Low-Resolution Satellite Imagery Change Detection Model

Samuel Alter | Reveal Global Consulting | 2025-06-06

Background and problem statement

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- Project needs

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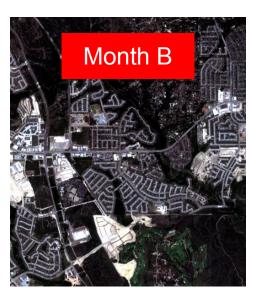
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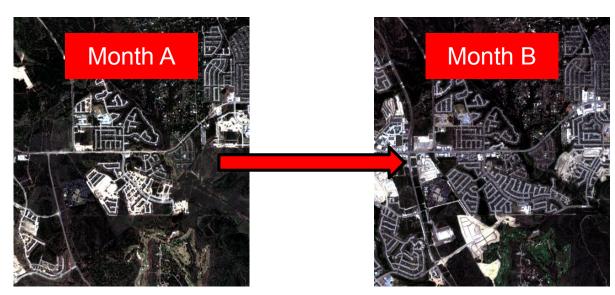


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- SOC currently provisions a very large area to for their tools to use...
- ...Which can get extremely large for places like Harris County, TX (1,780mi²)...
- ...But most of that area does not undergo construction

Problem Statement

Therefore, there is an opportunity to cut costs and decrease the time it takes to track construction.

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We could train a model that detects change between two time steps.

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Project Needs

Run cheaply

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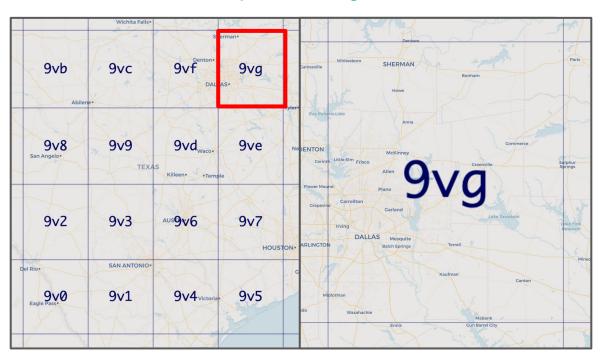
- Run cheaply
- Use readily-available imagery

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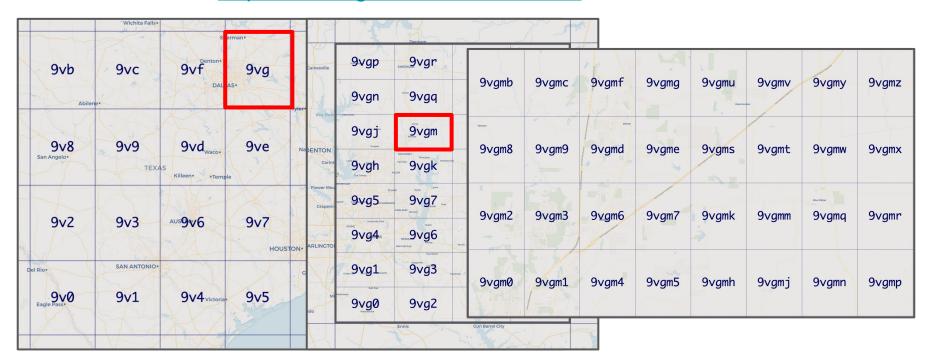
- Run cheaply
- Use readily-available imagery
- Potential to slot into the existing workflow of the SOC team and other teams at Reveal

