Spatial Distribution of Solar Photovoltaic (PV) Deployment: An Application of the Region-Based Convolutional Neural Network

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Background

MOTIVATION: Existing solar deployment data measures the number of solar systems. There are few attempts to measure the PV-to-roof ratio, or the proportion of roofs covered by solar panels. Little is known about how **natural environment, disaster vulnerabilities and local-level policies** shape rooftop solar deployment.

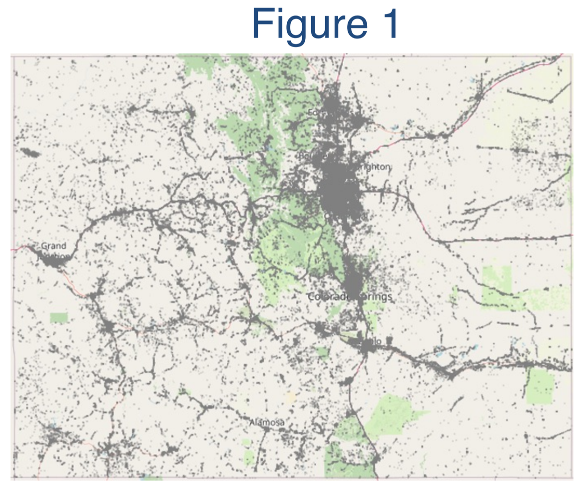
QUESTION: (1) How does rooftop solar deployment vary across neighborhoods in Colorado? (2) What are the predictors of rooftop solar deployment?

PURPOSE: This study aims to generate a novel and granular solar deployment dataset at the US census block group level using satellite imagery from the state of Colorado in 2021 and identify important predictors of rooftop solar deployment in Colorado.

Methods

AREAS OF INTEREST: 142K Census blocks in Colorado with at least 1 resident represented by the gray area in Fig 1.

Figure 1



DATA: (i) Rooftop solar Deployment data are from 652,795 satellite images collected using Google Maps API; (ii) Data of 43 environmental, socioeconomic, and infrastructure predictors of rooftop solar deployment from various sources (e.g., FEMA, HIFLD, USFS, NREL).

COMPUTER VISION: Faster-RCNN (Ren et al. 2015) to predict the size of roofs and PVs in all images. We manually annotated 367 images (as in Fig 2) and constructed training (80%), dev (10%) and test (10%) sets. Intersection over Union (IoU),

$$IoU = \frac{area(A_p \cap A_{gt})}{area(A_p \cup A_{gt})}$$

where A_p is the predicted frame and A_{gt} the ground truth frame, is 95% and 81% for detecting roofs and PVs, respectively.

