Third Party-Owned PV Systems: Understanding Market Diffusion with Geospatial Tools

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Abstract

Using geospatial methods, this paper informs the evolving field of research on the diffusion of residential Third Party Owned PV systems by analyzing 1) the spatial distribution of TPO systems, and 2) the influence of demographics on the adoption on the local level. This research is part of a multidisciplinary study into the diffusion of solar technology (SEEDS), using San Diego County as focus area. Our findings reveal a significant clustering of TPO PV adoption in San Diego County. TPO systems reached a similarly high market share across a large area in the central county in contrast to the installation of host-owned systems, which have been less evenly distributed across single-family households in the same area. The diffusion of TPO systems in San Diego County can be partially explained by looking at median income and percentage of people born in the US. The explanatory power of the model varies across the region.

Introduction

In recent years, third- party ownership PV systems (TPO) have gained significant market share in the residential PV sector in Southern California (Drury et al. 2012). San Diego County is leading the residential market in California with over 85MW of installed capacity (CSI statistics). New technology products diffuse into the market across space depending on a variety of factors such as demographic composition of adopters and interaction among agents. Therefore analyzing spatial relationships and patterns of TPO adoption can provide insights into how these systems diffuse in the residential PV market.

There is a growing body of research into the influence of environmental, social, economic and political variables on PV adoption assessing demographic drivers on a geographic level e.g. zip codes (Drury et al 2012; Kwan 2012). However, these models are derived by modeling tables of data values without taking spatial relationships among geographic units into consideration. Space can be a fundamental component of understanding data patterns. For example, it is a common concept in spatial research that attribute values of neighboring geographic units are more similar compared to geographic units that are further away (Mitchell 2009). While population demographics tend to vary across a large area, pockets of areas with similar demographic characteristics likely exist. The spatial variation of population demographics should therefore be considered in understanding diffusion of residential PV systems.

Recent studies (Drury et al 2012; Rai and Sigrin 2013) found that age, income and education are the primary demographic variables for predicting residential PV adoption. These studies, however, show contrasting findings with regards to whether TPO systems are more highly correlated to less affluent, younger and less educated population fraction than the customer demographic that is associated with customer owned PV adoption.

The purpose of this study is to build on existing research into PV diffusion by considering spatial relationships between geographic features, employing two well-established methods in geospatial analysis. First, to assess the spatial patterns of TPO systems in San Diego County we performed spatial cluster analysis. Second, we employed a Geographically Weighted Regression (GWR) model to investigate demographic drivers on TPO adoption. This type of analysis can give us insights into the question: To what extent can we predict/explain the adoption of TPO installations with demographics and how does the explanatory power of the demographics vary across an area?

Methodology

For this analysis, we filtered California Solar Initiative data to collect the number of TPO and host-owned systems installed through the end of March 2013 in San Diego County. This yielded a total of 3,362 TPO systems and a total of 11,560[1]host-owned systems. We grouped TPO systems and host-owned systems by Census Tracts (628 in San Diego County) by performing spatial joints in

[1] This number includes systems that were incentivized through the Emerging Renewables Program (ERP) and the Self Generation Incentive Program (SGIP).

ArcMap. To control for market size, we normalized the adoption of both system financing types by the number of owner occupied single-family buildings, for each census tract.

To analyze spatial clustering of TPO and host-owned systems we utilized the Anselin Local Moran's I Cluster and Outlier Analysis in ArcMAP (see Mitchell 2009 and ESRI 2014). Spatial Cluster analysis identifies clusters by comparing the attribute values between neighboring features to the distribution of values of the dataset as a whole. Moran's I analysis identifies statistically significant spatial clusters of similar values (either high or low) and statistically significant outliers by calculating I-values, z-scores, and p-values based on the nearest neighbor method (differences in mean between adjacent neighbors). A high positive z-score for a feature indicates that the surrounding features have statistically significantly similar values (either high values or low values). A negative Z-score for a feature indicates the feature is surrounded by dissimilar values (e.g., high next to low values).

The cluster analysis was performed selecting Euclidian distance, row standardized weighting to account for the influence of the amount of neighbor features on the target feature and the distance neighborhood threshold as defined by ArcMap to 32,644 meters.

