A Comparative Assessment of Tree Crown Detection and Segmentation Methods using OBIA Data Fusion, Convolutional Neural Networks, and Point Cloud Clustering

Capstone Project Proposal by Glenn Xavier

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About Me

- Environmental GIS Analyst
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Center for Environmental Management
MILITARY LANDS

Colorado State University

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Presentation Overview

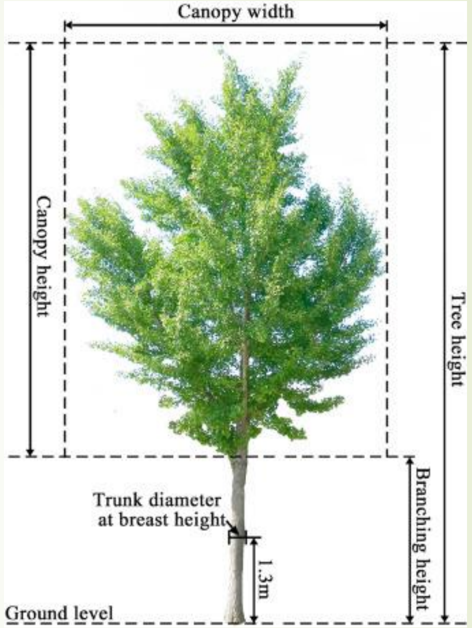
- Background
- Potential Solutions
- Project Goals and Objectives
- Study Areas
- Data Sources
- Workflow and Methodology
- Expected Results
- Project Timeline
- Questions and Comments

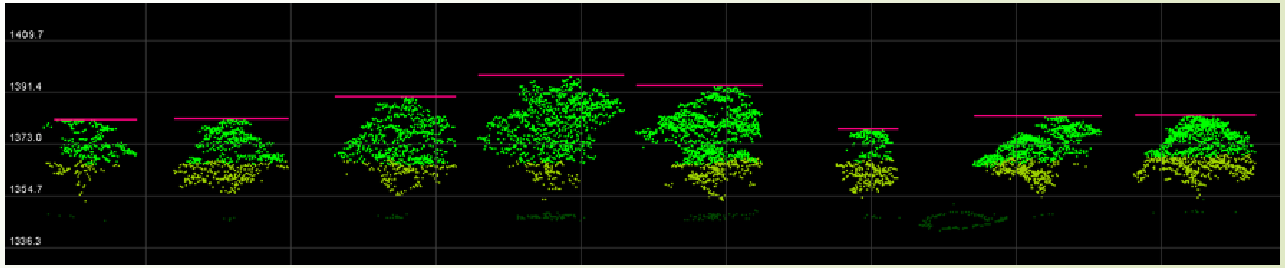
Background

- Federal law mandates natural resource management
- USAF Installations are small self-contained cities
- Bases contain a mix of urban/ suburban, and natural land cover
- Protect ESA and natural habitat
- Urban beautification
- Tree management relies on field-based measurements
  - Labor intensive
  - Sampling is sporadic

Background

- Remote Sensing data can supplement surveys
  - Lidar > 4 ppsm can extract individual tree metrics
  - Tree height, crown width, basal area, crown base height, crown volume
- USAF/AFCEC collects high resolution imagery and lidar
  - Lidar point clouds are minimally processed
  - Little institutional knowledge on how to extract features
  - Data mostly goes unused





Project Goals and Objectives

EXTRACT TREE CANOPY FROM IMAGERY AND LIDAR

SEGMENT TREE CANOPY INTO DISCRETE TREE CROWNS USING THREE METHODS

MEASURE AND REPORT ACCURACY OF SEGMENTED TREE CANOPY METHODS

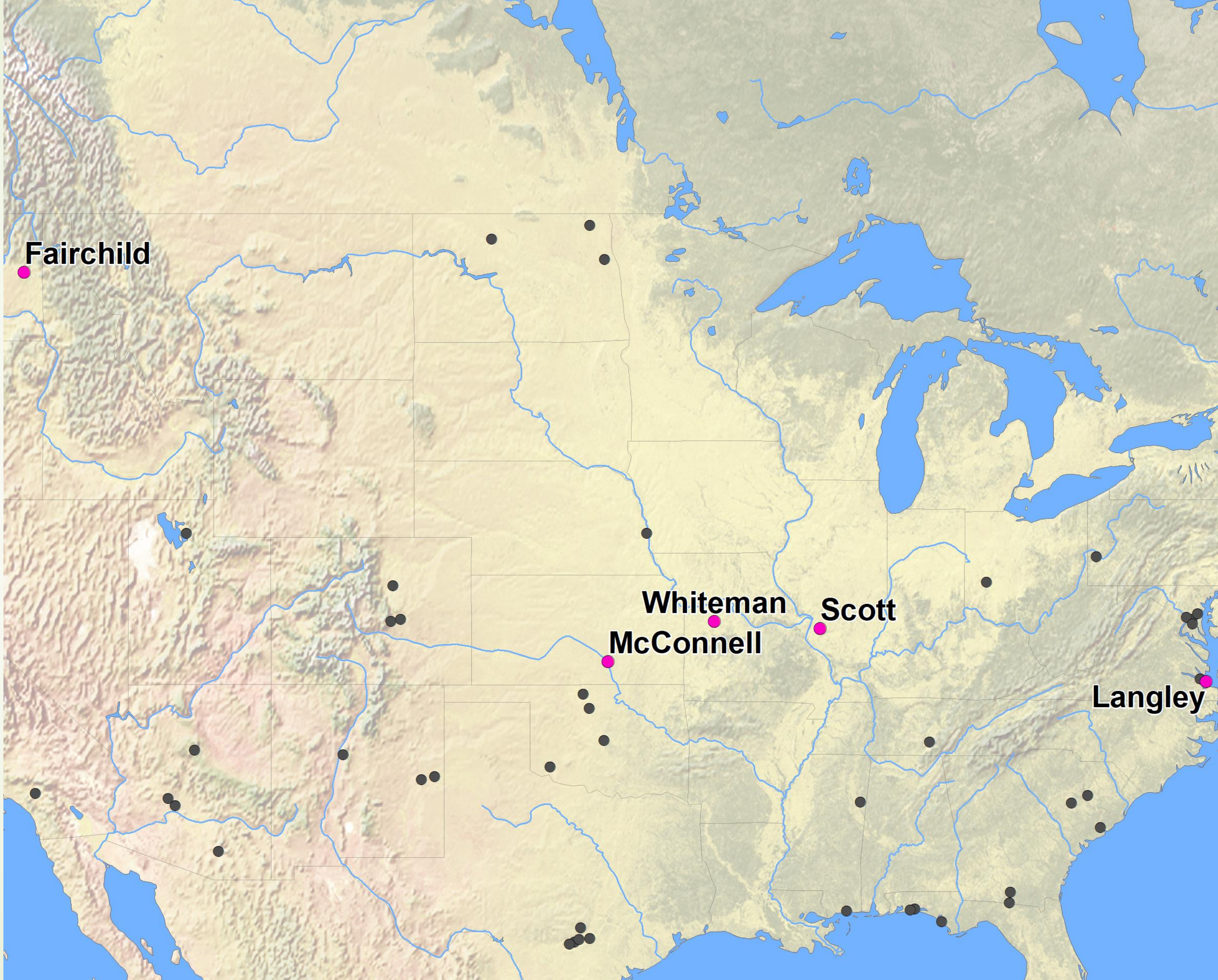
PROVIDE A RECOMMENDATION FOR ADOPTION

Potential Solutions

- Object-Based Feature Extraction to isolate tree canopy
  - Allows for fusion of imagery, lidar, and reference vector data
  - Rule-based, stepwise instructions
  - Can be general or fine-tuned
- Delineate Individual Tree Crown
  - **Method 1:** Watershed segmentation – easy but generalized
  - **Method 2:** Point cloud clustering – more difficult to implement
  - **Method 3:** Object detection with Convolutional Neural Network – time consuming to train model

