Memorandum

To: Portland General Electric (PGE)

From: Cadeo

Date: July 25, 2022

Re: Community Targeting Assessment

PGE contracted with Cadeo to develop an approach for considering diversity, equity, and inclusion (DEI), environmental, and resilience parameters within its distribution system planning process. Through this assessment, Cadeo developed a set of indices that will help PGE understand the geospatial distribution of these parameters in their service area and identify affected and most vulnerable populations. PGE can then use this to target services that account for these parameters in resource and program planning.

This memo overviews our study approach, including data inventory, variable selection, index development, and output summary. We have also presented a few application examples to show how PGE can integrate this toolkit into the distributed energy resources (DER) forecast model, AdopDER, and consider approaches for efficient targeting to influence program design, targeted deployment, and benefit optimization based on locational factors.

Introduction

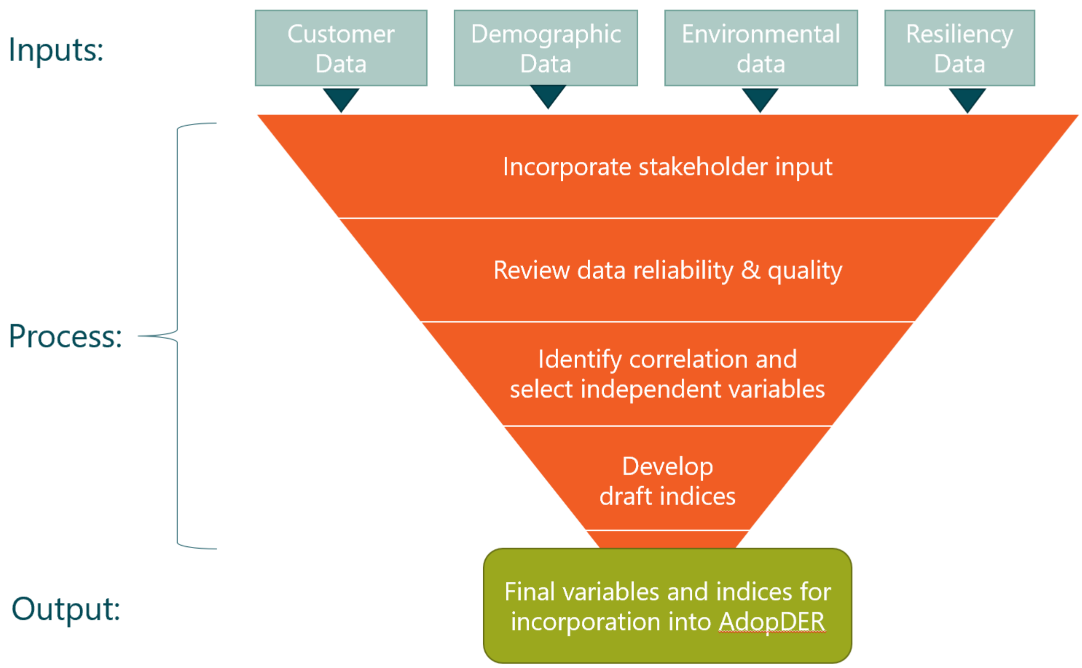
The objective of this study was to provide PGE a set of tools that would aid future resource and program planning and account for locational dimensions of key prioritization areas – these included: ***DEI*** (based on a range of demographic and socioeconomic factors), ***environmental*** (including air quality and other environmental justice criteria), and ***resilience*** (based on environmental risk factors, such as fire or flood vulnerability areas, and grid/system needs, such as long term outage locations). To this end, this study aimed to achieve the following steps:

- ***Review available data sources*** and ***solicit stakeholder feedback*** to identify specific criteria and key variables used to characterize DEI, environmental, and resilience parameters.
- ***Develop a set of indices*** to account for the various underlying variables and locational elements across DEI, environmental, and resilience prioritization areas.
- ***Summarize distributions*** of these indices to identify trends and ***consider future applications*** for resource planning, including siting locations for future non-wires solutions.
- ***Integrate with PGE's AdopDER model*** as a separate module for considering locational factors of DEI, environmental, and resilience relative to feeder-level DER adoption forecasts.

- ***Provide toolkit*** for PGE in future resource and program planning to consider targeted interventions based on DEI, environmental, and resilience criteria and optimization of benefits to customers, the grid, and the local community.

To achieve these outcomes, Cadeo developed an approach that accounted for a variety of public and utility/customer-specific data sources and input from PGE-led community engagement workshops that occurred concurrently to this research. We also applied statistical techniques to account for correlations between observed variables for index development. Finally, we developed a set of three indices to account for the composite effect of various criteria defining DEI, environmental, and resilience parameters. Figure 1 provides an overview of these steps used in our approach.

Figure 1. Community Targeting Assessment Approach



The remainder of this memo overviews several discrete study tasks:

- ***Task 1 – Variables Identification.*** Cadeo confirmed prioritization areas for each factor, based on stakeholder input from PGE facilitation with community-based organizations, review of existing policy guidance (e.g., House Bill [HB] 2165)[1], and inventory and assessment of available data sources.
- ***Task 2 – Indices Development.*** Through statistical and geospatial analyses, Cadeo summarized distributions of priority variables for DEI, environmental, and resilience

[1] Definition of "underserved communities" outlined in HB2165. Source: https://olis.oregonlegislature.gov/liz/2021R1/Measures/Overview/HB2165; Source: https://edocs.puc.state.or.us/efdocs/HAU/um2165hau1331.pdf

factors within PGE service area, assigning geospatial units to all attribute variables, accounting for correlation, and inputting any missing values to derive premise-level scoring for each.

- ***Task 3 – Example Strategies.*** Through discussions with PGE, the team identified several example strategies to highlight the application of this tool and specifically the intersection of DER adoption and areas with high concentrations of community-based impacts regarding DEI, environmental, and resilience factors.

Task 1. Variables Identification

In the first task of the project, Cadeo worked with PGE to confirm research objectives, define study priorities, identify variables of interest, assessed available data sources, and ultimately compile a database of selected variables, including a geographic scale (at census block/tract or customer levels) that would serve as the basis for indices development and subsequent analysis.

Informed by PGE guidance, we defined three priority areas for directing the construction of indices to identify disadvantaged communities and support locational targeting to increase impacts of key benefit categories associated with DER programs and distribution system planning services. These categories included:

- ***DEI*** – to identify underserved and/or disadvantaged communities (beyond traditional income eligibility)
- ***Environmental*** – to identify factors associated with localized air quality and other locational environmental justice impacts
- ***Resilience*** – to identify both environmental and grid-related factors contributing to resilience, including proximity to areas of high fire/flood/seismic risk and metrics related to historic frequency and duration of power outages.

At the outset, Cadeo developed an inventory of data sources (both public and utility-owned data) and an extensive list of potential variables/criteria to consider within each category. To this end, we received input provided from PGE stakeholder meetings, involving facilitated workshops with community-based organizations, centered on DEI in distribution resource planning. We also reviewed relevant state policies and definitions of underserved communities, such as HB 2165,[2] and other composite indices and tools for assessing DEI factors, environmental factors, and more. Several examples include the Environmental Justice Screening and Mapping Tool (EJScreen),[3] Washington Department of Health Environmental Health Disparities index (used as guidance for DEI in the 2019 Clean Energy Transformation Act),[4] and the White House's Climate and Economic Justice Screening Tool (currently under development).[5]

[2] HB 2165 – Relating to alternative fuel transportation.
[3] https://www.epa.gov/ejscreen
[4] https://fortress.wa.gov/doh/wtn/WTNIBL/
[5] https://screeningtool.geoplatform.gov/en/

We developed data for the three categories from a variety of sources, prioritizing publicly available data that allows for greater transparency and broader accessibility to the underlying sources used for this analysis. We then consolidated key fields from these sources into a comprehensive data set, assigning geospatial units (Census Block or Tract IDs) and merging with discrete PGE premise IDs. Additionally, using customer and grid-level data from PGE, we assigned premise geolocation, associated feeder and substation IDs, and merged additional customer-specific data from PGE, including historic payment data (e.g., arrearages, disconnections, energy assistance), primary heating and cooling equipment, public safety power shutoff (PSPS) data, and grid reliability data.

