

Mapping equity in California K-12 school solar adoption using computer vision

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SUMMARY

California is experiencing dramatic impacts from the climate crisis, facing wildfires, droughts, and power outages. In response, the state has prioritized clean and resilient energy, and solar photovoltaic (PV) power systems are a widely adopted solution. However, insight about solar adoption—an essential community resource—at educational institutions is lacking. We hypothesized that K-12 schools in California with lower percentages of socioeconomically disadvantaged students were more likely to adopt solar PV systems than schools serving higher percentages of disadvantaged students. To investigate this hypothesis, our study used a machine learning pipeline to identify solar PV installations from satellite and aerial imagery for all of California's public K-12 schools. Notably, we found a majority (55% or 5,503 out of 9,996 schools) of schools adopted solar in California, which was higher than any previous reporting. However, solar adoption is uneven: schools with 10% or less socioeconomically disadvantaged students exhibit much higher solar adoption percentages (69-73%) compared to those with over 90% disadvantaged students having much lower percentages (46%). Rural, forested Northern California counties, which also suffer from more frequent and prolonged power outages, also were associated with lower rates of solar adoption. We created an open-source interactive dashboard to help policymakers, school communities, and others understand K-12 solar PV adoption patterns and promote future policy interventions to support widespread solar adoption.

INTRODUCTION

California is confronted with growing vulnerability to climate change: unprecedented wildfires, severe droughts, and rolling blackouts have underscored the state's recent climate-fueled extreme events. In response, California is committed to building a clean electricity system that promotes energy resilience and cost reduction to achieve net-zero carbon emissions by 2045 (1). The potential for widescale solar photovoltaic (PV) deployment to help build a clean and resilient system is vast, particularly in educational institutions. A lack of available land area is a major constraint for solar infrastructure; however, educational institutions, which account for 14% of total U.S. commercial building footprints, could be a solution for this problem as they offer optimal conditions for solar infrastructure (2). Moreover, opportunities for solar PV systems in educational institutions nationwide is substantial. Projections find that for these institutions PV installations can satisfy 75% of building-level electricity

demand, equating to approximately 100TWh of electricity generation on a yearly basis, which is particularly relevant for high-solar irradiance and high-electricity consumption states like California, Florida, and Texas (3). California has the most public K-12 schools in the U.S., with nearly 10,000 schools as of 2025 (4). Recognizing this potential, California has supported solar initiatives in educational settings through funding mechanisms such as Proposition 39, which allocated over \$1.7 billion for energy efficiency and renewable energy projects, \$371 million of which went to schools from 2013 to 2021 (5).

California has recently scaled back its solar incentives, lowering the valuation for exported solar generation and reducing support for community solar programs. Recent changes under California's Net Billing Tariff (NEM 3.0) are likely having an impact on school solar adoption. Any solar project started after April 15, 2023 experienced a nearly 75% reduction in the financial value of exported solar under this revised net metering framework (6). Additionally, Governor Newsom vetoed Senate Bill 1374 in September of 2024 which would have enabled schools and multifamily properties to benefit from solar-generated electricity credits comparable to single-family homes (7). These changes have slowed solar deployments statewide, raising pressing questions about the future of solar PV distribution.

Previous research highlights that solar PV adoption and its associated benefits have not been equitably distributed. For instance, residential PV adoption across California consistently demonstrates significant disparities linked to socioeconomic, health, environmental, and demographic factors, underscoring the necessity of targeted equity-focused policies (8). Similarly, research indicates lower adoption rates of solar PV in disadvantaged communities across various non-residential sectors (educational, commercial, and governmental facilities) despite the considerable local and regional benefits of such projects (9). However, none of these studies have specifically addressed solar adoption disparities within K-12 educational institutions.

Knowing these large-scale changes are likely to influence the distribution of solar technology, we hypothesized that K-12 schools in California with lower percentages of socioeconomically disadvantaged students were more likely to adopt solar PV systems than schools serving higher percentages of disadvantaged students. To test our hypothesis, we analyzed solar detection and segmentation in relation to socioeconomic status. In the first stage, we utilized DeepSolar, a machine-learning framework developed at the Stanford Sustainable Systems Lab, to analyze satellite imagery to detect and locate solar panels across

