Change detection on 3D point clouds

Principles & Applications

June 2022, CloudCompare V2.12.1

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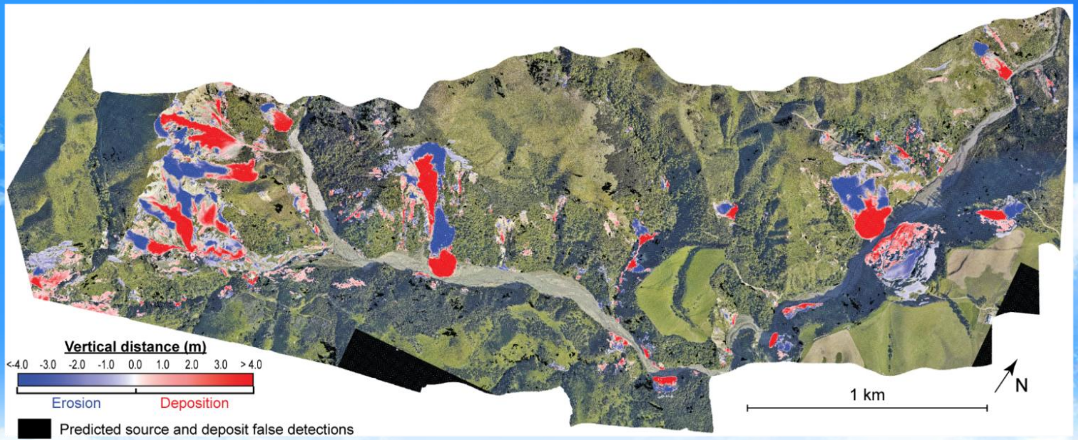


Workshop objectives

1. Measuring distance betwen two point clouds

- Approaches to register point clouds & quality control **(day 2)**
  → *need for metrics to evaluate the distance between two point clouds (M3C2*)
- Type of distance measurements
  - Feature matching (some examples but no practical)
  - **Featureless distances:** Cloud 2 Cloud, Difference of DEM, **M3C2**
- Source of uncertainties
  - Instrument, registration, method used….
  - How to include them in distance measurements ?
- Using a 3D distance field for scientific application
  - Example of automated clustering & volume calculation for landslides **(day 2)**

2. Improving your technicity in processing point clouds

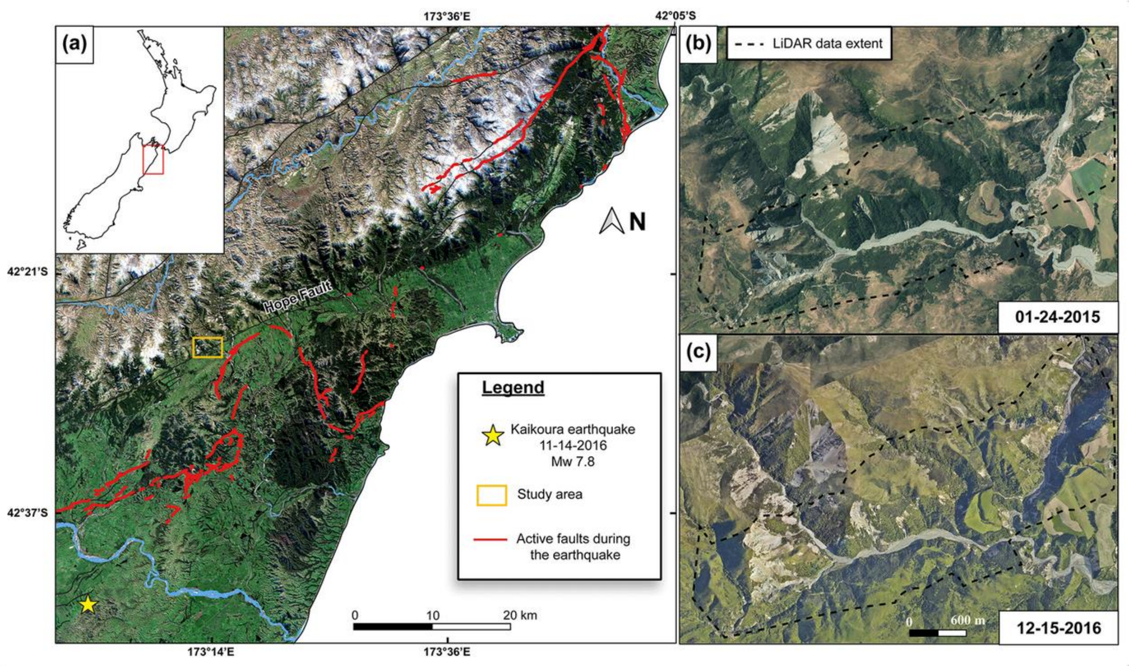
- With Cloudcompare (Rennes team)
- With Python (Potsdam team)

3. Try to solve some of the problems you face with your data

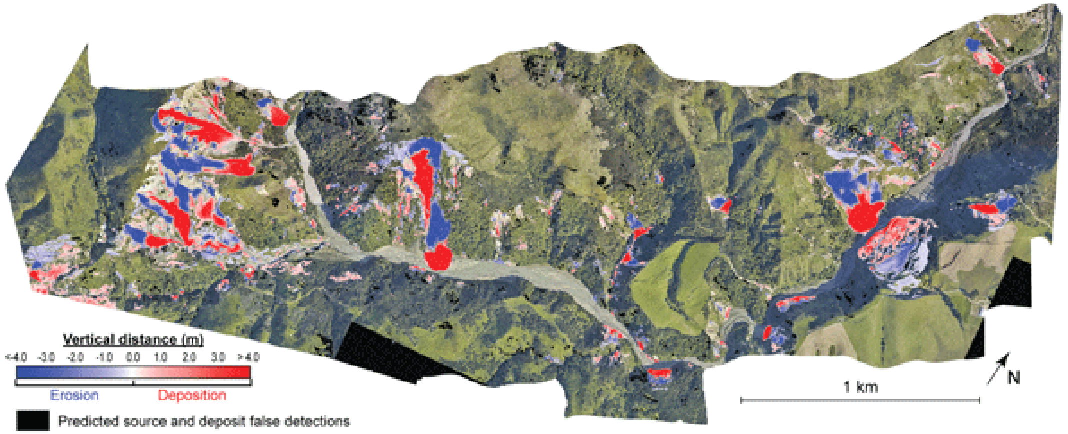
Datasets used in the practical : Airborne LiDAR