Figure. 2. (a) Original (b) Roofs (c) Solar PV

Methods

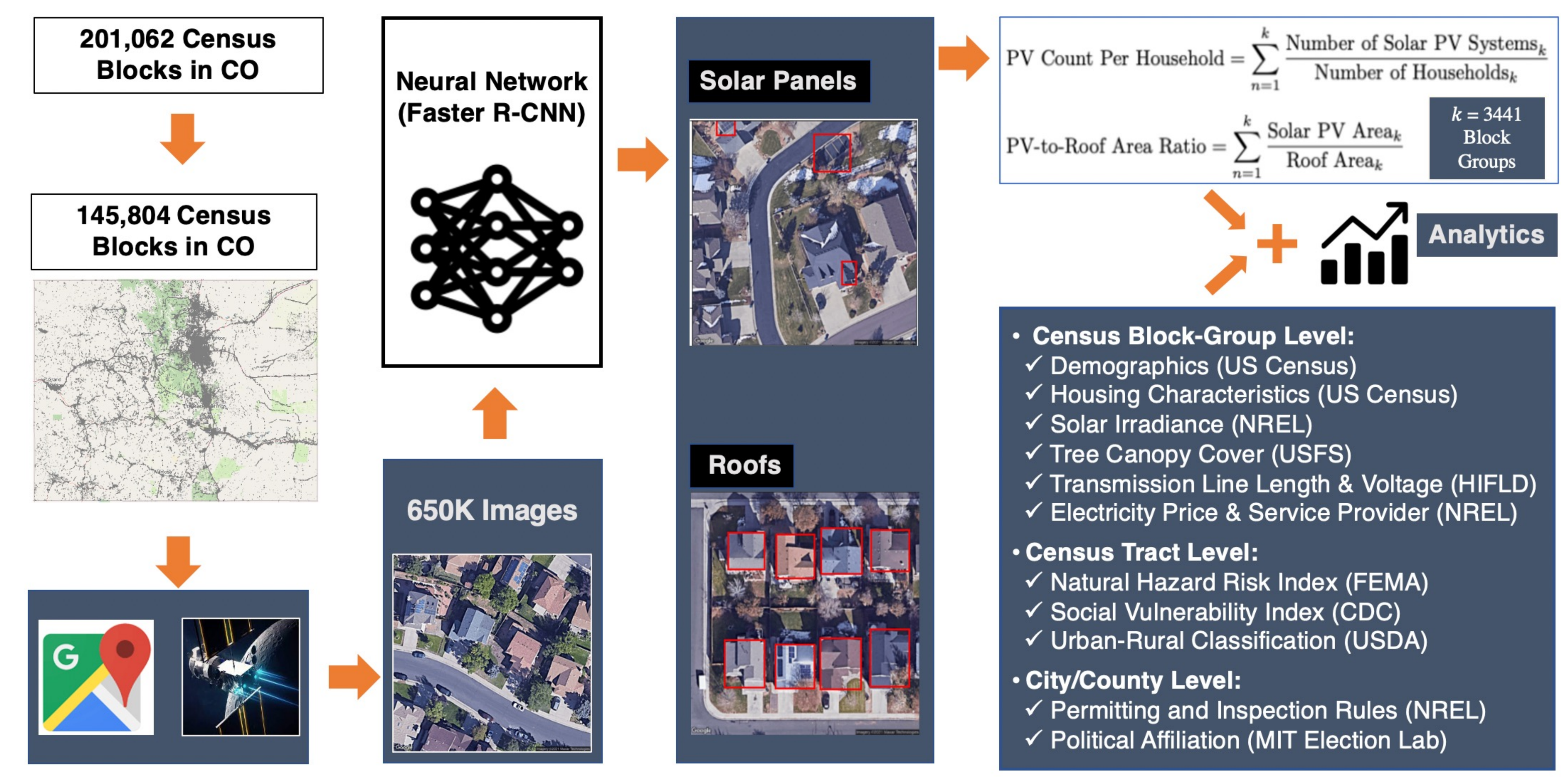