all K-12 schools in California based on their Geographic Information System (GIS) locations (10). In the second stage, we performed spatial analysis of socioeconomic data and K-12 school solar deployment from stage 1 to analyze the disparities in solar deployment across California K-12 schools. This method expands the literature by introducing a unified pipeline designed to detect and also explain the presence of PV systems. Additionally, by using detailed polygon boundaries rather than simple coordinate matches, our geospatial data collection and pre-processing aim to provide more accurate campus footprints. Our study found that a majority (55%) of California K-12 schools adopted solar, yet distribution remains uneven. Schools serving 90% or more disadvantaged students has almost 30% fewer adoption than schools serving 10% of less disadvantaged students. This research produces community-level impacts that can guide future work and policy interventions. It highlights where clean energy access is lagging and supports more informed decision-making for school districts, utilities, and state policymakers. By identifying which communities face the greatest barriers to solar PV adoption, future studies could build on this geospatial and equity analysis by adding qualitative interviews to understand meta-level engagement, like community opinion and policy design.

RESULTS

In this study, we investigated PV system adoption among 9,996 public and charter K-12 schools across California to understand geographic and socioeconomic disparities in access to renewable energy. We obtained GIS data on school locations from the California State Department of Education (11). To classify schools according to their solar installation status, we retrieved high-resolution satellite imagery using the Google Maps Static API and analyzed these images with the DeepSolar framework. Our analysis identified 5,503 schools (55%) with installed PV systems and 4,493 schools (45%) without PV. Additionally, to communicate our findings to the public, we developed an interactive ArcGIS StoryMap illustrating the geographic distribution of schools with and without solar installations (12) (**Figure 1a**).

Our analysis identified notable regional differences in solar adoption rates. Counties with higher median household incomes, calculated using census data of households within the county, such as Contra Costa, Santa Clara, and Alameda, exhibited greater adoption rates (88%, 81%, and 73%, respectively). In contrast, rural counties, defined based on descriptive geographic characteristics consistent with state and federal classifications, including Alpine, Del Norte, Modoc, Mono, Plumas, and Sierra, had no detectable school solar PV installation (**Figure 1b**).

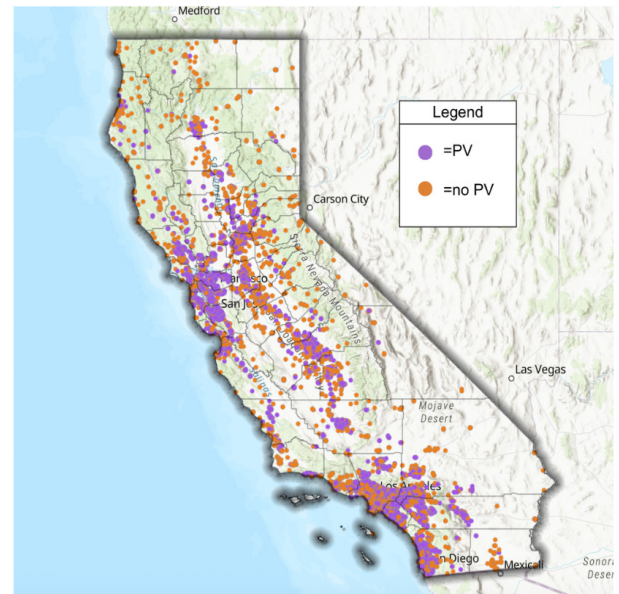
We also found that schools serving fewer socioeconomically disadvantaged students had higher solar adoption rates. Schools in the least disadvantaged group (0–10% of students disadvantaged) had a 73% PV adoption percentage, whereas those in the most disadvantaged group (90–100%) had only a 46% adoption percentage. The most notable drop in adoption occurred for schools with 30–40% and 40–50% disadvantaged students (**Figure 2**). This pattern suggests a critical socioeconomic tipping point where resource limitations substantially restrict schools' ability to

invest in renewable energy infrastructure.

DISCUSSION

Although previous studies have employed methods for detecting PV in imagery or analyzing socio-economic

A.



B.