Geographically weighted regression is a local form of linear regression used to model spatially varying relationships (ESRI 2014). For the GWR analysis we filtered the data by removing Census Tracts with fewer than 25 owner-occupied single-family buildings, so that tracts with few buildings to install PV systems would not skew the spatial regression analysis or its assumptions. This resulted in a dataset of 598 Census Tracts. Moreover, we only analyzed systems installed between 2008 and 2012. Census Tracts population demographics including multiple measures of income, education, and native distributions were compiled from the 2010 American Community Survey 5 year estimates.

As a first step in the GWR process, we identified an OLS Regression model performing stepwise regression, investigating of correlations between independent variables and testing of classical OLS regression assumptions. We then computed the GWR statistics in ArcMaps based on the demographics variables identified in the OLS Regression. The GWR analysis was run with the inputs: adaptive kernel (to account for the variant tract density in the county) and bandwidth of 40 neighbors.

Results

Spatial cluster analysis

The statistical cluster analysis of the percentage of TPO systems per single-family household buildings shows a large statistically significant cluster of census tracts containing a high TPO installation percentage (black) (Figure 1). TPO systems seem to have diffused well in single-family homes in the central region of the county. In contrast, the southwest corner of the county consists of a statistically significant clustering of tracts with low TPO percentages (dark blue). Interestingly, these areas contain quite a few 'outlier clusters' (orange) of tracts containing high TPO percentages.

Similarly to TPO systems, host-owned systems are significantly less represented in the southwest corner (Figure 2).[2] While host-owned systems also have a significant clustering of census tracts containing a high installation percentage in the central region, the cluster is much smaller. The differences between TPO and host-owned clusters imply that TPO systems were adopted much more evenly across single-family households in the central region compared to host-owned systems. While the later has a much larger penetration of systems in the market overall, it's diffusion across the central area was less cohesive among neighboring census tracts.

Geographically Weighted Regression

The OLS regression model analysis yielded a model containing the independent variables 'median income' and 'percentage native born. This model can explain almost 25% of the variance of TPO adoption in census tracts in San Diego County (R^2 =0.2498, adjusted R^2 =0.2472). Table 1 shows the OLS models that were considered and their model assumption test values.

Table 1. OLS models and test values of OLS model assumptions

Model*	AdjR2	AICc	JB	K(BP)	VIF
Medianinc	0.21	559.9	0	0.04	1
Meanincome	0.21	560.4	0	0	1
Medianage	0.14	606.8	0	0.02	1
Medianinc +Native	0.25	531.8	0	0.08	1.2

*All variables are statistically significant at p<0.01

The GWR method increased the explanatory power of the model to R^2= 0.54. Figure 3 shows that the model's explanatory power varies significantly across the region. A map depicting the standard deviations of residuals reveals that there are a few outlier tracts (dark red) (Figure 4).

[2] The cluster analysis results of host owned systems from 1999-2012 does not differ much to the cluster analysis of host-owned systems installed between 2008-2012.

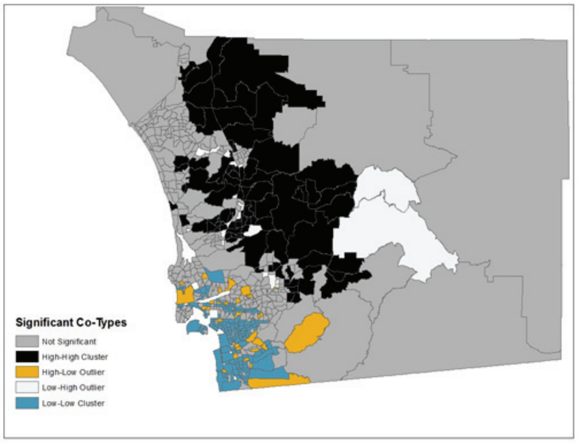

Figure 1. Local Moran's I Cluster Analysis for Third party owned systems weighted by Single-family households in Census Tracts

