

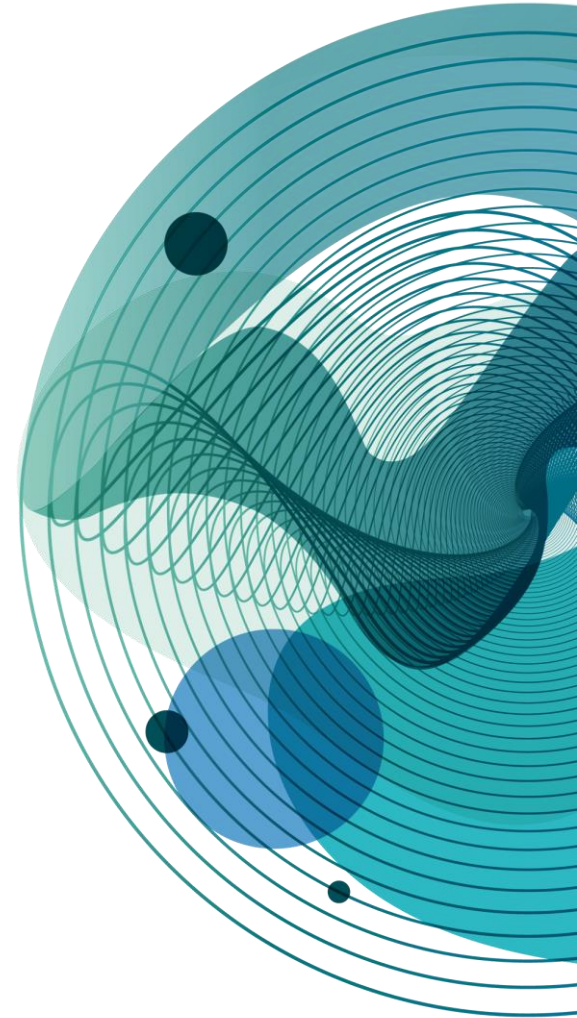
SCE Vegetation AI Study Final Presentation

Thursday June 6th 2024

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Provide a comprehensive readout on the progress made during the Vegetation AI Proof-of-Concept Project

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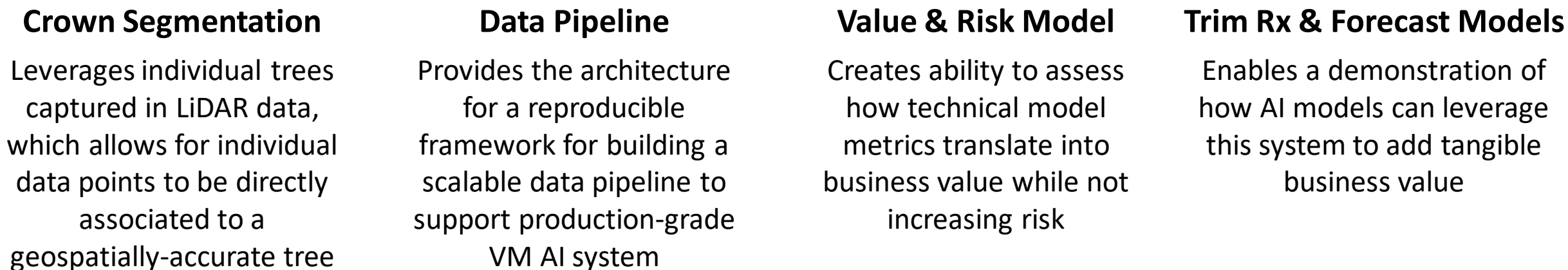


Industry-Leading Capabilities Unlocked via Data Fusion

Data fusion of structured and unstructured data demonstrated in this PoC sets foundation for industry-leading capabilities

Data Fusion

Combination of LiDAR, satellite images, and inventory/inspection data enables a unified dataset to be deployed for general purpose AI modeling and more



Scope of the Vegetation AI Study

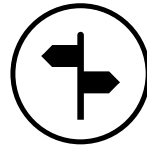


Create a PoC Consolidated Data Lake



- Ensure required data sources are available
- Document datasets used as inputs to AI models
- Determine data types to be used (e.g., LiDAR, satellite, environmental, etc.)

Assess Appropriate Data Granularity Path



- Evaluate data granularity paths (unique veg ID, canopy, span, circuit, etc.)
- Associate LiDAR to vegetation inventory
- Recommend a proposed data grain approach

Develop a Prescriptive Trim AI Model



- Train a model to prescribe trim work orders based on remote sensing data
- Evaluate model accuracy and business value
- Determine viability for operationalization

Develop a Trim Forecast AI Model



- Train a model to forecast the expected maintenance of a particular tree
- Evaluate model accuracy and business value
- Determine viability for operationalization

Overall Objective: *Demonstrate that vegetation AI models can provide business value without increasing vegetation risk*

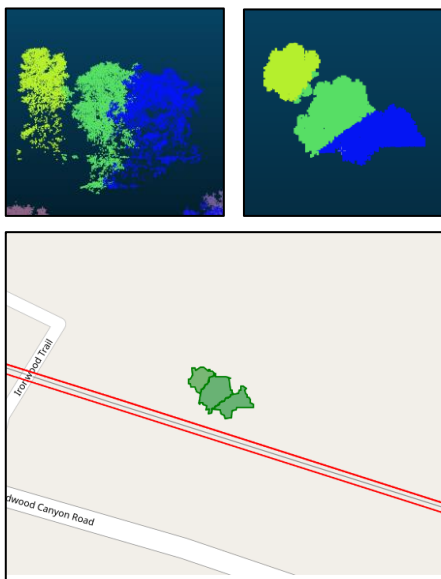
The Study Focused Upon Answering Three Primary Questions

1 Where is the tree?

Crown Segmentation Model

- Automatically **identifies distinct tree crowns from the LiDAR data**
- Tree crowns are **associated with the vegetation inventory for inspection** and work history

LiDAR tree crowns and crown polygons

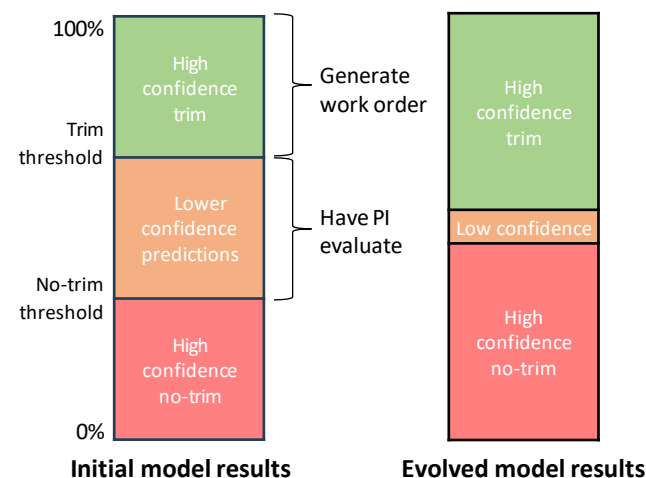


2 Does the tree need to be trimmed?

Trim Prescription Model

- Outputs a **trim prescription (trim or no trim)** and a confidence value
- Replaces human with AI trim pre-inspector** that dispatches work crews for high confidence trims or identifies points for human to evaluate for low confidence trims

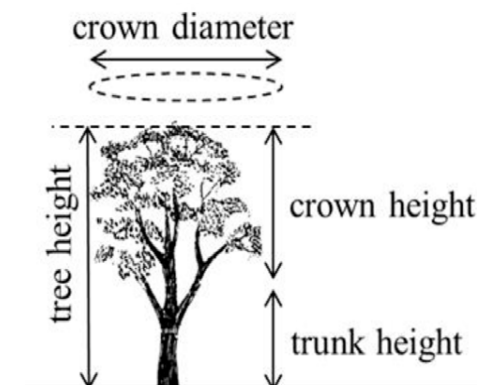
Over time, model will improve, and PI evaluations will become less frequent



3 What is the tree's future?

Trim Forecast Model

- Forward look at when a unique tree will need to be cut next** based on risk forecast
- Provides **planning insights for trim crew scheduling, remote sensing data collection, environmental request submission, NPV of tree maintenance, fire science, and more**

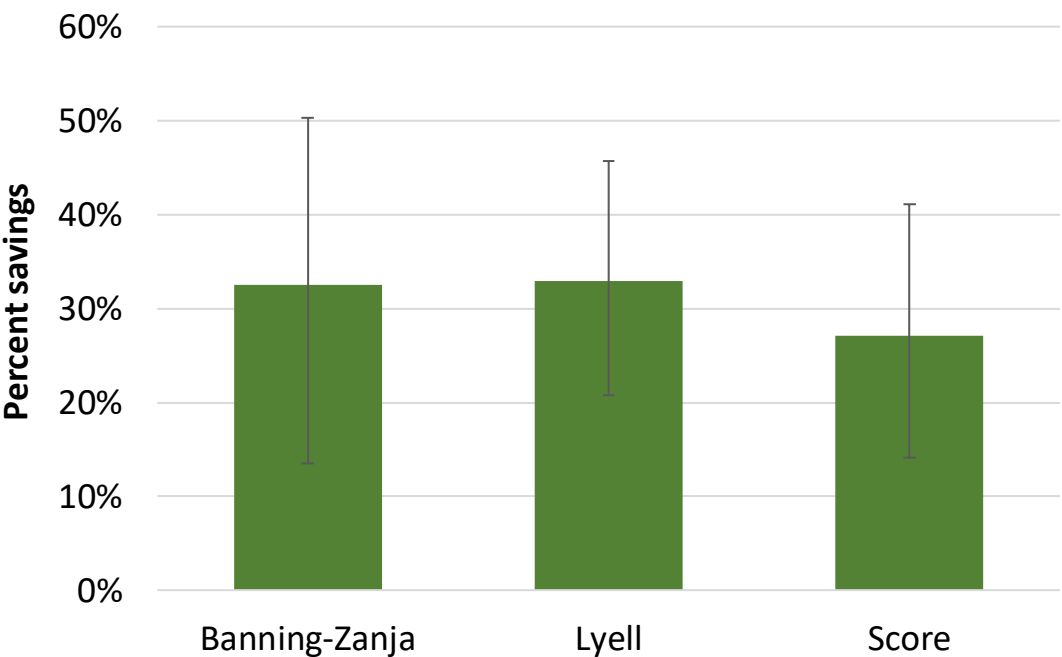




Why it Matters – Study Business Value Results

Initial business value will come from **replacing a proportion of human inspections with AI trim prescriptions**, avoiding the need for field inspectors. This replacement is only done **where the AI output is high confidence**.

Results: Cost savings by circuit



Anticipated Range of Business Value

Will increase over time as model performance improves

Initial annual operational savings from AI Trim Rx models based on field validated tests along Banning-Zanja, Lyell, and Score, using the percentage of replaceable inspections and an inspection’s unit cost.

	Initial Pre-Trim Inspection Automation	Cost Savings on Pre-Trim Inspections
Expected Results:	~30% of PIs replaced by AI	~\$14.2M of annual PI costs avoided
Worst Case Results:	~10% of PIs replaced by AI	~\$4.7M of annual PI costs avoided

It is critical to roll out AI models safely. They must only be used where they reduce operational costs without increasing risk.

Note: 1) Savings estimates are based on field-validated analysis. More circuits will be evaluated in next phase of the project for greater confidence in model performance based on a larger sample size. For more information, refer to the [Business Value & Risk](#) section. 2) Estimated annual savings are calculated as 30% x 1.2M inspections x \$39.52/inspection = \$14,227,200 and 10% x 1.2M inspections x \$39.52/inspection = \$5,690,880. Source for 1.2M trees is the total number of active trees from AGOL and Arbora that the team merged and de-duplicated. This likely undercounts total number of active trees.

Work to Do – Representative Training Data and Statistical Significance

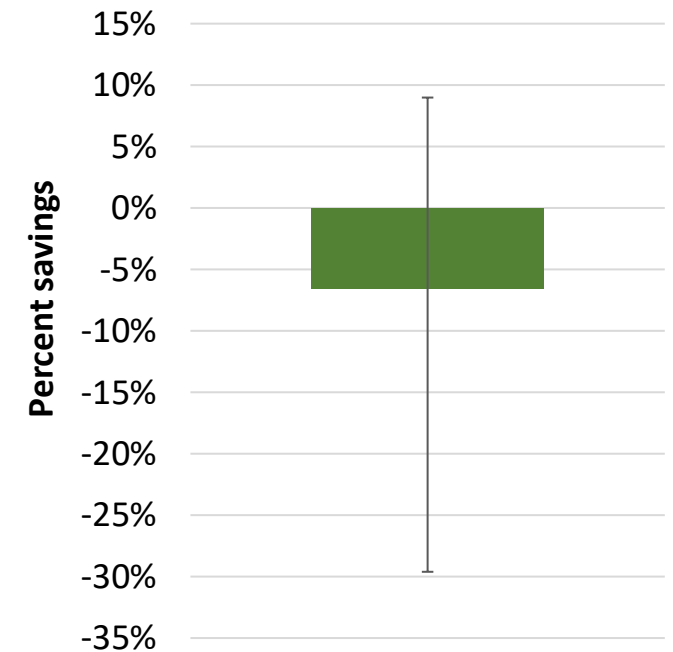


*Initial business value results are **directional only**. Robust numbers require larger, representative datasets, and the previous results may change with such a dataset.*

We require more data to build confidence and create generalizable models applicable across the network

- Distribution models are trained on Westfall and Hurst due to data limitations
- These models failed for Highway, showing that more and more representative data is necessary to create generalizable models
- The AI Pilot effort, starting now, will cover ~600 miles of HFRA and Non-HFRA Distribution and Transmission circuits to build statistical significance and provide a better representative sample of SCE territory

Results: Negative cost savings for Highway



The PoC evaluated feasibility and provides directional results only. Robust estimates of savings require models trained and evaluated on representative samples.

