baseline measure of total households in a county area in Model 4 has less than half the explanatory weight it did in Model 1. With the addition of sociopolitical variables in Model 4, all of the environmental measures are statistically significant (where $p < .10$). A one-standard-deviation increase in the percentage by which Democratic voters exceed Republicans increases the expected count of solar households by 18.0%. Similarly, local government involvement in ICLEI significantly increases the expected count of solar households in a county by 59.2%. The number of environmental nonprofits in a county area has no affect on the number of solar households ($B = .027$). In the inflated portion of the model, as the percentage by which Democratic voters exceed Republicans increases by a standard deviation, it significantly reduces (by 25.8%) the chances of a zero count of solar households. Interestingly, with the inclusion of sociopolitical measures, both temperature measures become significant predictors in the zero count model (where $p < .10$). Increasing the maximum temperature squared variable by one standard deviation increases the chances of a zero count by 108.7%.

Using the results from our most complete model, Model 4, we mapped the predicted numbers of households using solar heat in each county for the contiguous United States, both to visually assess the accuracy of our results, and to identify areas that appear to be behind or ahead of the curve according to our model. Figure 2 organizes the expected or predicted distribution of solar households using the same quintile intervals as Figure 1 to classify counties by numbers of solar households. The spatial prediction in Figure 2 looks quite reasonable compared to Figure 1. For example, Model 4 predicts the pocket of lower value counties in the Florida Everglades, the string of higher value counties on the Northeast Coast, the basic pattern in the Western Sunbelt, the cluster of high value counties in the Pacific Northwest, and the cluster of higher value counties in the southwestern tips of Lake Erie and Lake Michigan. On the other hand, our spatial predictions for solar use appear less accurate in the arid West and systematically overestimate zero count counties in the center of the country.

To pursue this further, we computed residuals (observed counts minus expected counts) and sought a statistically meaningful standard for interpreting them, since residuals of the same size have theoretically and statistically different meanings when observed numbers of solar households are high compared to when they are low. Because many counties have zero solar households, we cannot compute a meaningful percent residual error statistic: $(y - \hat{y} / \hat{y}) \times 100$ gives us 1,736 cases with a score of −100. Nor can we simply substitute standardized expected and observed counts in the percent residual error computation. (Such a procedure wrongly assumes that the conditional variance is constant throughout the distribution.) Instead, we evaluate the predictive accuracy of our full ZINB model by the magnitude of difference between the observed and the statistically