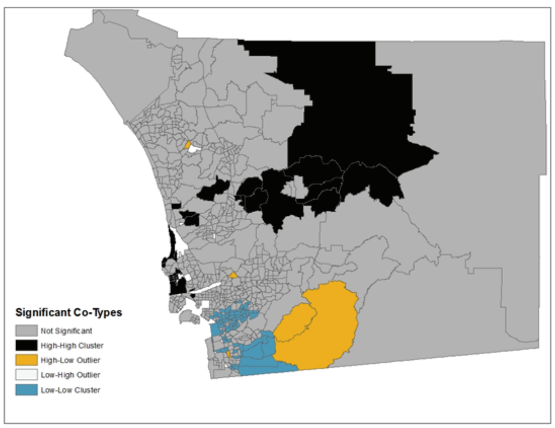

Figure 2. Local Moran's I Cluster Analysis for host-owned systems weighted by Single-family households in Census Tracts

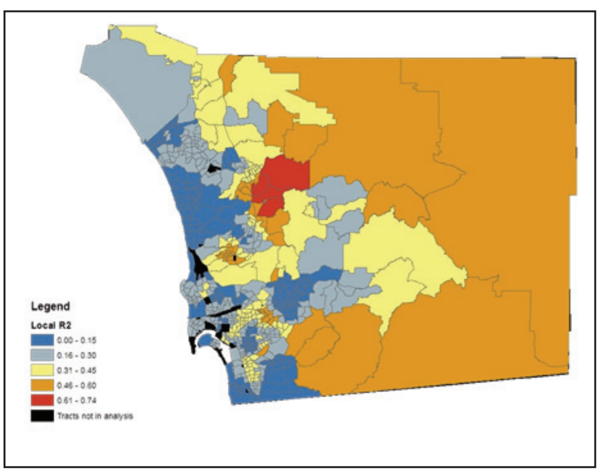

Figure 3. Geographically Weighted Regression: Local R2 for Third party owned systems weighted by Single family households in Census Tracts

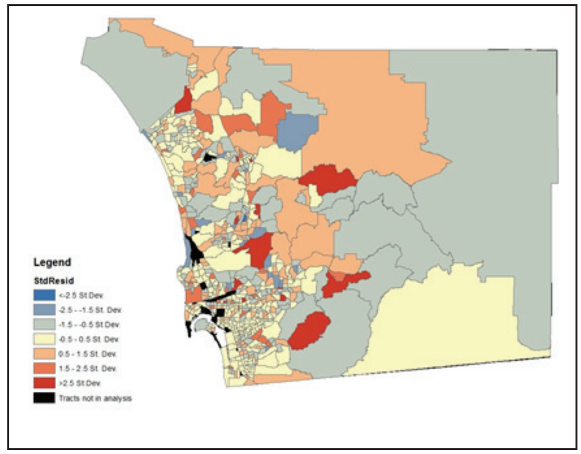

Figure 4. Geographically Weighted Regression: Standard Deviation of Residuals

Conclusion

This research adds to existing research into the diffusion of residential PV systems by analyzing spatial patterns of TPO system adoption. Geospatial analysis can aid in understanding drivers of diffusion of PV systems.

The spatial cluster analysis showed that TPO systems reached a similarly high market share across a large area in central San Diego County, in contrast to the installation of host-owned systems, which have been less evenly distributed across single-family households in the same area.

The diffusion of TPO systems can be partially explained by looking at demographics such as median income and percentage of people born in the US. The GWR analysis showed that demographics seem to only be strong drivers for the adoption of TPO systems in some areas (central census tracts) of the county. In other areas (e.g. coastal areas), adoption of TPO systems appears to be influenced by factors other than demographics.

These results provide some insights into possible non-demographic drivers of TPO diffusion in the residential PV market in San Diego County. The difference in spatial clustering between TPO and host-owned systems might have been influenced by the emergence of TPO installers and services in the residential solar market. These TPO installers sought to potentially enter new market segments in addition to the established customer segments, which had shown a high willingness to adopt PV systems (high shares of host-owned systems). In a next step, this diffusion research will be complemented with an analysis into the market penetration of TPO installers and its influence on the diffusion of TPO systems across San Diego County.

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