

Social Equity of Clean Energy Policies in Residential Solar



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Residential solar installations have rapidly increased in recent years with advancement of clean energy policies. This transition to the new energy system needs to avoid the uneven distribution of the service. To investigate the impact of such policies on the social equity, two questions have emerged:

- (1) Were there certain communities left out from incentive opportunities?
- (2) Do those current policies help the social equity?

INTRODUCTION

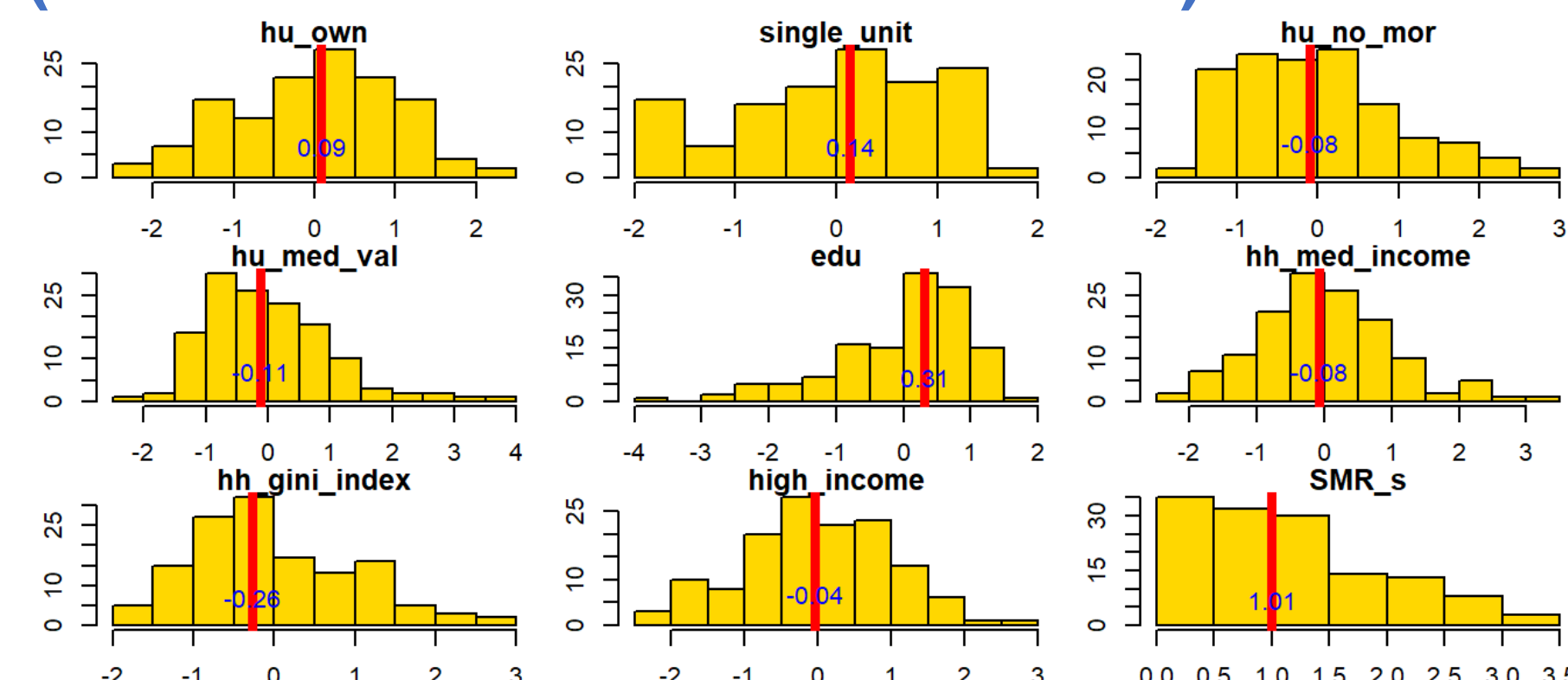
The transition to the new energy system could lead to undesirable impacts on some communities, for example, digital divide as shown in the case of telecommunication (Caperton et al. 2013).

The study performed a spatial analysis of the distribution of solar panel installed-buildings in terms of housing and socioeconomic characteristics based on census tract in Seattle.

DATA

Any patterns of residential (single family and multifamily) solar installations are examined in terms of spatial clustering patterns, and associations among variables through American Community Survey and City of Seattle data portal.