Art of Possible – Trim Rx Enabled Arbora Record

Mockup of auto-assigned Arbora work order that would be generated based on prescribed trim from AI model

Job Assignment
00014367

Status

Tree Species

DBH (in inches)

Work Type

QC Status

Total Unresolved Constraints

Auto-Assigned

(Predicted) Pine

(Predicted) 20in

Tree Trimming

None

0

✓

✓

Assigned

Overview

Work Type ⓘ
Tree Trimming

Program ⓘ
Drought Resolution Initiative

District
MENIFEE

Circuit #
15922

Status ⓘ
Auto-Assigned

Parent Job Assignment ⓘ

Grid
77-90

Circuit Name
SAUNDERS

Model Assessment Overview

Expected Risk
Grow-in

Observed Minimum Clearance
17ft under max sag

Species
(Predicted) Pine

Trim Rx Model Confidence
97%

Max Tree Height
35 ft

DBH
(Predicted) 20in

Related

More Actions

History

Service Appointments (1)

1 item • Sorted by Due Date • Updated a few seconds ago

	Appointmen... ▾	Work Type
1	SA-14421	Tree Trimming

Constraints (0)

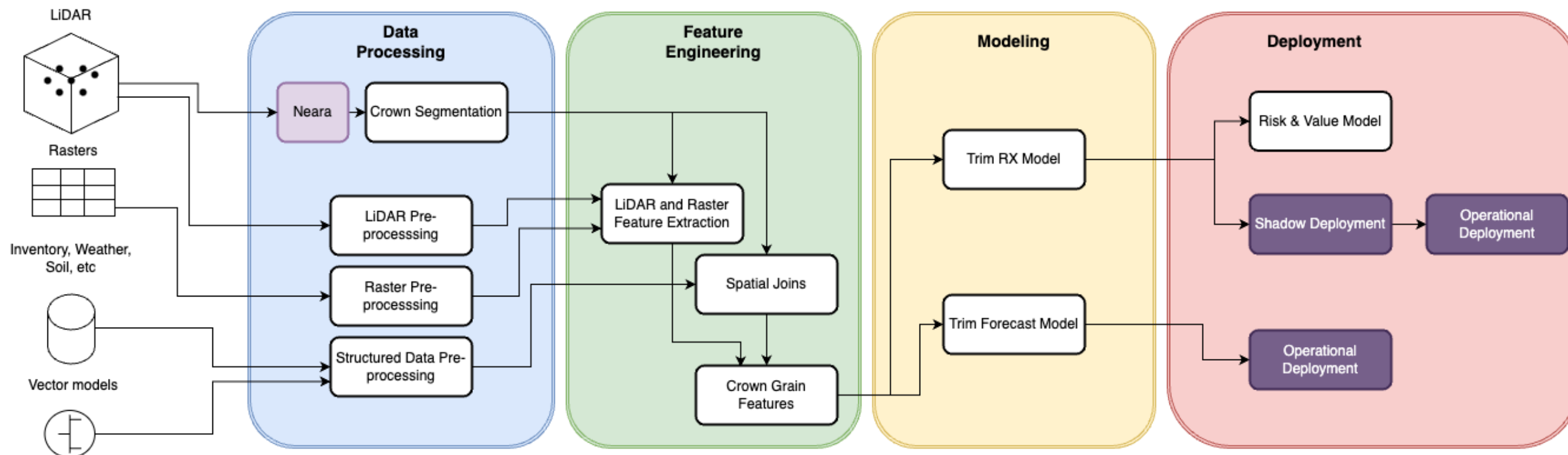
Notes (1)

1 item • Sorted by Last Modified Date • Updated a few seconds ago

	Notes Name	Type
1	N-0086	Model Assessment

Study Solution Overview

Solution builds the foundation of a platform that is currently used for Veg AI models, but also unlocks significantly more



The Trim Rx and Trim Forecast models are enabled by critical data fusion, platform integration, and deployment capabilities that can be expanded to additional use cases in the future

Overall Project Journey



Consolidated “Data Lakehouse”

Integrated disparate data sources into single repository capable of storing & geospatially associating **structured, semi-structured, and unstructured data** in a single place



Developed Data Processing Algorithms

Developed **efficient pipelines for ingesting and processing** LiDAR and images, segmenting crowns, and extracting features.

Validated data processing and relationships to real-world through field tests.



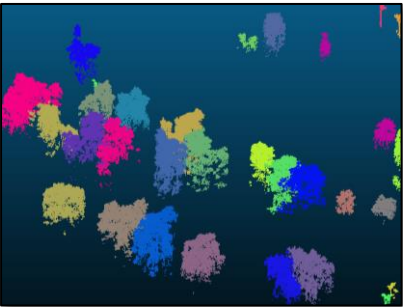
Segmented tree crown polygons (blue) next to conductors (red)



Decided to Employ Crown Grain

Evaluated data granularity options and selected new Crown grain as the optimal choice.

Developed methodology to join vegetation inventory with LiDAR derived crowns, creating ability to connect LiDAR-derived trees with work history & species info.



LiDAR point cloud with crown grain denoted through colors



Developed Trim Rx and Trim Forecast Models

Trained and evaluated AI models to:

- 1. Output a trim prescription (trim or no trim)** to replace and prioritize human pre-inspectors.
- 2. Forecast when a unique tree will need to be cut next** for planning future trim work, future remote sensing data collection needs, NPV of tree maintenance, etc.



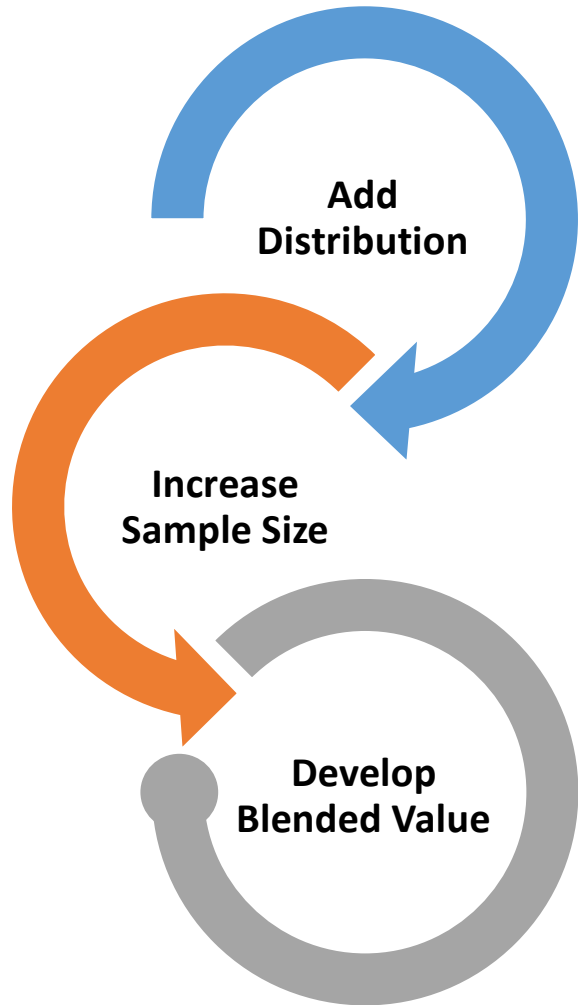
Created Vision for Model Deployment

Assessed the value of the Rx model, which is **expected to save ~30% of pre-trim inspection costs**, with ~10% expected in the worst case of model performance.

Consolidated recommendations for next steps and project deployment based on PoC.

Anticipated Range of Trim Rx Model Business Value	
Expected Results:	~\$14.2M of inspection costs avoided
Worst Case Results:	~\$4.7M of inspection costs avoided

Building Confidence in the Study's Directional Business Value



Evaluate Distribution Circuit Impacts Over the Next Few Weeks

- Analysis of Trim Rx model on Distribution is pending for Score, Highway & Lyell
- Business value analysis methodology will be the same as for Transmission

We Plan to Increase Sample Size in the Coming Months via Pilot

- Expand AI model evaluation to additional circuits with historical LiDAR
- Include & validate with additional T&D circuits across various geographies and terrains

Develop a Higher Confidence Blended T&D Value by End of Year







- Using a large sample size, we will increase the confidence in expected model-derived cost savings represented on previous slide (i.e., 30% expected, 10% minimum savings)
- Blended value statement will account for differing levels of risk for T&D (e.g., fines differ)
- Measure reliability and validity of QC process



AI Pilot Effort (Jun. – Sep. 2024)

The AI Pilot's goal is to validate the business value & improve ability to scale the Trim Rx and Forecast models from PoC

GOALS

-  **Develop production grade crown segmentation** algorithm
-  **Design crown joining approach** to integrate the crown algorithm maximum grow/fall and height in data lakehouse to integrate into SCE field tool
-  **Run Trim Rx model and perform field tests** on new T&D circuits across both HFRA and Non-HFRA
-  **Partner with SCE DPT/IT** to develop production system architecture design documentation
-  **Run Trim Forecast model and perform historical comparison** on new T&D circuits across both HFRA and Non-HFRA
-  **Investigate leveraging satellite images** and integrated dataset for inventory **species prediction**

DESIRED OUTCOMES

- Validate the Trim Rx and Forecast model on circuits across the network
- Build greater confidence in the expected cost savings and risk reduction expected from deploying AI models
- Prepare a crown segmentation algorithm for production and create a strategy to transition from existing vegetation points to crown + inventory points
- Understand and define the technical developments needed to operationalize the AI models

Will track deployment of tools across AI Pilot circuits:

XX%	XX%	XX%
Crown Segmentation	Trim Rx	Trim Forecast

CIRCUITS IN SCOPE:

From PoC: **67 OH miles** (18 Tran. and 49 Dist.)



To Pilot: **583 OH miles** (196 Tran. and 387 Dist.)

Appendix

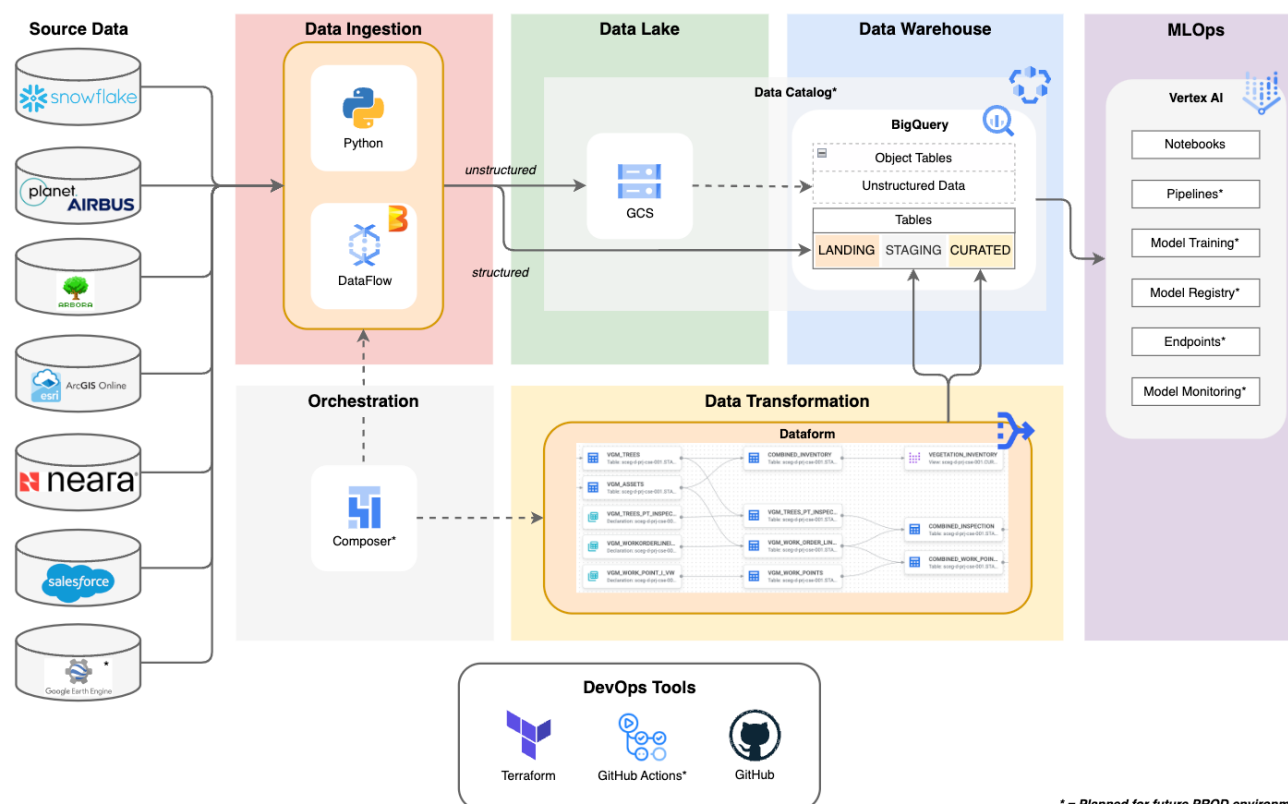
Technical Development Deep-Dive

Summary Data and Infrastructure for PoC Enablement

Ingestion, storage, and transformation of diverse data sources

Data is processed via an **ELT** approach and organized per the **Medallion Architecture** pattern

1. **Highly flexible:** easily accommodate new data sources and schemas
2. **Iterative value:** data is gradually refined through sequential layers
3. **Cloud native:** built to leverage fully managed Google Cloud services



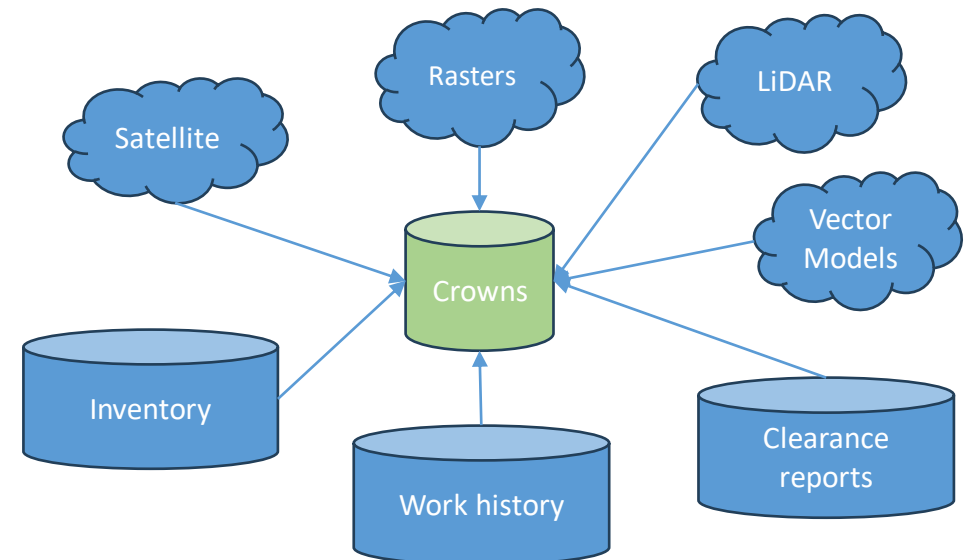
* = Planned for future PROD environment

Energy for What's AheadSM

Crowns and Join Logic

The Crown grain is highly precise and enables fusion of the multi-modal vegetation management datasets for machine learning

