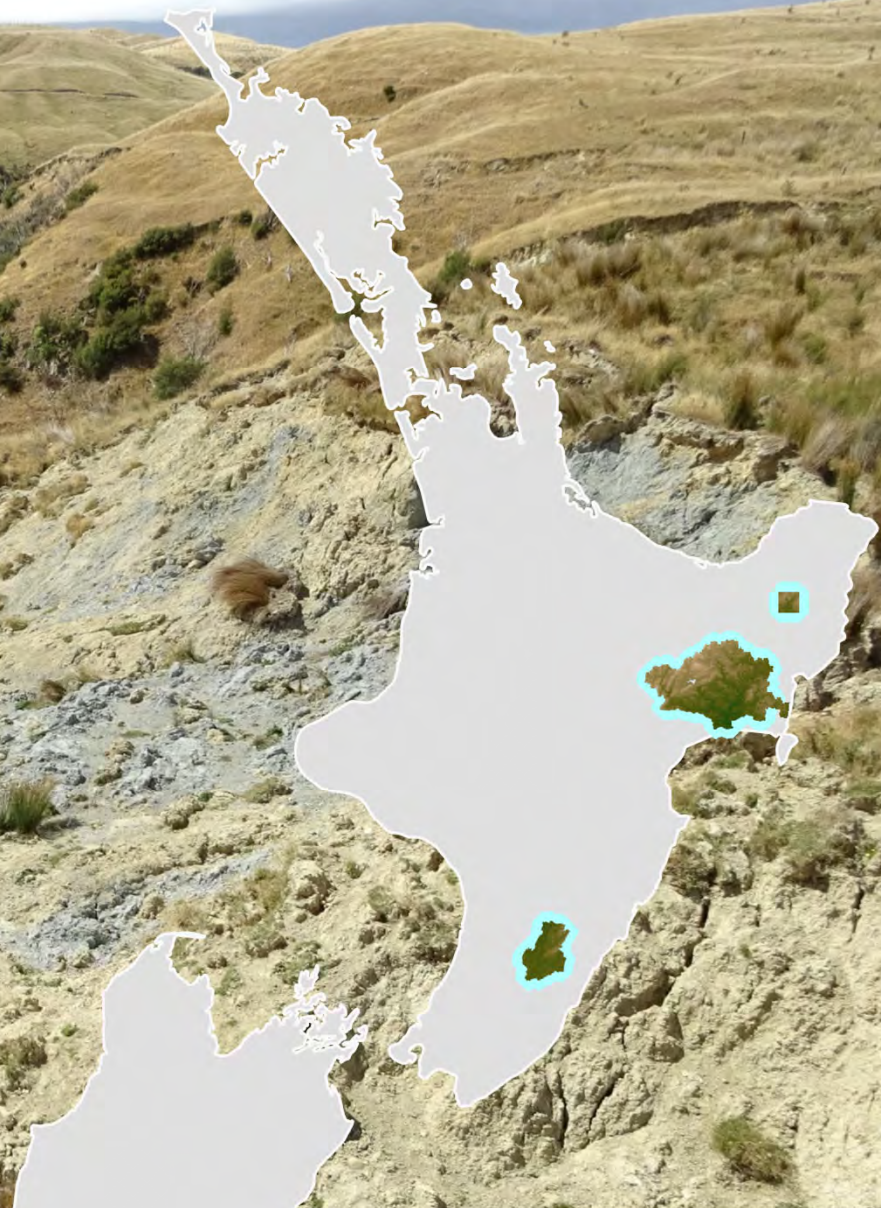


# KNOWLEDGE-BASED AND DATA-DRIVEN EROSION FEATURE MAPPING

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*STEC Meeting, 13/09/2023, Palmerston North*





## Knowledge-based earthflow mapping in the Tiraumea catchment

- Semi-automated detection of potential earthflows
- Object-based image analysis (OBIA) approach
- Based on LiDAR digital elevation model (DEM) and aerial photographs



- Hölbling et al., in preparation. Detection and delineation of earthflows in Tiraumea, New Zealand, using object-based image analysis.
- Hölbling, D., Abad, L., Spiekermann, R., Smith, H., Neverman, A., 2023. Semi-automated detection and delineation of earthflows in New Zealand using remote sensing - challenges and opportunities. EGU General Assembly 2023, Vienna, Austria, 24–28 April, EGU23-1670. <https://doi.org/10.5194/eqsphere-equ23-1670>
- Hölbling, D., Abad, L., Spiekermann, R., Smith, H., Neverman, A., Betts, H., 2022. Exploring knowledge-based and data-driven approaches to map earthflow and gully erosion features in New Zealand. EGU General Assembly 2022, Vienna, Austria, 23-27 May, EGU22-1013. <https://doi.org/10.5194/eqsphere-equ22-1013>

# Detection of potential earthflows

- Identifying earthflow characteristics that can be derived from aerial photography and DEM data
- Knowledge-based classification workflow

**Earthflow characteristics**

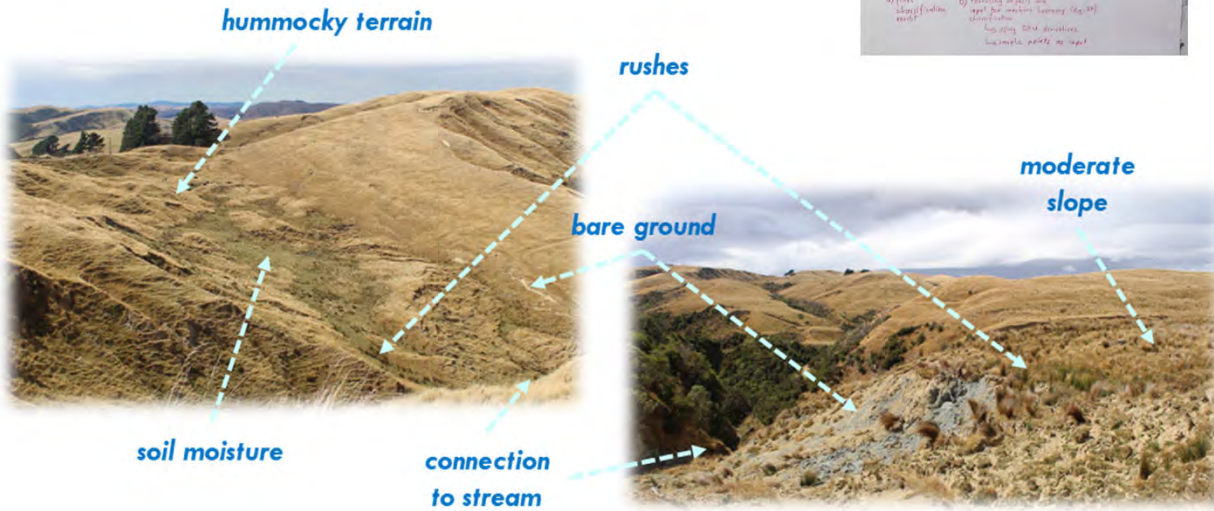
Vegetation	Possible metric (classification)
L1 - noveg: red/brown, often large areas, affected by weather → dark brightness	NDVI/1P imagery, NDVI, etc. GIMMS
L2 - pasture: potentially greener/darker than neighboring terrain due to high moisture content (in summer months)	Classify objects on preliminary product Difference to neighbors
L1 - Paving: Surface water an indicator	NDVI < 0, color darker than bare ground
L1 - Bare ground: either at the or landscape transition cracks	NDVI < ?, brightness
L2 - Connected to streams or the	Proximity to riverlines (object distance $rs < 2$ )
L2 - Morphological	
- Hummocky terrain	
- Mean slope $\sim 10^\circ$	
- Existence of debris	

**OBIA Workflow**

- 1) Segmentation → seed points
  - Classification: Color, Vegetation (Greenness), Bare ground
  - Thresholds derived from available imagery
  - Hierarchical classification considering 2nd class
- 2) Object relating on separate map
  - merging/splitting/grouping/extracting using spatial/feature/attribute
  - potential earthflow features

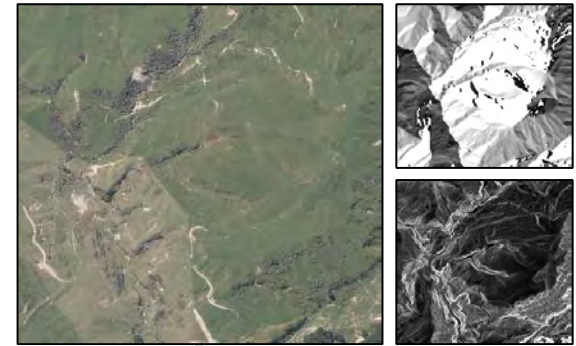
Final classification result

- a) Final classification result
- b) resulting objects are input for machine learning (see 10) using DEM derivatives to sample points on map!

