Socio-Political Factors Driving Solar Deployment: Streamlining US Energy Planning

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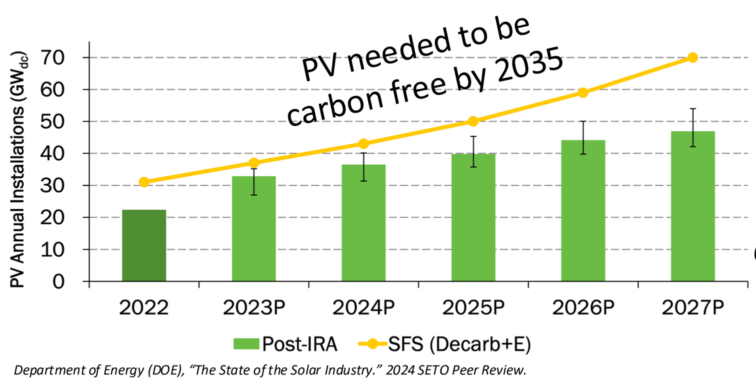
Background



How can we support more efficient solar deployment in future?

- Current solar resource models are largely based on techno-economic factors like GHI, environmental and geotechnical land constraints (Sengupta, M. *et al*., 2021)
- However, the impacts of socio-political factors reflecting NIMBY values remain largely underexplored

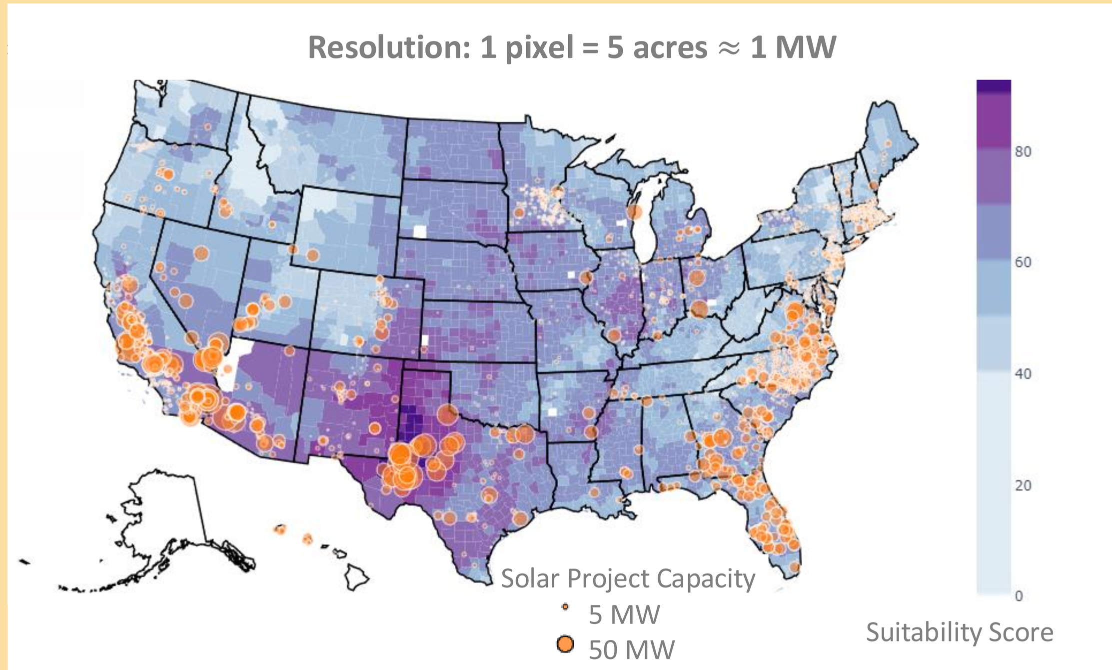


Figure 1. Argonne National Laboratory's Geospatial Energy Mapper (GEM) suitability model scores for US and installed solar projects (> 1 MW) from 1990-2021 across 681 counties (EIA-860)

Phase I. *Can socio-political factors explain the mismatch between suitable land for solar and installed solar?*

Phase II. *How can we incorporate these findings into energy planning models?*

Phase I.