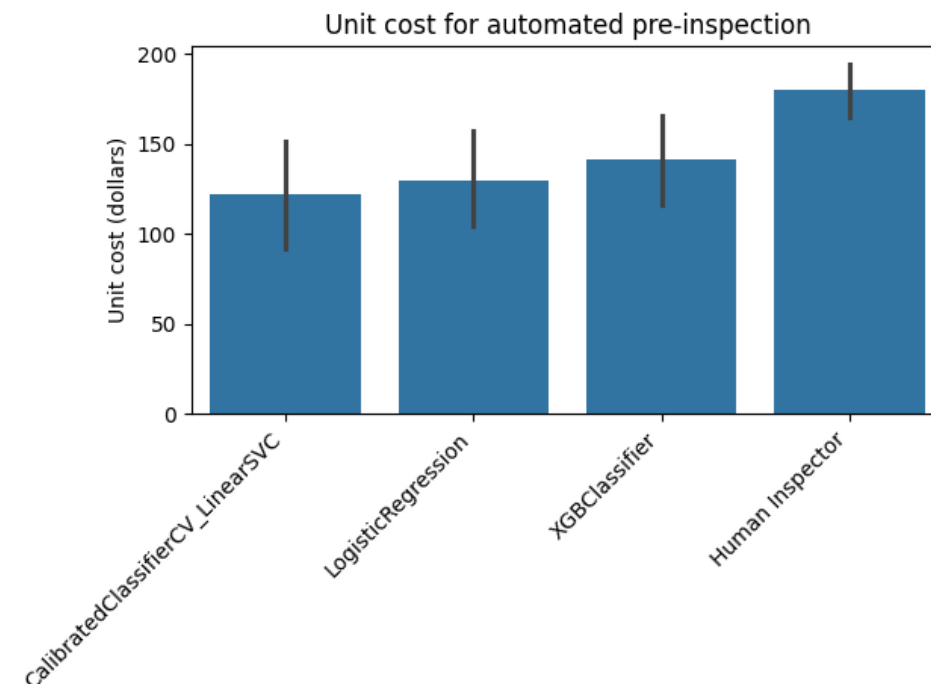
- Automatically generated from LiDAR
 - Open source algorithm Pycrown used to generate crowns
- Closely aligned with physical trees
 - Best granularity for trim prescription and trim forecast modelling due to spatial accuracy
 - Better targeting of work assignments
- Enable the multi-scale and multi-modal data fusion required for machine learning
 - A variety of geospatial joins are developed and assessed to join data with crowns
 - Software tools created to perform joins of unstructured data with crowns



Trim Prescription and Value

The trim prescription model predicts whether a tree will encroach on the circuit in the next 18 months

- Initial results for Banning-Zanja
 - Distribution circuits pending analysis
 - Testing data created via a field test
- Partial automation thresholds learned during training
 - Initial models trained to automate approximately 30% of pre-inspections
- Model value measured via risk weighted cost savings
 - Initial results suggest a 30% risk weight cost savings with worst case of 10% savings



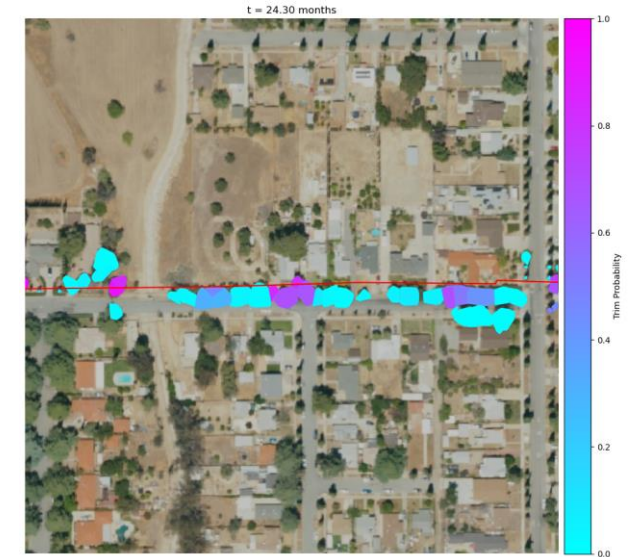
$$\text{unit business value} = c_{\text{current}} - c_{\text{model}}$$

$$c_{\text{model}} = \underbrace{\alpha \cdot \text{prob}(\text{false trim}) \cdot c_{\text{trim}}}_{\text{Risk of false trim}} + \underbrace{\alpha \cdot \text{prob}(\text{missed trim}) \cdot c_{\text{missed}}}_{\text{Risk of missed trim}} + \underbrace{(1 - \alpha) \cdot c_{\text{current}}}_{\text{Human inspected}}$$

Summary Trim Forecast and Value

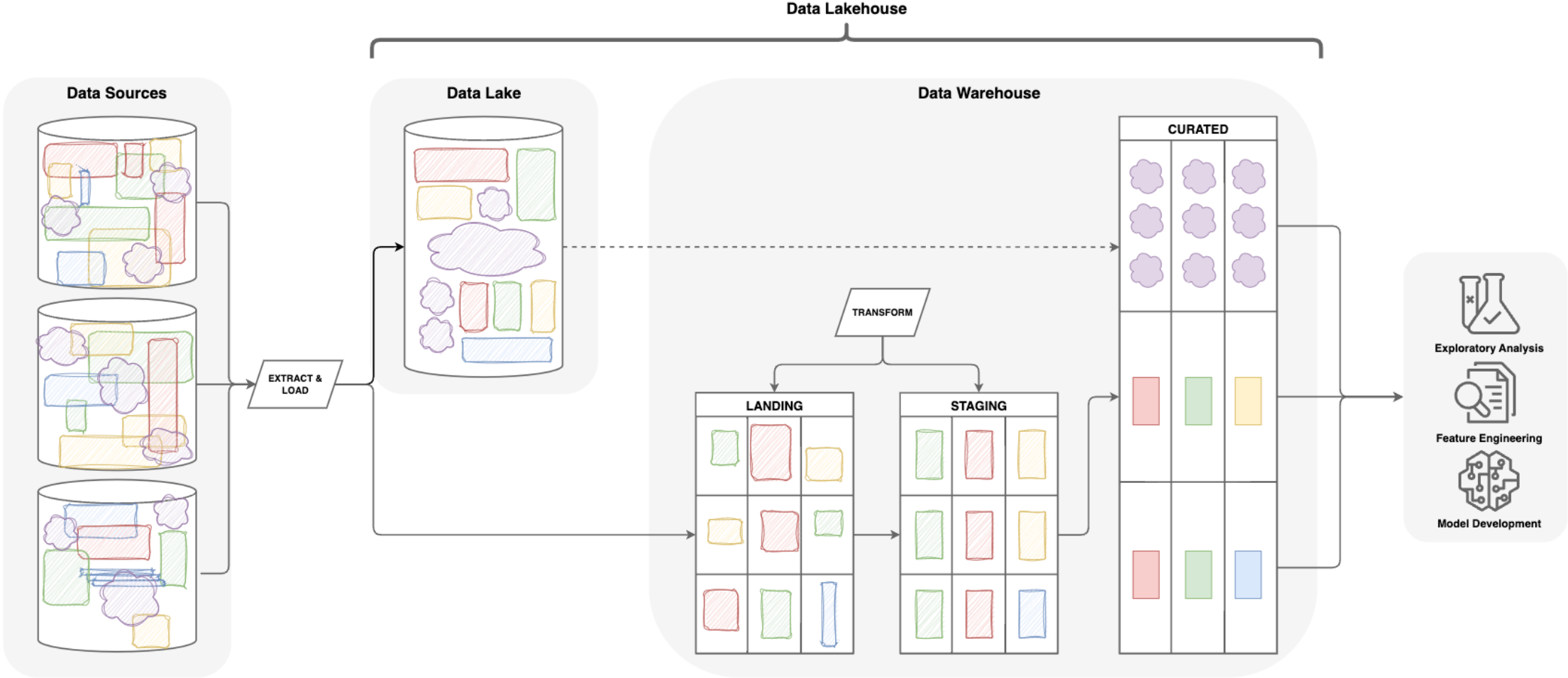
The trim forecast model predicts when a tree is expected to be flagged for maintenance

- Initial results for Banning-Zanja
 - Multiple LiDAR surveys enable training and back-testing
 - Integrated dataset enables predictive forecasts
- Probabilistic forecasts of maintenance provides a measure of risk
 - Expected trim intervals can be used to determine long term vegetation management costs
- Planning scenarios required to unlock value
 - Accurate forecasts enable VM economic analysis, risk-driven data refresh, circuit design scenario analysis



Data and Infrastructure

Data Engineering - Conceptual Flow



Google Cloud – Core Services



Dataflow Pipelines

Ingests diverse datasets from upstream sources and loads into GCS and BigQuery.



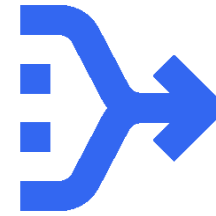
Cloud Storage (GCS)

Consolidates and organizes data in any format from disparate systems.



BigQuery

Provides tabular structure and cohesive platform for querying data via SQL.



Dataform

Clean and transform data via coordinated SQL pipelines.



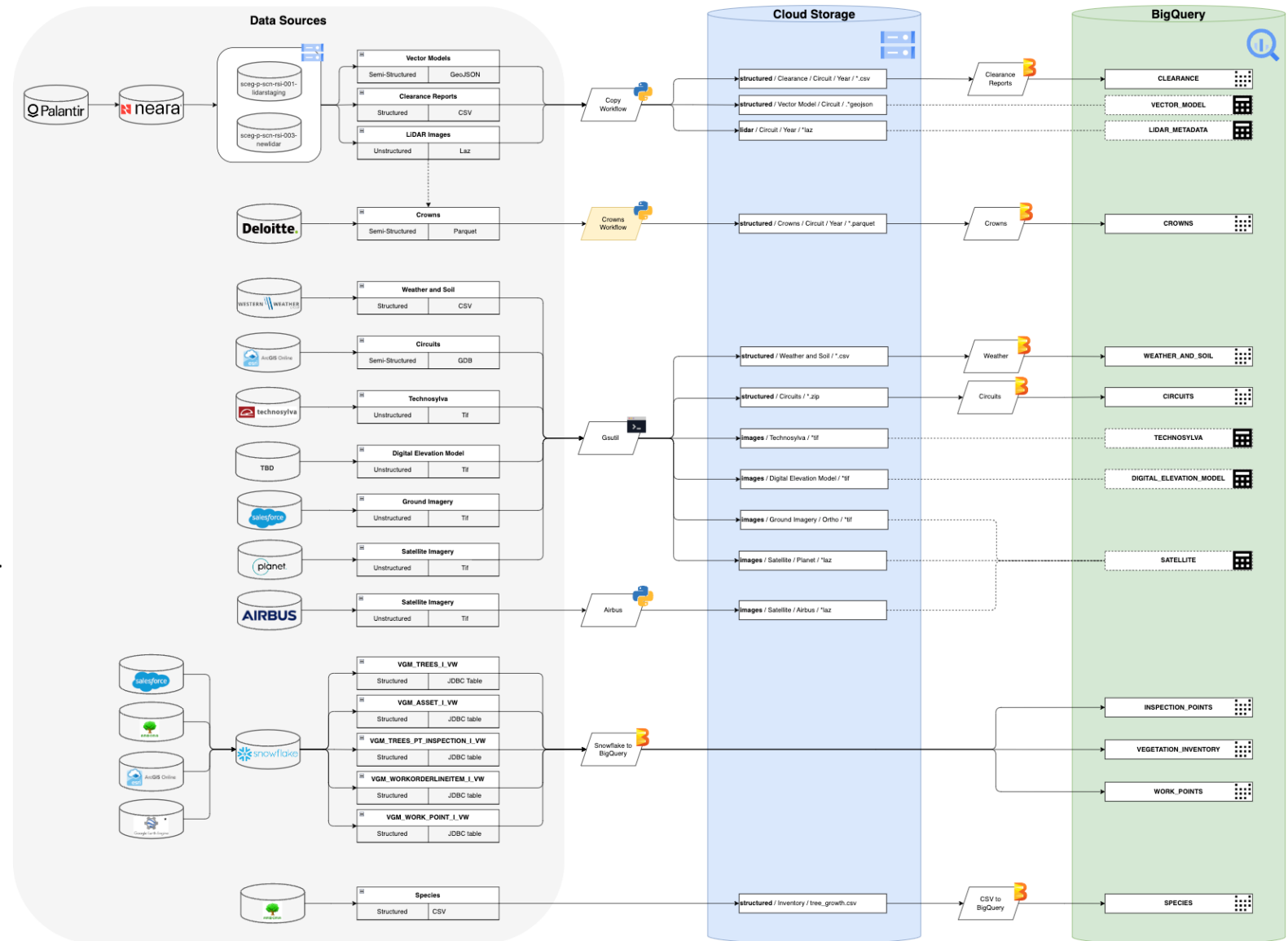
Vertex AI Notebooks

Explore datasets, perform feature engineering and train machine learning models

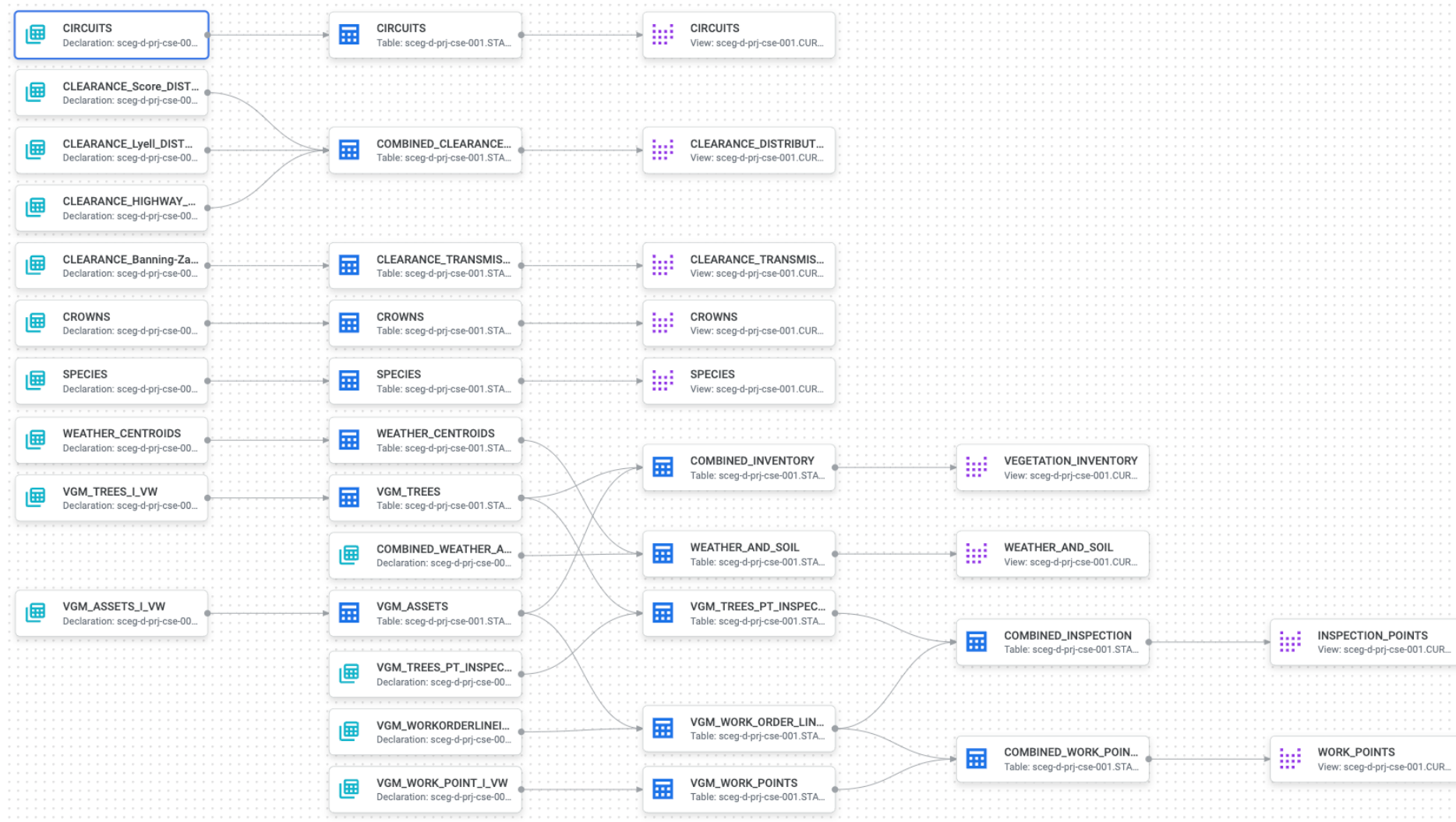
Ingestion Pipelines – Dataflow & Cloud Storage SDK



- Data is extracted and loaded from diverse sources to GCS and BigQuery
- We are using a combination of **Dataflow** (Apache Beam) and **Cloud Storage SDK** pipelines
- Additionally, **Gsutil CLI** simplifies ad-hoc file ingestion tasks



Transformation Pipelines – Dataform SQL





Data Challenges

Vegetation management datasets do not consistently use the SCE standard for geospatial coordinate system

SCE standard for geospatial coordinate system is NAD83 (datum) UTM 11 (projection)

- This standard works well for the vegetation management AI use cases

The standard is not consistently used, which introduces risk into AI automations

- Incorrect datum assumption can result in a distance error of up to two meters.

