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Inequitable access to distributed energy resources due to grid infrastructure limits in California

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Persistent social disparities in the adoption of distributed energy resources (DERs) have prompted calls for enabling more equitable uptake. However, there are indications that limits inherent to grid infrastructure may hinder DER adoption. In this study we analysed grid limits to new DER integration across California's two largest utility territories. We found that grid limits reduce access to solar photovoltaics to less than half of households served by these two utilities, and may hinder California's electric vehicle adoption and residential load electrification goals. We connected these results to demographic characteristics and found that grid limits also exacerbate existing inequities: households in increasingly Black-identifying and disadvantaged census block groups have disproportionately less access to new solar photovoltaic capacity based on circuit hosting capacity. Our results illuminate the need for equity goals to be an input in the design of policies for prioritizing grid upgrades.

Electricity systems are undergoing the most fundamental shifts since their inception. As with any transition, benefits and burdens may fall unequally, and some may be left behind[1,2]. A growing body of literature has documented persistent social disparities in customer adoption of distributed energy resources (DERs), with a particular focus on behind-the-meter solar photovoltaic (PV) systems. Residential PV adoption patterns have perpetuated financial[3–5], racial[6] and cumulative[7] inequities, even beyond those stemming from the typical requirements of owner-occupied households with favourable site characteristics[8–10]. In response, federal and state programmes intended to support more equitable uptake have emerged[3,6,11].

The distribution grid's ability to accommodate new PV systems depends on where and how they interconnects[12–14]. As deployment increases, grid limits will hinder new connections, leading to costly project delays[15–17] or interconnection denials[18], and/or necessitate circuit upgrades[19,20]. As we near the limits of DER deployment that the existing distribution equipment can accommodate, policymakers and regulators will need to establish criteria for which grid upgrades are worth increasing customer rates. If grid limits are not considered, further inequities may emerge.

To our knowledge, no systematic analyses have yet considered how equitably the existing grid can accommodate DERs. Studies of equity in PV deployment have focused on previous or existing adoption[4–7], rather than what the future may hold. Researchers evaluating grid capacity for DERs have focused on technical circuit models or isolated case studies rather than full electric grids, and have not considered customer demographics[14,21–25]. There is, therefore, a gap in our understanding of how grid limits within and across utility territories may impact future DER deployment, and the potential implications for equity and access to DERs. We do not ascribe causation to lower hosting capacity in certain communities. Rather, we strive to document disparities so that future policies do not exacerbate patterns of inequity and may even improve the state of affairs.

In this study we investigated the magnitude and distribution of electric grid constraints for DERs on circuits operated by California's two largest investor-owned utilities (IOUs), Pacific Gas and Electric (PG&E) and Southern California Edison (SCE), which together serve over 30 million people. We focused on identifying where constraints may limit DER growth and asked whether they may differentially impact demographic groups. We found that the distribution grid restrains households' ability to adopt DERs across these two IOU territories, and that hosting capacity is unevenly distributed. When all grid constraints were considered, we found that over half of residential households served by PG&E and SCE (57 and 59%, respectively) lack adequate hosting capacity for 4.5 kW of solar PV, the amount required to offset 100% of their annual electricity consumption, on average. In PG&E's territory, 39% of households lack access to even the least power-intensive new loads (space and water heating or level 1 electric vehicle (EV) charging), while 64% lack access to level 2 EV charging. Notably, hosting capacity for DERs decreases for households in increasingly Black-identifying and disadvantaged communities. Correlations between hosting capacity and race are the starkest among a variety of demographic indicators analysed, including those relating to income, housing characteristics and education. We do not make causal claims but seek to illuminate important correlations that exist in the data, which here include disparate access to grid resources falling along lines of race. This work points to the need for grid planners everywhere to analyse the equity of electrical capacity for DER adoption and demonstrates a way to do this. Such an analysis should be an input to planned grid upgrades so that the grid itself does not become a limitation to equitable DER uptake in the future.

Growth in DERs raises issues for equity and the grid

We were motivated here by two separate and robust sets of findings in the literature: that there exist inequities in DER adoption and that the electric distribution grid itself imposes limits on where DERs can interconnect. We considered how grid limits may impede continued DER deployment and assessed how they overlap with customer demographics. In doing so, we have built on the existing literature by (1) considering the importance of technical grid limits, which have largely been ignored in previous work on equity in DER adoption, and (2) using those grid constraints to consider the future equities of DER deployment, whereas others have focused on existing adoption.

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A rich literature has emerged concerning the inequities of solar PV adoption. Despite similar motivations for adopting solar[26], low- and moderate-income (LMI) communities experience disproportionately low PV penetration rates[3–5], even where there is relatively high potential for solar[3]. While policies designed to foster more equitable uptake have made a difference[11] and middle-income households have slowly increased their relative share of PV[4], low- and moderate-income households still lag behind.

Minority households are disproportionately vulnerable to energy poverty in the United States[27]. Yet PV adoption, which can reduce household electricity bills, skews to white-majority census tracts[6]. When multiple inequities are considered, persistently lower adoption is found in disadvantaged communities[7], as measured by the metrics in California's CalEnviroScreen indicator, which was developed to reflect the cumulative impact of environmental, socioeconomic and public health stresses[28].

Socioeconomic factors have also been found to influence EV adoption[29]. Yet just as the electric grid is a necessary enabling resource for DERs, public charging is an enabling technical resource for EV ownership, and public charging access is less widespread in low-income and minority communities[30].

To date DER deployment has perpetuated social inequities, and in the future, electric grid limits may constrain DER growth. Electric power systems in the United States were designed to rely on centralized power sources, but DERs, such as solar PV and EVs, now contribute growing shares of electricity supply and demand. Well-sited DERs can defer capacity upgrades[14], boost sagging line voltages, and reduce power losses[31]. However, DERs can also disrupt circuit protection schemes, increase thermal loading, cause overvoltages and create dangerous islanding conditions[32,33].

These grid impacts arise from increased current flow beyond what local equipment can handle. They may be avoided if both generation and load DERs are sited in the same location and their operation is synchronized in time; however, even if they complement each other on average, operating variations due to customer behaviour and weather will necessitate storage or demand response to fully defer system constraints. As these technologies are not mandated in California today, we have left this nuance to follow-on work and focused here on where DERs may connect to distribution circuits without necessitating complementary technologies.

The hosting capacity is the allowable capacity of DERs that an electric circuit can accommodate without upgrades. Calculating hosting capacity is not straightforward and several methodologies have emerged[34–36]. They differ in which circuit constraints are considered and which numerical methods are used to calculate violations (see Supplementary Note 1 for details). In California, hosting capacity information is available through Integration Capacity Analysis (ICA) maps, which also include data on existing distributed generation[37,38] (Supplementary Note 2). Hosting capacity values include the additional PV and load capacities that can be connected to a line segment without violating thermal, power quality/voltage or protection constraints[37]. PV capacity is reported with operational flexibility (OpFlex; in which case reverse power flow is not allowed beyond the substation bus) and without OpFlex (in which case reverse flow is allowed) constraints[37].

In this study we assessed how grid constraints may impact the equity of DER access. California offers a ripe case study of the implications of employing DERs to expand clean energy capacity. Aggressive policies and a responsive market have helped California lead the nation in PV capacity and EV adoption (Supplementary Note 3). Behind-the-meter PV comprised almost 30% of the state's solar PV capacity at the end of 2019[39], and is expected to remain a major category of renewables deployment due to a diversity of supporting policies[40,41]. Substantial economic benefits are available to California households that adopt rooftop solar[42]. In this context, disparate rates of access (whether due to structural or grid limits) are important, and we assessed here the extent to which making access to renewable energy specific to the location of one's home and the circuit to which it is connected may strain California's access and equity goals.

Despite documented inequities in current deployment, all ratepayers currently pay for the grid upgrades necessary to accommodate projected DER growth. Upgrade decisions have been based in part on historic deployment patterns, and SCE estimates that it will cost US$14–44 million annually from 2021 to 2023 to reinforce its circuits for DERs[43].

In California, small DERs have so far been allowed to bypass interconnection study requirements[19]. However, state regulators have indicated that hosting capacity values may be considered in future DER interconnection rules to avoid violating location-specific penetration limits[37,38,44]. Future grid upgrades with socialized costs, therefore, are not a guarantee. Policies that seek to address inequities in DER deployment will need to consider the limits imposed by the electric grid as it exists today, or investments associated with upgrading it.

Grid limits reduce access to DERs across utility territories

We calculated the proportion of households with DER access at deployment thresholds in the range 1.5–10.0 kW per household to account for varying capacity estimates for PV and load DERs (see Methods), for each DER type and for each census block group (CBG) within each utility territory (see Eqs. (14) and (15) in Methods). We found that per-household hosting capacity for load and generation DERs (Supplementary Note 4) varies widely across the PG&E and SCE service territories (Fig. 1 and Extended Data Figs. 1–3). We present the results for household access within each full utility territory and summary statistics by CBG in Figs. 2 and 3 (see Supplementary Tables 1–3 and Supplementary Figs. 1 and 2 for selected values and full results). The PG&E results pertain only to those sections of the territory with ICA data.

We found that the constraints on distributed generation limit how much PV can be deployed on distribution circuits in California. Due to thermal, power quality and protection grid constraints, 31 and 25% of households in the PG&E and SCE territories, respectively, lack access to 4.5 kW of behind-the-meter PV (which is, on average, enough to balance 100% of annual electricity usage). These values consider both the existing generation already deployed on circuit lines as well as remaining hosting capacity. With OpFlex constraints, substantially more households, approximately 57 and 59% served by PG&E and SCE, respectively, lack access to 4.5 kW of rooftop PV. Therefore, under current grid conditions, sufficient capacity exists for less than half of households to adopt PV.

