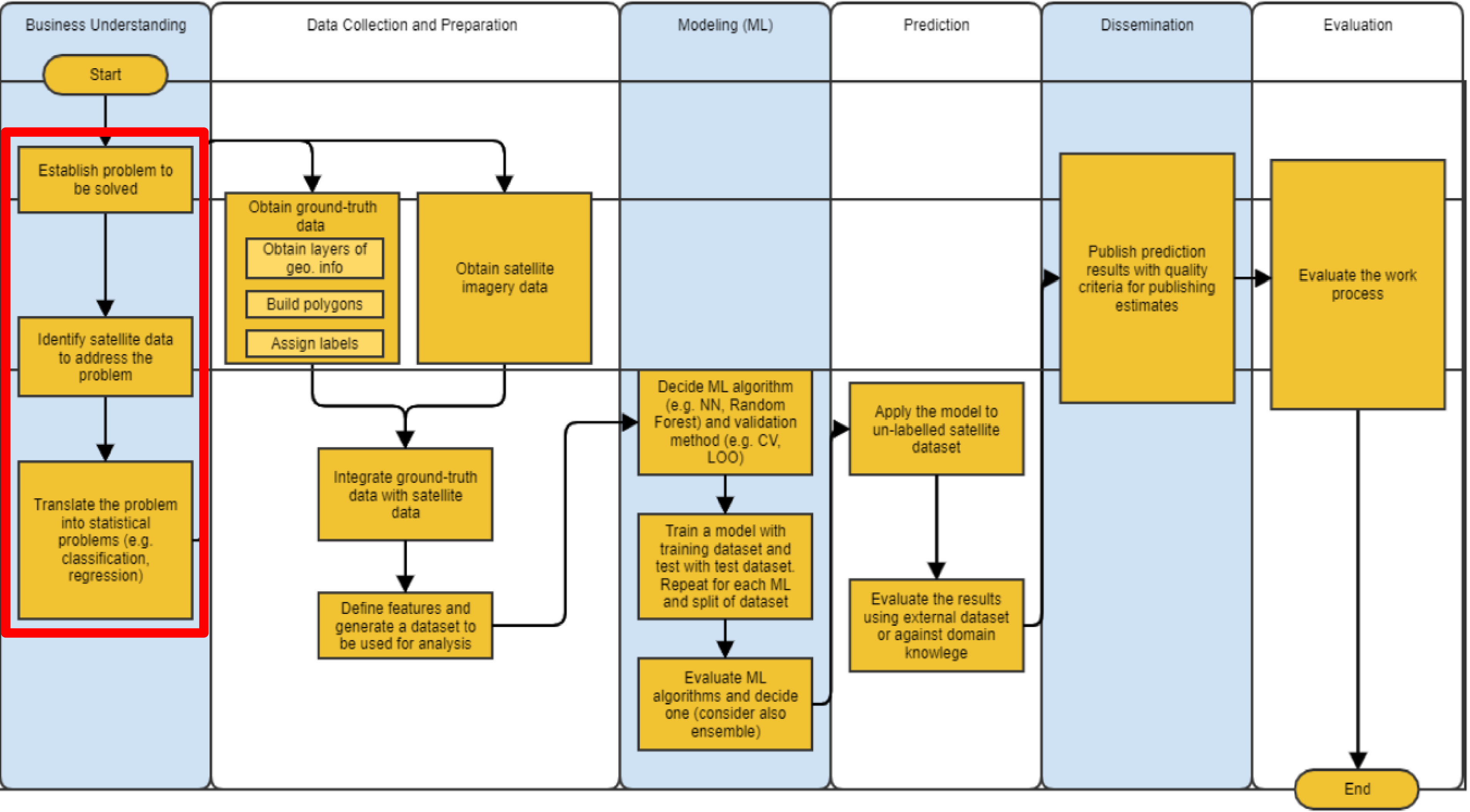
Aerial Image Address Use Classification using Machine Learning

Daniel Merkas
James Farnell
Australian Bureau of Statistics
Informing Australia's important decisions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Modeling (ML)
Prediction
Dissemination
Evaluation
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Identify satellite data to address the problem
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Australian Bureau of Statistics

The Address Register (AR)

Uses

Census

Survey Frames

Data Linkage

AR

100k New Quarterly

15 Million Addresses

Maintenance Processes

Admin Model and Business Rules

68%*

Desktop Canvassing

32%

AIR

(Automated Image Recognition)