Dataset	Datum	Notes
AGOL Veg inventory	NAD83	
SAP Assets	NAD83	
LiDAR	NAD83	
Technosylva	NAD83	
Vector Models	NAD83	Some deliveries have been inconsistent
LiDAR clearance reports	Unknown	Assumed to be NAD83
Salesforce Inventory	WGS84	
Satellite imagery	WGS84	
Fulcrum apps	WGS84	
Satellite clearance reports	Unknown	
Weather and Soil data	Unknown	Low risk, but should be standardized



Data Challenges

A variety of inconsistencies appear in datasets

- Clearance reports have inconsistent schemas
 - Fields include varied spelling, capitalization, and prefixes/suffixes
- Data duplication
 - Both duplicate records and fields exist across many source systems
- Inconsistent unstructured data cloud paths
 - Many sub-directories are inconsistently present or absent, including circuit and date
- Inconsistent tree species names
 - Vegetation inventory species names do not agree with species names in tree metadata table

Join Logic

Crown Segmentation

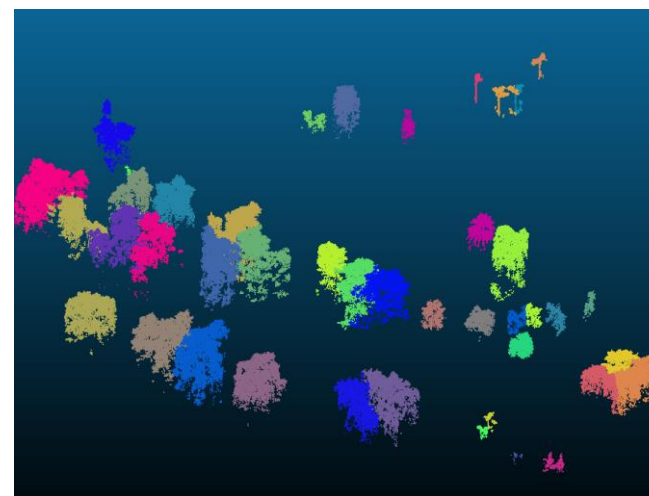
Crowns provide a flexible way to integrate multi-scale and multi-modal data



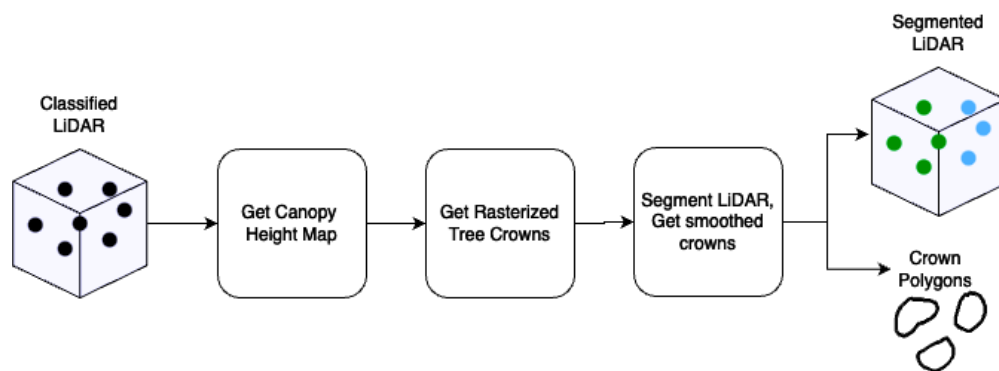
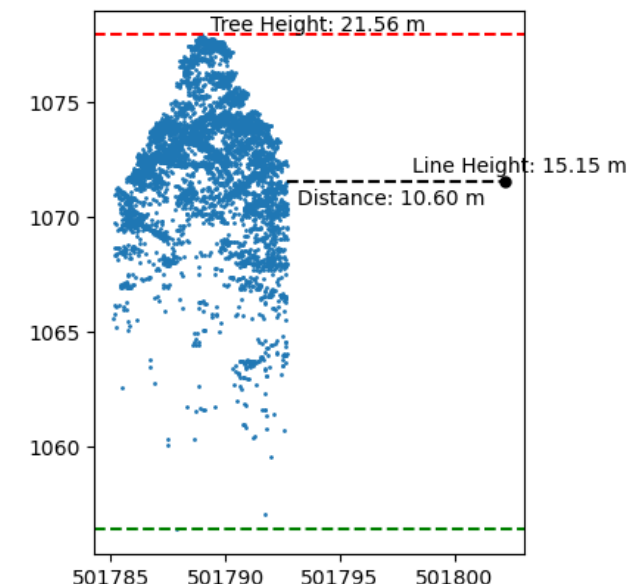
Notes

- GCP pipeline will automatically process LiDAR data as it arrives, extracting metadata and segmenting crowns

Segmented LiDAR



Automated Geometry Analysis



Inventory Field Test Results

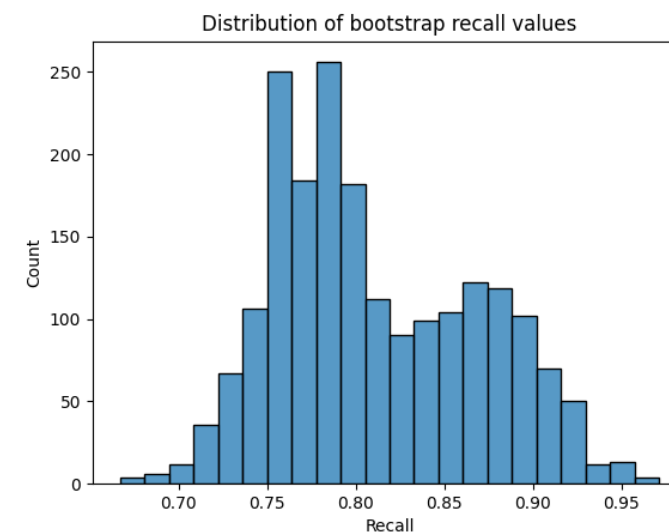
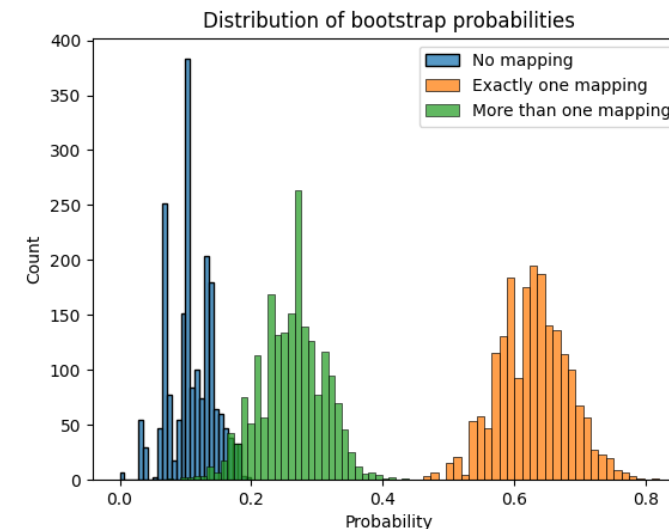
Inventory points have highly accurate tree characteristics but inaccurate spatial location

Goals

- Assess quality of inventory data
- Assess quality of crowns

Results

- The distribution and transmission circuits are broadly the same
 - Tests ran on Banning-Zanja (transmission) and Score (distribution)
- ~25% of inventory points correspond to multiple trees
- Inventory points have correct species ~85% of the time
- The crown segmentation process requires improvements before operationalization including:
 - Crown heights are generally lower than observed
 - Some missing crowns; this needs to be understood and fixed



Satellite Imagery

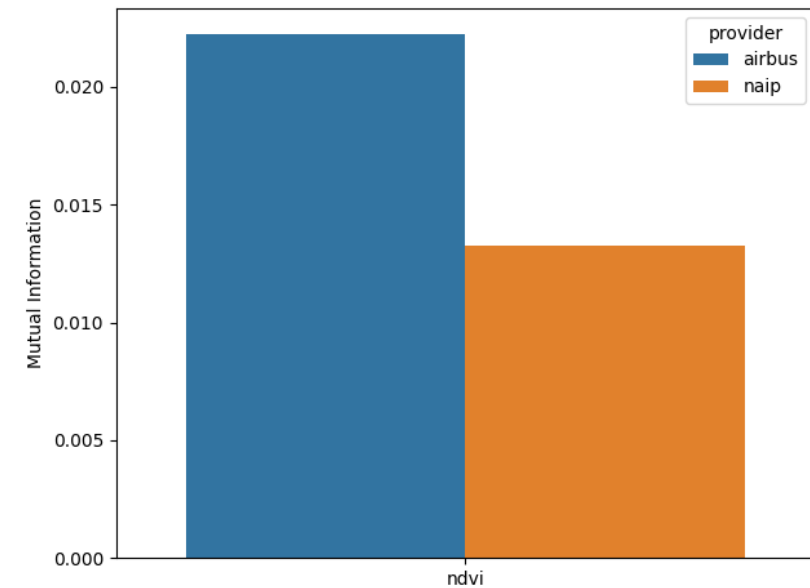
Satellite imagery appears have signal and likely more can be extracted



- Valuable data sourced unlocked by LiDAR derived crowns
- Tools created to fuse satellite images and more generally rasters with crowns
- Fused imagery allows for computation of many key features on the tree level
 - Health indices ndvi, gndvi, grvi, ndavi, ng, nr, nnir, rvi, and wavi are implemented
- More precise temporal and spatial resolution increases signal
- Imagery can likely be used to predict important tree characteristics like group or species



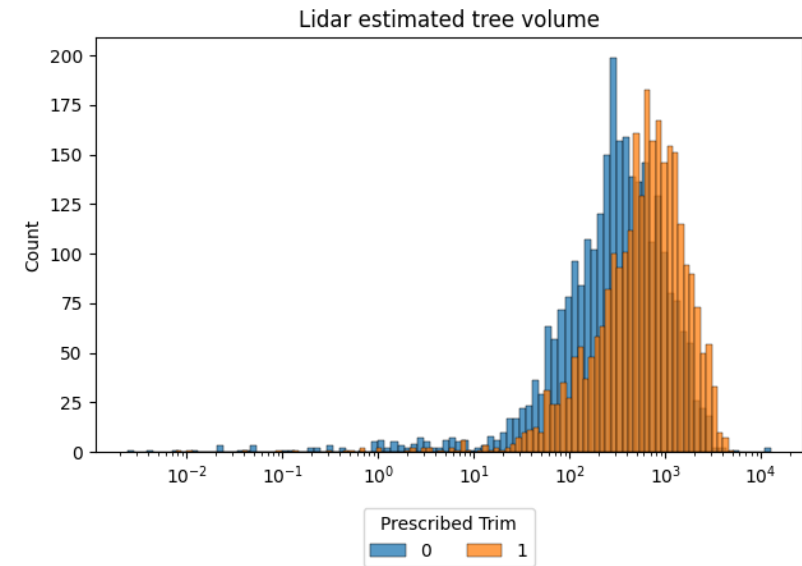
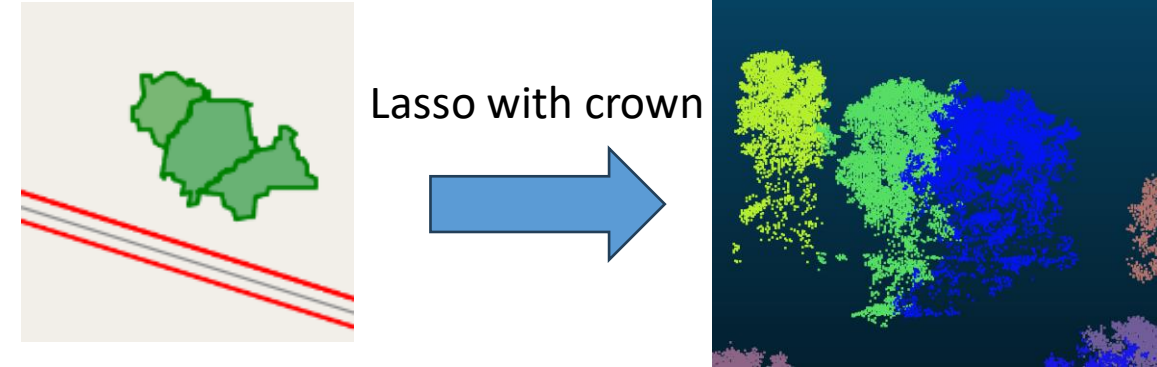
Clip to crown



LiDAR Point Clouds

LiDAR point clouds have significant signal

- Valuable data sourced unlocked by crowns
- Tools created to fuse point clouds with crowns
- Fused point clouds allows for computation of many key features on the tree level
 - Tree height, volume, density, and surface area
- Point clouds can likely be used to predict other important tree characteristics





Remote Sensing Data Fusion – LiDAR + Satellite + Others

Machine learning features extracted from fused data

Tree statistics

- Growth rate
- Risk rate
- Tree group and species
- Tree health indices
- Crown area
- Tree volume
- Tree density
- Tree surface area
- Tree height

