Reaching into the past

Deep learning and historic aerial imagery

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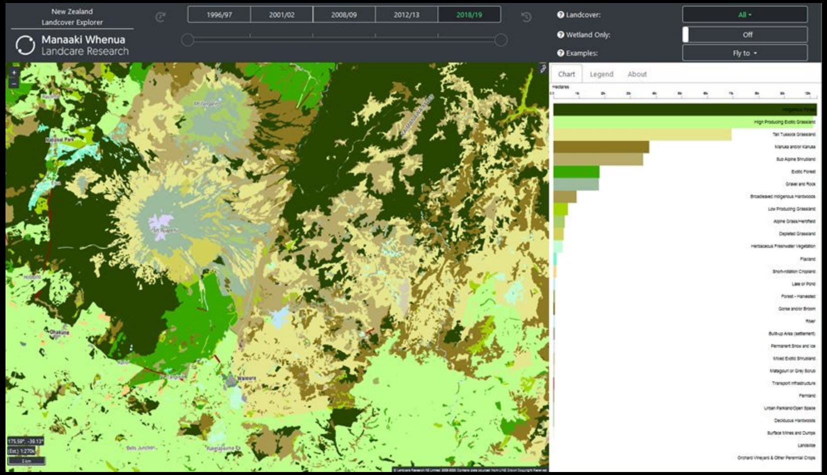
Manaaki Whenua Landcare Research

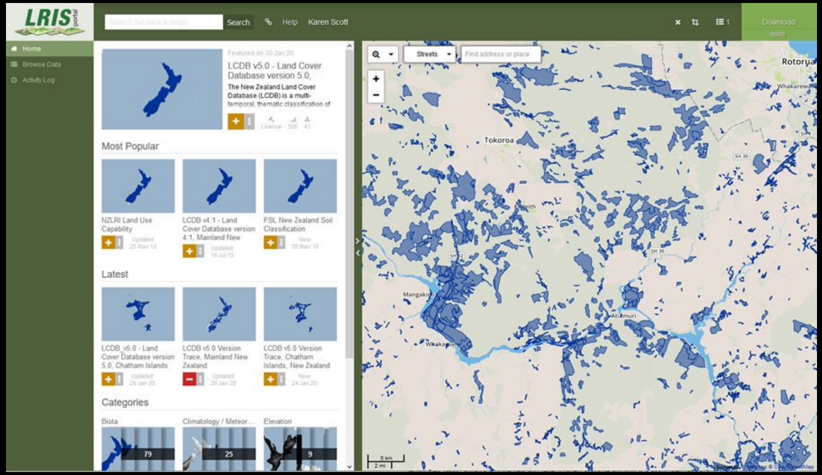
Remote sensing – more than meets the eye

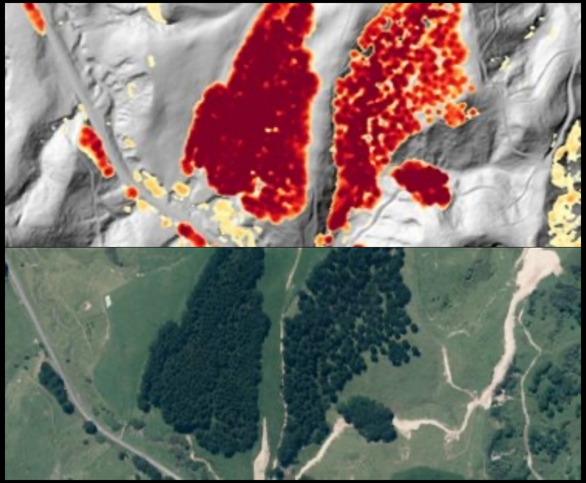
LINKOnline webinar

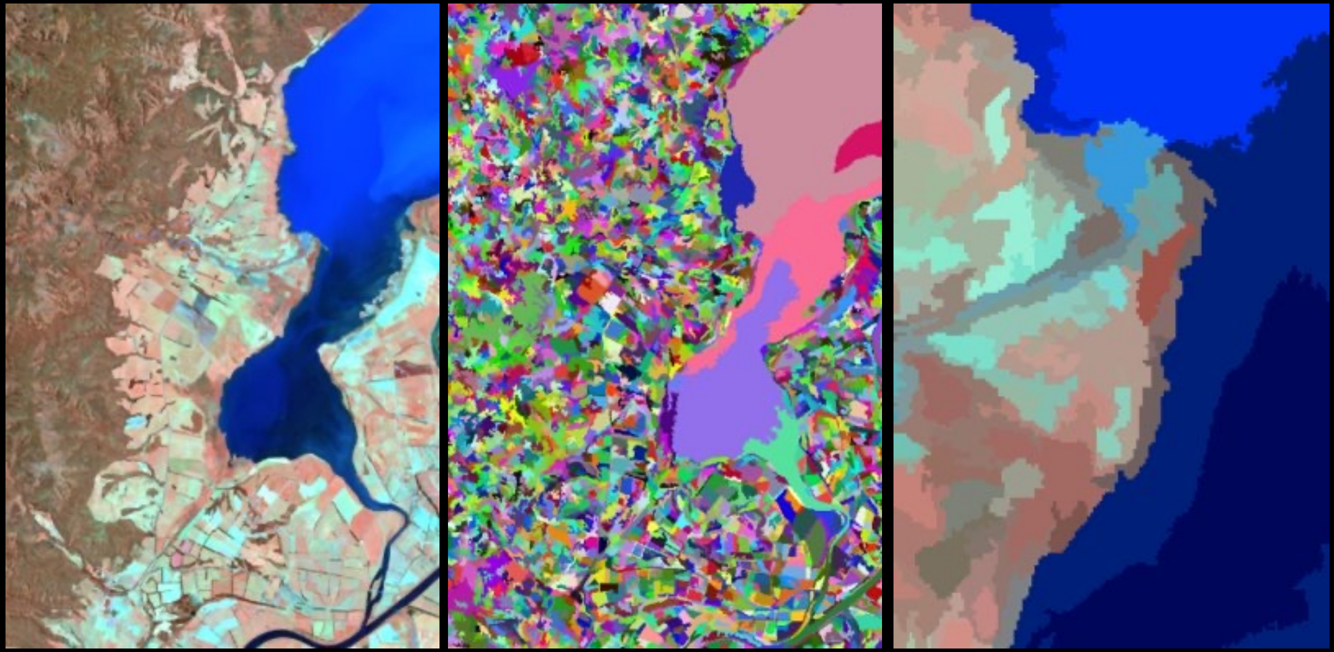
4th May 2022

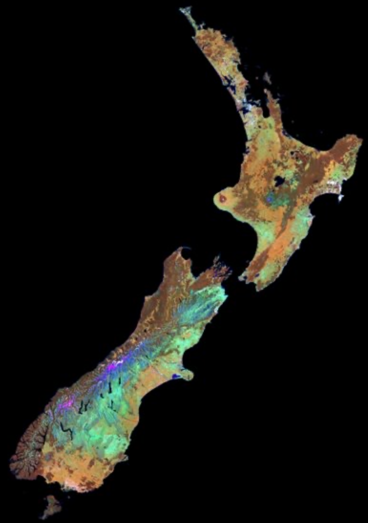
The data deluge: challenge or opportunity?