Study Areas

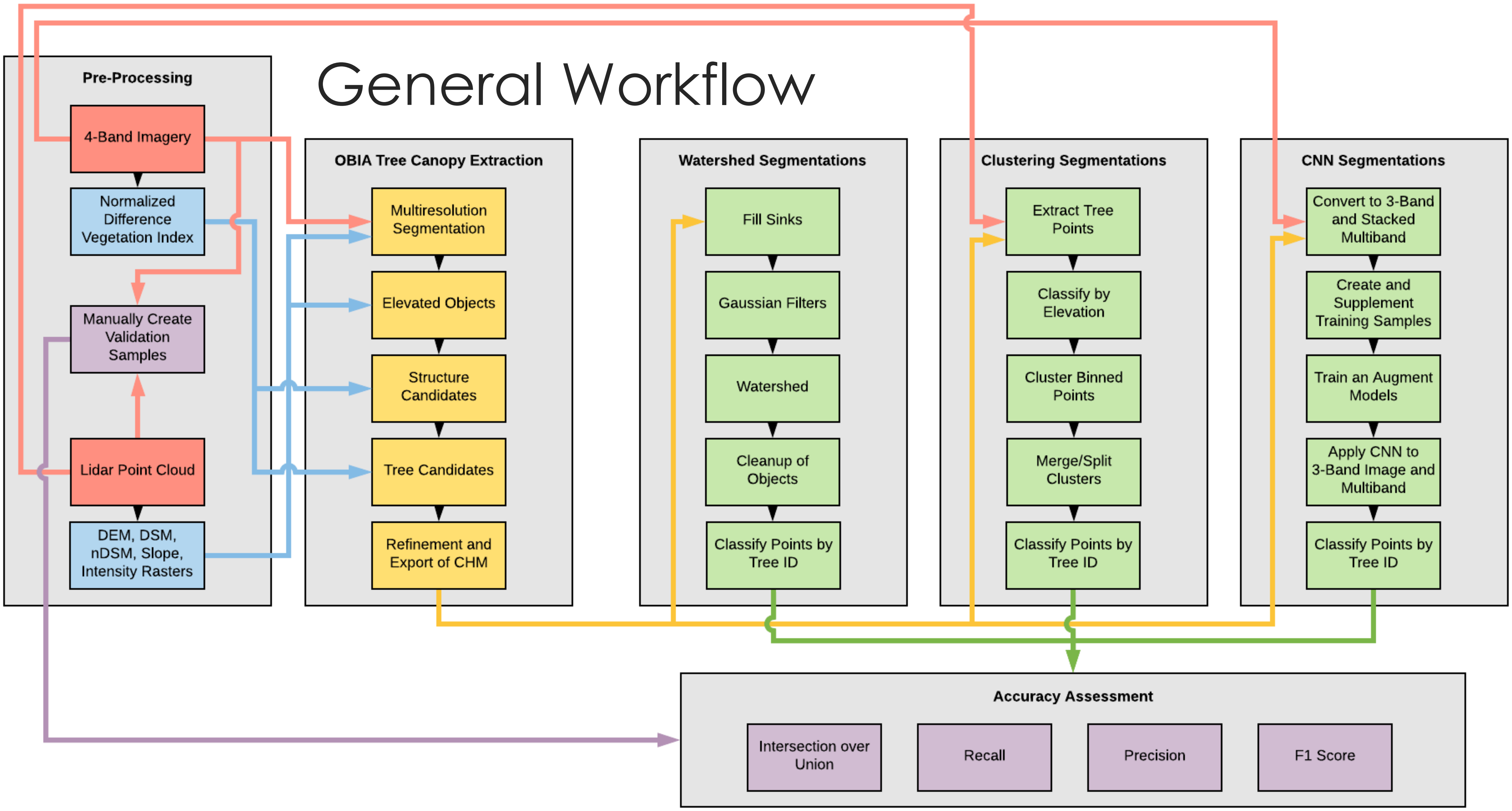
- Installations with high-resolution imagery and high density lidar
- Wide range of tree species and mixed land-use cover
- Availability of reference and validation data
- Additional bases available for validation



Data Sources

	Scott	McConnell	Whiteman	Langley	Fairchild
State	**Illinois**	**Kansas**	**Missouri**	**Virginia**	**Washington**
Date	**3/29/2020**	**12/5/2018**	**4/20/2019**	**4/17/2020**	**5/27/2018**
Imagery RGB,NIR	**7.62 cm**	**6 cm**	**7.5 cm**	**7.5 cm**	**7.62 cm**
Nominal Pulse Density (pulse/m^2)	**8 ppsm**	**8 ppsm**	**8 ppsm**	**20 ppsm**	**8 ppsm**
Returns	**7**	**5**	**7**	**7**	**5**
Typical Tree Point Density (all returns, points/m^2)	**20-40**	**10-20**	**20-40**	**40-80**	**10-20**
Urban Trees	Mostly ash and maple	Pear, oak, magnolia, well dressed and isolated	Very sparse oak	Bald cypress, London planes, hollies, elms, willow oaks	Mostly Conifer
Unmanaged Trees	Very dense wetland, Maple,Ash	Small Stands of Cedar	Dense Mixed oak dry forest, hickory, maple, cedar	Oak and loblolly	Mostly Conifer, Ponderosa Pine