Kaikoura Earthquake Dataset used in

Bernard, Lague and Steer, Esurf 2021 : **Beyond 2D landslide inventories and their rollover: synoptic 3D inventories and volume from repeat lidar data**



	Pre-earthquake lidar	Post-earthquake lidar
Date of acquisition	13 Mar 2014–20 Mar 2014	3 Dec 2016–6 Jan 2017
Commissioned by/provided by	USC–UCLA–GNS science/NCALM	Land Information New Zealand/AAM NZ
Availability	https://doi.org/10.5069/G9G44N75	Upon request from https://canterburymaps.govt.nz/about/feedback/
Original point density (points m^{-2})	9.02	19.2 ± 11.7
Number of ground points	10 660 089	63 729 096
Ground point density (points m^{-2})	3.8 ± 2.1	11.5 ± 6.8
Vertical accuracy (m, as ±1 SD)	0.068–0.165	0.04
Study area (m^2)	5 253 133	5 253 133



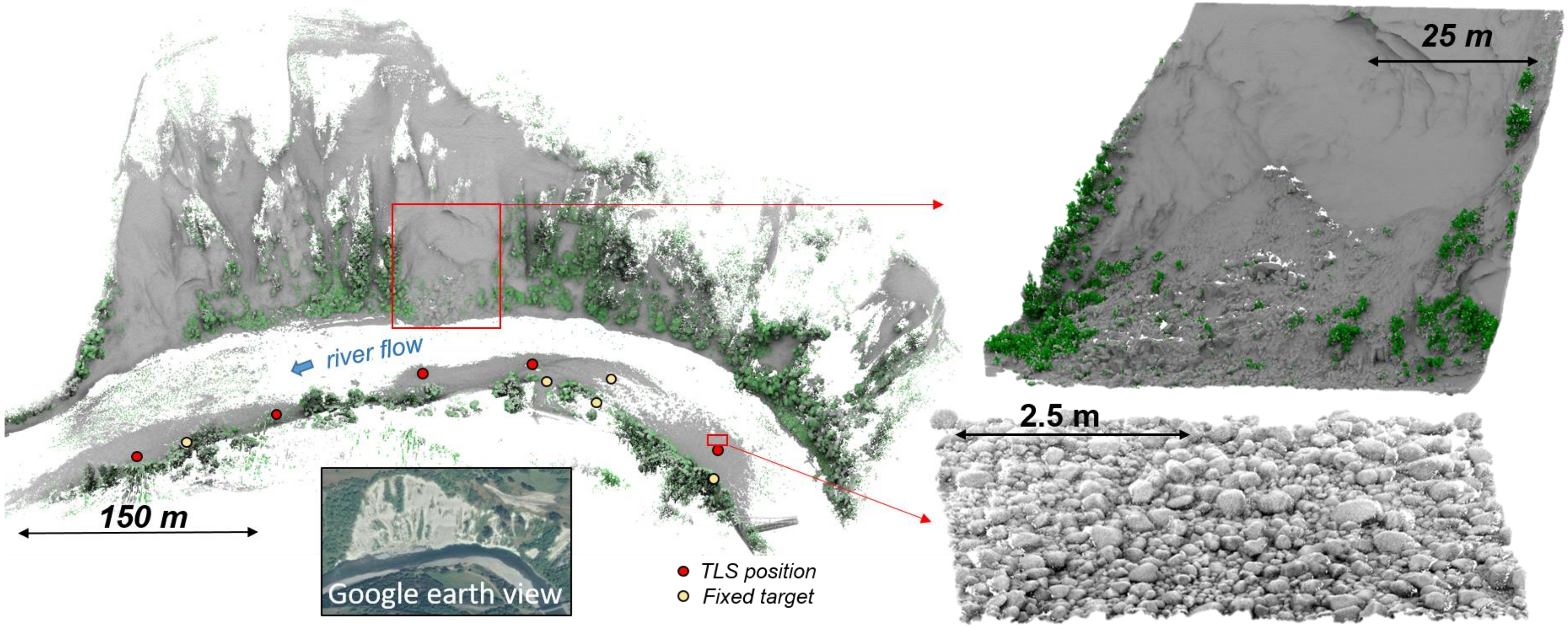
Note: the 2014 and 2016 surveys have been cut to not have the same spatial extent. This is to better highlight the sensitivity of various methods of change detection or registration.

Datasets used in the practical : Terrestrial LiDAR

Terrestrial LiDAR data from the Rangitikey river in NZ, used in

Lague, Brodu and Leroux, ISPRS 2013 : **M3C2 paper**

Lague, Dev in Earth Surf Processes, 2021 book chapter on Terrestrial Laser scanner applied to fluvial geomorphology



Surveys in 2009 and 2011

Variety of processes:

- Rockfalls
- Bed aggradation/erosion
- Bank erosion

Leica Scanstation 2 (slow but accurate !)

~ 1 -2 cm point spacing

Registration error ~ 3-5 mm (1 std)

Classification with Canupo, but voluntarily not perfect

Version subsampled at 2 cm for

Plan

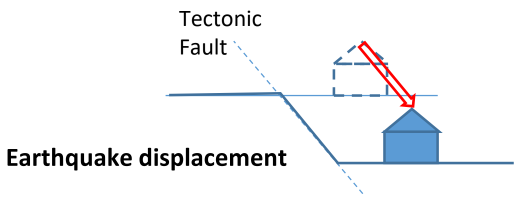
1. **Type of distance measurements**
    1. Feature based change detection
    2. Featureless distance measurement
        1. Cloud to cloud
        2. Difference of DEM
        3. M3C2 distance

2. **Sources of uncertainty**
    1. Components of uncertainty in 3D point cloud change detection
        1. Positional uncertainty
        2. Registration uncertainty
        3. Roughness uncertainty
    2. Background on uncertainties
    3. Examples

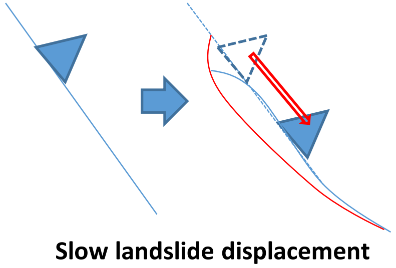
2 types of topographic change measurement