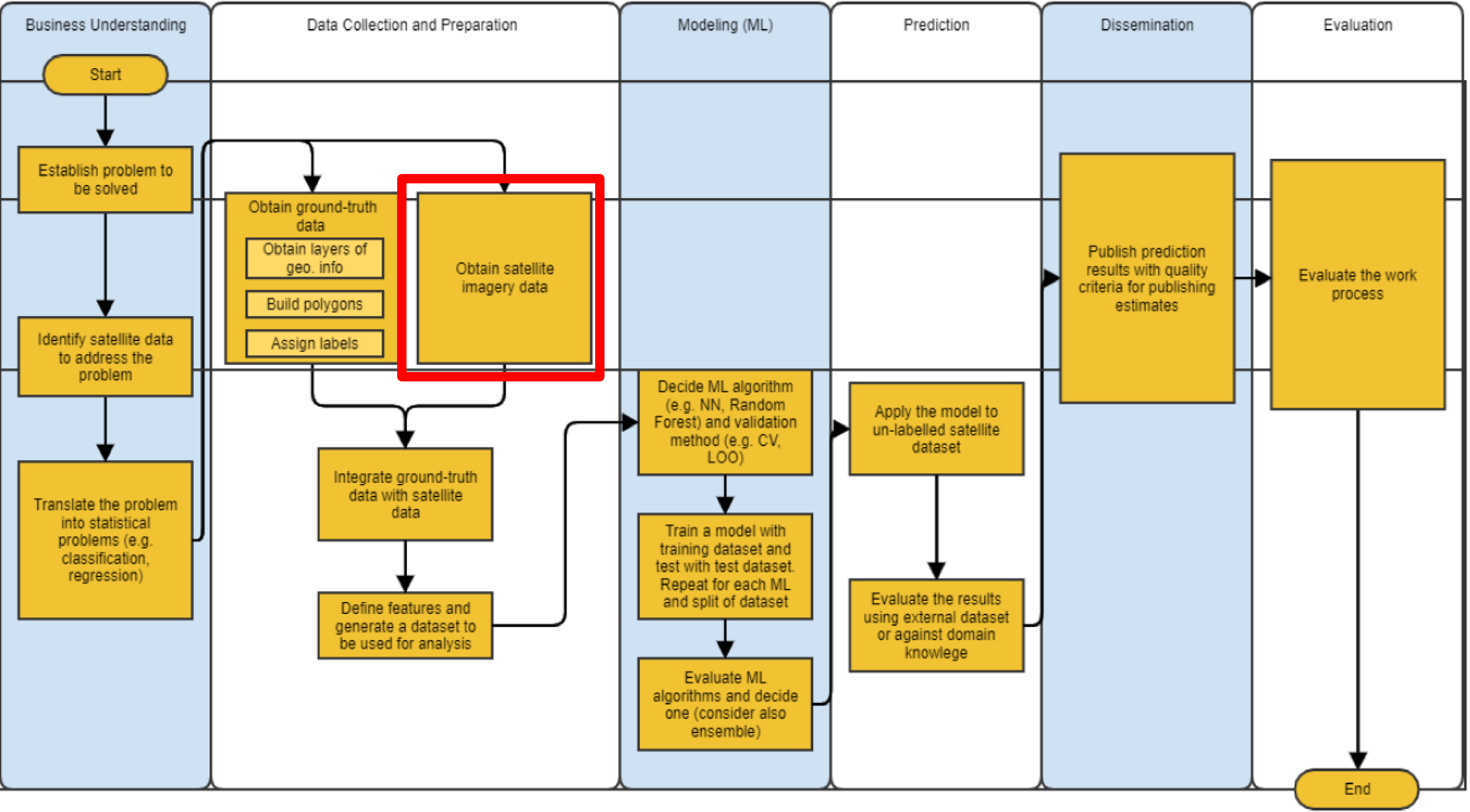

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Image Pipeline

Address
GANSW1047032

link

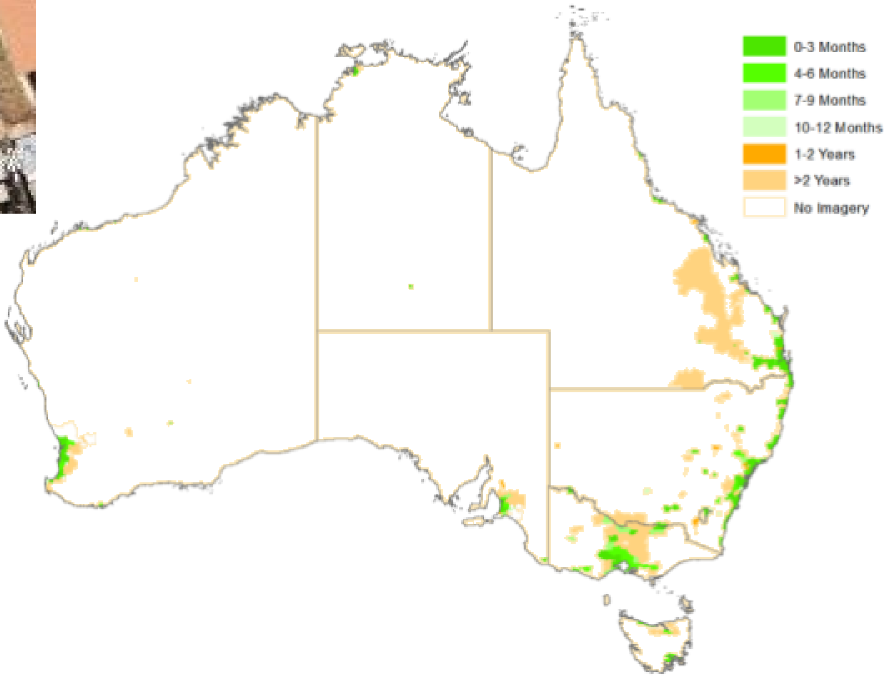
Lat/Long Point
-37.8136, 144.9631

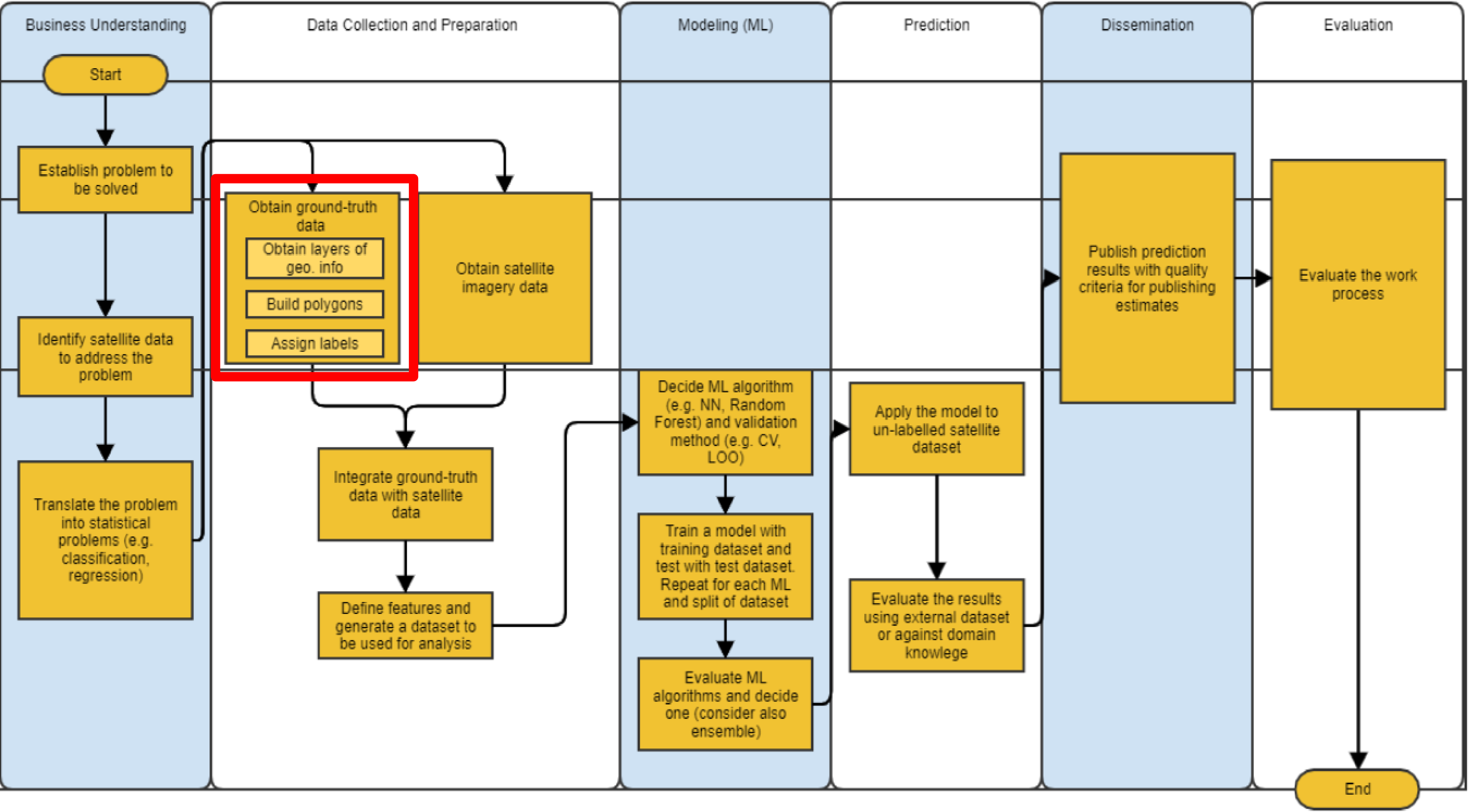
API call

Commercial Provider
-37.8136, 144.9631

- Coverage ✓
  89% of Australian population
- Recency ✓
  within 12 months
- Resolution ✓
  <23cm/pixel

download
150 x 150 pixel,
~30 x 30 meter,
lat/long center





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Parcel Overlay

- 75% of addresses link to cadasters
- Cadaster ≈ Address boundaries
- Overlay identifies small, complex addresses
- Improves speed / accuracy of hand-classification