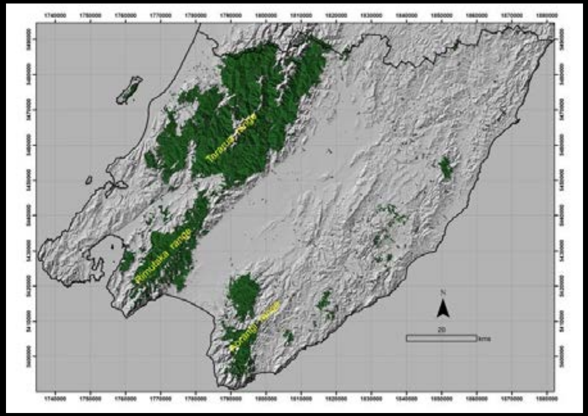




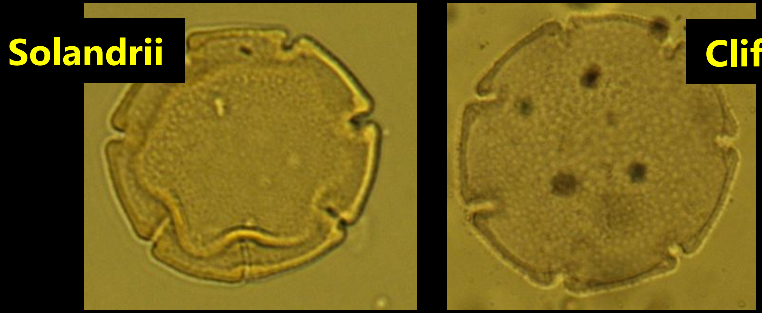








Computer vision at Manaaki whenua



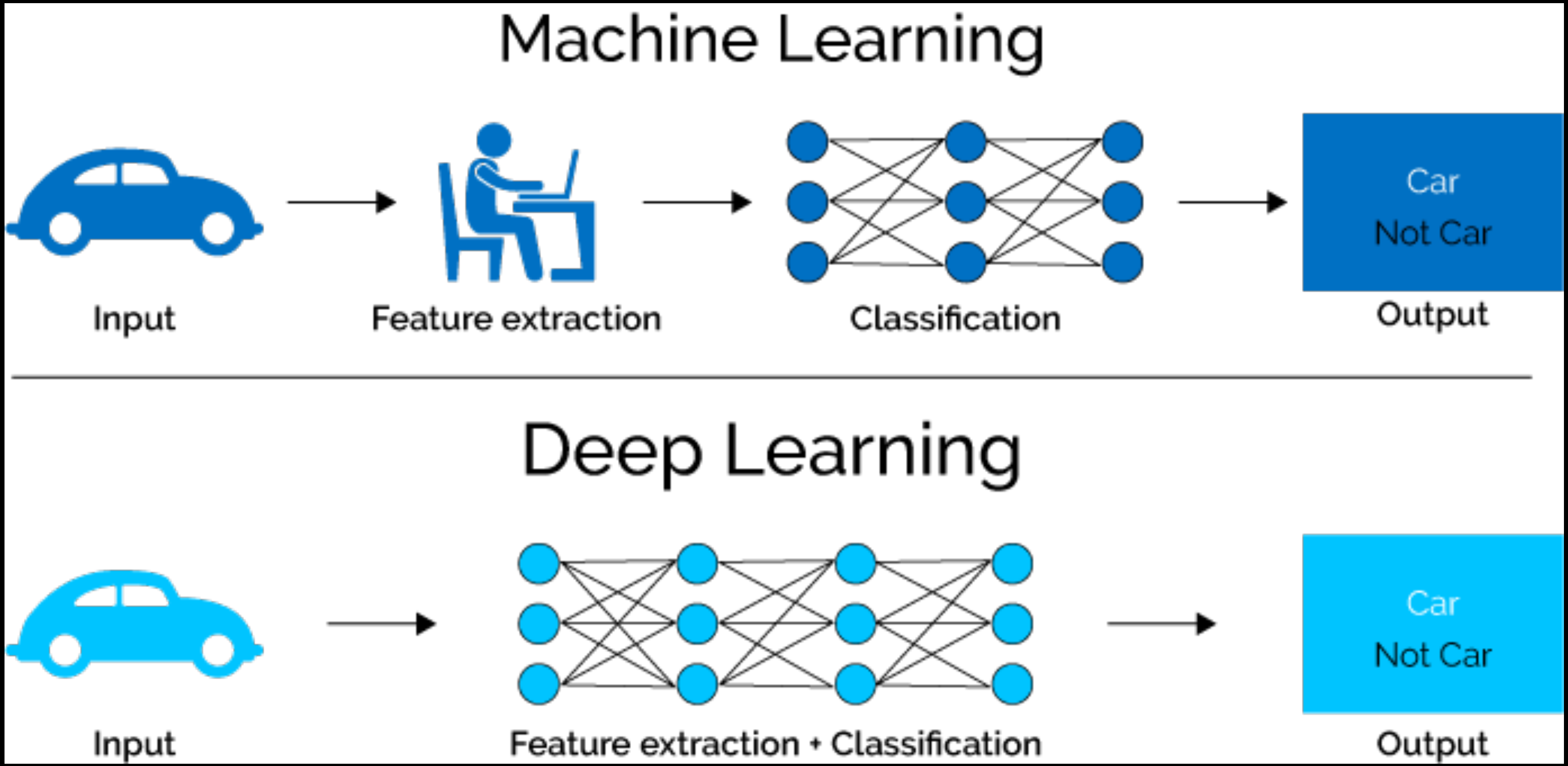
Species classification

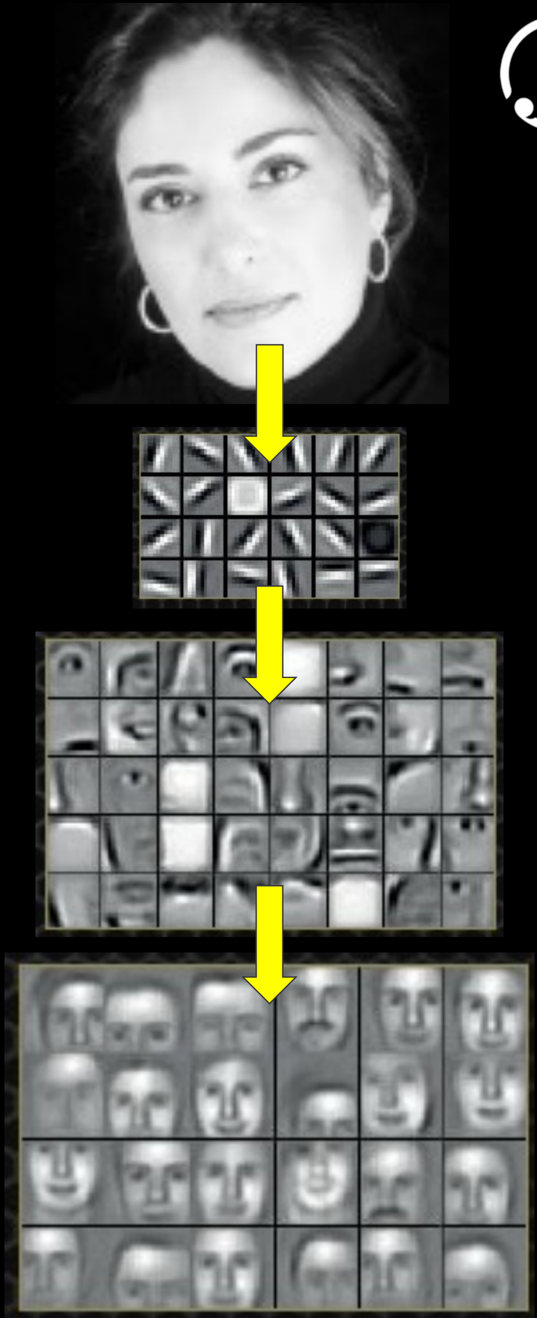
Predator detection

Land segmentation

