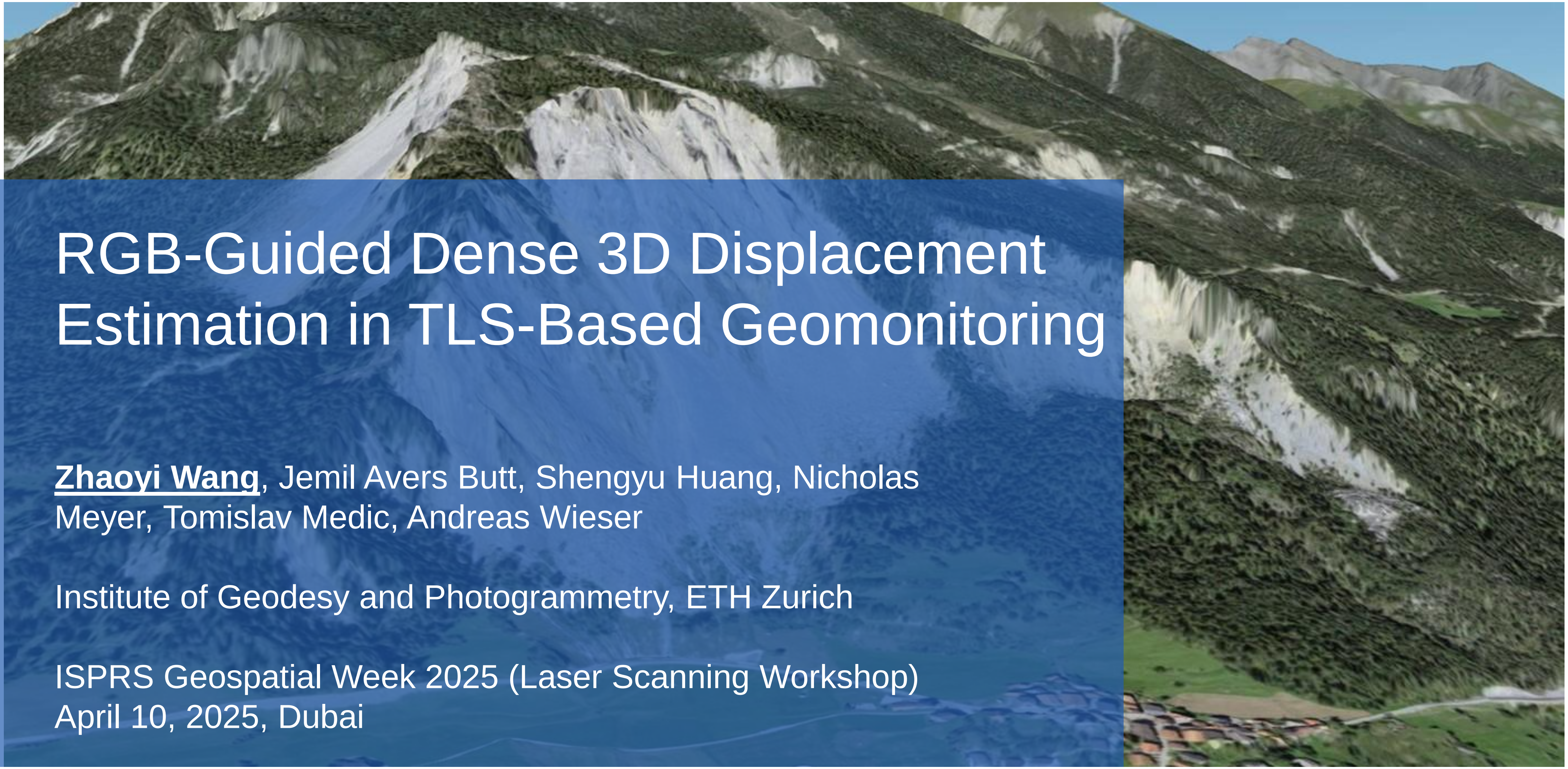
Geosensors and Engineering Geodesy (GSEG)
Institute of Geodesy and Photogrammetry (IGP)



RGB-Guided Dense 3D Displacement Estimation in TLS-Based Geomonitoring

Zhaoyi Wang, Jemil Avers Butt, Shengyu Huang, Nicholas Meyer, Tomislav Medic, Andreas Wieser

Institute of Geodesy and Photogrammetry, ETH Zurich

ISPRS Geospatial Week 2025 (Laser Scanning Workshop)
April 10, 2025, Dubai

Introduction

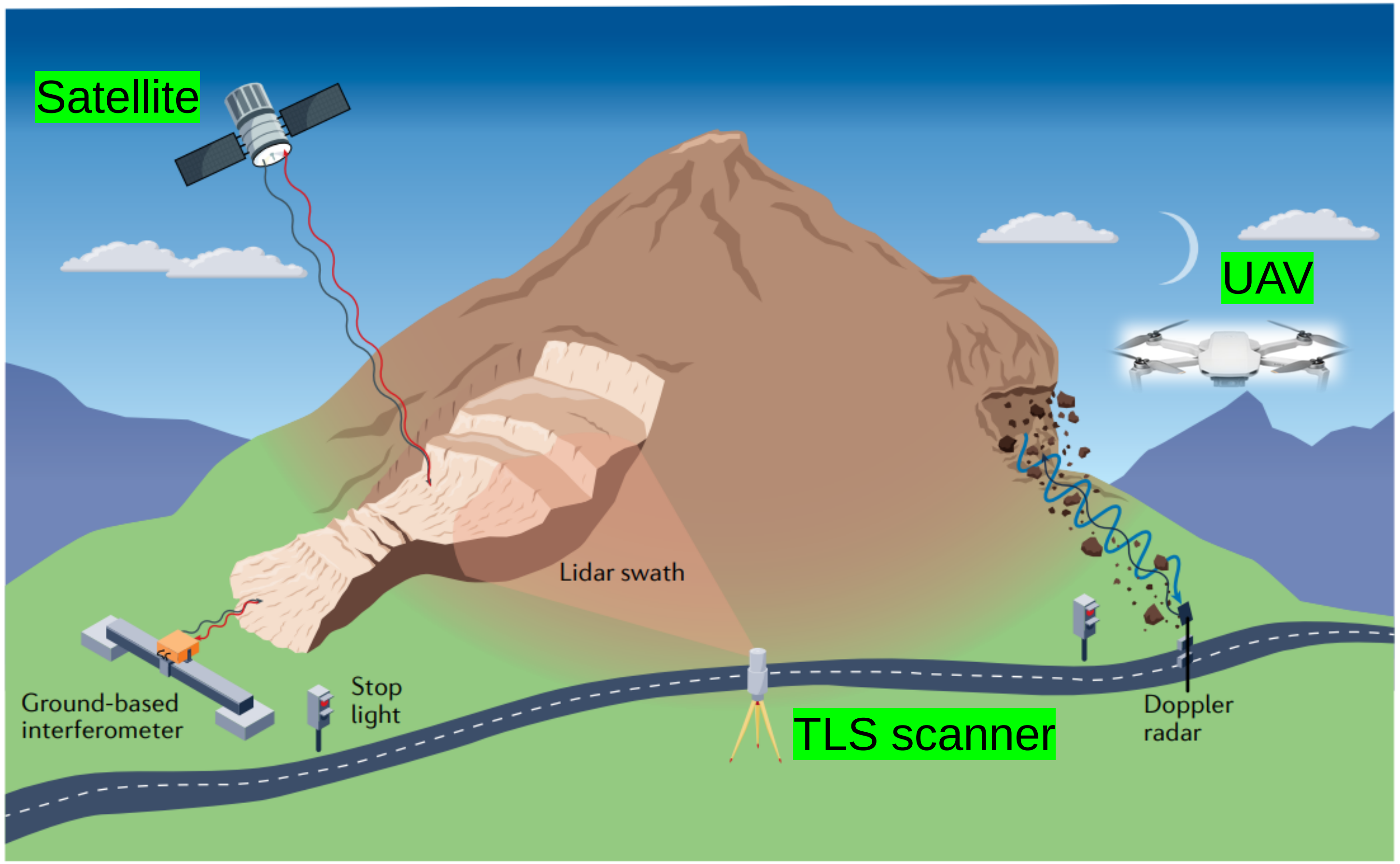


image source[1]

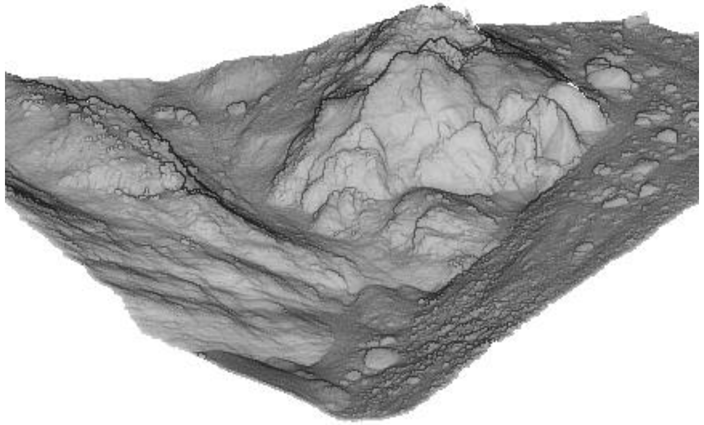
TLS scanner can provide dense 3D point clouds with high spatial resolution and measurement accuracy

1. Casagli et al. (2023). Landslide detection, monitoring and prediction with remote-sensing techniques. Nature Reviews Earth & Environment, 4(1), 51-64.