Biome

- Canopy cover
- Canopy height
- Fuels
- Elevation and slope
- Weather
- Soil

History

- Previous trims
- Previous inspections

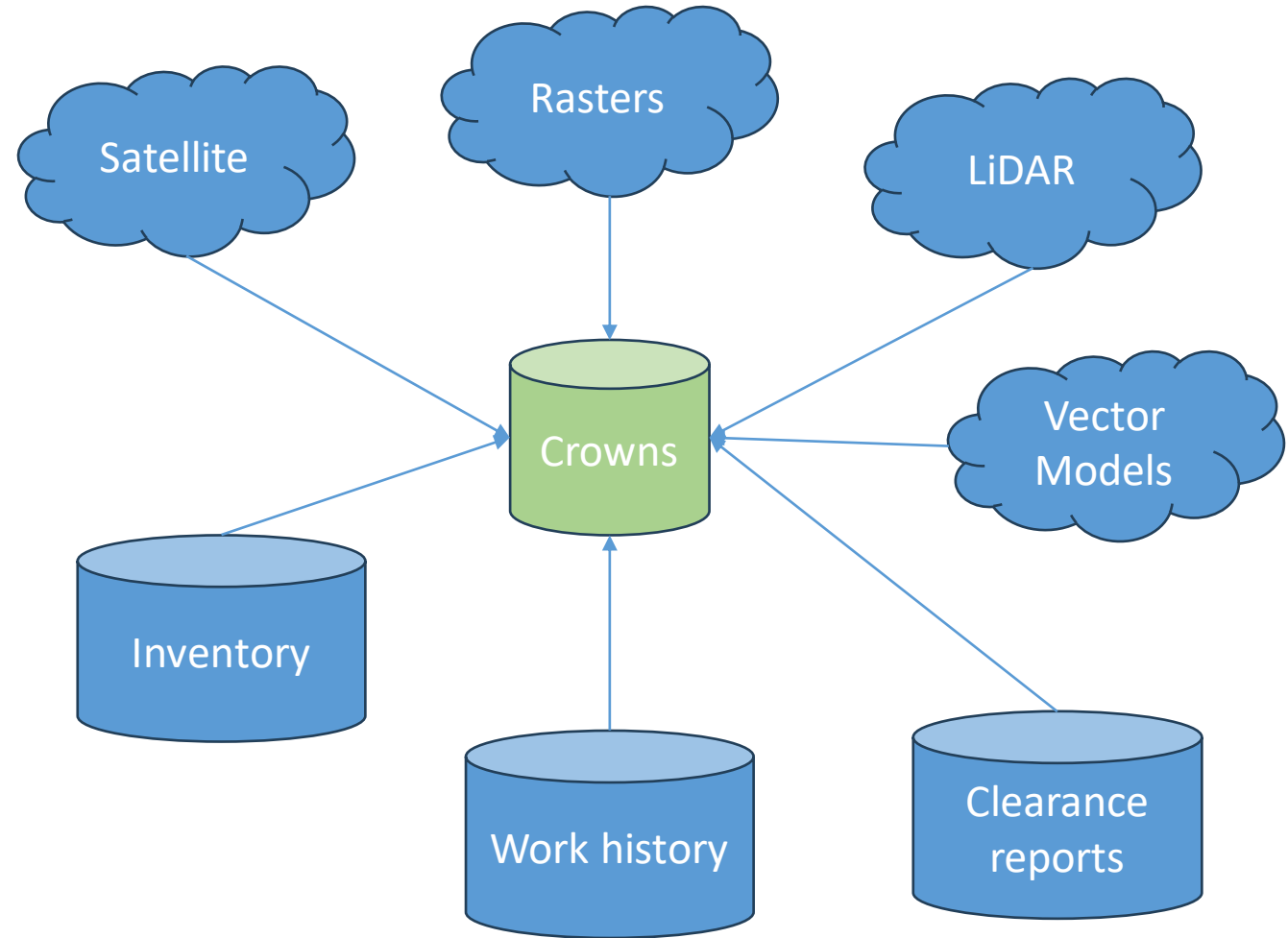
Clearance

- Clearance
- Hazard condition
- Conductor condition
- Span length
- Station location

Data Fusion

Data must be fused to create datasets for machine learning

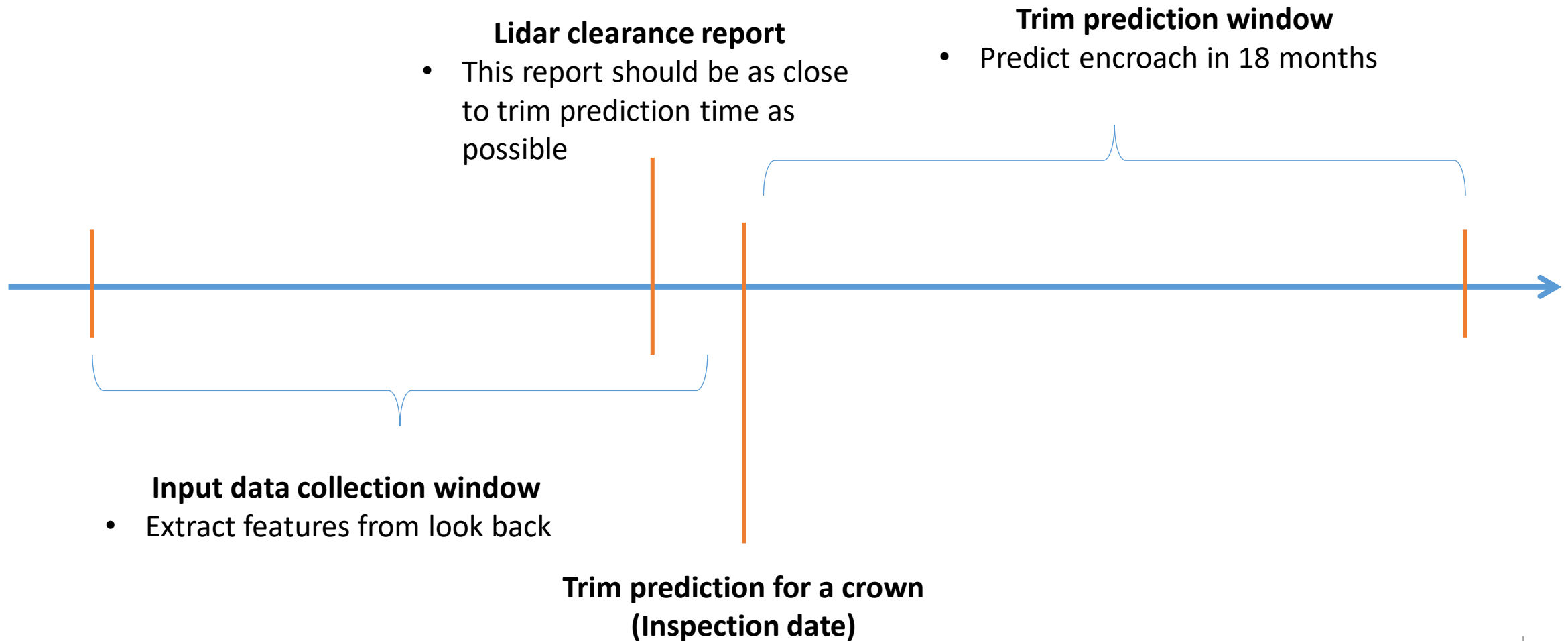
- Crown grain enables fusing multi-modal datasets for machine learning
- Not all crowns can be associated with inventory points
 - Reduces signal from inventory data
- Data used for machine learning PoC models can be found in ML_DEVELOPMENT database



Trim Prescription Model

Trim Rx Model

The trim Rx modeling problem is framed as a classification problem: on the Crown grain, predict whether a tree will encroach on the circuit in the next 18 months





Trim Rx Model

The definition of “encroach” depends on the circuit type and fire risk

Non-HFRA Distribution

- Clearance distance of 1.5ft or less in 18 months
- Fall-in can cause line strike and tree is unhealthy

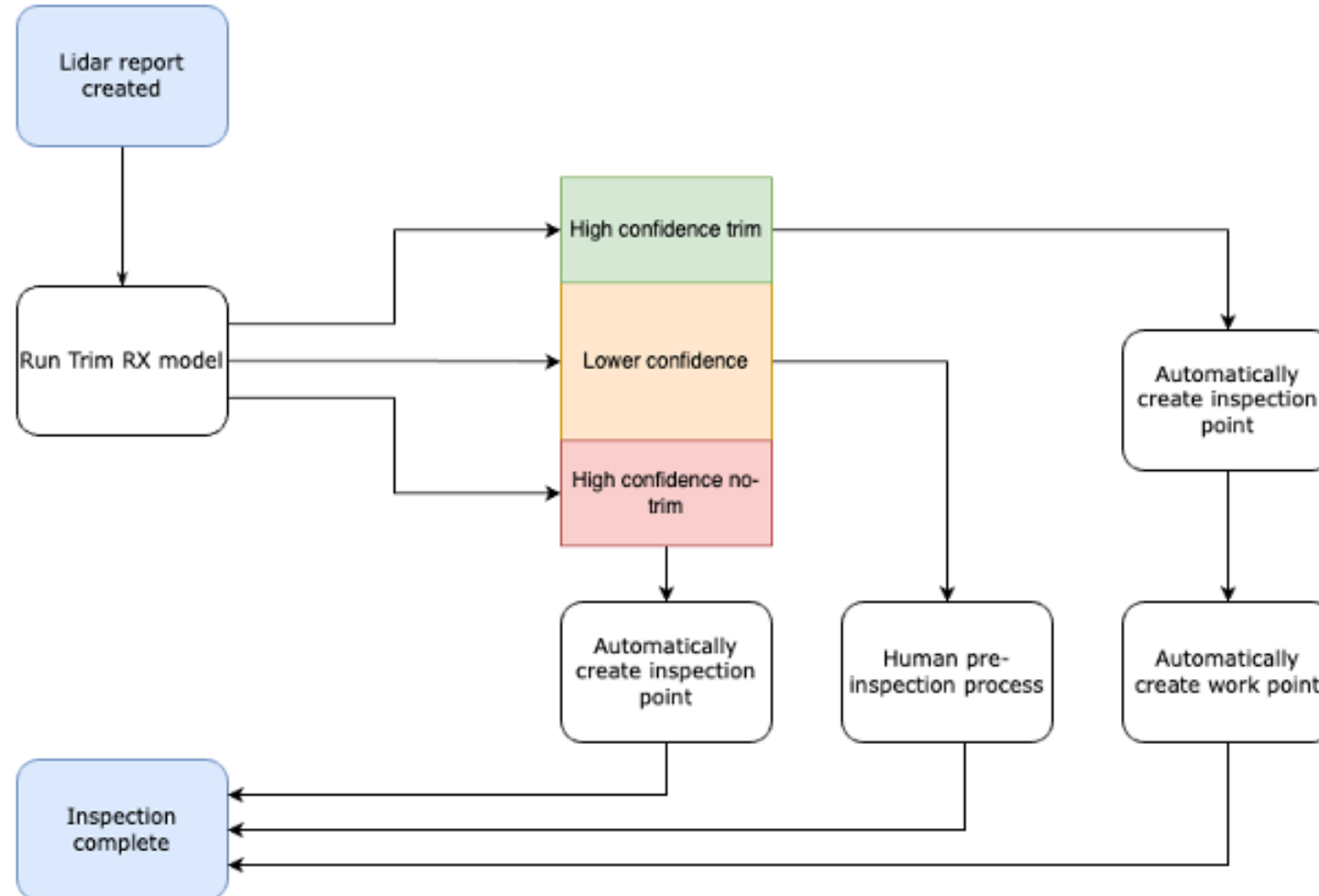
HFRA Transmission

- Clearance distance of 18ft or less in 18 months
- Fall-in can cause line strike and tree is on the ROW

- Other circuit types out of scope for PoC, but definitions are similar
- A transmission model and a distribution model are necessary, due to the difference in prediction targets
- Analysis of a wider sample of circuits required to identify best solution to HFRA versus non-HFRA
 - Additional models may be necessary

Trim Rx Model

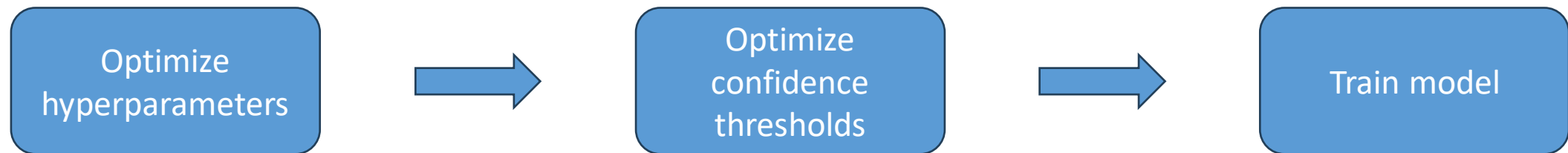
Leveraging model confidence allows for partial automation, which reduces risk while still driving value



Trim Rx Model

Models are trained and tuned on historical data

- Three modelling frameworks explored: Logistic Regression, LinearSVC, and XGBoost
- Transmission training data
 - Banning-Zanja 2022
 - ~3700 records
- Distribution training data
 - Hurst and Westfall 2022 through 2023
 - ~4000 records
- Upper and lower confidence thresholds optimized during training
 - Maximum coverage set at 30% to reduce overfitting, given the small training data size
 - Likely this percentage can be increased given more training data

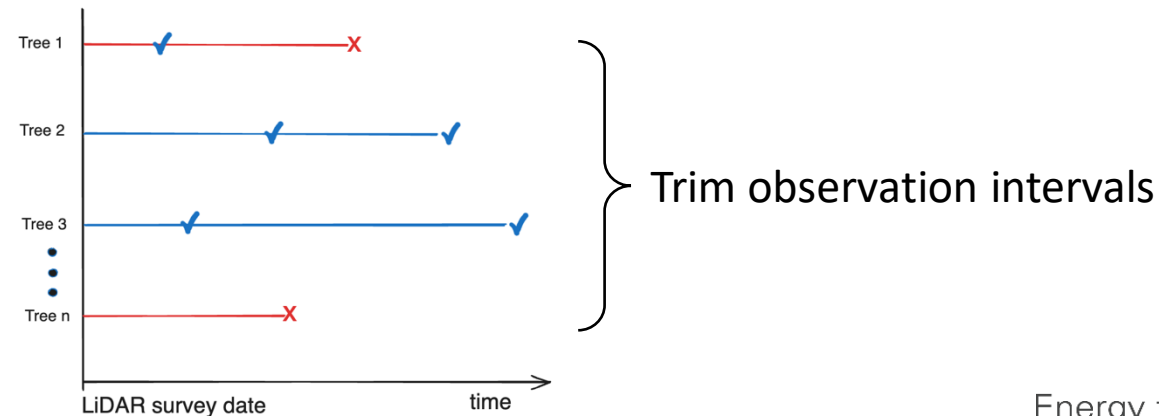


Trim Forecast Model

Trim Forecast Model

The trim forecast modeling problem is framed as a survival regression: predict the probability a tree will require a trim within a time interval