Socioeconomic and housing characteristics (2011 - 2015 ACS 5-Year estimates)

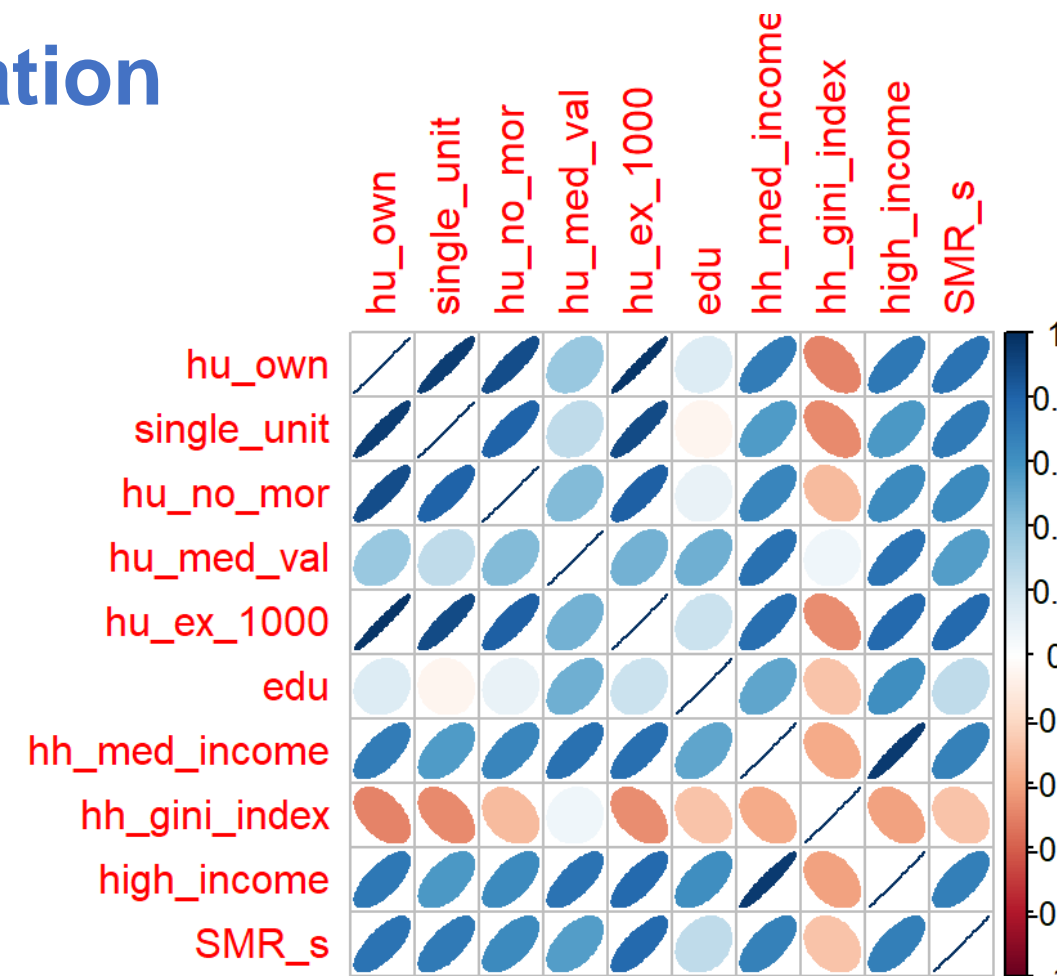


All variables are normalized except for SMR_s, which comes from Seattle solar electrical permit data portal.