Utilities box

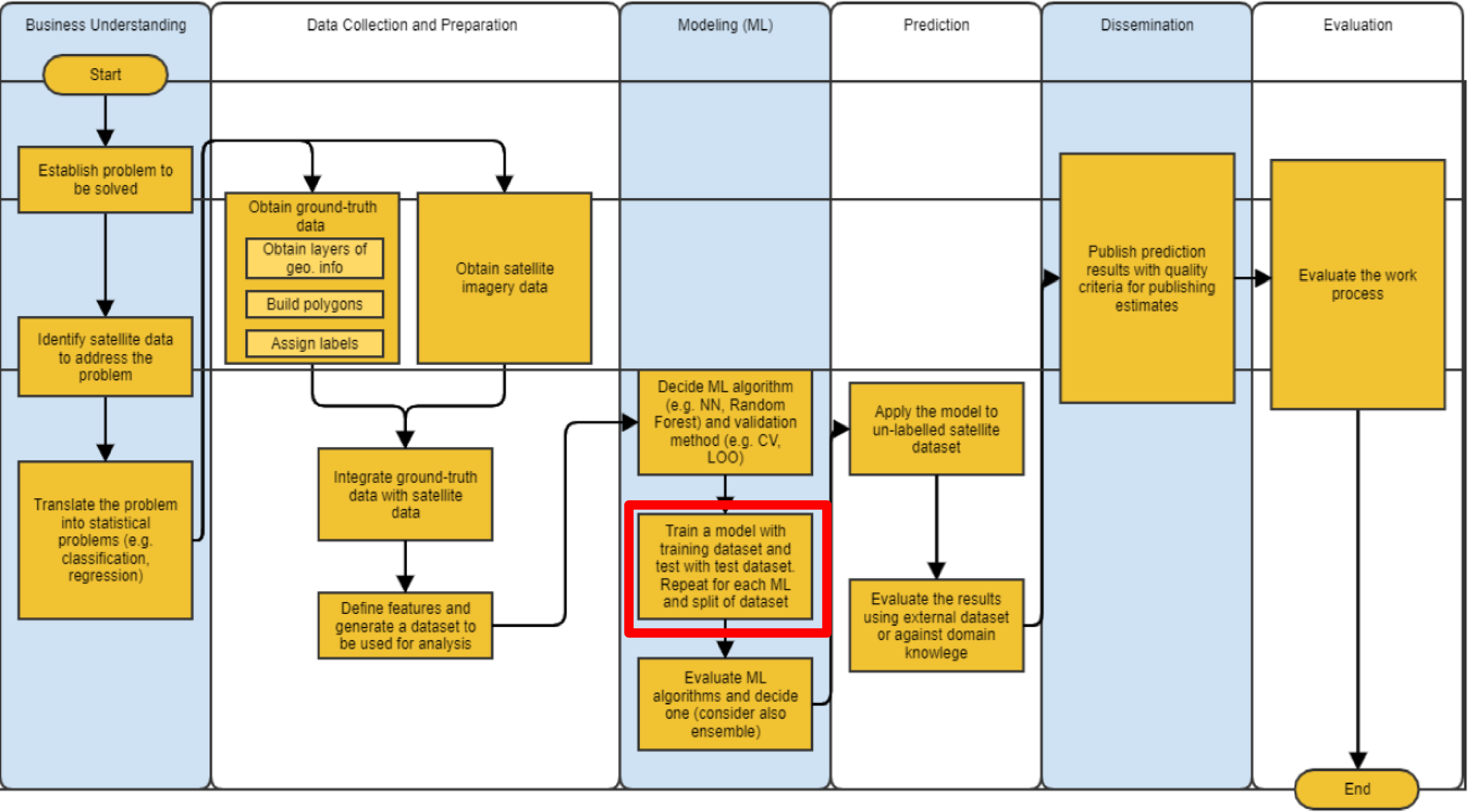
Parcel offcut

Common property

Easement

Image Categories

Private Dwelling	Vacant Property	Under Construction	High Density	Other/Commercial



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Training Data

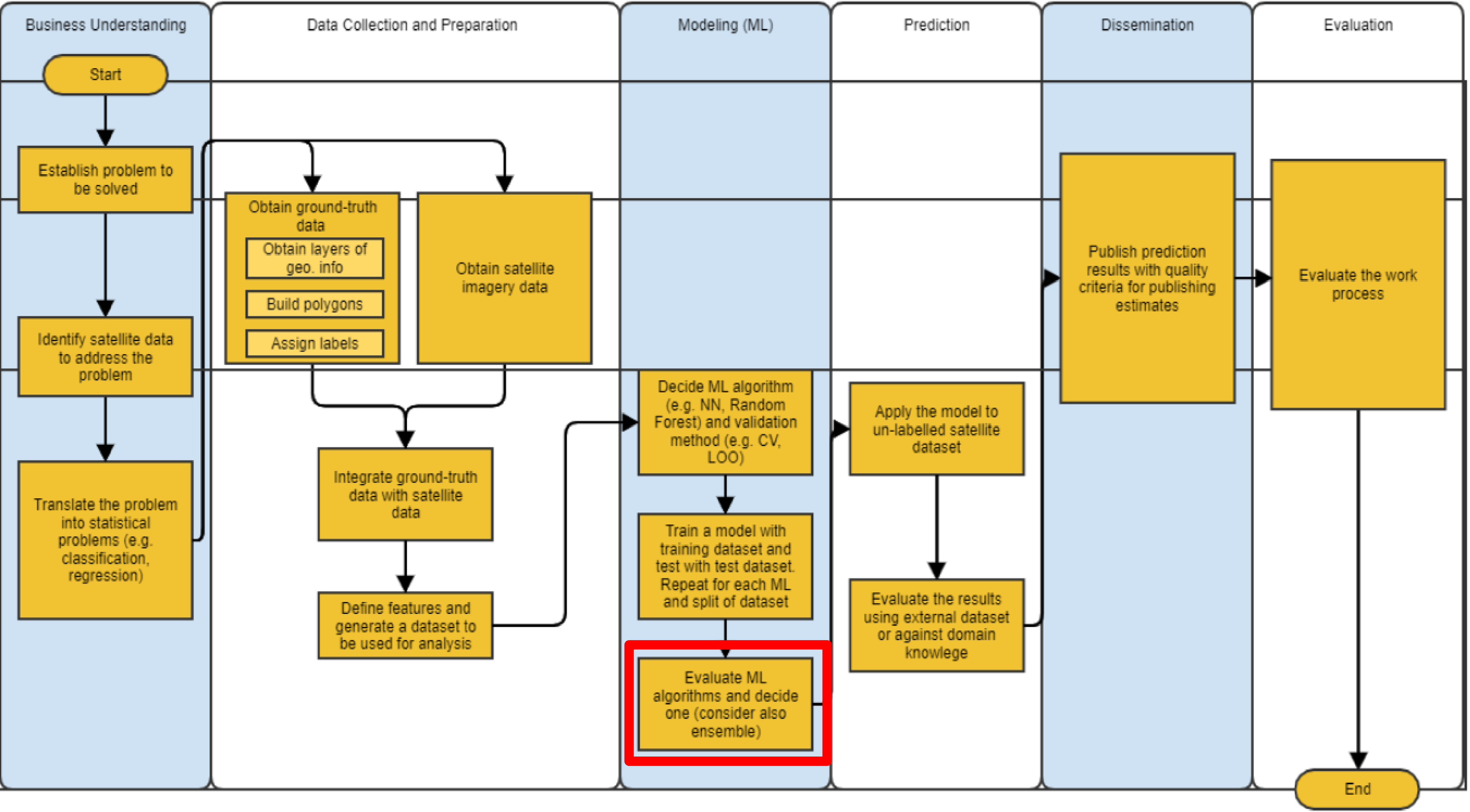
- Hand classified images split 80/20 training/validation
- Class balance ≈ real world frequency
  - Higher accuracy on larger classes
- Purposive, maximum variation sample
  - More generalizable with fewer images
- Iterative decision boundary improvement
  - Classify un-labelled images
  - Visual scan for mistakes
  - Correct classification
  - Feed into training set
  - Re-train