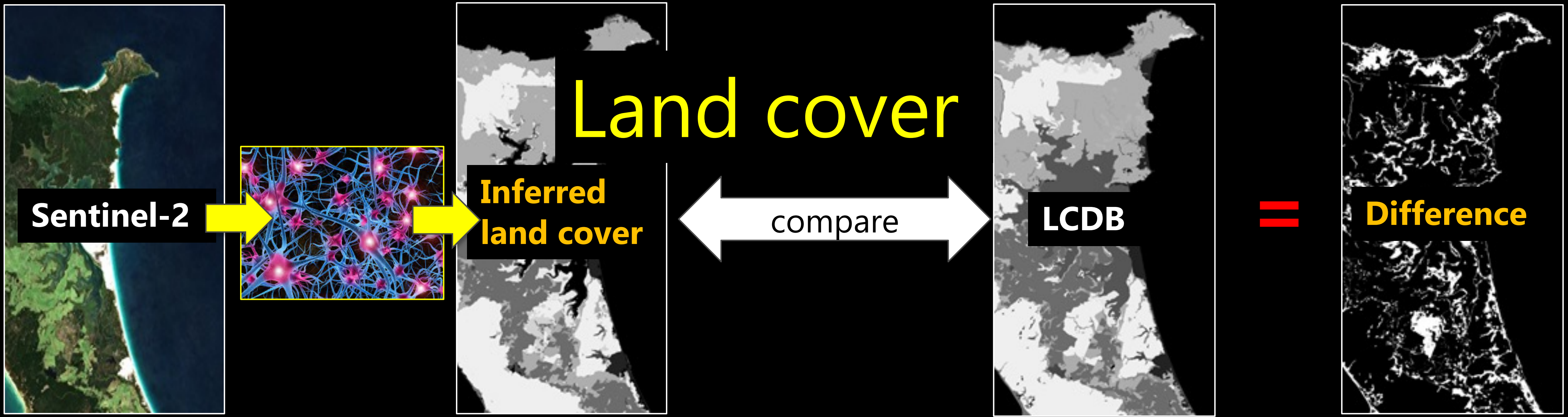
Autonomy

The deep learning revolution





Deep learning for remote sensing



Manaaki Whenua
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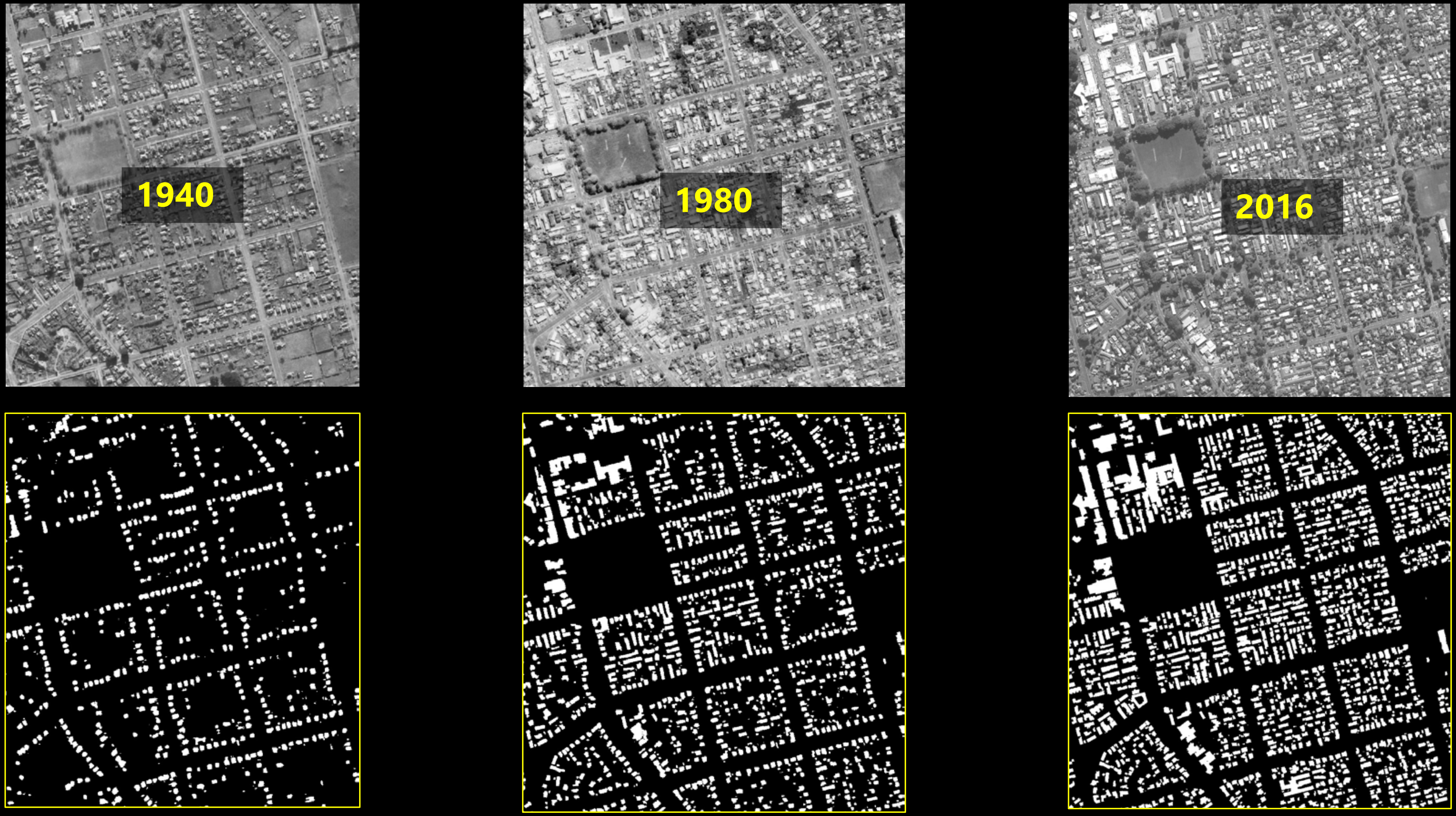
Urban Tree Map Explorer *Experimental*

