

# Exploring knowledge-based and data-driven approaches to map earthflow and gully erosion features in New Zealand

**EGU 2022 | Session: NH6.3**

**Daniel Hölbling<sup>1</sup>, Lorena Abad<sup>1</sup>, Raphael Spiekermann<sup>2</sup>,  
Hugh Smith<sup>2</sup>, Andrew Neverman<sup>2</sup>, Harley Betts<sup>2</sup>**

<sup>1</sup>Department of Geoinformatics, University of Salzburg, 5020 Salzburg, Austria

<sup>2</sup>Manaaki Whenua – Landcare Research, Palmerston North 4472, New Zealand

**May 27, 2022 – 13:26**

Read the  
abstract here:



<https://meetingorganizer.copernicus.org/EGU22/EGU22-1093.html>

# Knowledge-based earthflow detection

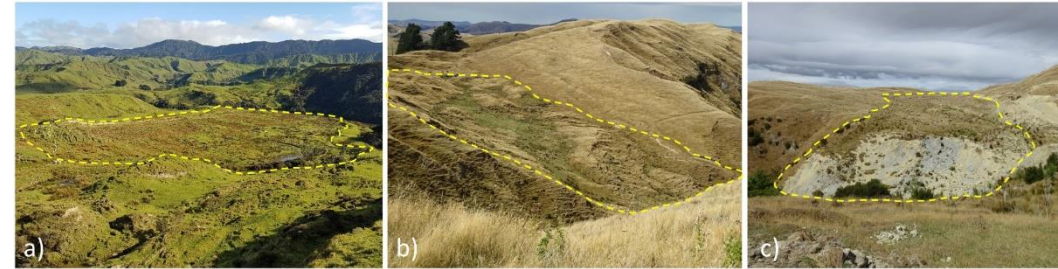
## 2. Concept and workflow definition

- Defining a workflow for semi-automated earthflow detection using object-based image analysis (OBIA)
- Identifying earthflow characteristics that can be derived from aerial photography and DSM data as input for the classification

Earthflow characteristics	Possible metric (descriptive stats)
<ul style="list-style-type: none"><li>Vegetation<ul style="list-style-type: none"><li>L1 - rules: red/brown, often large areas, attributed by moisture → dark background</li><li>L2 - pasture: potentially greener/darker than neighbouring terrain due to high moisture content (in summer months)</li></ul></li><li>L1 - Ponding: Surface water an indicator</li><li>L1 - Bare ground: Either at toe or headscarp tension cracks</li><li>L2 - Connected to streams at toe</li><li>L2 - Morphological<ul style="list-style-type: none"><li>Hummocky terrain</li><li>Mean slope ~10-25°</li><li>Existence of levees</li></ul></li></ul>	<ul style="list-style-type: none"><li>2016/17 imagery: NDVI, RGB, etc. GNDVI</li><li>Classify objects as predominantly pasture</li><li>Difference to neighbours</li><li>NDVI &lt; 0, colour darker than bare ground</li><li>NDVI &lt; ?, brightness</li><li>Proximity to riverlines (object distance &lt; 2)</li><li>Curvature, roughness (std DEM @ 5m / third DEM?)</li><li>Max-Min DEM normalised by slope length</li><li>Edge detection</li></ul>

## 1. Motivation

In New Zealand, earthflows and gullies are - next to shallow landslides - important erosion processes and sediment sources in hill country areas. Implementing effective erosion mitigation measures requires detailed information on the location, extent, and spatial distribution of these features.

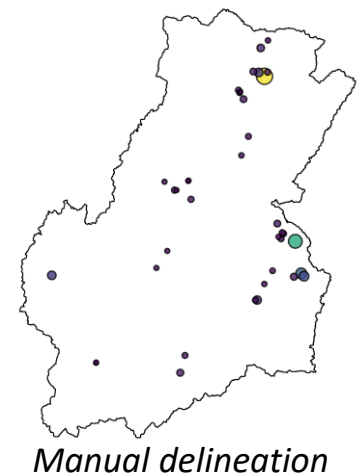
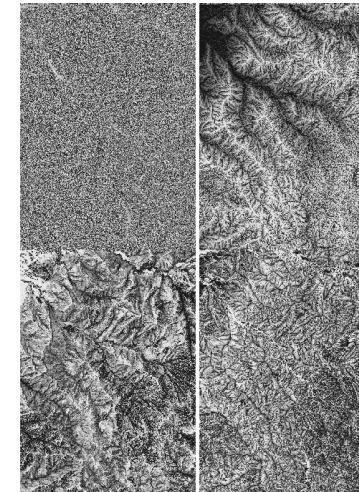


Earthflows in the Tiraumea catchment, North Island, New Zealand. Earthflows are indicated by the yellow dotted line (photographs: © Manaaki Whenua – Landcare Research (MWLR) (a), D. Hölbling (b, c)).