Table 1 provides a summary of data sources considered by type and application. A more detailed description of data sources considered in this analysis is provided in Appendix A: Data Source Details.

Table 1. Data Sources

Type	Source	Use
Geographic	PGE Shapefile / Census Geographies	Define service area boundary and unit of geographic analysis
Income/Demographics	ACS, PUMS PGE (CIS/Axiom); Greenlink[6]; DOE LEAD Tool	Characterize populations using DEI criteria
Environmental	EPA EJScreen;	Identify environmental indicators by location
Resilience	PGE (long duration outage locations, PSPS); US Forecast Service (wildfire risk); FEMA (flood risk); DOGAMI (seismic risk)	Identify areas at risk for long term outages due to natural disasters/extreme weather
Customer Arrearage	PGE (list of accounts with current and/or historical arrearages, assistance payments, disconnects / reconnects)	Characterize customers using DEI criteria

The following step after collecting the data sets was to conduct a quality control assessment. To this end, the team reviewed data quality and granularity to narrow down the data included in the customer database. To assess data quality, the team considered the amount of missing data and the match rate of the data to individual customers. Some variables provided different levels of granularity, for instance census block group, census tract, or premise level. Where there were

[6] Mostly based on Census and EJ Screen data sets

multiple data sets for the same or similar variable, we opted for the source that best optimized between data quality and smaller spatial granularity. A complete list of the data sets contained in the database can be found in Appendix A: Data Source Details. The final database comprises 26 variables under the DEI category, 11 under environmental, and 18 under resilience.

Task 2. Index Development

Latent Factor Analysis

Once data sources and key variables for each category had been identified and consensus reached on the final selection, we conducted a statistical analysis to determine independent variables for each index construction. To this end, we employed ***latent factor analysis***,[7] which is a powerful data reduction technique based on the covariance of variables to identify underlying factors and refine a final selection.

By grouping variables under factors or hidden variables, we reduced the number of initial variables by selecting those with higher weight under each factor, which are the ones that better explained the underlying (hidden) variable. A further consideration was to select variables with a bivariate correlation coefficient below 0.5 to ensure independent data sets and avoid skewing the results.

Results of the latent factor analysis led to the final variables used under each category for the development of the three indices (Table 2).

Table 2: Final Variable Selection for Index Development

DEI Category	Environmental Category	Resilience Category
Energy burden	Proximity to environmental hazard waste	Hour loss power substation
Housing type	Respiratory hazard index	Hour loss power transmission
Owner/renter	Ozone	SAIDI (duration of outages)
Race		Seismic risk
Households without internet		
Households with disabilities		

Index Scoring: Scorecard Approach

Once we selected the final set of variables, we proceeded with the index construction for each category by using a scorecard-based approach. Using this approach, we effectively applied weights to each variable (and attributes and/or distributions within each variable) within a

[7] The latent factor analysis assumes the covariation of the observed variables can be explained by latent or hidden variables (factors) that exert casual influence on the observed variables. http://support.sas.com/publishing/pubcat/chaps/55129.pdf

category, rather than applying an equal weight across all variables. This approach provides added flexibility to allow for determining tiers of variables within each category for prioritization and can provide PGE the means to incorporate stakeholder feedback and re-weigh variables in future iterations.

We constructed scores for each variable and associated weights through the following steps.

1. First, we assigned a baseline of 500 points to each index category.
2. Second, we assigned each variable within a category a ranking that would determine whether it would receive higher or lower weighting based on statistical analysis (latent factor results), stakeholder feedback (PGE-facilitated workshops), and professional experience.
3. Third, we assigned scores to each variable based on thresholds relative to the distribution of each variable, primarily based on quartile.

Finally, the assigned scoring for each variable would reflect differences based on the priority ranking (noted in step two), effectively resulting in higher relative scores for specific variables within each category.

To illustrate an example of this weighting, energy burden received the highest weighting (and associated scoring) within the DEI category. The decision to prioritize this variable over others within the DEI category was a function of the following:

1. Latent factor analysis results—energy burden received one of the highest explanatory capacities under the DEI category.
2. The community-based organization workshop conducted by PGE earlier this year, which positioned this variable as highly relevant to determine disadvantaged communities.

Within the energy burden variable, points were allocated based on the geographic distribution of the variable (using quartiles). Thus, to reflect a higher prioritization of energy burden within the DEI index, we assigned the highest score (Q4 value = 300) to premise IDs in census blocks within the highest quartile of average energy burden. The middle quartiles then received reduced scores (Q3/Q2 values = 150), with the lowest score assigned to the lowest quartiles (Q1 value = -50). Through this approach, customers with higher energy burden would receive more points than those falling in the middle of the distribution, while customers showing the least amount of energy burden were given negative points. We followed a similar approach for other variables; however, those variables with lower prioritization within a category, such as households with internet access for the DEI category, would have a lower point distribution that would effectively result in a lower weight for the index development (i.e., Q4 = 60, Q3/Q2 = 20, and Q1 = -20).

Finally, to build the index, each customer will sum or subtract points depending on where they sit on the distribution of each variable composing the index. See Appendix B: Scoring Details for score allocation within each variable distribution.

Comparison Between Scorecard and Composite Scoring Approach

As a point of comparison and quality control benchmark, we modeled an alternative (composite) scoring approach that assigned equal weighting to each variable within a category. For this approach, we applied a score from 1 to 10 based on the decile distribution for each variable by census tract and calculated a composite score that summed the scores for each premise ID across individual variables within a given index category. Our aim was to compare the scorecard and composite scoring approaches to determine key differences and whether the scorecard approach required any further calibration when comparing outputs of each approach.

The comparison of the composite and scorecard indices quintile distribution by census tract shows that there is compatibility between the methods, indicating robustness in the results (shown in Figure 2). As expected, the percentage matchup between methods is higher for the top and bottom quintiles (above 70% in most cases), indicating a similar resolution for both methods on the extremes, with the middle quintiles showing more versatility. Based on the different methodology used, the length of the quintiles for both methods might differ resulting in reduced percentage match.

Figure 2. Composite and Scorecard Indices Quintile Comparison*

Category	Quintile	Composite Method		Scorecard Method	
		Count of Census Tracts by Quintile	% Match between Approaches	Count of Census Tracts by Quintile	% Match between Approaches
DEI	Q1	79	0.75	78	0.76
	Q2	81	0.47	78	0.49
	Q3	75	0.53	78	0.51
	Q4	77	0.62	78	0.62
	Q5	78	0.82	78	0.82
Environment	Q1	80	0.70	76	0.74
	Q2	96	0.34	65	0.51
	Q3	66	0.23	70	0.21
	Q4	72	0.61	93	0.47
	Q5	76	0.83	86	0.73
Resilience	Q1	83	0.66	78	0.71
	Q2	80	0.50	78	0.51
	Q3	85	0.44	78	0.47
	Q4	64	0.39	78	0.32
	Q5	78	0.69	78	0.69

* Note – Each scoring approach will result in a slight difference in the number of census tracts occurring with the quintile distribution based on the configuration of tracts with similar scores. As such, we have included the distribution of tracts for each approach and the match rate between each approach.

For this study, we selected the scorecard method, given that it provides information at the premise level and has greater compatibility with AdopDER (i.e., allowing for customer-level scores and summary by other geographies, such as feeder). Additionally, the scorecard approach can be modified to adapt to new findings, market changes or stakeholder input by modifying the weight of the variables composing the index.

Distribution of Final Indices

Results of each index—DEI, environmental, and resilience—are shown in the figures below. To more easily visualize trends associated with each index, we have aggregated the premise-level scoring developed using the scorecard approach up to the census tract level and presented the quintile distributions.