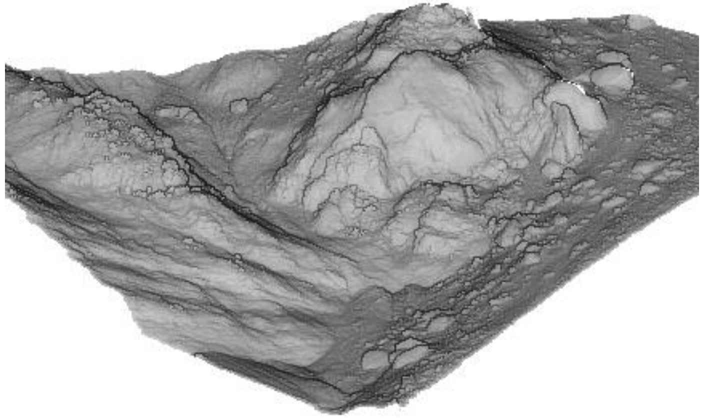
Motivation

TLS Point clouds

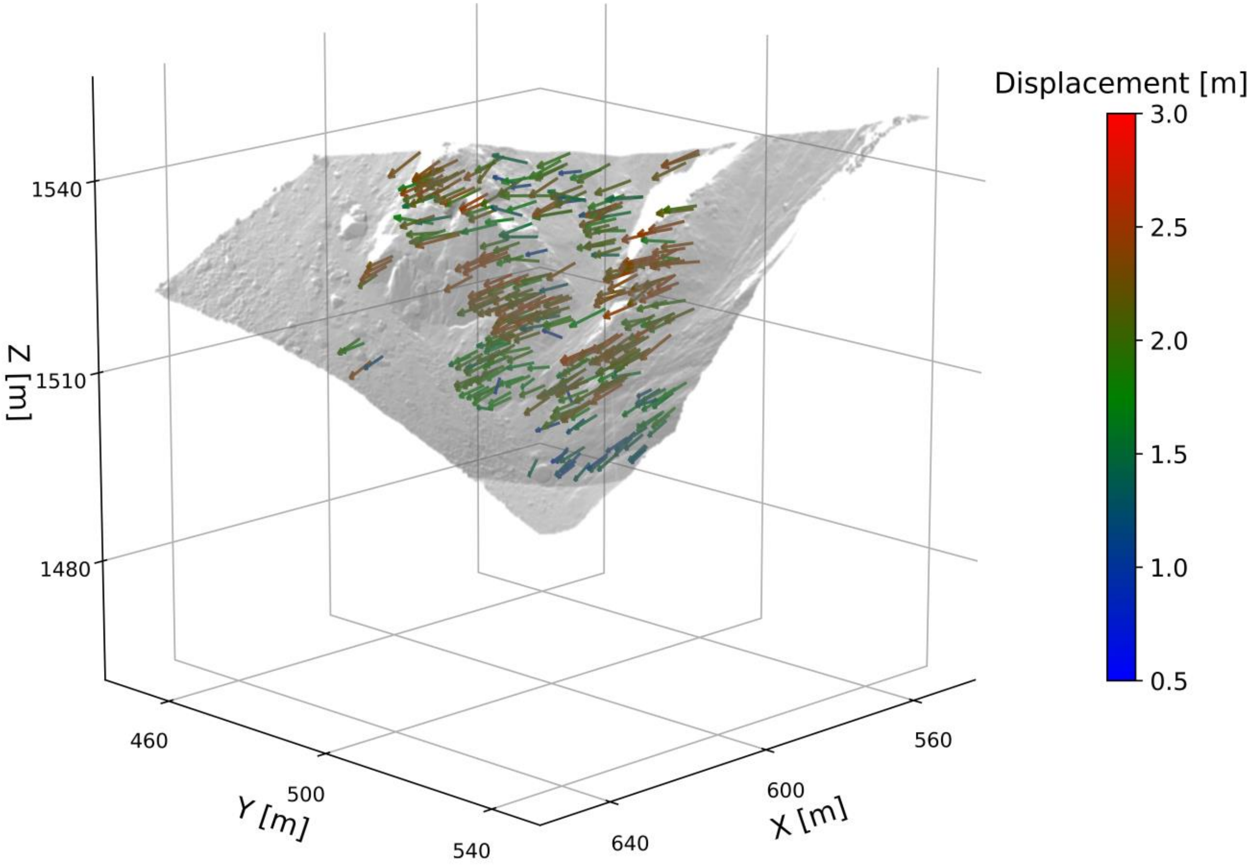
Epoch 1



Epoch 2



Estimated 3D displacement vectors (0.05%)