MAP ABOUT PRIVACY

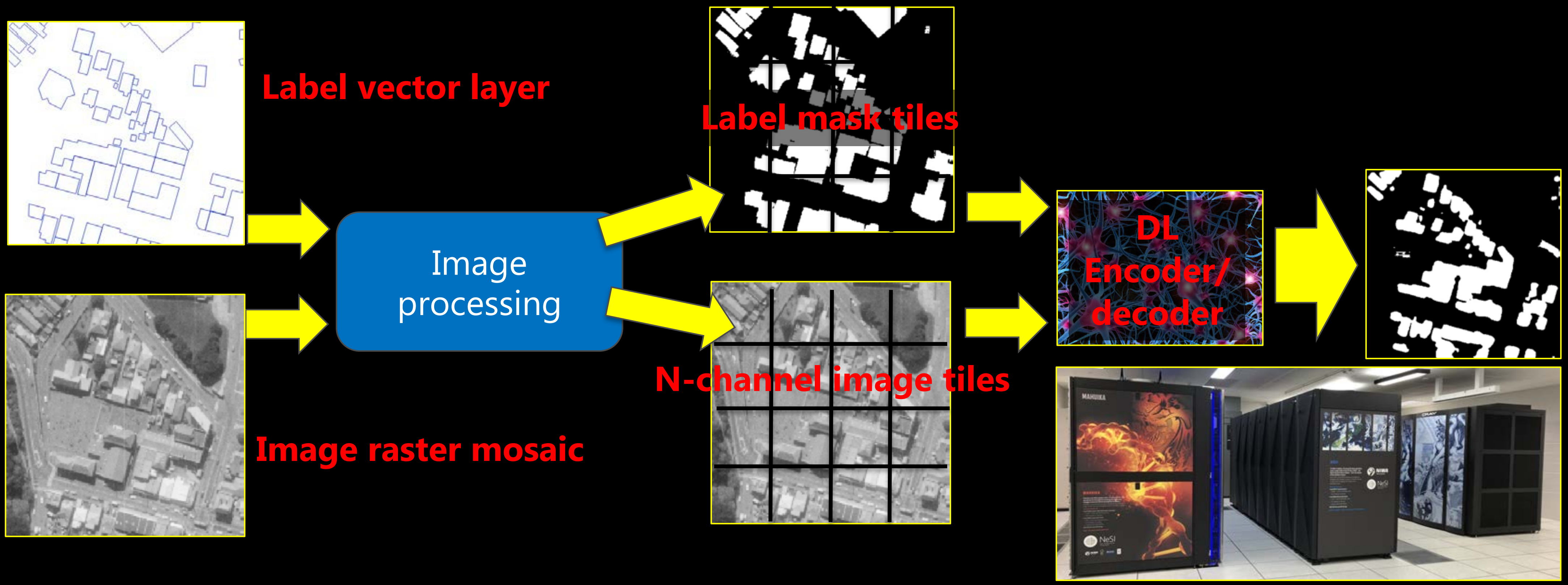
Map Layers

- [x] Tree Crowns
  - Tree Crowns
- [x] Aerial Photography

Goal: map urban built form change over time

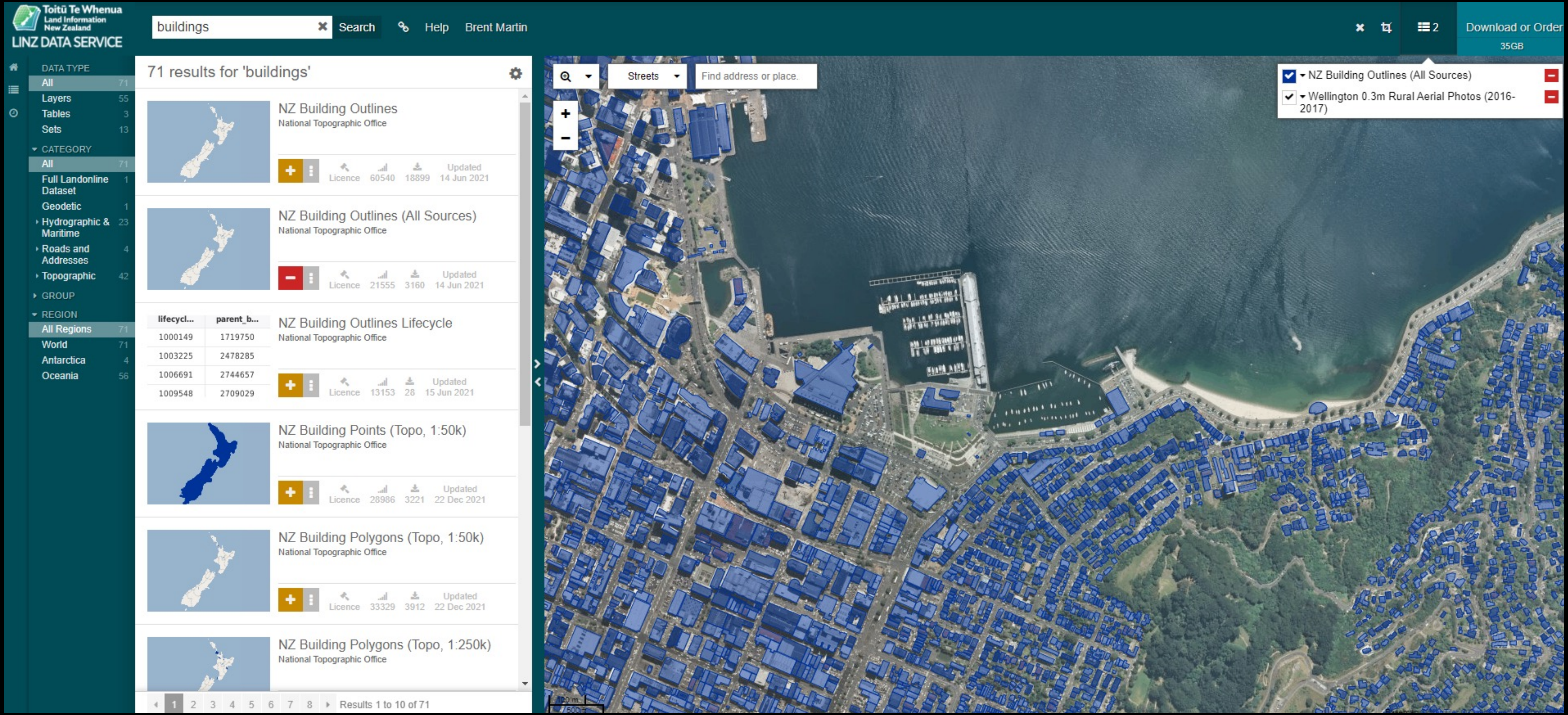


Approach: deep learning segmentation



- MWLR pipeline processes input data into image/label mask tile pairs for training/prediction