These numbers are highly sensitive to the deployment threshold used (Fig. 2). More households can adopt smaller PV sizes, although 23% (16% if OpFlex constraints are disregarded) in both territories still lack access to even 1.5 kW. At 10 kW, 78 and 79% of PG&E and SCE households, respectively, lack access (49 and 38% if OpFlex constraints are disregarded).

Fewer households can adopt PV if only remaining hosting capacity is considered. Approximately 77 and 70% of households served by PG&E and SCE, respectively, then lack access to solar (41 and 30% if OpFlex constraints are disregarded). This observation illustrates a tension around equitable deployment: if grid capacity is occupied by early adopters, efforts to improve equity in PV adoption may be caught in a race with continuing adoption among already well-represented demographic groups for the circuit hosting capacity that remains.

Physical building suitability may further reduce household access: based on data generated by previous researchers[9,10], we estimate that approximately 15% of small buildings in PG&E's territory and 9% in SCE's territory cannot host 1.5 kW of PV (Fig. 3). When combined with grid limits, the proportion of households lacking

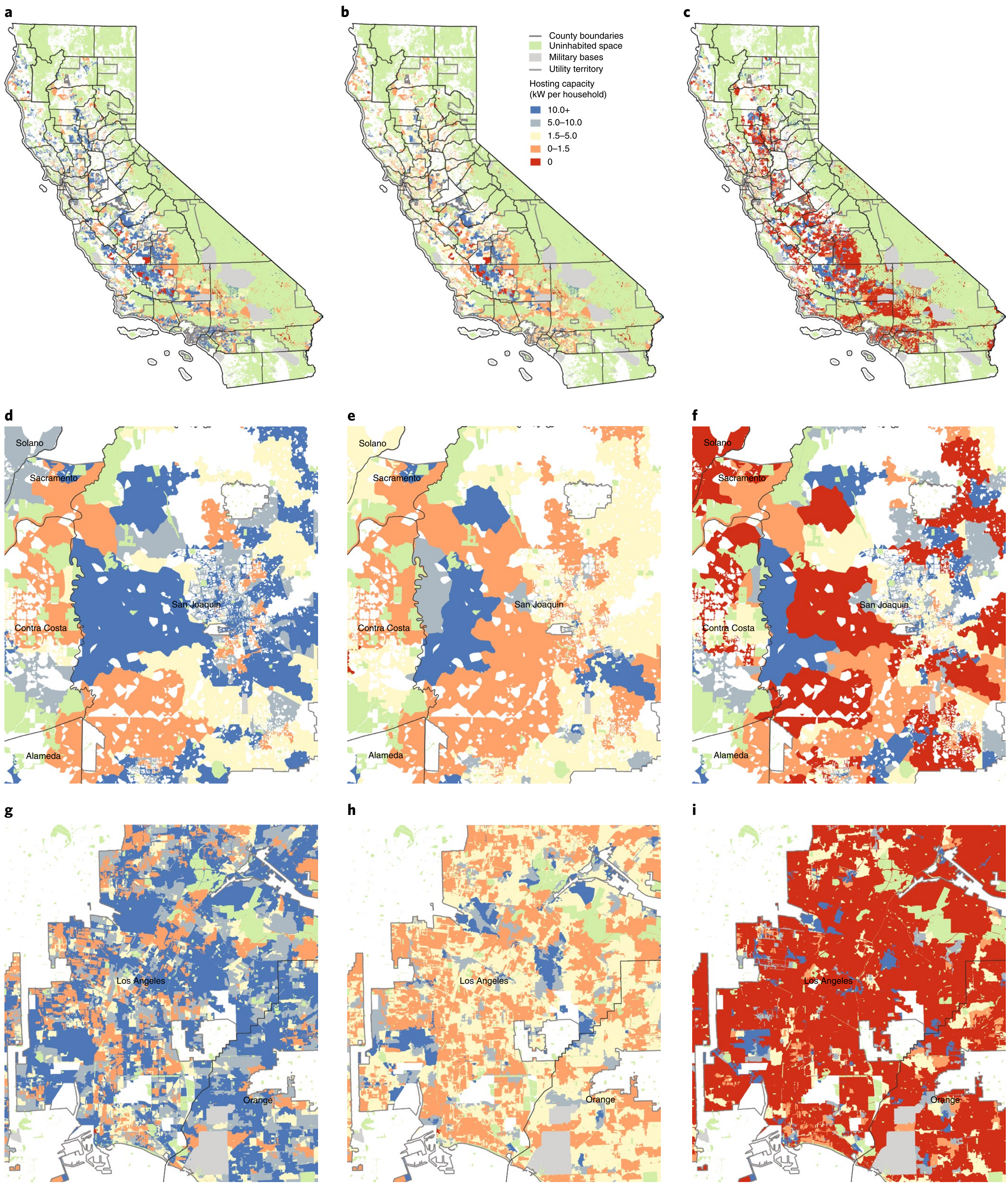

Fig. 1 | Household access varies by DER type and location. a–i, Per-household hosting capacity for PV (**a**,**d**,**g**), PV with OpFlex (**b**,**e**,**h**) and load (**c**,**f**,**i**) across the PG&E and SCE service territories (**a–c**), a portion of PG&E's service territory, including parts of San Joaquin County (and the city of Stockton; **d–f**), and a portion of SCE's service territory, including parts of Los Angeles and Orange counties (**g–i**). The code for the different colours and lines shown in all the maps is given in **b**. White areas indicate regions served by other utilities or, within PG&E's territory, locations with no ICA data. High-resolution versions of these maps are available in Extended Data Figs. 1–3 and at https://github.com/Energy-MAC/GridLimitsforDERs.

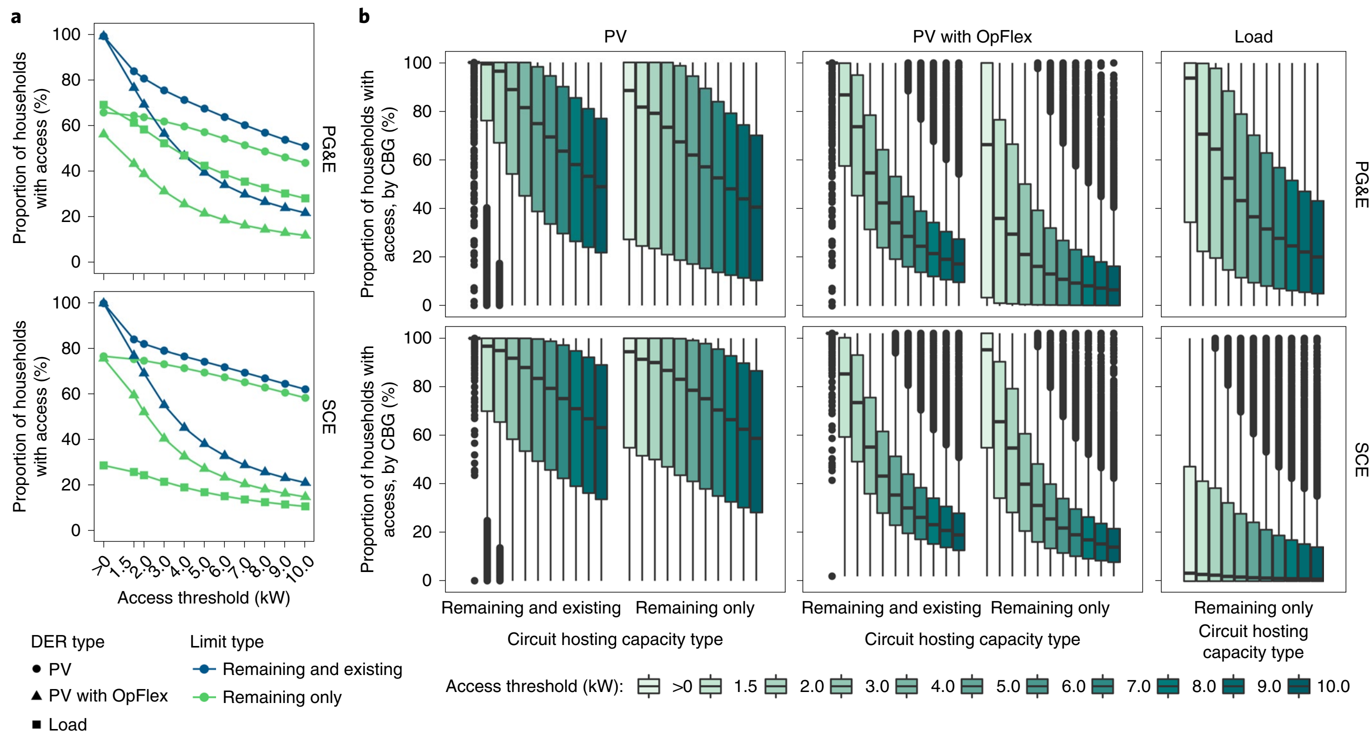

Fig. 2 | Results for household access to PV and load DERs. a, Access to PV and load DERs for all households within the PG&E and SCE utility territories. **b**, Boxplots showing hosting capacity at different access thresholds for each CBG included in the data. Each boxplot shown for PG&E represents 2.13 million households across 7,996 CBGs (this is less than the total number of households served by PG&E due to a lack of available ICA data for all circuits), and each boxplot shown for SCE represents 4.15 million households across 8,376 CBGs. All boxplots show the 25th, 50th and 75th percentiles of access results, with whiskers extending to the furthest point within 1.5 times the interquartile range. Further points are shown as outliers.

access to 1.5 kW of behind-the-meter PV increases, in PG&E's territory, from 16 to 27–30% under the worst- and best-case scenarios for combined suitability. In SCE's territory, the proportion of households lacking access increases from 16 to 23–25%. Similar declines in access occur for the OpFlex case.