Figure 3. DEI Index – Quintile Distribution

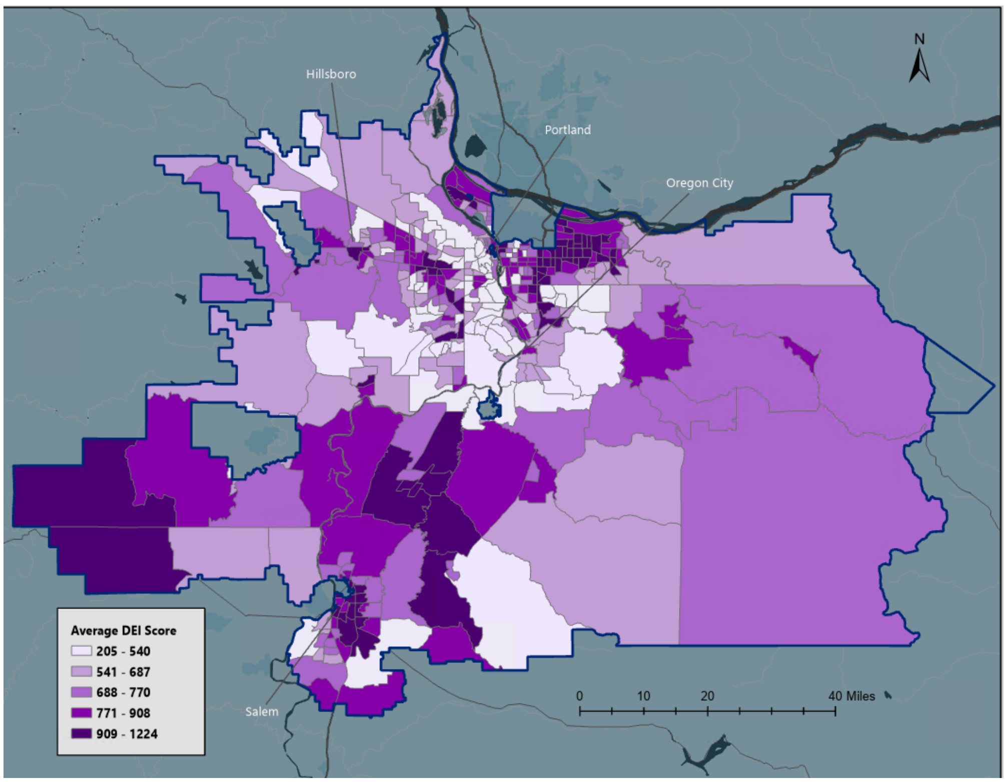


Figure 4. Environmental Index – Quintile Distribution

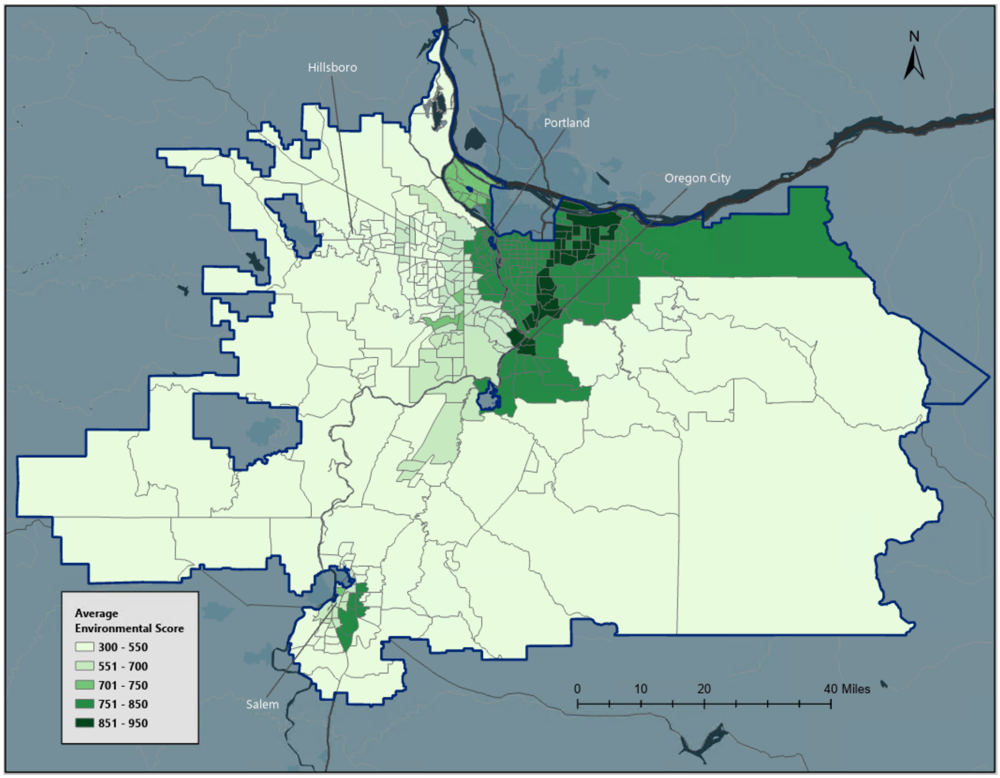
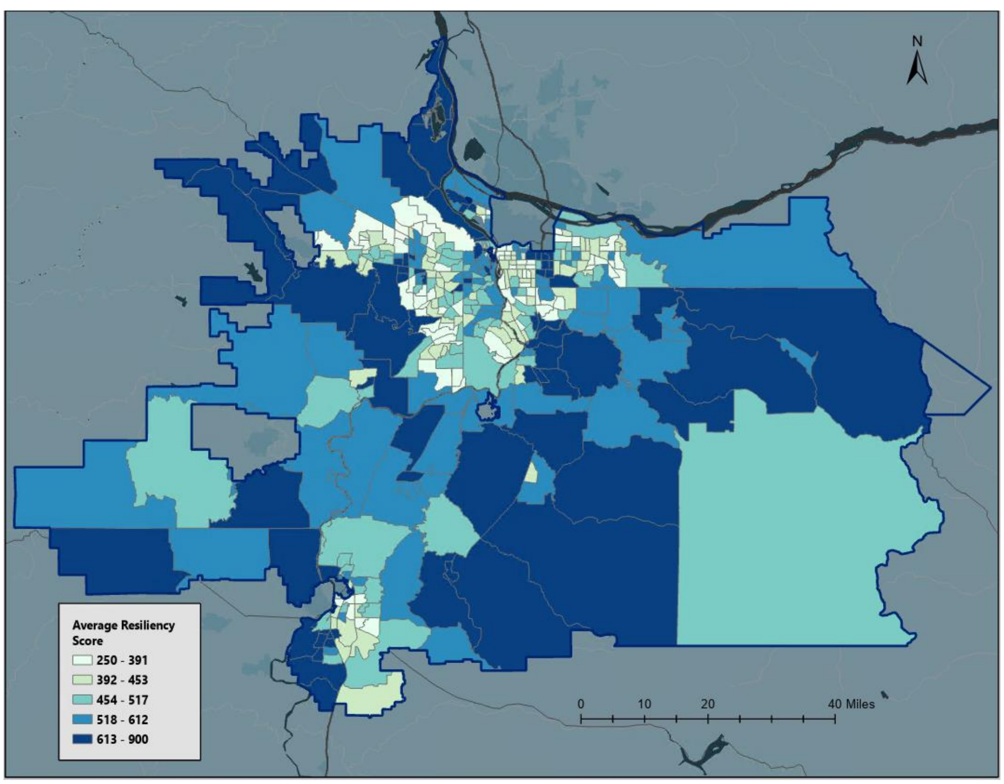


Figure 5. Resilience Index – Quintile Distribution



Note, there are 390 census tracts in the PGE service area. Table 3 provides a summary of census tract counts by quintile and shows the overlap of census tracts among DEI, environmental, and resilience indices quintiles.

