Peer Effects in Rooftop Solar Adoptions

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Motivation

How do visible peer installations affect solar installation decisions?

- Nearby panels
- Own panels

Why?

- Policy implications
  - non-pecuniary inducement for green behavior
  - “Conspicuous green consumption”
  - Externalities
- Marketing implications

Motivation

A common problem in peer effects studies is exogeneity of the peer variable.

- Visibility of a panel is plausibly exogenous.
  - North vs. South side of the street:

Motivation

Visibility is a function of both angle from street *and* obstructions

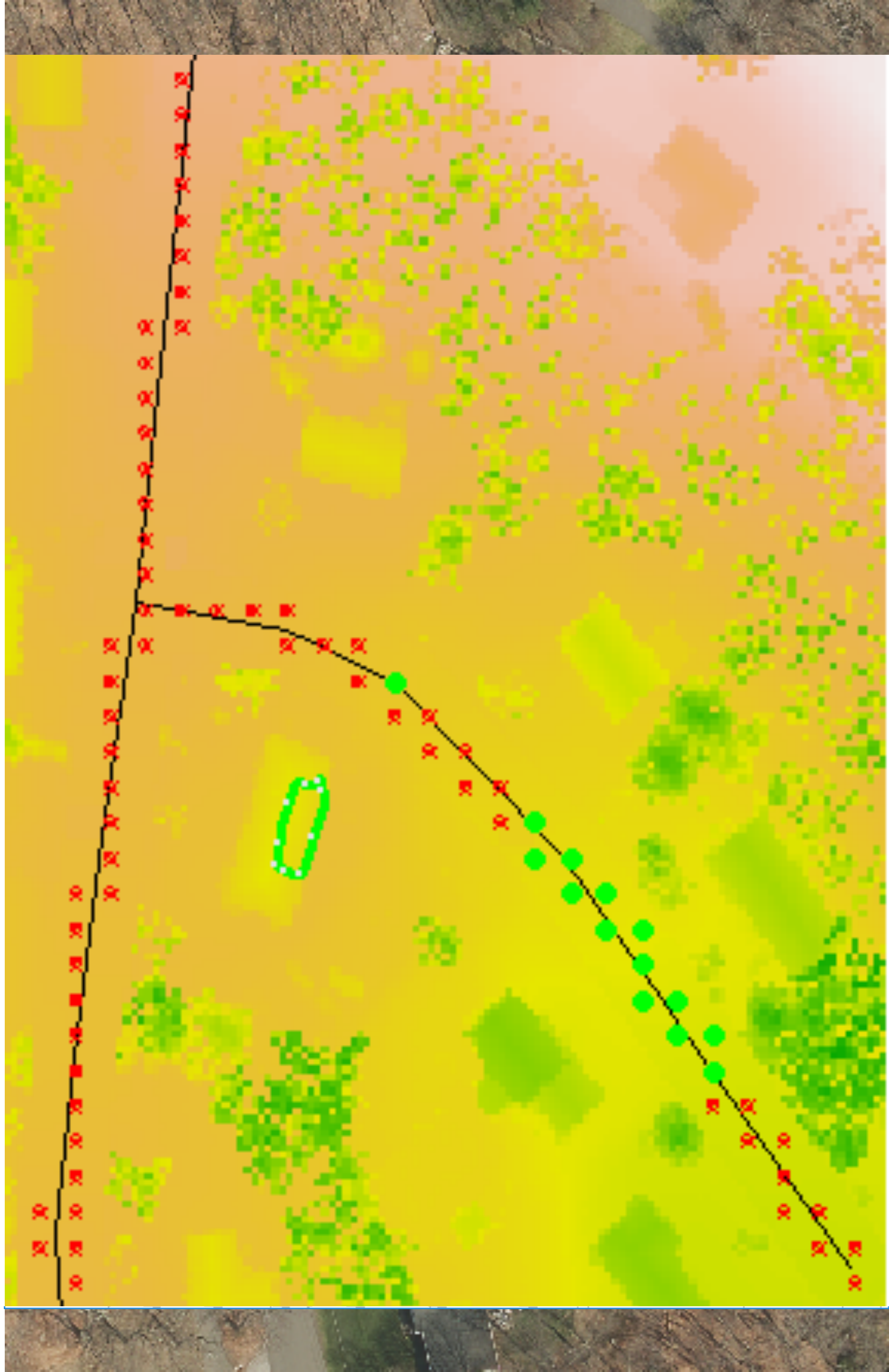
Naïve methods:

- Send RAs out to assess
  - Lang and Opaluch (2014) with turbines in RI
- “North side of street”
  - East/west streets and obstructions ignored

Overview

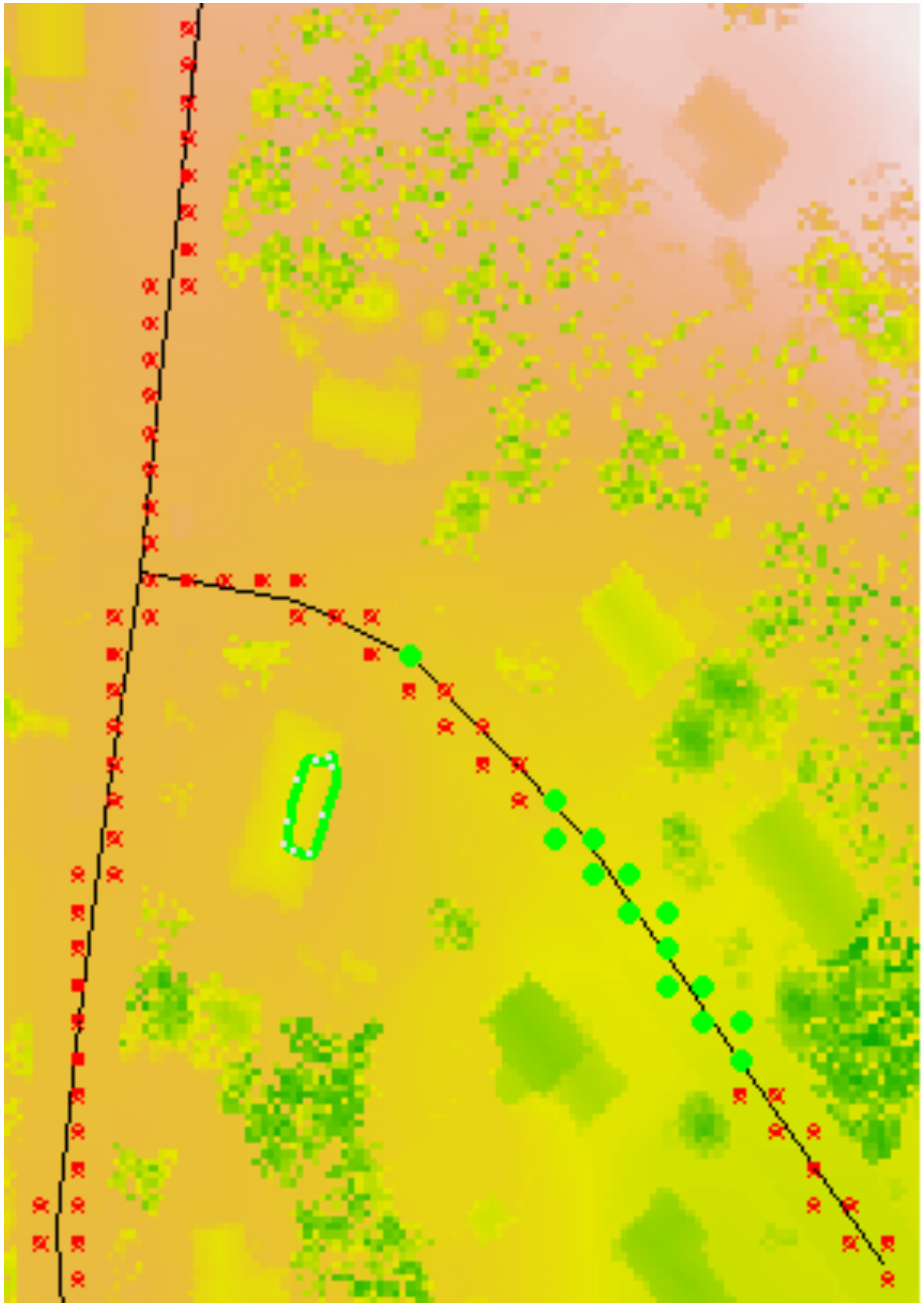
To assess the angle of visibility and obstructions in each solar panel:

1. CNN to recognize and bound panels
2. LiDAR (3-D point cloud) to test angle of visibility
3. LiDAR to assess obstructions
4. Generate panel-level measure of visibility



Overview

- Machine learning
  - Panel recognition
- Novel data application
  - LiDAR for visibility



Data Sources

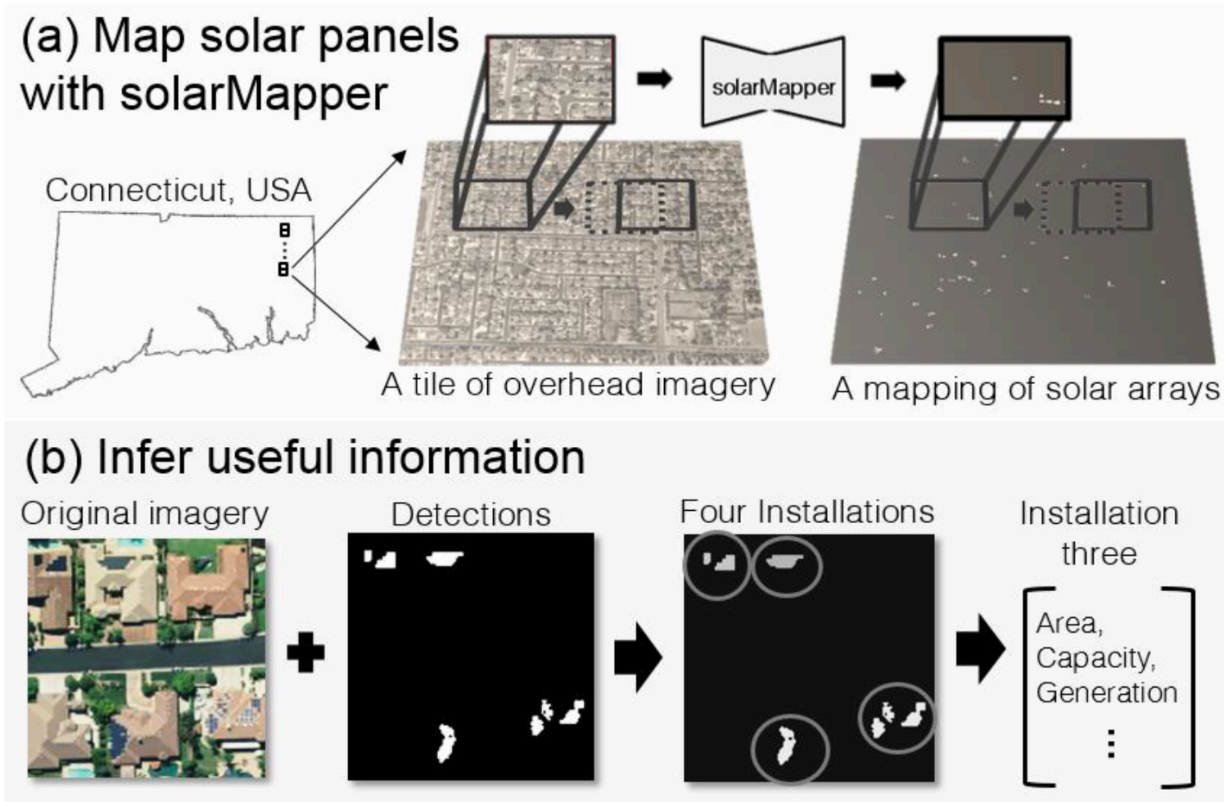
- 816k homes in CT (CoreLogic; Zillow Ztrax)
- 15,440 known solar installations w/address
  - Date applied, date completed
- Voter affiliations for 663k households
- Misc:
  - Geocode addresses to lat-lon
  - Streets from ESRI CT streetmap

Data Sources

- Google Project Sunroof (515k homes in CT)
  - Ordering of rooftop locations (w/ pitch, azimuth)
  - NPV of installation accounting for electricity rates
  - Spatial match to houses
  - Proprietary data