Ground movements displacing topographic features

Kaikoura EQ, GNS

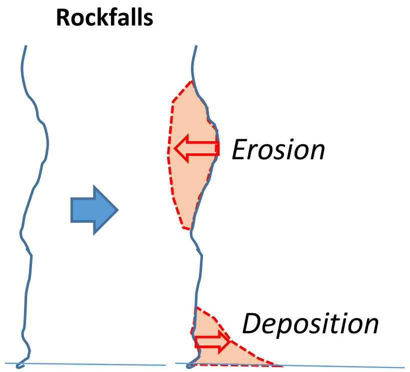


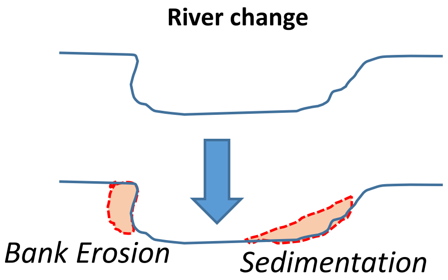
Chgega landslide, GEP



Feature matching
→ 2D-3D displacement field

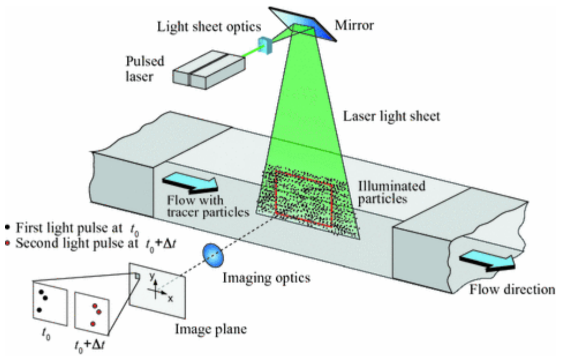
Geomorphic processes changing topographic features

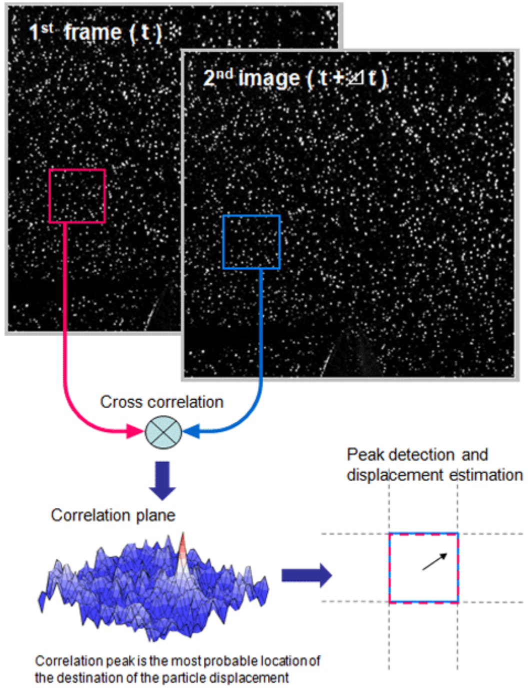




No features to match
→ distance & volume

Feature matching: deformation field using Particle Image Velocimetry (PIV) on DEM





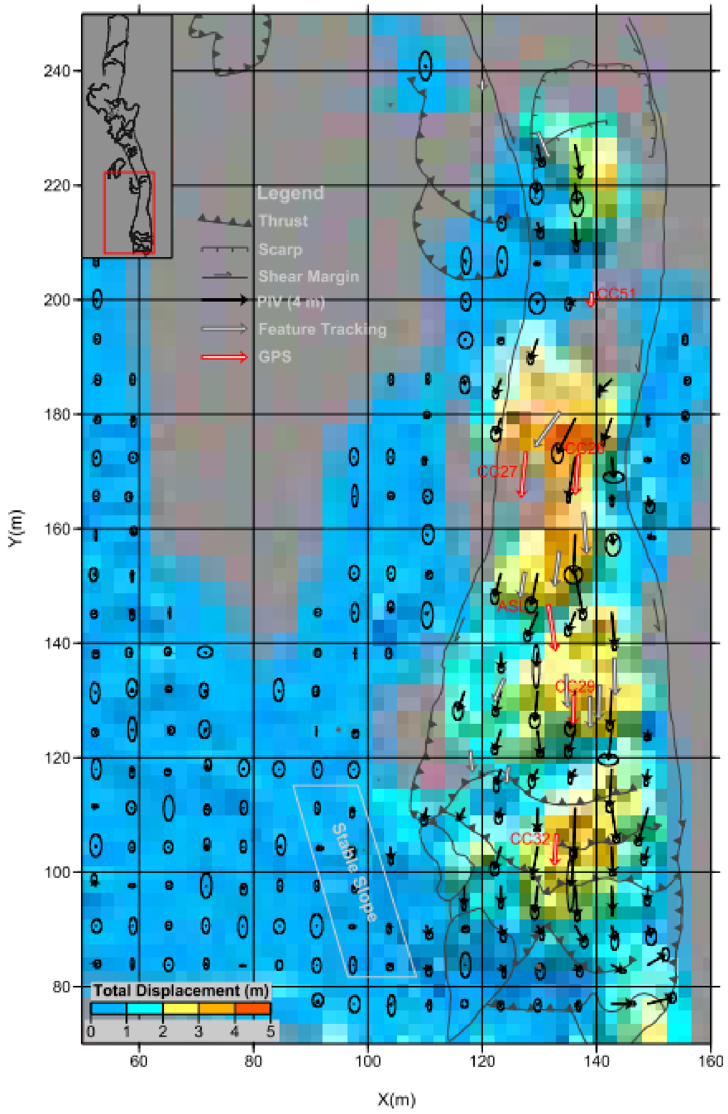
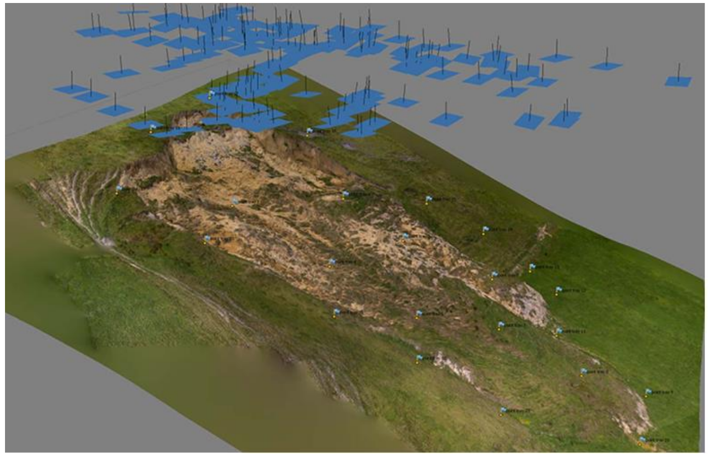