Methods and Data

Utilized multiple linear regression to predict county-wide deployment metrics according to technoeconomic and socio-political variables.

$$\boxed{Y_n} = \beta_0 + \boxed{\sum_{k=1}^{k}\beta_k X_{n,k}} + \boxed{\sum_{m=1}^{m-1}\gamma_{n,m} D_{n,m}} + \varepsilon_n + \boxed{\sum_{q=1}^{q}\eta_q S_{n,q}}$$

Techno-economic factors | State-fixed effects | Socio-political variables

Solar PV potential, unprotected land, habitat, slope, population sparsity, land cover (GEM factors; units: suitability from 0-100)

Technoeconomic factors

Capacity intensity (CI): MW / sq. mi. * 10,000
Project intensity (PI): No. projects / sq. mi. * 10,000
Average project size (AP): MW

Deployment metrics

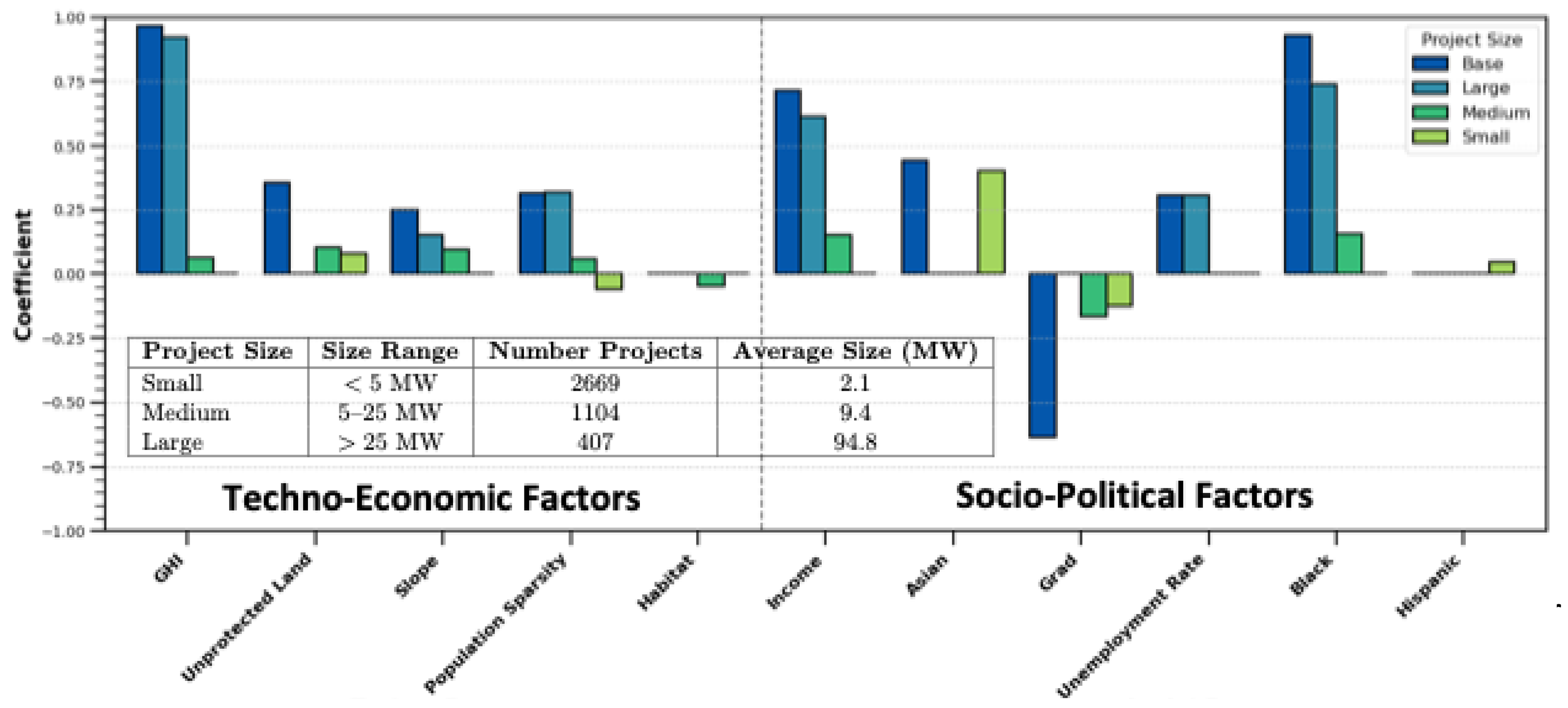
Ethnicity, education-level, median household income, political affiliation, unemployment rate, GDP per capita, prior wind deployment