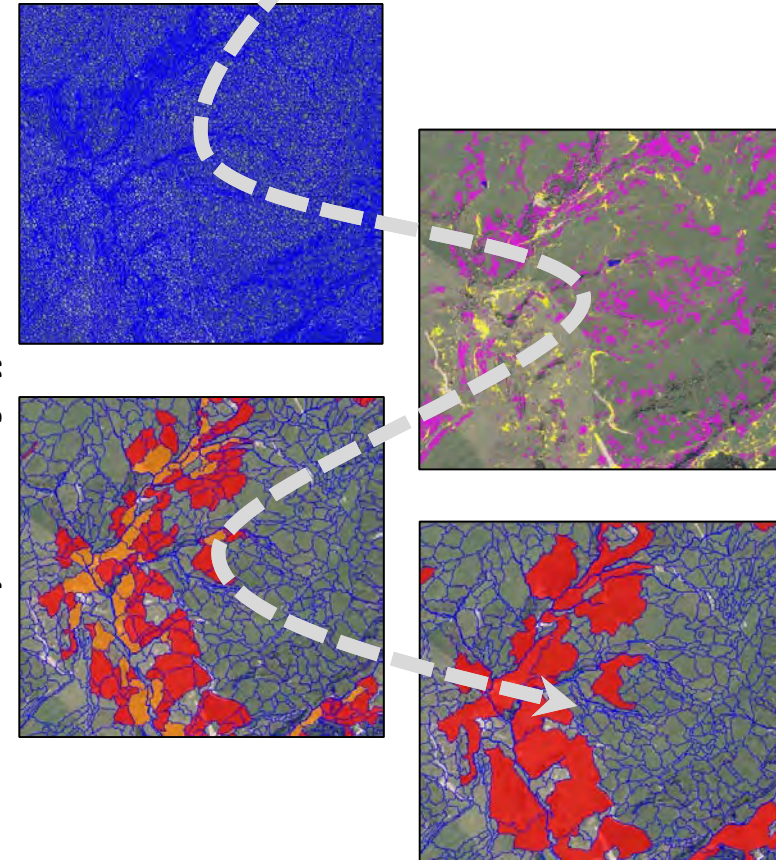


Photographs © L. Abad

Aerial photography and DSM derivatives as input data



Flexible OBIA workflow based on segmentation and classification using different characteristics

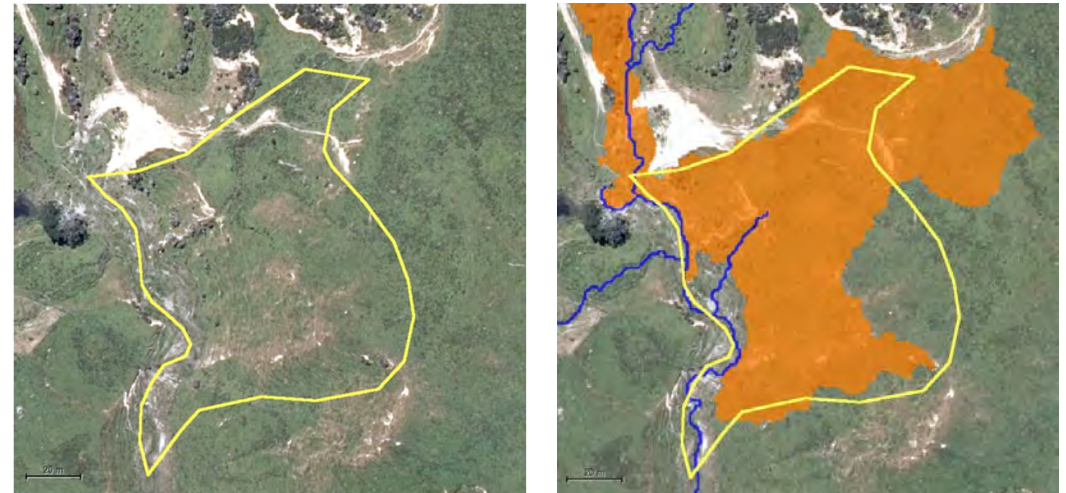


## Results & Validation

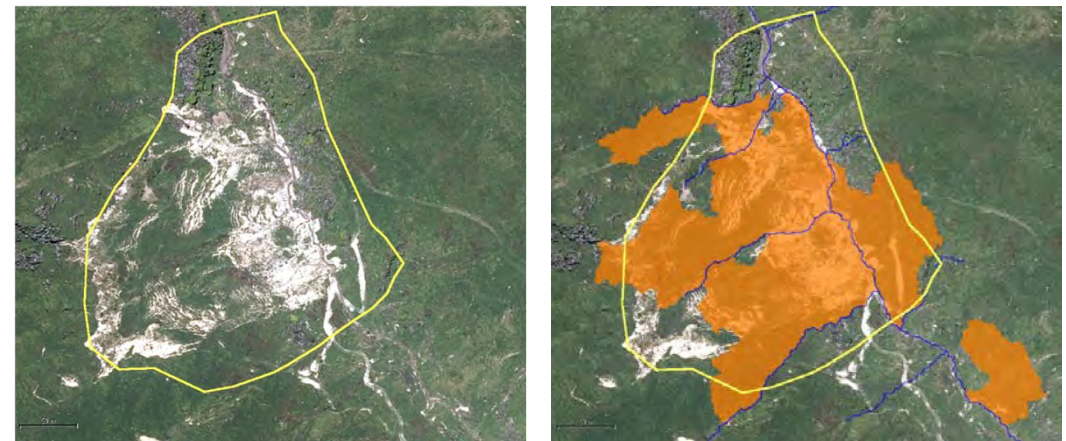
- Comparison of potential earthflows to manual mapping
  - Approx. 87% of the reference earthflow polygons were detected
  - Delineations can differ significantly
- Many additional potential earthflows were detected → further verification is needed



*Newly discovered earthflow (orange).*



*Earthflow mapping examples. OBIA mapping (orange) in comparison to reference data (yellow outline). Channel network is shown as blue lines.*



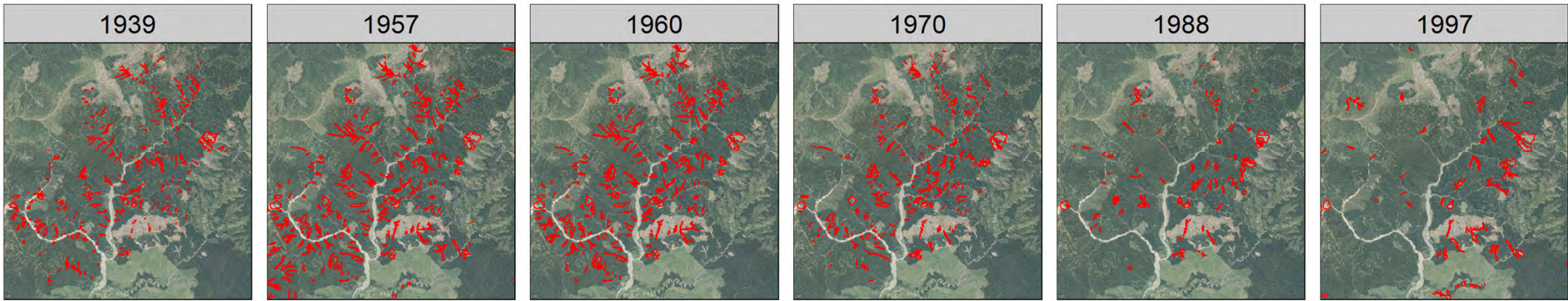


## Gully characterisation and detection with historical reference data in the Mangatu forest

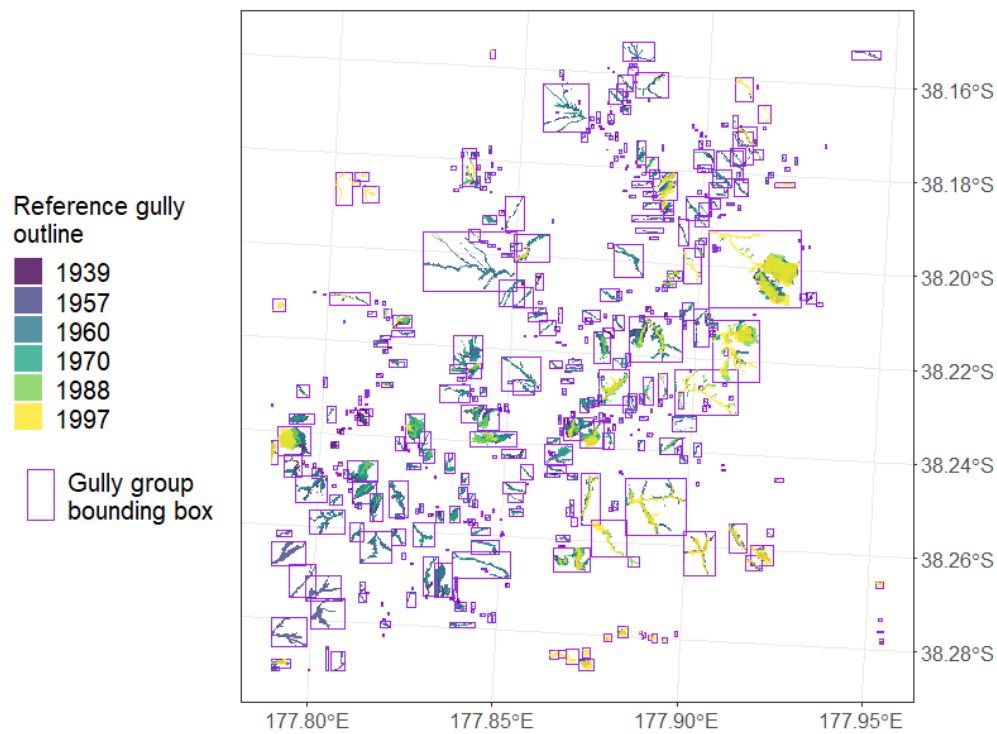
- Deep learning approach
- Based on LiDAR DEM from 2019
- Gully data from 1939 to 1997 for six different years