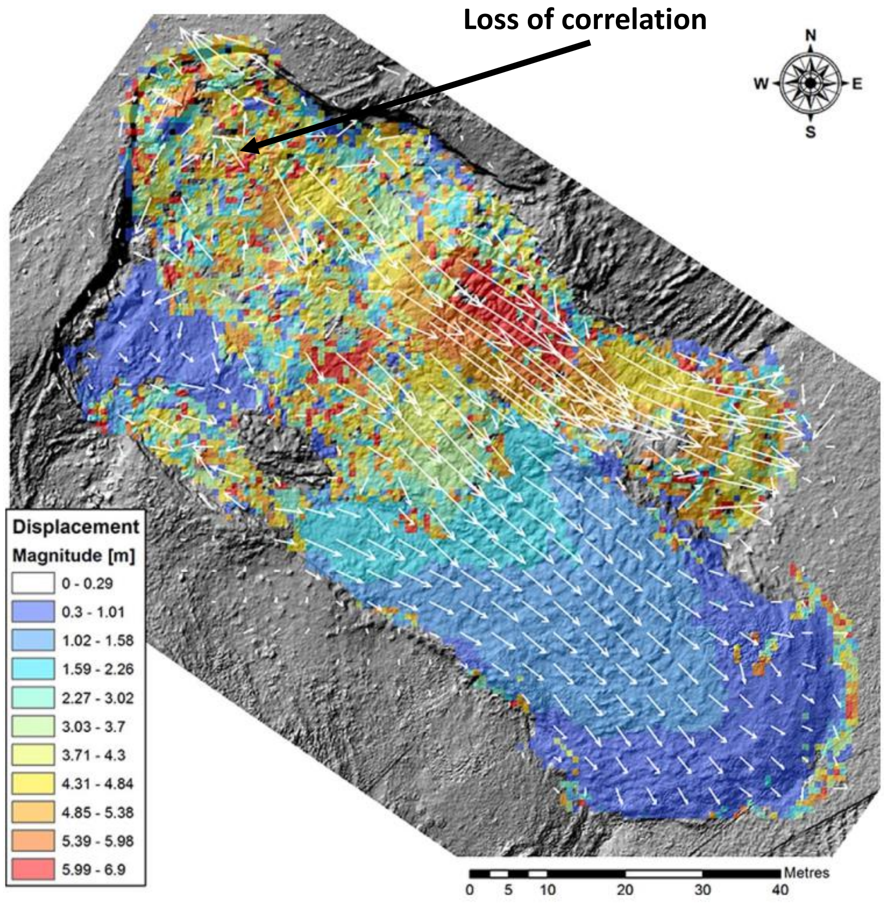
Figure 6. PIV estimated total displacement field and vectors (black) with error ellipses (95% significance) of CCL between June 2005 and January 2007. GPS horizontal-displacement vectors (red) and displacement vectors of features identifiable in the point cloud data (white) are plotted using the same scale as the PIV vectors. Landslide surface features (scarps, thrusts, and boundaries) are adapted from *Reid et al.* [2003].

- Derived from techniques of 2D image correlation but using a raster DEM
- *Aryal et al., JGR, 2012*: Using cross-correlation techniques developped for Particle Image Velocimetry

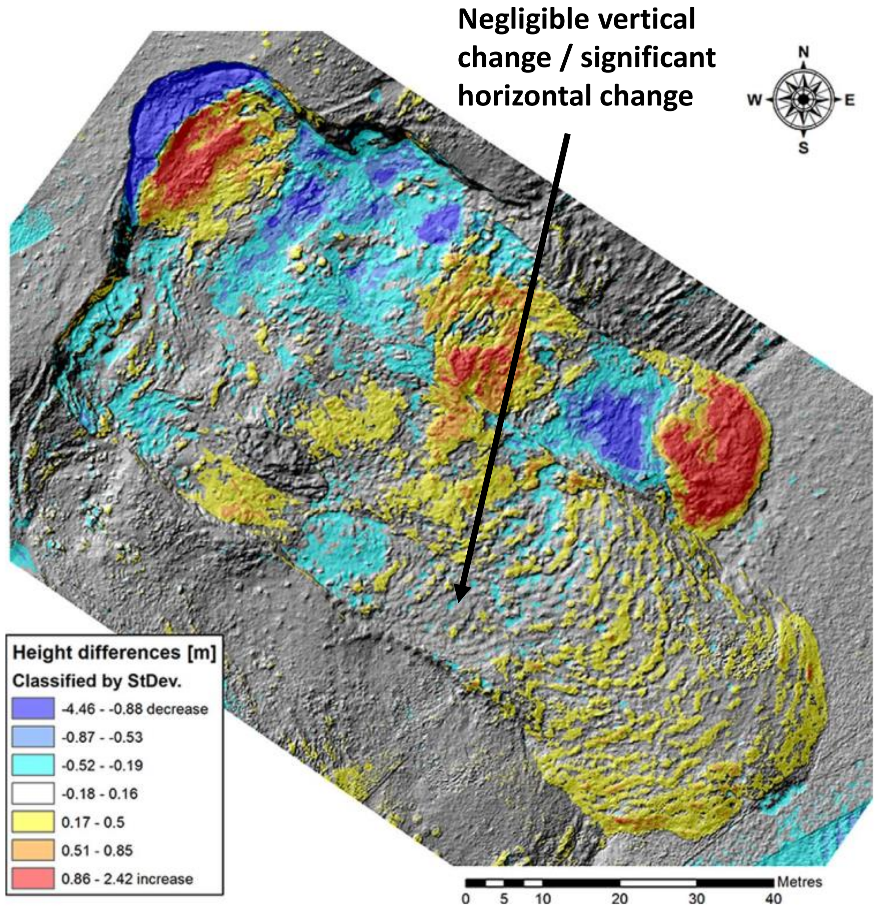
Feature matching: deformatin field using Particle Image Velocimetry (PIV) on DEM



1 cm DEM.
19 july 2011 to 10 Nov 2011
Vertical registration error ~ 1.7 cm



2D Displacement field from DEM correlation
using COSI-CORR (Leprince et al., 2007).



