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Using AI to Understand Residential Solar Power

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RESIDENTIAL SOLAR PANEL USAGE IS GROWING RAPIDLY, as more households use photovoltaic (PV) technology to convert sunlight into electricity. The percentage of solar PVs in the United States has risen from 4 percent in 2010 to 44 percent in 2020.

The deployment of new technologies that generate clean electricity is a crucial part of the global energy transition needed to help mitigate climate change. But the deployment of residential solar PV technology has been highly unequal across the United States. Low-to-moderate income households, for example, have deployed far less solar PV technology than wealthier households. This is a problem in and of itself, but it also poses a substantial barrier to widespread use of photovoltaic technology and the United States' ability to help the world move toward a sustainable energy future.

Confronted with this problem, open AI datasets and models can help us understand the deployment of solar PV in communities across America. In our paper, "DeepSolar++," we used computer vision to build a nationwide dataset on solar PV deployment in the United States—at fine resolution and large scale. In particular, we built a large dataset that captures information about solar PV deployment across time and geography in an automated and scalable manner. We also uncovered how socioeconomic factors shape adoption of solar PV in the United States, from the first installation to the widespread use of solar panels in different communities.

Key Takeaways

The United States has experienced a rapid adoption of residential solar photovoltaics (PV) technology, an electricity generation method that is a crucial part of efforts to decarbonize the energy sector.

We created a publicly available dataset of historical satellite and aerial imagery and a computer vision model to study variations in solar PV adoption over time in U.S. households. We found that lower-income communities are more delayed in adoption.

The effectiveness of incentive mechanisms for spurring adoption varies widely for different socioeconomic groups; while property tax incentives led to relatively more solar PV adoption in higher-income communities, performance-based incentives were more successful in boosting solar adoption among lower-income communities.

Policymakers should leverage open datasets and AI models to gain crucial insights into solar PV adoption and customize policies and financial incentives accordingly. Adopting computer vision techniques can not only help accelerate solar PV adoption but also make the clean energy transition more equitable.

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Studying the spread of solar PV technology in the United States is vital to identifying and tackling barriers to adoption. Our paper improves on previous research and demonstrates that computer vision is an essential technique for understanding residential solar usage in the United States and holds great promise for helping policymakers address the climate crisis.

Methodology

New clean electricity generation technologies like solar PV are an integral part of efforts to decarbonize the energy sector. However, we do not yet fully understand solar PV adoption across different demographic groups and different stages of the adoption process.

Existing studies have led to crucial insights but some gaps remain. For example, previous papers have not covered the full life cycle of solar PV adoption, from onset (the first installation of solar PV technologies) to saturation (when at least 95 percent of projected capacity has been met). They also have not captured the fluctuating uptake of solar PV technology across U.S. households. These limitations have constrained previous studies' insights into solar adoption, in particular when it comes to differentiating between low solar PV adoption and delayed adoption, and assessing what this means for boosting diffusion of such technologies in the United States.

In our paper, we tackle these limits by developing a computer vision model to identify solar PV panels in historical satellite and aerial imagery. We used this model to construct a spatiotemporal dataset—tracking solar PV adoption across geography and time—for installations across the country. Our dataset covers solar PV systems installed between 2006 and 2017 in 420 counties across 46 randomly sampled states.

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After compiling the dataset of solar PV installations, we used a Bass model—designed to capture technology diffusion over time—to model the adoption trajectories of residential solar PV and to identify different phases of community-level adoption. We studied communities on a census block level, using the same regional breakdown as the U.S. Census. We used a convolutional neural network (CNN), a type of AI model commonly used for image recognition, to classify each image as positive (i.e., contains solar) or negative (i.e., does not contain solar). The installation year for each site was classified as the first year the neural network identified solar in the image. Using additional techniques, we measured the correlation between solar PV adoption and factors such as income, education, share of renter-occupied housing units, and median household income.

A key contribution of our work is reducing our reliance on conventional data sources from state agencies, utilities, and incentive programs. Many researchers use only this data, which can result in the underrepresentation of communities in their studies. In addition, existing datasets of solar PV systems are often not comprehensive or granular enough in terms of both geography and time.

By contrast, our large-scale, nationwide dataset allowed us to capture the effects of varying federal- and state-level incentive programs as well as socioeconomic differences across census blocks. This enabled us to identify nuanced variations in solar PV adoption across different parts of the country. Furthermore, our approach can be applied to aerial and satellite imagery with sufficient resolution anywhere in the world. If new satellite and aerial images become available, our model can automatically integrate the updated data without researchers needing to retool the entire framework. We made our computer vision model and dataset publicly available to help academics and governments conduct precisely this kind of additional research on solar PV adoption patterns over time.