We also found that constraints on load may challenge the adoption of EVs and electrification technologies. The grid may require upgrades to meet electrification goals and air-conditioning needs; otherwise, it could hinder climate change mitigation and adaptation[45] efforts in California. However, the extent to which load DERs will stress the distribution grid requires further research. While ICA maps show hosting capacity by circuit segment for generation and load, IOU circuit analyses have so far focused on generation. Load information, particularly in SCE's territory, may systematically underestimate circuit hosting capacity[46]. Moreover, existing load analyses are technology-agnostic and IOUs could improve data interpretability by including analyses of specific load DERs, including EVs, air conditioning and heat pumps for space and water heating, which all have time-varying use profiles.

Based on currently available load data, widespread adoption of even the least power-intensive applications could strain distribution grids. Using a 1.5 kW demand threshold to analyse access to space and water heaters (together 1.6 kW) and level 1 EV charging (1.4–1.9 kW), we estimate that 39 and 74% of households served by PG&E and SCE, respectively, lack sufficient grid capacity for either electrified heating or EV charging (Fig. 2a). In PG&E's territory, 64% of households lack the grid access to install a level 2 EV charger.

If households implement all the climate change mitigation strategies that we considered, namely the conversion of natural gas-powered space and water heaters to electric, EV level 2 charging and new air-conditioning units, hosting capacity will be severely limited (Fig. 2). Although the full extent of distribution grid impacts from increasing load is not yet known, it is clear that the grid cannot currently accommodate fully electric homes across the state.

Grid limits reinforce demographic disparities in DER access

Variations in access across utility territories prompted us to consider how hosting capacity may be correlated with variables related to infrastructure, service, geography and demographics (see Supplementary Tables 6–8 and Supplementary Note 9 for variable descriptions). We were particularly interested in whether differences in hosting capacity may reflect demographic variations. We constructed linear and non-linear models to understand which variables, if any, may correlate to per-household hosting capacity. The model results indicate that no single demographic feature dominates in relative importance over the rest (see Supplementary Note 5 and Supplementary Fig. 3 for a full discussion). However, we did find notable relationships between consumer demographics and access to circuit capacity. In examining these, we focused on the demographic categories discussed in prior literature on DER adoption.

First, we validated our approach by examining the relationships between demographic indicators and existing distributed generation, and found that our results broadly support previous findings. For race and ethnicity, we observed higher median levels of existing distributed generation per household in CBGs with more non-Latinx white- and Latinx-identifying populations than Black- or Asian-identifying populations (Fig. 4a). For CBGs with more Black- and Asian-identifying populations, very few households are represented at higher percentages, leading to wide confidence intervals and indefinite trends above approximately 50%. Existing generation per household also declines overall with increasing diversity in the population. For disadvantaged communities (as defined in CalEnviroscreen[28]), we found stronger correlations between

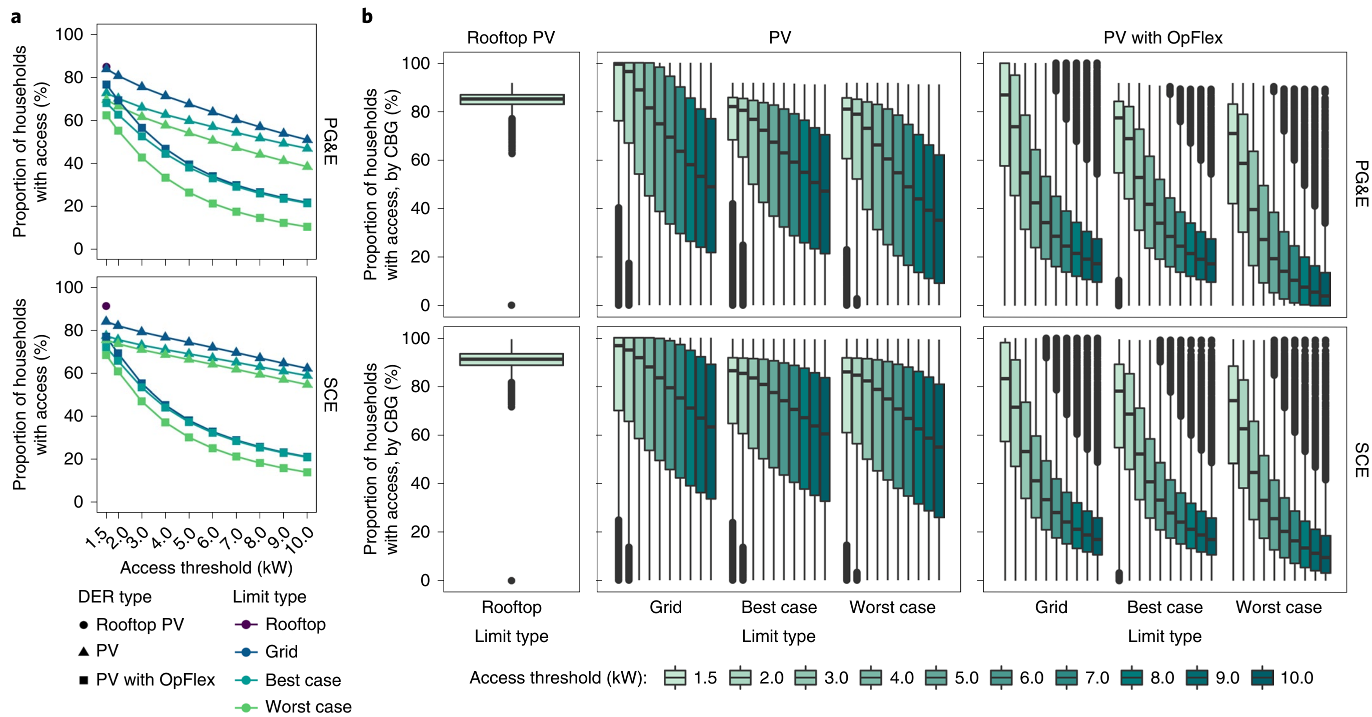

Fig. 3 | Results for household access to PV DERs considering grid (remaining plus existing capacity) and building suitability limits. a, Access to PV DERs for all households within the PG&E and SCE utility territories. **b**, Boxplots showing hosting capacity at different access thresholds for each CBG included in the data. Each boxplot shown for PG&E represents 2.13 million households across 7,996 CBGs (this is less than the total number of households served by PG&E due to a lack of available ICA data for all circuits), and each boxplot shown for SCE represents 4.15 million households across 8,376 CBGs. All boxplots show the 25th, 50th and 75th percentiles of access results, with whiskers extending to the furthest point within 1.5 times the interquartile range. Further points are shown as outliers. We note that building suitability estimates are available only for 1.5 kW PV systems[65]. The combined suitability at higher access thresholds (2–10 kW) was calculated assuming the higher threshold for grid limits, but still a 1.5 kW threshold for building suitability. This underestimates the contribution of building suitability to PV deployment limits at thresholds above 1.5 kW, while overestimating the proportion of households with access.

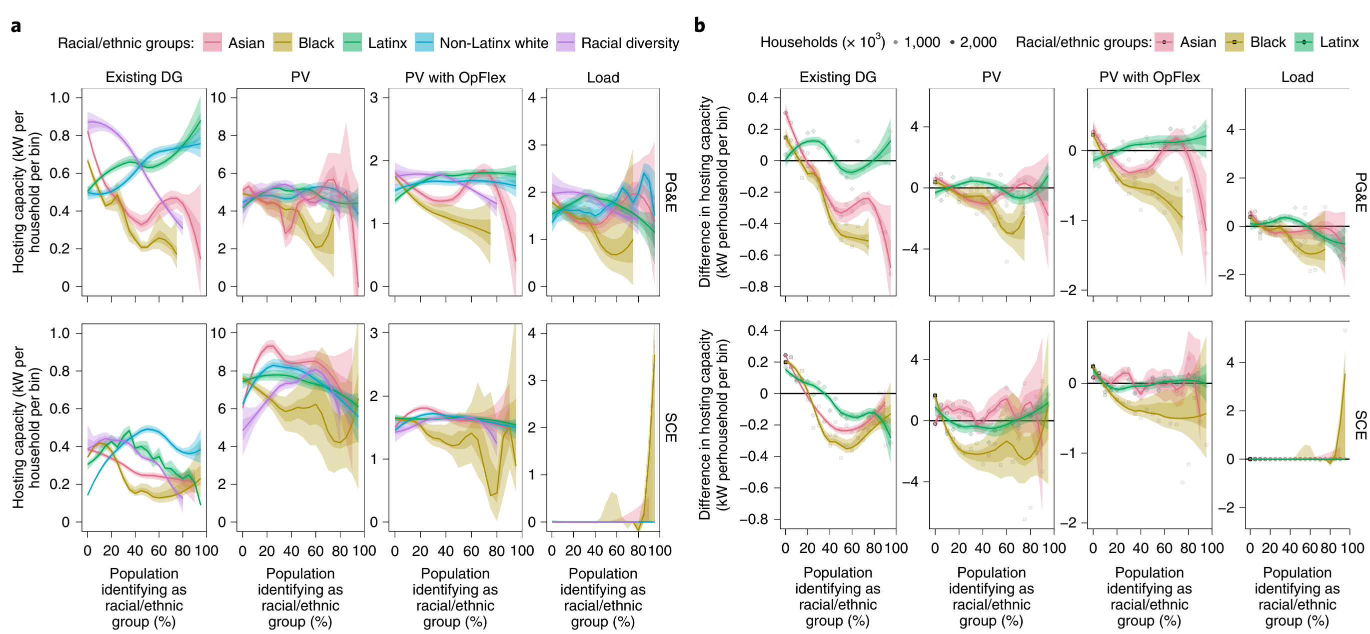

Fig. 4 | Hosting capacity results for race and ethnicity variables. a, Median existing generation or hosting capacity by race and ethnicity. **b**, Difference in median existing generation or hosting capacity between different racial and ethnic groups and the non-Latinx white population. The confidence intervals shown are 50% (darker band) and 90% (lighter band).