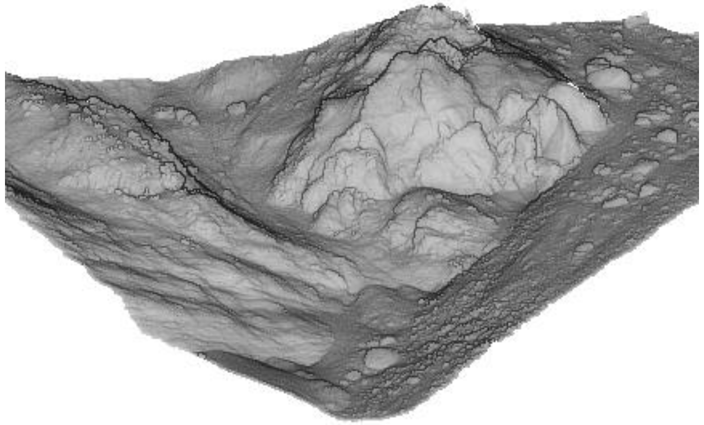


Motivation

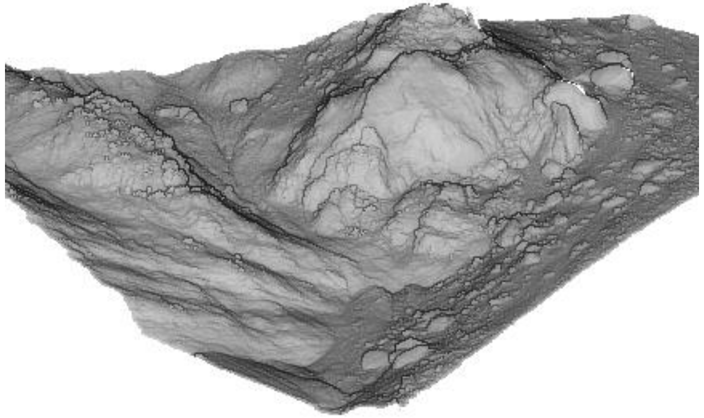
TLS Point clouds

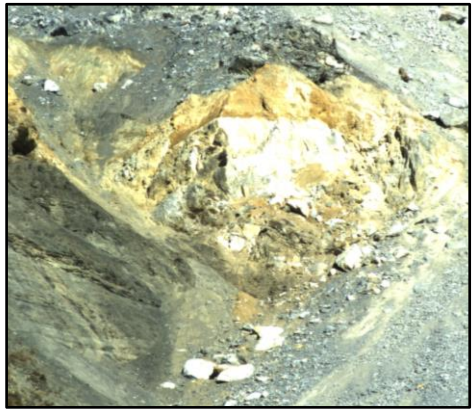
RGB images

Epoch 1



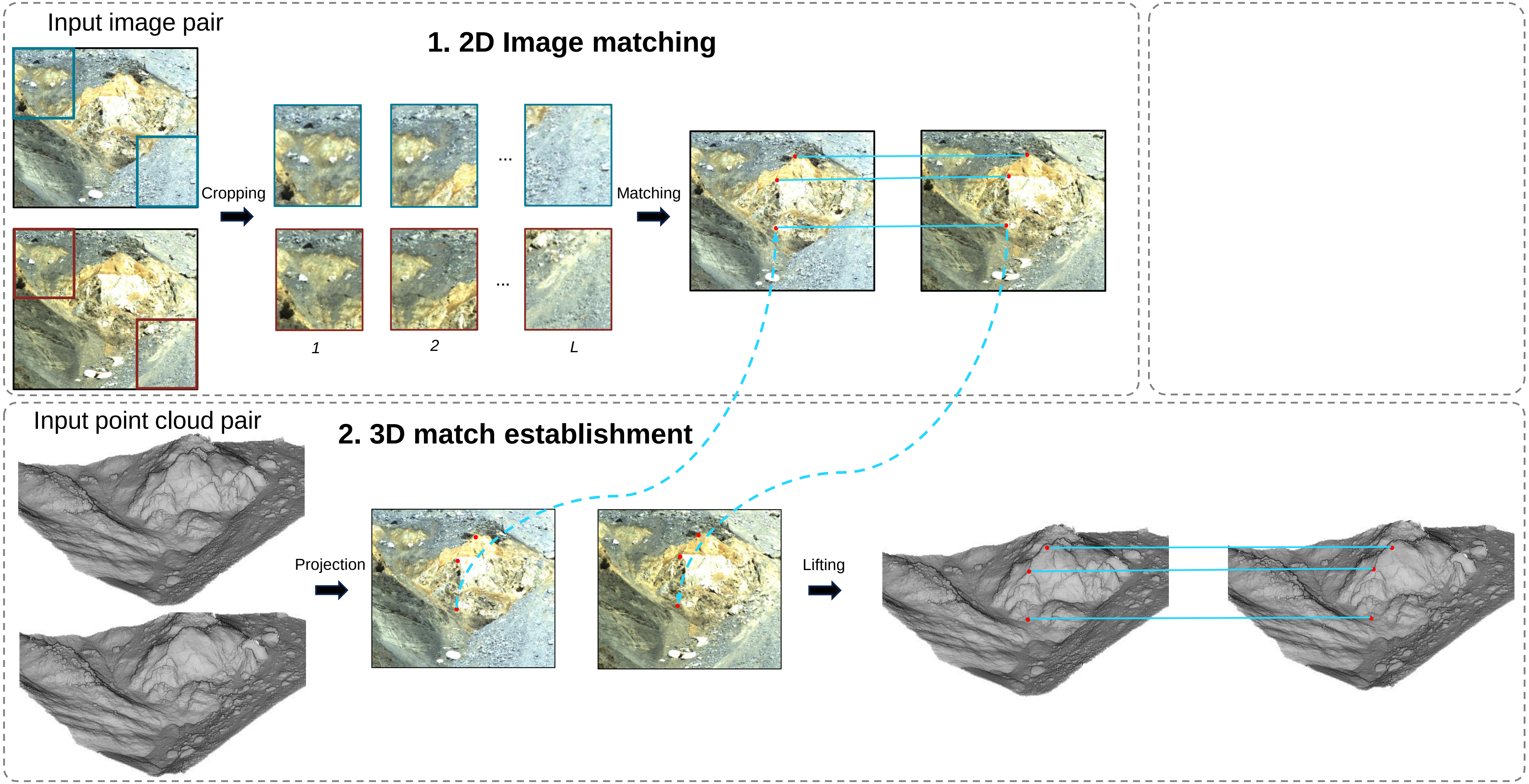
Epoch 2





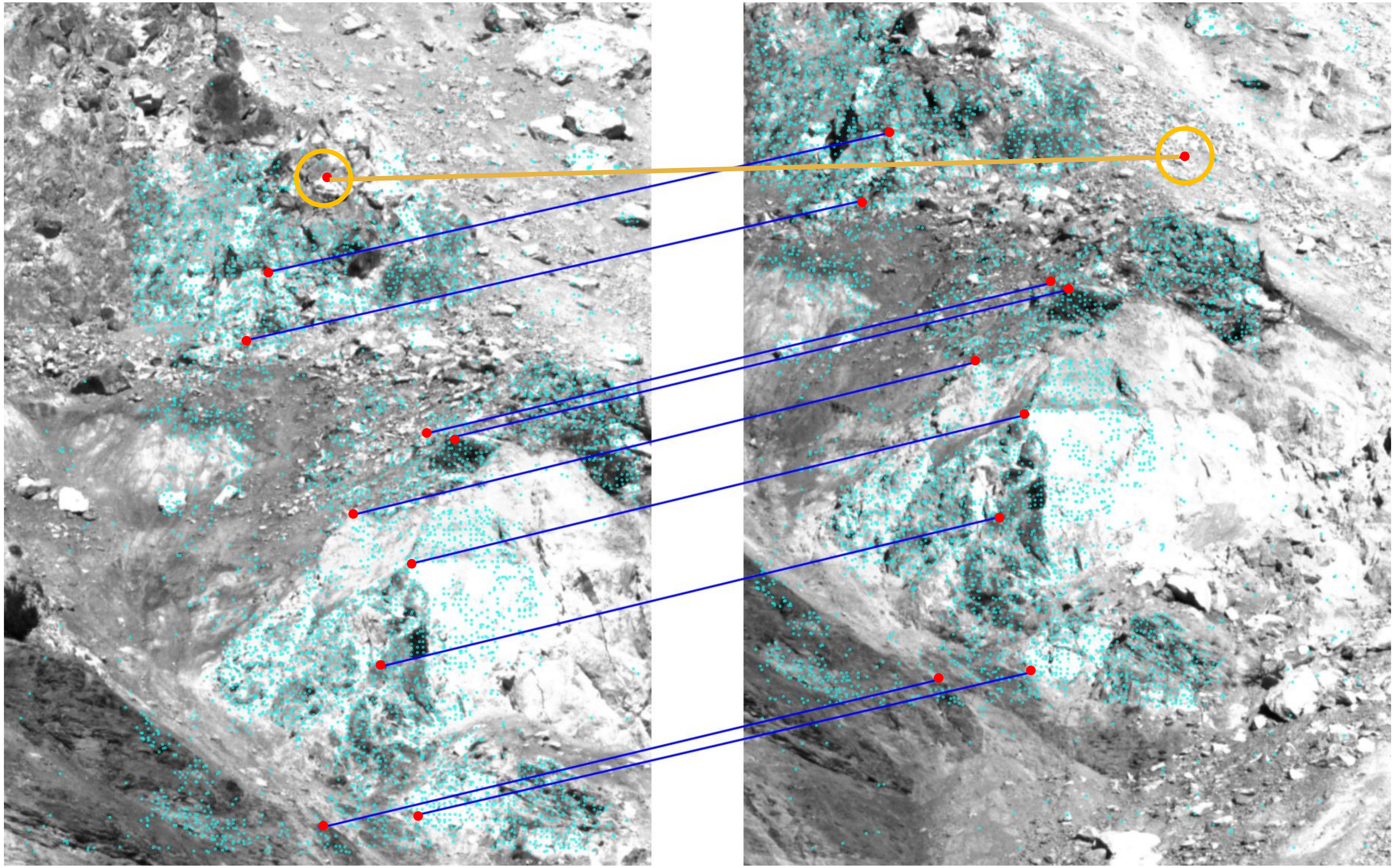
Can we estimate 3D displacements by using the RGB images?

Method Overview



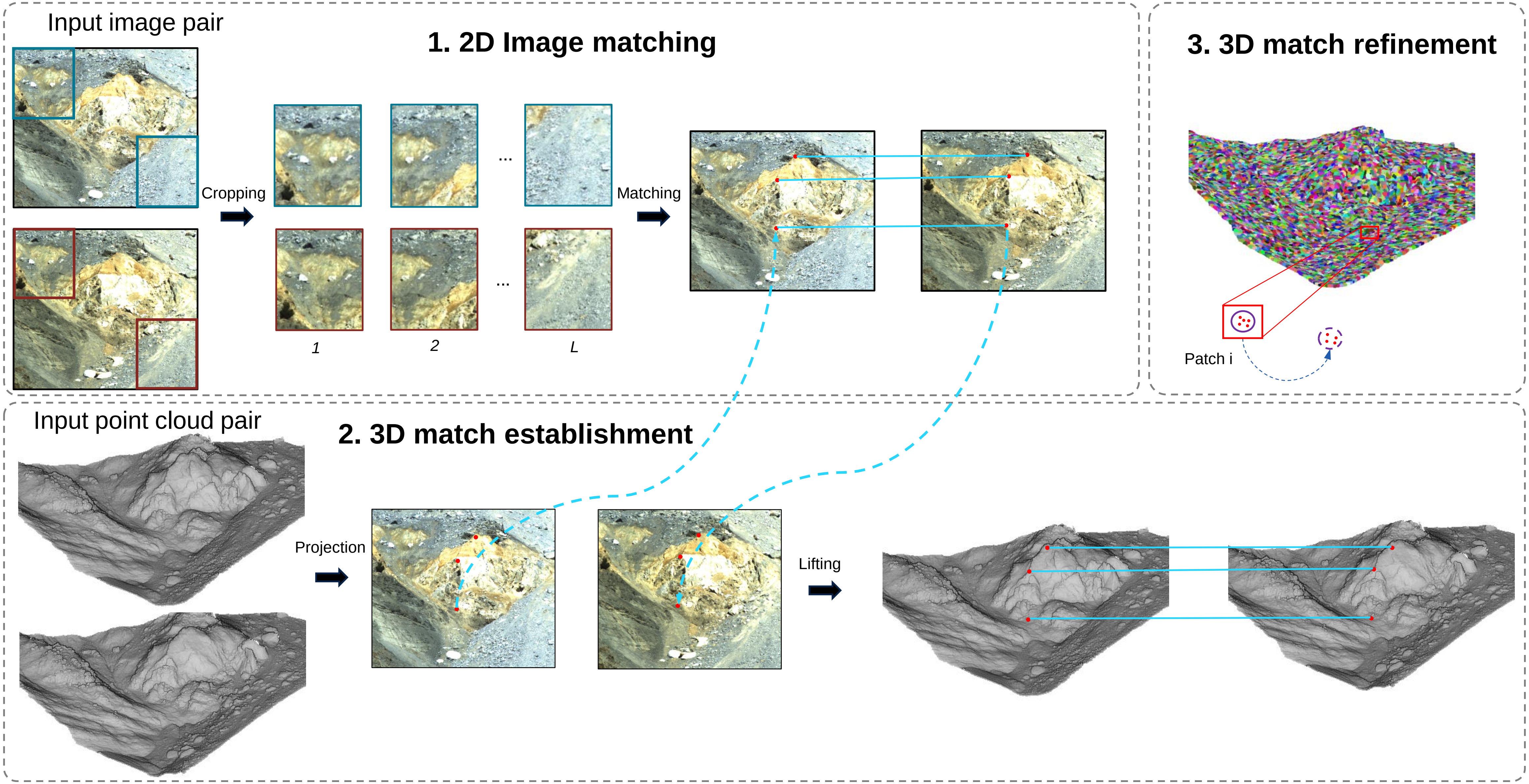
1. Wang, Y., He, X., Peng, S., Tan, D., & Zhou, X. (2024). **Efficient LoFTR**: Semi-dense local feature matching with sparse-like speed. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition (pp. 21666-21675).
2. Lin, Y., Wang, C., Zhai, D., Li, W., & Li, J. (2018). Toward better boundary preserved **supervoxel segmentation** for 3D point clouds. ISPRS journal of photogrammetry and remote sensing, 143, 39-47.

Image Matching



1. Wang, Y., He, X., Peng, S., Tan, D., & Zhou, X. (2024). **Efficient LoFTR**: Semi-dense local feature matching with sparse-like speed. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition (pp. 21666-21675).

Method Overview



1. Wang, Y., He, X., Peng, S., Tan, D., & Zhou, X. (2024). **Efficient LoFTR**: Semi-dense local feature matching with sparse-like speed. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition (pp. 21666-21675).
2. Lin, Y., Wang, C., Zhai, D., Li, W., & Li, J. (2018). Toward better boundary preserved **supervoxel segmentation** for 3D point clouds. ISPRS journal of photogrammetry and remote sensing, 143, 39-47.