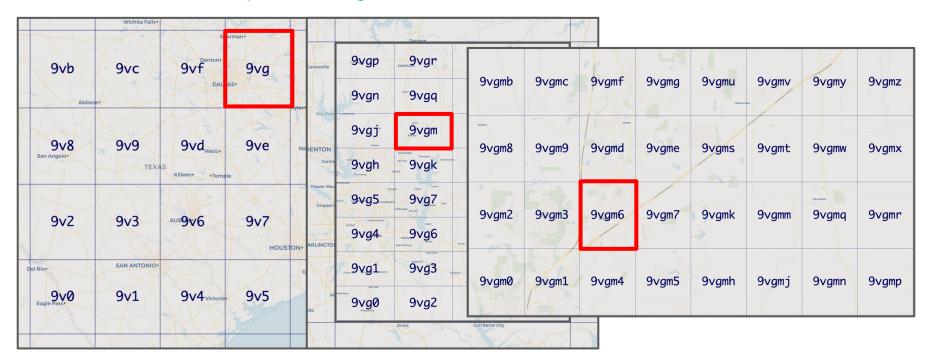
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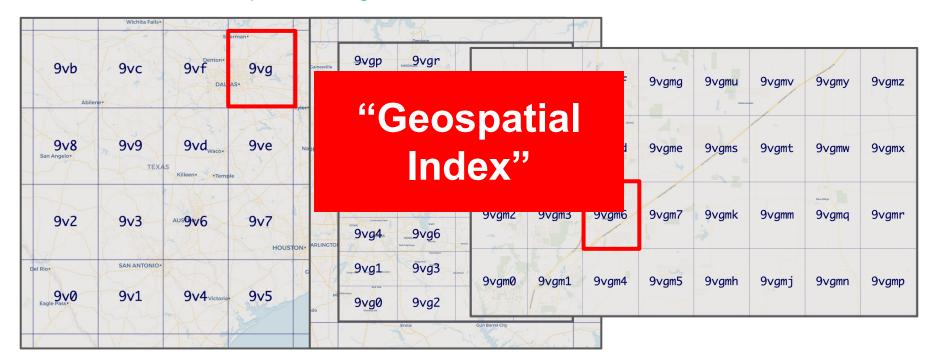
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- "Geohash" https://www.geohash.es/browse/
- Dataset

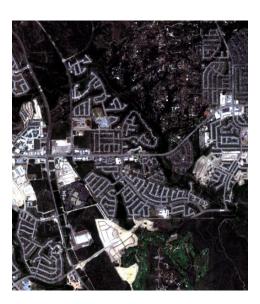
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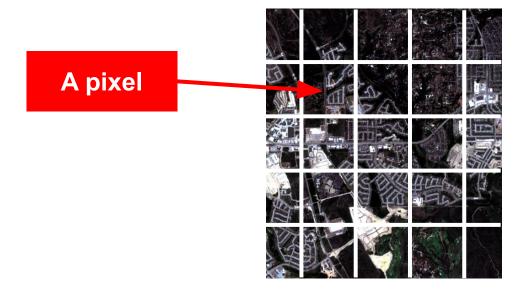
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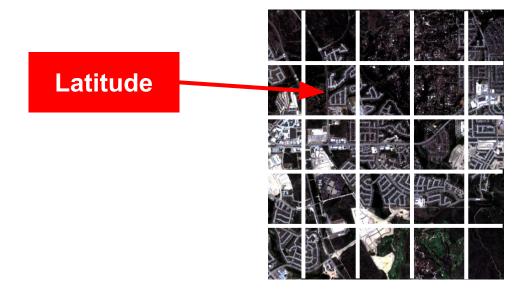
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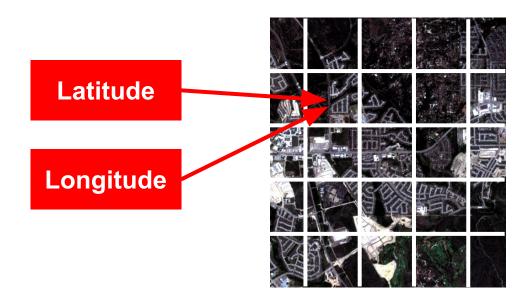
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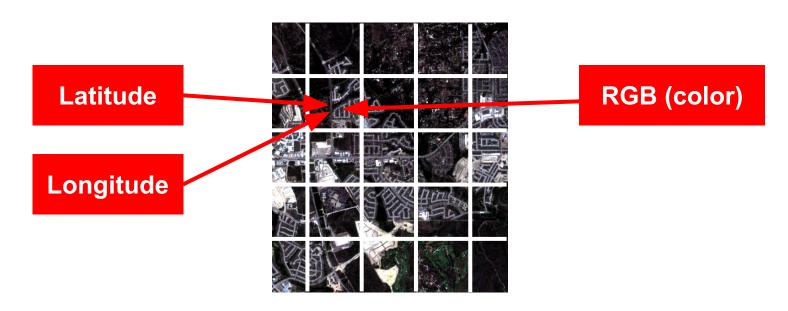
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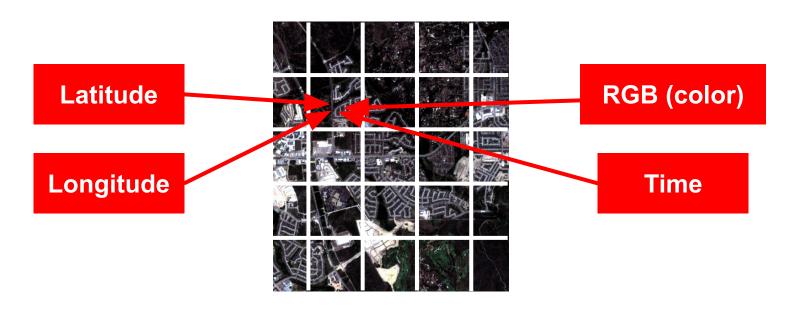
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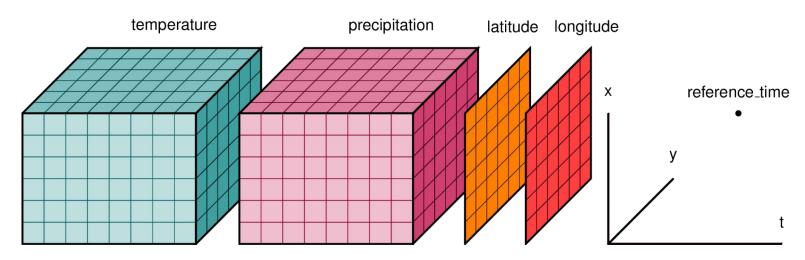
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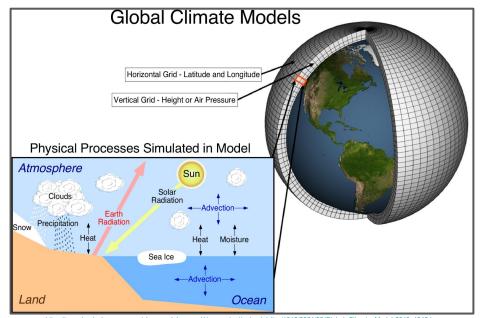
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https://pressbooks.bccampus.ca/physgeoglabmanual1/wp-content/uploads/sites/1318/2021/03/Global Climate Model-2048x1346.jpg