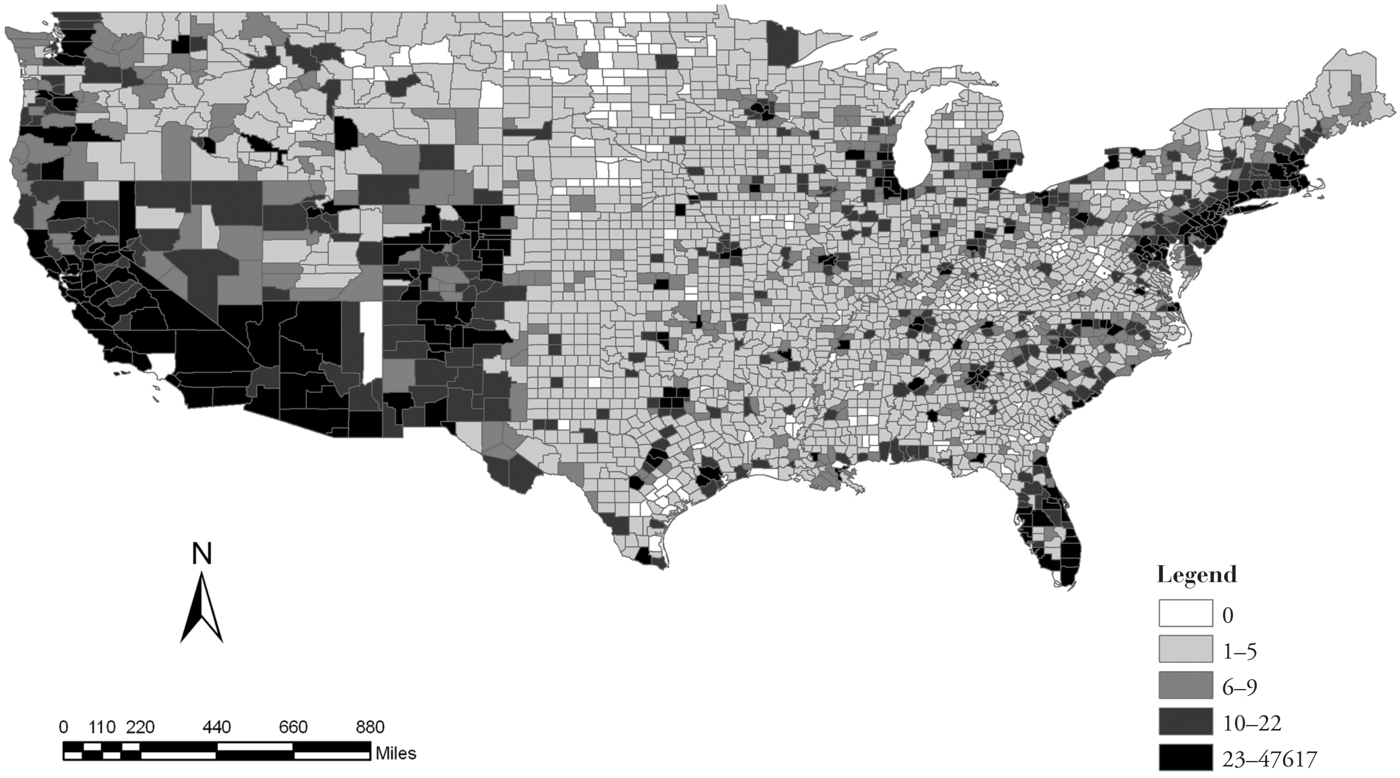

Figure 2. Predicted households heating with solar energy, by county quintiles.

expected count of solar households in standardized terms. Here, following Long (1997), we take the square root of the conditional variance for the full ZINB model.[8] This gives us an observed value's squared deviation from the expected mean generated by our ZINB model of environmental, sociopolitical, and economic predictors.

Table 4 shows the top- and bottom-ranked 30 counties in the nation according to their standardized residual values. Insofar as our fully specified model approximates the logic and context leading households to adopt solar technology, counties with positive standardized residual values are ahead of our expectations for adoption, and counties with negative values are behind our expectations. Table 4 shows that 26 of the bottom 30 counties are in Texas. McMullen County, Texas is two standard deviations below the count of solar households we would expect. Solar radiation in the bottom 30 counties averages 4.8 kWh/m^2/day, a full standard deviation above the national average of 4.3 kWh/m^2/day, indicating that though they have not adopted solar heating at the expected rate, they have the solar resources. The majority of the top-ranked 30 counties are in the southeastern portion of the country. These counties are below average in solar resources (4.1 kWh/m^2/day), are considerably lower than average in numbers of housing units (9,046 compared to 33,736), are strongly conservative (percentage of Democratic voters less percentage of Republicans averages −28.9), and are significantly below average on measures of wealth and human capital.

Finally, in Figure 3, we map standardized residual scores. Figure 3 divides the residual distribution into three groups: counties at least one standard deviation below the expected average (or behind expectations); counties at least one standard deviation above the expected average (or ahead of expectations); with the remaining counties colored in gray. Counties that are ahead of expectations are located in parts of the Northeast down through eastern Tennessee, and clustered in the Western Sunbelt. In contrast, counties that are behind expectations cluster in West Texas, Nevada, and at the Canadian border in northern parts of Montana and North Dakota. Overall, the number of counties within two standard deviations from the expected mean (2,758 counties) is far greater than the combined number of counties two standard deviations ahead or behind adoption expectation.

Table 4. Top and bottom 30 counties by standardized residual of solar households.