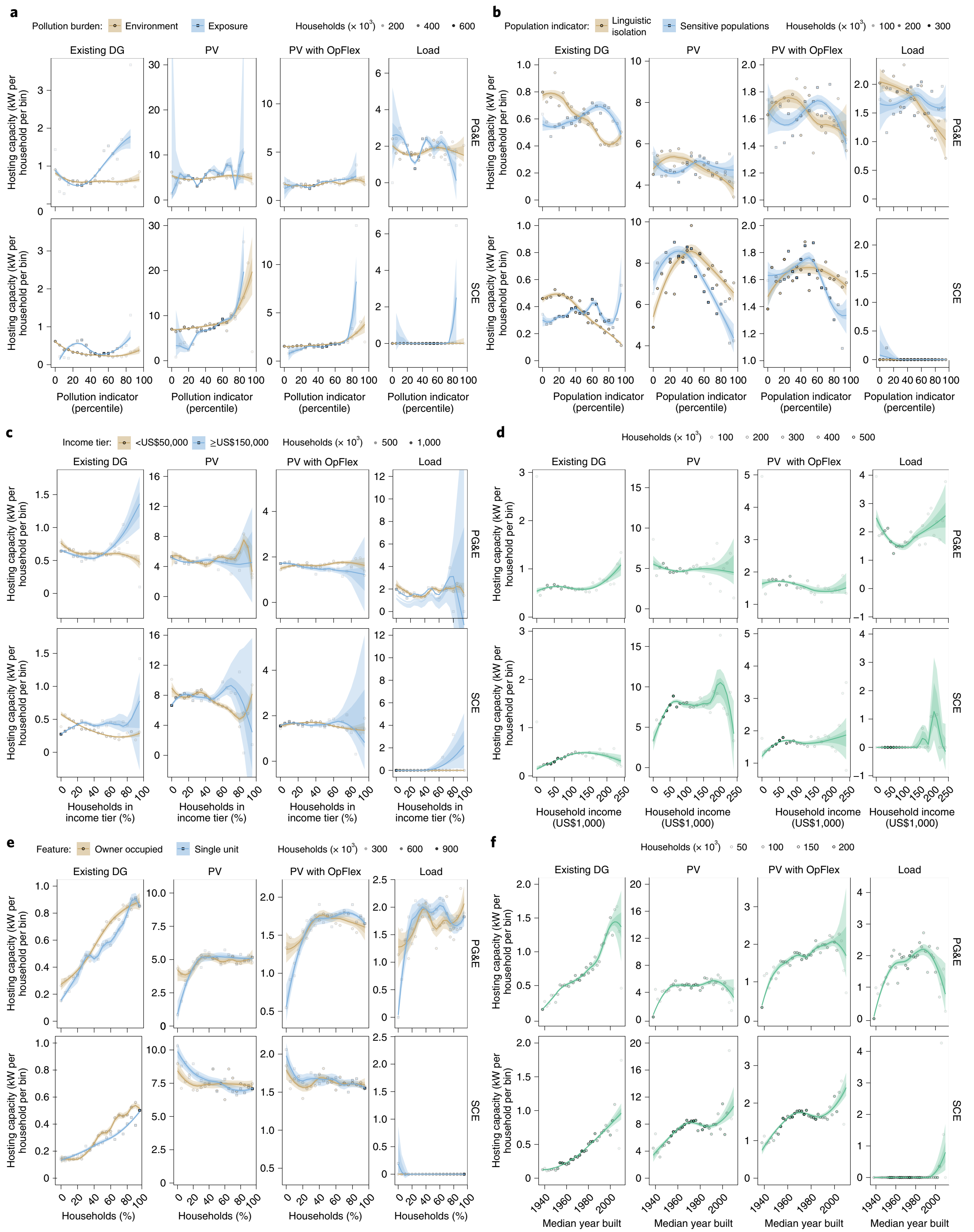

Fig. 5 | Hosting capacity for additional demographic variables. a,**b**, Median existing generation or hosting capacity for the CalEnviroScreen indicators of pollution (**a**) and population (**b**). **c**,**d**, Median existing generation or hosting capacity for income variables, analysing the proportions of the poorest and wealthiest households (**c**) and the median household income (**d**). **e**,**f**, Median existing generation or hosting capacity for housing characteristics, considering the proportions of single-unit and owner-occupied households (**e**) and median year of house build (**f**). The confidence intervals shown are 50% (darker band) and 90% (lighter band).

Table 1 | Independent variable groups for random forest regression and classification runs

Variable group	Description	Examples
(1) All	All variables included in any of the other three groups	–
(2) Infrastructure	Variables that describe characteristics of electricity infrastructure, sourced from PG&E and SCE directly	Nominal circuit voltage, circuit line lengths
(3) Service and geography	Variables that pertain to how electric infrastructure serves customers and the environmental conditions it is exposed to	Households per circuit polygon and kilometre of circuit length, number and percentage of residential customers served by each circuit, solar irradiance and heat metrics
(4) Demographic	Variables obtained from the American Community Survey[62] and CalEnviroScreen[28]	Percentage of population identifying as specific racial and ethnic groups and within specific income tiers, median household income, residential structure characteristics

A full list of variables in each category can be found in Supplementary Tables 6–8.

existing distributed generation and population metrics (measures of sensitive population and linguistic isolation, Fig. 5b) than pollution metrics (Fig. 5a; similar to Lukanov and Krieger[7]), most notably for the percentile of linguistic isolation in the population, which could reflect an information barrier to DER adoption. For income, our analysis supports previous findings that wealthier communities are more likely to have already installed DERs[4,5]. This effect broadly holds for the poorest and wealthiest CBGs (Fig. 5c), as well as the median household income (Fig. 5d), with some drop-off for data points representing fewer households. Finally, as expected for types of housing[8–10], existing generation capacity increases sharply with the percentage of owner-occupied and single-unit households, as well as with the median year of construction for residential housing (Fig. 5e,f).

Then, we extended our analysis to consider how total circuit hosting capacity for PV (existing plus remaining) and load (remaining capacity only, focusing on PG&E) correlates with these same demographic indicators.

With respect to race and ethnicity, we found that the total circuit capacity for generation decreases with increasing percentages of Black-identifying residents, and is disproportionately lower for CBGs with Black-identifying populations than for other racial and ethnic groups. Specifically, the trends in total circuit capacity for PV, with and without OpFlex constraints, show a notably lower capacity in Black-identifying CBGs than in non-Latinx white-, Latinx- and Asian-identifying CBGs for both utilities. To better see these differences, we plotted locally estimated scatterplot smoothing (LOESS) curves for the difference in median existing generation and hosting capacity between non-Latinx white-identifying population percentages and the other racial and ethnic groups (Fig. 4b). While the differences with Latinx- and Asian-identifying CBGs are small, the total circuit capacity is substantially lower for Black-identifying CBGs and largely decreases as Black-identifying percentages increase. This suggests that distribution circuits cannot currently support the same PV deployment, whether or not OpFlex constraints are active, in neighbourhoods with higher Black populations relative to other racial and ethnic groups. Circuit capacity values for remaining load are less interpretable (see the discussion above), but we see here that, in the PG&E territory, less circuit capacity is available with increasing percentages of Black-identifying residents than for other races.

Disadvantaged communities, as identified by the CalEnviroScreen sensitive and linguistically isolated population indicators[28], also experience inequitable circuit capacity for PV deployment. Some of the starkest trends occur for the population indicators: median generation hosting capacity decreases with sensitive populations above the 50–60th (for PG&E) and 30–50th (for SCE) percentiles, and decreases with linguistic isolation above the 20th (for PG&E) and 40th (for SCE) percentiles (Fig. 5b). The most disadvantaged populations in the state therefore face systematically lower circuit hosting capacity for PV. Opportunities for future DER deployment, especially of technologies that can shift electricity consumption patterns, such as solar plus storage, may be particularly salient for these communities[47], which tend to bear disproportionate local pollution impacts from California's natural gas peaker plants[48].

Income trends for circuit capacity are less consistent, suggesting that income variations are insufficient for explaining the relationships between circuit capacity and Black-identifying and disadvantaged communities. For the poorest households, the clearest trends are found in SCE's territory, where the hosting capacity for PV tends to decline slightly with increasing proportions of poor households. As the proportion of wealthy households increases, the total circuit capacity shows a slightly downward tendency in PG&E's territory, but stays relatively flat in SCE's territory (Fig. 5c). Above the 80th percentile, wide divergences in data are observed due to relatively few households falling into the highest-income bins. The circuit capacity for PV largely declines with median household income in PG&E's territory (excepting some values representing relatively few households in high-income brackets), but increases with median income up to approximately US$100,000 in SCE's territory (Fig. 5d). These mixed results suggest that the clearer trends for racial and ethnic groups and CalEnviroScreen population indicators are not driven by underlying income distributions.

Housing characteristics also show mixed results. The total circuit hosting capacity for generation and load tends to increase with single-unit and owner-occupied percentages in PG&E's territory, although plateauing earlier than for existing generation, while assuming the inverse trends in SCE's territory (Fig. 5e). For both utilities, the total circuit hosting capacity for generation tends to increase with year of construction (Fig. 5f); median housing age may correlate with the age of local grid infrastructure. In PG&E's territory, areas with the newest buildings have less hosting capacity than slightly older buildings.