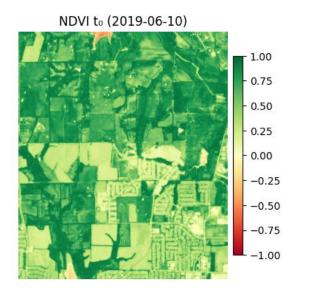
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- NDVI

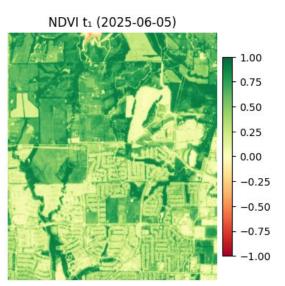
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- NDVI
 - "Normalized difference vegetation index"

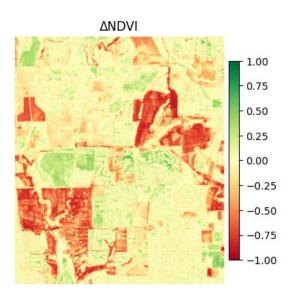
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 - Calculated using red and near-infrared
 - A measure of the health and density of vegetation

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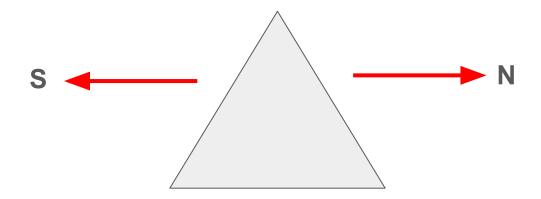






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- NDVI
- Aspect (and Elevation and Slope)

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 - Dataset tools

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 - Tool to produce results, i.e., "inference"

