

## Extracting Basic Landcover Classes From Metro's High Resolution Terrestrial Air Photos

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## Today's Presentation

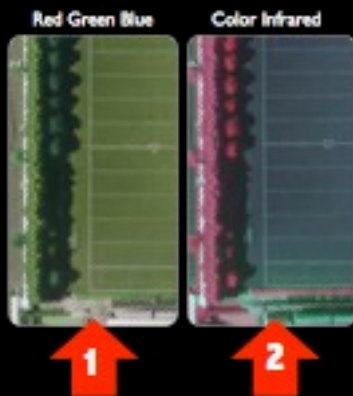
- Project Goals - Automation
- Data - High Resolution Color Infrared Orthophotos
- Methods - Object Oriented Extraction
- Results of Pilot Project
- Lessons Learned

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## Data - High Resolution CIR Orthos

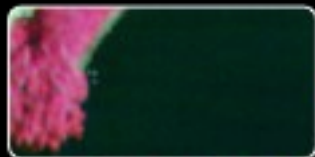
### Artificial Turf Field



- ADH40 Digital Camera
- Aircraft Platform
- Orthorectification using gps data and dtm
- 6 in per pixel native resolution
- RGB and NIR bands

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## Data Challenges



Scan lines in dark areas



Significant Shadows



NIR band not registered

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## Methods - Feature Analyst

- Visual Learning Systems - Feature Analyst
  - Object based classification
  - Uses inductive learning algorithms to model feature recognition process
    - User gives a sample of the features to be extracted
- Genetic Ensemble Feature Selection

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## Methods - 2 Processes

- Decision Tree
  - Used Multiple operation to maximize differences in the desired classes
  - Good for one image
- Multi Input Feature Extraction
  - One operation that makes use of a 4 class training layers
  - Can be batched to many images

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## Step 1- Image Fusion to NDVI



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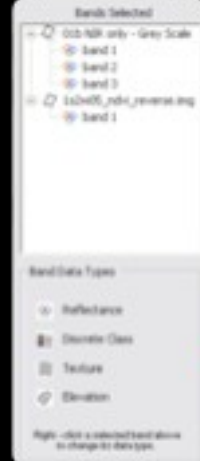
## Step 2- Extract Vegetation



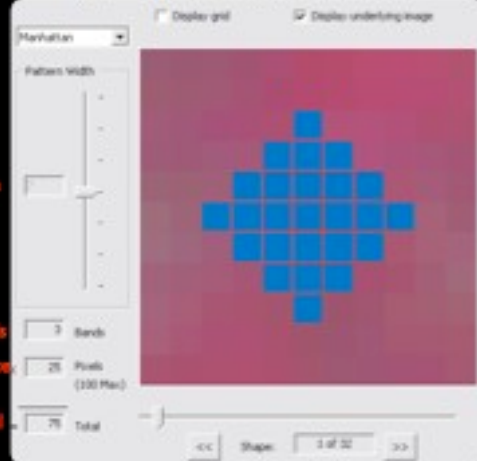
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## Set Up learning

### Band Selection

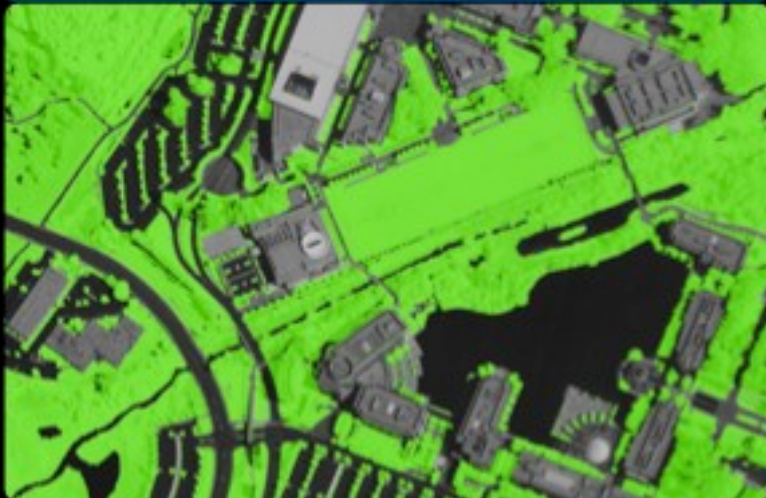


### Input Representation Selection



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## Step 2- Vegetation Result



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## Step 2- Extract Trees & Other Veg



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## Step 2 - Tree & Other Veg Results



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### Step 3 - Grass & Shrub Extraction



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### Decision Tree Results



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## Multi-Input Training



An aerial photograph of a city area, likely a university campus, used for multi-input training. The image shows various buildings, roads, and green spaces. Several objects are highlighted with colored bounding boxes: yellow boxes highlight a large central building, a smaller building to its left, and several smaller structures and vehicles; green boxes highlight a building on the right and a small structure near the bottom right; white boxes highlight a building on the left and a small structure near the bottom right. The image is used to illustrate the concept of multi-input training, where different inputs (e.g., different views or features) are used to train a model.

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## Multi-Input Results



An aerial photograph of a campus with various buildings, roads, and green spaces. The map is overlaid with a color-coded analysis, likely representing a multi-input model's output. The colors include shades of green, yellow, orange, and red, indicating different levels of risk or suitability. A large, irregularly shaped area in the center-right is colored yellow, while a smaller, more defined area in the bottom-left is colored red. The rest of the map is predominantly green, with some yellow and orange patches scattered throughout. The buildings are shown in grey, and the roads are in black.

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## Decision Tree Accuracy

| Reference Data       |            |       |       |      |       |                  |                |
|----------------------|------------|-------|-------|------|-------|------------------|----------------|
| Classification Data  | background | Grass | Shrub | Tree | Total | Users Accuracy % | K <sup>A</sup> |
| background           | 93         | 0     | 0     | 0    | 93    | -                | 1.00           |
| Grass                | 0          | 19    | 0     | 1    | 20    | 95               | .94            |
| Shrub                | 0          | 2     | 20    | 3    | 25    | 80               | .77            |
| Tree                 | 0          | 2     | 3     | 57   | 62    | 92               | .88            |
| Total                | 93         | 23    | 23    | 61   | 200   |                  |                |
| Producers Accuracy % | -          | 83    | 87    | 94   |       |                  |                |

Overall Accuracy = 94.50%

Overall Kappa = .9171

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## Multi-Input Accuracy

| Reference Data       |            |       |       |      |       |                  |                |
|----------------------|------------|-------|-------|------|-------|------------------|----------------|
| Classification Data  | background | Grass | Shrub | Tree | Total | Users Accuracy % | K <sup>A</sup> |
| background           | 92         | 0     | 1     | 1    | 93    | -                | .96            |
| Grass                | 0          | 15    | 0     | 2    | 20    | 88               | .86            |
| Shrub                | 0          | 7     | 18    | 5    | 25    | 60               | .55            |
| Tree                 | 1          | 1     | 3     | 54   | 62    | 91               | .87            |
| Total                | 93         | 23    | 22    | 62   | 200   |                  |                |
| Producers Accuracy % | -          | 65    | 82    | 87   |       |                  |                |

Overall Accuracy = 89.50%

Overall Kappa = .8418

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## Lessons Learned

- Need more reference points to asses accuracy
- Need reference points based on field data
- The analysis would benefit from lidar to resolve vegetation in shadows and shrub area.
- At some point a method is needed to extract water and turn the "background" class into a credible impervious class.

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Thank You

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