- Deep learning encoder-decoder network (Unet64) learns to generate mask tiles (512x512 pixels)
- Masks stitched back together (50% overlap)

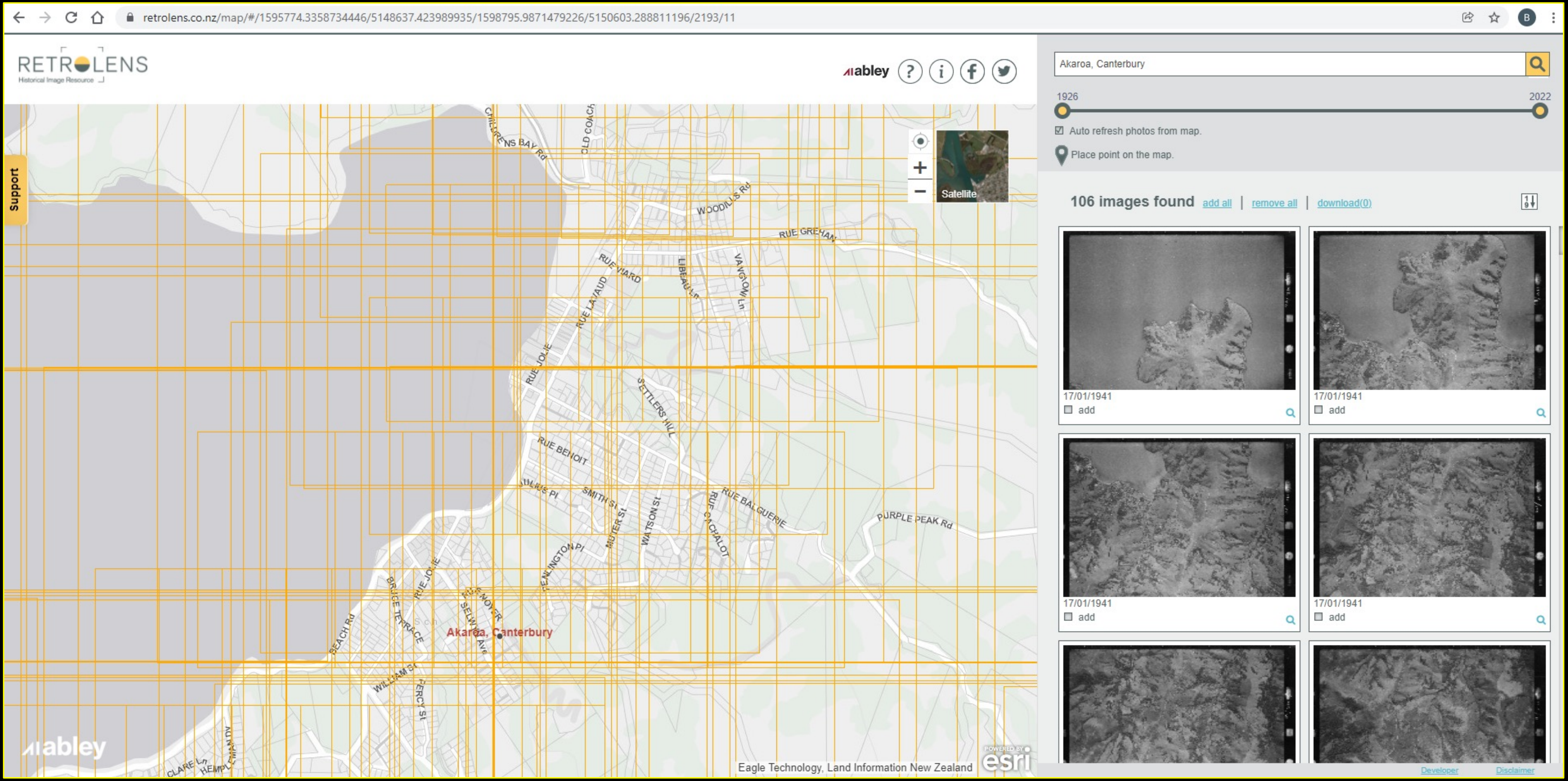
Training data: LINZ 2016



Imagery: 2016 0.3m aerial photos

Labels: NZ building outlines

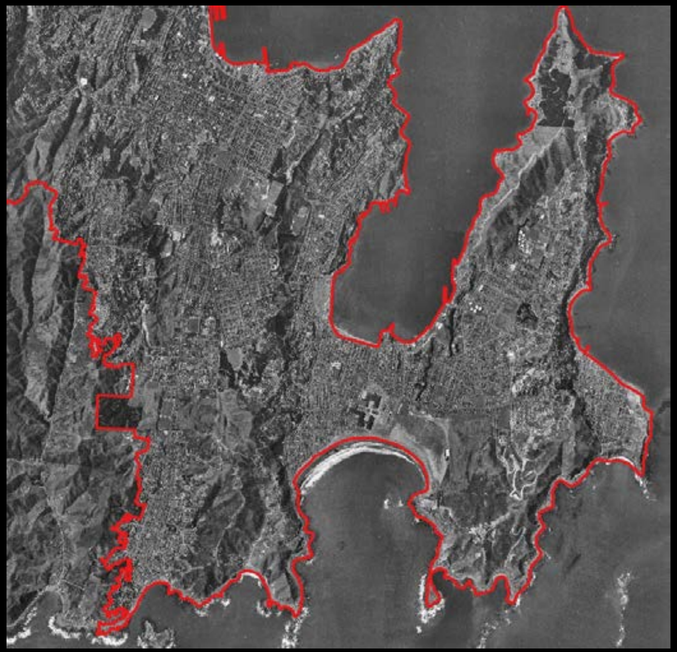
Historic imagery: Retrolens/LINZ



The challenge: training the model

How to train the network for all time periods and cities?