- A trim forecast prediction is an estimate of when a tree will require maintenance, accounting for inherent uncertainty (and risk)
- Forecasts can be driven by different strategies:
 - Growth models, that describe the evolution of tree dimension over time
 - Historical observations, from which growth patterns can be inferred
- Survival (or time-to event) analysis establishes a connection between covariates (features) and the time of an event
- Extract trim/no trim observation intervals from the inspection dataset, using date of LiDAR survey as the beginning of the interval



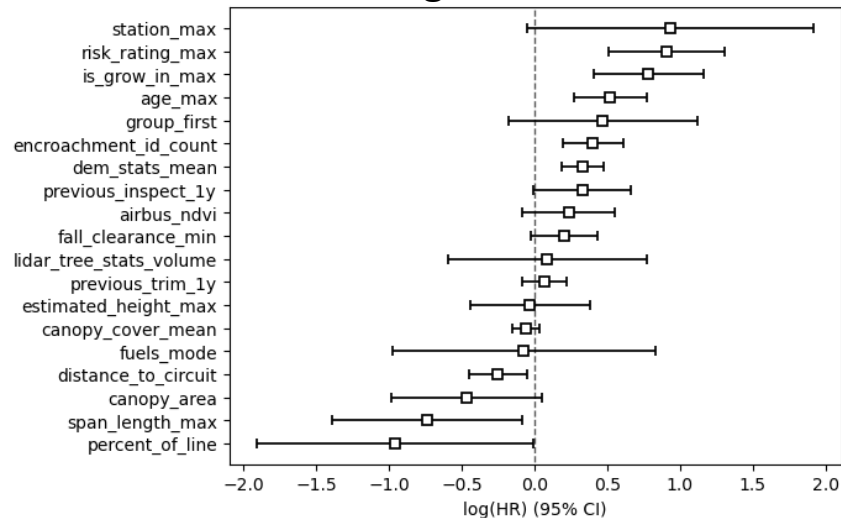


Trim Forecast Model

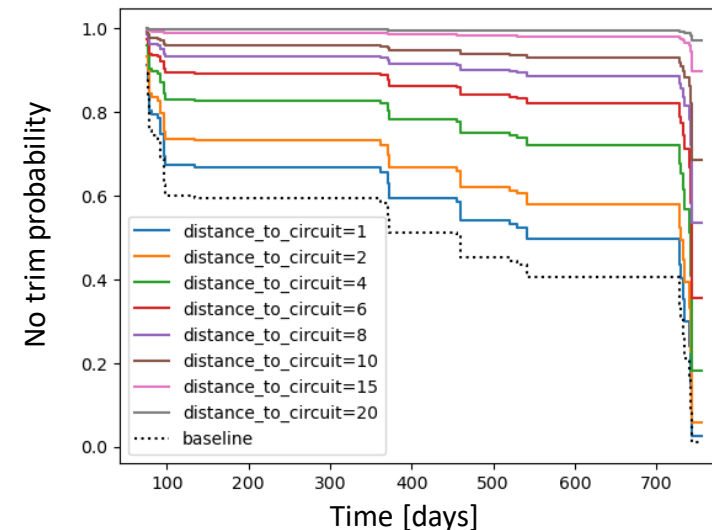
Model is trained on historical inspection data

- Multivariate Survival Analysis regression models explored: Cox Proportional Hazard Model¹
- Transmission training data
 - Banning-Zanja Feb 2022 (training)
 - Banning-Zanja Nov 2022 (test)
 - Banning-Zanja Nov 2023 (predict)
- Concordance index of 0.64 achieved on test dataset (ROC AUC measure)

Training Data coefficients



Partial dependance - distance



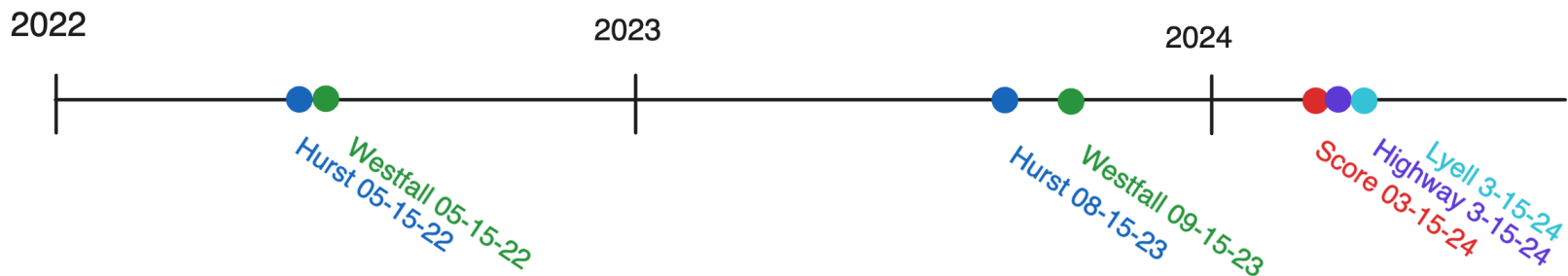
¹Davidson-Pilon, (2019). lifelines: survival analysis in Python. Journal of Open Source Software, 4(40), 1317, <https://doi.org/10.21105/joss.01317>



Trim Forecast Model

Model is trained on historical inspection data

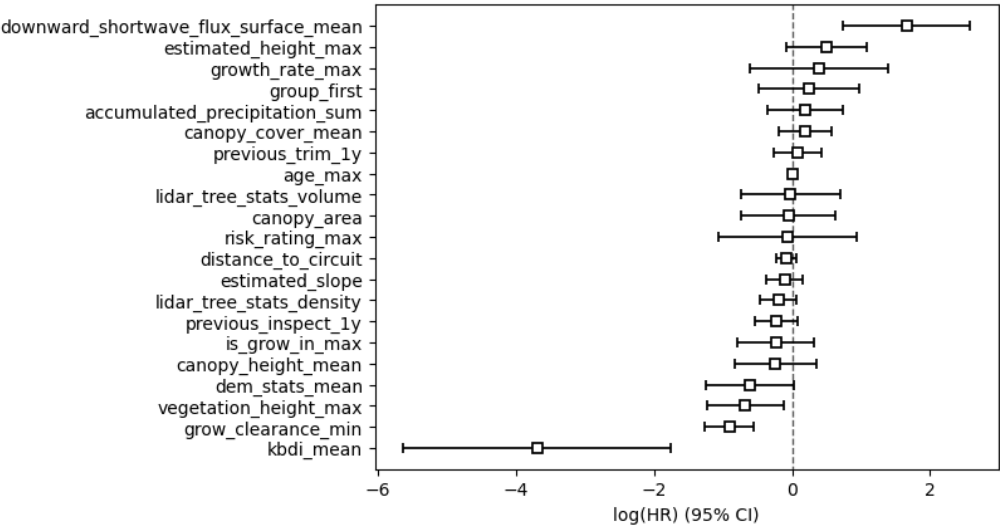
- Forecast model methodology applied to 2 HFRA distribution circuits



- Forecast model c-index on test dataset (ROC AUC measure)

Circuit	Training points	Test points	c-index
Hurst	476	163	0.553
Westfall	270	169	0.658

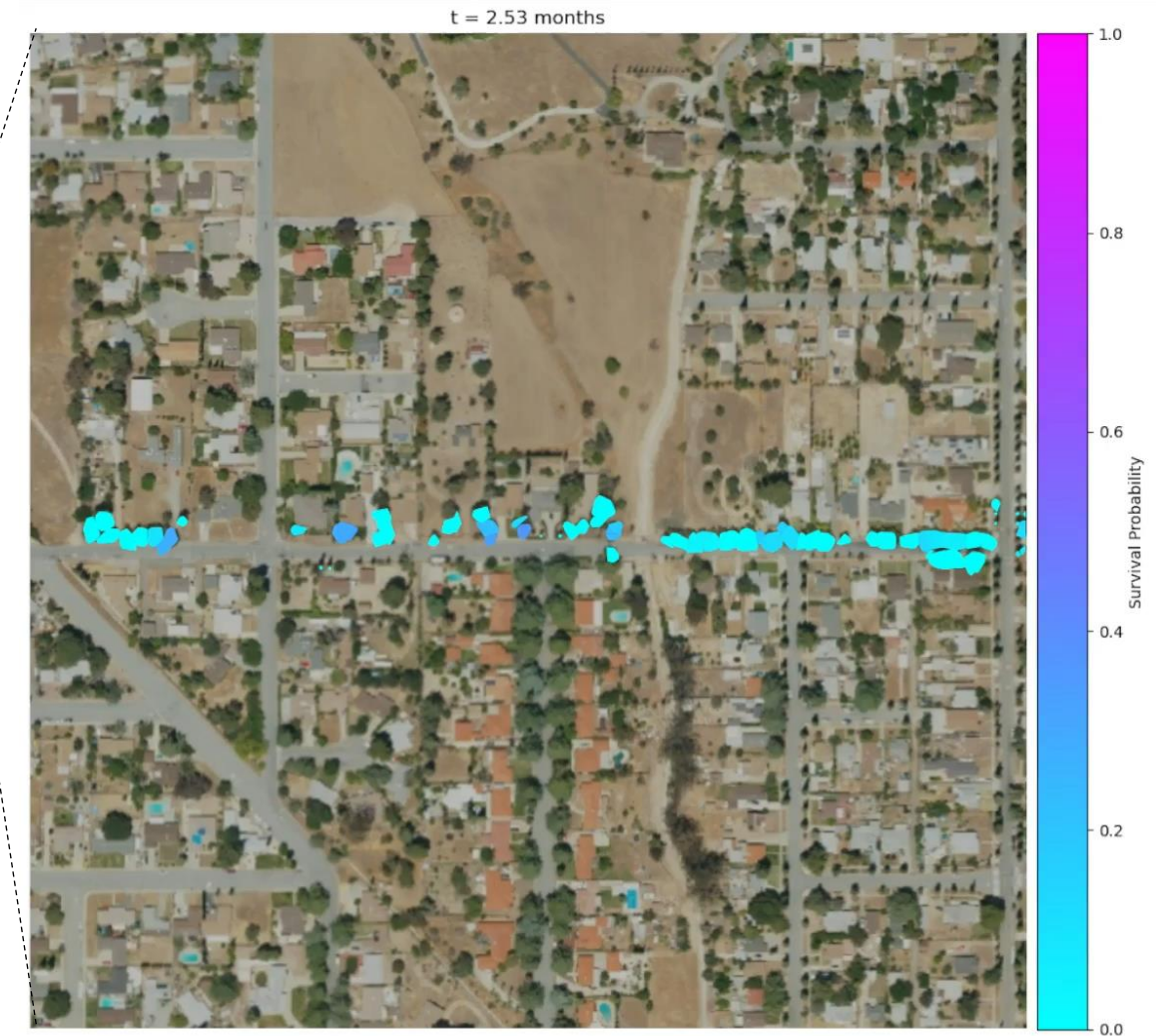
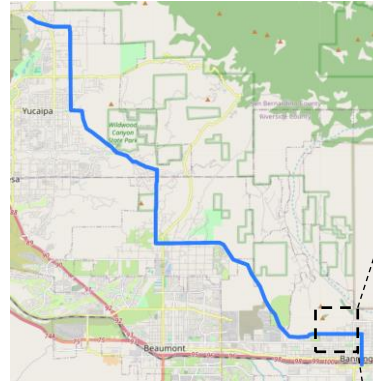
Dist. Model Coefficients



Trim Forecast Model

Prediction on BZ Nov 2023 LiDAR survey

- Forecast predictions give the probability of trim at different time intervals
- Expected values can also be generated for individual trees
- In addition to planning, evolution of risk can be used to assess data refresh, total cost of tree maintenance, planning scenarios



Business Value



Trim Rx Model Metrics

Model metrics measure the mathematical correctness of a model

- Precision and recall measure model errors
 - Higher precision, fewer false trims
 - Higher recall, fewer missed trims
- Letting M be the model and A the actual state of the world,

$$\text{precision} = \text{prob}(A = \text{trim} | M = \text{trim})$$

$$\text{recall} = \text{prob}(M = \text{trim} | A = \text{trim})$$

Trim Rx Business Metrics

Business metrics assess model utility



Costs

$c_{current}$ = current unit cost
 c_{model} = unit cost utilizing a model

$c_{inspect}$ = cost of one inspection
 c_{trim} = cost of one trim
 c_{missed} = cost of one missed trim

Deployment settings

α = proportion of automated Rx

Model

M = model prediction
 H = human prediction
 A = actual state of the world

$$\text{unit business value} = c_{current} - c_{model}$$

$$c_{current} = \underbrace{\text{prob}(A = \text{no trim} \ \& \ H = \text{trim}) \cdot c_{trim}}_{\text{Human risk of false trim}} + \underbrace{\text{prob}(H = \text{no trim} \ \& \ A = \text{trim}) \cdot c_{missed}}_{\text{Human risk of missed trim}} + \underbrace{c_{inspect}}_{\text{Cost of pre-inspector}}$$

$$c_{model} = \underbrace{\alpha \cdot \text{prob}(A = \text{no trim} \ \& \ M = \text{trim}) \cdot c_{trim}}_{\text{Model risk of false trim}} + \underbrace{\alpha \cdot \text{prob}(M = \text{no trim} \ \& \ A = \text{trim}) \cdot c_{missed}}_{\text{Model risk of missed trim}} + \underbrace{(1 - \alpha) \cdot c_{current}}_{\text{Human inspected}}$$

Estimating Costs (Transmission)

Baselines estimated using historical data on Banning-Zanja

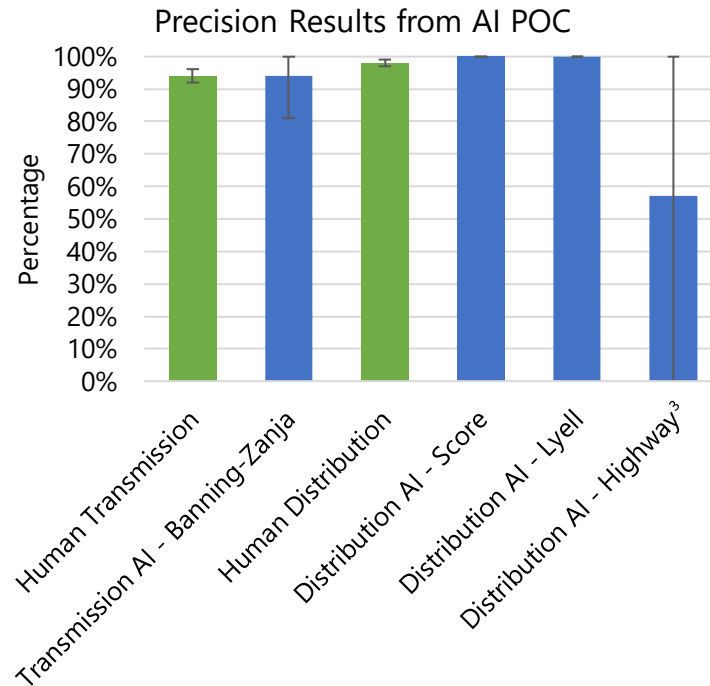
Cost	Value	Description	Source
$c_{inspect}$	\$39.52	Unit cost of human pre-inspection	SCE analysis
c_{trim}	\$441.11	Unit cost of a trim	SCE analysis
c_{missed}	\$1830	Unit cost of missing a trim	Estimated from regulatory fine and bootstrapping

$$c_{missed} = \underbrace{prob(violation|missed)}_{\substack{\text{Probability missed trim} \\ \text{results in violation;} \\ \text{estimated from data}}} \cdot \underbrace{prob(fine|violation)}_{\substack{\text{Probability violation} \\ \text{results in a fine; .01} \\ \text{used as a best guess}}} \cdot \underbrace{1,000,000}_{\substack{\text{NERC-critical} \\ \text{fine}}}$$