Socio-political variables

Purpose: control for unobserved, time-invariant differences between states that could bias estimates e.g. long-term state policy support

State-fixed effects

How does suitability score impact deployment metrics?



Key finding #1: Techno-economic variables weakly explain deployment, affecting large (>25 MW) more than small installations (< 5MW)

Key finding #2: Incorporating socio-political variables strengthens model explanatory power, factors most impactful are ethnicity and economic resources.

Creation of propensity scores

From estimated coefficients, empirical siting likelihood is calculated for each county, *i*

$$S_i = \frac{\widehat{D}_i - \min(\widehat{D}_i)}{\max(\widehat{D}_i) - \min(\widehat{D}_i)}$$

$$D_i = \widehat{\boldsymbol{\beta}}_0 + \widehat{\boldsymbol{\beta}}_1 income_i + \widehat{\boldsymbol{\beta}}_2 asian_i + \widehat{\boldsymbol{\beta}}_3 grad_i + \widehat{\boldsymbol{\beta}}_4 unemp\_rate_i + \widehat{\boldsymbol{\beta}}_5 black_i$$

Phase II.

Backtesting validation

Can county-level solar deployment patterns be predicted by leveraging prior empirical findings, using propensity scores (i.e., a solar deployment likelihood index)?

Canonical capacity expansion objective function

$$\min \sum_{g\in G}\left(FixedCost_g * CAP_g + \sum_{h\in H} VarCost_g * GEN_{g,h}\right) + \sum_{h\in H} NSECost * NSE_h$$

Incorporation of solar propensity score

$$+\ SolCost * SolCAP_g + \lambda \sum_i (1 - S_i) * SolCAP_i$$

$S_i = propensity\ score\ for\ county\ i$
$SolCAP_g = capacity\ for\ each\ solar\ generator$
$\lambda = tradeoff\ parameter$

Model: *Switch-USA* capacity expansion model
Temporal resolution: Solve for 12 representative weeks in 2024
Spatial resolution: Western Electricity Coordinating Council (WECC), aggregating at county level to solve at the ReEDS zonal level (34 zones)

Step 1. Fix all inputs, prescribe 2024 zonal solar capacity additions, and solve for where solar is sited across each zone
Step 2. Disaggregate at county level and compare predicted vs. observed deployment using mean squared error (MSE)