Table 3: Counts of Census Tract Overlaps between Indices by Quintile

Quintile	Overlap by Index Combination			
	DEI/ENV	DEI/RES	ENV/RES	DEI/ENV/RES
1 (bottom)	12	11	12	3
2	7	15	13	1
3	11	14	22	3
4	17	16	22	4
5 (top)	26	14	9	2

Task 3. Example Strategies

In this section we provide several example strategies or use cases that highlight the integration of these indices and PGE's locational DER forecast. Below, we have included maps presenting the overlay of the top quintile of different combinations of indices and how these relate to the adoption forecast in year 2030 for different technologies (i.e., solar photovoltaics [PV] and electric vehicle [EV] ownership). Given that there are a wide range of potential metrics and iterations for consideration, we have selected only a limited set of outputs for these examples in addition to several researchable questions that may help guide future applications of this toolkit.

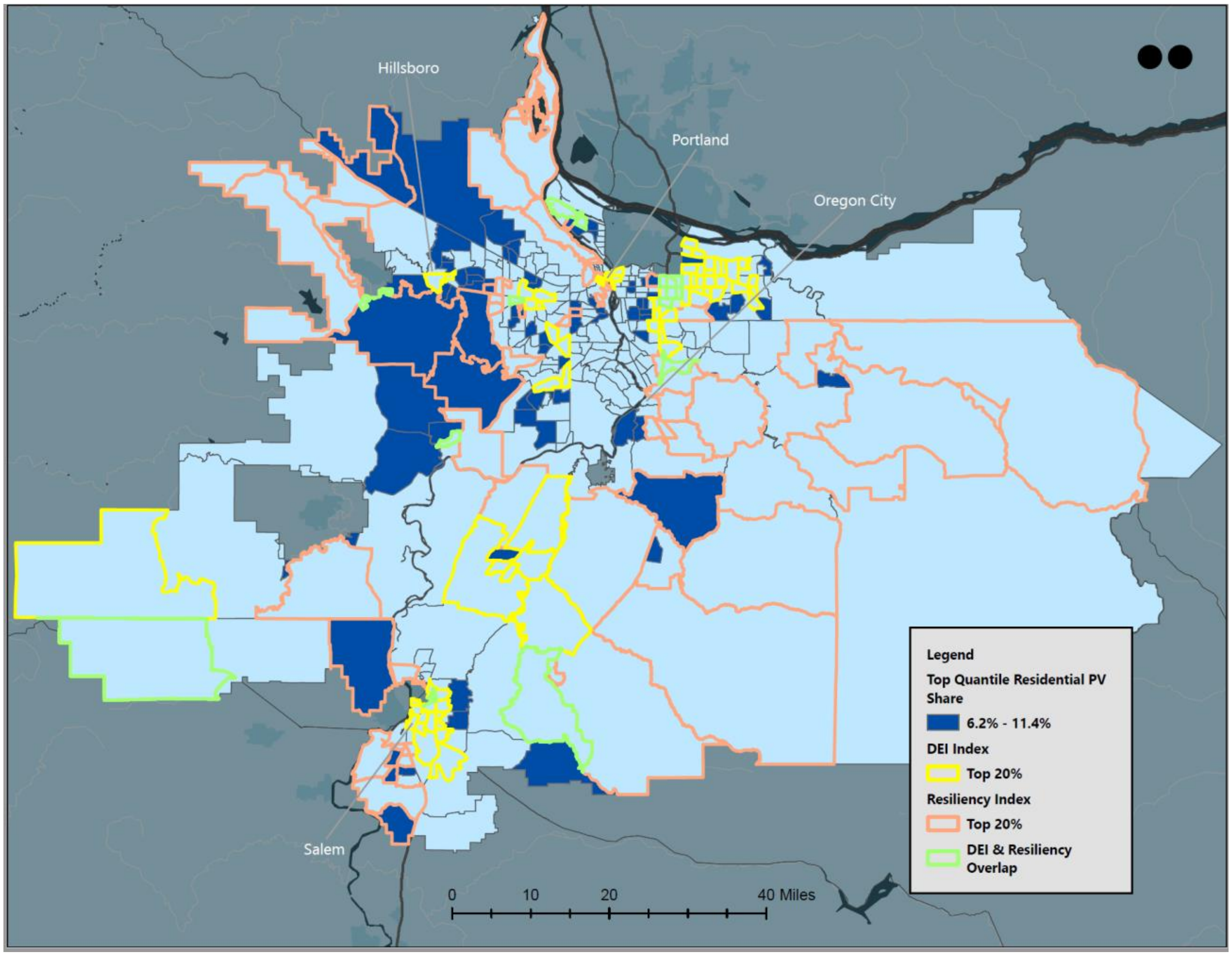
For more information on PGE's DER forecast model, ***AdopDER***, including methods and underlying assumptions used in this forecast, please see Appendix G of PGE's 2021 Distribution System Plan.[8]

PV Example Strategy

Figure 6 presents a map of PGE service area with an overlay of the top quintile of census tracts with the highest scores for DEI and resilience Indices, and the top quintile of census tracts with highest PV adoption (represented as a percentage of total residential households) by 2030. Figure 7 depicts a more granular map of the Portland area.

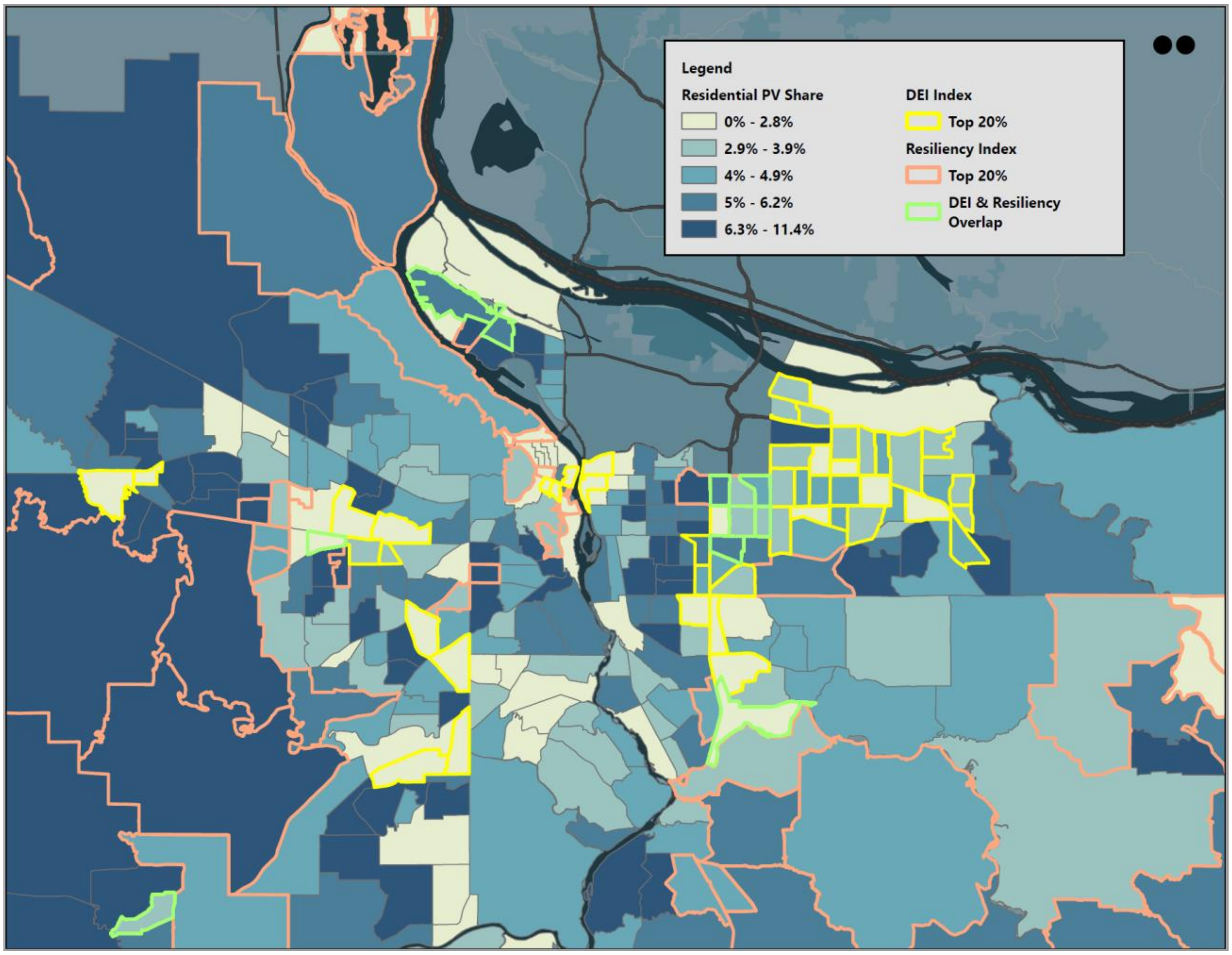
[8] https://assets.ctfassets.net/416ywc1laqmd/i9dxBweWPkS2CtZQ2lSVg/b9472bf8bdab44cc95bbb39938200859/DSP_2021_Report_Full.pdf

Figure 6. PV Example Strategy – Intersection of PV Adoption with DEI and Resilience Indices



* Note –residential solar adoption share reflects the number of residential units (including single family and multifamily) that are predicted to adopt solar by 2030 divided by the total number of residential units within a given census tract. Thus, this share includes the population of residential units, including those that may have technical feasibility issues that prevent installation under current conditions.