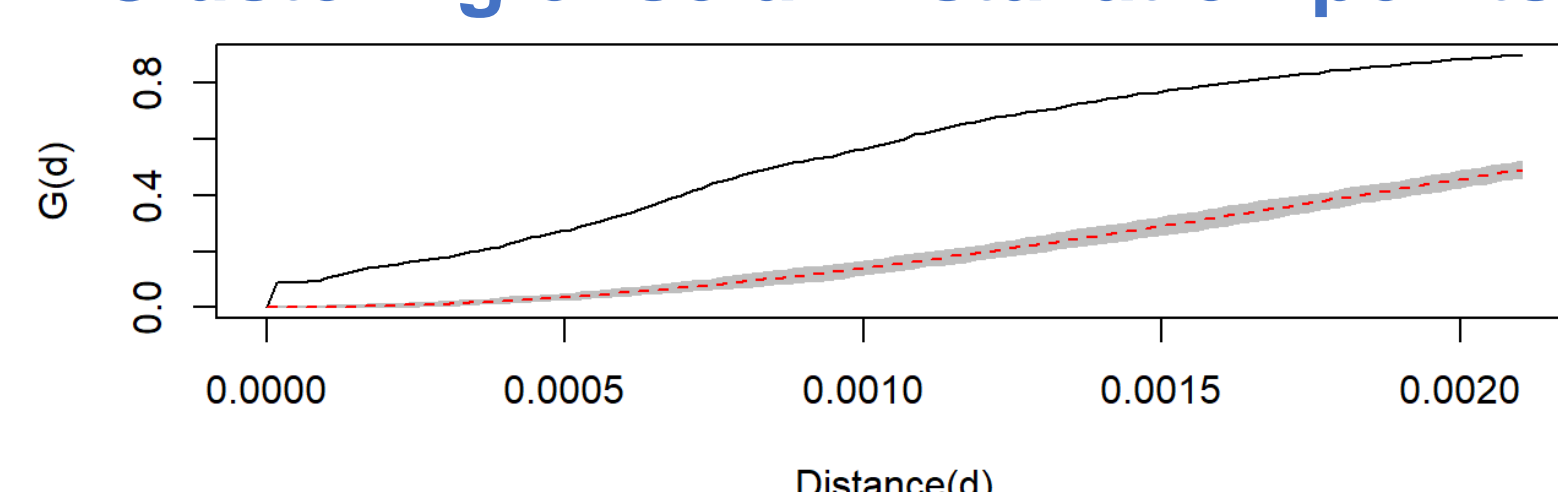
- hu_own**: owner-occupied housing units
- single_unit**: single family housings
- hu_no_mor**: owner-occupied housing units without a mortgage
- hu_med_val**: median value of owner-occupied housing units
- edu**: population above high school degree
- hh_med_income**: household median income
- hh_gini_index**: household GINI Index of income inequality
- high_income**: high income households
- SMR_s**: the ratio of solar installation to the expected number of installations in regard to the total number of the residential housing units of the given census tract (2003 – 2018)

Covariates correlation

Some groups of variables show the similar correlations each other.



Clustering of solar installation points



G estimate shows a clustered pattern for spatial dependency of solar installations.

METHODS

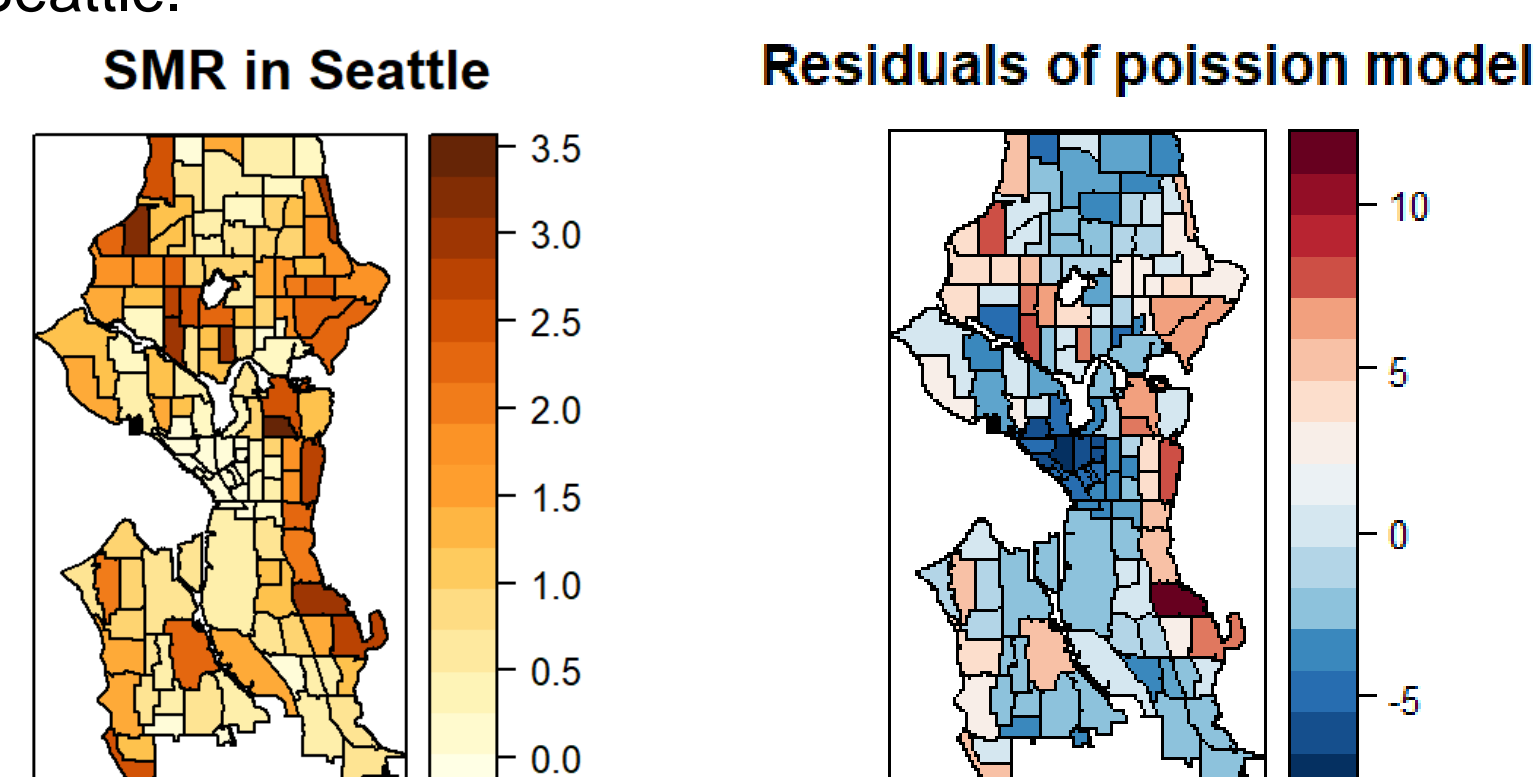
The rate of residential solar in a census tract (SMR) is defined by the number of residential solar (Y) over the expected number of residential solar (E) given the estimated proportion, which is the total number of residential solar over the total number of housing units in Seattle.