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Google Earth Engine



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- Google Earth Engine
 - 13 bands including:
 - Red, Green, Blue (true-color)
 - NIR, IR (vegetation)
 - Ultra Blue (coastal, aerosol)

https://www.appgeo.com/wp-content/uploads/GoogleEarthEngine.png

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xarray





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 - Builds "datacubes"





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AWS S3



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- AWS S3
 - Bucket: rgc-zarr-store



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https://images.icon-icons.com/2699/PNG/512/pytorch_logo_icon_169823.png

Dataset key facts

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- Dataset key facts
 - Normalize each channel (R, G, B, NDVI, Elevation, etc.)
 to dataset global max/min

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 - Add time-derived channels (delta-time, day-of-year)

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 to dataset global max/min
 - Add time-derived channels (delta-time, day-of-year)
 - Add NDVI-derived channels to control for seasonal variations
 - Replace aspect channel with two channels to control for 350° ≅10°

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Dataset TL;DR:

Create a
multi-dimensional
dataset that provides
the model cues
beyond just visual
imagery to help it
detect change.

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Architecture key facts

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- Architecture key facts
 - Unsupervised learning

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 - Unsupervised learning
 - "Fully-convolutional variational auto-encoder"

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 - Learns to encode input data into a compressed representation

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 - 128x128→64x64→32x32→
 16x16, then back out
 16→32→64→128

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 - "Fully-convolutional variational auto-encoder"
 - Learns to encode input data into a compressed representation
 - 128x128→64x64→32x32→
 16x16, then back out
 16→32→64→128
 - Preserves 2D structure of inputs

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 - "Hard-negative mining"

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- Training key facts
 - "Hard-negative mining"
 - Uses reconstruction error as a proxy for labels: high error
 - → change has likely occurred

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 - Local save of S3 datasets

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 - Local save of S3 datasets
 - Sets time pairs with 7-day intervals, weighted sampling of these pairs

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 - Sets time pairs with 7-day intervals, weighted sampling of these pairs
 - Per-patch (128x128) metrics

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 - Early stopping

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 - Ramp up of β-VAE over time

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Trained on Dallas, TX imagery

Training key facts

occurred

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Hyperparameter search key facts

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- Hyperparameter search key facts
 - Optuna orchestrates HP search over key parameters like learning rate, weight decay, latent dimension, etc.



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 - Strives to reduce validation loss metric as its target



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 - Strives to reduce validation loss metric as its target
 - Notifies via email when complete, giving best parameters



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Layer (type)	Output Shape	Param #
=======================================		
Conv2d-1	[-1, 32, 64, 64]	3,776
BatchNorm2d-2	[-1, 32, 64, 64]	64
ReLU-3	[-1, 32, 64, 64]	0
AdaptiveAvgPool2d-4	[-1, 32, 1, 1]	0
Conv2d-5	[-1, 4, 1, 1]	132
ReLU-6	[-1, 4, 1, 1]	0
Conv2d-7	[-1, 32, 1, 1]	160
Sigmoid-8	[-1, 32, 1, 1]	0
SEBlock-9	[-1, 32, 64, 64]	0
Conv2d-10	[-1, 64, 32, 32]	18,496
BatchNorm2d-11	[-1, 64, 32, 32]	128
ReLU-12	[-1, 64, 32, 32]	0
Conv2d-13	[-1, 128, 16, 16]	73,856
BatchNorm2d-14	[-1, 128, 16, 16]	256
ReLU-15	[-1, 128, 16, 16]	0
Conv2d-16	[-1, 18, 16, 16]	2,322

Total params: 99,190 Trainable params: 99,190 Non-trainable params: 0

Input size (MB): 0.81

Forward/backward pass size (MB): 6.29

Params size (MB): 0.38

Estimated Total Size (MB): 7.48

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- Methods overview:
 - Dataset tools
 - Build the dataset
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Model TL;DR:

The model is
designed to generate
pixel-wise
change-detection
heatmaps at
resolution equal to
the input.
Trained on imagery
from Dallas, TX area.