Methods

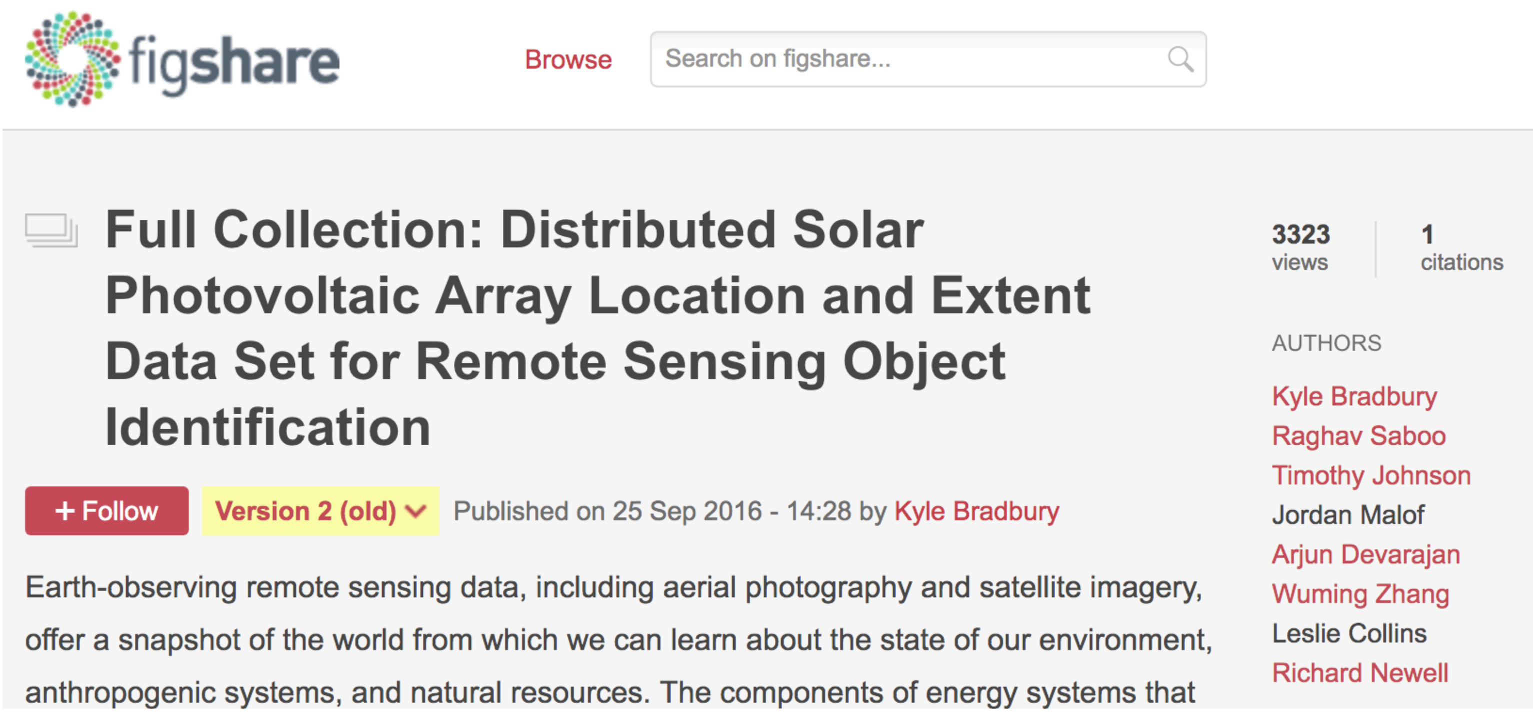
- CNN semantic segmentation (Malof et al., 2016, 2019)



- Pixelwise prediction of presence of solar panel
- Fit to maximize *Intersection over Union* (IOU)

Methods

- Trained on publicly accessible Duke California Array Dataset (Bradbury et al., 2016)
- 16,000 labeled arrays in 400km^2 of imagery