$$SMR_i = \frac{Y_i}{E_i}$$

Considering its rare proportion with respect to the denominator (the total housing units) in a census tract in addition to the fact that the number of residential solar is count data, Poisson count model is (β_0 is constant):

$$Y_i \sim \text{Poisson}(E_i e^{\beta_0})$$

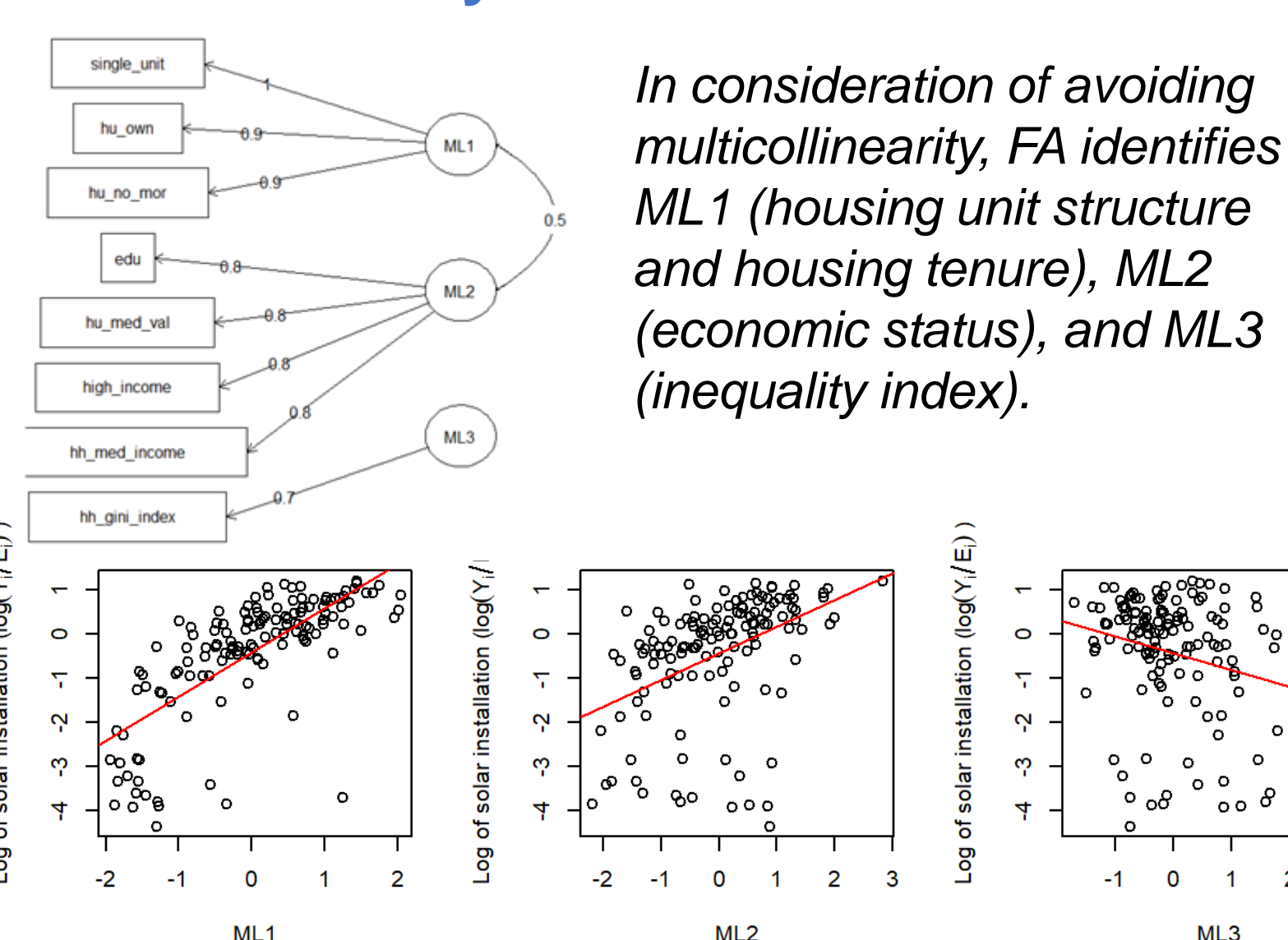
The residuals of the model indicates that there is strong evidence of spatial dependency among the regions in Seattle.