Top-ranked counties			Bottom-ranked counties		
Rank	County	Standardized residual score	Rank	County	Standardized residual score
1	DeSoto County, FL	18.3	3108	Vermilion County, IL	−2.7
2	Crenshaw County, AL	17.3	3107	McMullen County, TX	−2.1
3	Wayne County, TN	15.4	3106	La Salle County, TX	−2.1
4	Patrick County, VA	14.9	3105	Karnes County, TX	−2.1
5	Attala County, MS	13.9	3104	DeWitt County, TX	−2.0
6	Fleming County, KY	13.7	3103	Crane County, TX	−2.0
7	Benton County, MO	12.9	3102	Loving County, TX	−2.0
8	Grant County, IN	12.9	3101	Jim Hogg County, TX	−2.0
9	Nelson County, VA	12.8	3100	Frio County, TX	−1.9
10	Allen County, KY	12.6	3099	Bee County, TX	−1.9
11	Dade County, MO	12.4	3098	Union County, FL	−1.9
12	Morrow County, OH	12.2	3097	Willacy County, TX	−1.9
13	Surry County, NC	12.1	3096	Reagan County, TX	−1.9
14	Wythe County, VA	12.0	3095	Refugio County, TX	−1.9
15	Mason County, KY	11.6	3094	Kleberg County, TX	−1.9
16	Tift County, GA	11.6	3093	Winkler County, TX	−1.9
17	Glascock County, GA	11.4	3092	Jackson County, TX	−1.9
18	Lincoln County, KY	11.3	3091	Live Oak County, TX	−1.9
19	Hardee County, FL	10.9	3090	Sutton County, TX	−1.9
20	Mitchell County, GA	10.9	3089	Zapata County, TX	−1.9
21	Rockingham County, VA	10.2	3088	Brooks County, TX	−1.9
22	Labette County, KS	10.1	3087	Kenedy County, TX	−1.9
23	Lewis County, KY	9.9	3086	Kimble County, TX	−1.8
24	Putnam County, OH	9.2	3085	Aransas County, TX	−1.8
25	Johnson County, IL	9.1	3084	Goliad County, TX	−1.8
26	Dallas County, MO	9.1	3083	Calhoun County, TX	−1.8
27	Claiborne Parish, LA	9.1	3082	Runnels County, TX	−1.8
28	Clinton County, KY	9.0	3081	Clinch County, GA	−1.8
29	Choctaw County, MS	9.0	3080	Stone County, MS	−1.8
30	Perkins County, NE	8.8	3079	Crockett County, TX	−1.8

Discussion

In this article, we sought to explain the geographic distribution of household solar energy use at the county scale for the contiguous United States. The distribution of solar households in Figure 1 revealed more in the western Sunbelt, the Great Lakes, and along the Atlantic Coast. With a few exceptions, household heating with solar energy can roughly be characterized as a phenomenon of the coasts, where the bulk of the U.S. population now resides (Rappaport & Sachs, 2003).

Our ZINB regression models indicate that predicting solar energy users is more than a question of numbers of housing units. Environmental, economic, and sociopolitical variables are significant. Solar radiation available is particularly important. All else equal, the number of households heating with solar power in a county increases with the solar radiation it receives. This relationship is particularly strong at top of the distribution. Adjusting for the total number of households, counties at least one standard deviation above the mean in solar radiation are almost two times more likely to have at least five households heating their homes with solar energy (where $p < .000$). Results from Model 4 also indicate that temperature is a significant predictor of household solar energy adoption. Of particular interest is the negative relationship we observed between maximum temperature squared and solar households. As expected, this result suggests that neither areas with high