Figure 7. PV Example Strategy – Intersection of PV Adoption with DEI and Resilience Indices (Zoom to Portland Area)



Researchable Questions:

- What is the geographic distribution of residential solar adoption in PGE service area, and where are areas with highest concentrations of predicted adoption?
- How do areas with highest solar adoption compare to geographic distributions of the DEI and resilience indices, reflecting adoption levels for underserved communities and adoption in areas with higher potential for outages and general resiliency concerns, respectively?
- Are there disparities between predicted solar PV adoption and underserved areas characterized by higher DEI index scoring?

- Are there disparities between predicted solar PV adoptions and areas with high resilience index, which may yield increased benefits from distributed generation (including impacts affecting health, risk, reliability, energy security, and resilience)?

Based on an analysis of the date shown in Figure 6, 78 census tracts reflect the top quintile (20%) of the geographic distribution of residential solar adoption. By 2030, the top census tracts for PV adoption do not align with the top scoring DEI index census tracts, suggesting that these installations occur in lower frequency in areas with highest concentration of customers meeting DEI criteria. However, a higher proportion of census tracts within top resilience scoring areas overlap with top PV adoption areas (15 census tracts, 19% of quintile total). In both cases, there is opportunity to increase promotion and targeted outrage and delivery strategies to increase solar uptake in the following areas:

(1) Areas reflecting the highest concentration of customers meeting DEI criteria.
(2) Areas with highest resilience concerns that would potentially yield increased grid and customer benefits.

Table 4 provides additional detail regarding where the PV adoption distribution intersects with the top DEI and resilience scoring census tracts. Though high resilience scoring census tracts are a bit more aligned with higher PV adoption areas (approximately 51% in the top two quintiles), only 10% of the highest DEI scoring census tracts align with top two PV adoption quintiles.

Table 4. Distribution of Top Quintile DEI and Resilience Census Tracts by PV Adoption Quintile

PV Adoption		DEI Index - Top Quintile Distribution		Resilience Index - Top Quintile Distribution	
Quintile Rank	Distribution	# of Census Tracts (n=78)	% of Census Tracts in Top Quintile	# of Census Tracts (n=78)	% of Census Tracts in Top Quintile
1 (bottom)	0–2.8%	30	38%	12	15%
2	2.9–3.9%	26	33%	14	18%
3	4–4.9%	14	18%	12	15%
4	5–6.2%	8	10%	25	32%
5 (top)	6.3–11.4%		0%	15	19%

To provide additional context, Table 5 provides a comparison of different customer characteristics of those census tracts within the top quintiles of distributions of residential solar adoption and each DEI and resilience index. As shown, top DEI census tracts reflect different distributions of key categories compared to PV adoption such as higher proportions of multifamily, renters, people of color, and customers with limited English, while the top Resilience areas are more comparable.

Table 5. Comparison of Customer Characteristics in Top Quintiles of PV Adoption and DEI and Resilience Indices

Category	Quintile	Distribution of Customers Within Top Quintiles		
		PV Adoption	DEI Index	Resilience Index
Building Type	Single Family	86%	62%	79%
	Multifamily	13%	34%	18%
	Manufactured	2%	4%	2%
Ownership	Owner	80%	60%	75%
	Renter	20%	40%	25%
Race	Person of Color (POC)	16%	25%	14%
	Non-POC	84%	75%	86%
Language	Limited English	2%	8%	3%
	Non-Limited English	98%	92%	97%
Total Counts	Census Tracts	78	78	78
	Premise	150,307	150,067	135,738

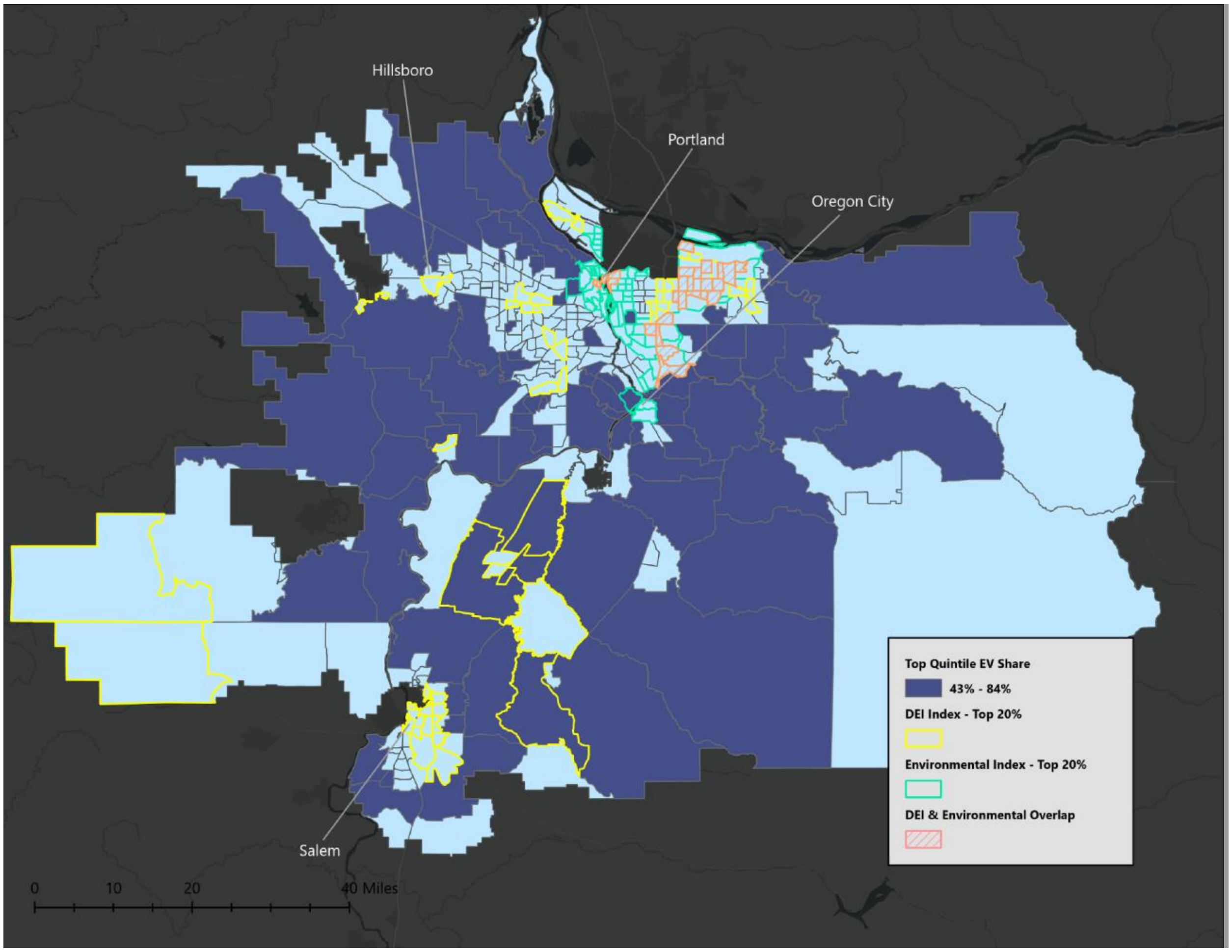
* Note – Building type and ownership distribution of customers in top quintiles were obtained from AdopDER output and reflect forecasted values for 2030. Race and language distribution of customers in top quintiles reflect 2019 Census data.