1. Dimension reduction of covariates
2. Poisson lognormal spatial model using BYM2 method to address the spatial autocorrelation issue
3. K-means clustering analysis to identify similar regions in terms of socioeconomic and housing patterns
4. Geographically weighted regression (GWR) by taking into account of the local spatial dependency
5. Prediction based on covariates

RESULTS

1. Factor analysis



2. Integrated Nested Laplace Approx.

$$Y_i | \beta_0, \beta_1, \beta_2, S_i, \epsilon_i \sim_{ind} \text{Poisson}(E_i e^{\beta_0 + \beta_1 I_{1i} + \beta_2 I_{2i}} e^{S_i + \epsilon_i}),$$

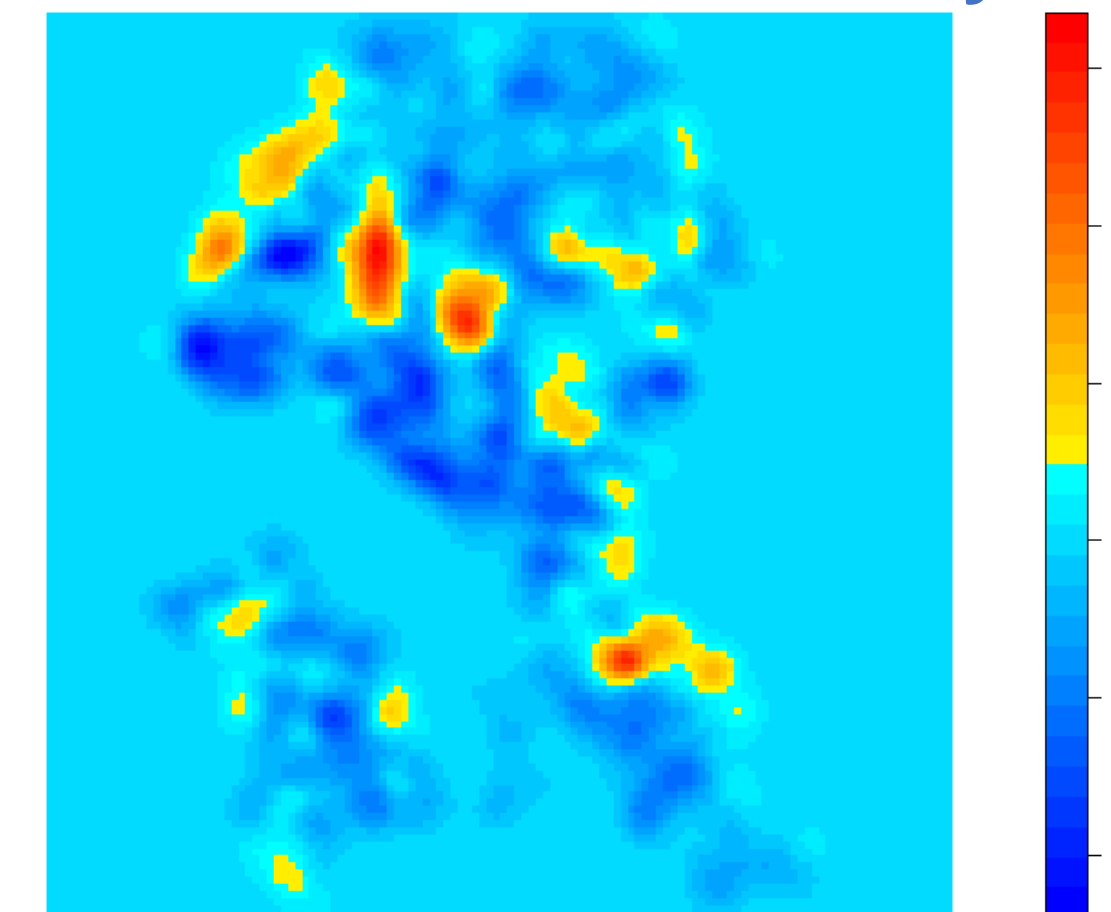
$$\epsilon_i | \sigma_\epsilon^2 \sim_{iid} N(0, \sigma_\epsilon^2), \quad \text{Intrinsic Conditional}$$