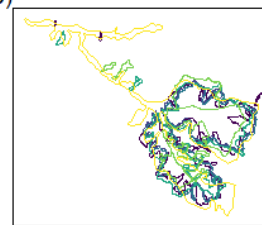
- Abad et al., in preparation. Gully characterisation and mapping based on LiDAR data using deep learning and historical training data.
- Hölbling, D., Abad, L., Spiekermann, R., Smith, H., Neverman, A., Betts, H., 2022. Exploring knowledge-based and data-driven approaches to map earthflow and gully erosion features in New Zealand. EGU General Assembly 2022, Vienna, Austria, 23-27 May, EGU22-1013. <https://doi.org/10.5194/equsphere-egu22-1013>



a)



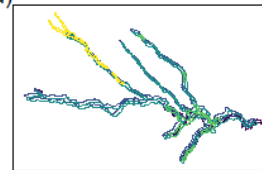
b)



c)



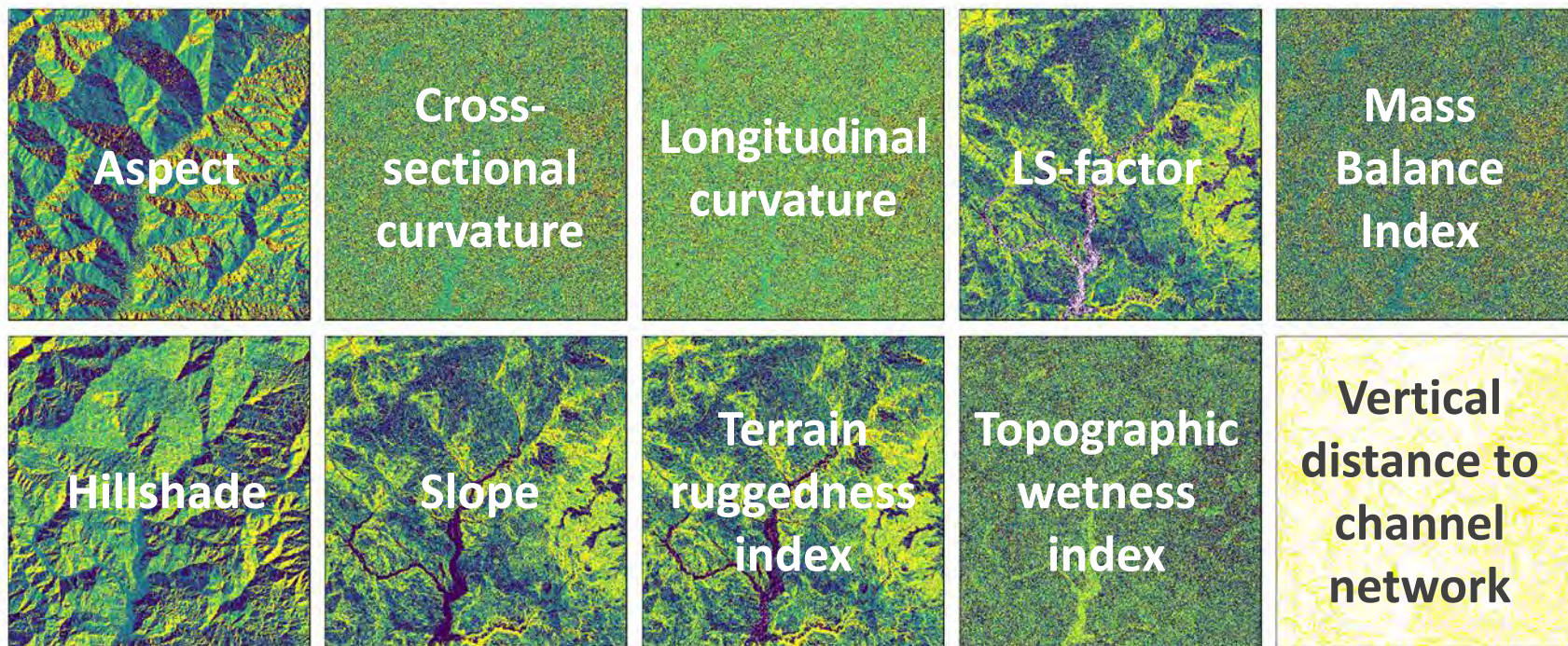
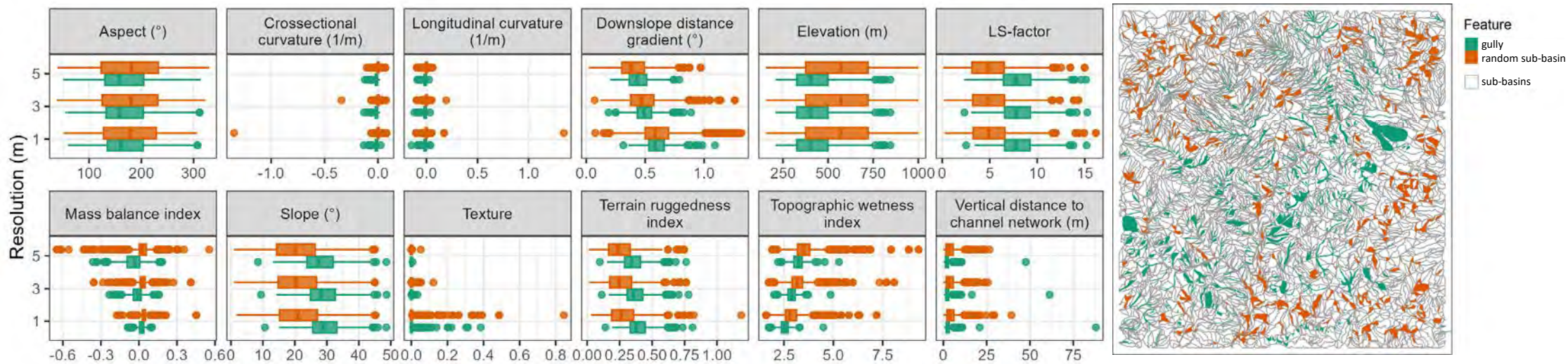
d)



- Historical data from Marden et al. (2012 & 2014)
- Co-registration errors were partially fixed
- Most errors come from the manual delineation using oblique aerial imagery
- Grouping based on topological relation of the historical data can help understand the evolution of gullies

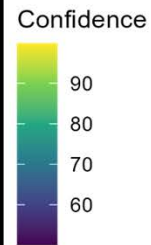
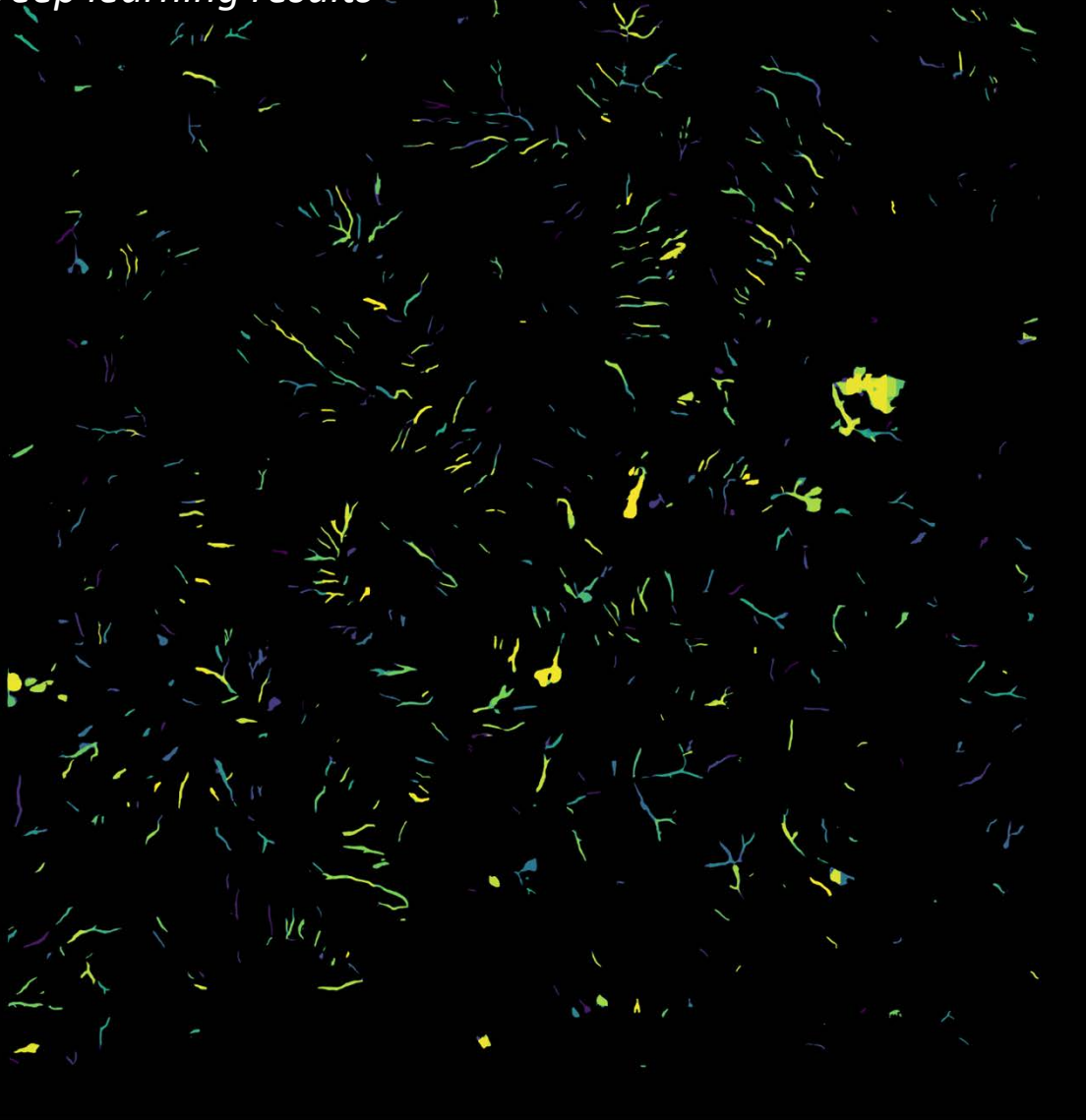
**a)** Spatio-temporal grouping of reference gully features. **b)** Example of gully complex evolution over time. **c)** and **d)** Examples of co-registration mismatch of reference data for different years.