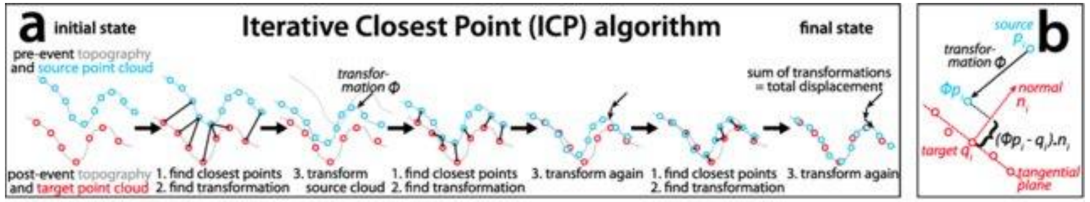
Vertical difference of DEM

Lucieer et al., Progress in Phys. Geography, 2014

Feature matching on 3D point cloud change detection by piecewise ICP

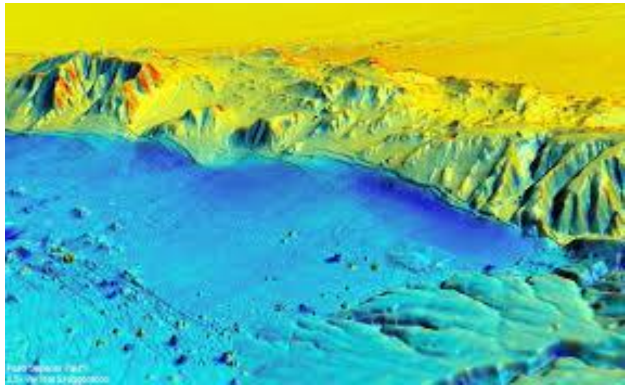
Piecewise ICP (Iterative Closest Point):

- PC is divided in smaller clouds
- a registration is performed between the two epochs
- Gives a local 3D displacement vector

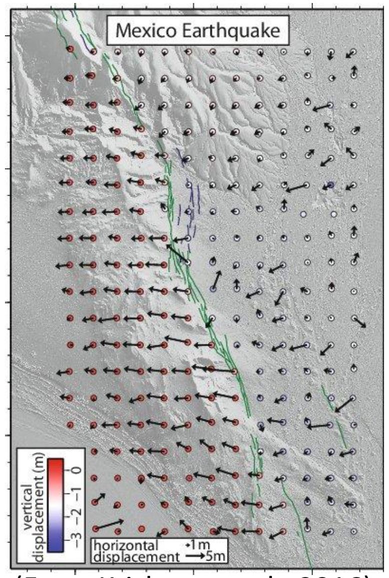


From Ed Nissen's course on OpenTopography

Airborne Lidar : tectonic displacement



Vertical displacement across a fault (Ed Nissen)



(From Krishnan et al., 2016)

Teza et al., 2007,2008 **TLS : landslide displacement**

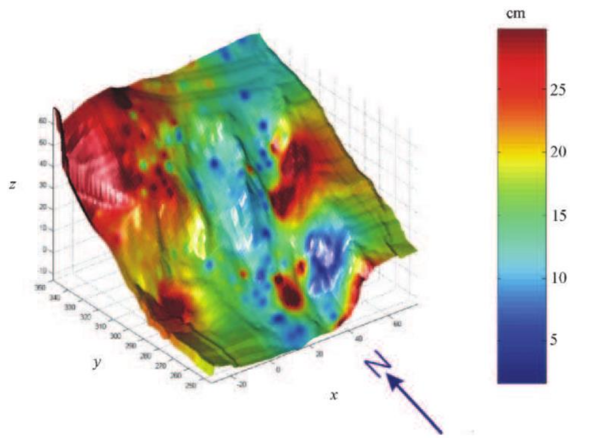


Figure 9. Summary of the results obtained at Perarolo di Cadore, in the period from December 2002 to July 2005, transformed into yearly displacements. The colours are proportional to displacement intensities.

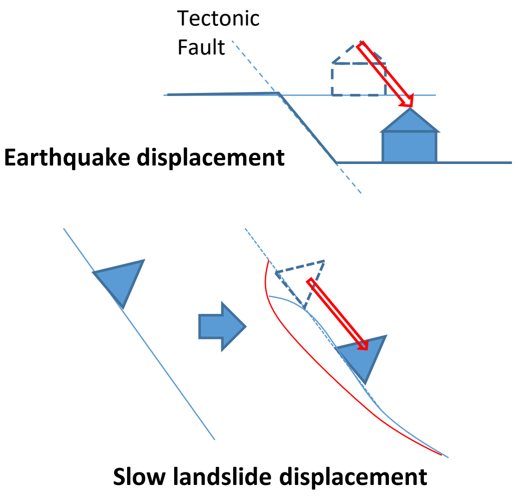
Benefits:

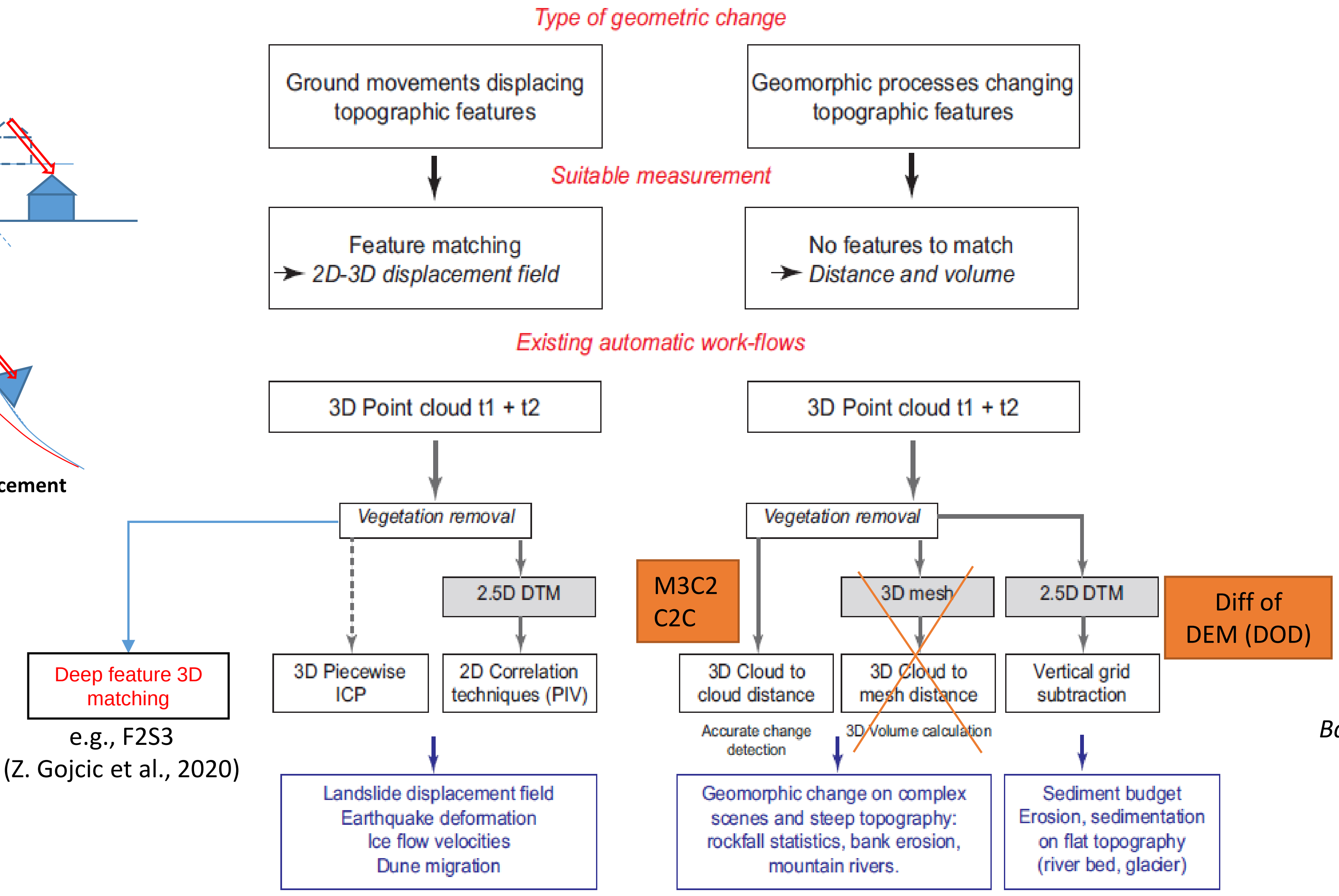
- **Works directly on 3D point clouds**
- **3D displacement field**
- **Potentially very accurate**

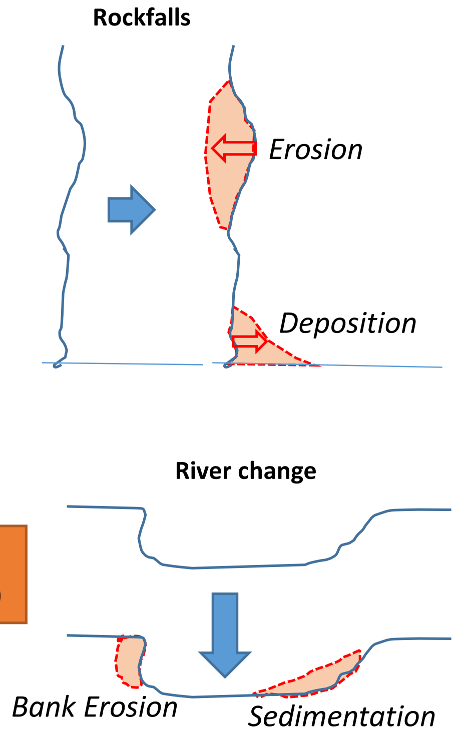
Current Limits:

- Requires a surface with topographic complexity or features (e.g., buildings)
- Features must be preserved after the event
- Range of displacement cannot be too large