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Inference key facts

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 - Runs the patches through the saved best model
 - Builds full-scene heatmap and change mask from the patches

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 - "Patches" test dataset just like in training
 - Runs the patches through the saved best model
 - Builds full-scene heatmap and change mask from the patches
 - Produces PDF report with figures and summary tables

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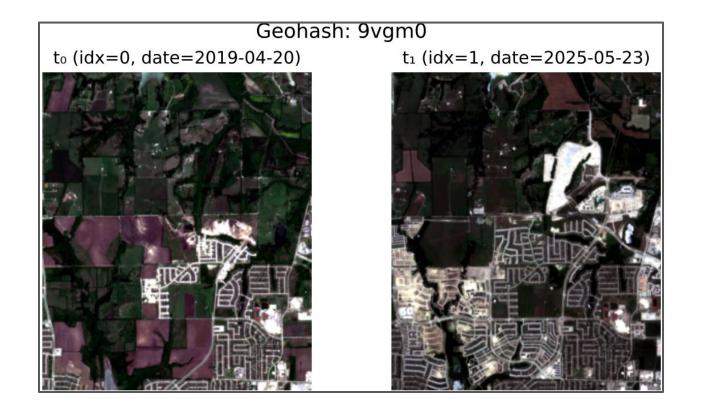
Inference TL;DR:

Runs test dataset
through trained
model to output
full-size heatmap,
change mask, before,
after, summary
tables... all in a PDF
report.

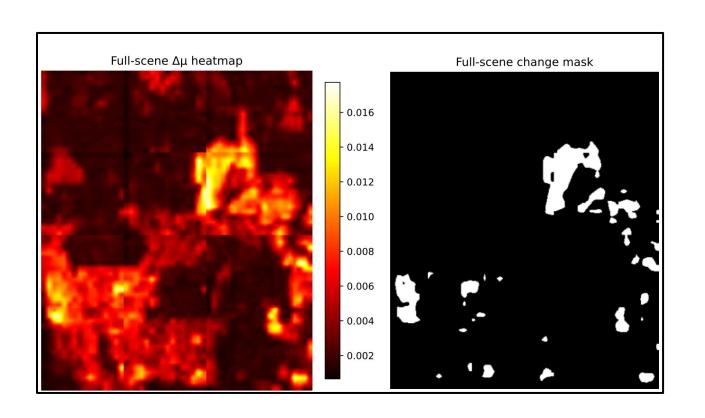
Agenda

- Background and problem statement
- Project needs
- Definitions
- Methodology
- Results
- Discussion
- Acknowledgements
- Questions

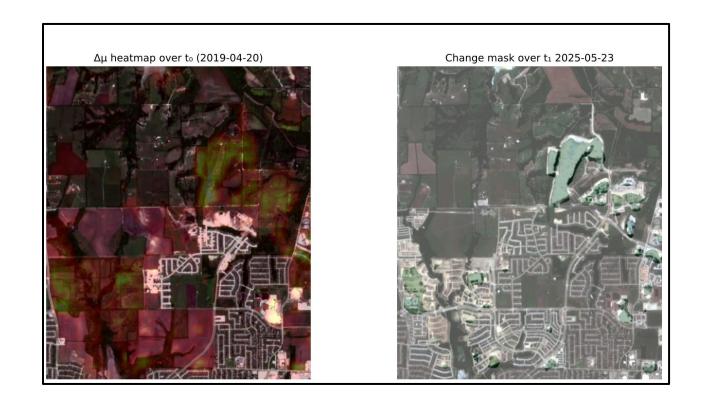
Results - See the Demo!



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- ...Though the model appears to handle cloudless change detection scenes well
- We could expand model training to encompass more landscapes beyond suburban Texas

Did it meet the goals?

Run cheaply

Use readily-available imagery

Potential to slot into workflow of SOC and other Reveal teams

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Acknowledgements

 Thank you to Dwarakh Nayam, Elo Lewis, Lei Peng, DJ Walker, Taylor Wilson, Cameron Milne, Angi Lee, Jackson Chen, and the rest of the Reveal team

Questions?

Project GitHub link:

https://github.com/RevealGC/low-res-change-detection/tree/main

My GitHub:

https://github.com/sralter

My LinkedIn:

https://www.linkedin.com/in/samuel-alter/