Marden, M., Arnold, G., Seymour, A., & Hambling, R. (2012). History and distribution of steep-land gullies in response to land use change, East Coast Region, North Island, New Zealand. *Geomorphology*, 153–154, 81–90.  
 Marden, M., Herzig, A., & Basher, L. (2014). Erosion process contribution to sediment yield before and after the establishment of exotic forest: Waipaa catchment, New Zealand. *Geomorphology*, 226, 162–174.



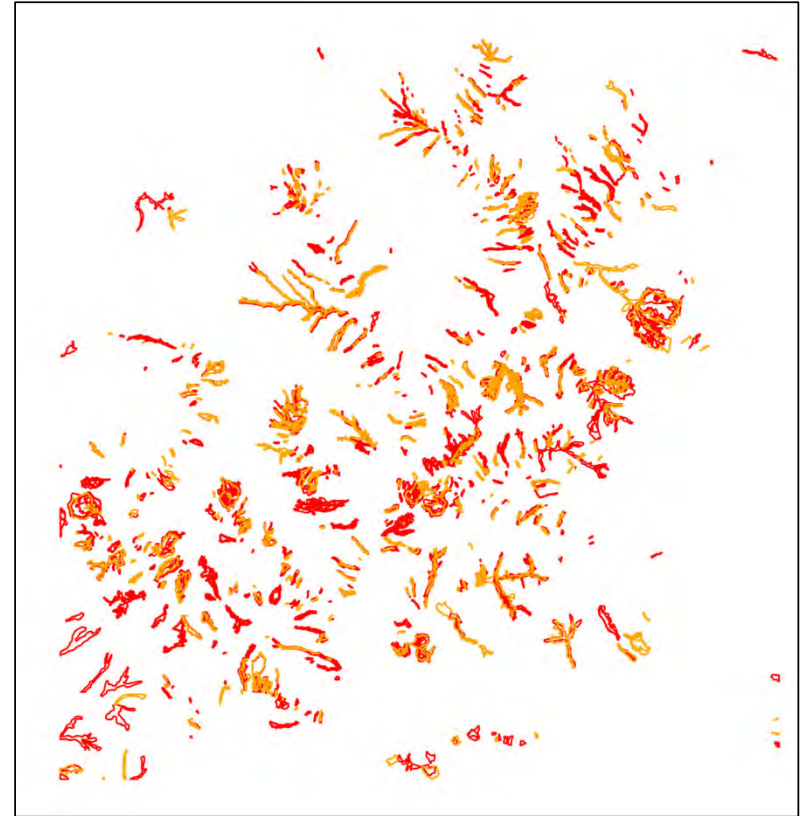
- Several terrain derivatives were computed and compared for sub-basins with and without gullies
- The most distinctive derivatives were used for training deep learning models

## Deep learning results



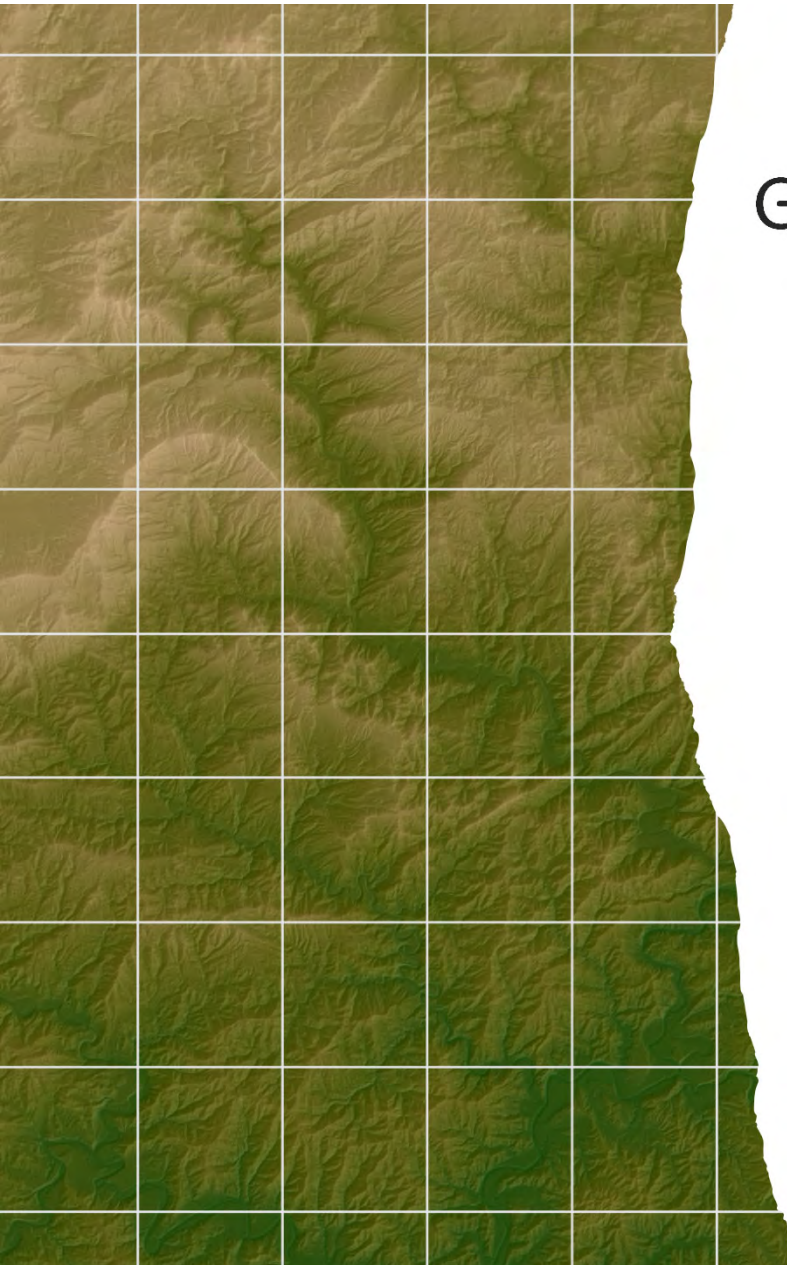
## Detected Gully Features

Reference features. Training in red and testing in orange.