Figure 3. Data Processing Workflow

Results

Fig 4a. Predictors of PV-to-Roof Area

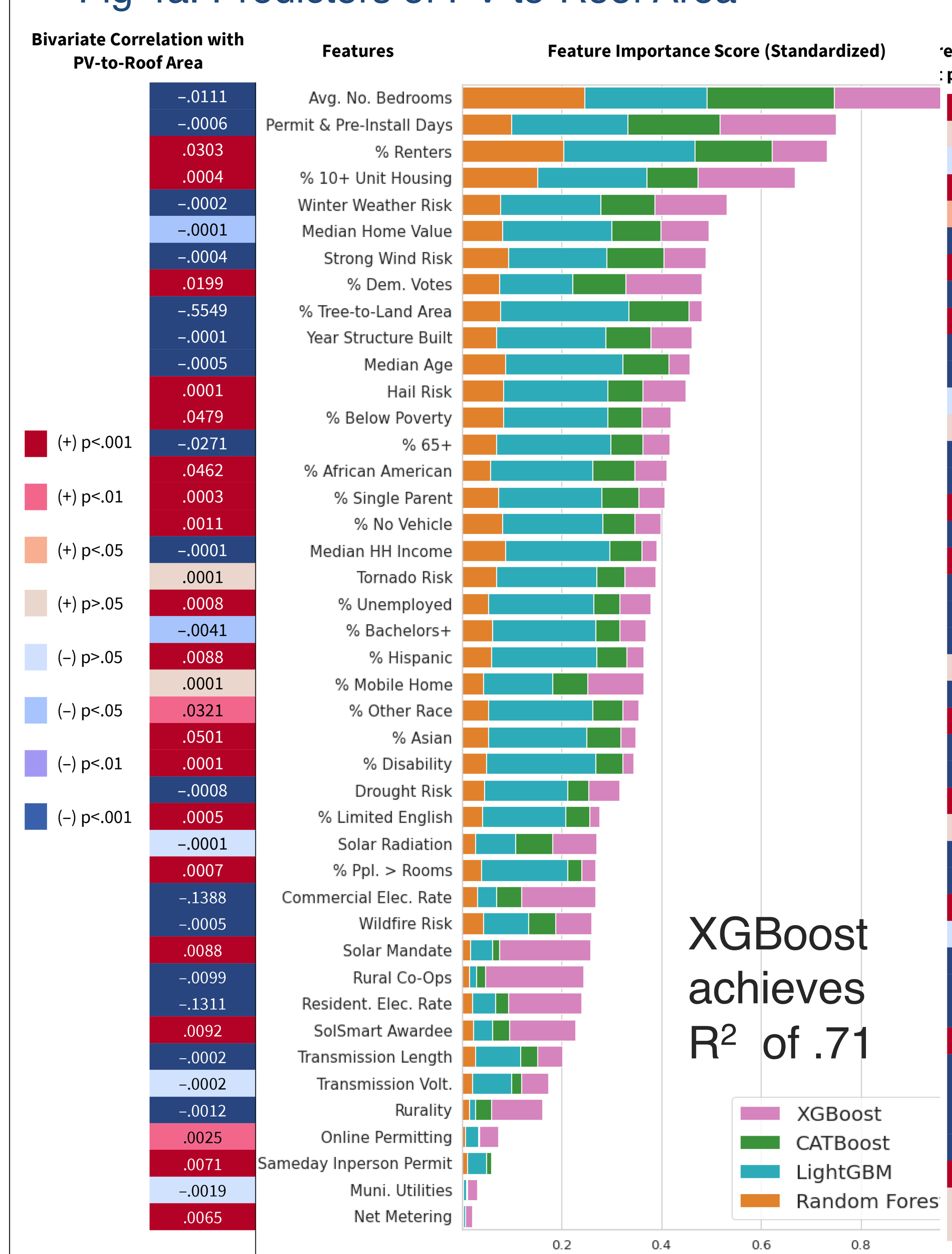
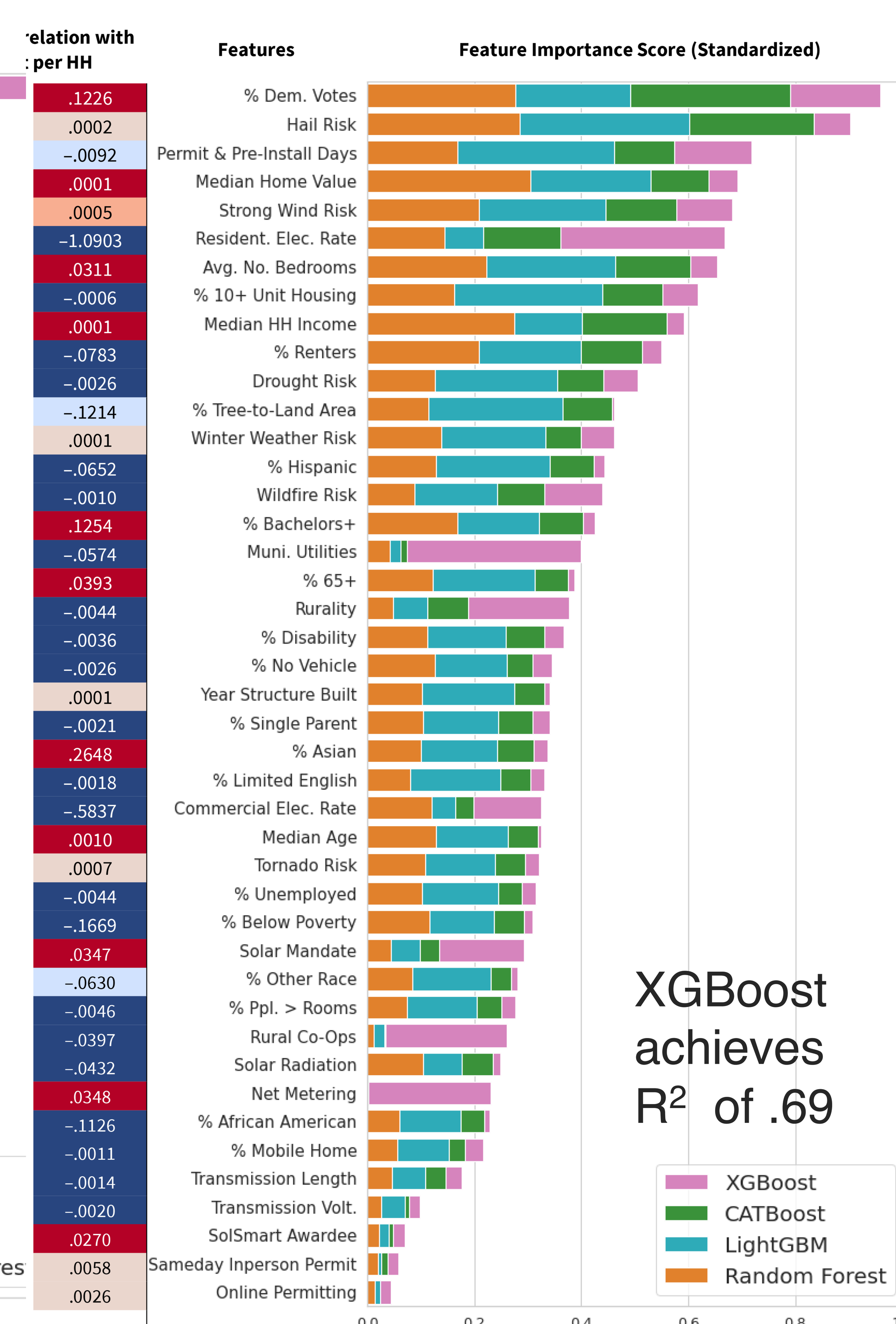