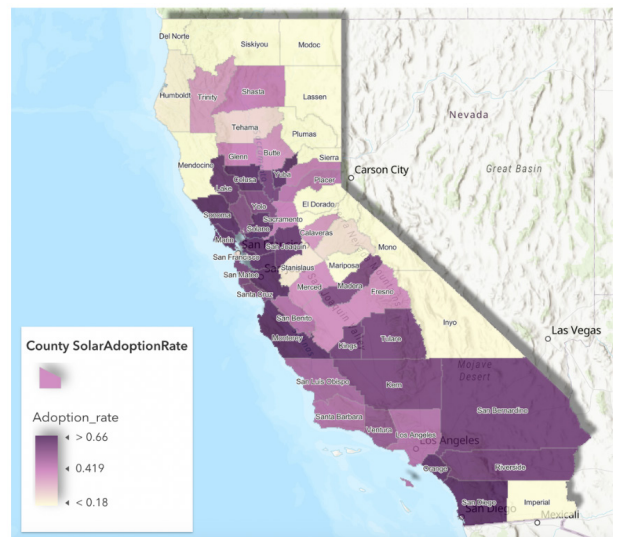


Figure 1: Geographic distribution of PV system installations across California schools. Panel A with 5503 purple dots represent schools with installed PV systems, while 4493 orange dots indicate schools without solar installations. Individual pinpointing provides exact geographic information and yes/no indications, revealing clustering patterns. Panel B illustrates the proportion of schools with PV systems installed, aggregated by county. Darker purple shades indicate higher adoption rates, while lighter yellow shades indicate lower rates, highlighting geographic disparities in school solar installations statewide. County adoption rates were calculated by dividing the number of schools with solar installations by the total number of K-12 schools in each county. Data compiled from satellite imagery analysis using DeepSolar and California Department of Education school records. See the corresponding interactive ArcGIS Storymap: <https://storymaps.arcgis.com/stories/e88be1e2c5ef14cf18a283dc4b041573b> to explore further.

indicators, our work integrates these stages into a unified pipeline designed to detect and explain the presence of PV systems. Our investigation revealed considerable disparities in solar PV system adoption among California K-12 public schools, confirming our hypothesis that schools serving more disadvantaged students demonstrate a lower rate of solar PV adoption. We also found that 5,503 schools (55%) have installed solar energy systems, which marks a substantial increase from the 2,926 schools reported in the Generation 180 2022 study, which evaluated schools that self-reported having solar systems (13). We believe the higher adoption rate identified in our study reflects a more accurate assessment of the solar adoption landscape. By using detailed polygon boundaries rather than simple coordinate matches, our geospatial data collection and pre-processing aim to provide more accurate campus footprints. Because our method does not rely on self-reported participation, it is less susceptible to sampling bias and can capture non-publicized systems. Our algorithm achieved approximately 93% overall accuracy with a precision rate of 91% when detecting PV systems from aerial imagery, with most errors being false negatives. Among the 55% of schools that have solar, schools in disadvantaged communities make up only 30.2%. Despite these advancements and California’s investment of over \$1.7 billion in school energy efficiency and clean energy projects through Proposition 39, 45% of K-12 schools still lack solar installations following the expiration of that proposition in 2021 and subsequent reductions in solar incentives.

This disparity in school solar installation rates is particularly pronounced in areas that serve more socioeconomically disadvantaged students and rural communities—areas that are also prone to frequent and prolonged power outages, especially in Northern California. When correlating school solar installations with outage durations, we found that rural, forested northern counties have experienced especially prolonged outages (14). These counties, served by Pacific Gas & Electric, show low rates of school solar adoption in our study (Figure 1b). The inequitable distribution of school solar adoptions and the critical role schools play in grid resilience emphasize the urgent need for new state legislation and unified utility backing to support solar deployment in California K-12 schools. Addressing this gap is particularly important for California’s ongoing energy resilience efforts, which underscores the impact of our research.

Given the expiration of Proposition 39 and the decline in state-level solar incentives post-2021, there is an urgent policy gap. Without renewed and equity-oriented funding mechanisms, schools in the communities most in need of clean and resilient energy infrastructure may continue to be left behind. Our findings raise important questions regarding the equity of solar PV adoption across California’s K-12 schools, and the potential they have in bolstering community resilience. How can the most disadvantaged areas be included in legislative dialogue? How can partnerships with community organizations help facilitate resources and engagement in schools with low adoption rates? Addressing these questions will guide future initiatives and help advance equitable access to renewable energy technologies for all schools.

From a climate change perspective, focusing on accuracy in detecting PV installations is important because it improves

our understanding of where solar resources are already deployed and where further adoption could be targeted. More precise identification and mapping of PV systems could inform policymaking, ensuring that resources and incentives are directed where they have the greatest potential impact.