Our key results are broadly consistent across both utility territories. The most notable differences between customers served by the two utilities pertain to the relative proportions of non-Latinx white- and Latinx-identifying populations, and residents' pollution exposure (Supplementary Fig. 6 and Supplementary Note 7). These demographic indicators do not show strong trends in our results.

This work enables us to consider where inequities may be exacerbated in the future. As net-metered solar frequently carries tangible benefits for its adopters, including an attractive economic proposition[42] and more stable electricity bills, these inequities run the risk of limiting its benefits along demographic lines.

Conclusions

Taken together, our results indicate that grid limits pose constraints for future DER deployment across utility territories and may exacerbate existing inequities related to DER adoption. With all grid constraints enforced, over half of households served by PG&E and SCE (57 and 59%, respectively) lack grid access to adopt sufficient PV to offset their annual electricity consumption, on average. If we consider only remaining circuit hosting capacity, up to three-quarters of households served by PG&E and SCE (77 and 70%, respectively) lack access. As existing PV adoption has tended to skew towards wealthier, whiter and less-disadvantaged households, these results raise concerns that the grid may hinder efforts to increase equity in DER adoption.

Grid capacity may also limit the amount of new load that can be added to residential distribution circuits through electrification programmes, EV adoption or increased air-conditioning demands. In PG&E's territory, 39% of households lack access to even the least power-intensive new loads (space and water heating or level 1 EV charging), while 64% lack access to level 2 EV charging. Household access results are sensitive to the size capacity of the DERs deployed per household and, for generation, to whether OpFlex constraints are enforced.

Furthermore, we have found important disparities in household access by demographic characteristics that are consistent with disparities in existing PV capacity. Median per-household circuit capacity for DERs is lower for CBGs with higher Black-identifying populations than other racial and ethnic groups, and decreases with rising proportions of Black-identifying residents. Grid capacity for DERs also decreases for more disadvantaged communities, as measured by the CalEnviroScreen sensitive and linguistically-isolated population indicators.

In this work we sought to document existing patterns in circuit hosting capacity and their potential impacts on access to DERs. Our primary aim was to illuminate these patterns for consideration in future grid planning and policy. However, we do offer two hypotheses about how the disparities we report could have come to pass. First, we know that circuit upgrades to accommodate DERs have already occurred, and are continuing to occur, on some circuits[43]. It is possible that those upgrades may have enabled excess hosting capacity beyond what was needed for the DERs that prompted them. If those upgrades have occurred in neighbourhoods that tend to be early adopters of DERs, that could have inadvertently led to more hosting capacity in areas populated by early adopters. Second, circuits designed for areas where additional housing development was expected to occur may have been built with excess capacity that could translate to more hosting capacity for DERs today. It is possible that these areas of projected housing expansion could correlate to certain demographic characteristics. Testing either of these hypotheses would require data that we do not have and that may not exist. Therefore, we offer these to share possible explanations for how social disparities in these engineered systems could have arisen, not to indicate how they did.

Notably, we have assessed the grid limits for generation and load DERs in isolation. If their operation is synchronized in time and space, these technologies could complement each other and reduce their impact on the grid. To accomplish this, policy requiring co-located storage or demand response would be required, and evaluating the potential impacts of this is a potential direction for future work.

To meet its decarbonization goals, the State of California will need to make tremendous investments in grid capacity, which will require both time and money to implement. Our results illuminate that current policy promoting site-specific distributed generation may face obstacles to equity from physical systems, including those that fall along racial lines. Enabling all distribution circuits in the state to host adequate DER capacity for desired generation and electrification needs will not happen simultaneously without massive investment in staff and resources. Currently, SCE prioritizes distribution circuits for upgrades that are intended to boost hosting capacity on the basis of projected DER deployment. Yet targeting grid investments could reduce existing inequities. For example, there is an opportunity to put at the front of the queue communities with historically low DER adoption rates who are served by distribution circuits with low available hosting capacity.

Remaining hosting capacity will decrease as more households adopt PV and EVs, electrify heating loads and opt to acquire or operate air conditioners, and electric distribution systems will draw closer to their limits, potentially creating obstacles to timely and equitable DER access. Nationwide and elsewhere, policymakers and regulators will increasingly confront grid limits as a barrier to renewable energy adoption. Evaluating the implications of these limits will be critical to reaching equity goals for the deployment of distributed energy resources.

Methods

Residential households are matched to distribution circuits. In this study we used recent advances in electric distribution grid data availability in the State of California. To begin, we matched residential customers to PG&E and SCE distribution circuits. Our goal was to estimate where residential utility customers live and which circuit lines provide them with electric service. Our analysis relied on two key assumptions. First, we assumed that residential customers are evenly distributed within the potentially inhabited areas of each CBG, which we estimated here to be those areas that are not protected open space (for example, parks or wilderness areas) or military bases. We also assumed, similar to a study included in California's Fourth Climate Change Assessment (CCCA4) report[49], that electricity customers are served by their nearest electric system equipment. Here, this means residential customers are grid-connected to the nearest distribution circuit segment.

All spatial processing was conducted in ArcGIS 10.6[50] in coordinate system NAD 1983 California Teale-Albers[51]. Starting with the CBGs[52], we erased areas that comprise protected open space[53,54] and military bases[55] to exclude them from consideration, leaving us with potentially inhabited land area. For each CBG, we calculated:

$$\mathrm{InhArea\_Wt}_i = \frac{\mathrm{InhArea}_i}{\mathrm{OrigArea}_i} \tag{1}$$

where $\mathrm{OrigArea}_i$ is the original area of block group i and $\mathrm{InhArea}_i$ is its potentially inhabited area (both in m^2), and $\mathrm{InhArea\_Wt}_i$ is the proportion of the original area that is potentially inhabited. Then, we clipped the potentially inhabited areas of the CBGs by the PG&E and SCE utility territory boundaries[56]. For each block group located fully or partially within each utility's territory, we calculated:

$$\mathrm{IOUarea\_Wt}_i = \frac{\mathrm{IOUarea}_i}{\mathrm{InhArea}_i} \tag{2}$$

where IOUarea is the portion of block group i's potentially inhabited area located within the IOU's territory (m^2; for example, Supplementary Fig. 4a), and $\mathrm{IOUarea\_Wt}_i$ is the portion of the potentially inhabited area that falls within the IOU's territory.

We then used the Euclidean Allocation tool of ArcGIS to assign 10 m^2 grid cells to their nearest one-, two- or three-phase circuit segment. (Using PG&E's feeder data[57] and SCE's customer type data[58], we excluded circuits that serve fewer than 1% residential customers.) We converted the raster output to simplified polygons to produce smooth boundaries. We obtained polygons that mimic a Voronoi tessellation, but are formed around line segments rather than point locations (for example, of substations, as in the CCCA4 study[49]).

Next, we performed a union of these circuit-segment polygons with the CBGs. We combined the resulting features by circuit name to create circuit polygons that describe spatial areas that are unique combinations of (1) the service area for a given circuit j and (2) a given CBG i. For each circuit polygon we calculated:

$$\mathrm{CpolyA\_Wt}_{ij} = \frac{\mathrm{CpolyA}_{ij}}{\mathrm{IOUarea}_i} \tag{3}$$

where CpolyA_{ij} is the area (m^2) served by circuit j within block group i and $\mathrm{CpolyA\_Wt}_{ij}$ is the portion of the block group's potentially inhabited area that circuit serves within the IOU's territory (Supplementary Fig. 4b).

This approach allowed us to calculate the estimated number of customers served by electric distribution lines within each circuit polygon:

$$\mathrm{tothh\_Cpoly}_{ij} = \mathrm{tothh\_bg}_i \times \mathrm{IOUarea\_Wt}_i \times \mathrm{CpolyA\_Wt}_{ij} \tag{4}$$

$$\mathrm{totpop\_Cpoly}_{ij} = \mathrm{totpop\_bg}_i \times \mathrm{IOUarea\_Wt}_i \times \mathrm{CpolyA\_Wt}_{ij} \tag{5}$$

$$\mathrm{totstr\_Cpoly}_{ij} = \mathrm{totstr\_bg}_i \times \mathrm{IOUarea\_Wt}_i \times \mathrm{CpolyA\_Wt}_{ij} \tag{6}$$

where tothh, totpop and totstr pertain to the total number of households, people and residential structures, respectively, within a circuit polygon ($\_\mathrm{Cpoly}_{ij}$, calculated) or CBG i ($\_\mathrm{bg}_i$, from the 5-year estimates from the 2015 American

Community Survey[59]), $IOUarea\_Wt_i$ is the portion of each block group's potentially inhabited area served by the IOU and $CpolyA\_Wt_{ij}$ is the portion of area served by circuit j. We did not multiply by the proportion of area that is potentially inhabited, thereby effectively reallocating the full reported block group population to potentially inhabited areas.

To check our approach, we compared our estimated number of households per circuit to the total residential customer base reported by each utility for each circuit. A perfect matching would give us a slope and R^2 of 1. Our slopes are 1 and 0.82, with R^2 values of 0.867 and 0.721 for PG&E and SCE, respectively (Supplementary Fig. 5). While we avoid drawing conclusions about specific circuits, we will discuss overall trends in grid limits for DER access aggregated across CBGs and each utility territory.

Hosting capacity is spatially allocated to households. After matching residential households to distribution circuits, we allocated hosting capacity available on those circuits to the households. The circuit polygons described in the previous section formed our units of analysis. Further allocation and data processing was performed in R (version 3.6.1)[60]. Within each circuit polygon, the number of households, residential structures and people estimated by Equations (4)–(6) were assigned (1) the demographic characteristics of the associated block group i and (2) the characteristics of the electric infrastructure j serving them and its existing distributed generation and estimated DER hosting capacity. We used electric infrastructure data from the final PG&E and SCE ICA map updates in 2019[57,61].

