

Using A Deep Learning Object Detection Model to Identify Manufactured Units and Validate ACS Housing Counts

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Introduction

Due to sampling challenges in rural and lower density areas it is difficult to adequately know about the location of **older manufactured homes** and the potential demand for replacement of units.

Purpose:

Pilot project to develop a methodology to count manufactured housing units in rural and other low density areas.

In particular, our Member service areas across Appalachia



Introduction

- With construction costs and productivity being some of the greatest barriers to housing affordability, **manufactured homes are increasingly seen as a viable solution to the housing crisis.**
- Manufactured homes are an important source of housing for millions of Americans, with approx. **7% of households living in 6.8 million manufactured homes (U.S. Census Bureau).**
- Manufactured units make up a significant proportion of the housing supply across the regions we serve e.g. rural.
- Manufactured housing does not follow the “rules” of regular subdivision – **especially relevant as it pertains to zoning and ownership.**

Despite the prevalence and importance of manufactured housing, there is **currently no systematic way to count the total numbers and locations** of these properties.

Data, Tools and Methods

Data:

- USDA NAIP Aerial Images
- Local administrative data sets (property data)

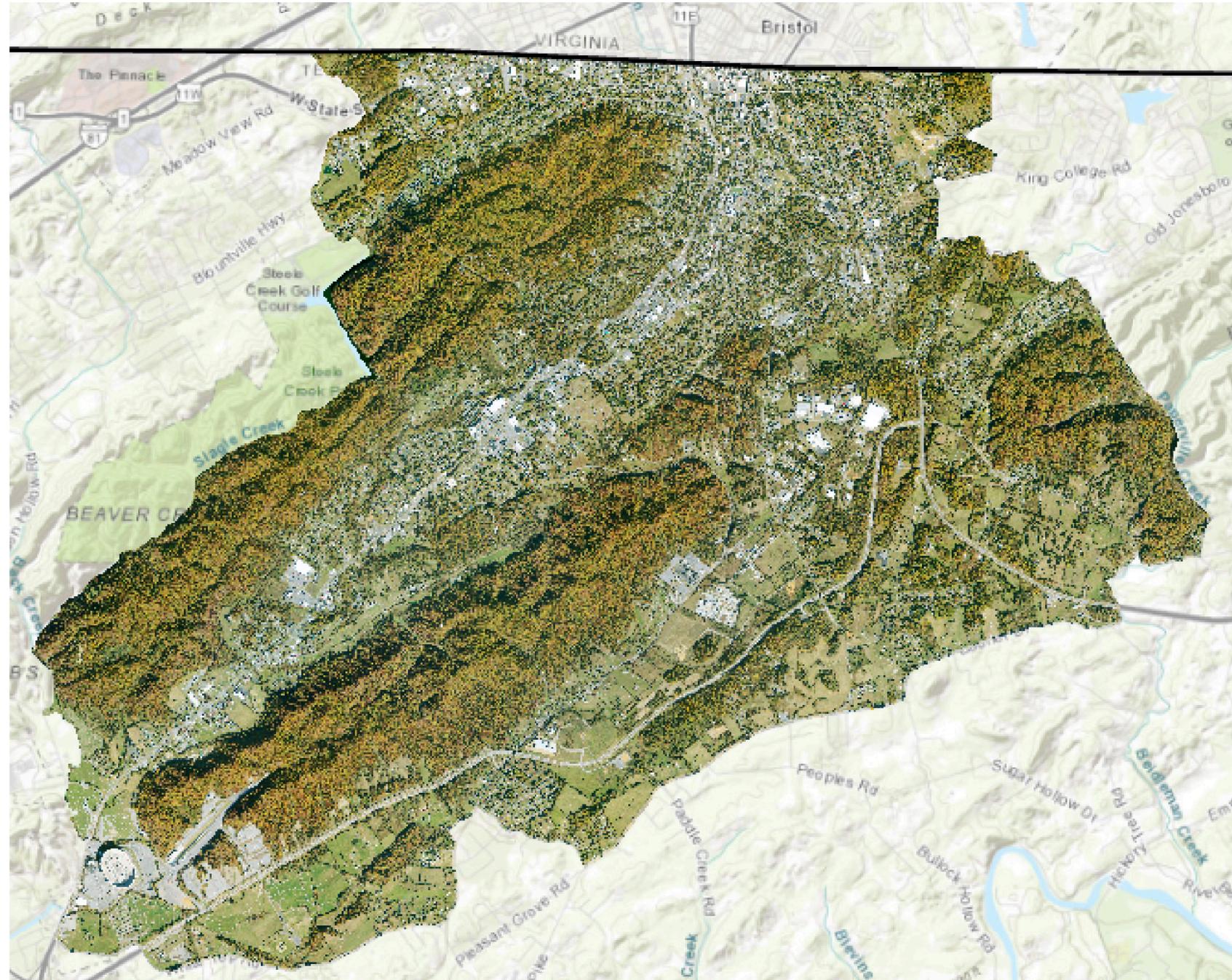
ACS Data: 5-year 2023

- Units in structure (B25024)

Tools & Methods:

- Machine learning - Object Detection
 - RCNN Mask
- Geographic Information Systems (GIS)
 - ArcGIS Pro v 3.4