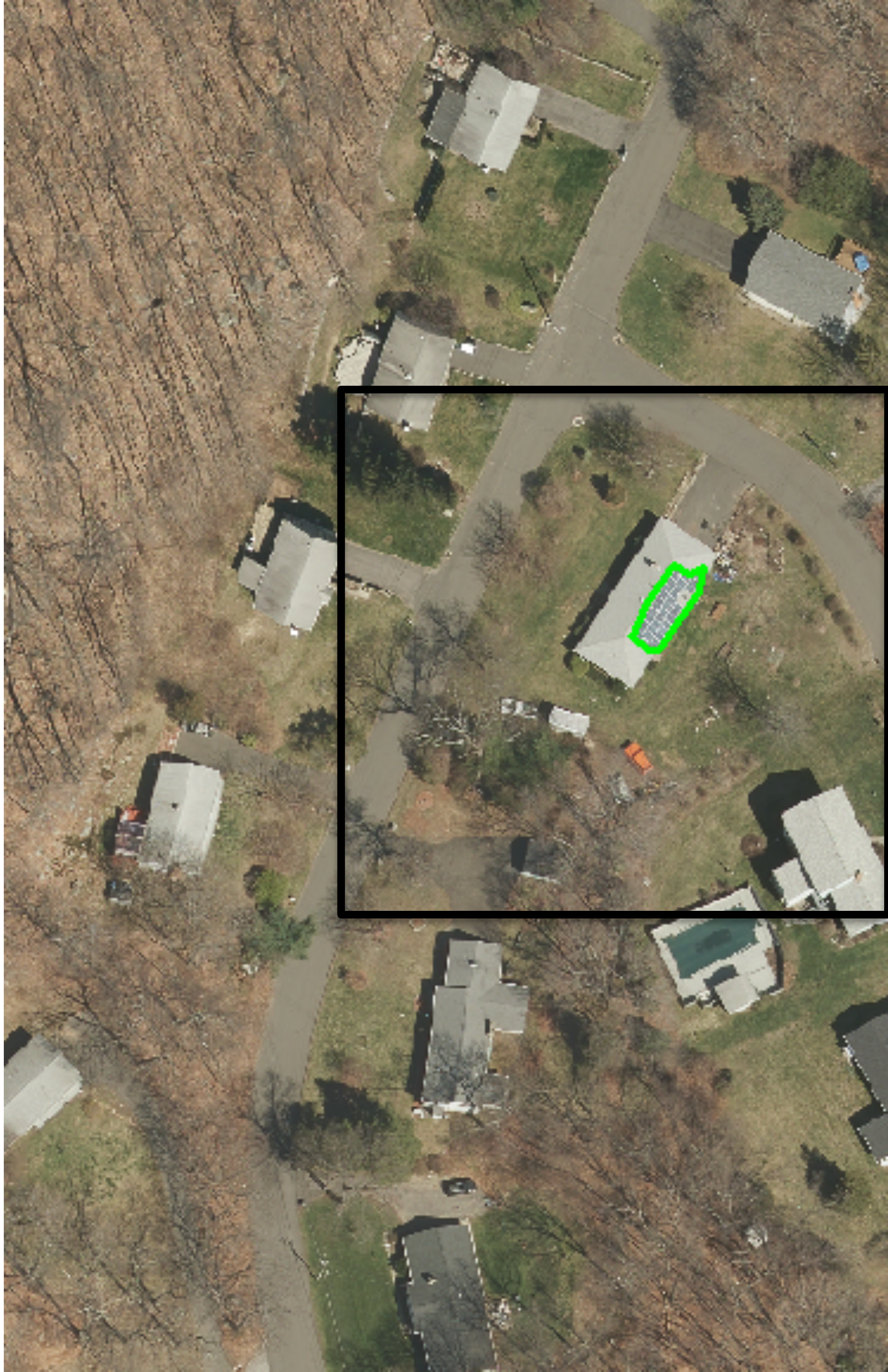


Methods

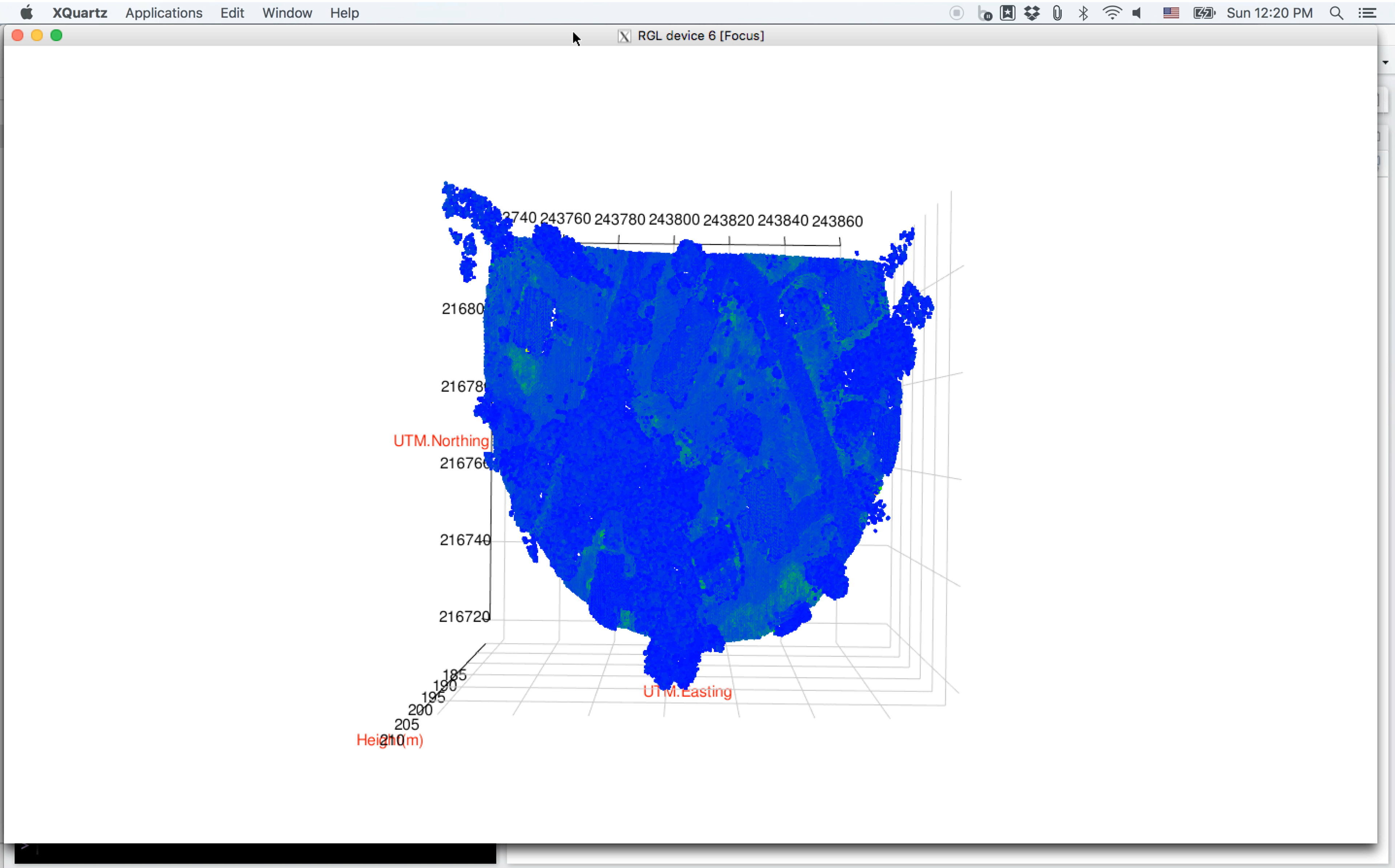
Transfer learning method to apply to Connecticut.

Using [UCONN CTEO]() satellite imagery (2016)