- Can a model trained on 2016 be used for historic B&W imagery?
- Can training transfer between cities?



Transfer between time periods

2016: excellent

1940: poor

2016 model fails to transfer to historic imagery

The issue: inconsistent image quality

2016: digital
Standardised brightness/contrast
Minimal noise
Sharp focus
High spatial accuracy
Shadows

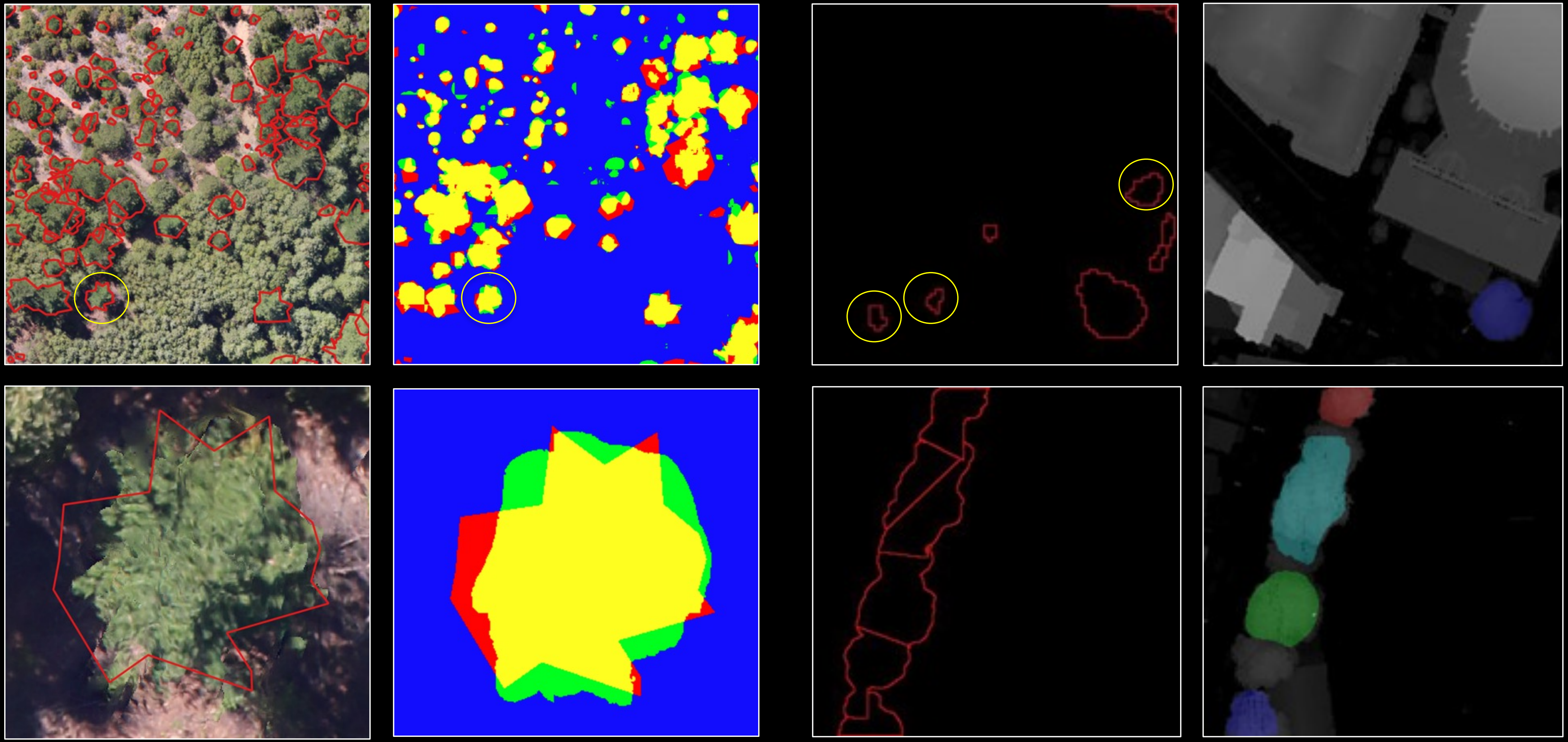
1980: film
Flat contrast
Grainy
Moderate focus
Moderate spatial accuracy
Short shadows

1940: film
Variable brightness/contrast
Grainy
Variable/poor focus
Spatial distortion/displacement
Long shadows

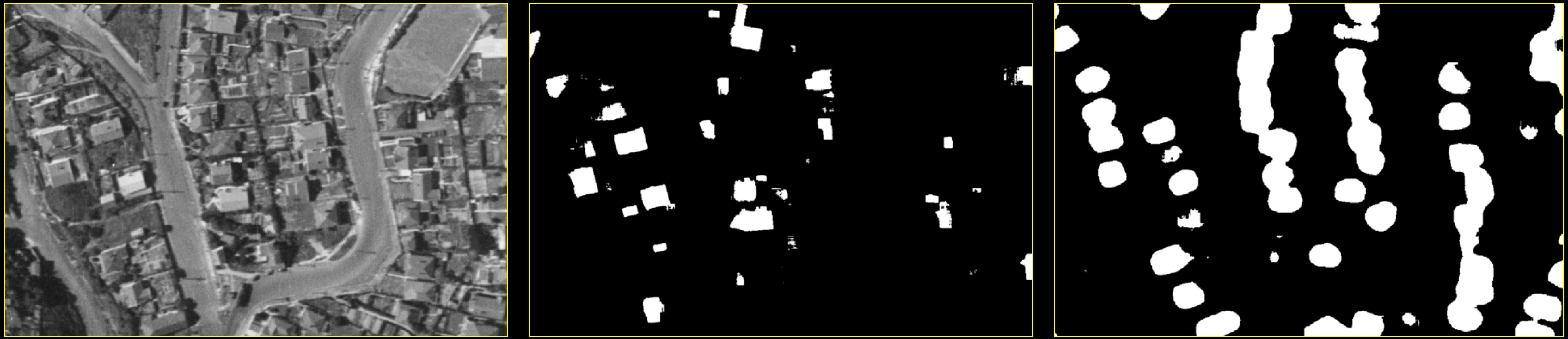
The solution: imperfect training data

- Train model on historic imagery but *current* labels?
  - Buildings may have been built, demolished or modified
  - Image may be displaced because of distortion issues
- Select tiles with "reasonable" match
  - What is "reasonable"?
  - Enough tiles?