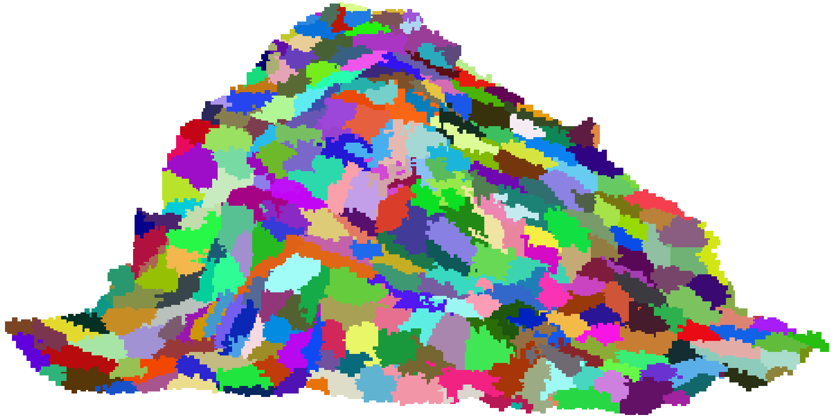
3D Match Refinement

Assumption: as-rigid-as-possible, i.e., movement in a small area is assumed as rigid

- If the patch size is
  - too small --> it includes mainly noise
  - too large --> it breaks the object boundaries

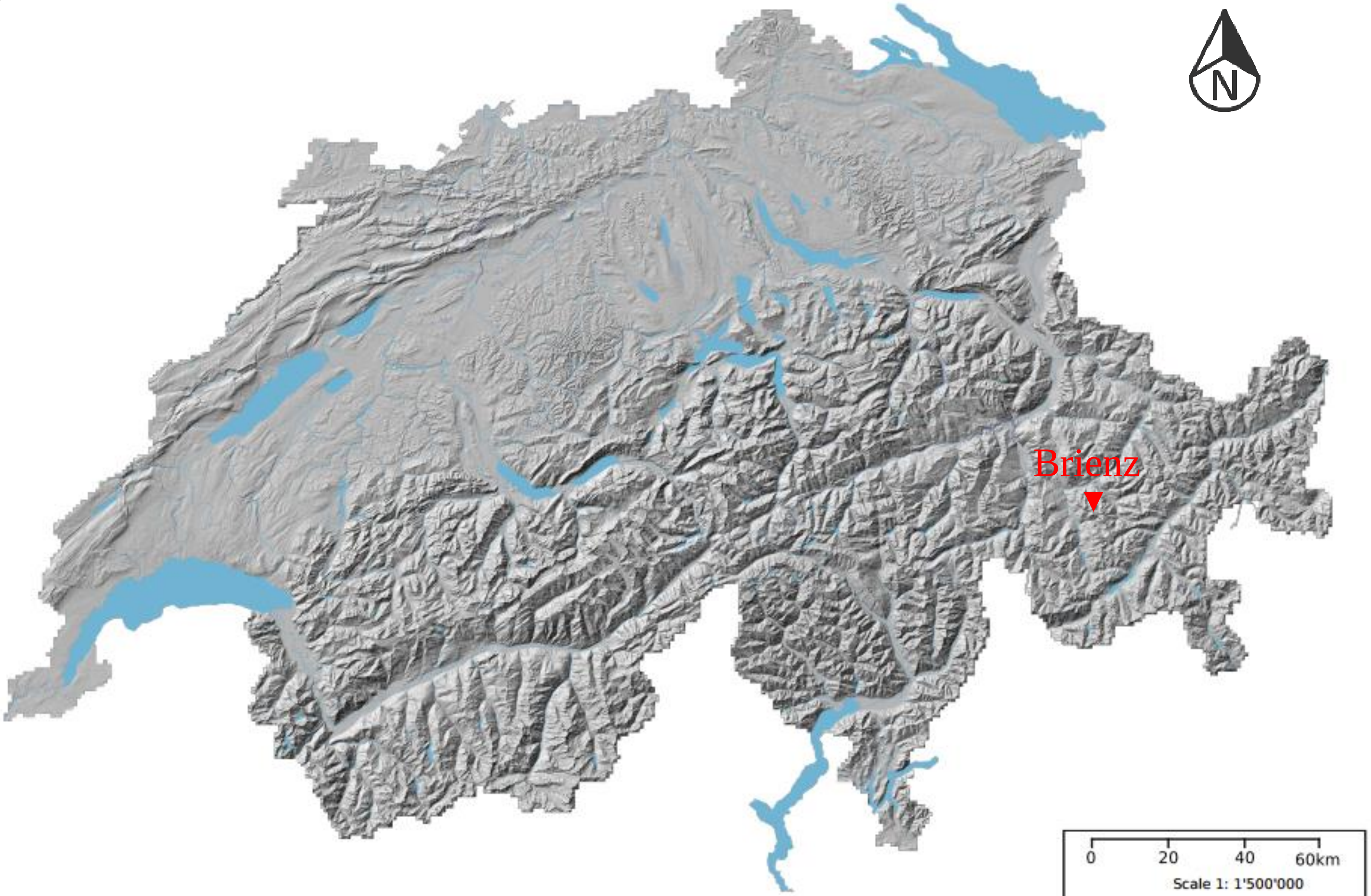
Colored point cloud

Clustering result[1]



1. Lin, Y., Wang, C., Zhai, D., Li, W., & Li, J. (2018). Toward better boundary preserved **supervoxel segmentation** for 3D point clouds. ISPRS journal of photogrammetry and remote sensing, 143, 39-47.