- Deep learning results are partially inconclusive
- Time difference between historical reference data and LiDAR data
  - Delineations differ





## Gully and cliff detection in the Wairoa catchment

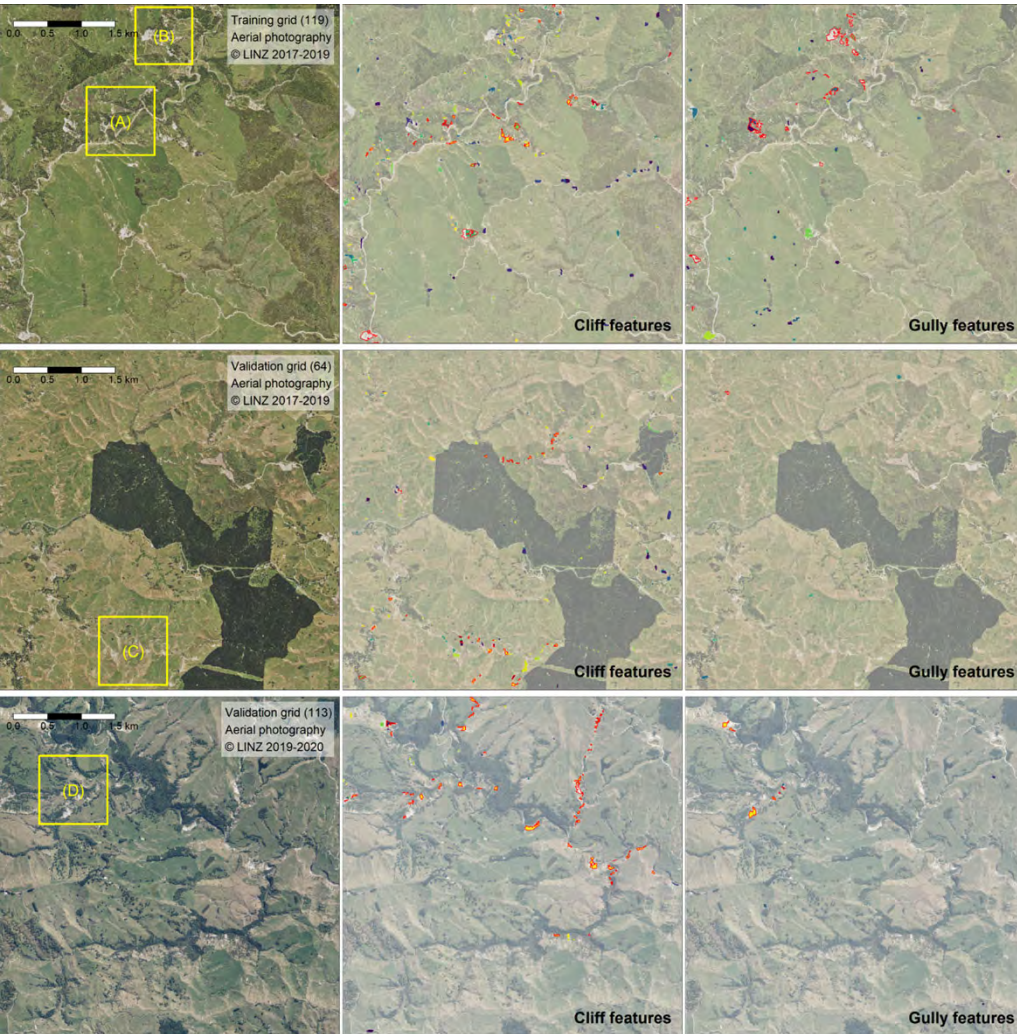
- Data-driven approach:  
deep learning Mask R-CNN
- Knowledge-based OBIA  
approach
- Based on LiDAR DEM and  
aerial photographs



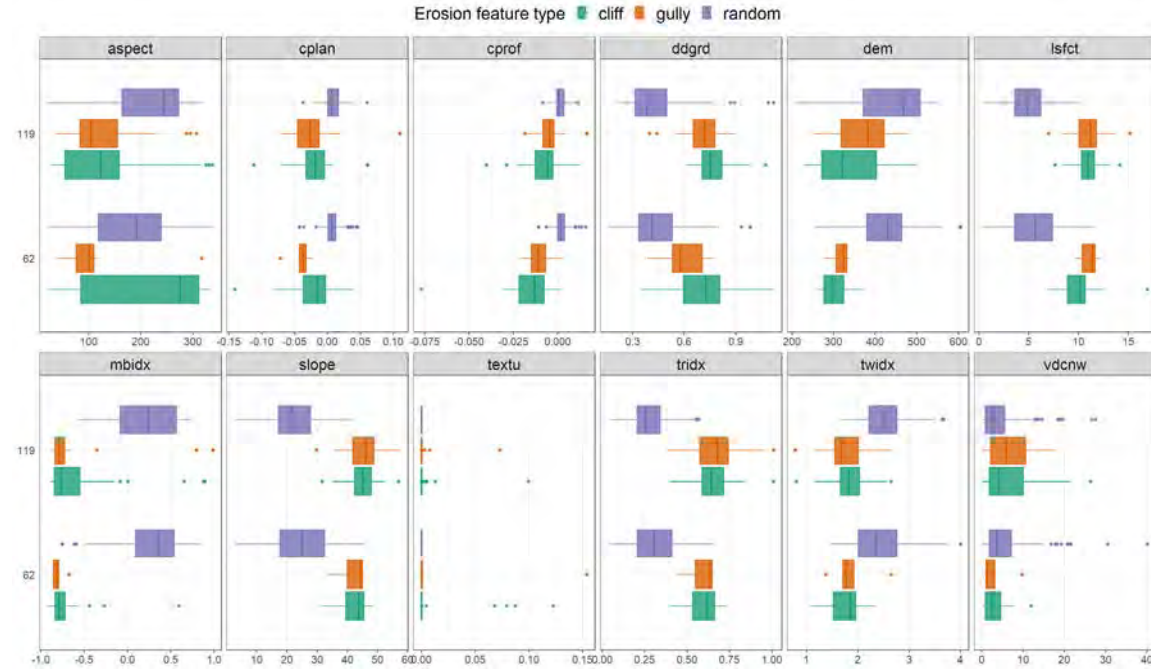
- Abad et al., in preparation. Data-driven and knowledge-based mapping of gully and cliff erosion features in Wairoa.
- Abad, L., Hölbling, D., Smith, H., Neverman, A., Betts, H., Spiekermann, R., 2023. Expert-based and data-driven gully and cliff erosion feature detection in New Zealand. 28th IUGG General Assembly, Berlin, Germany, 11-20 July. <https://doi.org/10.57757/IUGG23-0228>
- Abad, L., Hölbling, D., Smith, H., Neverman, A., Betts, H., Spiekermann, R., 2023. Gully and cliff erosion feature detection in the Wairoa catchment in Hawke's Bay, New Zealand. EGU General Assembly 2023, Vienna, Austria, 24-28 April, EGU23-1468. <https://doi.org/10.5194/egusphere-equ23-1468>

# Deep Learning

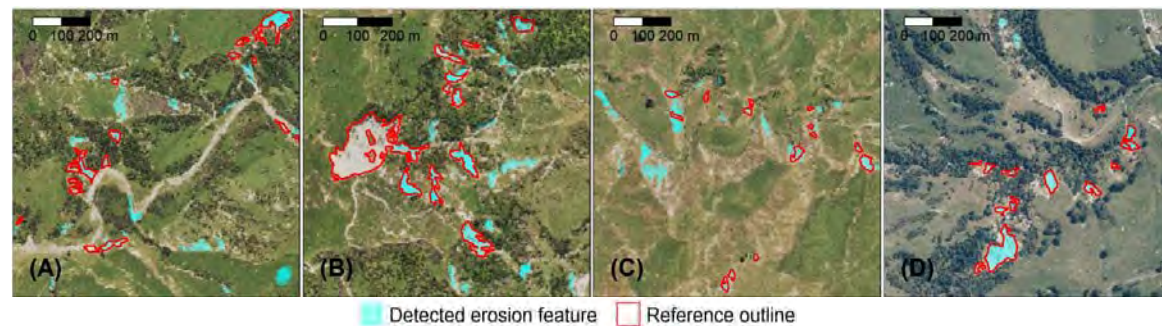
Terrain derivatives differentiate between random features and erosion features, but the differentiation between gullies and cliffs is difficult.



Several parameter iterations for model training were tested, using different grids as training and validation regions. Results are based on the band combination R, G, NIR, slope, LS-factor.

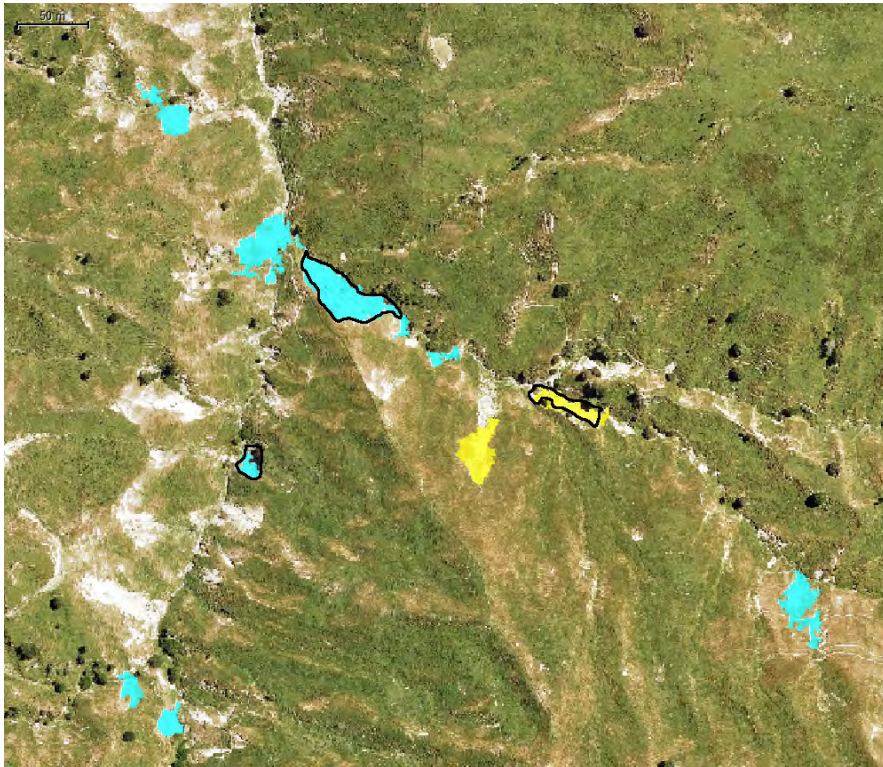


Comparison of deep learning results and reference data.