PG&E and SCE report the existing, queued and total distributed generation on each circuit. The utilities' hosting capacity calculations consider the current state of the feeder and therefore factor in the existing distributed generation already interconnected to circuit lines[57]. In estimating the number of households with access, we wanted to consider existing capacity alongside remaining hosting capacity. These values are provided at the full circuit level, and we allocated them to circuit polygons by the proportion of households we estimated to receive service there:

$$\mathrm{DER\_exist}_{ij}\ (\mathrm{kW\ per\ household}) = \mathrm{ExistDG}_j\ (\mathrm{kW}) \times \frac{\mathrm{tothh\_Cpoly}_{ij}}{\mathrm{tothh\_ctot}_j} \times \frac{1}{\mathrm{tothh\_Cpoly}_{ij}} \tag{7}$$

where $\mathrm{ExistDG}_j$ is the existing distributed generation located on circuit j, $\mathrm{tothh\_ctot}_j$ is the number of households served by circuit j, $\mathrm{tothh\_Cpoly}_{ij}$ is the number of households located within the circuit polygon formed by CBG i and circuit j (from Eq. (4)), and $\mathrm{DER\_exist}_{ij}$ is the existing distributed generation we estimate to be located in circuit polygon ij. For PG&E, we also scaled by the percentage of households served by portions of the circuit with ICA data, given that existing capacity can be located anywhere along the circuit, not just where ICA information exists. This method effectively estimates that each household located anywhere on a given circuit has access to the same amount of existing generation. (Other researchers have reported the locations of existing distributed generation (PV) by zip code and census tract[5,62]. However, we found that scaling our allocations of existing generation within a circuit by these values does not substantially impact our results.) The type of DER is not specified for existing generation. To remain conservative with respect to grid limits, we added the per-household value to each type of generation DER: PV, uniform generation, and their variants with operational flexibility limits.

In addition to existing distributed generation capacity connected to a particular circuit, ICA maps also report the remaining hosting capacity of load DERs and PV and uniform generation DERs (with and without operational flexibility constraints) that individual three-phase circuit segments can still accommodate. SCE provides ICA values for all of its three-phase circuit segments. As of December 2019, PG&E has reported ICA values for approximately 55% of all circuit segments (distributed throughout its territory); our results and discussion apply only to the segments with available data. (See Supplementary Note 6 for additional discussion of available ICA data and how they are used.) We compared service areas by demographic indicators to assess whether the portions of PG&E's territory with data are representative of the whole territory (Supplementary Fig. 6). We found no major differences (see the full discussion in Supplementary Note 7).

These hosting capacity values indicate how much additional DER capacity can be connected to that portion of the circuit without issue. However, adding DER capacity in one location may affect remaining hosting capacity elsewhere on the circuit; that is, the reported capacity allowances cannot be satisfied simultaneously. Moreover, hosting capacity values can vary widely within a given circuit due to constraints along different lines. According to SCE, 'the minimum values of all the feeders [represent] the value which can be connected anywhere [...] without exceeding the category limit'. In contrast, the maximum values can be accepted by some feeders 'based on location of interconnection'[63].

We allocated hosting capacity to circuit polygons using an approach designed to err towards less restrictive per-household grid limits while minimizing duplication. First, we selected the maximum values for each DER type reported for any circuit segment within a particular circuit polygon. We weighted these values by the proportion of households served by that portion of the circuit (Eq. (8)) and normalized to preserve each circuit's total maximum hosting capacity (Eq. (9)):

$$\mathrm{DER\_max\_hhWt}_{ij}\ (\mathrm{MW}) = \mathrm{DER\_max\_Cpoly}_{ij}\ (\mathrm{MW}) \times \frac{\mathrm{tothh\_Cpoly}_{ij}}{\mathrm{tothh\_ctot}_j} \tag{8}$$

$$\mathrm{DER\_max\_hhWt\_n}_{ij}\ (\mathrm{MW}) = \mathrm{DER\_max\_hhWt}_{ij} \times \frac{\mathrm{DER\_max\_ctot}_j}{\sum_j (\mathrm{DER\_max\_hhWt}_{ij})} \tag{9}$$

where $\mathrm{DER\_max\_Cpoly}_{ij}$ is the maximum hosting capacity (MW) reported within circuit polygon ij, which corresponds to the overlap between block group i and the estimated service area of circuit j, $\mathrm{tothh\_Cpoly}_{ij}$ is the number of households within circuit polygon ij (from Eq. (4)), $\mathrm{tothh\_ctot}_j$ is the total number of households estimated to be served by circuit j, $\mathrm{DER\_max\_hhWt}_{ij}$ is the household-weighted maximum hosting capacity (MW) for circuit polygon ij, $\mathrm{DER\_max\_ctot}_j$ is the maximum hosting capacity anywhere on circuit j and $\mathrm{DER\_max\_hhWt\_n}_{ij}$ is the normalized household-weighted maximum hosting capacity for circuit polygon ij.

For a small minority of circuit polygons (0.05–1.60%, depending on DER type), the normalized hosting capacity value exceeds the maximum allowed hosting capacity in that circuit polygon. In these cases, we adjusted the value back to its allowed maximum:

$$\begin{aligned}\mathrm{DER\_max\_hhWt\_nadj}_{ij}\ (\mathrm{MW}) &= \text{If } \mathrm{DER\_max\_hhWt\_n}_{ij} > \mathrm{DER\_max\_Cpoly}_{ij},\\ &\quad \text{then } \mathrm{DER\_max\_Cpoly}_{ij},\ \text{else } \mathrm{DER\_max\_hhWt\_n}_{ij}\end{aligned} \tag{10}$$

where $\mathrm{DER\_max\_hhWt\_nadj}_{ij}$ is the adjusted normalized hosting capacity value. Finally, we calculated the remaining per-household hosting capacity ($\mathrm{DER\_remain}_{ij}$) in kilowatts for each circuit polygon:

$$\mathrm{DER\_remain}_{ij}\ (\mathrm{kW\ per\ household}) = \frac{\mathrm{DER\_max\_hhWt\_nadj}_{ij}\ (\mathrm{MW})}{\mathrm{tothh\_Cpoly}_{ij}} \times 1,000 \tag{11}$$

Supplementary Table 4 contains these calculations for an example SCE circuit that spans eight CBGs and therefore creates eight circuit polygons. Supplementary Fig. 7 summarizes the resulting per-circuit hosting capacities for each utility.

Our final per-household hosting capacity (DER_{ij}) can then be estimated to be

$$\mathrm{DER}_{ij}\ (\mathrm{kW\ per\ household}) = \mathrm{DER\_exist}_{ij} + \mathrm{DER\_remain}_{ij} \tag{12}$$

for each of the four generation DERs (where $\mathrm{DER\_exist}_{ij}$ comes from Eq. (7)), and $\mathrm{DER\_remain}_{ij}$ for the load DER. As there are some considerable outliers in the data, we capped all hosting capacity values to a maximum of 50 kW per household and a minimum of −10 kW per household for further analysis (negative values exist only for the load DER in SCE's territory).

Households need kilowatts of circuit capacity for DER access. We estimated the amount of circuit capacity needed to accommodate generation and load DERs, and, using the per-household hosting capacity values (Eq. (12)), assessed the ability of households to adopt these technologies given their local circuit limits. We focused our analysis on behind-the-meter PV deployment and potential new load due to EV charging, electrification and air-conditioning adoption.

In California, on average, a household consumes approximately 6.7 MWh of electricity annually[64], while a small building rooftop PV array produces approximately 1.48 MWh of electricity annually per killowatt of installed capacity[65]. A 4.5 kW PV system is therefore required, on average, to balance 100% of a household's annual electricity demand.

Researchers have previously defined access to behind-the-meter solar PV as the ability to install a 1.5 kW system. This threshold was chosen to be inclusive of existing adoption patterns: of the small (≤10 kW) PV systems installed prior to 2014, 96% were greater than 1.5 kW, and raising the threshold to 3 kW would exclude 19% of them[8,65]. However, residential PV arrays have grown over time: the median system increased from 2.4 to 6.3 kW between 2000 and 2017 (Supplementary Fig. 8). Of the systems installed in 2017, 99% were over 3 kW and 94% were over 4 kW. The changing sizes of residential PV suggest that 1.5 kW may no longer be a reasonable threshold for future access, that is, if the economics show sufficient benefit at larger scales[62], the ability to install only a small amount of solar may prevent someone from installing it at all.

We evaluated 'access' at 4.5 kW to estimate the ability of California households to offset their electricity consumption with onsite PV generation, and additionally for a range of thresholds (1.5 kW, for consistency with prior work, and then 2–10 kW by 1 kW increments) to track how this variable may influence limits to deployment. We assumed that every household would functionally have access to behind-the-meter PV if they had the ability to host 10 kW.

Yet access to behind-the-meter PV is not only limited by grid constraints. Other factors may also restrict the ability to adopt, including lack of suitable rooftop space, access to financing and home ownership. We considered economic and housing factors as demographic features, but combined building suitability limits with our estimates of grid constraints to calculate access to behind-the-meter PV based on technical limits. Researchers have estimated the percentage of small buildings (92.9–464.5 m^2) within specific metropolitan areas and nationwide that are suitable to host 1.5 kW of PV on the basis of tilt, azimuth, shading and contiguous rooftop area[9,10]. Small-building suitability percentages are available by zip code; we used census zip-code tabulation areas (ZCTAs)[66] to assign zip-code level values to block groups. (Some circuit polygons cross more than one ZCTA; for these, we averaged the values corresponding to all intersecting zip codes.)

