Applying Remote Drone Imaging and Deep Learning Techniques to Plant Growth Change Detection in a Post-Mining Environment

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Introduction

Plant growth uplift in post-mining environments is an integral part of post-operational mine site environment restoration. As such, we present an exploration of multiple Change Detection (CD) models and architectures applied to the problem of detecting and tracking change in plant growth using drone imagery from a coal mine in the Bowen Basin, QLD, Australia.

Method

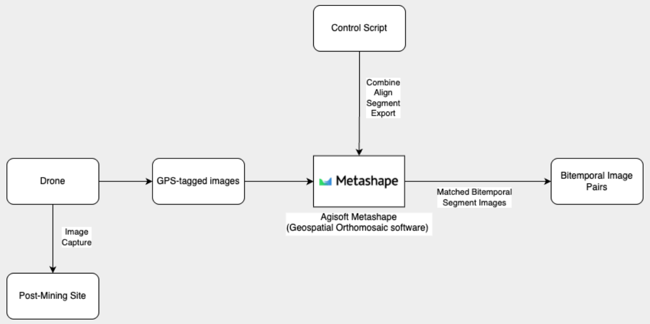

Figure 1: Bitemporal Image Pair Extraction Pipeline

An initial set of 9,635 drone images taken in 2021 and 8,501 drone images taken in 2023 at the same site were processed to produce a set of matching bitemporal image pairs upon which to perform change detection.

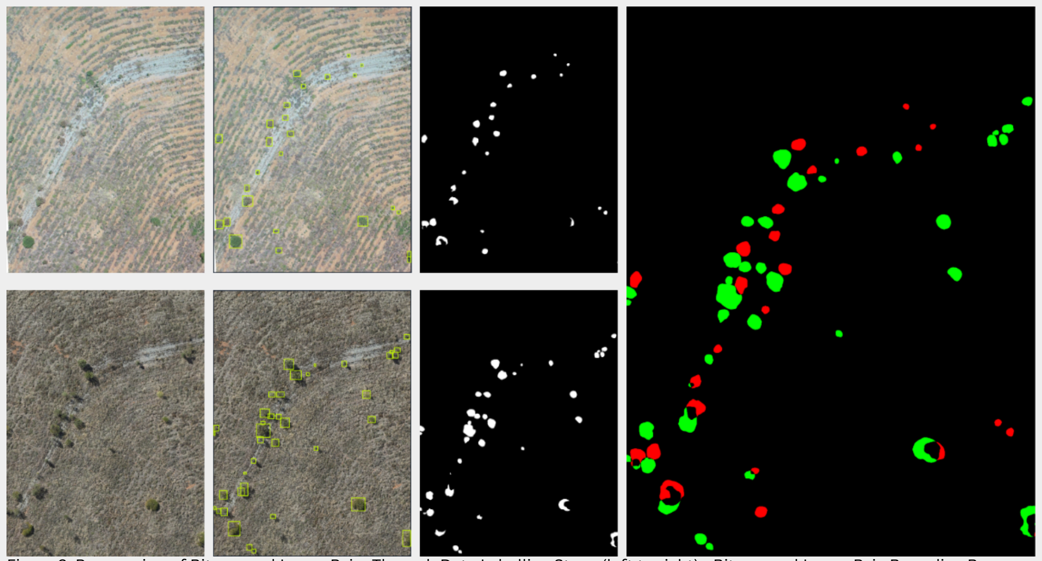

Figure 2: Progression of Bitemporal Image Pairs Through Data Labelling Steps (left to right) - Bitemporal Image Pair, Bounding Box Labeling, Segment Generation, and Red/Green Positive and Negative Change Label Generation

The bitemporal image pairs were first labelled with bounding boxes, this allowed for training of both a separate bounding box object detection model for comparison as well as forming the input to generate the segmented change labels for training the CD models. Using the same bounding box labels and images for both the object detection approach as well as the CD images allows for a direct comparison of the approaches against the same input data.

Results

Change Detection Models

	F1 Score	Precision	Recall	IoU
BIT [2]				
Positive Change	23.4	23.2	23.6	13.3
Negative Change	13.4	45.4	7.9	7.2
All Change (combined)	19.7	26.4	15.8	11.0
ChangeFormer [3]				
Positive Change	34.0	26.3	48.0	20.5
Negative Change	41.6	57.1	32.8	26.3
All Change (combined)	36.7	33.6	40.4	22.5
HANet [4]				
Positive Change	37.7	32.3	45.4	23.3
Negative Change	38.7	53.11	30.5	24.0
All Change (combined)	38.1	38.3	38.0	23.5

Figure 3: Test Set Per-Pixel Performance of CD Model Architectures on Positive/Negative Change Labels

With the help of Open-CD [1], an open source change-detection toolbox, a number of modern published CD models were explored using a singular platform. Two model instances were trained for each architecture, one for the negative (red) change inferences, and one for the positive (green) change inferences.