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Research Outcomes

We found that as of 2016, 55 percent of the census block groups we analyzed across the United States had not even started installing residential solar PV. As of 2016, only 15 percent of the analyzed block groups had reached solar PV saturation—defined as having met more than 95 percent of projected capacity.

There remain considerable gaps in solar PV adoption across the country broadly as well as between communities. Breaking the block groups into high-, mid-high-, mid-low-, and low-income groups, based on each state's quartile of income distribution, we found that a consistently larger share of high-income block groups (top 25 percent) have started solar PV adoption compared to low-income block groups (bottom 20 percent). In 2016, for example, 61 percent of high-income block groups had started adopting solar PV, while only 30 percent of low-income block groups had. Higher-income block groups are also more saturated in solar PV deployment than lower-income ones. Meanwhile, lower-income block groups are delayed in adopting residential solar PV technology, though we found that they saturate more quickly when they do begin adopting this household solar technology.

Our research also examined the relationship between demographics, solar policy, and solar PV adoption. Solar PV-related rebates and grants, which subsidize the cost of using solar technology for households, are of course more relevant for lower-income households that may not otherwise be able to afford to install solar. In that vein, we found that the decision to adopt residential solar PV in low- and middle-income communities is more dependent on PV rebate and grant benefits than in high-income communities.

Analyzing our large dataset of satellite and aerial data revealed that performance-based incentives, property tax incentives, and rebate programs are positively associated with a community's level of solar PV saturation. Importantly, the effectiveness of incentives differs across economic groups. For low-income communities, performance-based incentives are especially impactful, while property tax incentives are less effective in those contexts. In higher-income communities, by contrast, property tax incentives are more strongly correlated with saturated adoption levels of solar PV technology.

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Policy Discussion

Solar PV adoption is vital to reducing the environmental burden of energy usage from individual homes and to moving the United States, and the world, toward a sustainable energy future. Measuring this adoption across the country is essential for policymakers, researchers, scientists, journalists, advocates, and other stakeholders seeking to understand delays or inequities in adoption and overcome barriers to comprehensive implementation.

Policymakers should consider employing computer vision techniques to study solar PV deployment—particularly because this approach is both automated and scalable. Traditional approaches to measuring residential solar usage often rely on surveys and third-party reporting, but this can bias the data toward high-adoption areas or communities that already have robust reporting systems for solar PV installations. Using satellite and aerial imagery solves this problem, given the large amount of granular satellite imagery data available in the United States.

Our dataset also enables researchers, policymakers, and other groups to analyze solar adoption both spatially and temporally. This differs notably from other datasets, such as Google's Project Sunroof, which only capture imagery at a single point in time. Our dataset enables analysis of solar PV adoption at the aggregate level as well as more granular analyses across regions and over time. The underlying AI technology could make use of satellite and aerial imagery data to tackle other challenges, such as monitoring usage of natural resources and land.

This research shows that incentivizing solar adoption, rather than just waiting for individuals to use solar PV technology in their homes, is necessary to advance sustainable energy progress. Policymakers must recognize that performance-based incentives are more impactful in low-income communities, where they could help overcome the current plateau of low adoption rates, while property tax incentives are more effective in higher-income communities. Policies and financial incentives to boost solar PV adoption should therefore be adapted to communities based on their demographics and stage of adoption. Findings of this kind, based on AI analysis of spatial and aerial imagery, can also help identify additional ways to accelerate solar PV adoption.

Our research is not without limits. The dataset we built, for instance, includes data through 2017 and does not cover all solar PV systems installed in the United States up through the present day. Additionally, the Bass model, used here to analyze the saturation of solar PV in a given community, is best at *measuring* but not *predicting* saturation. Creating new models, or combining this data with other analyses, could help estimate the potential effects of new policies or incentives for solar. Policymakers should consider the potential for open datasets and AI models to facilitate additional study of solar PV use around the world.

Residential use of solar PV technology is undergoing explosive growth. But low adoption rates in some communities, especially lower-income areas, could prevent millions of people from accessing clean, low-cost energy. Unequal adoption also contributes to a slower uptake of solar energy in the United States on the whole, when it could be contributing to decreased emissions and improved air quality. Better-targeted policies and clean energy incentives can help address this inequity, and computer vision applied to spatial and aerial imagery can help achieve that objective.

The original article is accessible at Zhecheng Wang et al., "**DeepSolar++: Understanding Residential Solar Adoption Trajectories with Computer Vision and Technology Diffusion Models**," *Joule* 6, no. 11 (November 2022): 2611-2625, https://www.sciencedirect.com/science/article/abs/pii/S2542435122004779.

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