Future research could involve qualitative assessments to reveal the nuances of local policies, school district funding, and community engagement and their impact on renewable energy projects, since all factors play a crucial role in influencing solar adoption. Although our dataset is extensive and captures quantitative correlations between solar PV adoption, geography, and socioeconomic status, qualitative methods, like case-study interviews with school administrators and stakeholders in disadvantaged communities, can provide deeper insights into barriers faced by schools lacking solar installations. Additionally, future research could use multivariate analysis, such as regression modeling, to investigate the correlation between specific socioeconomic variables and the likelihood for schools to adopt solar. Unlike our descriptive analysis, regression modeling would allow researchers to control for multiple variables to provide a deeper understanding of which factors most strongly influence solar adoption.

In conclusion, while our research demonstrates promising strides in solar adoption in California’s K-12 schools, it also highlights critical gaps that must be addressed. With climbing utility rates across California – with some rate hikes over 13% – solar PV systems can help alleviate the pressure on school budgets by substantially reducing costs (15). Among the California schools that have adopted solar projects, large districts have reported annual savings averaging \$500,000, while smaller districts have saved around \$200,000 each year (16). Beyond cost savings, these infrastructure systems also allow schools to become living laboratories for students to be engaged in Science, Technology, Engineering, and Mathematics (STEM) and expand climate-conscious education. The striking differences in adoption rates based on socioeconomic status and geographical area point to systemic

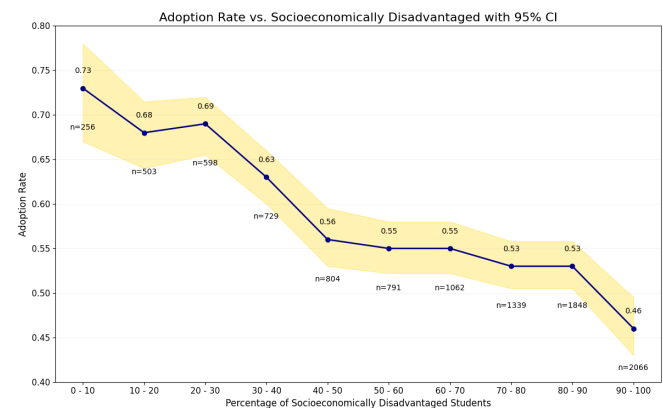


Figure 2: Adoption rate of PV systems at California schools versus the percentage of socioeconomically disadvantaged students. The adoption rate decreases as the proportion of socioeconomically disadvantaged students increases, highlighting disparities in solar energy adoption. Each point represents the mean adoption rate within a decile of socioeconomic disadvantage, with the shaded region indicating the range between the 2.5 percentile and 97.5 percentile.

inequities that require a focused effort from legislators and community stakeholders to ensure all schools access the benefits of clean, affordable energy.

MATERIALS AND METHODS

We implemented an approach that combines geospatial data processing, machine-learning-based image classification, and socioeconomic analysis to assess the factors influencing solar PV adoption on school campuses. We compiled our dataset from several sources: the California School Campus Database (CSCD) by Stanford’s GreenInfo Network (2021), Google Maps Static API (2025), and the California Schools 2023-2024 dataset from the California State Department of Education (data resolution and coverage may vary by variable) (17) (18) (19). The final dataset spanned 9,996 schools across California, providing a broad basis for the statistical evaluation of solar adoption factors.

We read and harmonized the positional information of schools, represented as polygonal boundaries of the schools’ property into a geodatabase, with an external database containing latitude–longitude coordinates of each school. We then combine these polygons with the school coordinates by matching a unique identifier (County-District-School (CDS) Code). If no exact CDS code match was found, we performed a point-in-polygon check, where the latitude–longitude point was tested against all polygons in the geodatabase to see if it lay within the boundary of a single school site. This integrated, “surgical” approach helps ensure that accurate boundaries or approximate areas of interest are identified for subsequent image downloads and can be applied to other building footprints or land uses to support further climate-related analyses. A brief graphical overview of our geospatial data collection and preprocessing approach is provided in **Figure 3**.

Once the geographic area for each school was determined, we retrieved high-resolution satellite images (zoom level 20 at 400×400 pixels) from Google Maps Static API (18). Image acquisition occurred across two months, from December 2024 to January 2025, ensuring all schools were analyzed using temporally consistent imagery. Over 500,000 of these school parcel images were retrieved and used in this research. Image retrieval examples and the tiling process based on our bounding-box approach is displayed in **Figure 4**. Each tile was classified using a Vision Transformer (ViT) architecture with the DeepSolar tool. DeepSolar uses transfer learning to train a convolutional neural network (CNN) classifier with simple image-level labels (positive or negative) to identify whether panels are present (**Figure 5**). It uses greedy layer-wise training to process clear boundaries of solar panels to help with identification and generation of the activation map, where we applied a threshold of 50% probability of solar presence. We then aggregated the tile-level predictions at the school level: if any tile for a given school was classified as having PV, the entire school was labeled “PV”. In contrast, if no tile exhibited a positive signal, the school was labeled “no PV”.