Program design and delivery strategies addressing the disparity of PV installations will create more equitable opportunities for DEI communities to participate in the energy transition and benefit from access to local renewable energy. Specifically, residential rooftop and community solar projects yield the largest impact to individual customer energy burdens (compared to other energy projects) through offsetting potentially significant proportion of home energy bills.

EV Example Strategy

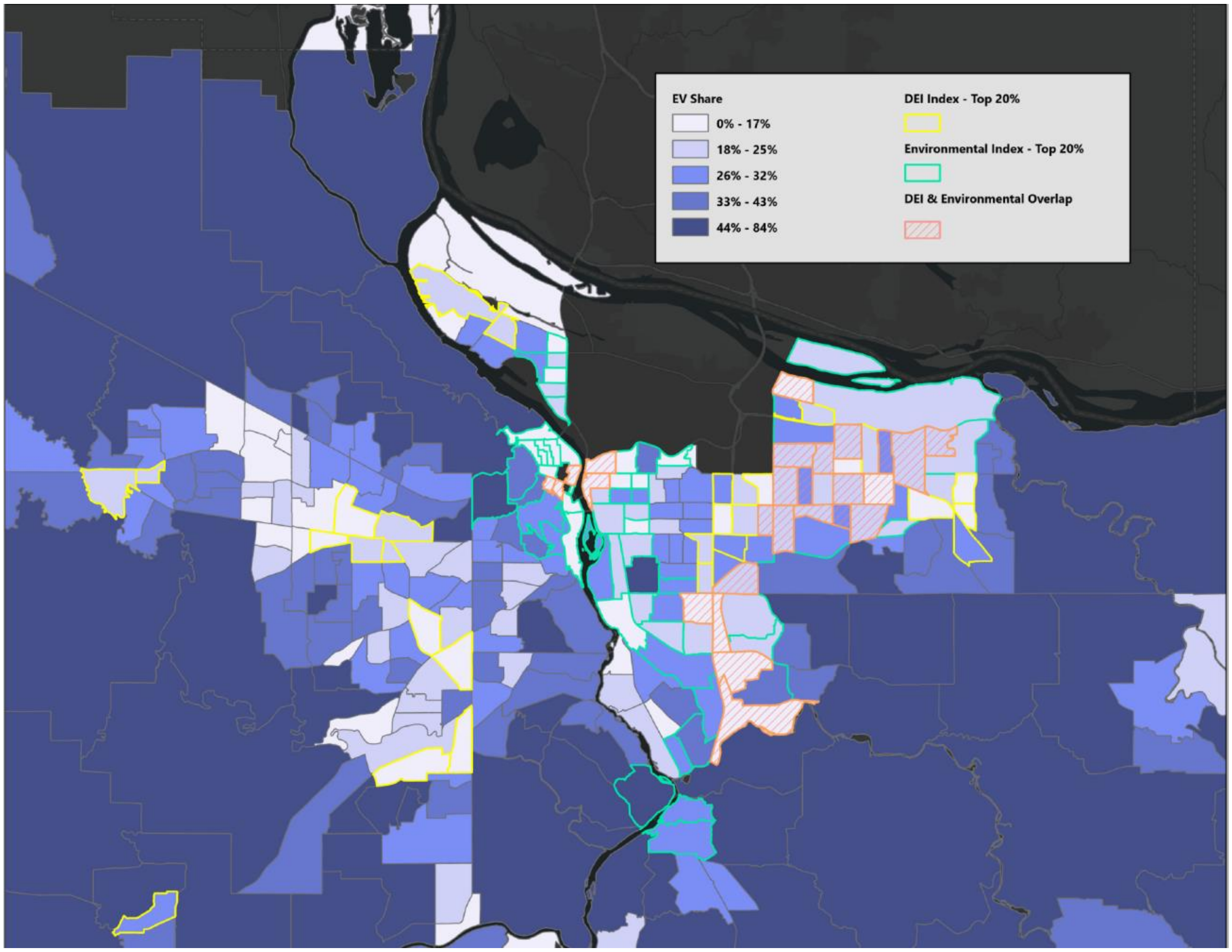
Figure 8 presents a map of PGE's service area with an overlay of the top quintile of census tracts with the highest scores for DEI and environmental indices, and the top quintile of census tracts with highest EV adoption (represented as a percentage of total residential households) by 2030. A more granular map of the Portland area is depicted in Figure 9.

Figure 8. EV Example Strategy – Intersection of EV Adoption with DEI and Environmental Indices



*Note – AdopDER tracks EV adoption at the premise level based on address-level vehicle registration data that PGE obtained and mapped to premises in its service area. However, multifamily premises can appear in multiple ways in PGE's customer data: as a single premise with multiple dwelling units or as multiple premises (one for each dwelling unit). Therefore, it is difficult to get a precise count of the number of dwelling units in each census tract based on PGE's data. For this reason, we counted the number of EVs in a census tract and then divided it by the number of dwelling units in the tract to avoid overcounting due to EV adoption in single premises with multiple customers.

Figure 9. EV Example Strategy – Intersection of EV Adoption with DEI and Environmental Indices (Zoom to Portland Area)



<u>Researchable Questions:</u>

- What is the geographic distribution of residential EV adoption in PGE service area, and where are areas with highest concentrations of predicted adoption?
- How do areas with highest EV adoption compare to geographic distributions of the DEI and environmental indices, reflecting adoptions levels for underserved communities and adoption in areas with poorer air quality, respectively?
- Are there disparities between predicted EV adoption and underserved areas characterized by higher DEI index scoring?
- Are there disparities between predicted EV adoptions and areas with high environmental index, which may yield increased benefits from avoided emissions of displaced internal combustion engine vehicles and associated health improvements (e.g., lower asthma rates)?

As shown in Figure 8, approximately 78 census tracts reflect the top quintile (20%) of the geographic distribution of residential EV adoption. By 2030, only four census tracts in the top quintile of DEI index align with the top census tracts for EV adoption, suggesting that these installations are occurring in lower frequency in areas with highest concentration of customers meeting DEI criteria. Similarly, only five census tracts within top environmental scoring areas overlap with top EV adoption areas.

Table 6 provides additional detail regarding where the EV adoption distribution intersects with the top DEI and environmental scoring census tracts. For both indices, approximately 10% to 11% of the highest scoring census tracts align with top two EV adoption quintiles.

Table 6. Distribution of Top Quintile DEI and Environmental Census Tracts by EV Adoption Quintile

EV Adoption		DEI Index - Top Quintile Distribution		Environmental Index - Top Quintile Distribution	
Quintile Rank	Distribution	# of Census Tracts (n=78)	% of Census Tracts in Top Quintile	# of Census Tracts (n=86)	% of Census Tracts in Top Quintile
1 (bottom)	0–16%	27	35%	28	33%
2	17–25%	32	41%	28	33%
3	25–32%	9	12%	21	24%
4	32–42%	5	6%	6	7%
5 (top)	43–84%	5	6%	3	3%

To provide additional context, Table 7 provides a comparison of different customer characteristics of those census tracts within the top quintiles of distributions of residential EV adoption and each DEI and environmental index. As shown, top DEI and Environmental census tracts reflect different distributions of key categories compared to EV adoption such as higher proportions of multifamily and renters, while proportions for people of color and limited English customers are highest for top DEI areas.