We compared the restrictiveness of building characteristics to grid limits. We also proposed two approaches for combining building suitability and grid constraints to estimate the percentage of households unable to host solar due to either restriction. In the best case, we maximized double-counting of buildings deemed unsuitable due to either rooftop or grid limits by choosing the lower of the two percentages for a given circuit polygon. In the worst case, we maximized the number of households excluded by either criterion by adding the proportions of households without access.

Beyond solar PV, other DERs also require access to electric distribution circuits. For example, residential households with EVs typically rely on the ability to charge at home. EVs may use level 1 chargers, which require only a typical household outlet, or level 2 chargers, which enable much faster power delivery. While the power drawn by either type depends on the vehicle model, level 1 charging typically requires 1.4–1.9 kW. Level 2 charging can draw between 3.3 and 19.2 kW, with most vehicles requiring around 7 kW[67,68]. Faster charging technologies can draw substantially more power, but they are less common at the household level, and we omitted them from consideration here.

Load electrification and air conditioning will also impact distribution circuits. California state policy has set targets for switching residential fossil fuel uses to electricity through the adoption of electric heat pumps for water and space heating. These technologies will create additional demand for electricity as these appliances become more widespread to support state policy to advance climate change mitigation and adaptation in California. Air conditioning, although already an electric appliance, will also increase load on the grid as additional households deploy new units to cope with increasing temperatures. In particular, low-income households are currently less likely to have air conditioning than high-income households[69].

We estimated the peak per-household electricity demand from electric water heating, space heating and air conditioning to be 0.6, 1.0 and 2.0 kW, respectively, using household energy consumption data from the 2009 California Residential Appliance Saturation Study[69] and hourly electricity consumption profiles from Energy and Environmental Economics[70]. Details of the calculations are provided in Supplementary Note 8 and Supplementary Table 5.

For each DER type reported in the ICA data, we next calculated the percentage of households with access (hhwacc) within each circuit polygon for access thresholds of 1.5–10.0 kW per household:

$$\begin{aligned}
&\textbf{If } \mathit{DER}_{ij}(\text{kW per household}) > \mathit{threshold} \textbf{ then } \text{hhwacc_Cpoly}_{ij} < -100\% \\
&\textbf{else} \\
&\text{hhwacc_Cpoly}_{ij} < -\mathit{DER}_{ij}\ (\text{kW per household})/\mathit{threshold}\ (\text{kW per household}) \\
&\textbf{end}
\end{aligned} \tag{13}$$

where hhwacc_Cpoly_{ij} is the proportion of households located within circuit polygon ij that have access to the given DER type. Separately, we also calculated the proportion of households with greater than zero hosting capacity for each DER. We then aggregated our results up to the CBG and full utility territory levels by first summing over all circuit polygons ij within CBG i, then over all block groups:

$$\text{hhwacc\_bg}_i\ (\%) = \frac{\sum_j \text{hhwacc\_Cpoly}_{ij}\ (\%) \times \text{tothh\_Cpoly}_{ij}}{\sum_j \text{tothh\_Cpoly}_{ij}} \tag{14}$$

$$\text{hhwacc\_IOU}\ (\%) = \frac{\sum_i \text{hhwacc\_bg}_i\ (\%) \times \text{tothh\_bg}_i}{\sum_i \text{tothh\_bg}_i} \tag{15}$$

where hhwacc_bg_i is the proportion of households located within CBG i that have access to the given DER type, and hhwacc_IOU is the proportion of households located within that IOU's territory that have access to the given DER type. The block group-level results provide context for the distribution of access within a utility territory through meaningful units of contiguous geographic data within counties and census tracts. We relied heavily on boxplots to visualize the access results by block group. All boxplots in this work show the 25th, 50th and 75th percentiles of results, with whiskers extending to the furthest point within 1.5 times the interquartile range. Further points are shown as outliers.

Connecting household access results to demographic features. Hosting capacity values vary across IOU service territories, as do customer demographics and other indicators relevant to electric infrastructure and the customers it serves. We wanted to understand the relationship between these differences and hosting capacity (and, potentially, customers' ability to adopt DERs) among households for each DER type.

We constructed machine learning models to understand which features, if any, correlate most to per-household hosting capacity, and which are most important in building the models. We weighted our samples by tothh_Cpoly_{ij} to ensure the models appropriately emphasize circuit polygons that contain more households.

Linear and logistic regression models were used to determine whether linear relationships exist between our independent and dependent variables. When fitting, we normalized our independent variables to have a mean of zero and standard deviation of one. We used the regression coefficient and corresponding standard error of each feature to rank features in order of importance. We also calculated weighted root mean square errors (RMSEs) and R^2 values for the linear regression runs, and weighted score, precision and recall values for logistic regression.

Random forest regression and classification models were used to determine whether non-linear relationships exist in the data. We applied regression models to (1) all values of per-household hosting capacity and (2) the subset of hosting capacity values less than or equal to 10 kW per household (to specifically focus on the range where access may be limited). For each model, we used the lowest RMSE, as identified by tenfold cross-validation, to select the proportion of features considered at each split (all features, one-third of all features or the square root of all features), and used those results to calculate model outcomes and feature importances. We used the weighted RMSE (for regression) and the weighted score, precision and recall statistics (for classification) to evaluate model performance.

For each model, we used four combinations of infrastructure and demographic indicators as the independent variables: (1) all variables, (2) infrastructure variables only, (3) service and geographic variables, and (4) demographic variables. More information about each variable group is provided in Table 1, and a full list of variables is presented in Supplementary Tables 6–8.

Linear regression and random forest regression models used the per-household hosting capacity for each DER type as the dependent variable, while logistic regression and random forest classification models used a boolean value indicating whether the per-household hosting capacity surpasses a set threshold. We tested two thresholds: 1.5 and 10.0 kW per household.

We fitted and evaluated all models using the entire dataset rather than performing a train-test split. Our data correspond to the entire population in SCE's and PG&E's service territories (given available data); therefore, we were more interested in building models that represent the entire population than in predicting hosting capacity for unseen data.

Moving beyond machine learning models, we also evaluated the distribution of median hosting capacity across features. We focused in on the demographic features to evaluate how hosting capacity changes across feature values. We created bins for the available values of each demographic feature, then calculated the median per-household hosting capacity for each bin. LOESS curves were drawn on the plotted median values. These were weighted by the total number of households represented by each bin value and used span (smoothing) values calculated by generalized cross-validation. Confidence intervals were constructed using a bootstrap method with 1,000 replications, as described previously[6], and we show the 50 and 90% confidence intervals for each LOESS curve.

Data availability

The definitions of features used in the demographic analyses are available in Supplementary Information Note 9 for convenience. Utility circuit data are available publicly from repositories that update approximately monthly and currently lack archive capability. The specific circuit data used in this study (from the last circuit map updates in 2019) are available at https://github.com/Energy-MAC/GridLimitsforDERs. Source data are provided with this paper.

Code availability

The code is available at https://github.com/Energy-MAC/GridLimitsforDERs.

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Author contributions

A.M.B., J.C. and D.C. conceptualized the research. A.M.B. and J.C. performed the research and wrote the paper. D.C. guided the research and edited the paper.

Competing interests

The authors declare the following competing interests: since completing the research described herein, J.C. has accepted employment at SCE. A.M.B. and D.C. have no competing interests.