Class	Images
Private Dwellings	11,100
Under Construction	2,200
Vacant Property	4,400
High Density	1,500
Other/Commercial	1,700

Augmented Data

- Random transforms for each training image, each epoch
- Prevents model from memorizing training images
- Transformation limited to realistic class examples

+ Zoom / Aspect ratio shift
+ Brightness shift
+ Skew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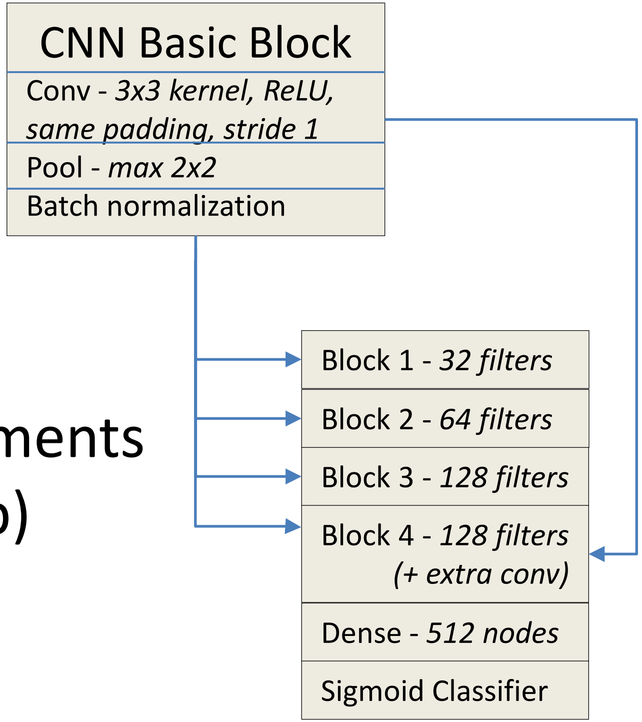
AIR Architecture

- 5 convolutional layers
  + 1 dense hidden layer
- No residual links
- R / Keras / TensorFlow
- Moderate computational requirements
  (150 epochs in 20 hours on laptop)
- Strong augmentation
  + L2/ Ridge regularization