## 3. Data preparation

- 32 terrain derivatives were computed from the LiDAR DSM
- Manual delineation of reference polygons and calculation of statistics for the terrain derivatives → supports the threshold selection in OBIA

Tiraumea study area (subset)



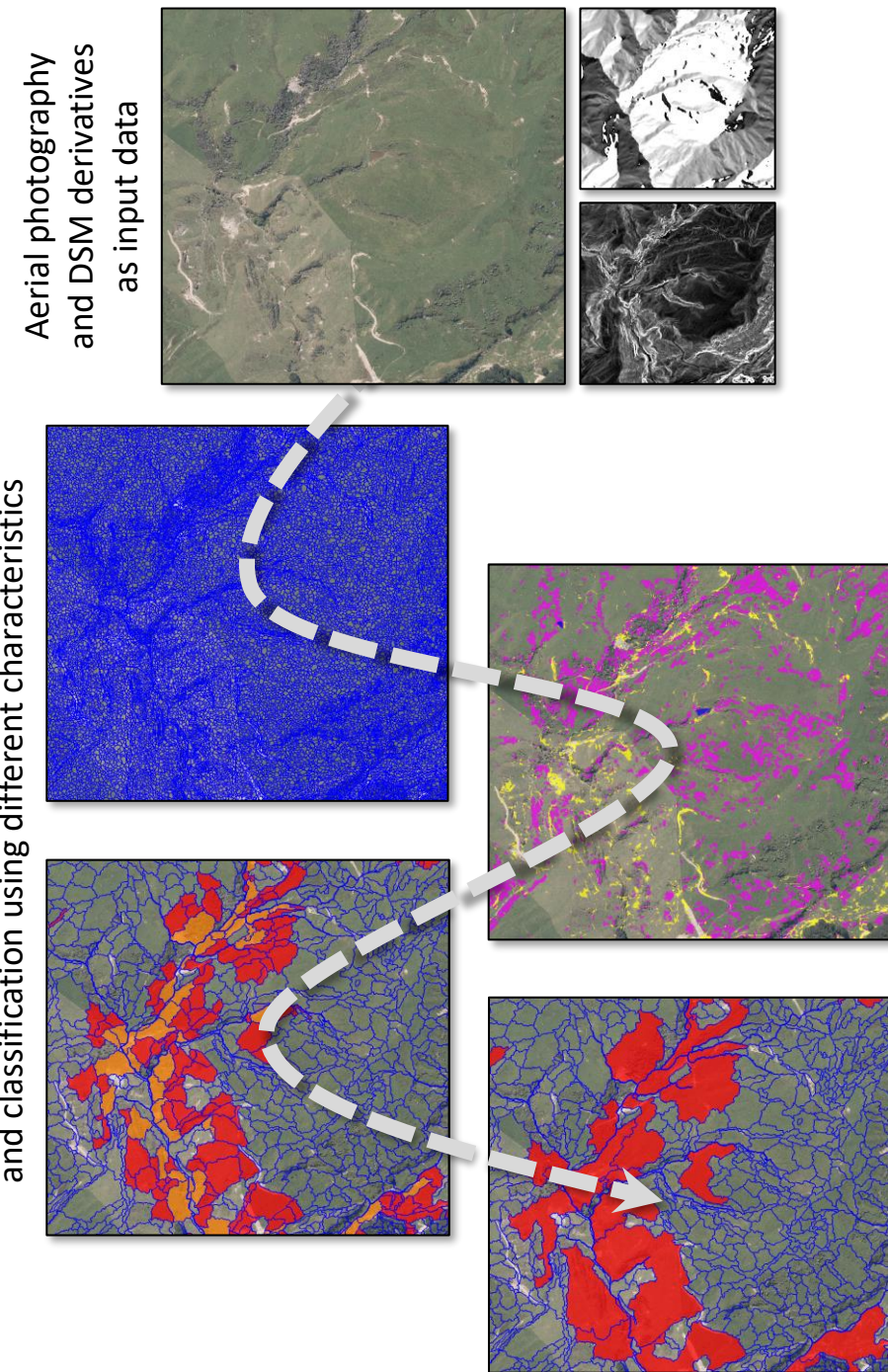
Manual delineation

# OBIA earthflow mapping

- Creation of a knowledge-based earthflow detection ruleset using the eCognition software
- Identification of potential earthflow locations based on spectral, spatial, morphological, contextual and hierarchical characteristics
  - Calculation of additional layers based on the aerial photography, e.g. NDVI, NDWI, brightness