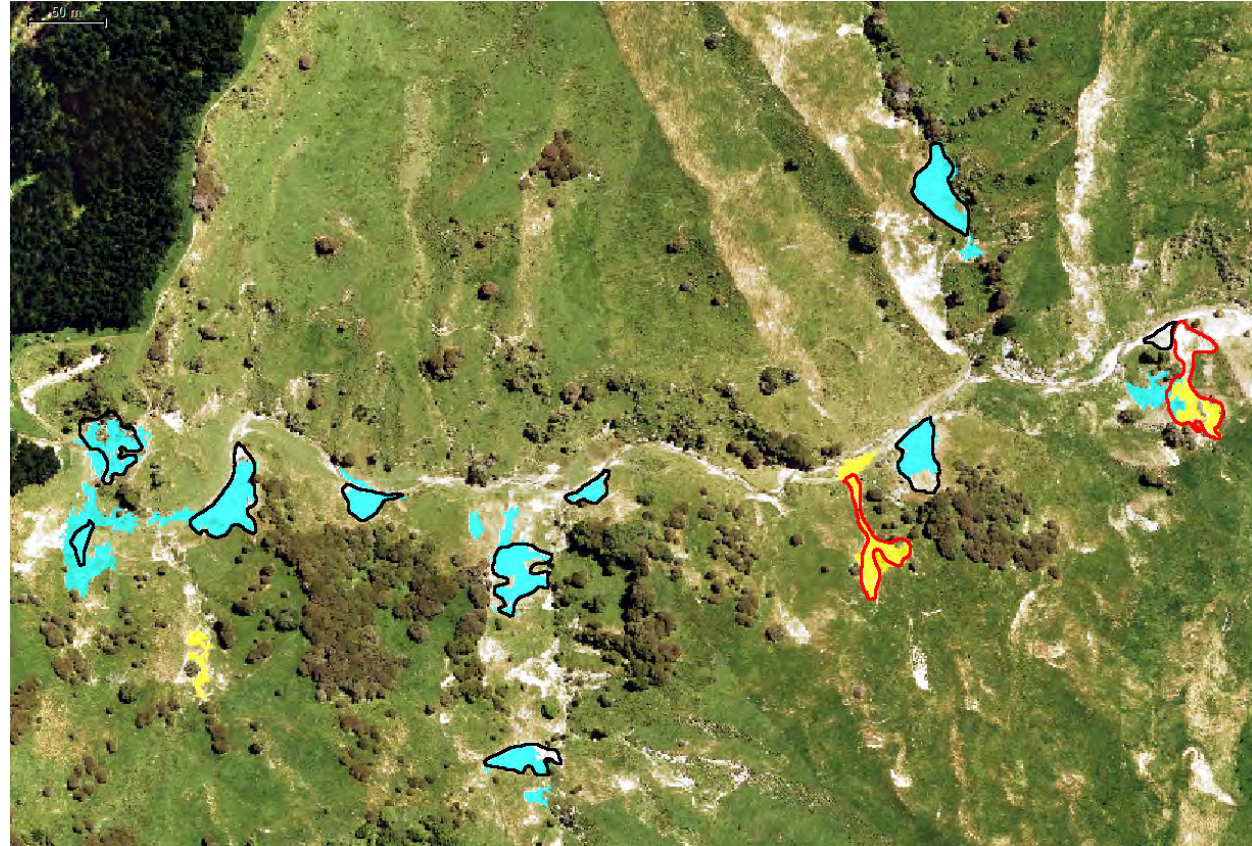


# Knowledge-based OBIA

- Creation of homogenous image objects by automatically grouping neighbouring pixels
- Classification of objects by combining spectral, spatial, and morphological characteristics of features

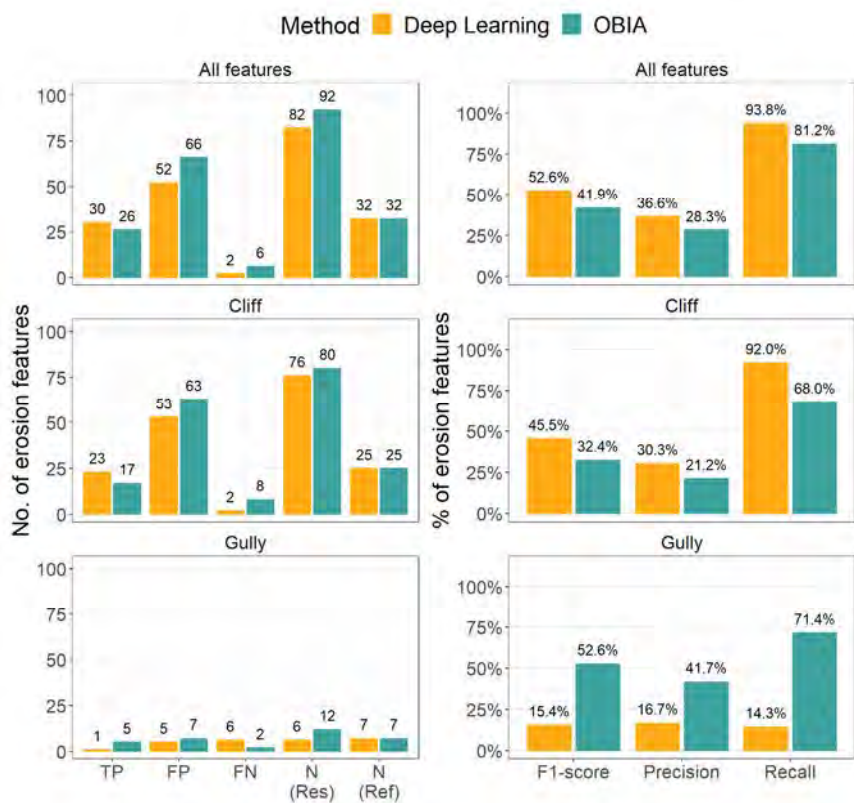


□ Reference cliff   □ Reference gully   ■ Detected cliff   ■ Detected gully



- Integration of expert knowledge in a flexible segmentation and classification workflow
- Challenges are mainly the creation of suitable image objects and the differentiation of different erosion features