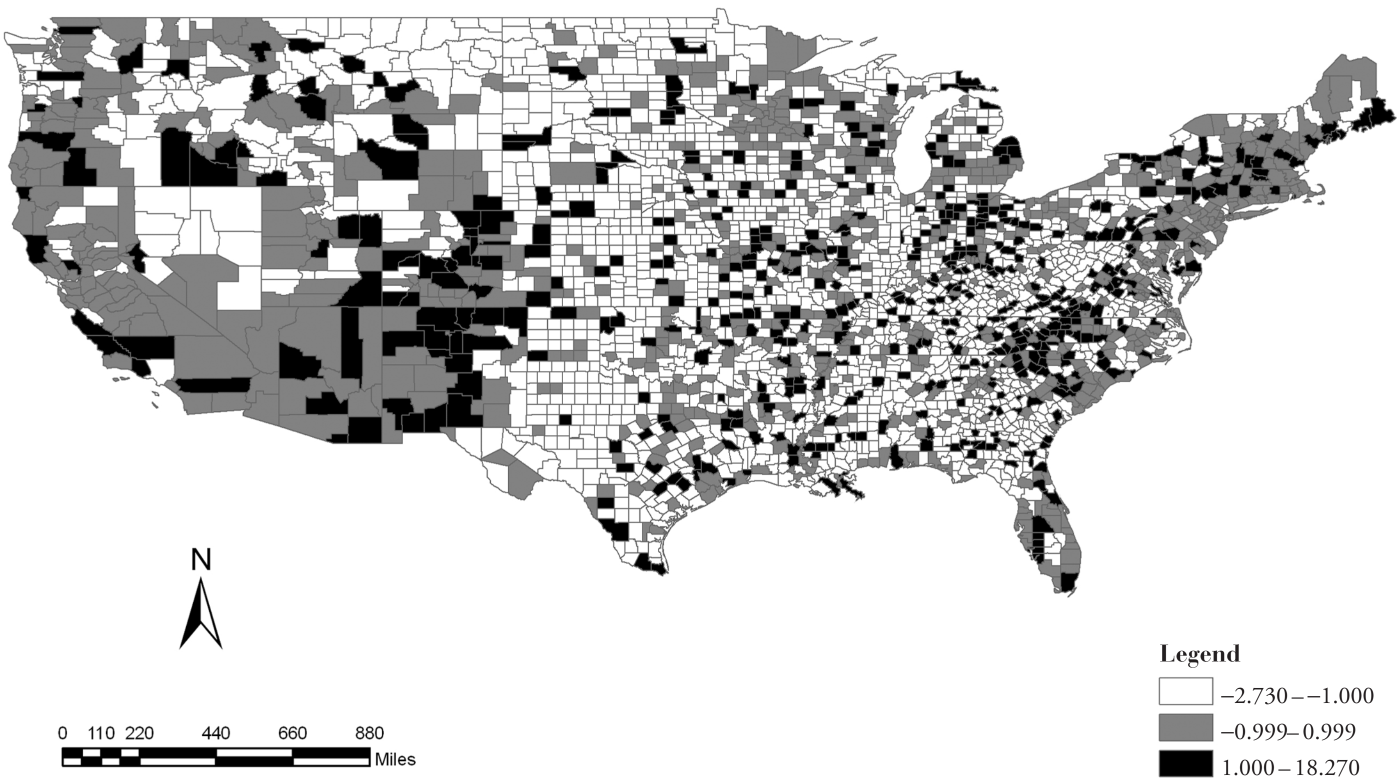

Figure 3. Standardized residuals for households heating with solar energy, by county.

maximum temperatures nor those with low maximum temperatures have many households using solar heat.

In addition, our ZINB regression results indicate that economic variables help explain spatial variation in household solar use. The number of solar households in a county is a positive function of wealth (operationalized as median home value), urbanization, and the percent of residents in the peak period of the lifecycle-consumption curve. Together, these economic variables partially support the claim that adoption of solar energy technologies is class inflected. Ideal environmental conditions are not enough. Requisite levels of wealth and budget flexibility are needed to adopt the technology.

It is interesting that having a solar energy technology provider in the county did not appear to be significant. At least three possibilities explain this. First, the measurement is inadequate. One can safely assume that not all local solar energy providers are members of the SEIA. For example, Sun Electric Systems, Inc., an independent provider of solar energy solutions in Colorado, does not appear on the SEIA's membership list. Although we suspect that many providers are not members of SEIA, we have no reason to believe that this coverage error is nonrandom. Second, the market for solar heating technologies may be inefficient, creating pockets of potential unmet demand. If this were true it would present considerable opportunity for solar energy and policy entrepreneurs. Third, some solar households certainly purchase solar systems from retailers outside the counties where they live and from internet-based retailers.