Fig 4b. Predictors of PV Count per HH



Average number of bedrooms (–) and permit and pre-install timelines (–) are two of the most important predictors of PV-to-roof area. % of democratic voters (+) and hail risks (–) are two of the most important predictors of PV count per household.

Results

Fig 5a. PV-to-Roof Area

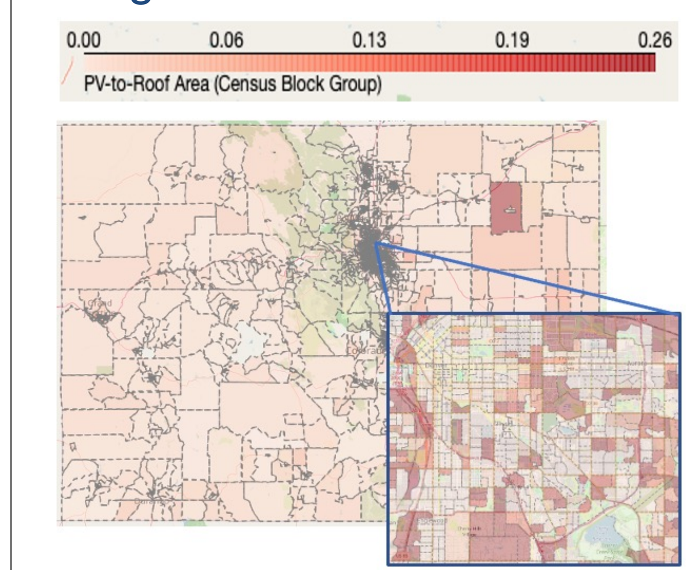
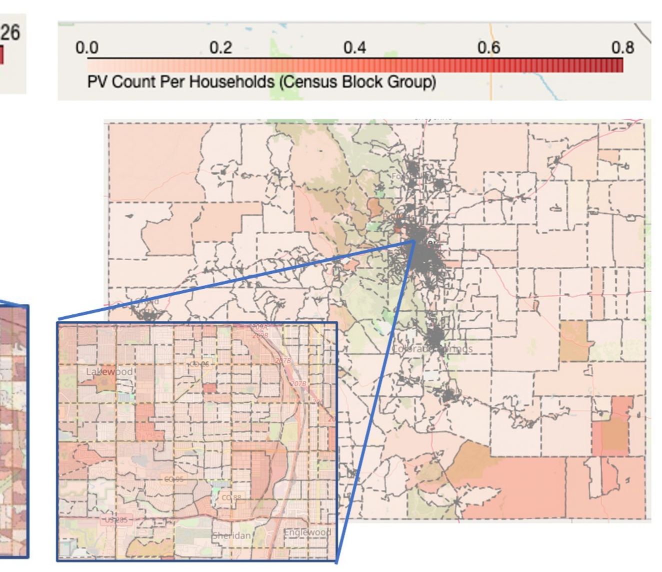
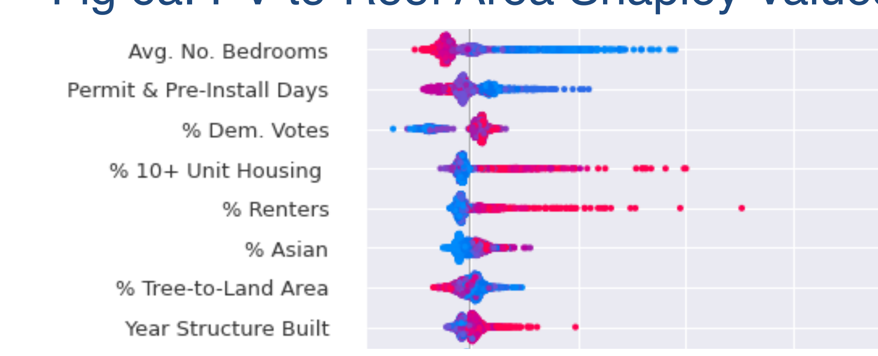


Fig 5b. PV Count per HH



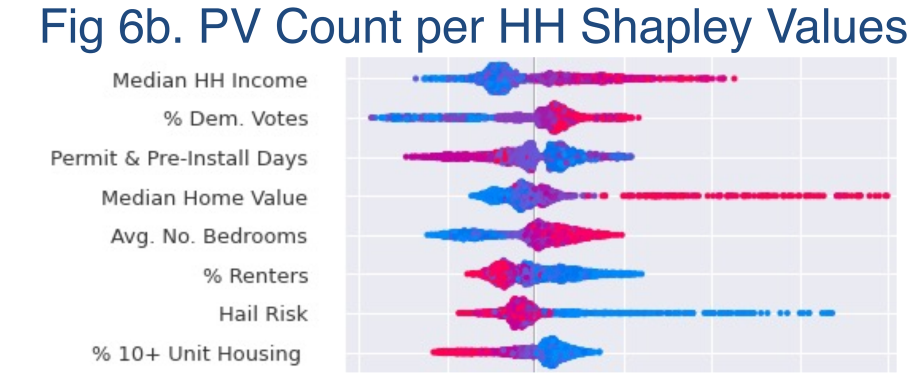
In Colorado, 2.5% of roofs are covered by solar panels on average (Fig 5a), and 7% of households have solar panels on their roofs (Fig 5b).

Fig 6a. PV-to-Roof Area Shapley Values



% tree-to-land area and median house age negatively predict PV-to-roof area.

Fig 6b. PV Count per HH Shapley Values



% Dem. votes and median HH Income positively predict PV Count per HH.

Discussion

(i) High variation in PV count per HH (CV = 1.33) and medium-high variation in PV-to-Roof area (CV = .78); (ii) Shorter permitting and inspection timeline may promote solar deployment; (iii) The relationship between HH income and solar deployment may depend on racial/ethnic composition of regions (Fig 7); (iv) natural disaster vulnerability (e.g., hails) can discourage solar PV deployment

Fig 7. Differential Average Marginal Effects of Median HH Income