Additional information

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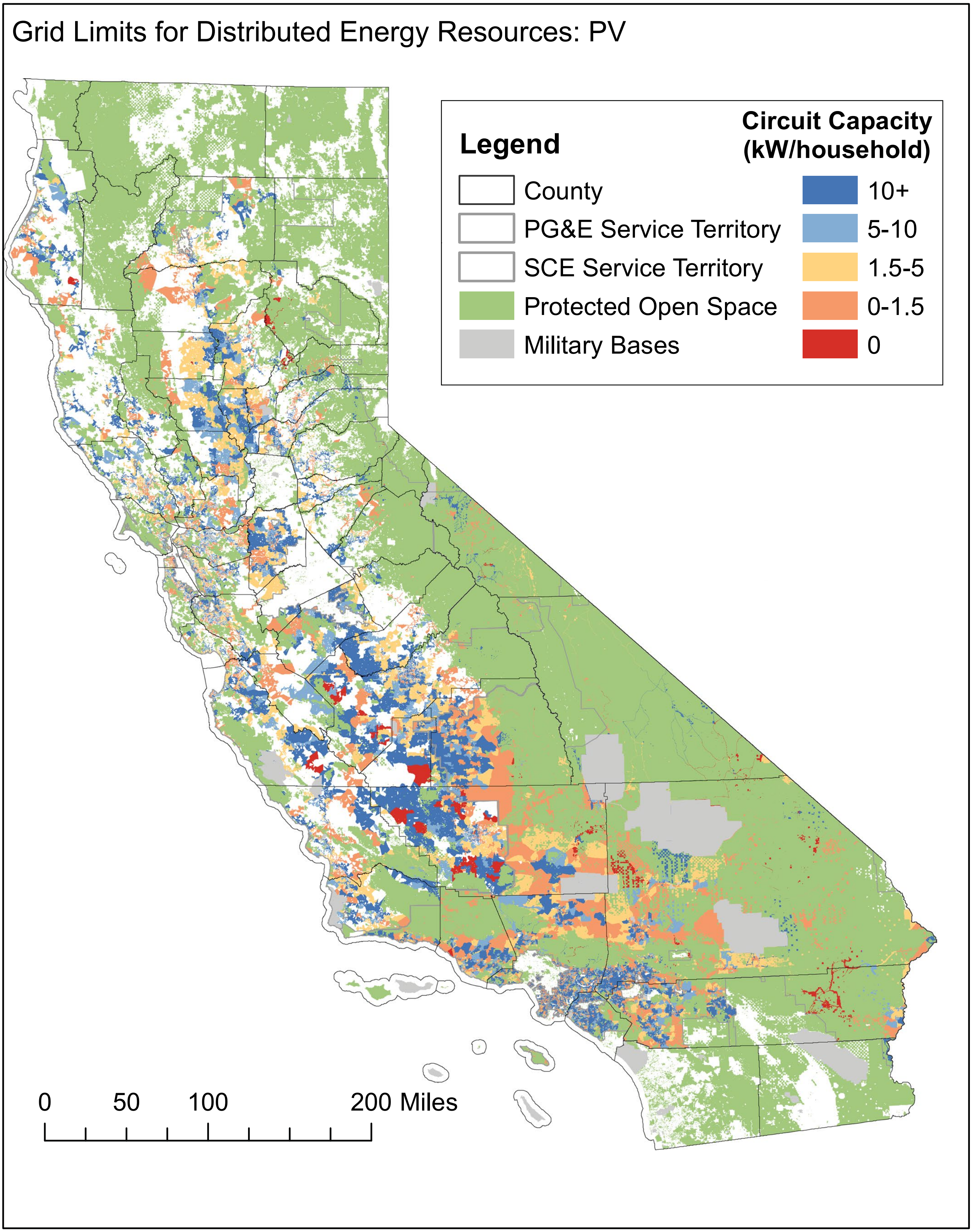
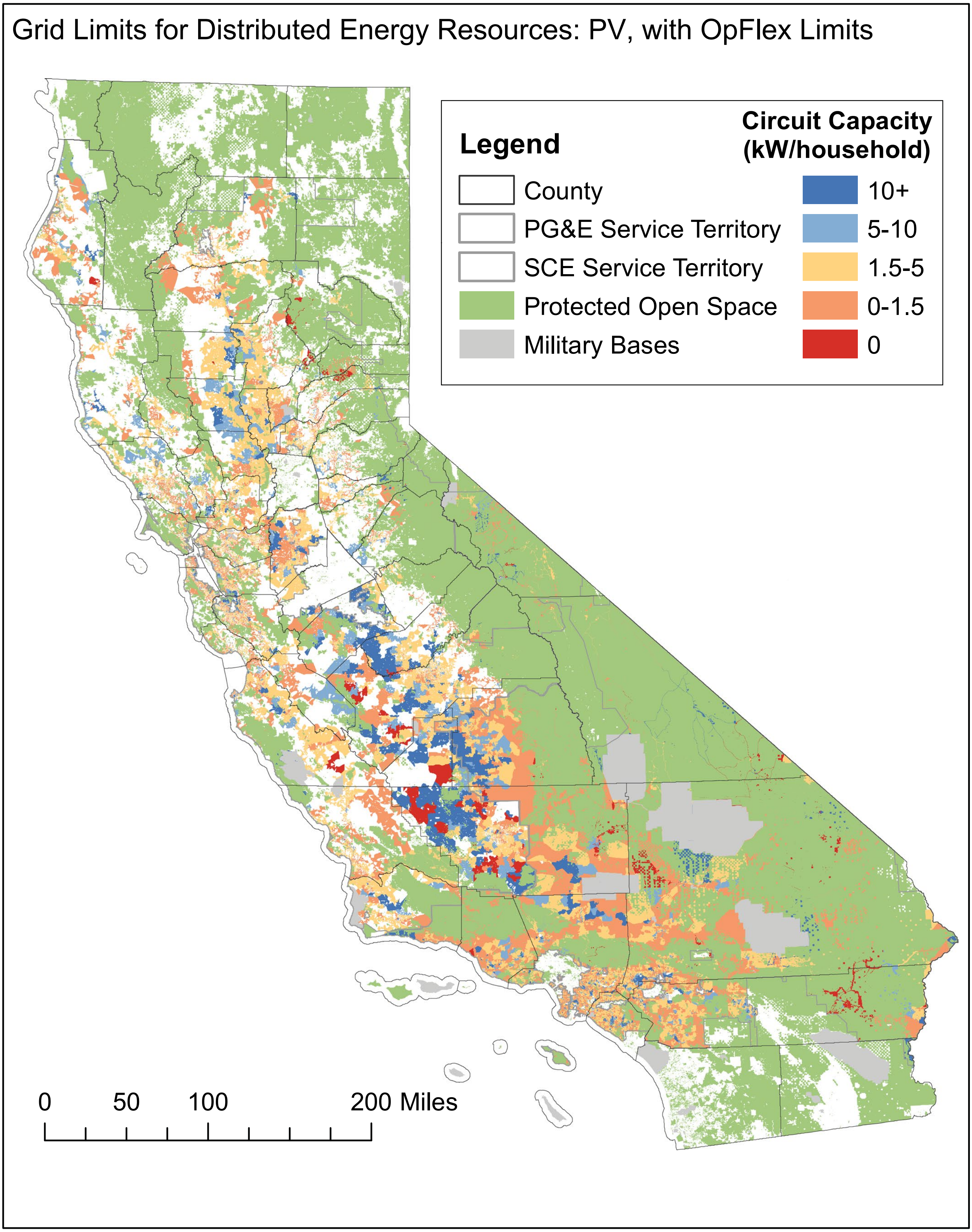
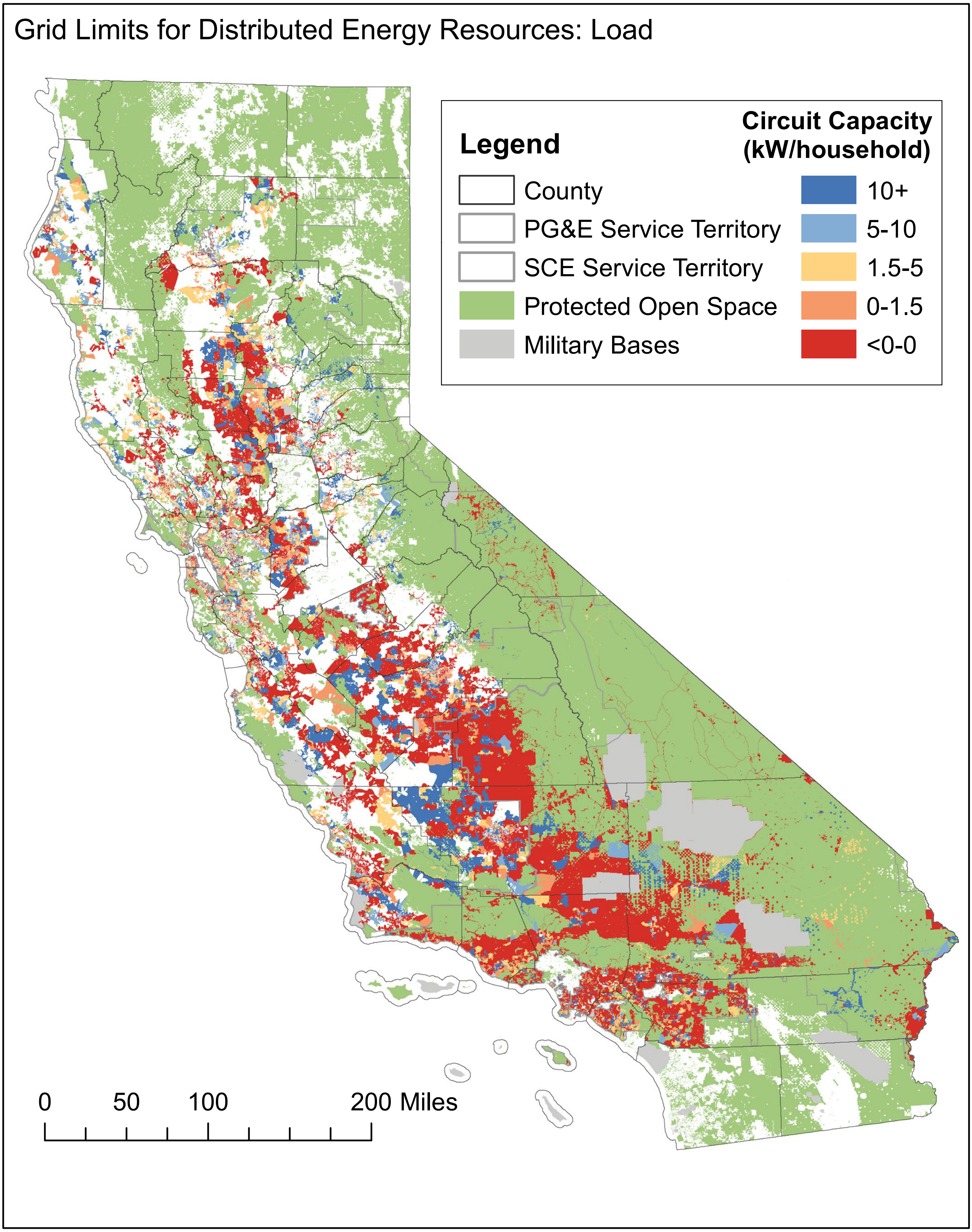


Extended Data Fig. 1 | Grid limits for distributed energy resources: PV. High-resolution version of Fig. 1a, showing hosting capacity limits for PV per household across PG&E and SCE service territories.



Extended Data Fig. 2 | Grid limits for distributed energy resources: PV, with OpFlex limits. High-resolution version of Fig. 1b, showing hosting capacity limits for PV with Operational Flexibility limits enforced per household across PG&E and SCE service territories.



Extended Data Fig. 3 | Grid limits for distributed energy resources: Load. High-resolution version of Fig. 1c, showing hosting capacity limits for Load per household across PG&E and SCE service territories.