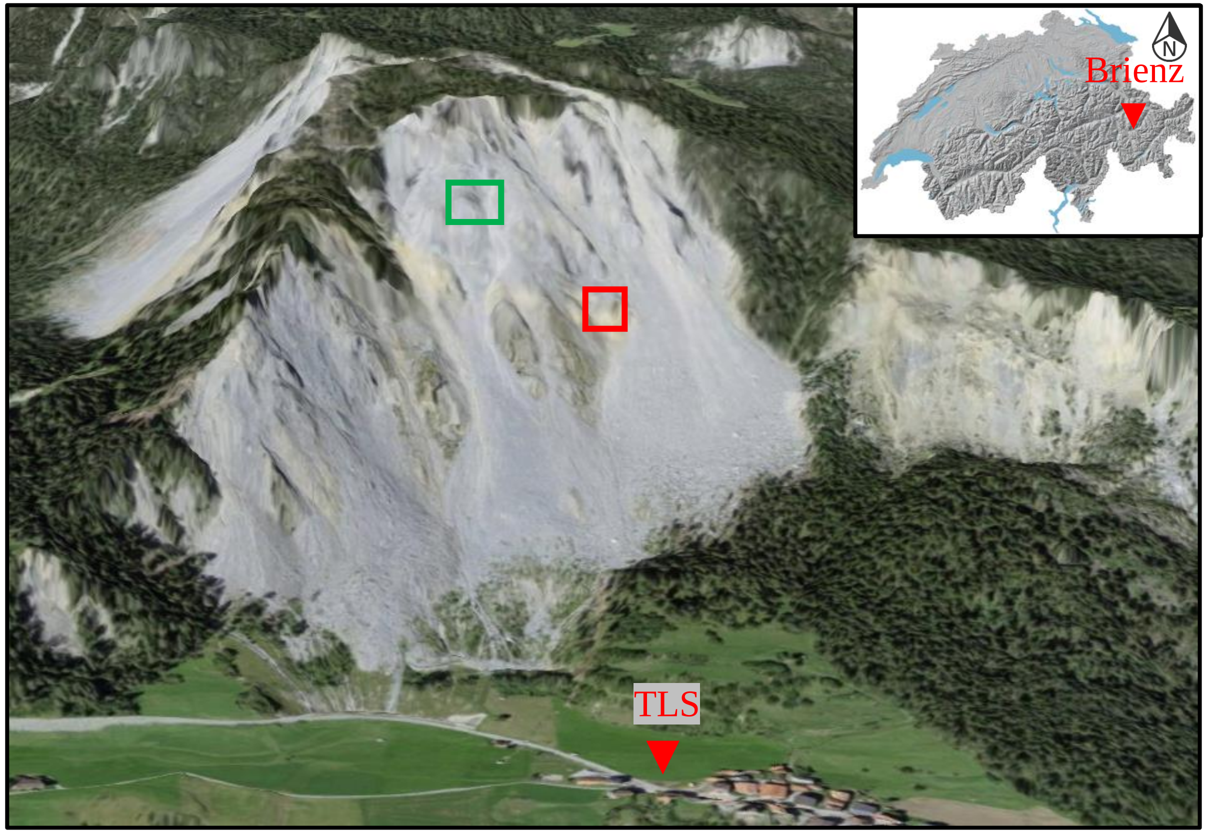
Study Case



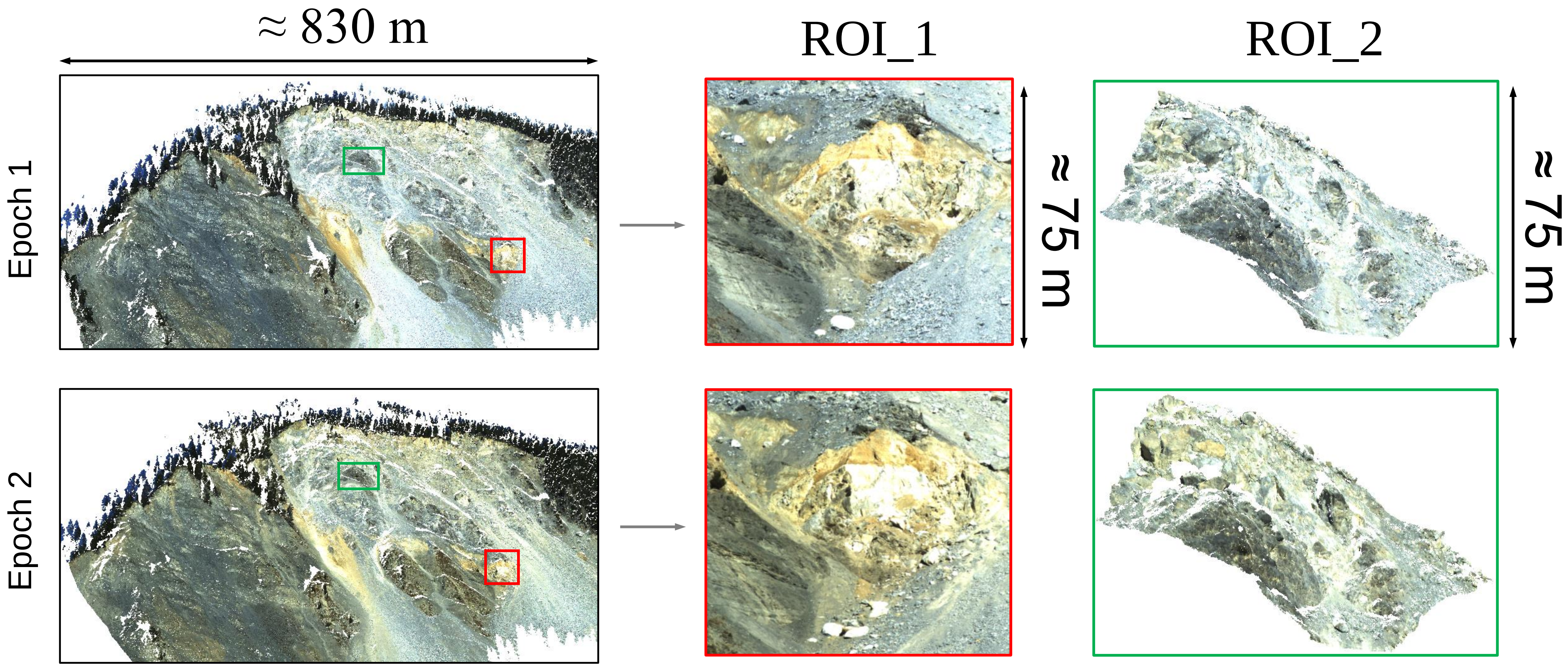
Study Case

Real-world landslide in Brienz village, Switzerland

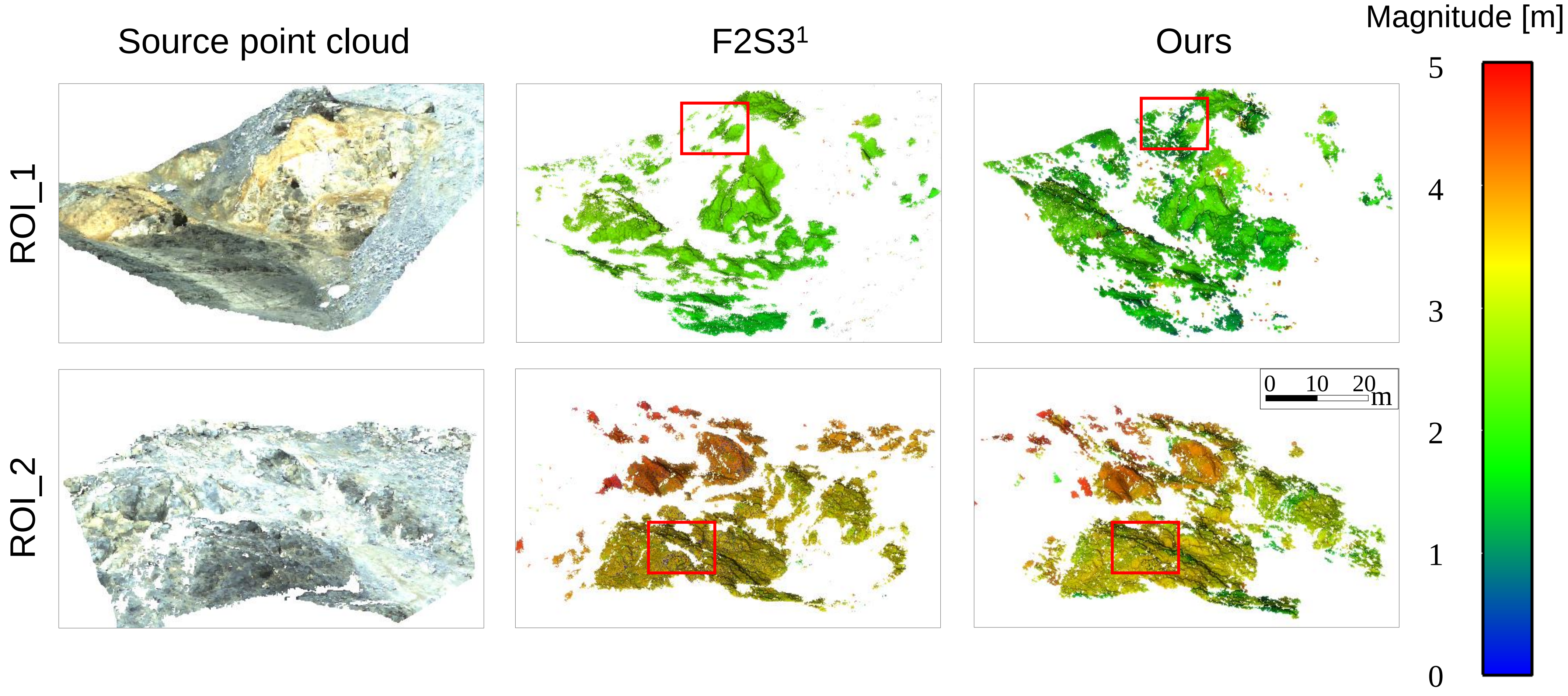
- Displacement type:
  - active slope movements (several meters per year)
- Data acquisition:
  - measurement campaign: Feb. and Nov. of 2020
  - Riegl VZ-6000, approx. 0.08 m at 1.5 km
  - built-in calibrated cameras, 0.05 m/pixel GSD



ROIs

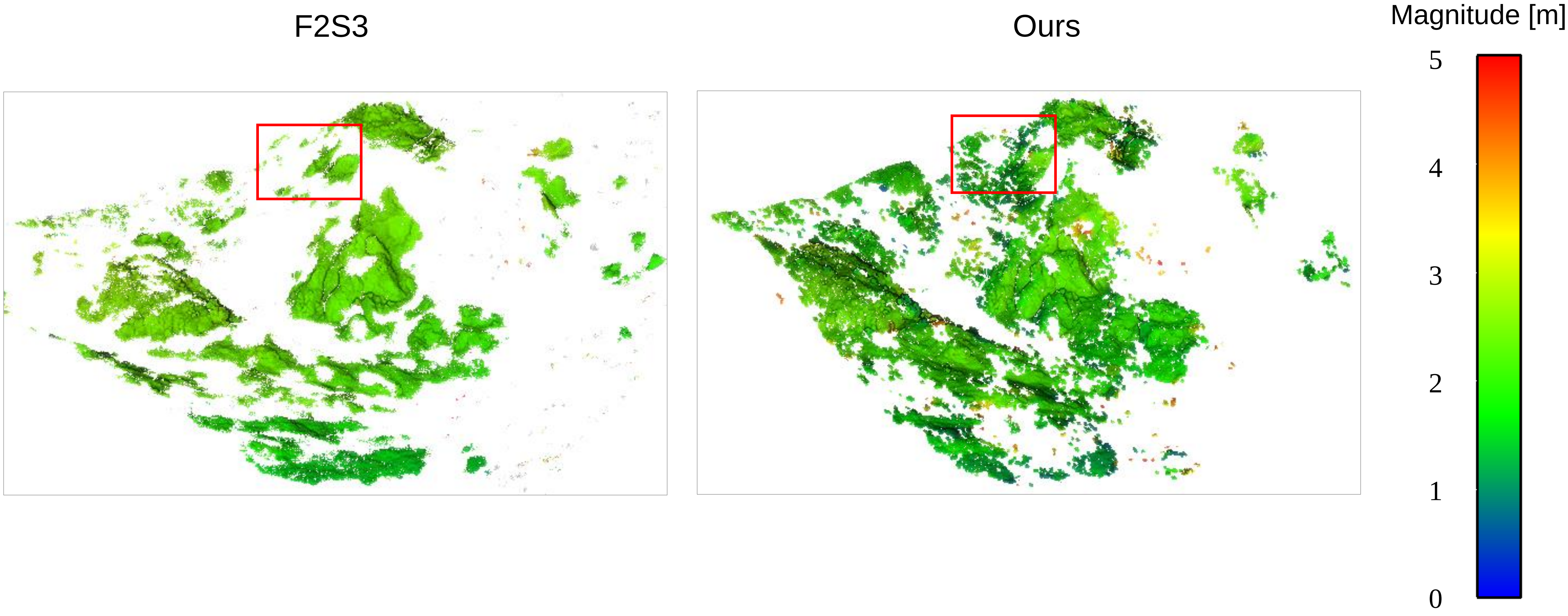


Qualitative Results



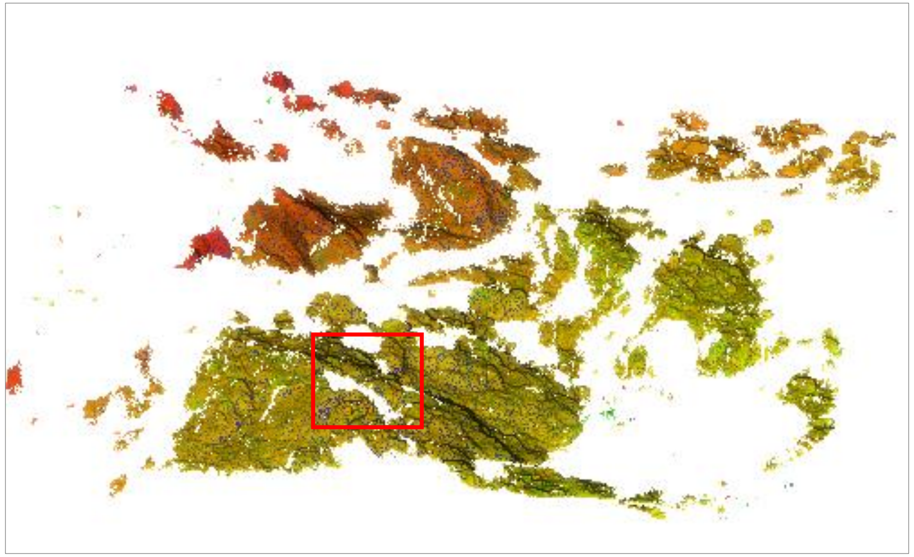
1. Gojcic, Z., Schmid, L., & Wieser, A. (2021). Dense 3D displacement vector fields for point cloud-based landslide monitoring. Landslides, 18, 3821-3832.