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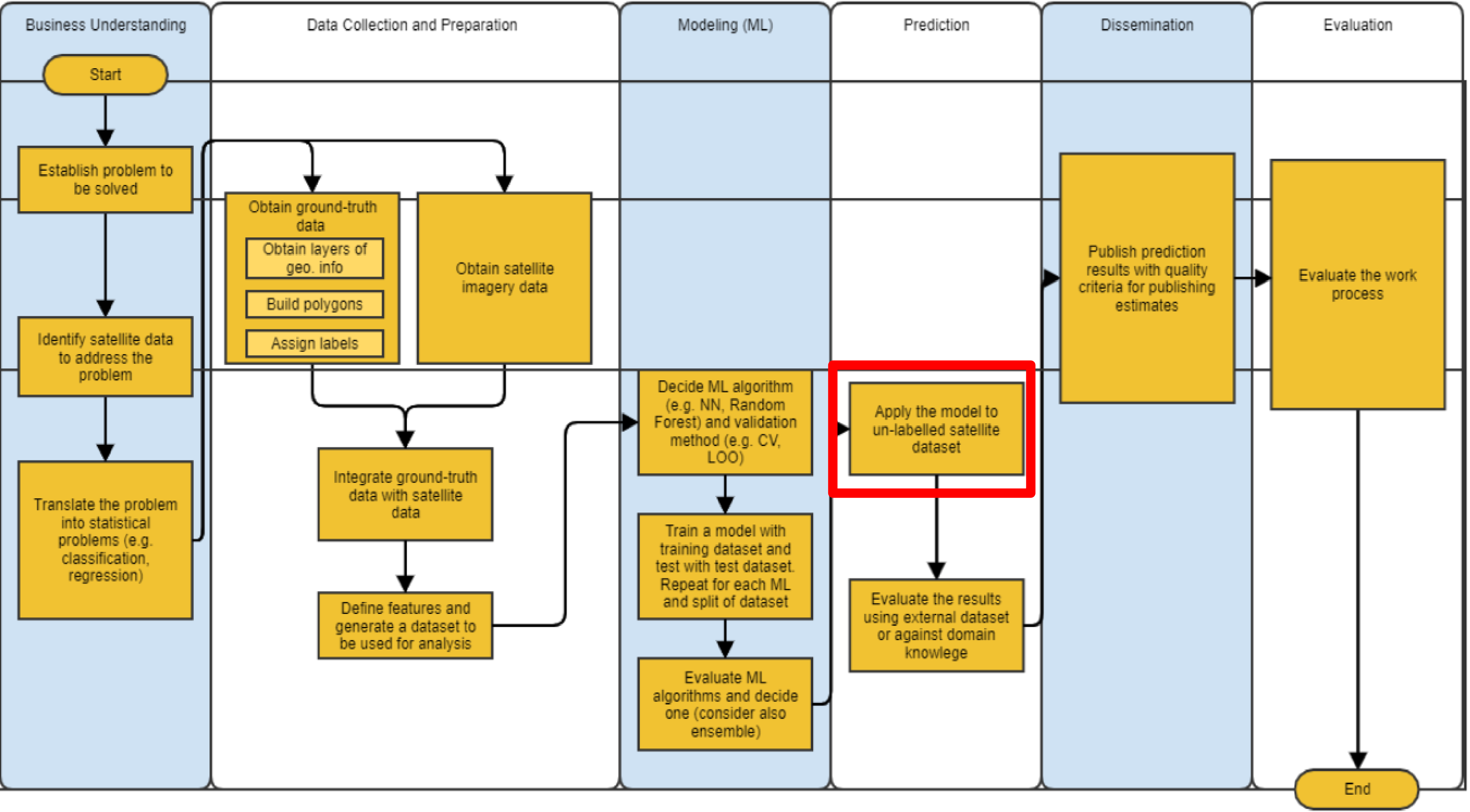
Evaluation Set

- Representative, randomly sampled, hand-classified set
- Green
  - Clear category definitions
  - Trusted without/above admin
- Red
  - Complex categories
  - Requires confirming admin /desktop canvassing