Generic approaches to detect topographic change on point clouds







From Passalacqua et al., 2015

Plan

1. **Type of distance measurements**
    1. Feature based change detection
    2. **Featureless distance measurement**
        1. Difference of DEM
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2. **Sources of uncertainty**
    1. Components of uncertainty in 3D point cloud change detection
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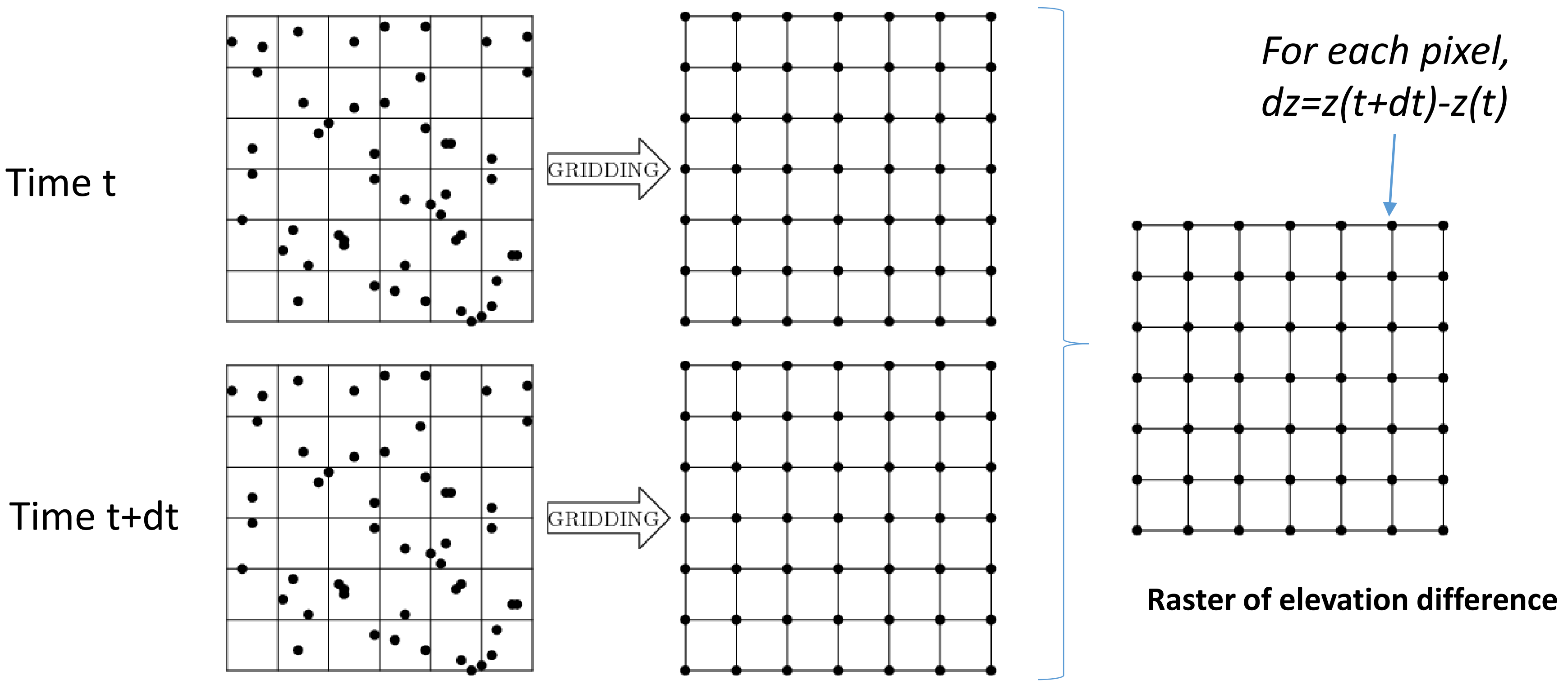
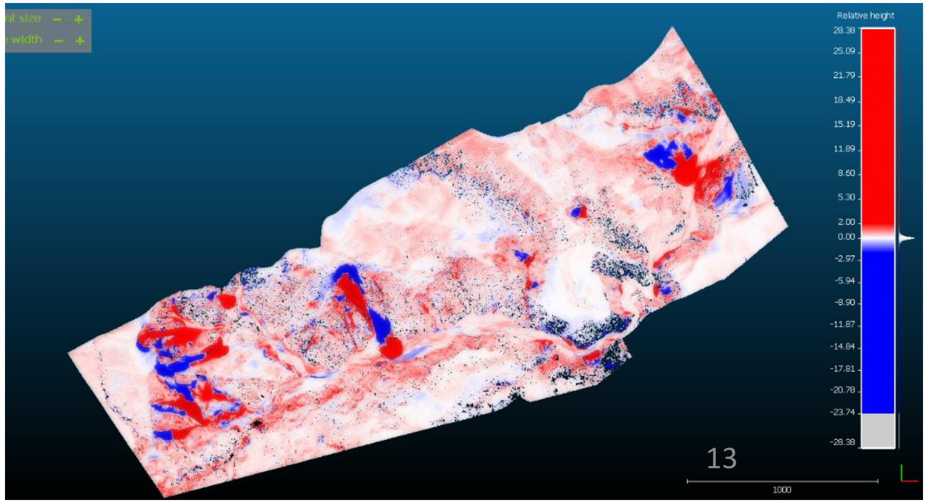
Classical approach: vertical Difference of DEM (DoD)



- The classical approach in Geomorphology and Earth Sciences
- Very easy to perform on any GIS
- Can also be done in Cloudcompare, but not necessarily optimal
- Very advanced packages existing for fluvial analysis *(Geomorphological Change Detection Toolbox, Wheaton et al. 2010)*

Cloudcompare application

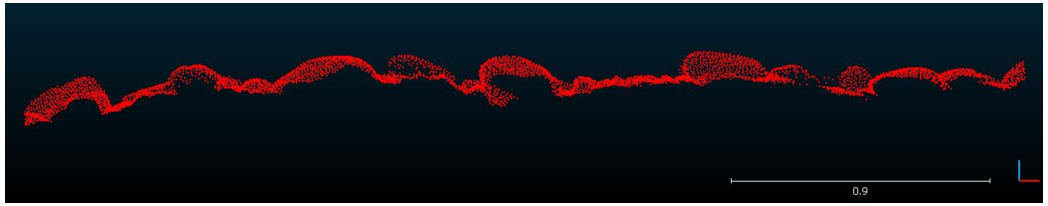
- **Kaikoura EQ Lidar dataset** (2014 and 2016, ground data only)
  - Load the 2 datasets
  - Tools -> volume -> compute 2.5D volume with a step of 1 m
    - Note the added and removed volume
    - Note the % of matching cells
  - Export grid of height difference raster
  - NOTE: the height difference is automatically calculated on the same grid



Principle of the SDDS test

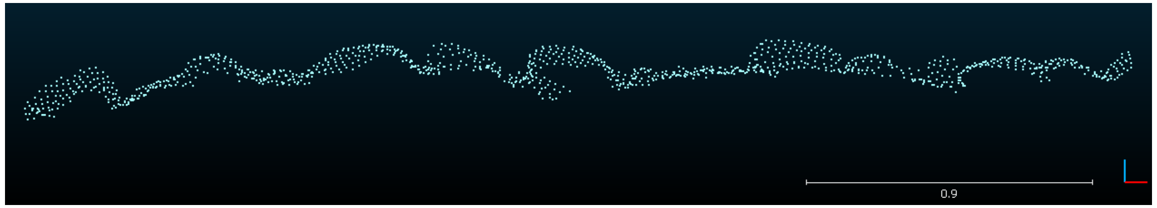
- **SDDS tests : Same Data Differing Sampling tests** (Lague et al., 2013; Bernard et al., 2021;)
  - **Same underlying surface but different sampling**
  - Take into account the noise in the data and the surface roughness without the registration error

    → **no change should theoretically be measured by the change detection technique**