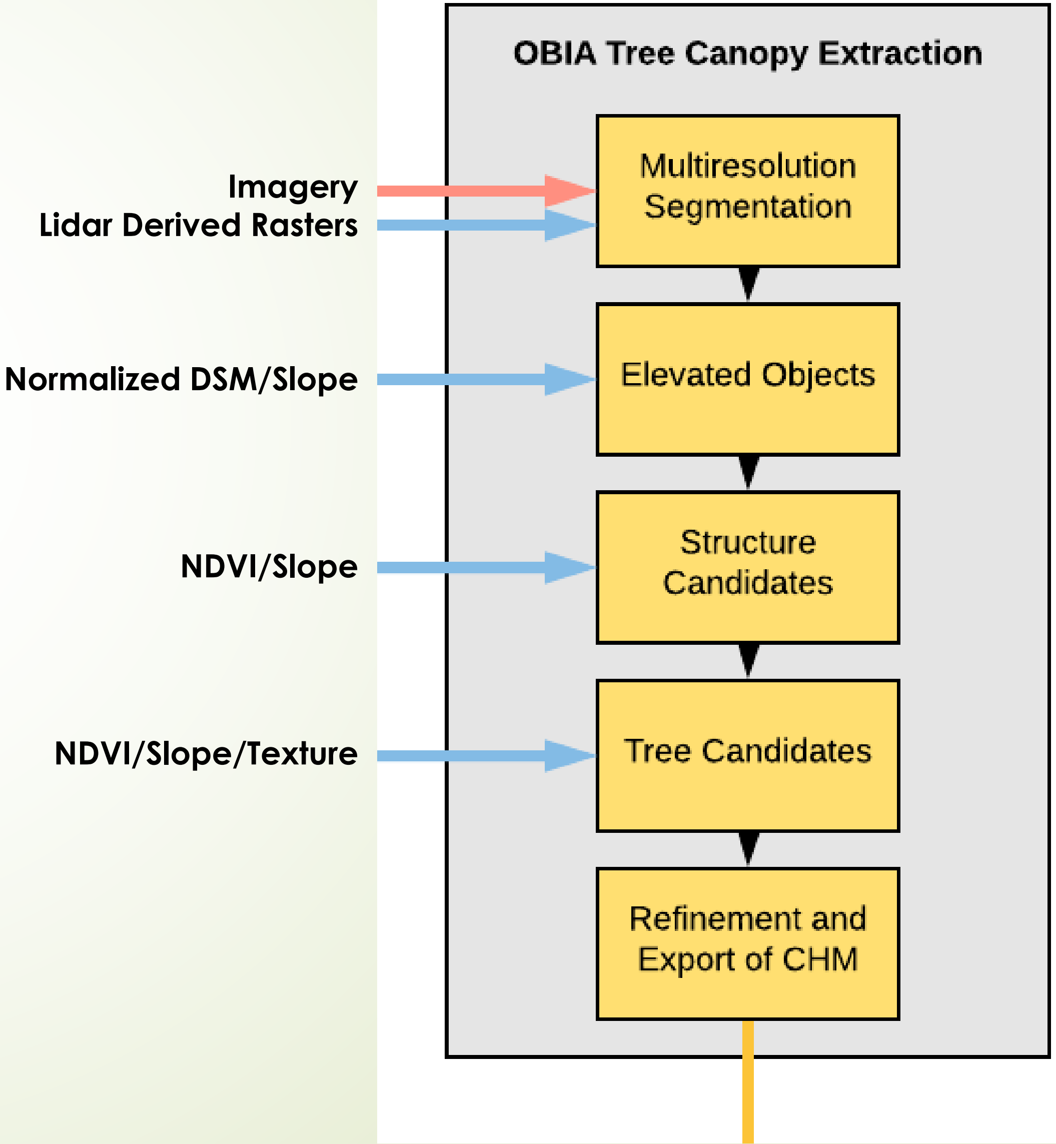
General Workflow



Object-Based Image Analysis (OBIA)

do
- segment
  - delete 'Level 1'
  - 40 [shape:0.4 compct.:0.5] creating 'Level 1'
  - at Level 1: copy creating 'Level 2' below
- classify structureCandidates
  - elevated, structureCandidate2, structureCandidate, treeCandidate at Level 1: unclassified
  - unclassified with Mean nDSM >= 4 at Level 1: elevated
  - elevated with Mean NDVI <= 0.1 at Level 1: structureCandidate
  - structureCandidate at Level 1: merge region
  - loop: elevated, structureCandidate with Rel. border to structureCandidate >= 0.4 and Mean NDVI <= 0.5 at Level 1: structureCandidate
  - structureCandidate at Level 1: merge region
  - structureCandidate with Density <= 1.8 and Number of pixels <= 10000 at Level 1: elevated
  - structureCandidate with Number of pixels <= 10000 at Level 1: clutter
- classify treeCandidates
  - elevated with Mean NDVI >= 0.18 at Level 1: treeCandidate
  - treeCandidate at Level 1: merge region
  - unclassified with Rel. border to treeCandidate >= 1 at Level 1: treeCandidate
  - treeCandidate at Level 1: merge region
  - treeCandidate with Density <= 1.5 and Number of pixels <= 10000 at Level 1: elevated
  - structureCandidate with Mean NDVI >= 0.15 and Mean Slope >= 50 at Level 1: treeCandidate
  - treeCandidate at Level 1: merge region
  - loop: elevated, unclassified with Rel. border to treeCandidate >= 0.5 and Mean NDVI >= 0.15 and Mean nDSM >= 5 at Level 1: treeCandidate
  - treeCandidate at Level 1: merge region
  - unclassified with Rel. border to treeCandidate >= 0.9 and Mean nDSM >= 1 and Mean NDVI >= 0.3 at Level 1: treeCandidate
  - treeCandidate at Level 1: merge region
  - treeCandidate with Number of pixels <= 1000 at Level 1: clutter
  - unclassified with Rel. border to treeCandidate >= 0.8 and Mean nDSM >= 1 and Mean NDVI >= 0.2 at Level 1: treeCandidate
  - treeCandidate at Level 1: merge region
  - loop: clutter with Rel. border to treeCandidate >= 0.3 and Mean Slope >= 50 at Level 1: treeCandidate
  - loop: unclassified with Rel. border to treeCandidate >= 0.3 and Mean Slope >= 50 and Mean nDSM >= 2 and Mean NDVI >= 0.4 at Level 1: treeCandidate
  - loop: unclassified with Rel. border to treeCandidate >= 0.7 and Mean Slope >= 50 and Mean nDSM >= 0.5 and Mean NDVI >= 0.4 at Level 1: treeCandidate
  - unclassified with Rel. border to treeCandidate >= 1 at Level 1: treeCandidate
  - treeCandidate at Level 1: merge region
- export
  - treeCandidate at Level 1: export object shapes to ObjectShapes