Publicly available as *SolarMapper*



Methods – LiDAR



Data Sources - LiDAR

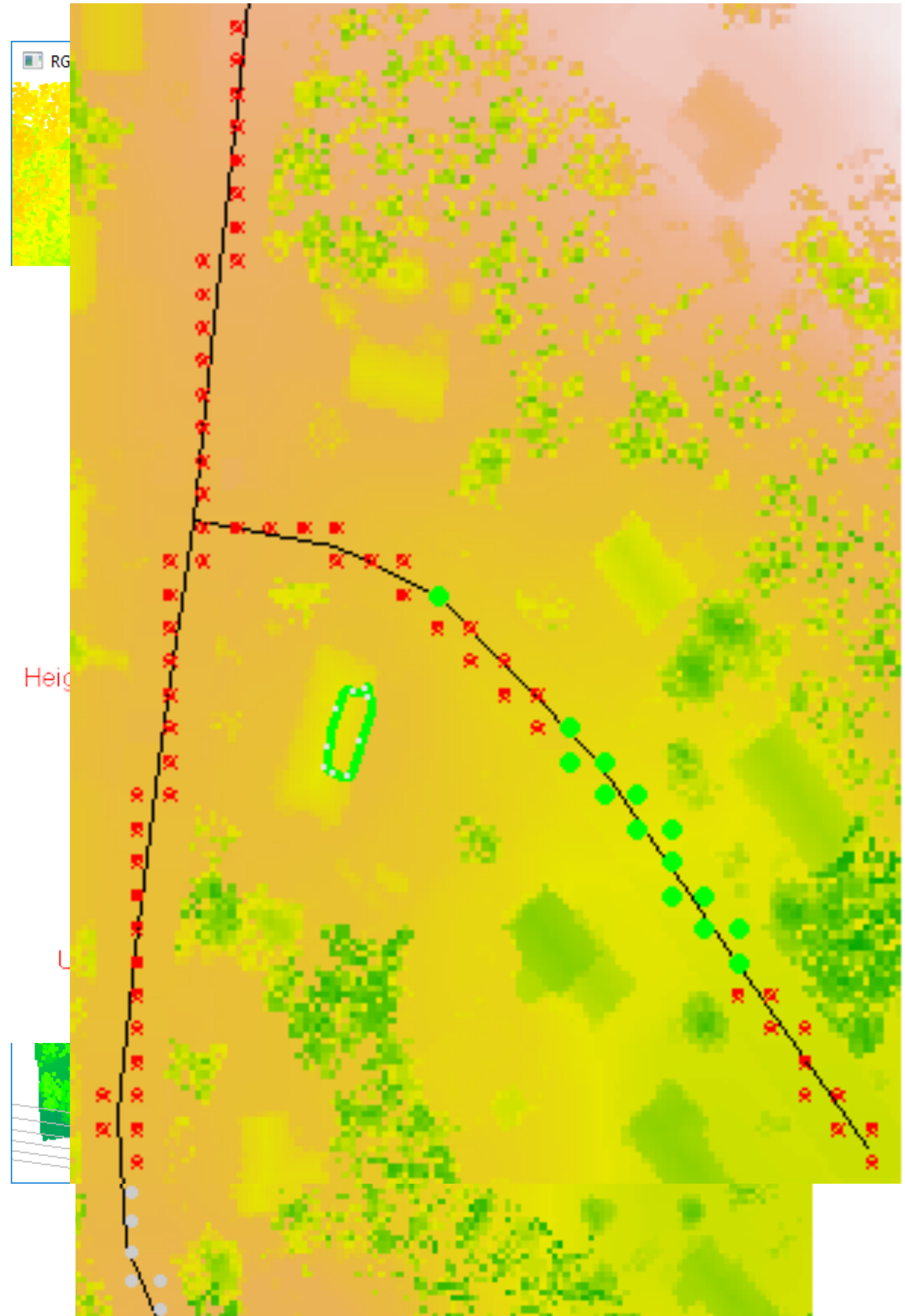
- "Light Detection and Ranging"
  - 3-D Point Cloud

- Publicly available: NOAA and USGS
  - Hurricane Sandy, floodplain mapping
  - Frequently found alongside DEM and DSM surface models