Table 7. Comparison of Customer Characteristics in Top Quintiles of EV Adoption and DEI and Environmental Indices

Category	Quintile	Distribution of Customers Within Top Quintiles		
		EV Adoption	DEI Index	Environmental Index
Building Type	Single Family	82%	62%	62%
	Multifamily	9%	34%	37%
	Manufactured	9%	4%	1%
Ownership	Owner	87%	60%	64%

	Renter	13%	40%	36%
Race	POC	14%	25%	15%
	Non-POC	86%	75%	85%
Language	Limited English	2%	8%	4%
	Non-limited English	98%	92%	96%
Total Counts	Census Tracts	78	78	86
	Premises	161,799	150,067	181,418

* Note –Building type and ownership distribution of customers in top quintiles were obtained from AdopDER output and reflect forecasted values for 2030. Race and language distribution of customers in top quintiles reflect 2019 Census data.

Based on mapping outputs, increasing promotion and targeted outreach and delivery strategies to increase EV adoption in (1) areas reflecting the highest concentration of customers meeting equity criteria, and (2) areas with highest environmental concerns, would result in positive community impacts (e.g., reduced emissions, improved air quality) and increased customer benefits (e.g., access to clean transportation, improved respiratory health, reduced fuel costs).

Appendix A: Data Source Details

This appendix provides additional detail regarding specific data sources considered for this study.

Public data sources included:

- **US Census Bureau's American Communities Survey (ACS) Data.** We extracted much of the demographic data for the final data set from the 2019 ACS 5-year estimates at the census block group-level. This data reflects the proportion of the population within each of the census block group associated with a given demographic characteristic. These characteristics include racial composition, homeownership, education level, median income, internet access, English proficiency, and median household age. We merged ACS data onto the customer account data provided by PGE after geocoding each provided customer latitude and longitude. It is important to note that since ACS data is not customer-specific, our team associated the same census block group-level information with every PGE customer residing within the census block group. Each census block contains approximately 680 households on average, and the ACS values assigned to each account are based on the households of the census block group in which they fall and are not specific to each account.
- **Department of Energy (DOE) Low-Income Energy Affordability Data (LEAD) Tool.** We extracted energy burden data and tribal area data from the DOE LEAD Tool, a public resource designed to help aid the development of programs and policies that better serve low-income households. The data is available at the census tract level. Energy burden is the percent of median yearly income that households pay for electricity and gas bills. The tool also identifies which census tracts contain tribal areas within them.
- **Environmental Protection Agency (EPA) EJScreen Data.** Cadeo extracted much of the environmental data for the data set from the EJScreen tool. According to the EPA's landing page for the tool, "EJScreen is an environmental justice mapping and screening tool that provides EPA with a nationally consistent data set and approach for combining environmental and demographic indicators."[9] The tool pulls together publicly available data to create these indicators, which are available for download from the EJScreen website. We extracted data on air quality, air toxics cancer risk, respiratory hazard index, proximity to traffic, proximity to environmental hazards, and proximity to hazardous waste sites. We extracted this data at the census tract level and combined it with the customer database.
- **Wildfire Risk to Communities Data.** We collected publicly available spatial fire risk data from the US Forest Service. The data was in the form of a raster file that spatially shows the expected annual relative housing unit (EAHU) risk, an index of the expected damage to, or loss of, housing units within a summary polygon due to wildfire in a year. The team

[9] https://www.epa.gov/healthresearch/tools-support-environmental-justice

used ArcGIS to overlay the customer locations (with the latitude and longitude provided by PGE) onto the raster file and identify their EAHU risk. We added these data to the database for consideration in the resilience index.

- **Earthquake Data.** Cadeo collected publicly available spatial seismic risk data from the US Geological Survey. This data was in the form of polygons. Like the process for wildfire risk, the team used ArcGIS to identify the seismic risk for a particular customer by overlaying the customer points with the spatial polygon data. We added these data to the database for consideration in the resilience index.
- **Flood Data.** We collected flood data from the National Flood Hazard Layer, which uses all flood insurance rate map databases published by the Federal Emergency Management Agency (FEMA) to identify the flood risk of a geographic location. We downloaded this data in polygon form and identified each customer’s flood risk by overlaying the customer points with the data in ArcGIS. We included these data for consideration in the resilience index.

Key utility data sources from PGE included:

- **Active Customer Account Data.** This data set contains customer’s latitude and longitude, premise number, rate code, and associated feeder code and substation.
- **Customer Nonpayment Data.** Data granularity is at the premise level and contains information about the number of disconnects due to nonpayment in a 12-month period, as well as the number of notices the customer received as warning for disconnection. It also includes information about whether that customer received payment assistance in a 12-month period and how much payment assistance they received.
- **Heating and Cooling Type and Fuel.** The set contains the type of HVAC equipment for primary heating and cooling and the type of fuel the system operates on.
- **PSPS Data.** This data lists the premises located in one of the seven PSPS zones in the PGE service area.
- **Grid Reliability Data.** Data informed at the feeder level and provided annual outage and reliability data for 2019, 2020, and 2021. This includes an outage count, outage hours originating from by transmission and substation issues and other reliability metrics such as system average interruption frequency index (SAIFI), system average interruption duration index (SAIDI), and major event days.

Table 8. Full Variable List by Category and Source

Variable	Description	Data Source
DEI Category		
Racial Composition	% of the census block population is non-white	ACS
Homeownership	% of households in census block group that is renting	ACS
Households with Above Average, High, or Severe Energy Burden	Energy Burden is the percent of median yearly income that households pay for electricity and gas bills. Households nationally on average pay about 3% of their income on energy bills. A household that pays more than 6% of their income on energy bills is considered to have high energy burden, while a household that pays more than 10% is considered to have severe energy burden. These indicators show the number of households with energy burdens above the 3% national average, the 6% threshold for high energy burdened, or the 10% threshold for severe energy burden across different census tracts	DOE LEAD
Education	% of households in census block group with no high school diploma	ACS
PGE Payment Issue	Household with one or more need criteria: payment assistance, disconnection due to lack of payment, late notices (1 or 0)	Derived from PGE data
PGE Payment Issue Score	Households with payment issues get a score of 1-3 with a point for each issue: payment assistance, disconnection due to lack of payment, late notices	Derived from PGE data
Notices of Disconnection due to nonpayment	Number of times that an account received 5-day notice of disconnection for nonpayment in a 12-month period	PGE
Disconnections due to Nonpayment	Number of times that an account was disconnected for nonpayment in a 12-month period	PGE
Payment assistance - number of times in a year	Number of times that an account (PremID) received payment assistance in a 12-month period	PGE
Payment assistance - $ in a year	Dollars of payment assistance received by an account in a 12-month period	PGE
Poverty level - 200%	Percent of households at or below 200% of the federal poverty level	NHGIS
Poverty level - 100%	Percent of households at or below the federal poverty level	ACS
Poverty level - 200% - Number of households	Number of households in the census block group at or below 200% of the federal poverty level	NHGIS

Variable	Description	Data Source
Tribal Communities	Oregon’s nine recognized Native American tribes: Burns Paiute Tribe, Confederated Tribes of Coos, Lower Umpqua and Siuslaw Indians, Coquille Tribe, Cow Creek Band of Umpqua Tribe of Indians, Confederated Tribes of the Grand Ronde Community of Oregon, The Klamath Tribes, Confederated Tribes of Siletz, Confederated Tribes of the Umatilla Indian Reservation, and the Confederated Tribes of the Warm Springs Indian Reservation	DOE LEAD
Native American Populations	% of population in census block group that is Native American	ACS
Native American Census Block Group Flag	In a census block group where more than 5% of the households are Native American (This is the 90th percentile of census block groups	ACS
Rural Communities	The rural-urban commuting area (RUCA) codes classify US census tracts using measures of population density, urbanization, and daily commuting. A second data set applies 2010 RUCA classifications to ZIP code areas by transferring RUCA values from the census tracts that comprise them. The most recent RUCA codes are based on data from the 2010 decennial census and the 2006-10 American Community Survey. The classification contains two levels. Whole numbers (1-10) delineate metropolitan, micropolitan, small town, and rural commuting areas based on the size and direction of the primary (largest) commuting flows	RUCA
Frontier Communities	People residing 75 miles by road from a community of less than 2,000 individuals	ACS
Coastal Communities	People residing west of Oregon’s Coastal Mountains	ACS
Housing Type	Single, multifamily, or manufactured home	PGE
Lack of Internet Access	Median percentage of homes that do not have internet subscription	ACS
Population with Disabilities	Percent of population with disabilities	ACS
Income Stress	Median household income	ACS
Energy Burden	The average percent of median yearly income that households pay for electricity/gas in the census tract	DOE LEAD