$$S_1, \dots, S_n | \sigma_s^2 \sim \text{ICAR}(\sigma_s^2). \quad \text{Auto-Regressive (ICAR)}$$

The large variance is due to the spatial dependency with ϕ of 0.96 (ϕ is between 0 and 1, closer to 1 means higher spatial dependency).

	mean	0.025quant	0.5quant	0.975quant
(Intercept)	-0.3012	-0.3604	-0.3008	-0.2437
I(ML1)	0.5551	0.4121	0.5549	0.6985
I(ML2)	0.182	0.04388	0.1816	0.3222
Total SD	0.6523	0.7902	0.6576	0.5488
Phi for ID	0.959	0.828	0.9749	0.9986

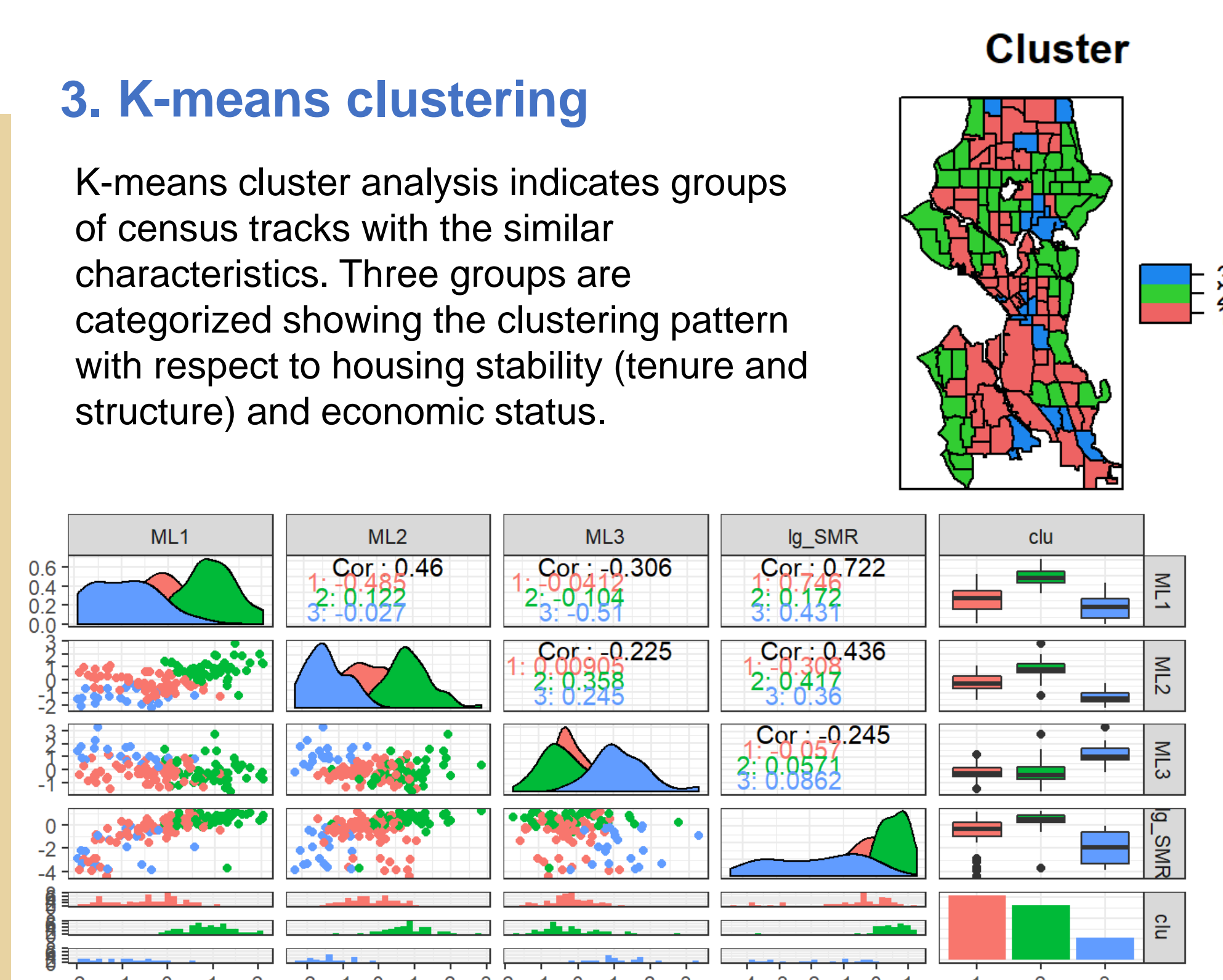
Residential solar density in Seattle



Solar density normalized by the number of residential house units.

3. K-means clustering

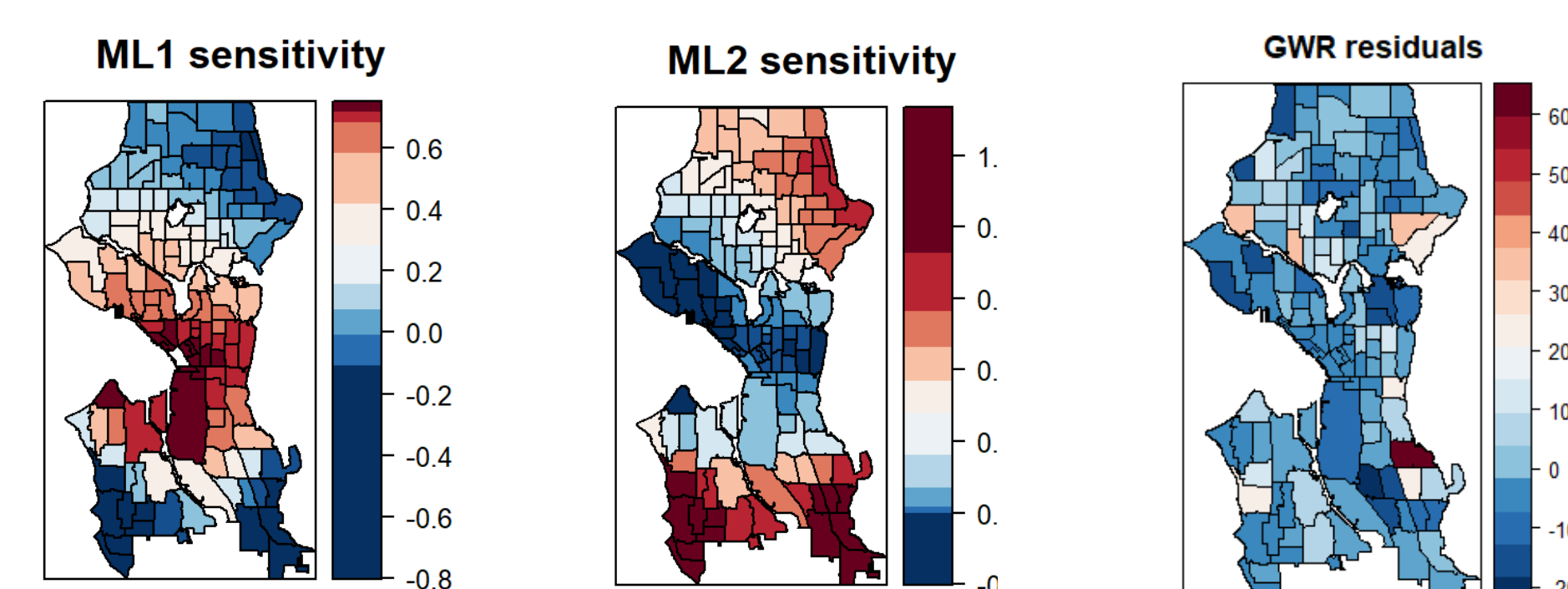
K-means cluster analysis indicates groups of census tracts with the similar characteristics. Three groups are categorized showing the clustering pattern with respect to housing stability (tenure and structure) and economic status.