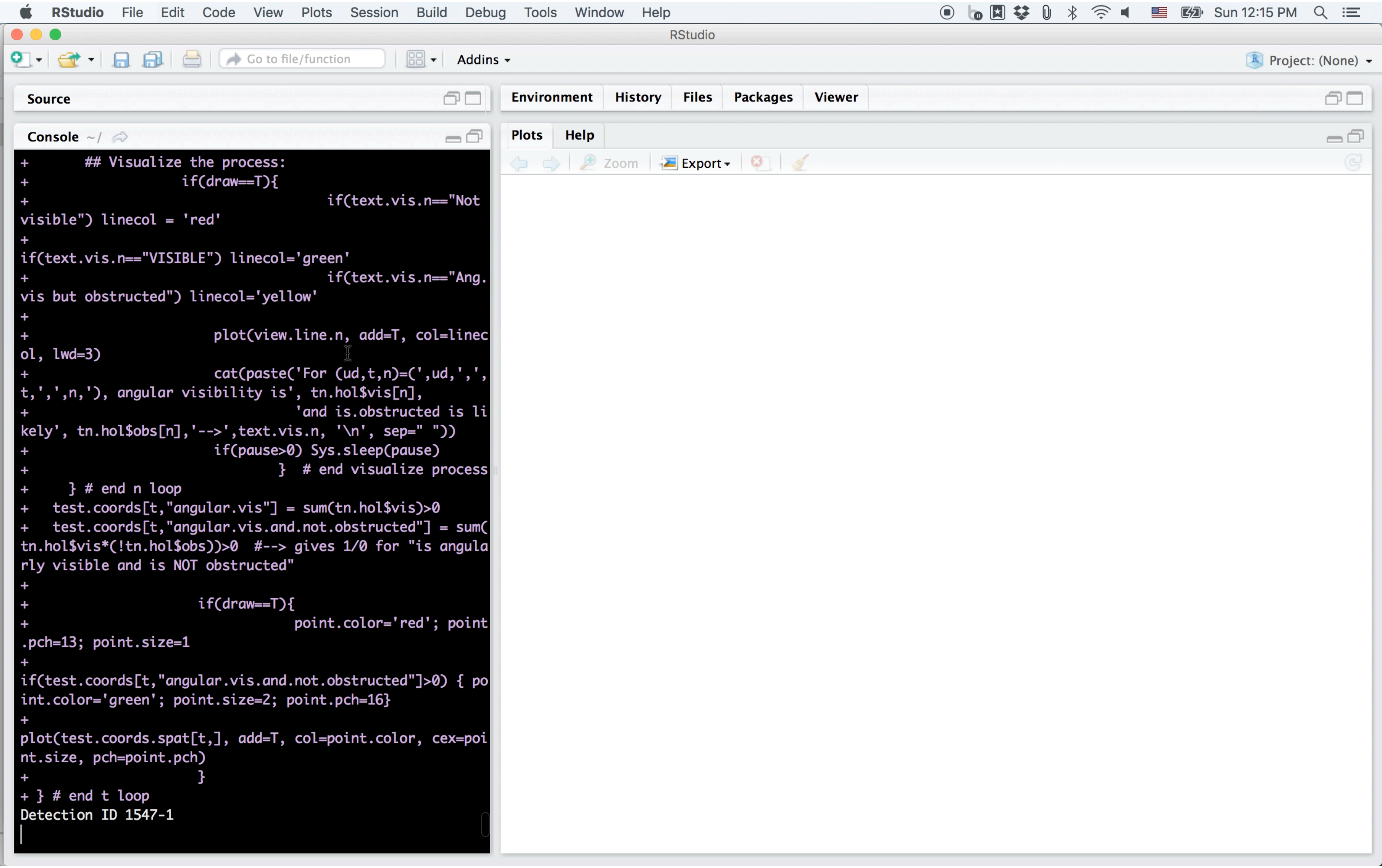
- Processing with *rlas* in R
  - Generate queryable tile mapping
  - Process over 15,400 known solar installations

Methods - LiDAR

- For each panel, download all LiDAR within 120m
- Subset to those LiDAR points within the panel polygon
- Regress Z on X + Y to get pitch
- For obstructions, rasterize surrounding area.
  – Fill grid cells with some function (max, median) of LiDAR points



Methods - LiDAR



18 Mohawk Cir - Google Maps
Justin
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18 Mohawk Cir
Danbury, Connecticut
Street View - Jul 2014
Mohawk Cir
Mohawk Circle
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Terms
Report a problem

Other uses

- Assessing disamenity value
  - Wind turbines (Lang and Opaluch, 2014)
  - Presence of fracking
  - Hedonic models

- Proxy for information set
  - Knowledge of environmental bad
  - Questions regarding salience

Model

Linear probability model:

$$y_{it} = \alpha[CT]_{it} + \gamma_1[Vis]_{it} + X_{it}\beta + \epsilon_{it}$$

$$y_{it} = \alpha[CT]_{it} + \gamma_1[Vis]_{it} + \gamma_2[EV_i \times Vis]_{it} + X_{it}\beta + \epsilon_{it}$$

$[y_{it}]$	Binary indicator for installation in month t
$[CT]_{it}$	Count of peer installations.
$[Vis]_{it}$	Degrees of visibility from the street of **peer** installations.
$[EV]_i$	Own-value (NPV) of installation (Google Sunroof)
X_{it}	Control variables, including fixed effects, Solarize.

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