# Deep Learning vs. OBIA

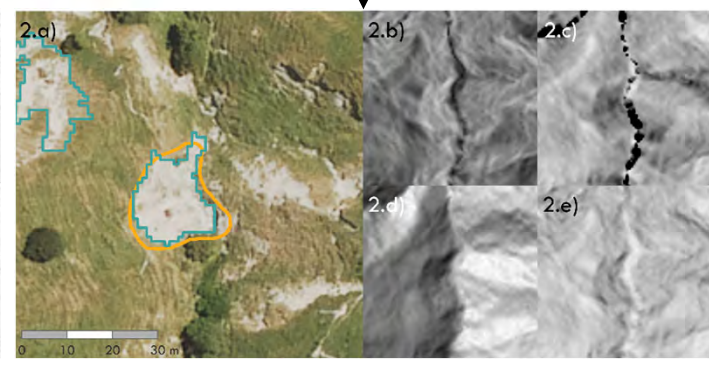
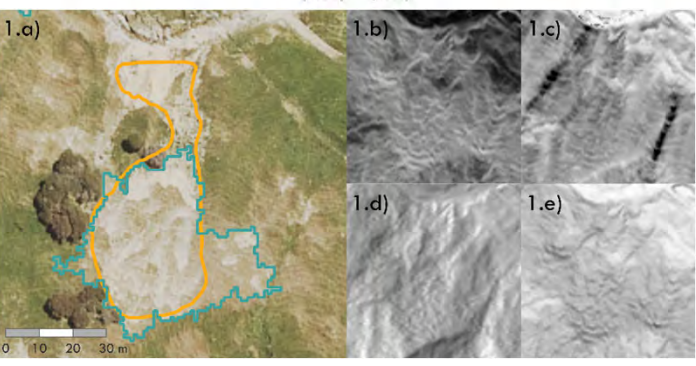
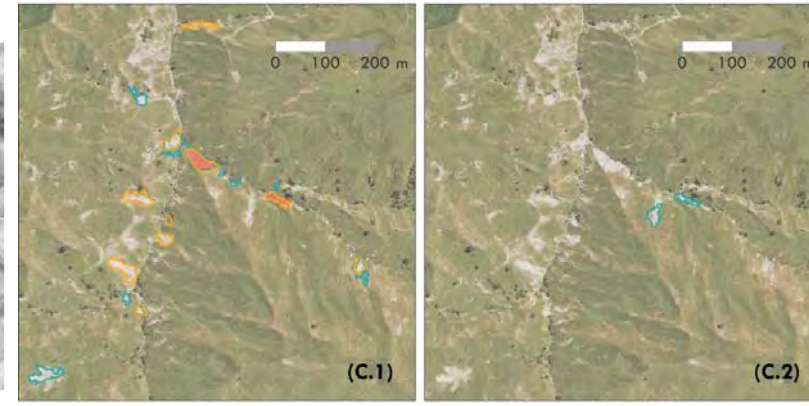
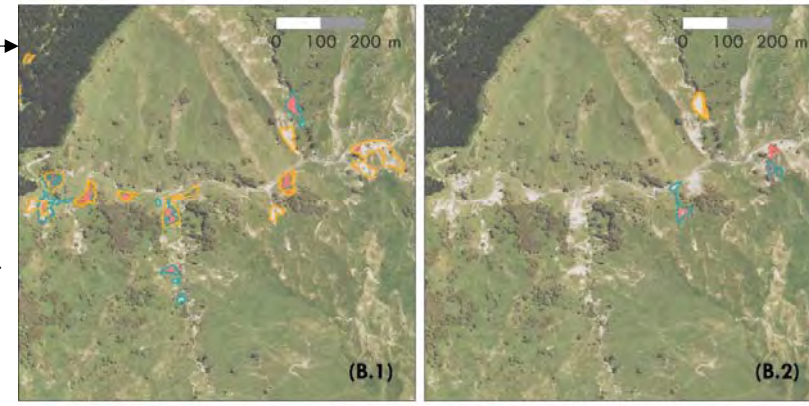
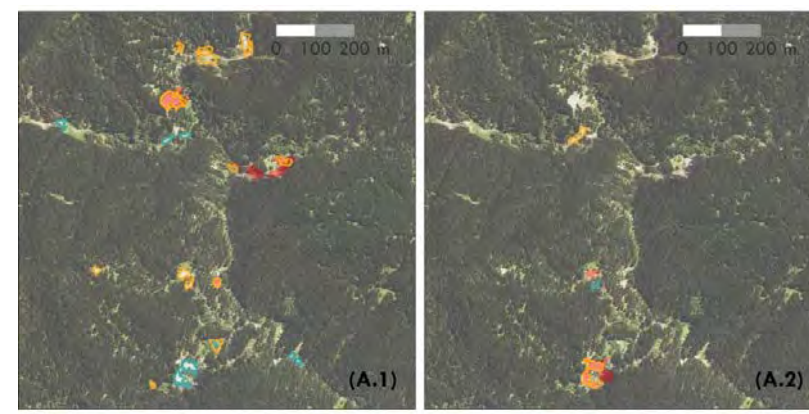


Accuracy measures according to the detection method. The upper panels compare all reference data without differentiation of classes.

Feature detection examples in zoom regions (A, B, C). (1) shows features classified as cliffs, (2) shows gully features.

Close-up view of two (1 & 2) cliff features classified as false positives (FP) by both methods. a) Aerial imagery and detected features per method, DEM derivatives for the close-up area: b) slope, c) LS-factor, d) hillshade, e) terrain ruggedness index.

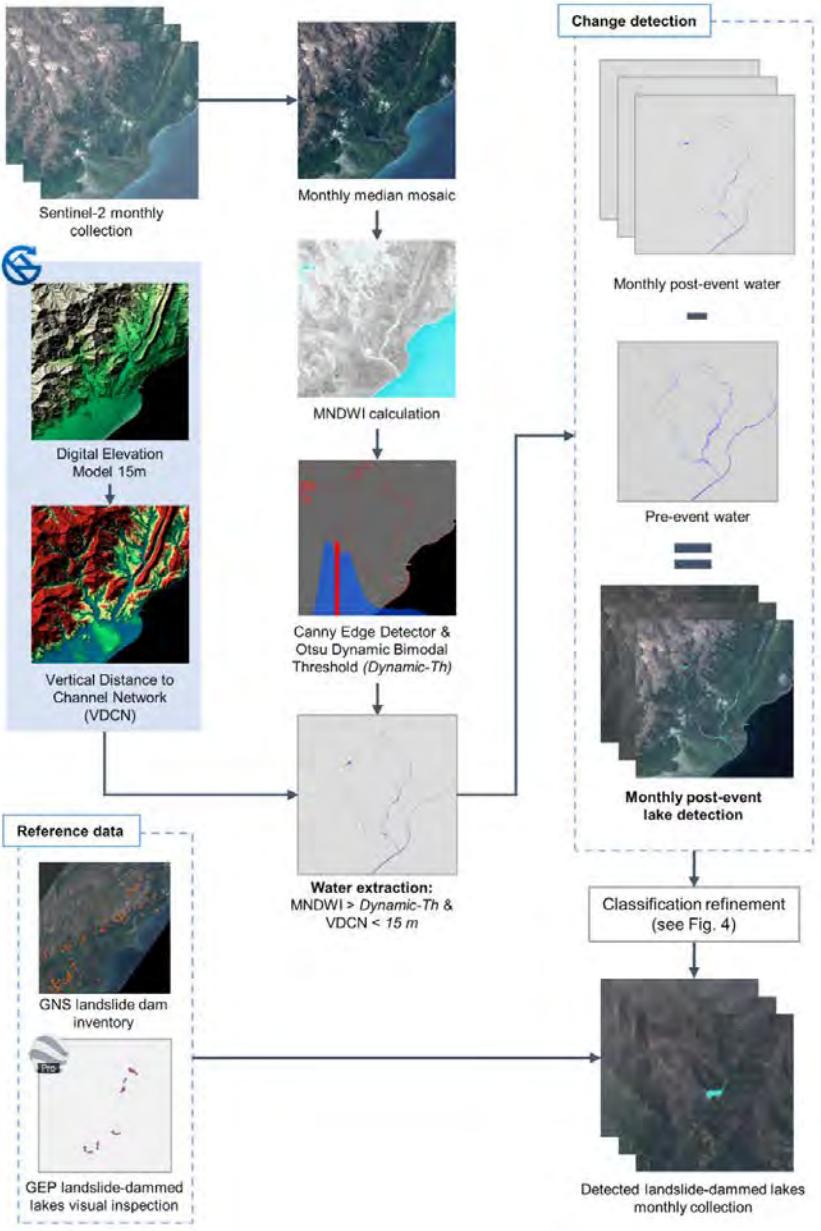
Reference (red), Deep Learning (orange), OBIA (cyan)



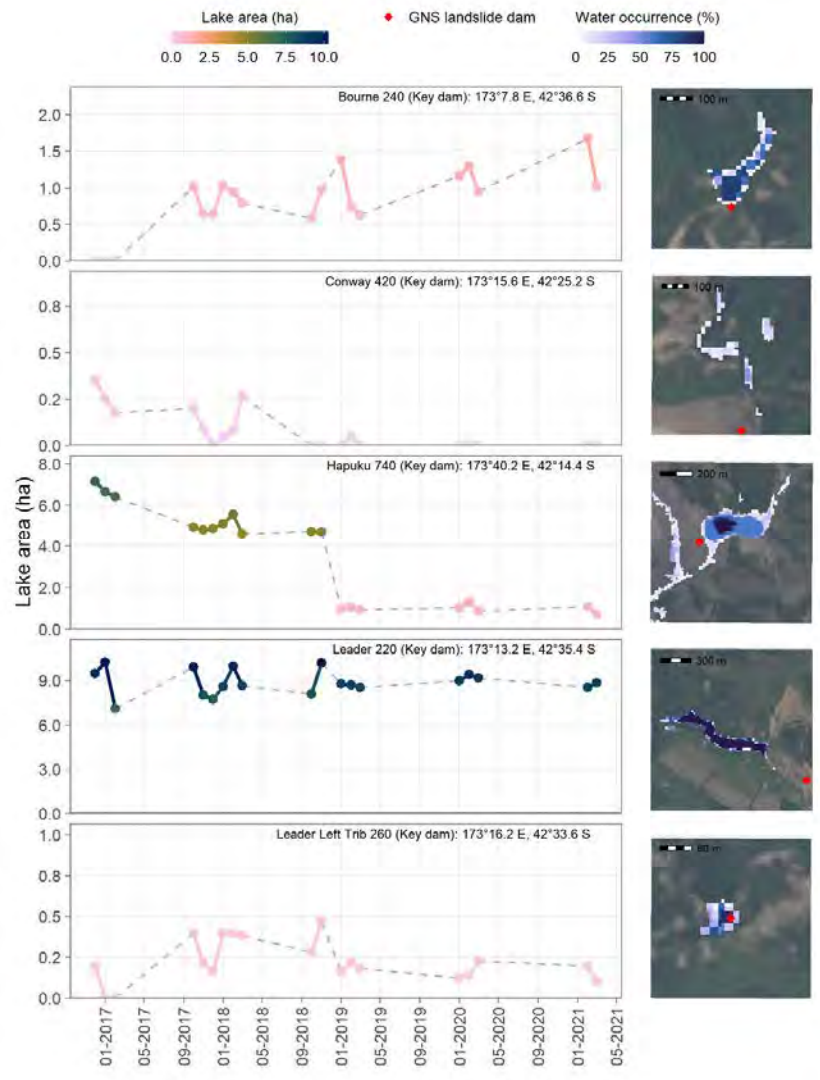
# Mapping and monitoring landslide-dammed lakes