Area of Interest

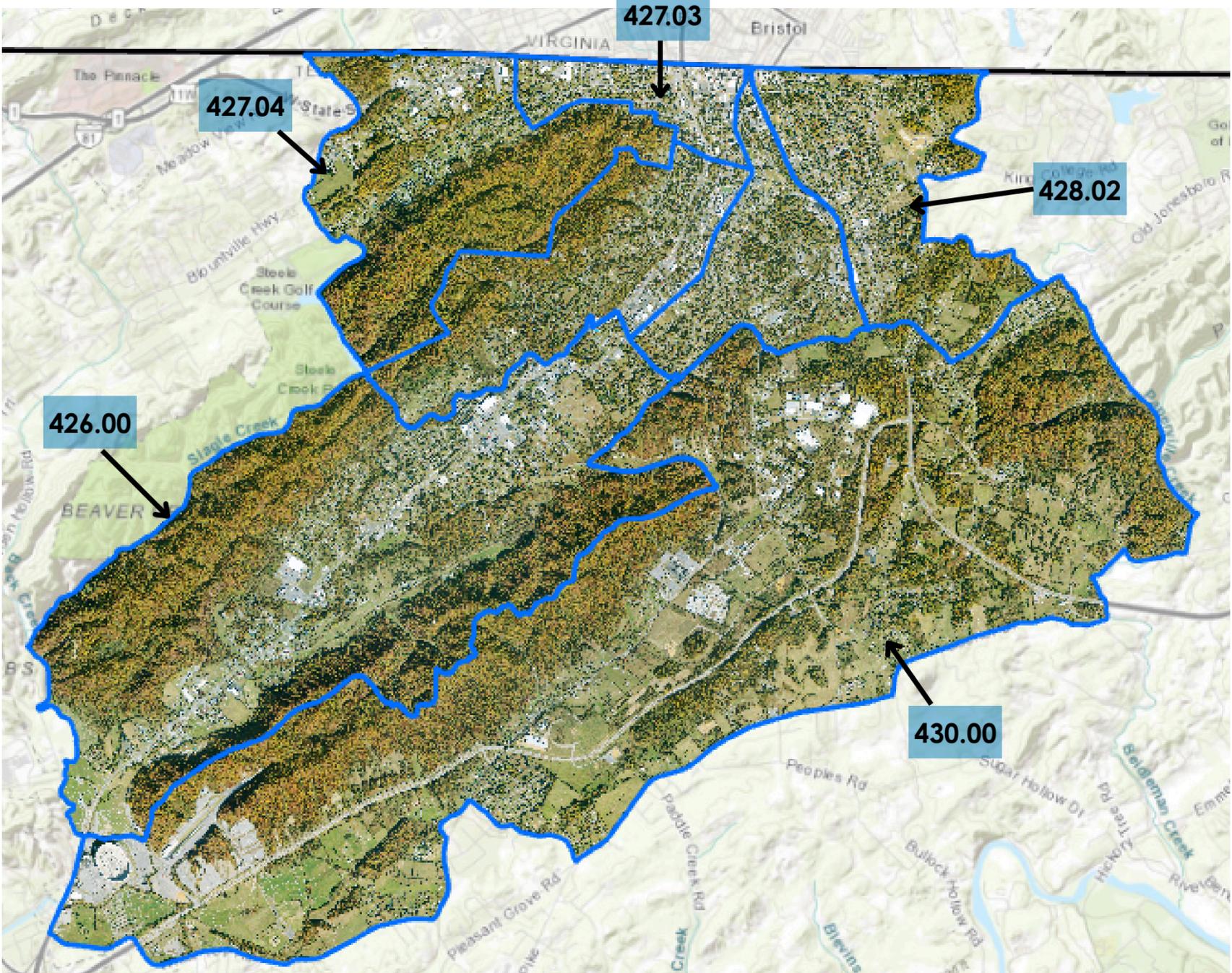


NE region of Sullivan County, Tennessee

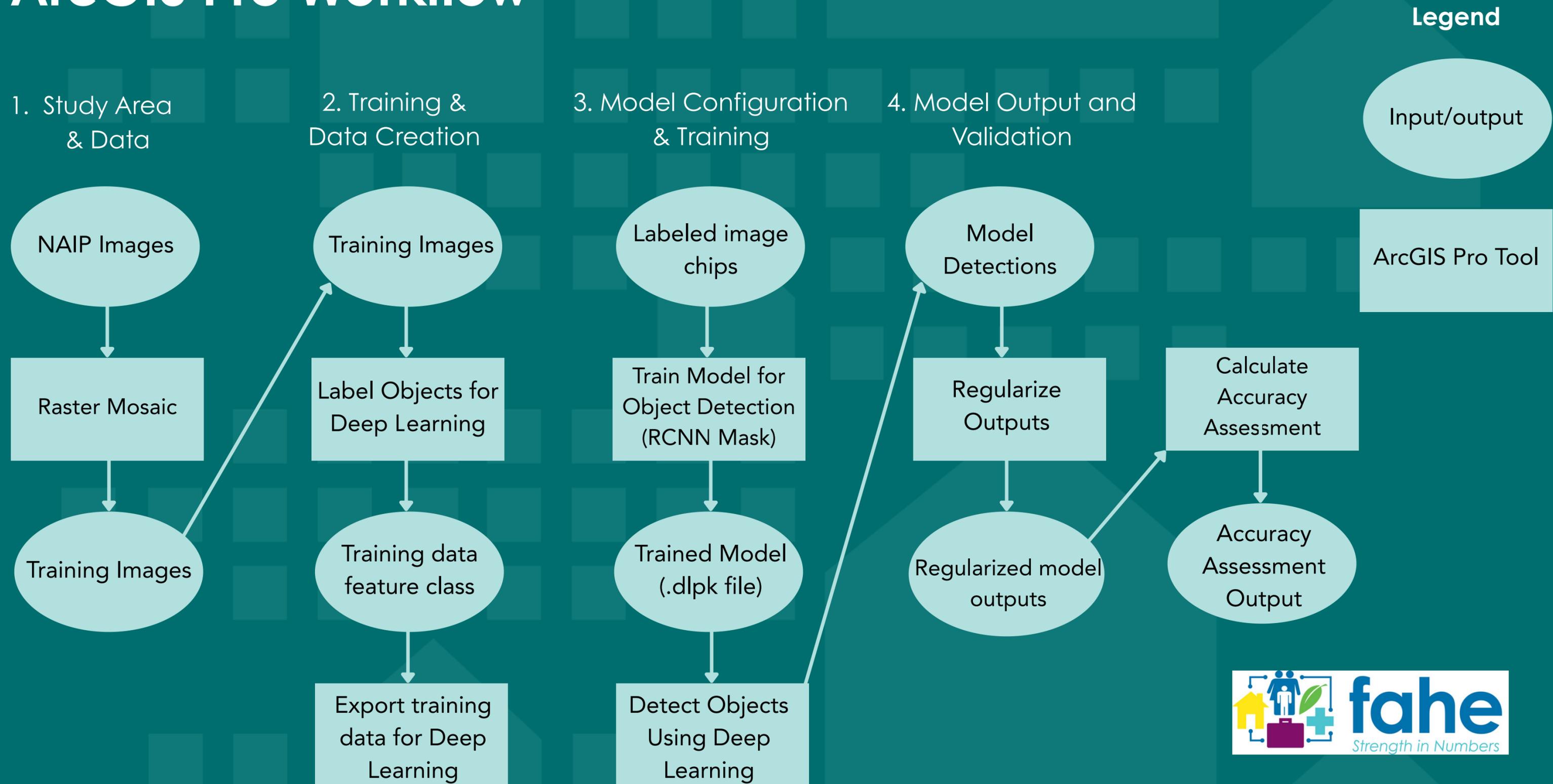
Area of Interest

Census Tracts

- 1. Tract 426.00
- 2. Tract 427.02
- 3. Tract 427.03
- 4. Tract 427.04
- 5. Tract 428.01
- 6. Tract 428.02
- 7. Tract 430.00



ArcGIS Pro Workflow



Training Image Samples



Manufactured Home Community

- A form of *alternative housing*
- Mixed with single and double wide units.
- More closely resembles “formal subdivision” infrastructure.
- Most units + land likely owned by residents

Mobile Home Park

- A form of *informal housing*
- Primarily single wide units. Some units are partially covered with tree canopy, creates challenges for visibility.
- Residents likely own the unit, but not the land.