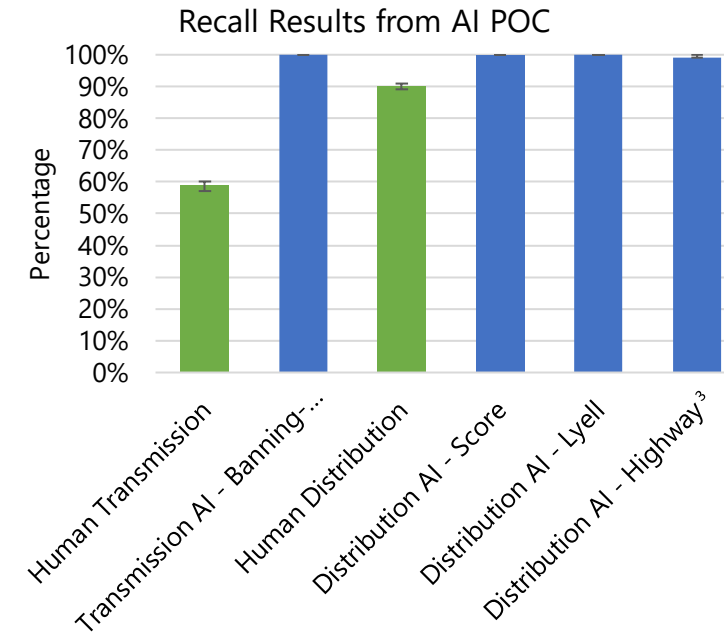
POC Directional Comparison of AI Models and Humans

AI models in POC were trained to accept some risk of false trims (false positives) but virtually no risk of missed trims (false negatives)

Precision measures likelihood of assigning a “correct” trim. The **closer the precision is to 100%**, the **less likely** inspection will result in a **false trim**



Recall measures likelihood of assigning a “correct” no-trim. The **closer the recall is to 100%**, the **less likely** inspection will result in a **missed trim**



Key: ■ Human result¹ ■ AI model result²

Results are preliminary and based on a limited sample size.
We will gather statistical significance via the AI Pilot project

Note: 1) Human distribution precision and recall is based performance measured on Hurst and Westfall due to lack of LiDAR availability on POC circuits. 2) AI model results are only reported where the model returned a high-confidence trim/no-trim prediction. This demonstrates performance of the AI models as they would be deployed through partial automation. 3) AI results on Highway demonstrate the need for a larger set of training data of greater statistical significance. Its outputs show clear indications of model overfitting to the currently limited training data.

Estimating Human Baselines (Transmission)

Baselines estimated using historical data on Banning-Zanja and previous cost estimates

- Human precision estimated from work records
- Human recall estimated using LiDAR
 - Missed trims identified by looking back from LiDAR clearance reports
- Current cost estimated using previous formula

Metric	Value	95% confidence interval
<i>precision</i>	.94	(.92, .96)
<i>recall</i>	.59	(.57, .60)
$C_{current}$	\$180	(165, 194)

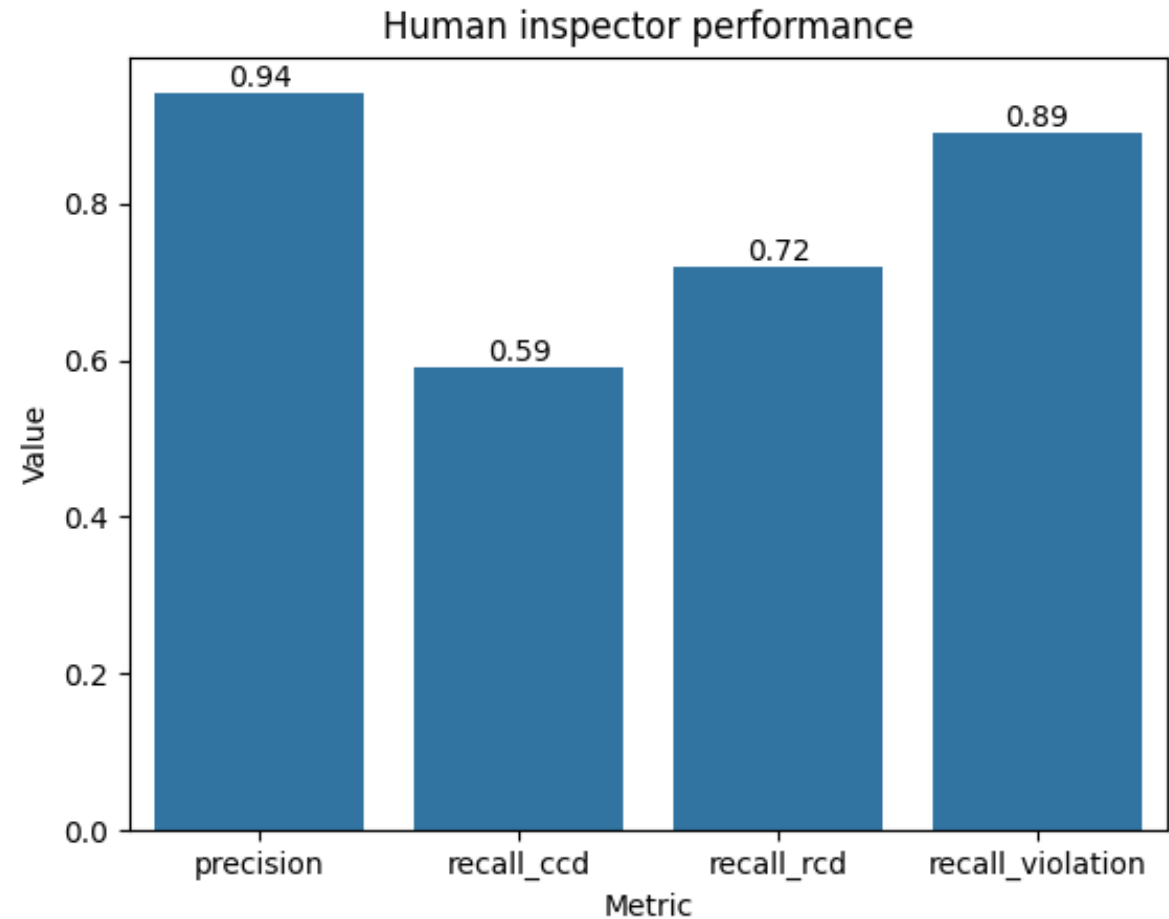


LiDAR identified missed trim

Estimating Human Baselines (Transmission)

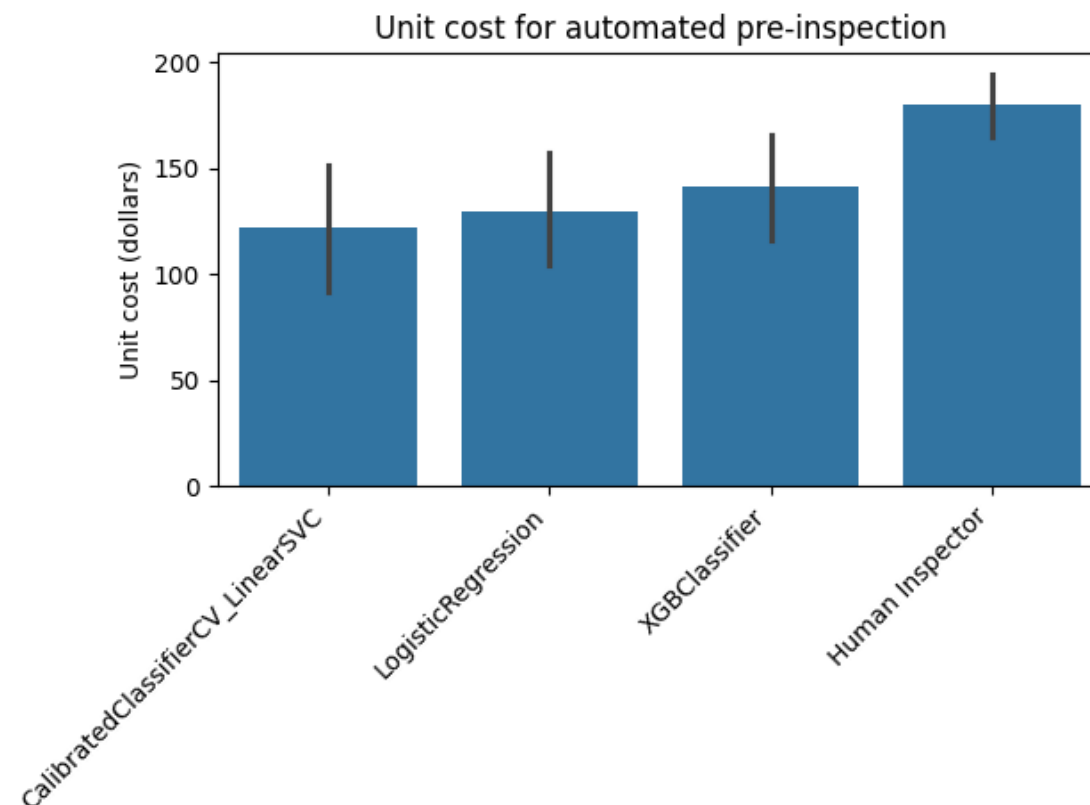
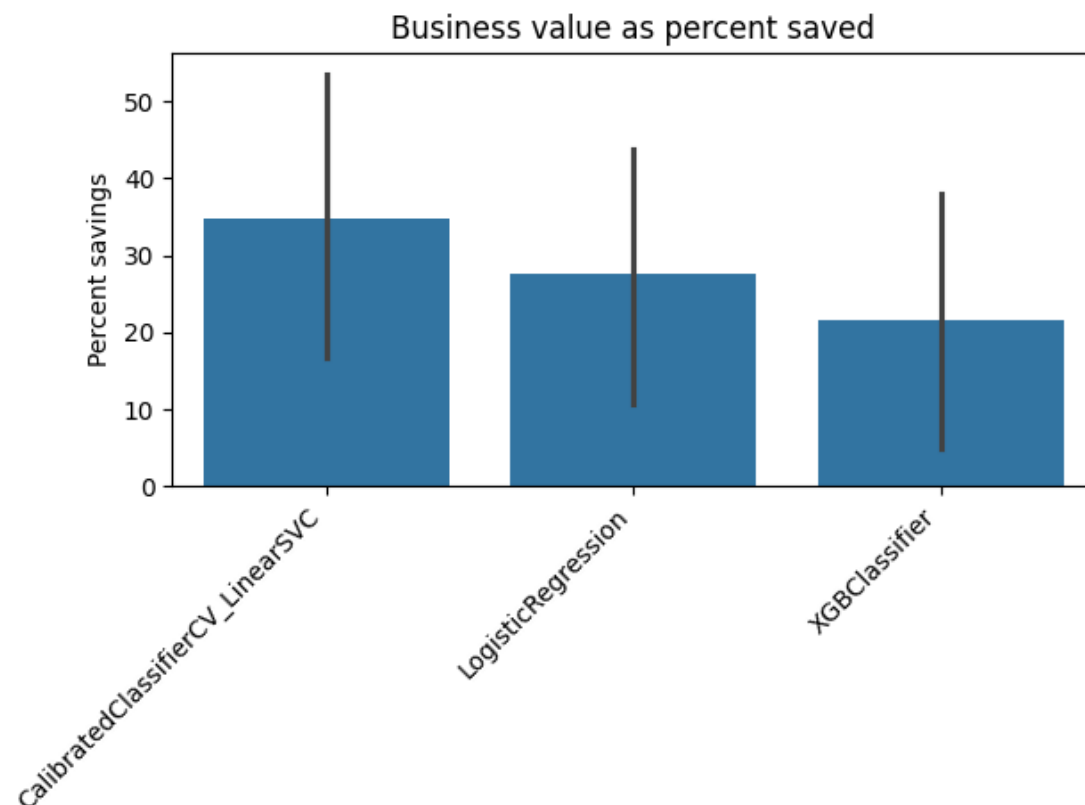
Human recall improves with encroachment severity

- Estimated using Banning-Zanja historical data
- Human recall for CCD encroachment is the recall used to assess models
- Human recall for flagging trees that will become violations is high



Trim Rx Business Metric Results (Transmission)

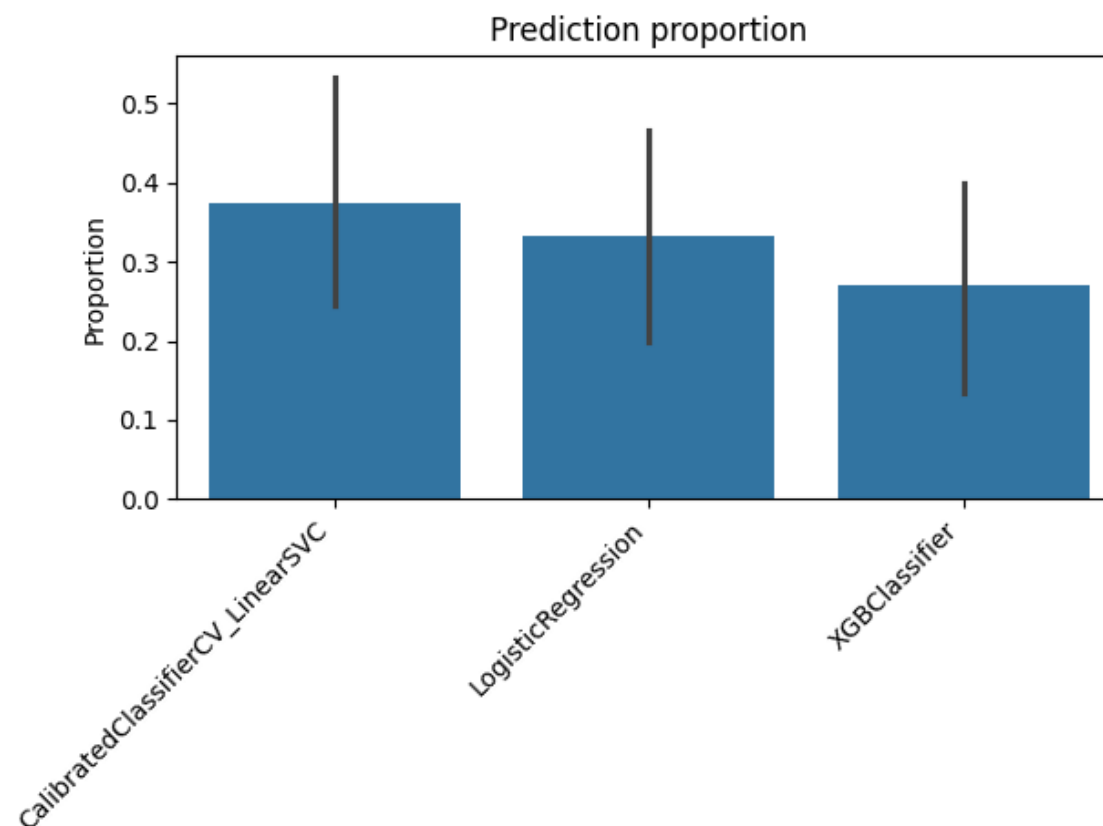
Results suggest transmission models can save ~30% with worst case savings of ~10%