Finally, we confirmed that households heating with solar energy increase with the percentage of persons who vote for the Democratic Party in presidential elections and that counties involved in ICLEI are significantly more likely to contain solar households. Increasing both the percentage of citizens who vote for Democrats and local government involvement in ICLEI by one standard deviation produces an effect greater than does increasing average solar radiation per square meter per day by one kilowatt. Clearly, economic and sociopolitical factors have influence equal to or greater than that of solar radiation.

Our study demonstrates that fostering the adoption of solar energy is not solely a technological or private marketing issue, but is also influenced by local community characteristics. Local government can play an important role by responding to these socioeconomic, political, and geographic conditions with specific planning strategies. In this sense, increasing solar energy use falls squarely into the domain of land use and environmental planning.

The limited resources available to increase the use of solar energy throughout the United States suggests that counties that are behind expectations, such as those listed in Table 4 (almost all in Texas), should implement policies to encourage the adoption of solar technology and foster the development of more sustainable communities. Focusing on these counties should be efficient, given that their abundant solar radiation combined with their socioeconomic capacity makes them ripe for solar adoption. This approach would target last the counties our research shows to have low opportunity and low adoption rates.

Once a locality has assessed its profile (e.g., using Table 4 or future analyses) for adopting active solar energy systems, it can offer customized policies and programs to enhance the probability that residents will opt for solar technology or other renewable energy alternatives where appropriate. For example, a county with large amounts of solar radiation and a wealthy, environmentally oriented population could consider adopting a solar ordinance to guarantee access to sunlight by setting limits on the amount of shading new construction may create (Roseland, 2005). The City of Ashland, Oregon, has been promoting the use of solar energy since 1981, when it passed one of the first citywide solar access protection ordinances in the United States. This ordinance contains solar setback provisions designed to ensure that shadows at the north property line do not exceed a certain height, depending on the zone in which the property is located.

In contrast, a county with warm temperatures, ample sunshine, and an urban population, but lower levels of wealth may want to consider offering residents and industry financial incentives. Financial incentives can offset the high front-end costs of solar energy installation and compress the payback period. Rebates, such as the Clean Energy Rewards program of Montgomery County, Maryland, provide incentives for purchasing clean energy through certified suppliers. Residential consumers receive a credit of one cent for each kilowatt hour of eligible clean energy purchased. Nonresidential customers, such as businesses, receive 1.5 cents per kilowatt hour. The county's Department of Environmental Protection, which administers the program, estimates that credits will offset 40% of the incremental cost of clean energy. Tax incentives can be especially persuasive for potential residential solar users living in lower income jurisdictions. For example, in 2006 the city of Boulder, Colorado, established a solar sales and use tax rebate for photovoltaic and solar water heating installations. Solar users can receive a rebate (essentially a tax refund) drawn from the unrestricted tax revenues collected from solar energy sales (Database of State Incentives for Renewable Energy, 2007). Financial incentives can be spatially targeted within a community using solar overlay zones, special taxing districts, investment zones, or other planning mechanisms. These are just a few of the strategies jurisdictions can implement once they understand their biophysical, socioeconomic, and political composition.

Conclusion

While our study provides several insights into the geography of household solar use at the county scale, it should be considered only a first step in examining the topic. First, we analyzed only a handful of environmental, sociopolitical, and economic variables. Future research should include additional predictors and map them at a greater level of spatial specificity, perhaps at the census tract or block levels. In particular, Leadership in Energy and Environmental Design (LEED) and green building programs and local energy cost variables should be included in future models predicting solar usage. A more complete model would increase explanatory power and provide even greater insights into solar adoption across the United States.

Future research could also examine specific communities within counties to better understand subcounty variation in solar energy adoption and why some residents make the leap to solar energy and others do not. While our analysis of every county in the contiguous United States provides important information at a broad statistical level, future research could select counties at both ends of the spectrum for case study analysis. Such an approach would provide the detailed understanding of preferences and social background variables that broad statistical analysis cannot. Finally, our study examined only the number of households in each county reporting that they use solar energy to heat their homes. Where good data are available, additional study should examine the specific solar energy technologies used, and whether certain types of technology prevail in certain parts of the country.