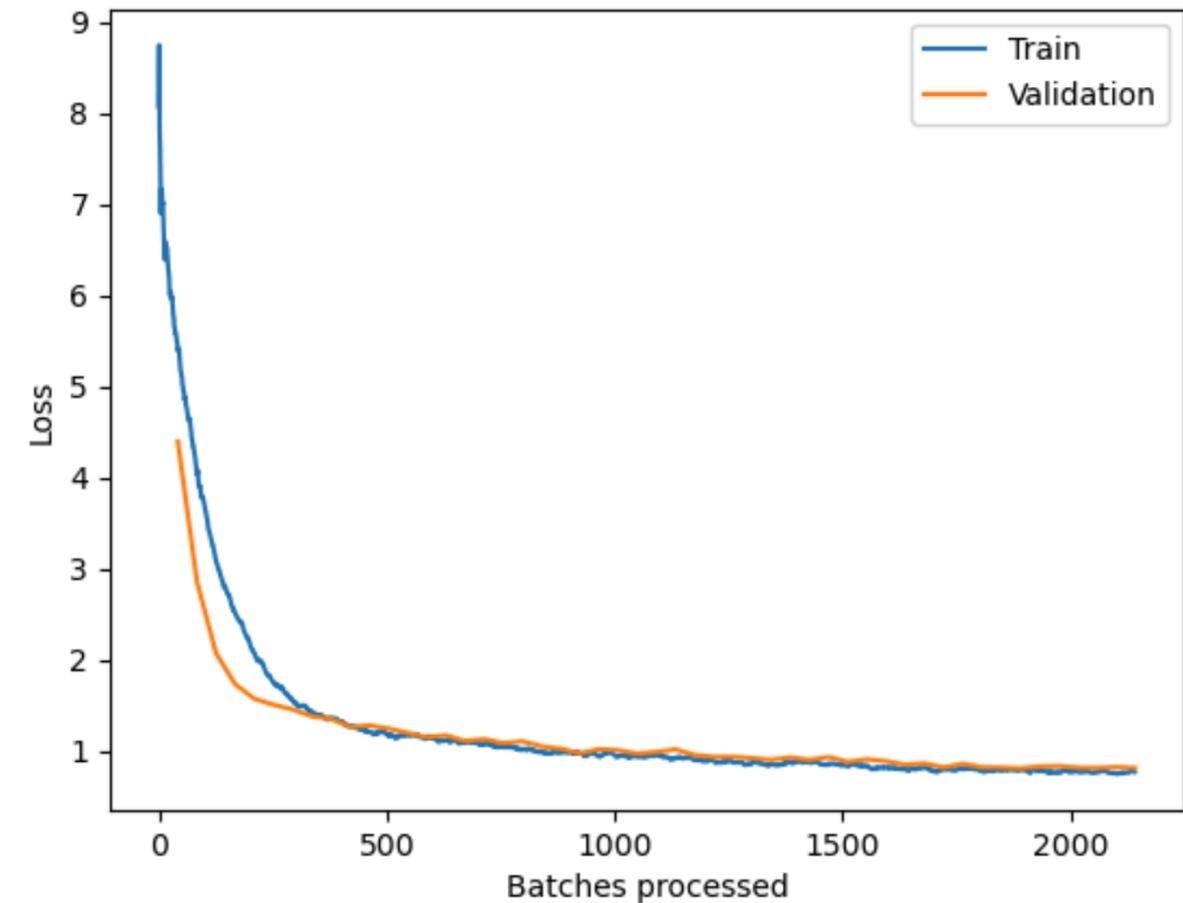


An estimated 80% of households in MHPs own their homes, however **only 14% own the land** (HAC 2011). It is more common for contemporary MHP's to be **cooperatively owned by residents or housing nonprofits** (Sullivan, 2018).