Segmentation label error tolerance



Imperfect data results: 1940



Wellington: 1940 image

2016-based mask

1940 imperfect data mask

Training on 1940s imagery with imperfect data significantly improved

Imperfect data results: 1980

Wellington: 1980 image

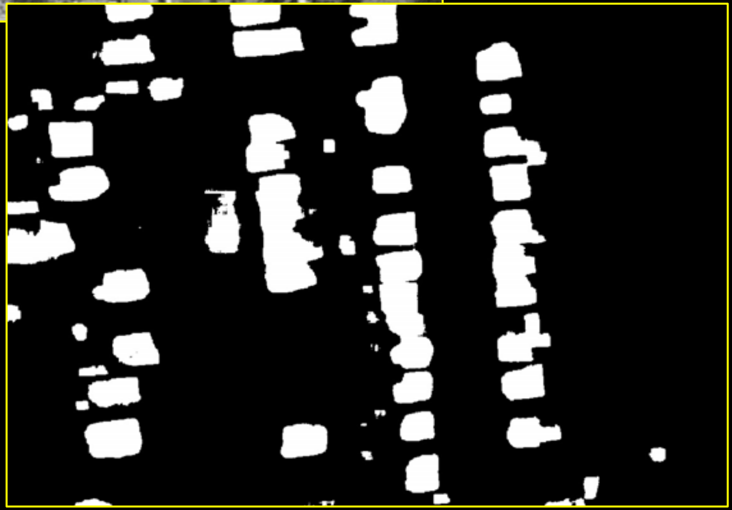
2016-based mask

1980 imperfect data mask

1980: significantly improved recall (but reduced shape precision)