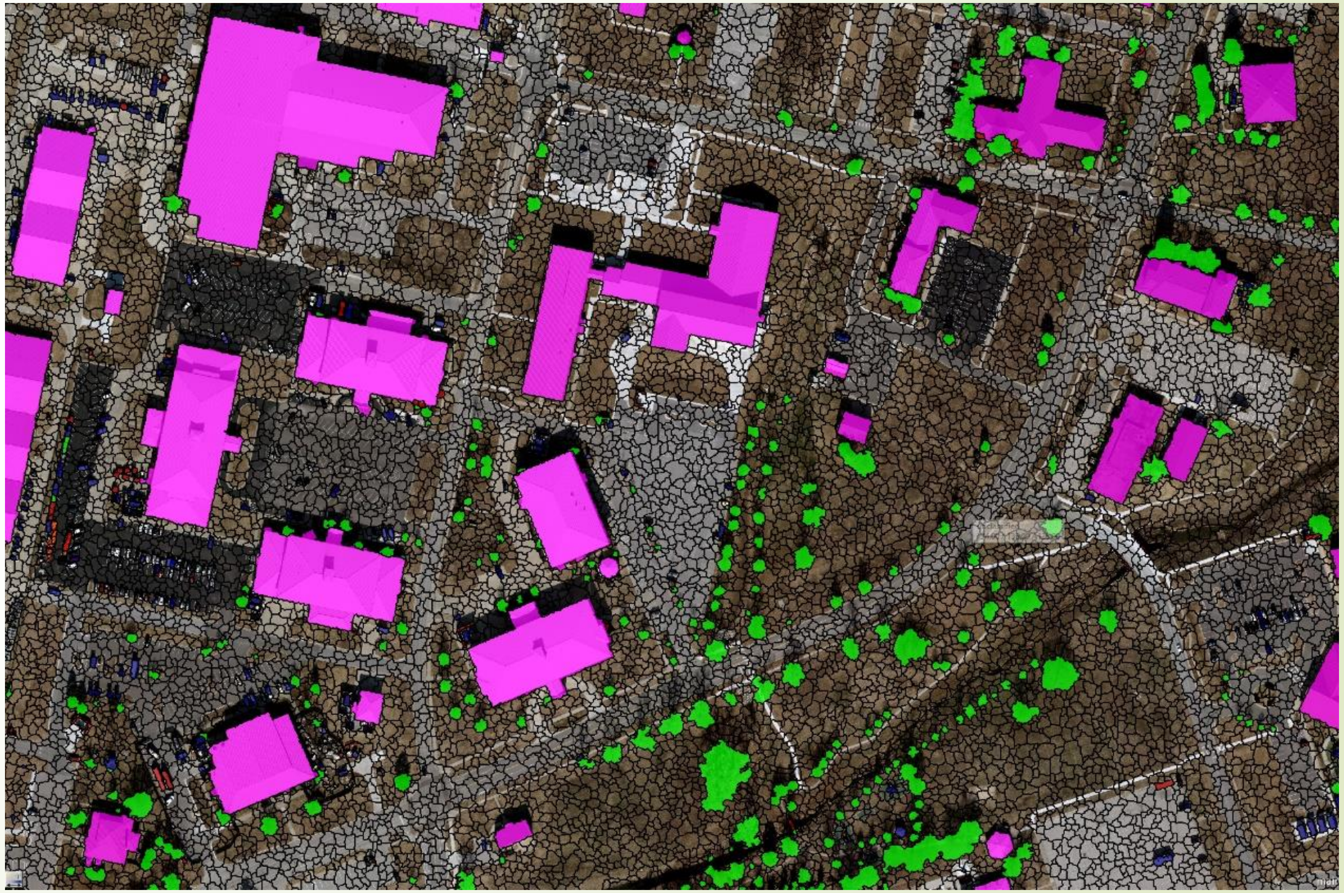
Pilot study rules for Whiteman and McConnell



Object-Based Image Analysis (OBIA)

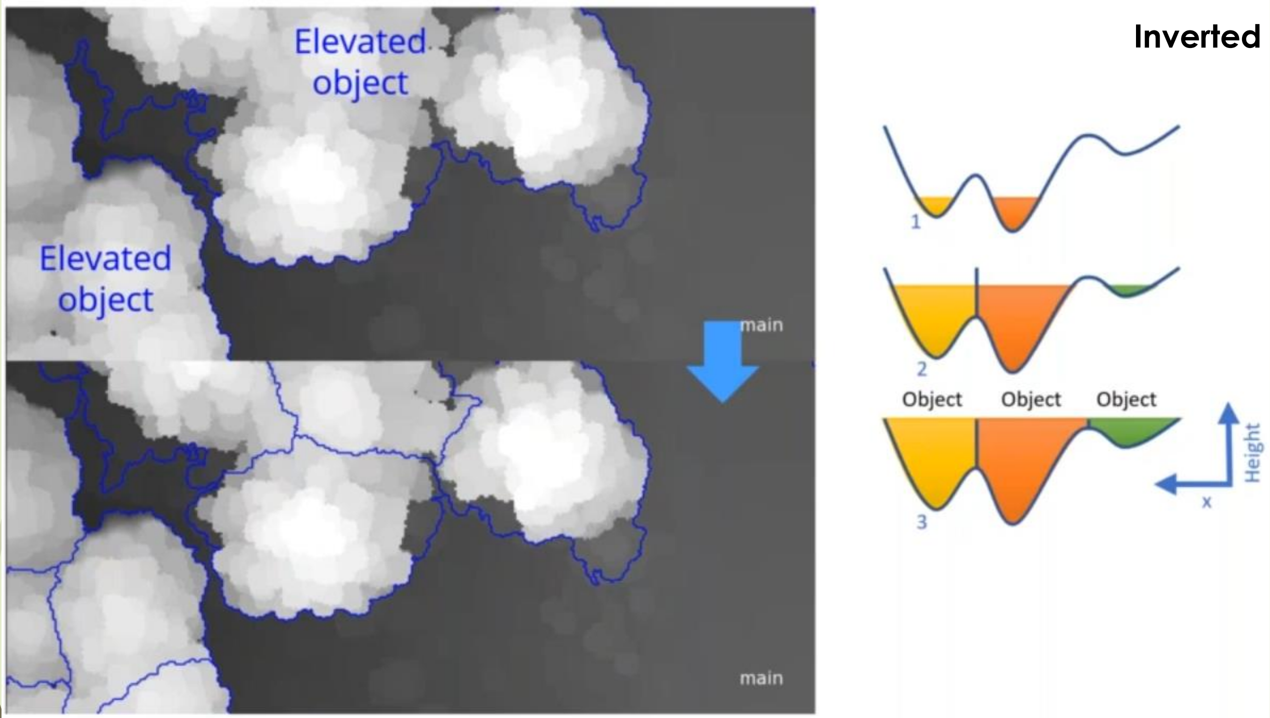
- Allows for fused data
- Shape and texture
- Easy to implement
- Flexible
- Can add segmentation algorithms to ruleset