Qualitative Results



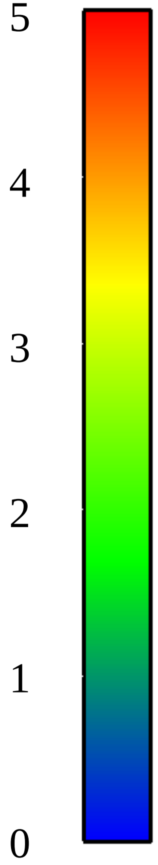
Qualitative Results

F2S3



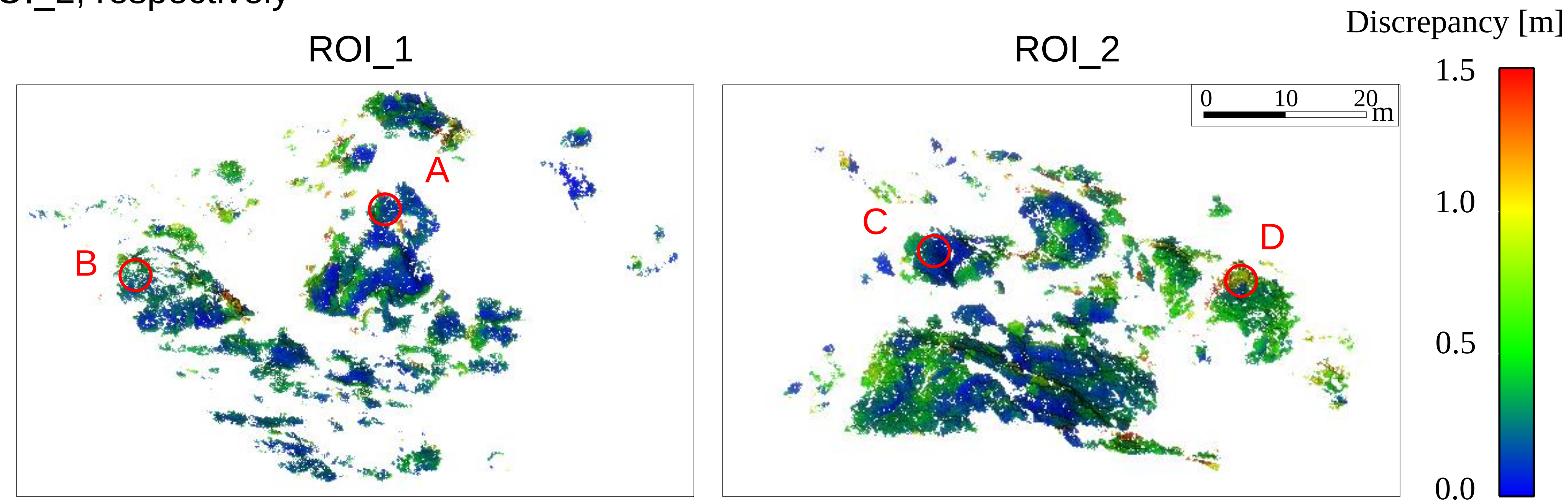
Ours

Magnitude [m]



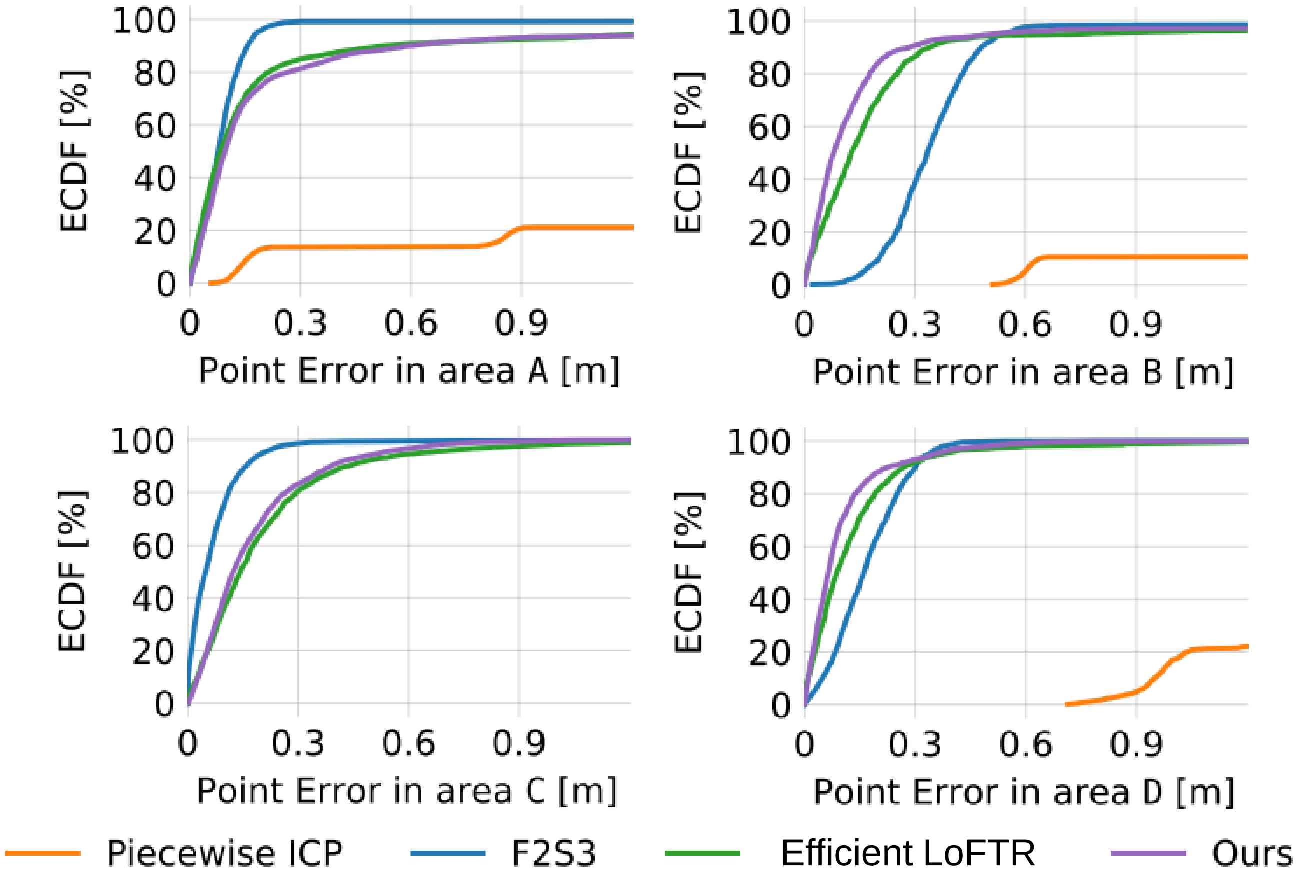
Qualitative Results

- The average discrepancies between F2S3 and our method are 0.32 m and 0.36 m on ROI_1 and ROI_2, respectively



Quantitative Results

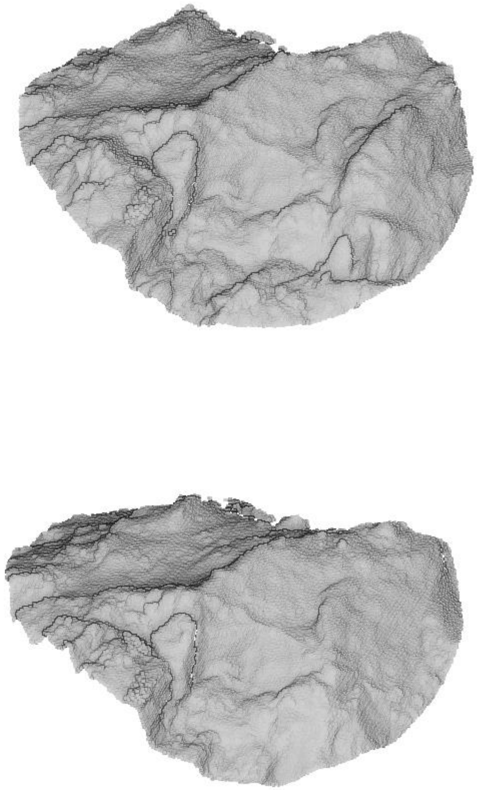
- The dense point errors reflect the overall distribution of displacements in these selected areas