As seen in the low F1 Score and IoU results, detection of change is the harder half of the binary detection problem of changed and unchanged pixels. All models in Figure 2 displayed >97% precision and recall on unchanged (black) pixels, which represent the vast majority of data in the training images. However, for the purpose of applicability, the performance on changed pixels is the more relevant metric.

Bounding Box Object Detection Model

	F1 Score	Precision	Recall	IoU
Training Set				
Positive Change	74.2	64.6	87.1	59.0
Negative Change	70.3	60.9	83.2	54.2
All Change (combined)	72.5	62.9	85.4	56.8
Test Set				
Positive Change	66.0	58.1	76.3	49.3
Negative Change	64.0	64.7	63.3	47.0
All Change (combined)	65.0	60.9	69.8	48.2

Figure 4: Per-Pixel Performance of Object-Detection Inferred Positive/Negative Change Labels

The published CD model architectures above were compared with a finetuned YOLOv11 [5] bounding box object detection model combined with a Segment-Anything-Model (SAM) [6] segmentation step and a post-segmentation image combination script.

The YOLOv11 bounding box object detection model was trained on the bounding box image labels used to generate the change-detection segment pixel labels. Using this approach, the model is not directly learning to detect change, we transform the change-detection problem into the simpler subproblems of: object-detection, segment generation, and combination of the bitemporal image segments.

Discussion

Change Detection Model Architectures

From the exploration of multiple change detection architectures during initial training, it appears the problem of plant change detection greatly favours architectures that can encode a concept of hierarchy (HANet and ChangeFormer), in particular models that focus on detection of change and learning at multiple object scales through the use of pooling and downsampling layers.

Bounding Box Object Detection

From direct comparison with the CD models, it was seen that the bounding-box object detection plus segmentation approach produces significantly higher F1 Score and IoU results when applied to change-detection of plants in post-mining environment rehabilitation. As such when combined with a higher quality dataset this approach has a high feasibility of allowing for accurate change detection in real-world post mining environments.

Limitations

One of the main drawbacks in the input data was low resolution and GPS accuracy in the 2021 dataset. As a result, the CD models are potentially hampered by both the lack of clarity in the 2021 images, as well as the potential for the slight geographical drift limiting the ability of the model to detect true change vs. GPS shift in the images.

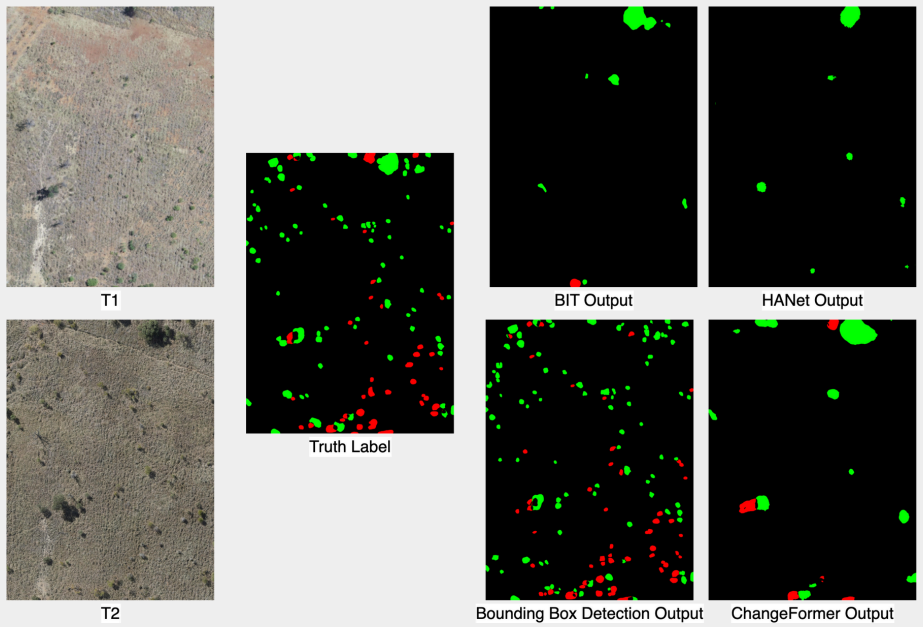

Figure 5: Test Set Image Pair Example Model Outputs

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CREATE CHANGE

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References

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