- Needs eCognition
- Initial segmentation is computationally expensive

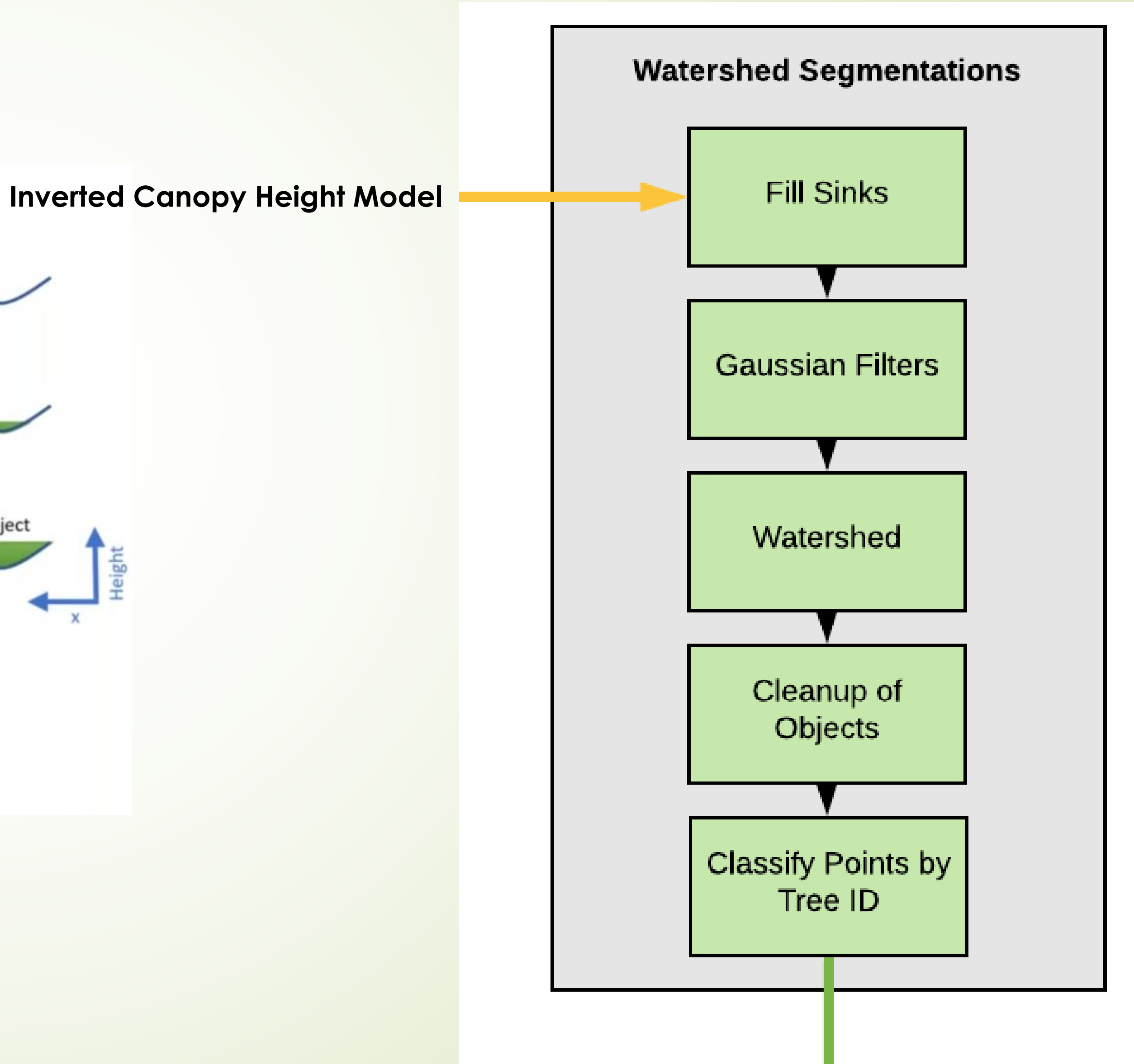


McConnell AFB

Watershed



Keith Peterson, Trimble (2020)

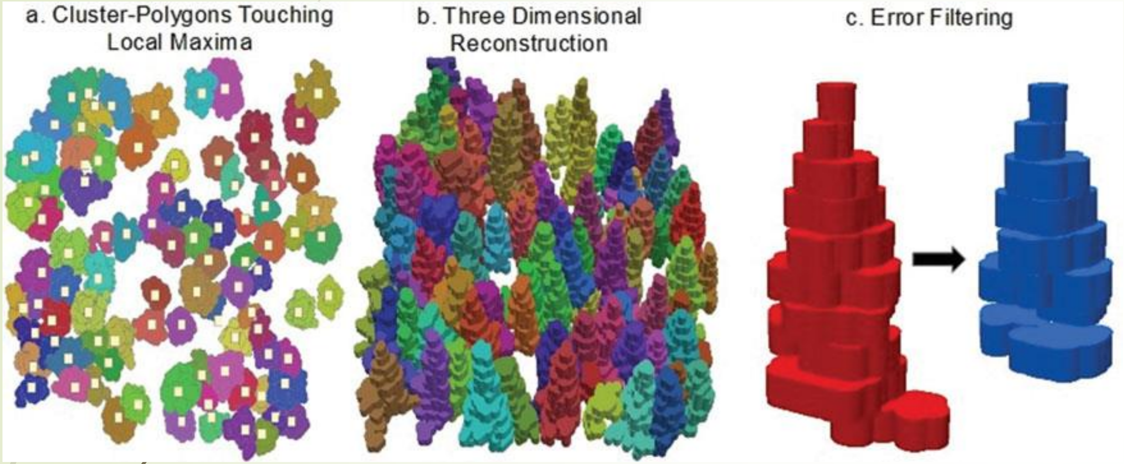


Watershed

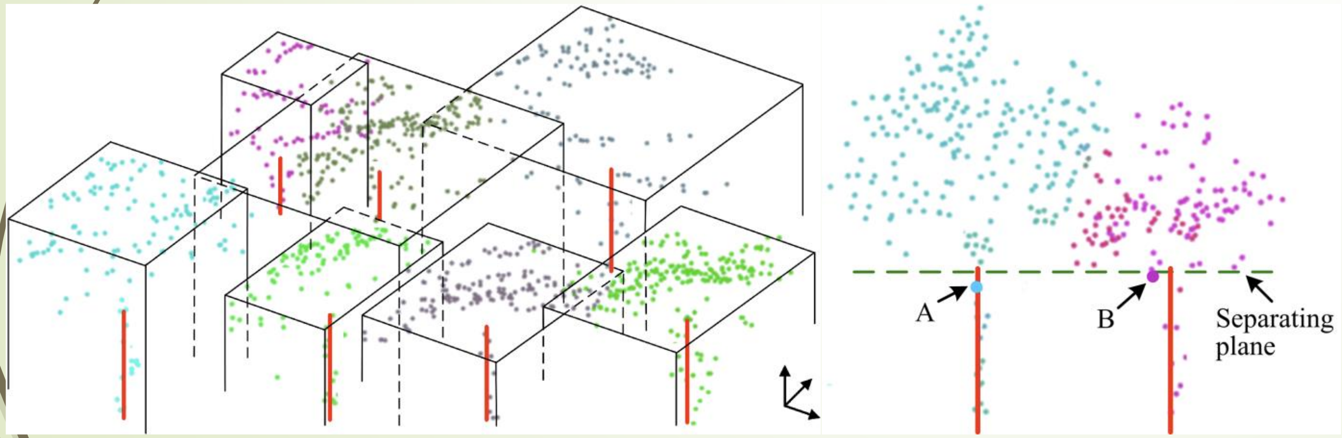
- Very easy to implement
- Efficient
- Works as benchmark algorithm
- Can be used for extra CNN training samples