- Time series analysis using Sentinel-2 images
- Automated analysis at regional scale
- Knowledge-based OBIA approach on local scale





# Detecting landslide-dammed lakes and monitoring their spatio-temporal evolution following the Kaikōura earthquake

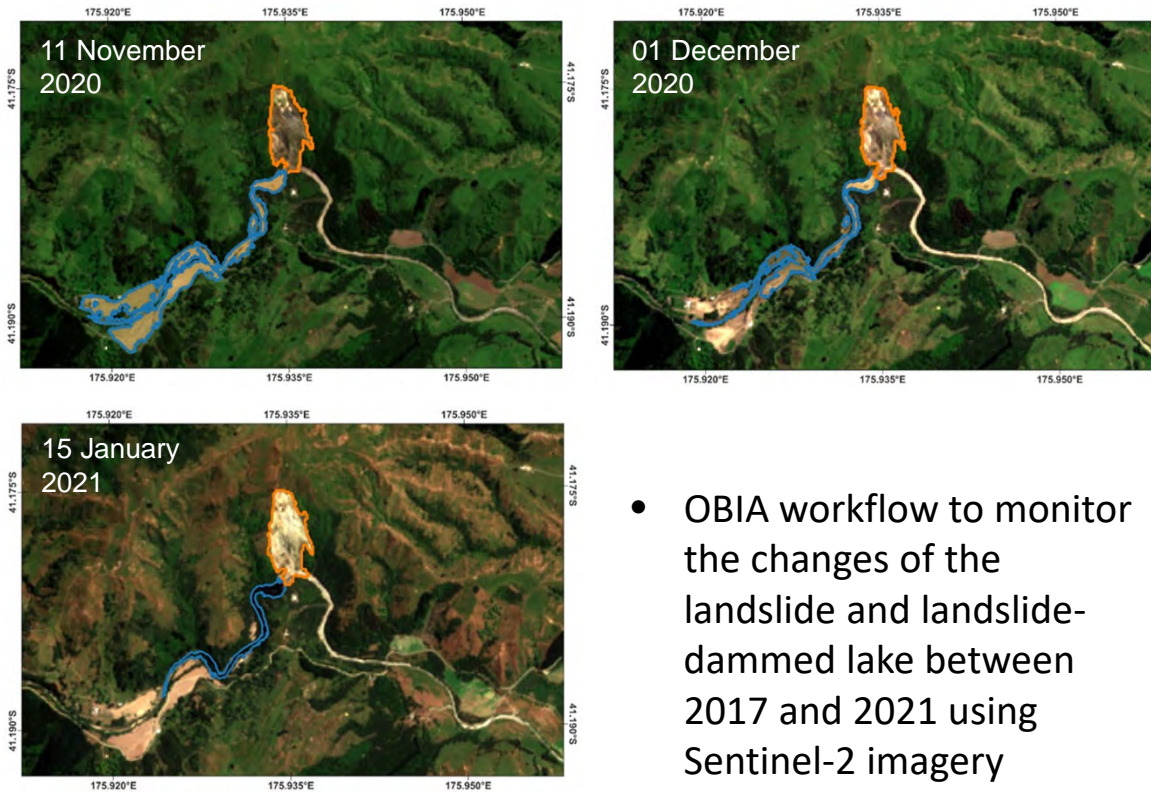


Dammed lakes are categorised into four groups based on their spatio-temporal evolution:

- 1) constant
- 2) increasing
- 3) decreasing
- 4) variant

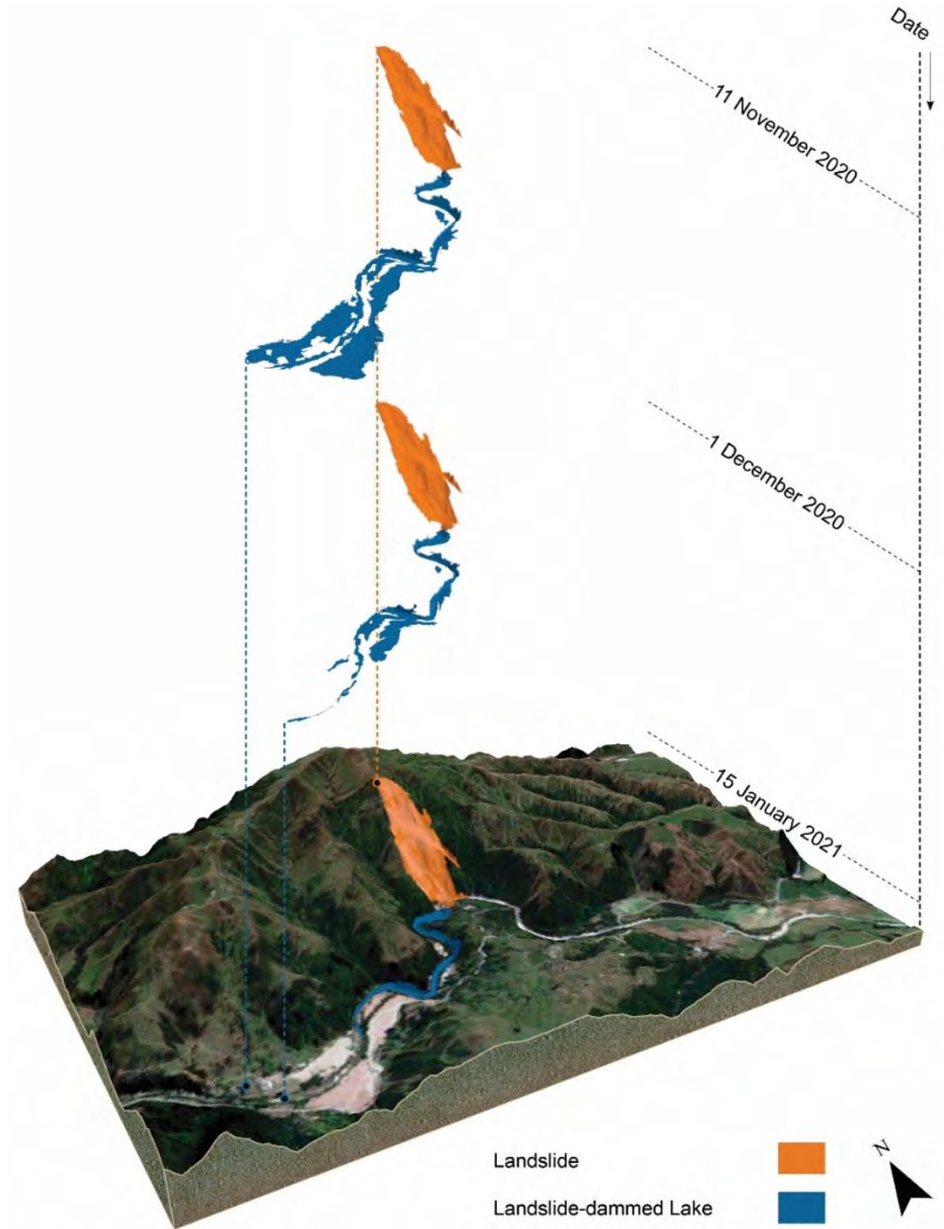
Abad, L., Höbbling, D., Spiekermann, R., Prasicek, G., Dabiri, Z., Argentin, A.-L., 2022. Detecting landslide-dammed lakes on Sentinel-2 imagery and monitoring their spatio-temporal evolution following the Kaikōura earthquake in New Zealand. *Science of The Total Environment*, 820, 153335. <https://doi.org/10.1016/j.scitotenv.2022.153335>

# Monitoring the evolution of the Kaiwhata landslide and landslide-dammed lake



- OBIA workflow to monitor the changes of the landslide and landslide-dammed lake between 2017 and 2021 using Sentinel-2 imagery
- Semi-automated knowledge-based OBIA approach

Pooladsaz, K., Hölbling, D., Brus, J., accepted. Monitoring the Evolution of the Kaiwhata Landslide in New Zealand using Object-based Image Analysis and Sentinel-2 Time Series. *GI\_Forum*.



# Conclusions

- Reliable analysis methods are needed to better understand the spatial and temporal occurrence of erosion features
  - Improved representation of erosion processes in catchment sediment budget models
  - Implement effective erosion mitigation measures
  - Support disaster risk reduction
- Remote sensing and advanced image analysis techniques provide remarkable opportunities for erosion feature mapping and monitoring
  - Integration of expert knowledge and modern data-driven methods
- International collaboration was very fruitful
  - Developed technologies and joint research contributed to an increased science understanding
  - Mutual benefit: exchange of knowledge, methods, and ideas; joint fieldwork; joint publications





Thank you for your  
attention!

## Contact:

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