Discussion: Geometry vs. RGB information

- Areas (e.g., area A) where RGB information is weak

Point clouds



RGB images

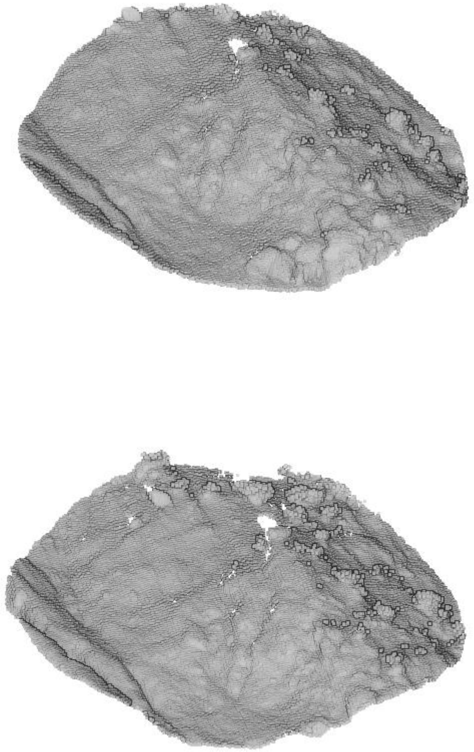
Table 1 Feature richness

Geometry	RGB
0.143	0.108

Discussion: Geometry vs. RGB information

- Areas (e.g., area B) where geometric structure is planar

Point clouds



RGB images

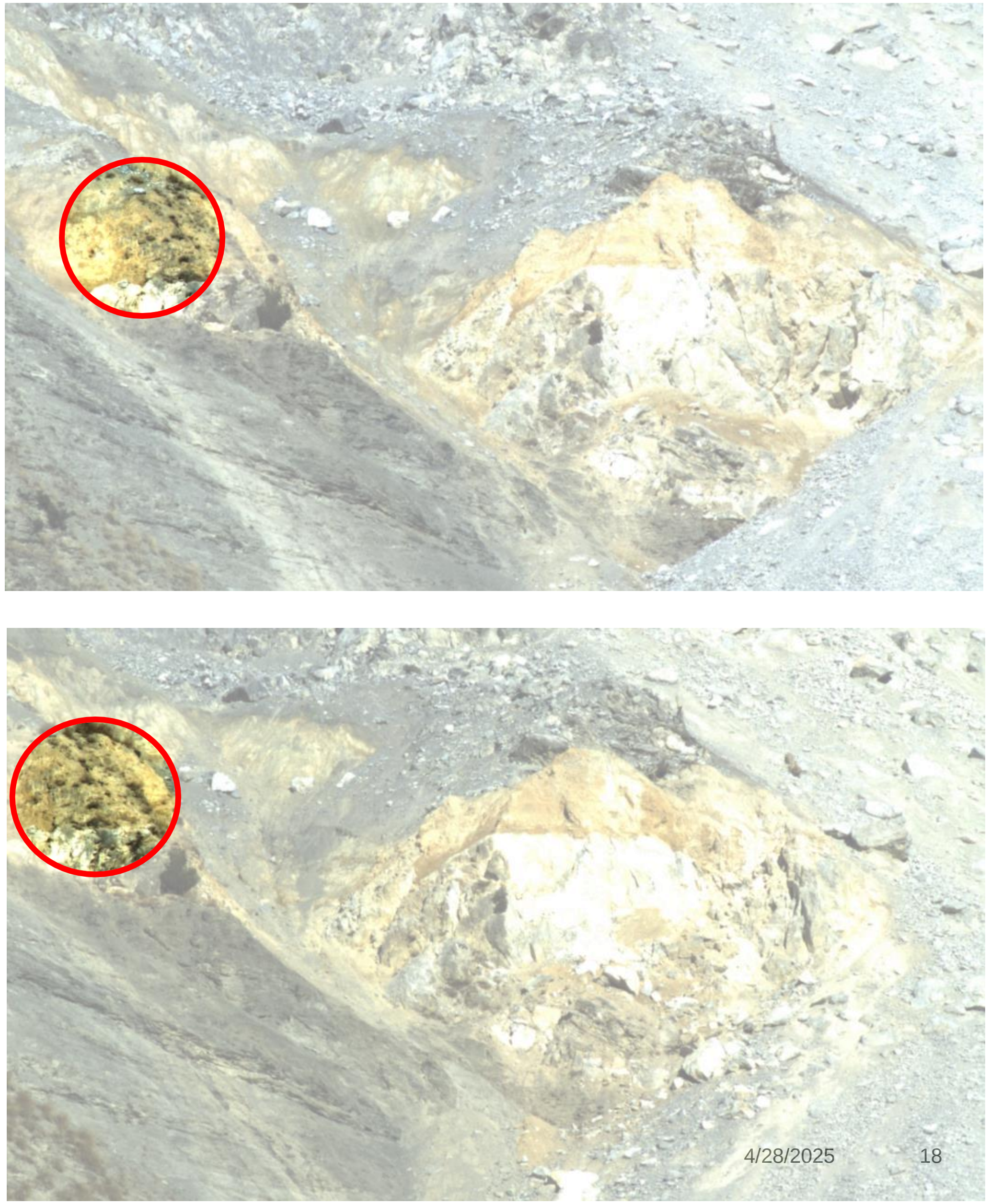


Table 2 Feature richness

Geometry	RGB
0.093	0.140

Discussion: Efficiency

- Our RGB-Guided method runs 2.8 times (31 s vs. 86 s) faster than geometry-based method (F2S3)
- The efficiency gain could become significant when applied to real-time monitoring applications

Table 3 Runtime comparison of F2S3 and our method (unit: second)

Method	2D matching	Refine.	3D feat. extraction	3D matching	Total ↓
F2S3	-	-	41	45	86
Ours	18	13	-	-	31

Take-home Message

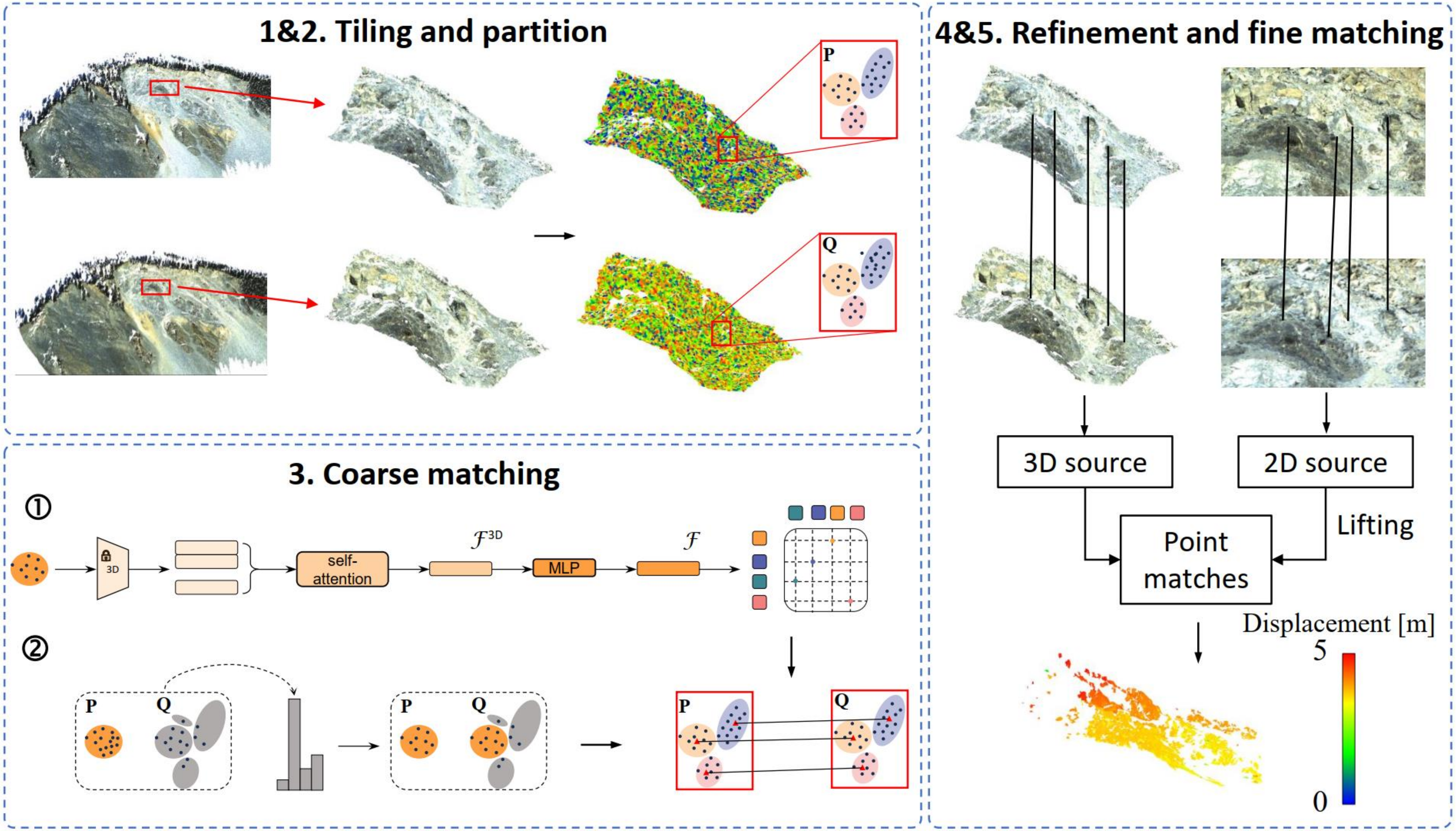
Conclusion:

- Our RGB-Guided method can
  - achieve accuracy comparable to existing geometry-based methods
  - achieve higher efficiency due to fast 2D search
  - potentially complement geometry-based methods (e.g., improving coverage)

Limitations:

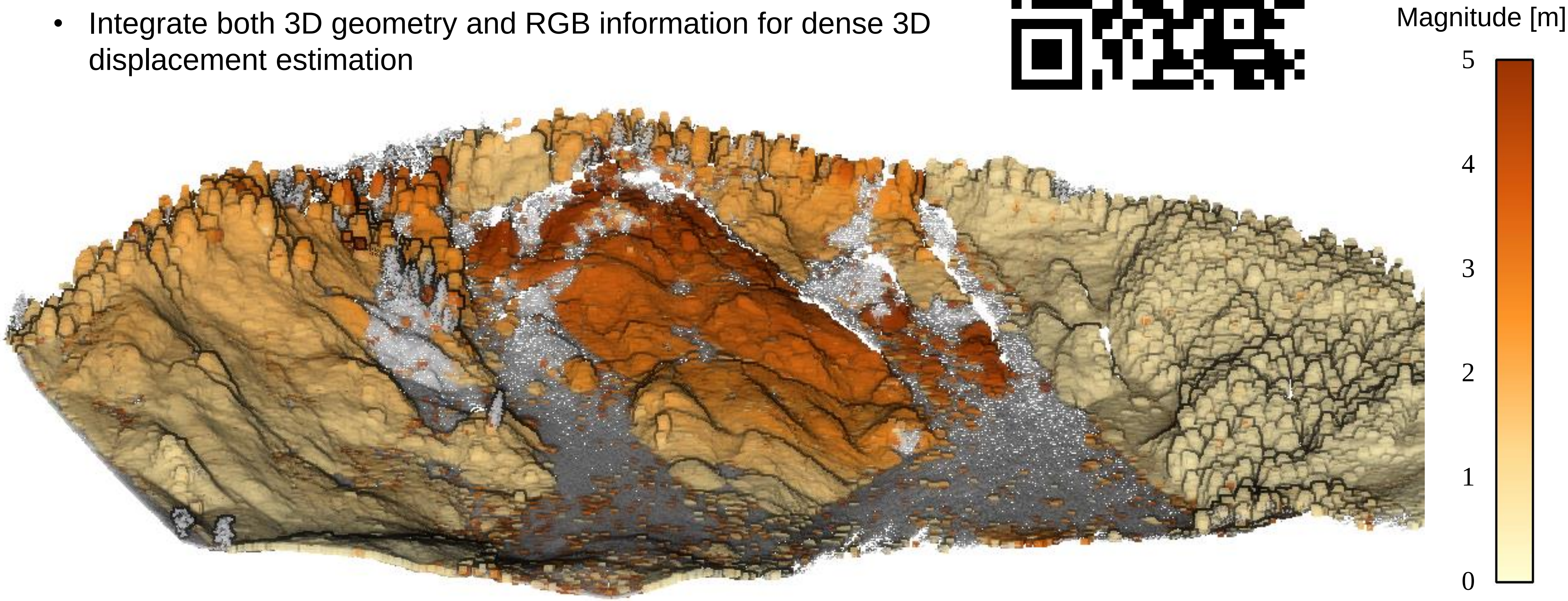
- Sensitivity to external factors: illumination changes, co-registration accuracy, etc
- Fundamental constraint: like geometry-based methods (F2S3), it struggles with motions that completely alter object appearance