  - Detection of bare ground, rushes and water on a fine segmentation level
  - Classification of potential earthflows on a coarser segmentation level if objects contain bare ground, rushes and water on the finer level and based on various image object characteristics
  - Merging potential earthflow objects
  - Removing false positives based on DSM derivatives
- Comparison to manual mapping & field validation



Flexible OBIA workflow based on segmentation and classification using different characteristics



# Data-driven gully mapping with deep learning

## 1. Aim

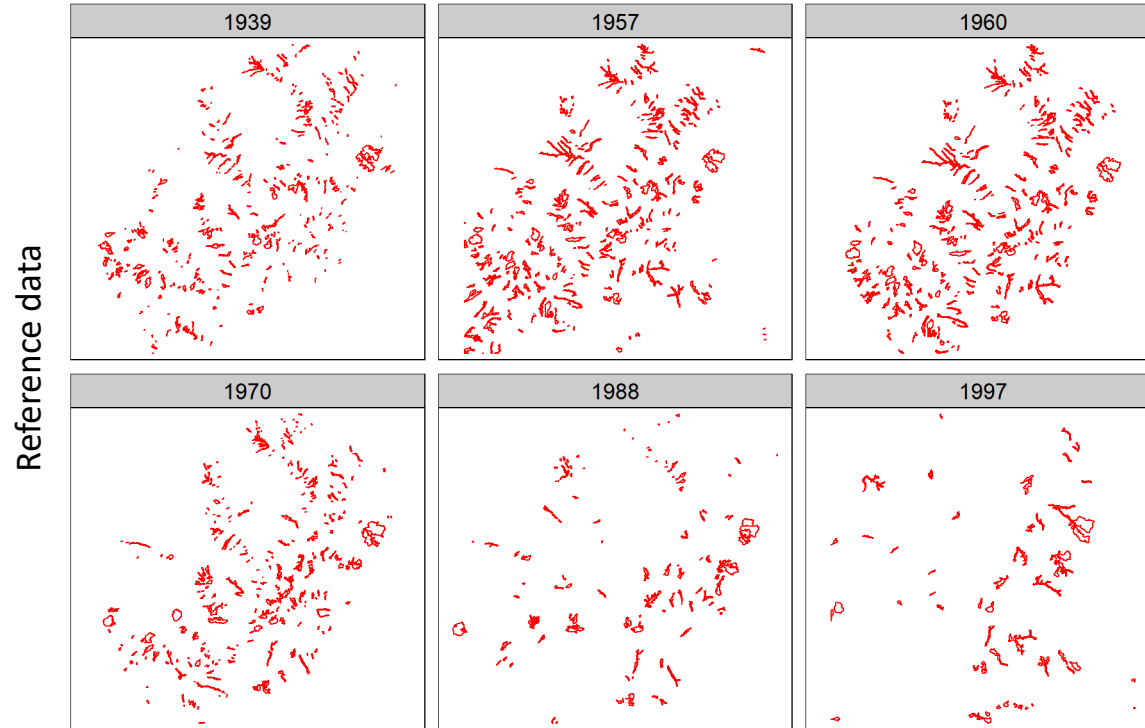
Train a deep learning model to identify and map gully erosion in the Mangatu catchment in New Zealand.