We merged the derived PV status with a table of social and economic attributes such as enrollment size, demographic composition, financial resources, and local political representation to evaluate socioeconomic patterns.

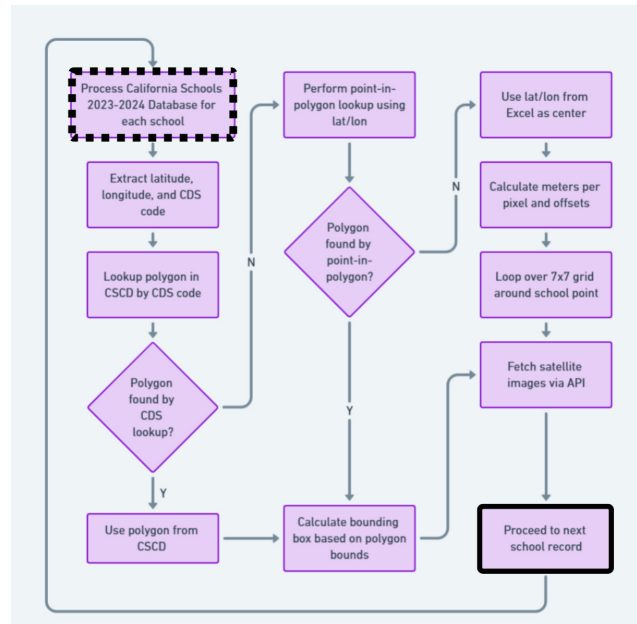


Figure 3: School polygon and tile lookup process. The flowchart, ordered in dotted box to solid box, details the first step in our three-step methodology for identifying and extracting school boundary polygons and corresponding satellite imagery tiles using the California Schools 2023-2024 Database. Procedures include initial latitude/longitude extraction, polygon identification through California School Campus Database (CSCD) or California Department of Community Services (CDS) lookup or GIS-based point-in-polygon analysis, bounding-box determination, and satellite imagery retrieval via a grid-based API query.

We classified students as being socioeconomically disadvantaged according to the California Department of Education’s official definition, which includes eight qualifying



Figure 4: Tiling examples. Shown are sample outputs from the geospatial data preprocessing pipeline. Only images (tiles) intersecting the school’s assessor parcel are requested and subsequently fed into DeepSolar for PV classification, all of which were classified as positive. The methodology involved GIS-based polygon bounding and satellite image API retrieval.

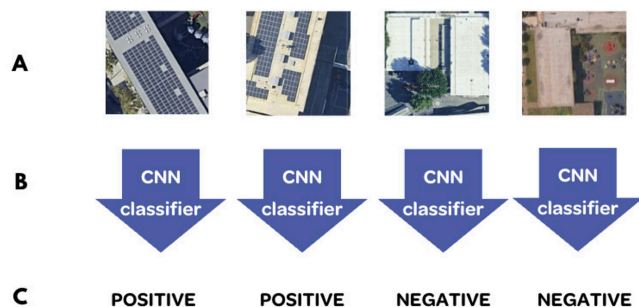


Figure 5: Example output of the DeepSolar model's panel detection. The algorithm's activation map highlights regions of the satellite image likely to contain PV panels (those exceeding the 50% probability threshold for solar presence). In this example, the identified tiles indicate that the school site would be classified as having PV installed.

criteria such as eligibility for free or reduced-price meals, homelessness, foster youth status, and other factors (20). This classification system, used across state accountability reports, provides the most standardized measure to evaluate equity when investigating California's K-12 schools. School demographic and socioeconomic datasets were compiled from the California State Department of Education's 2024–2025 dataset, which was last updated September 19, 2024 (21). This information, being the most recently updated socioeconomic data on California schools, aligns closely with the timing of the GIS images acquired from Google Maps Static API, minimizing potential discrepancies that could arise from mismatched timeframes. We then computed descriptive statistics (mean, median, standard deviation, and range) for schools with PV vs. without PV. This approach identified patterns among socio-economic indicators in a cross-sectional setting but can also be expanded to more rigorous causal inference procedures if longitudinal data become available.

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