Whiteman AFB

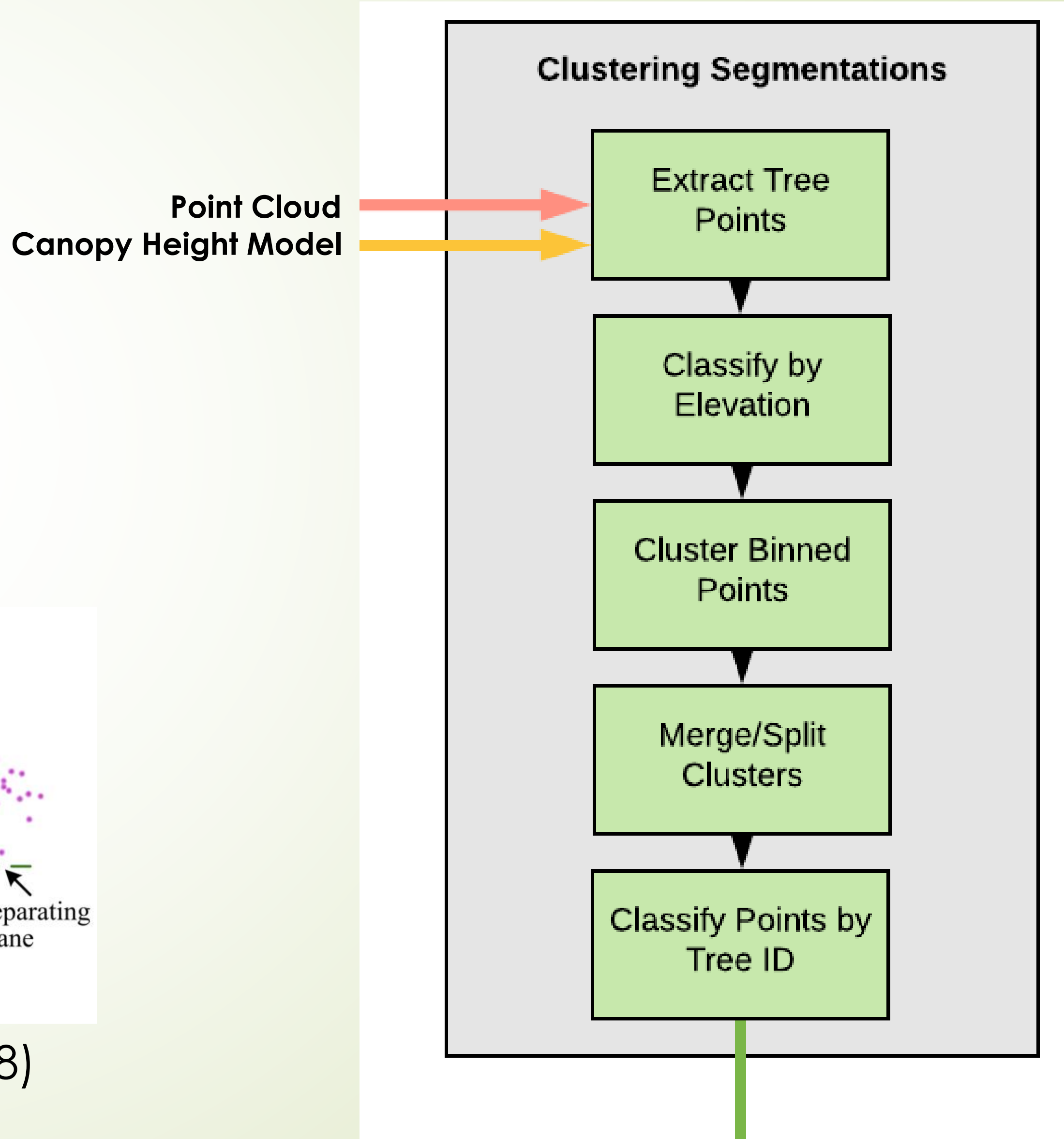
Point Cloud Clustering



Layer Stacking (Ayrey et al., 2017)

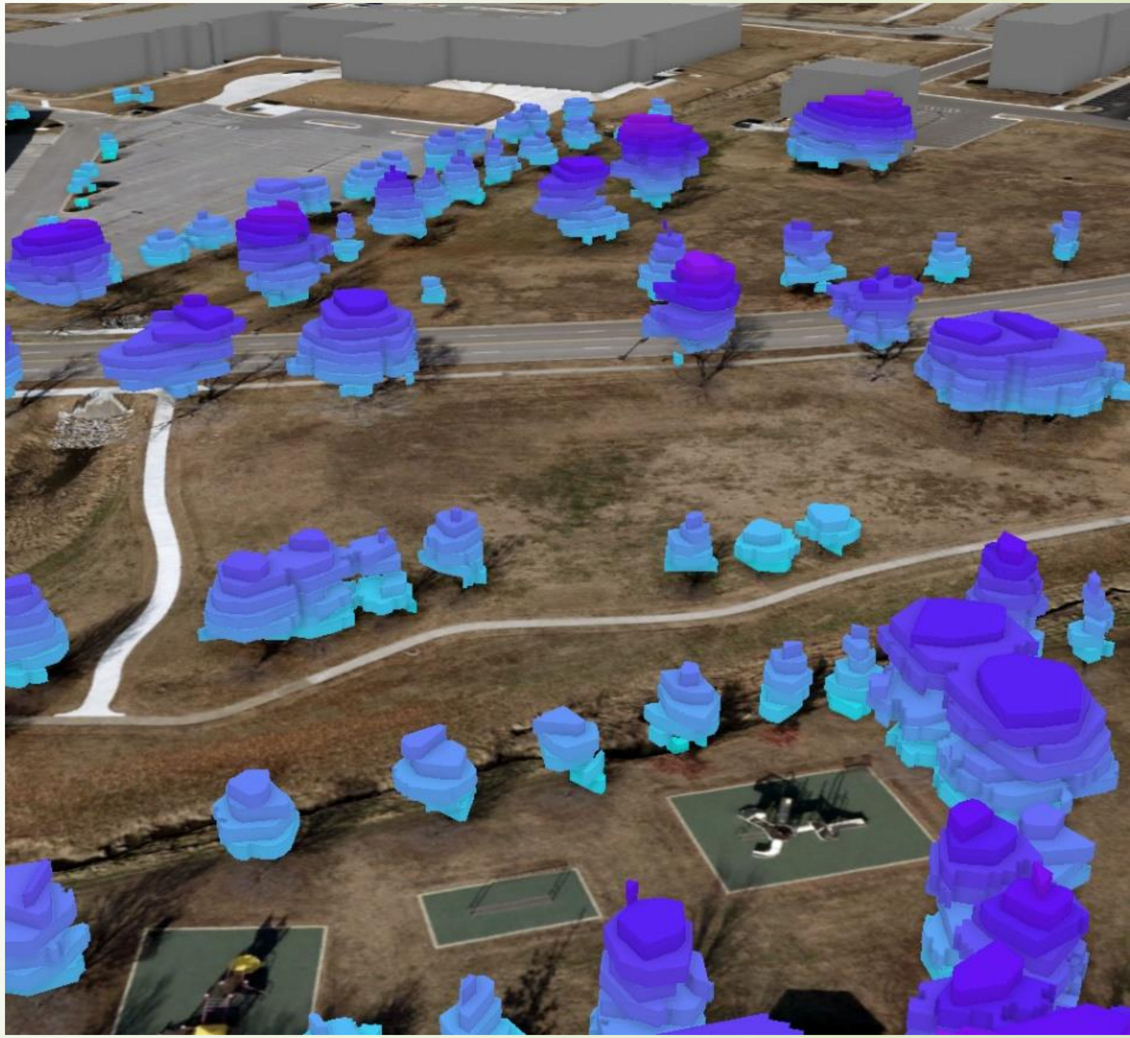


Means shift clustering (Chen et al., 2018)