Estimated using field validated ground truth on Banning-Zanja; more circuits are required to obtain a more robust estimate of savings

Trim Rx Business Metric Results (Transmission)

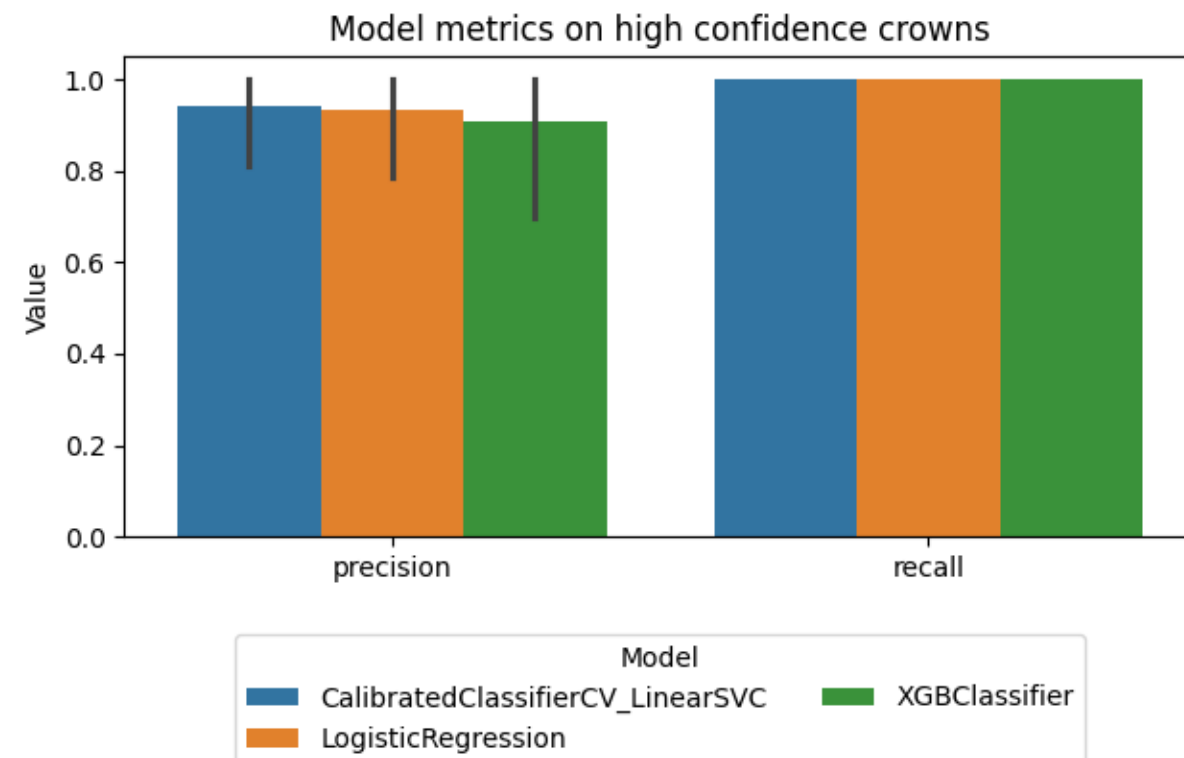
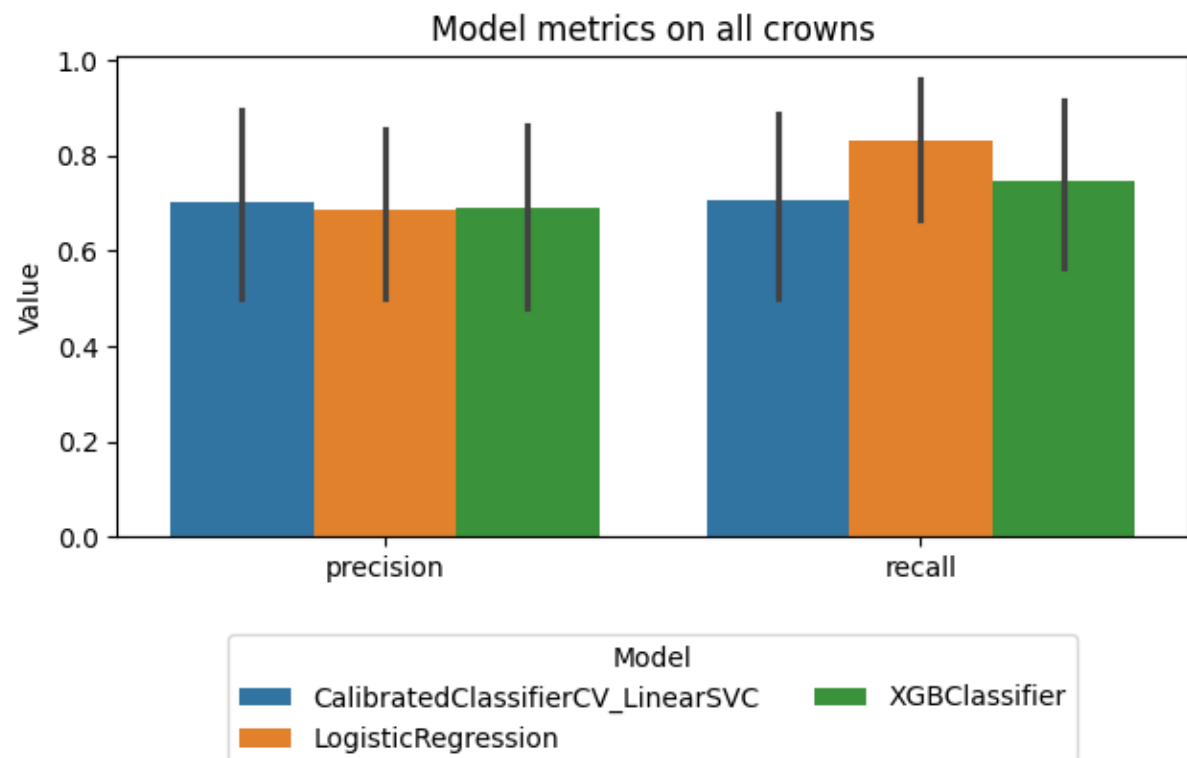
Models make predictions on approximately 30% of records, which is expected from thresholds learned during training



Estimated using field validated ground truth on Banning-Zanja

Trim Rx Model Metric Results (Transmission)

Reducing to high confidence crowns improves metrics and thereby reduces deployment risk



Estimated using field validated ground truth on Banning-Zanja

Forecast Model Value Scenarios

Forecast model value realized through planning/design scenarios

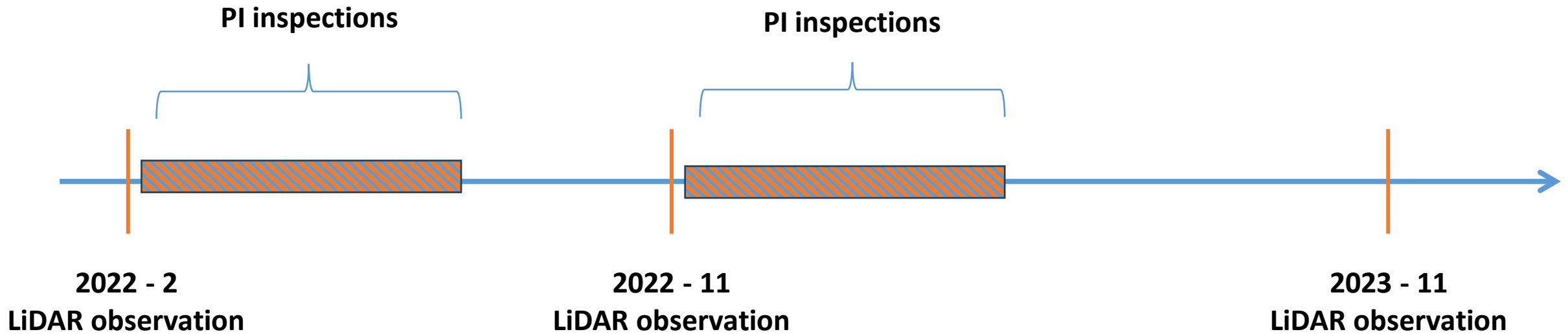
- Optimization of maintenance scheduling
 - Model impact of different scenarios
- Risk-based data refresh strategies
 - Aggregated risk over time can be assessed for circuits
 - Plan data refresh to manage risk/minimize cost
- VM economic analysis
 - Determine NPV of lifetime cost of tree maintenance
- VM circuit design tool
 - Assess impact of vegetation position on maintenance costs/risk
 - Evaluate VM costs of proposed circuit designs given vegetation scenarios



Estimating Human Recall

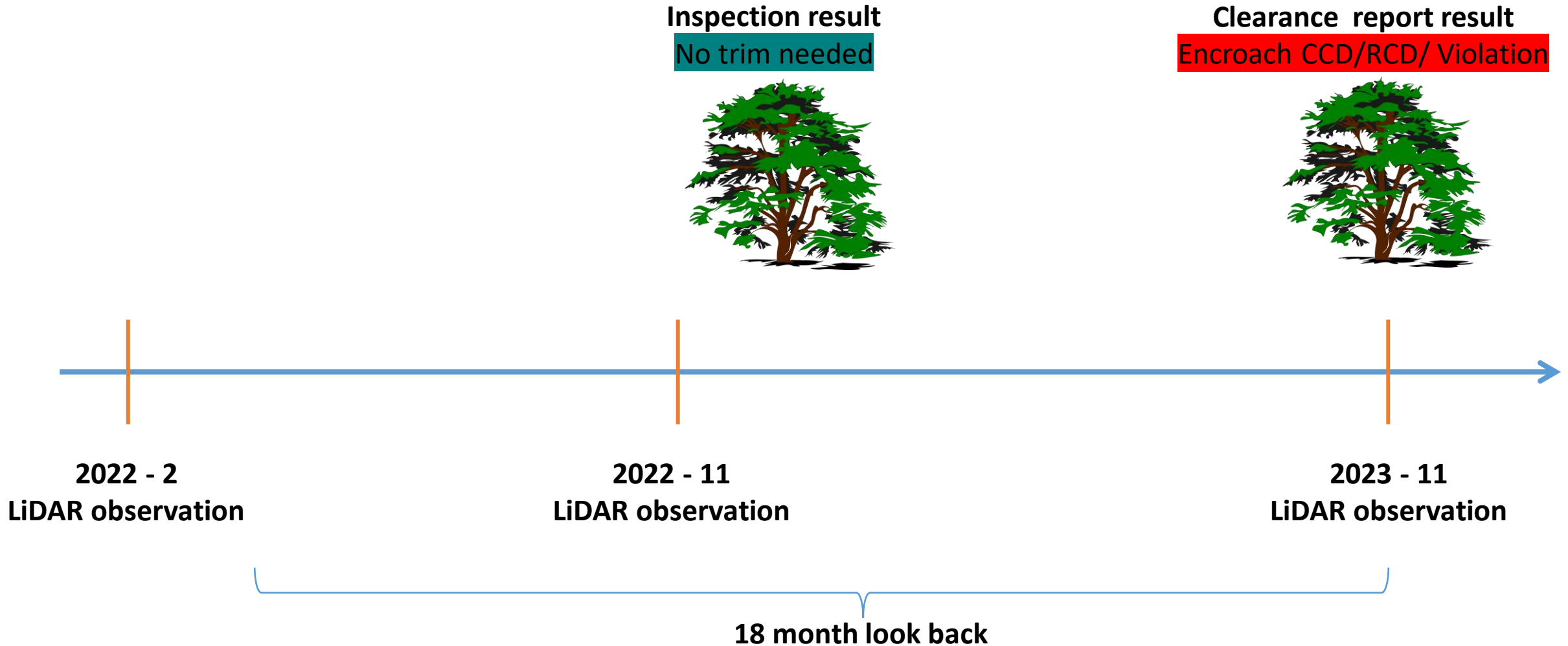
LiDAR and Inspection Workflow

LiDAR observations and subsequent PI inspections for Banning-Zanja



LiDAR Identified Missed Trim Prescriptions

Looking back from LiDAR observations identifies when a PI misses a trim prescription



LiDAR Identified Missed Trim Prescriptions

An example of a missed trim prescription on Banning-Zanja

May 2023 inspection point;
no trim required



Nov 2023 RCD
encroachment point



Methodology and Assumptions

Methodology is designed to give human PIs the benefit of the doubt

Methodology

Crowns are mapped to all inspection points within 20ft.

- If any one of these inspection points in the look back window prescribed a trim, the crown is assumed to have been prescribed a trim.

A crown is considered CCD/RCD/non-compliant if such an encroachment point is within 3ft.

- This reduces the chance of an encroachment point being erroneously mapped.

Only grow-in risk is assessed

- Fall-in risk is much lower, so excluding this risk type is unlikely to impact results
- Fall-in risk is harder to accurately calculate as it depends on exact width of the ROW.

Assumptions

- Crowns without associated inspection points are assumed to have been inspected and that the PI determined that no trim was needed



Recall Calculations

Formal calculations of human recall from LiDAR data.

Recall captures the likelihood of missed prescriptions

$$\text{recall} = \text{prob}(\text{trim prescribed} \mid \text{trim is needed})$$

Since the PI precision can be estimated, we have

$$TP = \text{true prescriptions} \approx \text{count}_{\text{prescriptions}} * \text{precision} = \text{count}_{\text{prescriptions}} * .94$$

We cannot directly count true positives since the full 18 months may not have passed.

Leveraging LiDAR

$$FN = \text{lidar missed prescriptions} \leq \text{actual missed prescriptions} = \widehat{FN}$$

LiDAR missed prescriptions under count since the full 18 months may not have passed.

Putting these together, we have an upper bound on human recall

$$\text{LiDAR estimated recall} = \frac{TP}{TP + FN} \geq \frac{TP}{TP + \widehat{FN}} = \text{recall}$$