Notes

1. There are few scientific studies of households' experiences with active solar energy systems, but Sawyer and Wirtshafter (1985) discovered that 73% of solar users reported serious technical problems with system performance. They found that average annual repair expenditures topped 4.5% of initial purchase price, far exceeding what product payback models had assumed. Yet, despite such high malfunction rates, 40 of 60 homeowners using solar energy systems in Florida reported high satisfaction with the products.

2. In addition to the lapse of solar tax credits, the low price of conventional fuels from 1990 to 2000 may account for the observed decline in household solar energy use. Measured in constant 2006 U.S. dollars, the average price of a barrel of crude oil remained below the 50-year (1947–2006) world average of $25.56 and the U. S. average of $23.67 throughout the 1990s; even dipping below the median U. S. and world price of $18.43 in both 1994 and 1998. Researchers note a positive relationship between the price of conventional fuels and household solar energy use (Dukert, 1985; Durham, Colby, & Longstreth, 1988). The historically low price of crude oil during the 1990s stretched the payback period in areas of low solar irradiance beyond the average 15-year useful life of solar heating products, making it uneconomic to adopt such products (Pimentel et al., 1994). Many who adopted solar heating systems in the 1980s likely did not update them in the mid-1990s because conventional fuel costs were so low. We expect household solar use will rise again with the price of crude oil at a historic high.

3. Concern for climate change partially accounts for the renewed interest in solar energy (Gadsden, Rylatt, & Lomas, 2003). The thermometric instrumental record indicates that global average surface temperature is increasing, up by about 0.6 degrees Celsius in the last 100 years. The scientific community is increasingly certain that greenhouse gas emissions are primarily responsible for observed variation in temperature change (Oreskes, 2004). The expected risks of temperature change are many, including coastal flooding and beach erosion, extreme weather events, loss of habitat and species, fluctuations in crop yields, and increased spread of vector-borne diseases like malaria and encephalitis (Hurd, Callaway, Smith, & Kirshen, 2004; Parry et al., 2001; Scheraga & Grambsch, 1998; Smith, Lazo, & Hurd, 2003). To mitigate the expected risks of climate change, planners and policymakers advocate a switch to energy sources that limit carbon dioxide emissions and concentrations in the atmosphere. For example, the state of California recently passed the Million Solar Roofs Plan (SB1), calling for 1 million solar roofs across the state by 2018. The plan explicitly addresses climate change: with 1 million rooftops of solar power, officials expect to reduce the greenhouse gas emissions by 3 million metric tons, the equivalent of removing 1 million cars from the road.

4. The choices for answering the question are: “Gas: from underground pipes serving the neighborhood”; “Gas: bottled, tank, or LP”; “Electricity; Fuel oil, kerosene, etc.”; “Coal or coke”; “Wood”; “Solar energy”; “Other fuel”; “No fuel used.”

5. For Census 2000, this includes all territory, population, and housing units in urbanized areas and urban clusters. The urban classification may cut across other geographic entities; for example, there is generally both urban and rural territory within both metropolitan and nonmetropolitan areas.

6. The NCSS core file merges descriptive information from three cumulative files compiled by the IRS: the business master file, the return transaction file, and the statistics of income file. The NCCS conducts standardized checks on all information, making its core file “the most complete and highest quality data source ever available on nonprofit organizations” (Lampkin & Boris, 2002, p. 1683). However, because it counts only organizations with $25,000 dollars or more in gross receipts, it probably undercounts environmental groups for our purposes, potentially missing highly motivated, but smaller grassroots environmental organizations.

7. To provide a sense of the metric, 1 kWh runs a typical space heater.

8. The conditional variance is computed as: $Var(y_i I x_i, z_i) = \mu_i (1 - \psi_i) [1 + \mu_i (\psi_i + \alpha)]$

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