Point Cloud Clustering

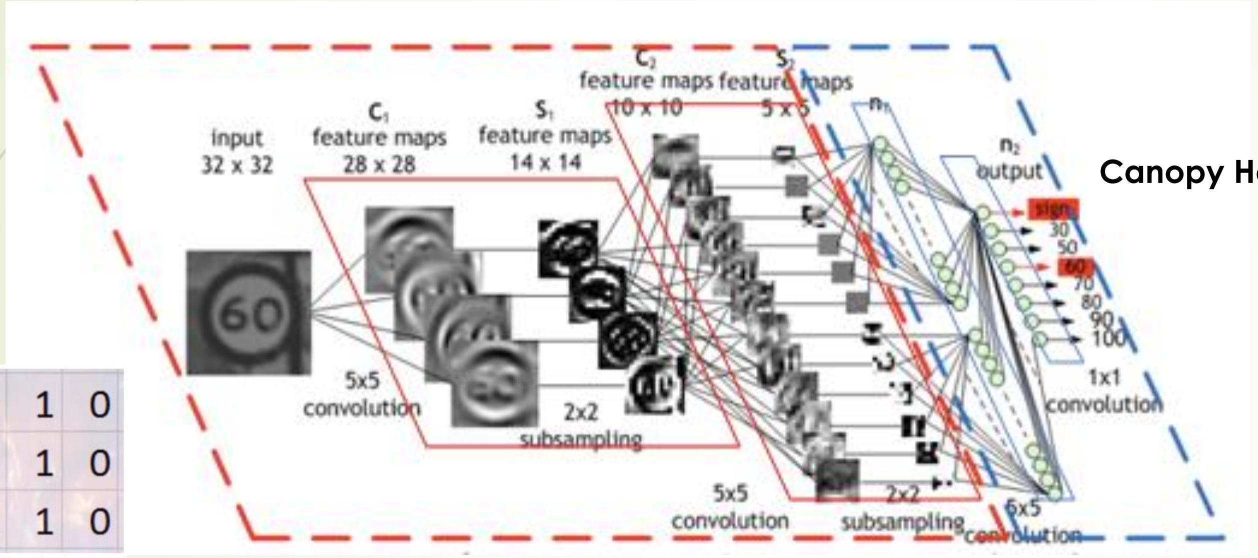
- More complex to implement
- Uses all lidar data
- Can be highly accurate
- Reliant on # of returns, density
- Must deal with outliers and clutter

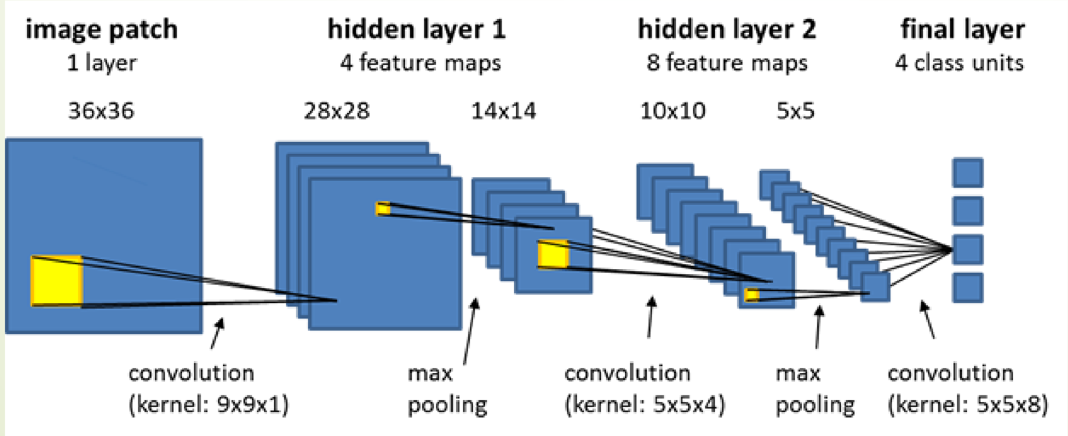


McConnell AFB

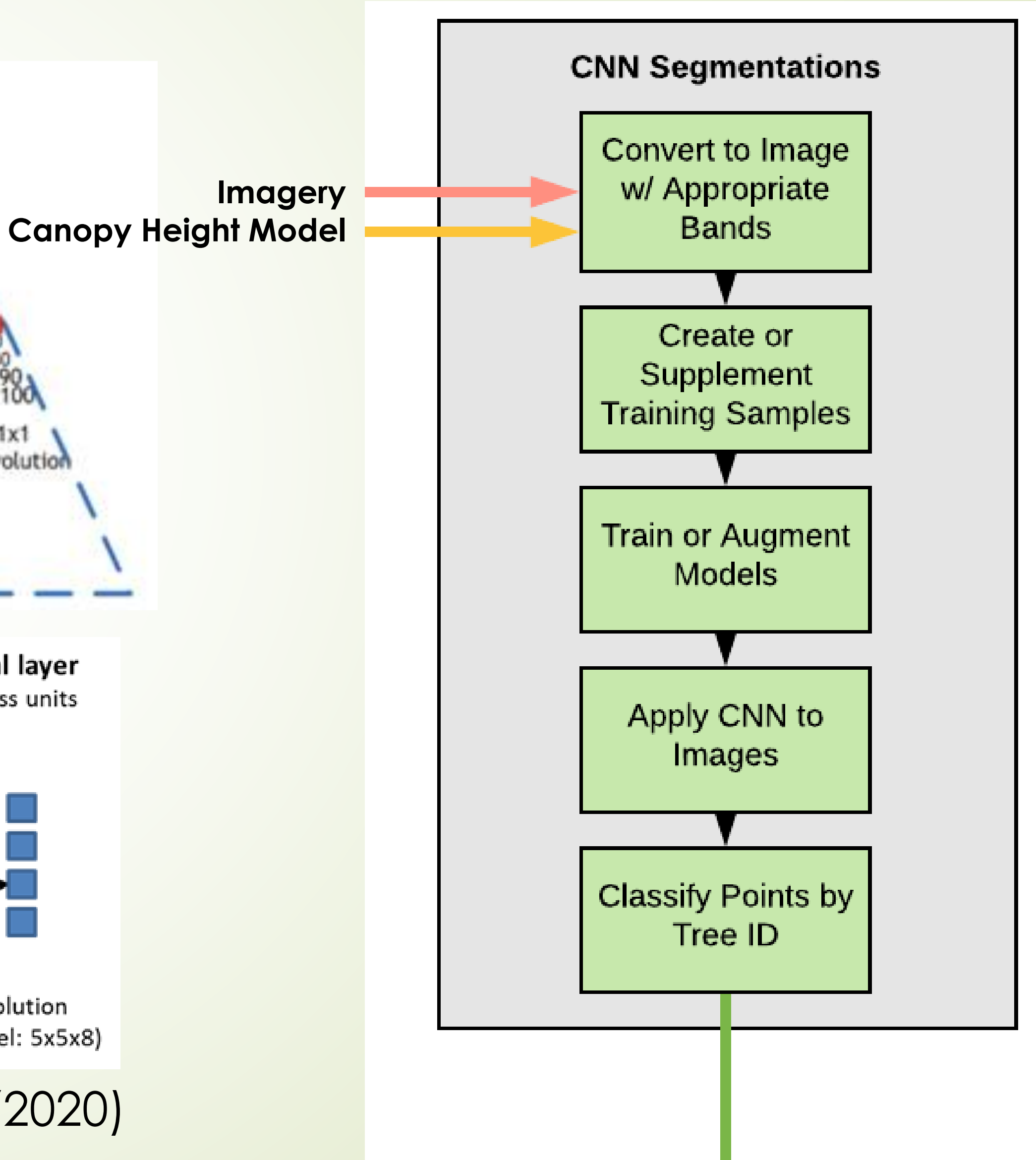
Convolutional neural network (CNN)