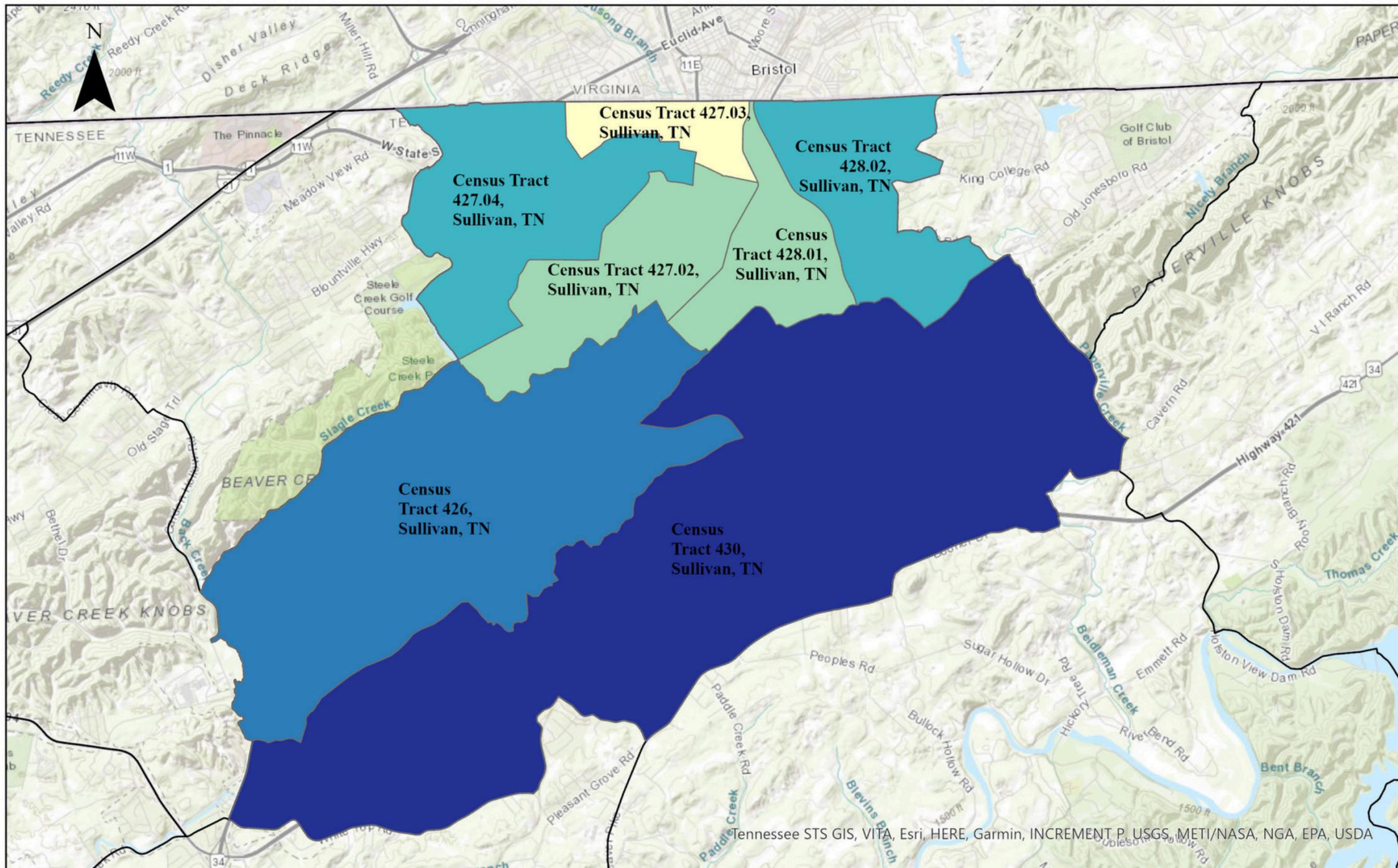
Interpreting Model Performance

Training vs. validation loss

- Both training loss and validation curves drop quickly and converge
- Lower validation loss = model is effectively learning patterns
- Reaches optimal “generalization” or learning performance between 500-1000 batches
- **AP score = 81.9%**



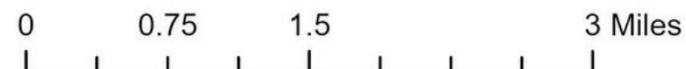
Number of Mobile Homes in NE Tennessee Census Tracts