Forward-looking capacity expansion model in 2030

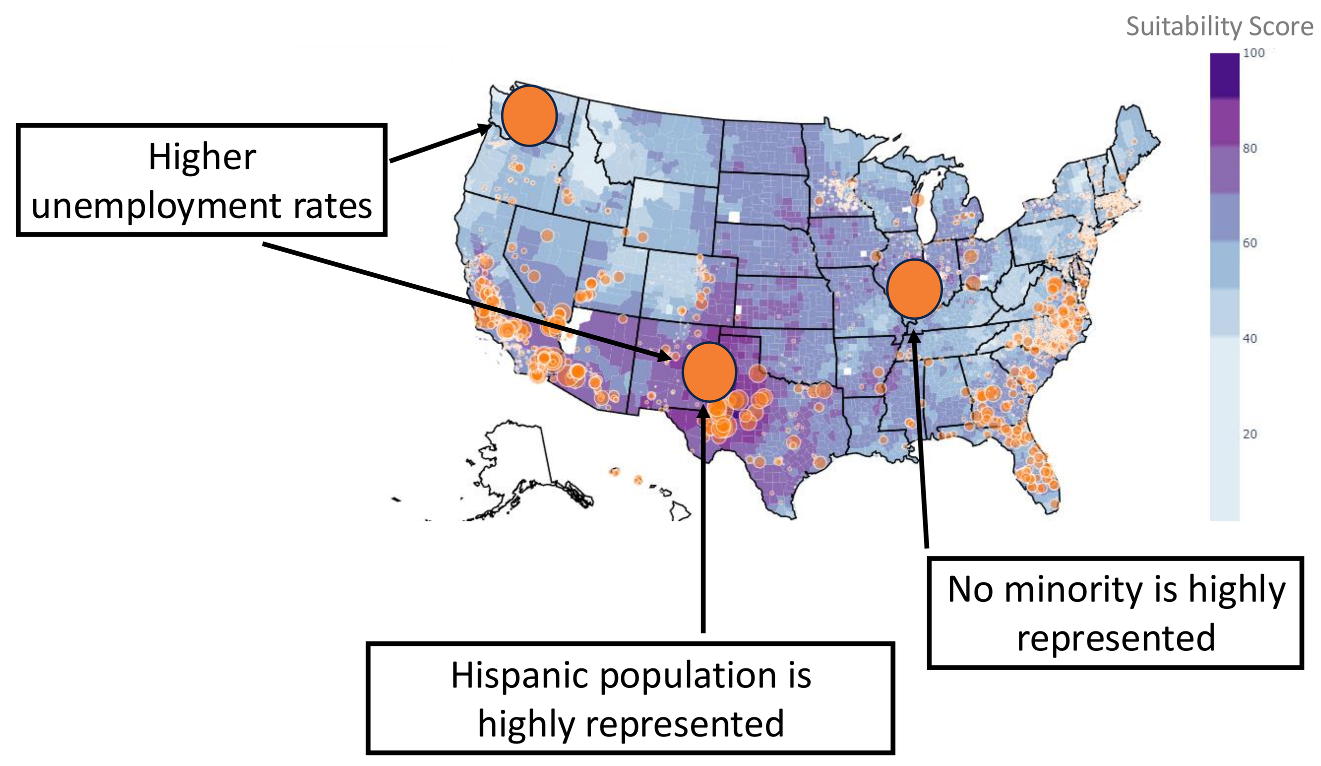


Figure 3. GEM suitability model scores for US, overlaid with potential new development based on US Bureau of Labor statistics and Census Population estimates.

Our expected findings will elucidate trade-offs between siting solar in lower-resource areas to avoid cost penalties from low propensity scores, and the need for additional transmission when these sites are distant from demand centers.

Equity constraints
How can we proactively respond to the equity implications?

Create set of priority counties, P
At least 25% (α) of all $SolCAP_g$ must be in P

$$\sum_{i\in P} SolCAP_i \geq \alpha \sum_{i\in P} SolCAP_i$$

Define jobs, $Jobs = SolCAP_i * Jobs/MW$
J_{min} be certain threshold of jobs created

$$\sum_{i\in P} Jobs_i \geq J_{min}$$

Conclusions/Future Work

- Socio-political factors impacting historical solar deployment were identified with race and economic resources as most significant, while techno-economic factors weakly explain these trends.
- Through calculating propensity scores, we can integrate these empirical findings into a WECC-based capacity expansion model, enhancing the accuracy of progress assessments toward decarbonization goals by accounting for spatial and socio-political variation.
- We plan to investigate the equity implications of building according to historical trends and will implement constraints to proactively respond to potentially unfair outcomes.

Nicolas, J.R.; Davidson, M.R.* Quantifying the Impact of Socio-Political Factors on U.S. Utility-Scale Solar Deployment Patterns. (2026). [Manuscript submitted]