4. Geographically weighted regression (GWR)

GWR model considers spatial dependence in a local level by changing the coefficient values of covariates. Housing stability impacts more on the central Seattle while North and South Seattle are more sensitive to the economic status for the residential solar.

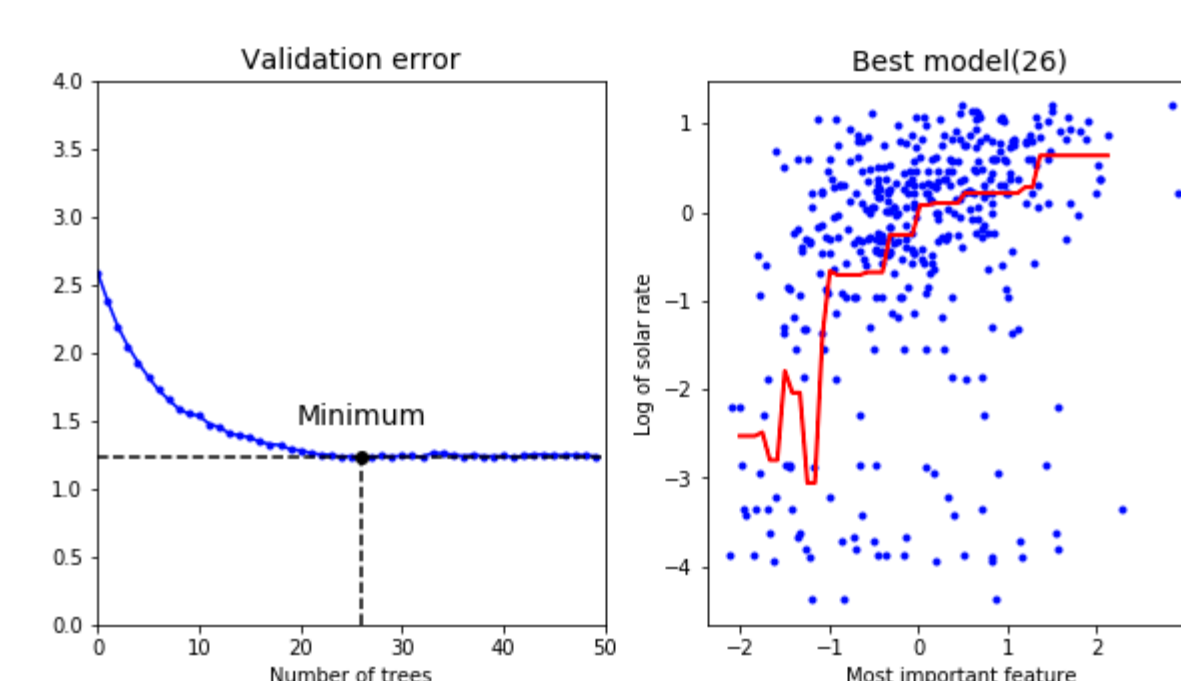
$$Y(s) = E(s) e^{(\beta_0 + \beta_1(s)X_1(s) + \beta_2(s)X_2(s) + \epsilon(s))}$$



5. Prediction (gradient boosted random forest)

- Max depth=2
- Learning rate=0.1
- Estimators=50
- Train to test=0.8

26 tree estimators predict the best and the most important feature in this model is ML1.



CONCLUSIONS

Residential solar installations are influenced by (1) mostly housing stability (single family house unit proportion and housing tenure) and (2) moderately economic status (income level and house value).

The results answer the questions that there are certain communities left out from using the renewable energy technology due to the resources (i.e., housing and finance). It is necessary to address the issue by coming up with policies such that encouraging the underserved communities to take advantage of the clean energy technologies and incentives.

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