Class	Rate	F1 Score	$\frac{TPR + TNR}{2}$
Overall		**82.2%**	**81.2%**
Private Dwellings	63%	90%	83%
Under Construction	4%	63%	82%
Vacant Property	19%	77%	83%
High Density	6%	56%	74%
Other/Commercial	8%	48%	67%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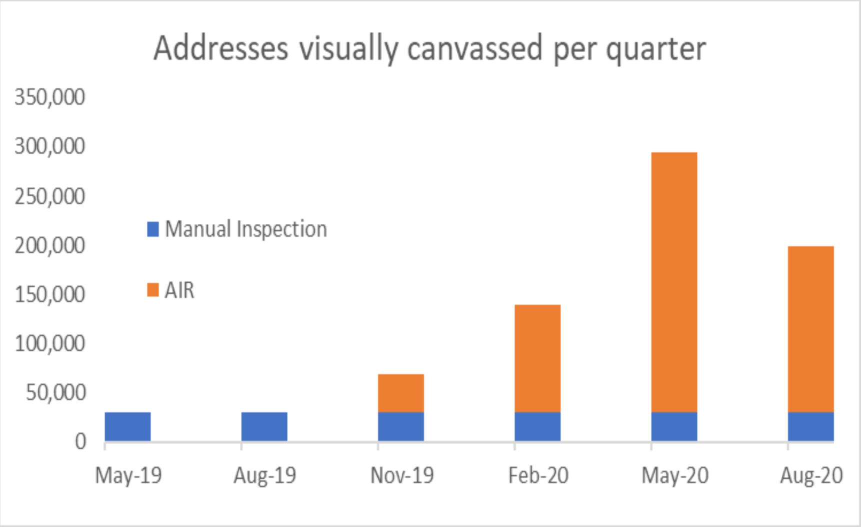
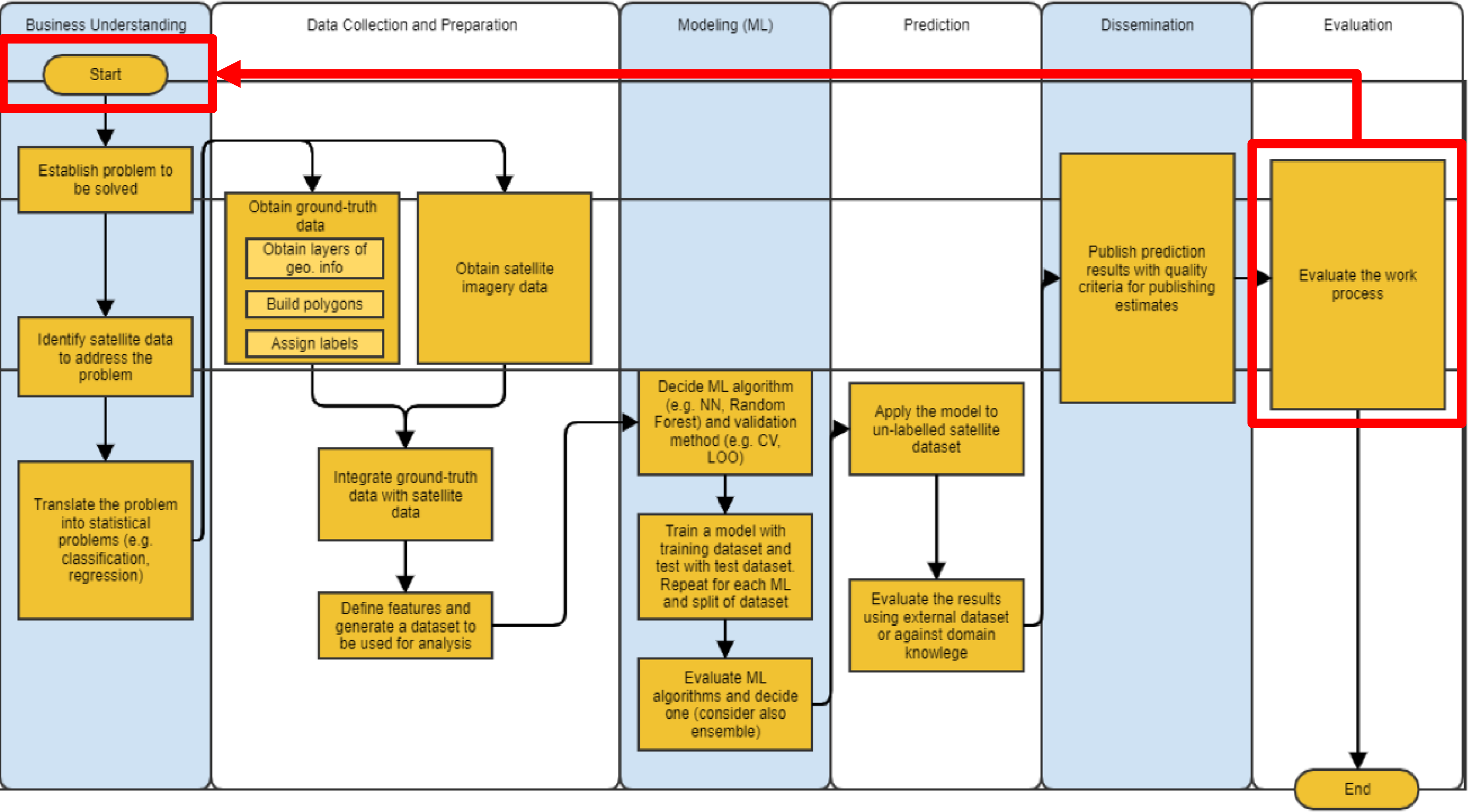
Timeliness

- Desktop Canvassers
  - High accuracy
  - 1000 addresses per week
- AIR
  - Good accuracy for major address types
  - Deployed to:
    - Simple new addresses
    - Monitoring construction
    - Monitoring demolitions
    - Re-inspecting addresses





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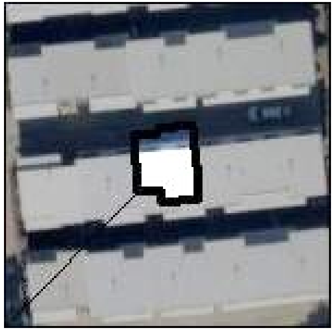
Model Refresh

- Parcel cutouts
- More training images
- Unbalanced classes
- Deeper ML network
- Representative evaluation set

Performance Evaluation – Parallel Run

- Parallel run on 25,000 images
- Major Changes
  - Less reliance on desktop canvassing ~15%
    eg: *Flat roofed residential buildings classified directly to Private Dwelling*
  - Coverage improvement ~2.8%
    eg: *Under Construction/Vacant to Private Dwelling*



Questions?