Kernel

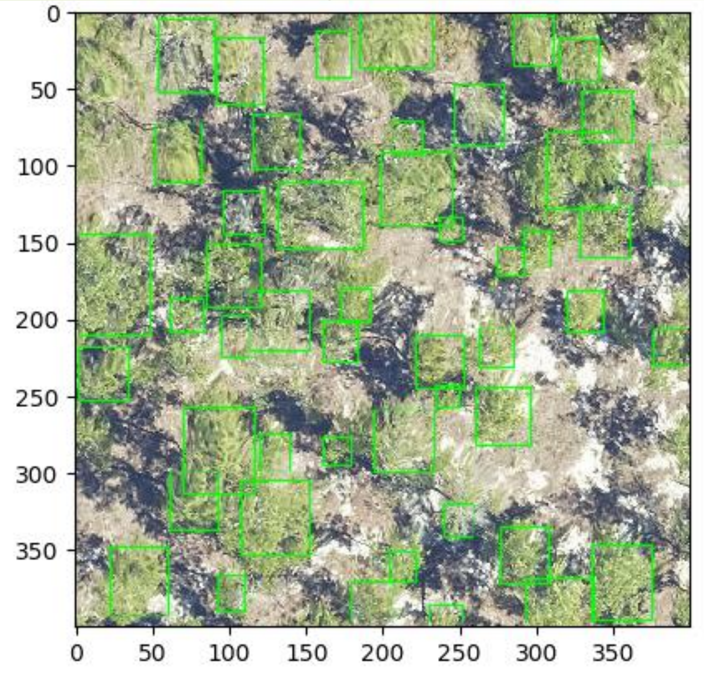




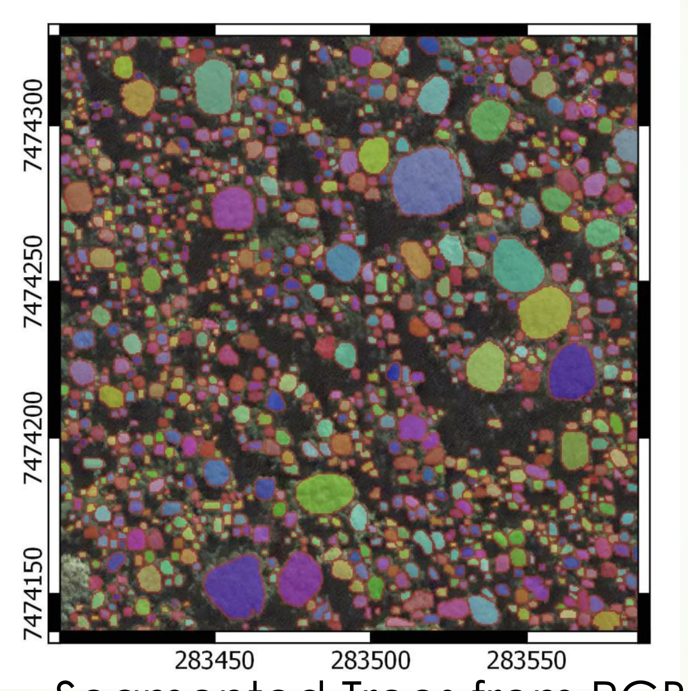
Trimble (2020)



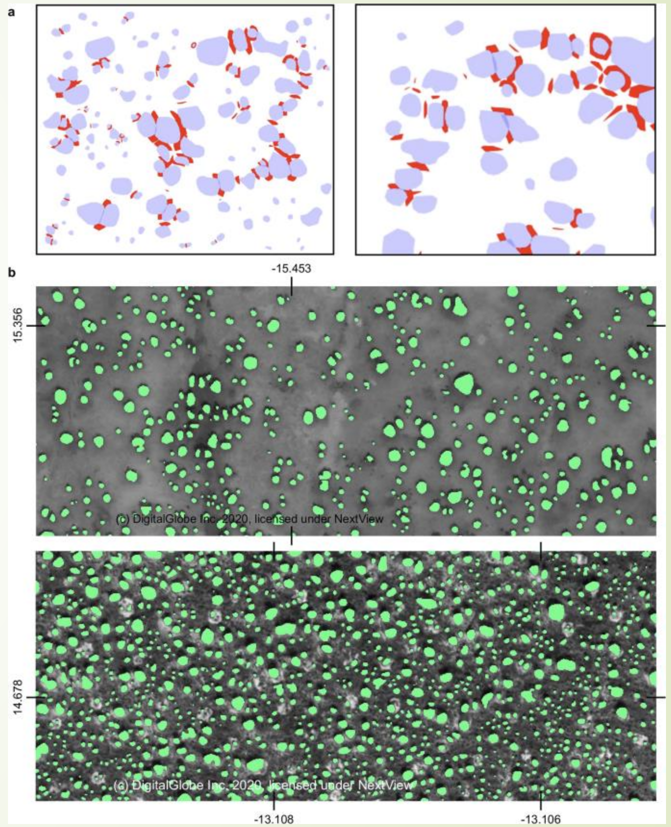
Convolutional neural network (CNN)



Detected Trees from RGB image w/ DeepForest (Weinstein et al., 2020)

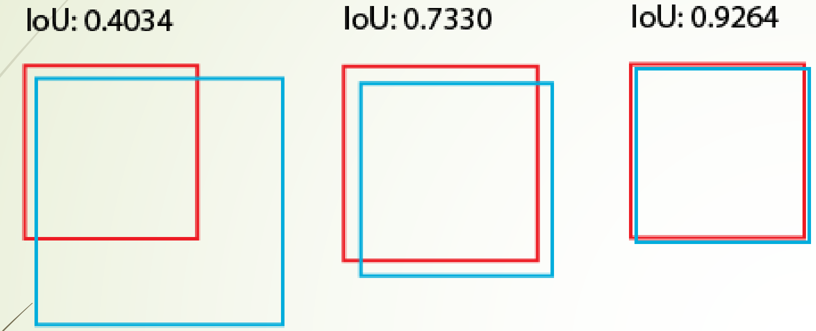


Segmented Trees from RGB image w/ r-CNN (Braga et al., 2020)



Segmented Trees from NDVI + Pan w/ U-Net (Brandt et al., 2020)

Accuracy Assessment



$$IoU\ (A, B) = \frac{|A\ \cap\ B|}{|A\ \cup\ B|}$$

$$Recall\ (A, B) = \frac{A}{|A\ \cap\ B|}$$

$$Precision\ (A, B) = \frac{B}{|A\ \cap\ B|}$$

$$F_1 Score = 2\ \frac{Precision \times Recall}{Precision + Recall}$$

Expected Results

- Accuracy will vary depending on:
  - Species
  - Forest density
  - Distribution of interlocking crown
  - Presence of understory
  - Quality of source data
  - Segmentation method
- Ideal urban tree canopy likely >85% mean accuracy
- Un-managed forest stands anywhere from 50-70%

Project Timeline

September
Pilot study and data examination

October
Project proposal presentation

November
Project implementation and analysis

January
Continue analysis, accuracy assessments, draft paper

March
Prepare paper, results, and capstone presentation

May
Shop paper to journals, present capstone project

Questions and Comments