Current Work



Current Work

- Automatic processing for an entire landslide dataset
- Integrate both 3D geometry and RGB information for dense 3D displacement estimation



Geosensors and Engineering Geodesy (GSEG)
Institute of Geodesy and Photogrammetry (IGP)

RGB-Guided Dense 3D Displacement Estimation in TLS-Based Geomonitoring

Zhaoyi Wang, Jemil Avers Butt, Shengyu Huang, Nicholas Meyer, Tomislav Medic, Andreas Wieser

Email: zhawang@ethz.ch

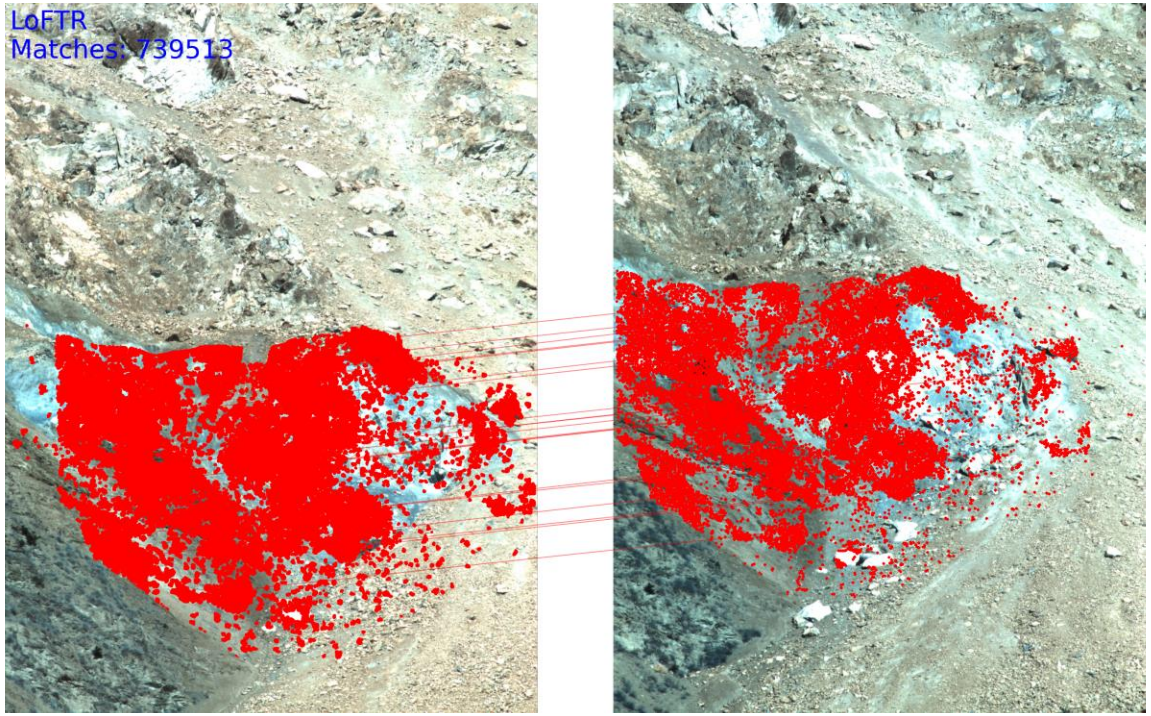
Code is available at: github.com/zhaoyiww/fusion4landslide

Supplementary Materials

Supplementary Materials

How to generate these results?

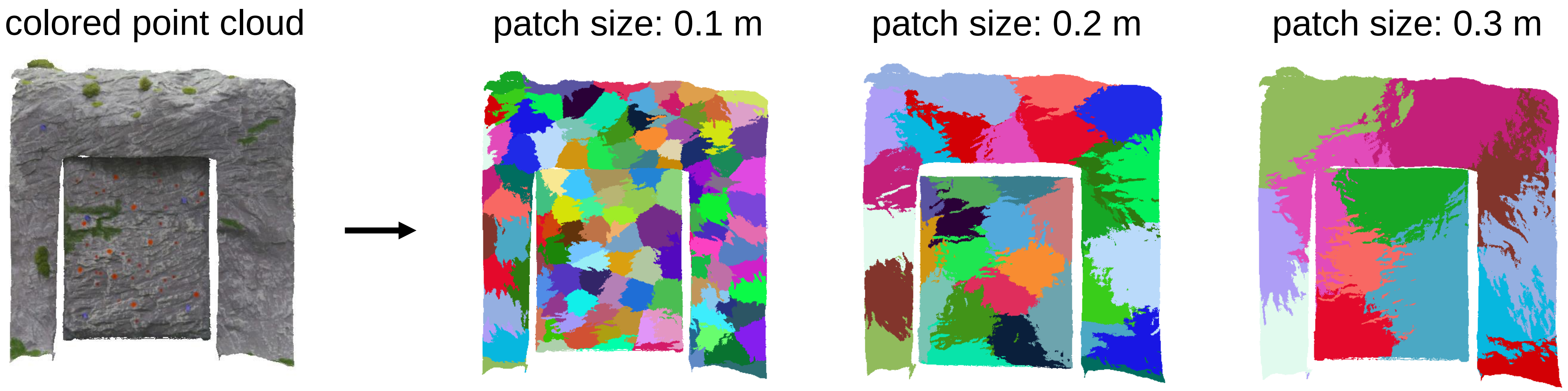
- ❑ do image matching using Efficient LOFTR [CVPR, 2024]
- ❑ project 3D points on images using transformations from raw project
- ❑ find closest 2D matches (< 5 pixels) for projected pixels
- ❑ filter matches with actual 3D dist. > 10 m



3D Match Refinement

Assumption: as-rigid-as-possible, i.e., movement in a small area is assumed as rigid

- If the patch size is
  - too small --> it includes mainly noise
  - too large --> it breaks the object boundaries

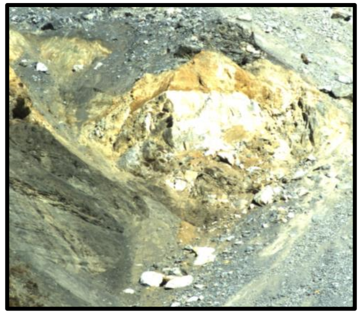


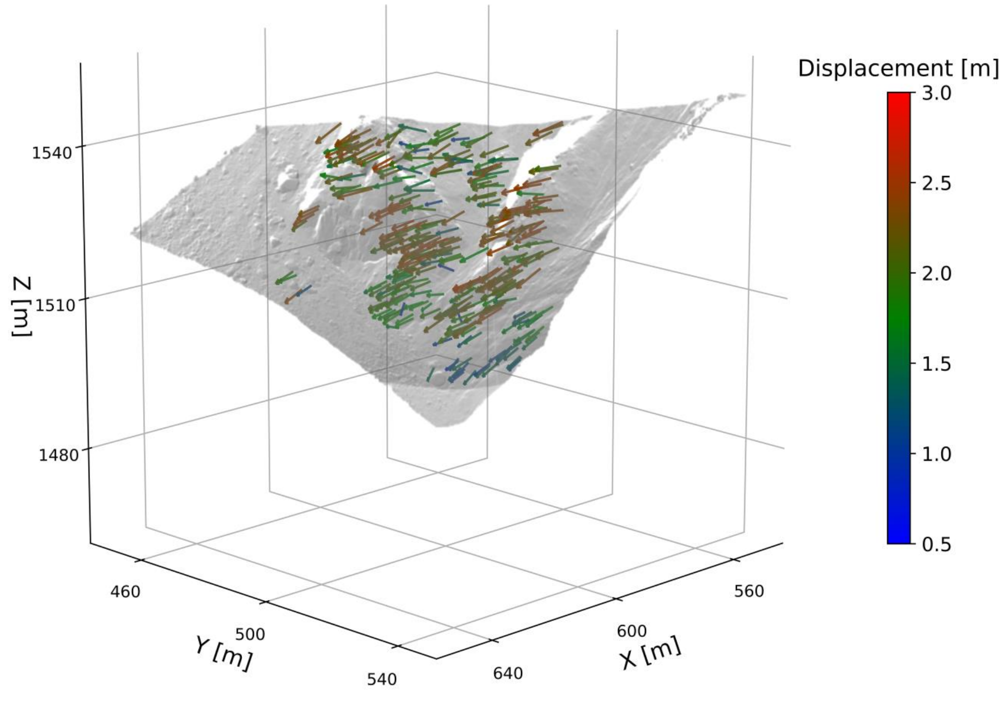
Motivation

- M3C2[1] and most of its variants
  - only 1D
- Piecewise ICP[2]
  - sparse 3D
- Hillshade[3]
  - a bit less sparse, but still sparse 3D
- F2S3[4]
  - dense 3D (current SOTA)

Epoch 1

Epoch 2





All these existing methods rely on 3D geometry

1. Lague et al. (2013). Accurate 3D comparison of complex topography with terrestrial laser scanner: Application to the Rangitikei canyon (NZ). ISPRS journal of photogrammetry and remote sensing, 82, 10-26.
2. Friedli et al. (2016). Identification of stable surfaces within point clouds for areal deformation monitoring. In Proc. of 3rd Joint International Symposium on Deformation Monitoring (JISDM).
3. Holst et al. (2021). Increasing spatio-temporal resolution for monitoring alpine solifluction using terrestrial laser scanners and 3d vector fields. Remote Sensing, 13(6), 1192.
4. Gojcic et al. (2021). Dense 3D displacement vector fields for point cloud-based landslide monitoring. Landslides, 18, 3821-3832.

Estimated 3D DVFs

- The vectors reflect the overall displacement pattern in this selected region
- Only 0.05% of vectors are visualized for better readability