Mobile Home Unit Count

- >16
- 16-20
- 21-88
- 89-149
- <500

Sullivan
County
Census Tracts

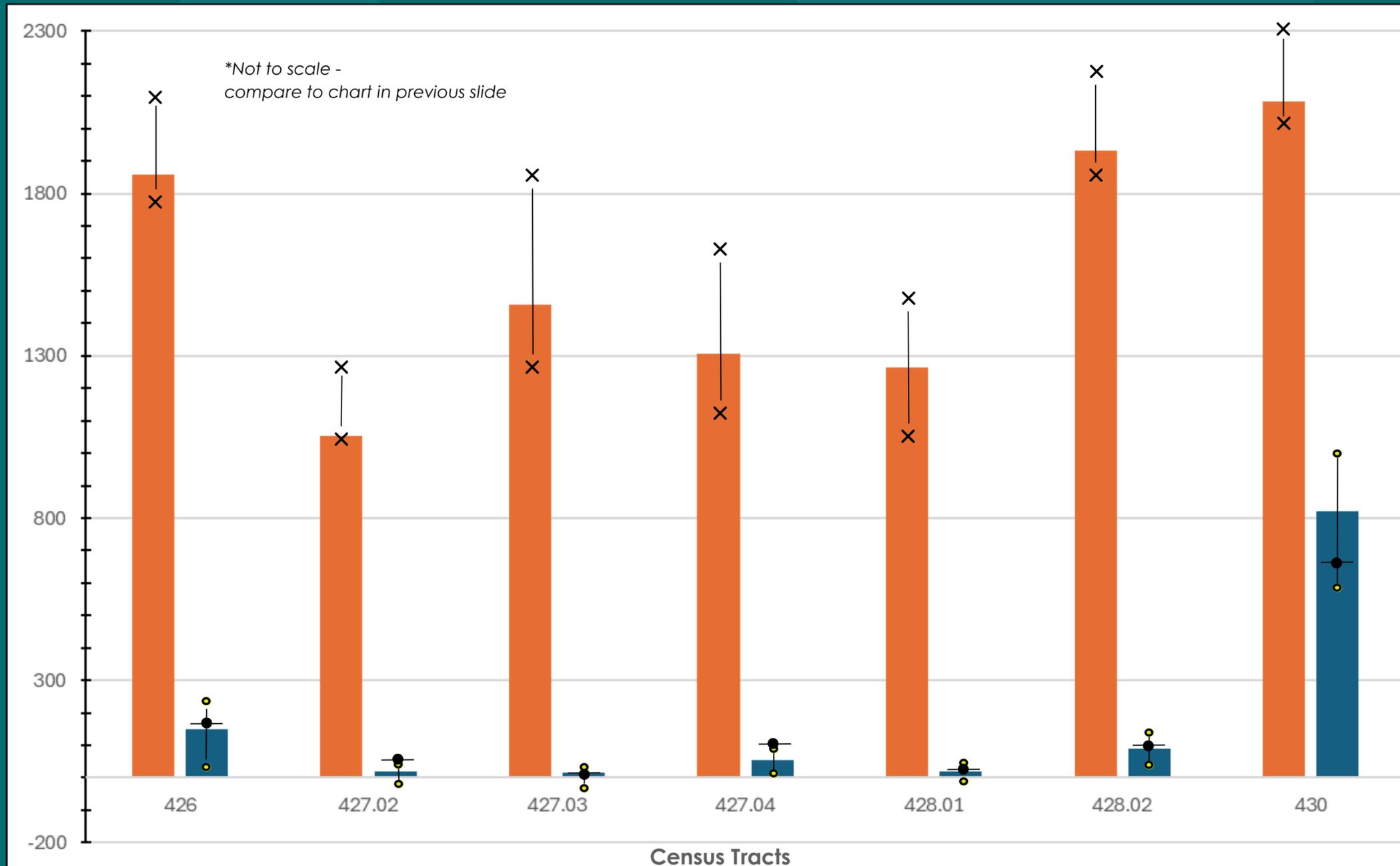


Tennessee STS GIS, VITA, Esri, HERE, Garmin, INCREMENT P, USGS, METI/NASA, NGA, EPA, USDA

Model Output Compared to ACS 2023 5-YR Units in Structure Data Table

TRACT	TOTAL HOUSING UNITS	MARGIN OF ERROR (+/-)	MOBILE HOMES	MARGIN OF ERROR (+/-)	MODEL COUNT	% MODEL ACCURACY
426.00	1857	155	149	84	196	62.8%
427.02	1053	127	18	21	64	84.4%
427.03	1456	304	15	26	11	0%
427.04	1305	243	55	36	104	76%
428.01	1264	177	20	21	43	0%
428.02	1932	142	88	57	114	35.1%
430.00	2083	215	821	191	621	91.8%

Visualizing the Model Counts Compared to ACS



Housing units total per tract (ACS) ■ Housing units MOE (+/-) × Model count ●
 Mobile units total per tract (ACS) ■ Mobile units MOE (+/-) ●

Interpreting Model Performance

- **Average Precision (AP)** is a common metric for object detection tasks. It evaluates the quality of the model's bounding box predictions and classifications across different confidence thresholds.
- Our initial model AP: **67.3%**, which indicates that the model learned to identify manufactured housing units to a **moderate degree**. This means that on average, the model was successful 2 out of 3 predictions. Our model is making some incorrect detections (**false positives**) and/or failing to detect some actual units (**false negatives**).

Understanding the Patterns in the Model's Mistakes

- **False Positives:** What is the model incorrectly identifying as manufactured housing? Are there common features confusing it?
- **False Negatives:** What manufactured housing units is the model missing? Are they too small, occluded, or have unusual appearances?
- **Localization Errors:** Are the bounding boxes and masks accurate for correctly classified objects?

Model Improvements

Overfitting: when a model learns the training data too well and cannot make accurate predictions on new, unseen data

How to overcome this:

- Improve training sample dataset
 - increase number of samples
 - Use multiple images to increase diversity
- Attempt running the model with a variety of parameters to test differences in outputs
- Collection of ground truth points for validation of accuracy

Challenges and Limitations

Limitations

- Computational power
- Human labor constraints

Challenges

- Aerial imagery
 - processing
 - spatial resolution
- Nature of the study area
 - Tree cover
 - Changes in slope
 - Shadows

Next Steps

- **Our purpose is to help practitioners identify areas of need and support planning by local developers.** It can also help inform future policy and program development.
- **Expand on other pre-trained building footprint models.** We would like to successfully replicate this approach where local property data may not be available to help validate administrative sources.
- **Recruiting and training volunteers and staff to help build our database of observations to use for validating model training (ArcGIS Survey123)**
- **Moving beyond Appalachia and identifying any systematic biases that might exist in ACS sampling** (i.e. are some areas consistently under or over counted in ACS relative to the observations - why might that be?)
 - local zoning
 - Hard to reach places
 - Urban v rural

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Thank You