Mangatu study area

## 2. Data

- Reference data: outlines of **erosion features**, in particular active gullies, available from **1939 to 1997** for 6 different years
- Chip generation is done by the combination of **terrain derivatives** calculated from a LiDAR DEM



Reference data

Terrain derivatives



LS Factor

Hillshade

Terrain  
Ruggedness  
Index

## 3. Methodology

- Workflow tested with ArcGIS Pro, where a **Mask RCNN model** was trained
- Possibility to create RGB chips with a combination of **three bands**
- Model was trained with 20 epochs and a ResNet50 backbone model

Export Training Data for Deep Learning

Train Deep Learning Model

Detect Objects Using Deep Learning

### Chip characteristics:

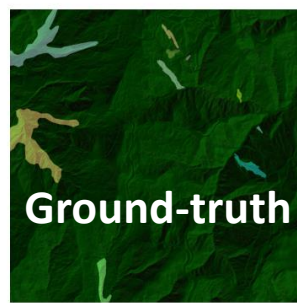
Chip size: 2048x2048

No. of chips: 604

Gully features: 8977

Gully features/image: 15 (mean)

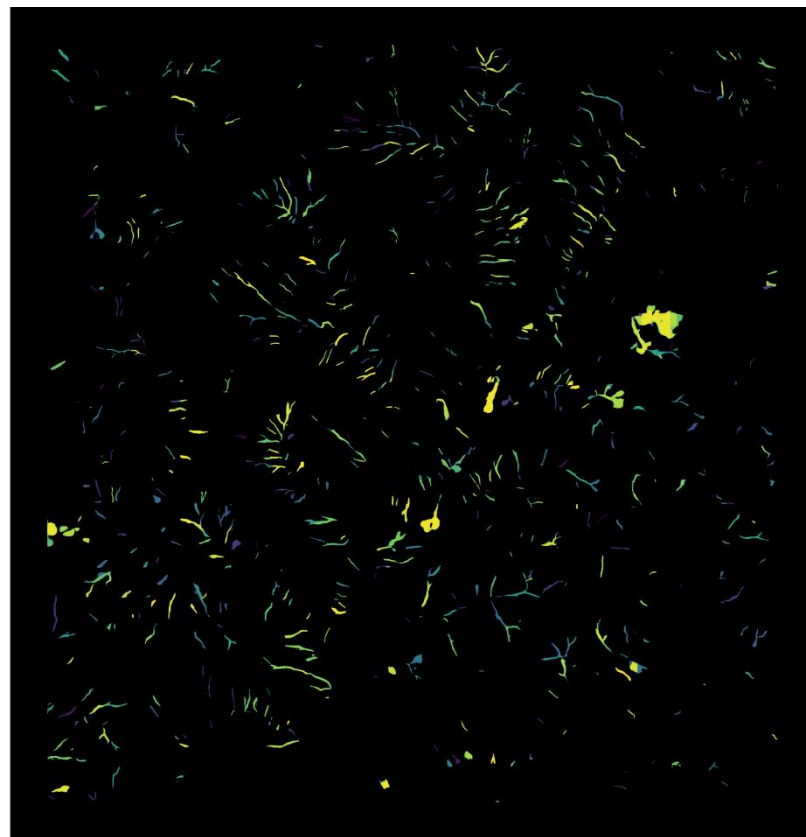
# Detected gully features - validation



60%  
overlap

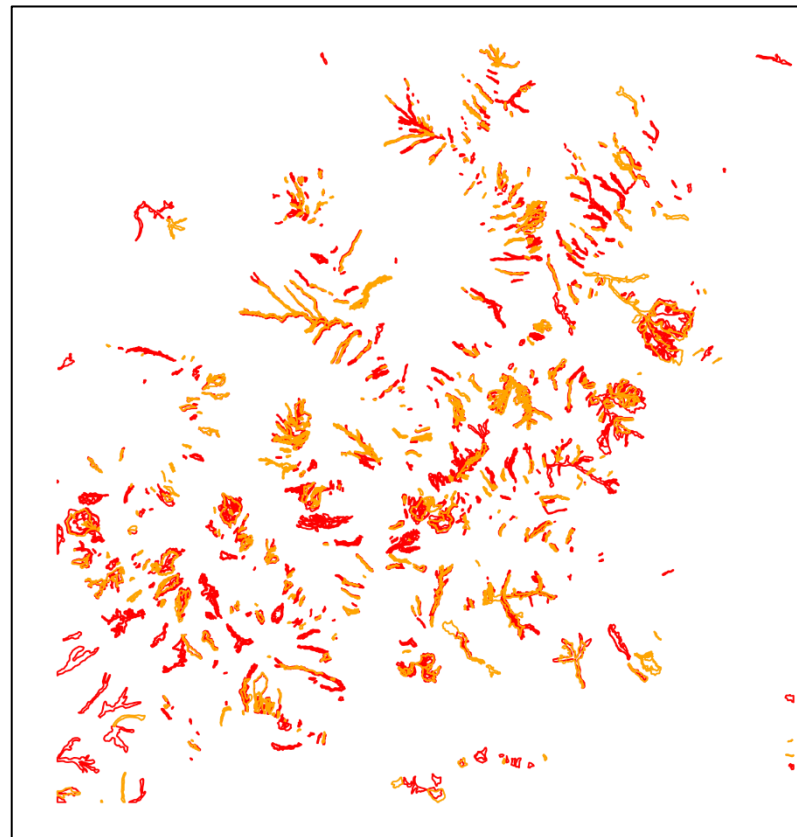
## Mapping results

Indicating the detection confidence level

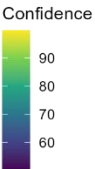
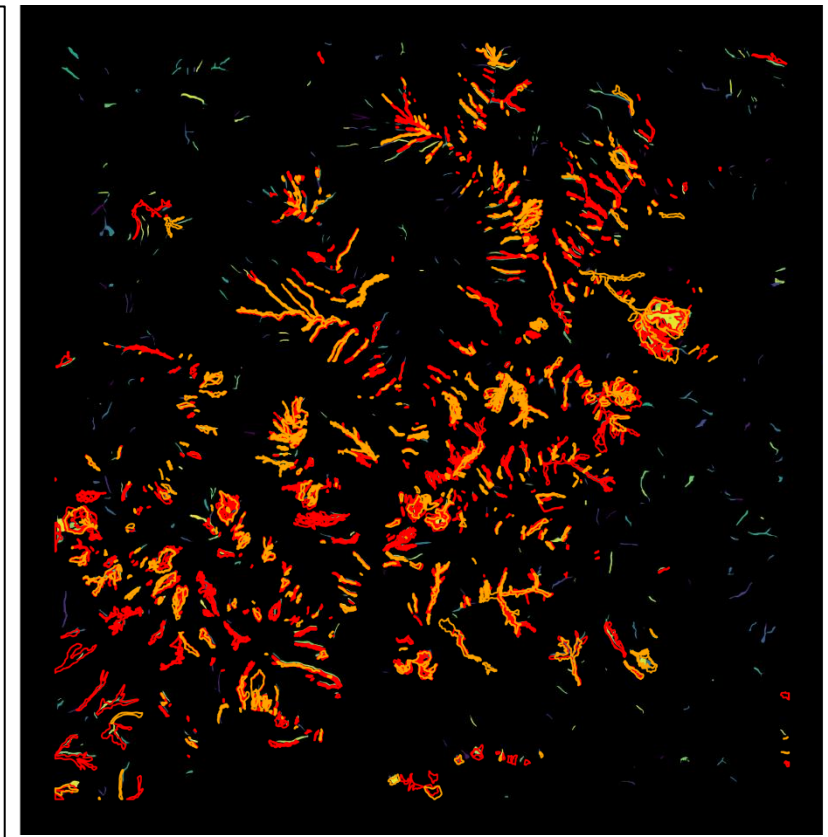


## Reference features

Training in red and testing in orange



303/505 gully features from the test set  
intersect with the resulting gully features



# Discussion & Conclusion

- Semi-automated earthflow detection is **very challenging**
- Earthflows are complex and there is a **lack of distinct characteristics** to differentiate them from other features
- Gully detection shows **more promising** results, despite the **time mismatch** between reference and training data
- **Testing** the model in a **neighboring catchment** will help evaluate the model performance better
- Overall, **reliable and targeted analysis methods** are needed to better understand the spatial occurrence of earthflows and gullies
- This will enable **improved representation** of these erosion processes in catchment sediment budget models


## Acknowledgements

This work is supported by the New Zealand Ministry of Business, Innovation and Employment through the project STEC (Cost-effective targeting of erosion control to protect soil and water values; contract no. 1819-38-010 J).


## Contact


Risk, Hazard and Climate Lab

 <https://plus.ac.at/risk-hazard-climate>

 [@riskhazclimlab](https://twitter.com/riskhazclimlab)

Lorena Abad

 [lorena.abad@plus.ac.at](mailto:lorena.abad@plus.ac.at)

 [@loreabad6](https://twitter.com/loreabad6)

Daniel Hölbling

 [daniel.hoelbling@plus.ac.at](mailto:daniel.hoelbling@plus.ac.at)