Variable	Description	Data Source
Energy Burden for Households below 200% FPL	The average percent of median yearly income that households under 200% FPL pay for electricity/gas in the census tract	DOE LEAD
Limited English	% of households in census block group with limited English	ACS
Householder's Age	Disclosure of ages of heads of household - those in charge of decisions about improvements	ACS
Asthma	Median percentage of adults (populations age 18 or older) with asthma in census tract	CDC 500 Cities
Environmental Category		
Air quality (PM2.5)	Particulate matter (PM2.5) levels in air, micrograms per cubic meter (µg/m^3) annual average. Source: EPA Office of Air and Radiation	EPA EJ Screen
Air quality (O_3)	Ozone summer seasonal avg. of daily maximum 8-hour concentration in air in parts per billion. Source: EPA Office of Air and Radiation	EPA EJ Screen
Air toxics cancer risk	Lifetime cancer risk from inhalation of air toxics, as risk per lifetime per million people. Source: EPA National Air Toxics Assessment	EPA EJ Screen
Respiratory hazard index	Air toxics respiratory hazard index (the sum of hazard indices for those air toxics with reference concentrations based on respiratory endpoints, where each hazard index is the ratio of exposure concentration in the air to the health-based reference concentration set by EPA). EPA National Air Toxics Assessments	EPA EJ Screen
Diesel PM	Diesel particulate matter level in air in micrograms per cubic meter (µg/m^3). Source: EPA National Air Toxics Assessments	EPA EJ Screen
Proximity to Traffic	Count of vehicles per day (average annual daily traffic) at major roads within 500 meters (or nearest one beyond 500 m), divided by distance in meters. Calculated from US Department of Transportation National Transportation Atlas database, Highway Performance Monitoring System	EPA EJ Screen
Proximity to Environmental Hazards Waste	Count of hazardous waste management facilities (TSDFs and LQGs) within 5 km (or nearest one beyond 5 km), each divided by distance in km. Calculated from EPA RCRAInfo database	EPA EJ Screen

Variable	Description	Data Source
Superfund Proximity	Count of proposed and listed NPL sites within 5 km (or nearest one beyond 5 km), each divided by distance in km. Count excludes deleted sites. Source: Calculated from EPA CERCLIS database	EPA EJ Screen
RMP Facility Proximity	Count of RMP (potential chemical accident management plan) facilities within 5 km (or nearest one beyond 5 km), each divided by distance in kilometers	EPA EJ Screen
Underground Storage Tanks (UST)	Count of LUSTs (multiplied by a factor of 7.7) and the number of USTs within a 1,500-foot buffered block group	EPA EJ Screen
Wastewater Discharge	Modeled toxic concentrations at stream segments within 500 meters, divided by distance in km	EPA EJ Screen
Resilience Category		
Public Safety Power Shutoff Zone	Sites are marked as in a PSPS zone and are more likely to experience safety shutoffs due to natural disasters like fires	PGE
Wildfire Risk - Expected Annual Relative Housing Unit Risk (EAHUrisk)	EAHUrisk is an index of the expected damage to, or loss of, housing units within a summary polygon due to wildfire in a year. This is a long-term annual average and not intended to represent the actual losses expected in any specific year. It is calculated as the product of HUexposed (housing units exposed) and MeanRPS (MeanRPS is the housing-unit weighted mean of the Risk to Potential Structures raster within a summary polygon)	US Forest Service
Flood Risk	The National Flood Hazard Layer data incorporates all flood insurance rate map databases published by FEMA, and any Letters of Map Revision that have been issued against those databases since their publication date. The primary risk classifications used are the 1-percent-annual-chance (or 100-year) flood event, the 0.2-percent-annual-chance (or 500-year) flood event, and areas of minimal flood risk	RLIS-FEMA
Flood Risk – 100-yr flood zone	Based on pct_flood_risk, this customer will get a 1 if they are in an area with 1% chance of flood	RLIS-FEMA
Flood Risk – 500-yr flood zone	Based on pct_flood_risk, this customer will get a 1 if they are in an area with 0.2% chance of flood	RLIS-FEMA
Floodway	Area is in a designated flood area	RLIS-FEMA
Levee protected area	Area is in an area with reduce flood risk due to a levee	RLIS-FEMA

Variable	Description	Data Source
Seismic Risk	The peak acceleration value that is shown by this layer is an estimate of the worst amount of shaking due to earthquakes experienced in the place indicated on a map in about a 500year time frame Predicted horizontal acceleration (shaking) values in this data set are expressed as a percentage of the acceleration of gravity (g). The values in this data set do not exceed 100, so keep in mind a 100 on the map means the model is predicting a value greater than or equal to 100% g, violent or extreme shaking. (100% g is an acceleration of 9.80665 m/s^2	DOGAMI
CMI	Average annual customer minutes interrupted - total customer outage time for a sustained outage	PGE SAM
CELID24	Average percentage of customers exceeding 24 hours of outage duration including Major Event Days	PGE SAM
Loss of supply substation - count	Average annual number of losses of supply substation outages at feeder level. Major event days excluded	PGE SAM
Loss of supply substation - hours	Average annual customer hours interrupted due to loss of supply substation outages. Major event days exclude	PGE SAM
Loss of supply transmission - count	Average number of losses of supply transmission outages. Major event days excluded	PGE SAM
Loss of supply transmission - hours	Average customer hours interrupted due to loss of supply transmission outages. Major event days excluded	PGE SAM
MED	Average number of major event days that occurred during the year (SAIDI exceeding a threshold value)	PGE SAM
SAIFI	SAIFI for the feeder (frequency of outages). Major event days excluded	PGE SAM
SAIDI	SAIDI for the feeder (duration of outages). Major event days excluded	PGE SAM
Sustained outages	Average number of sustained outage events (classification based on exclusion criteria). Major event days excluded	PGE SAM

Appendix B: Scoring Details

Table 9, Table 10, and Table 11 provide additional detail regarding specific distributions and assigned points used in the development of the DEI, environmental, and resilience indices, respectively. As noted, scores were individually developed for each residential customer. For each index, we assigned 500 points as a base value a customer received 500 points and then were assigned

Table 9. DEI Index – Scorecard Detail

Variable	Value	PGE Customer Distribution (%)	Points
Base		100%	500
Energy burden	<2%	25%	-50
	2%	50%	150
	>2%	25%	300
Housing type	SF	63%	-80
	MF	33%	150
	MH	4%	250
Race	<10%	25%	-100
	10 to 26%	50%	20
	>26%	25%	100
Unit renters	<18%	25%	-80
	18 to 57%	50%	80
	>57%	25%	150
Households without internet	<3%	25%	-20
	3 to 12%	50%	20
	>12%	25%	60
Households with disabilities	<16%	25%	-40
	16 to 31%	50%	0
	>31%	25%	40

Table 10. Environmental Index – Scorecard Detail

Variable	Value	PGE Customer Distribution (%)	Points
Base		100%	500
Proximity to Environmental Hazard Waste	>3	25%	50
	0.02 to 3	50%	0
	<0.02	25%	-100

Respiratory Hazard Index	>0.6	25%	250
	0.4 to 0.6	50%	150
	<0.4	25%	-100
Ozone Index	>37	25%	150
	34 to 37	50%	50
	<34	25%	-100

Table 11. Resilience Index – Scorecard Detail

Variable	Value	PGE Customer Distribution (%)	Points
Base		100%	500
Loss of supply substation - hours	=0	75	-100
	>0	25	200
Loss of supply transmission - hours	=0	75	-100
	>0	25	100
System average interruption duration index	>136	25%	300
	29 to 136	50%	150
	<29	25%	-50
Seismic risk	<15	25	-80
	=15	50	0
	>15	25	80