City transfer: Wellington to Auckland

1980



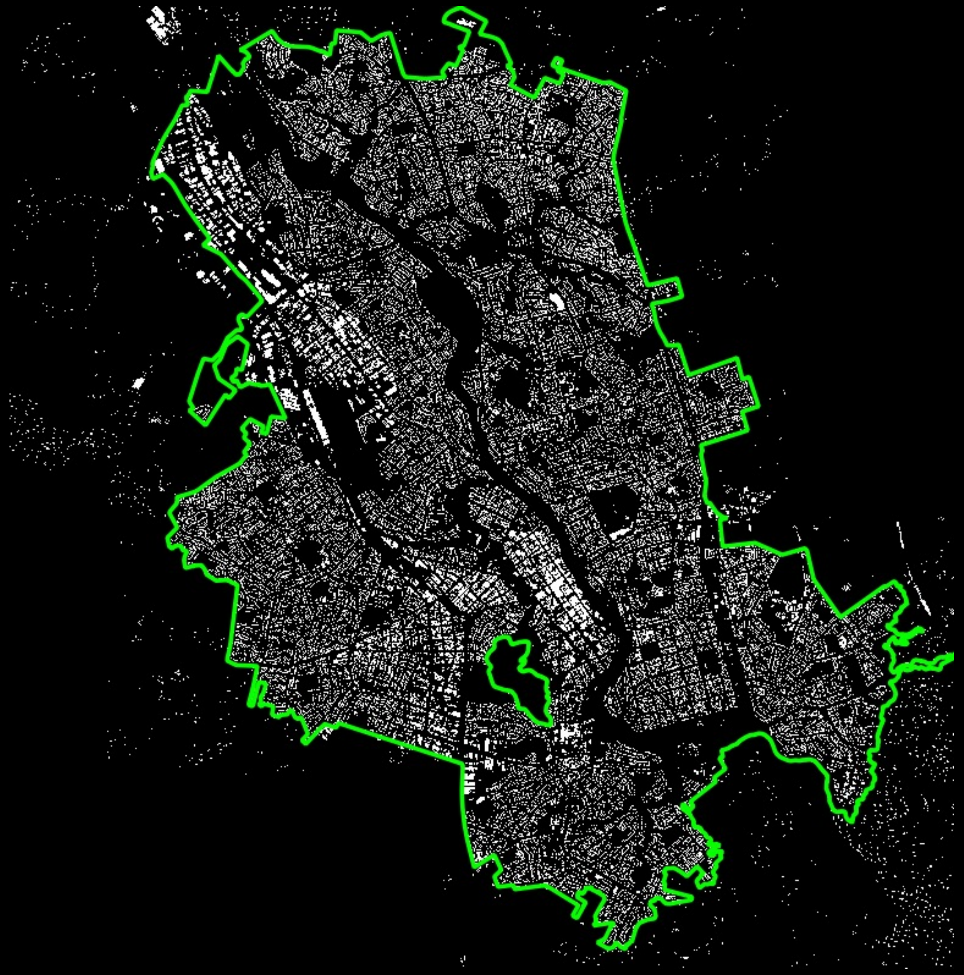
1940

Wellington models transfer well to Auckland

Hamilton

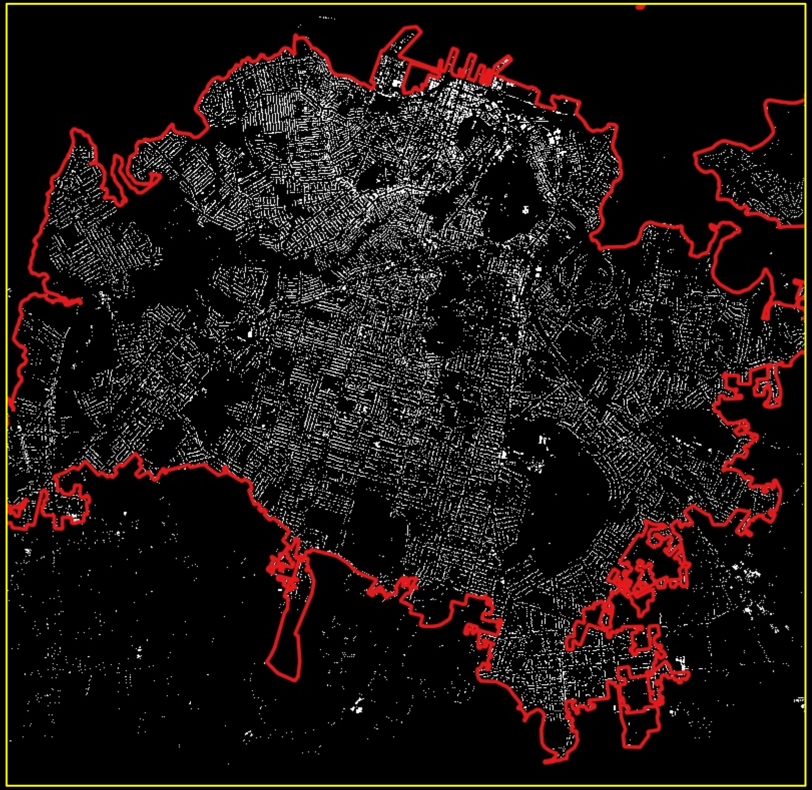
1940

1980

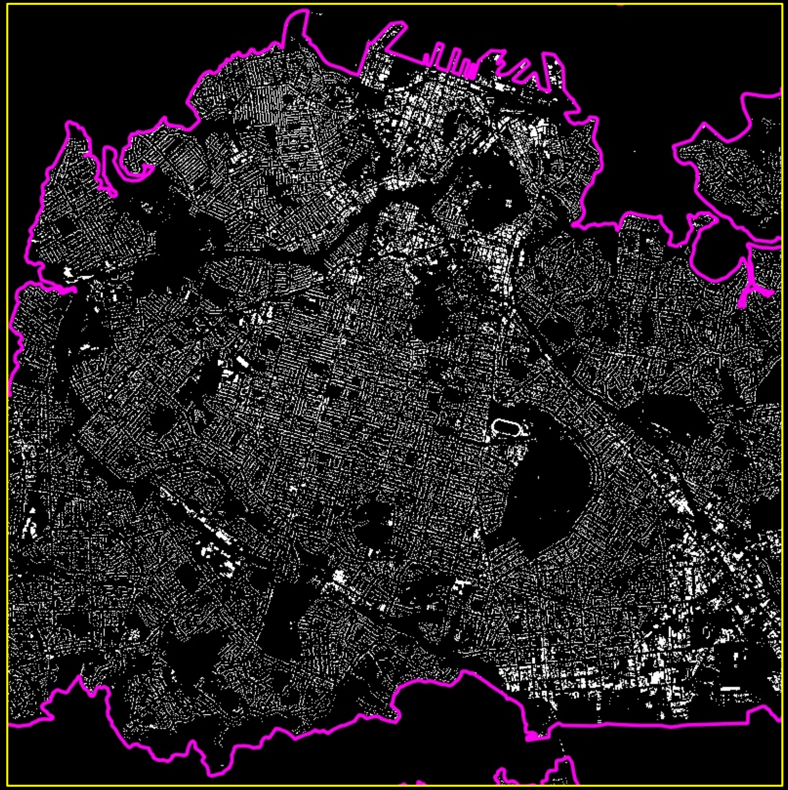


2016

Auckland



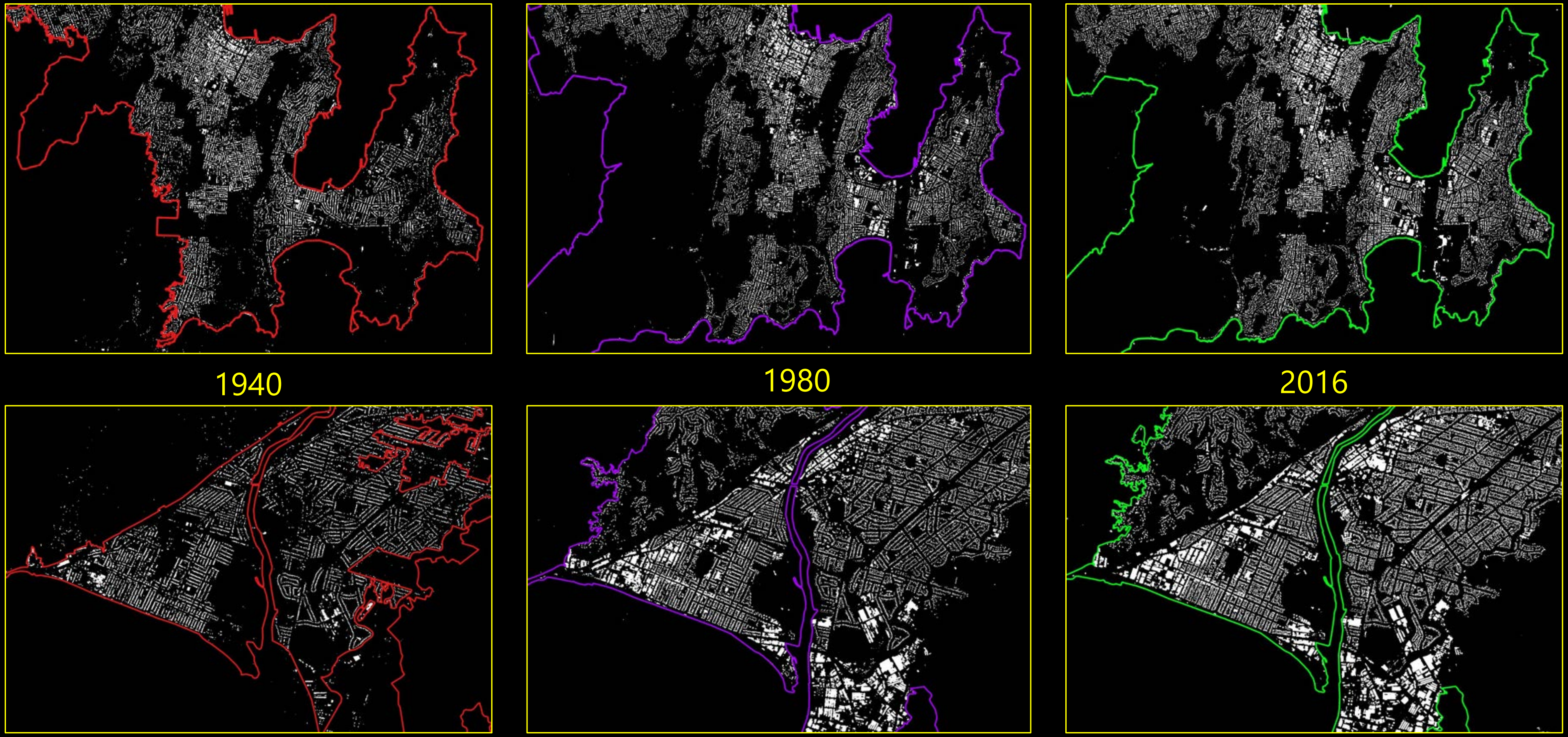
1940



1980

2016

Wellington and Lower Hutt



Summary

- Acquiring training data is a big challenge
- Learning from imperfect data reduces this burden
- Deep learning has great potential for taming the data deluge