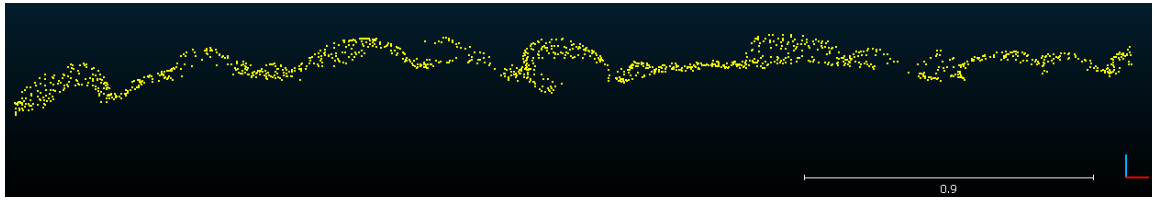


Original Data (gravel river bed)

Subsampling with min distance 1400 pts



Random Subsampling with 1400 pts



Applications:

- Testing robustness of change detection method
- Testing robustness of cloud matching approaches (ICP,…)
- Indirect validation of statistical models for significant change detection

SDDS test with DoD

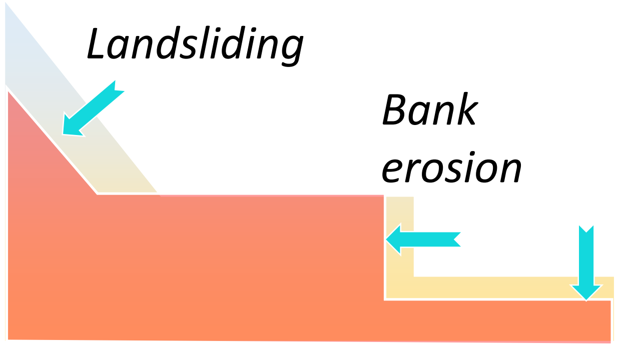
Kaikoura 2016 EQ Lidar dataset

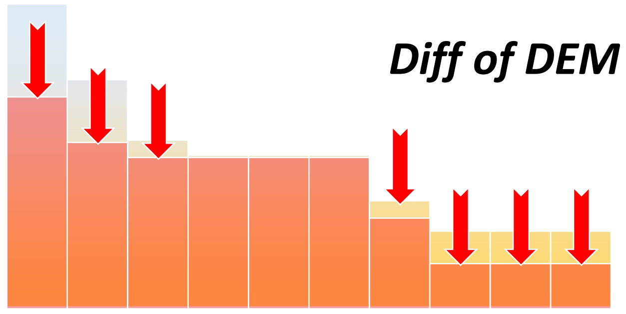
- Subsample with 0.5 m min distance -> **2016_sub0.5**
- Subsample randomly to have ~ 9.5 million points -> **2016_rand**
- Tools -> volume -> compute 2.5D volume with a step of 1 m
- What do you observe ?
- Compute the std deviation of the height difference (tools -> statistics -> compute stat params -> gauss)

Difference of DEMs : Pros an Cons

- **Pros**
  - **Regular sampling of topographic change**
  - **Compact format**
  - **Easy vertical differencing** (Difference of DEM=DoD)
  - **Simple volume calculation = sum of the vertical difference x pixel area**
  - **Well integrated in traditional workflow using DEM**

- **Cons**
  - **Loss of resolution as topographic slope increases**
    - ***Cannot represent vertical surfaces***
  - **No oriented difference**
    - ***E.g., bank erosion and bed aggradation correctly***
  - **Interpolation on complex surfaces**
    - ***"Creation" of data whose accuracy is unknown***
      - *You generally lose the information on where interpolation occured*
  - **Loss of sub-pixel information**
    - ***Did you have 100 pts in your pixel or 1 ?***
    - ***Was the sub-pixel geometry flat or rough ?***
  - **Cannot represent 3D above ground features**
    - ***Did you have 100 pts in your pixel or 1 ?***





Measure distance in 3D, directly on point clouds

Plan

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    1. Feature based change detection
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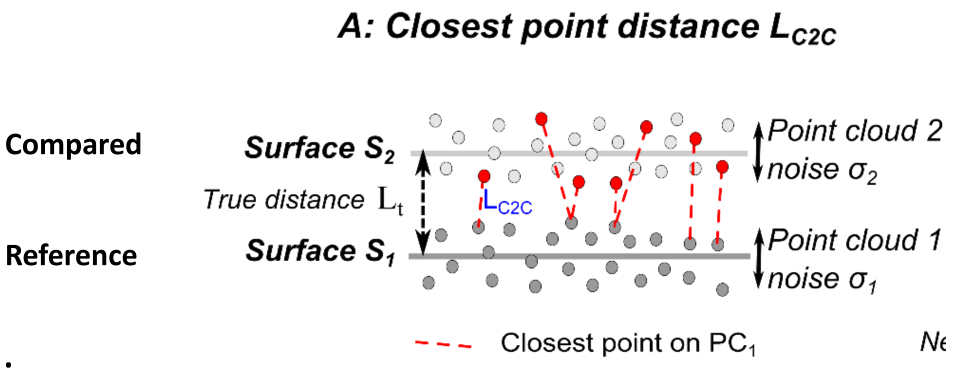
3D Cloud to cloud distances
Simplest approach : nearest point distance (cloud 2 cloud aka C2C)



For each point in the compared PC, look for the nearest neighbour in the reference PC and compute the 3D distance

Pro:

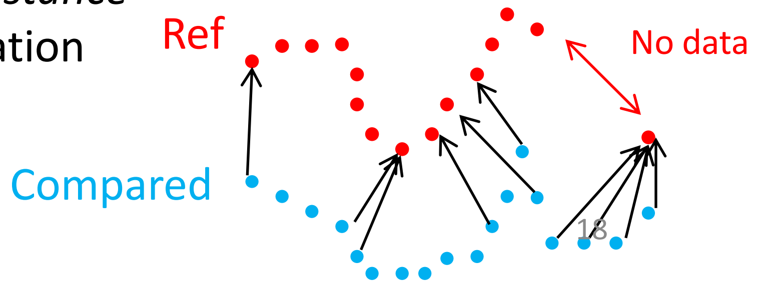
- **A 3D measurement directly on point clouds : can be used on horizontal or vertical surfaces**
- **Super fast and simple (no need to rasterize)**
- **Highest resolution possible**

Con:

- **Underestimation of true distance due to noise**
- **No normal calculation**

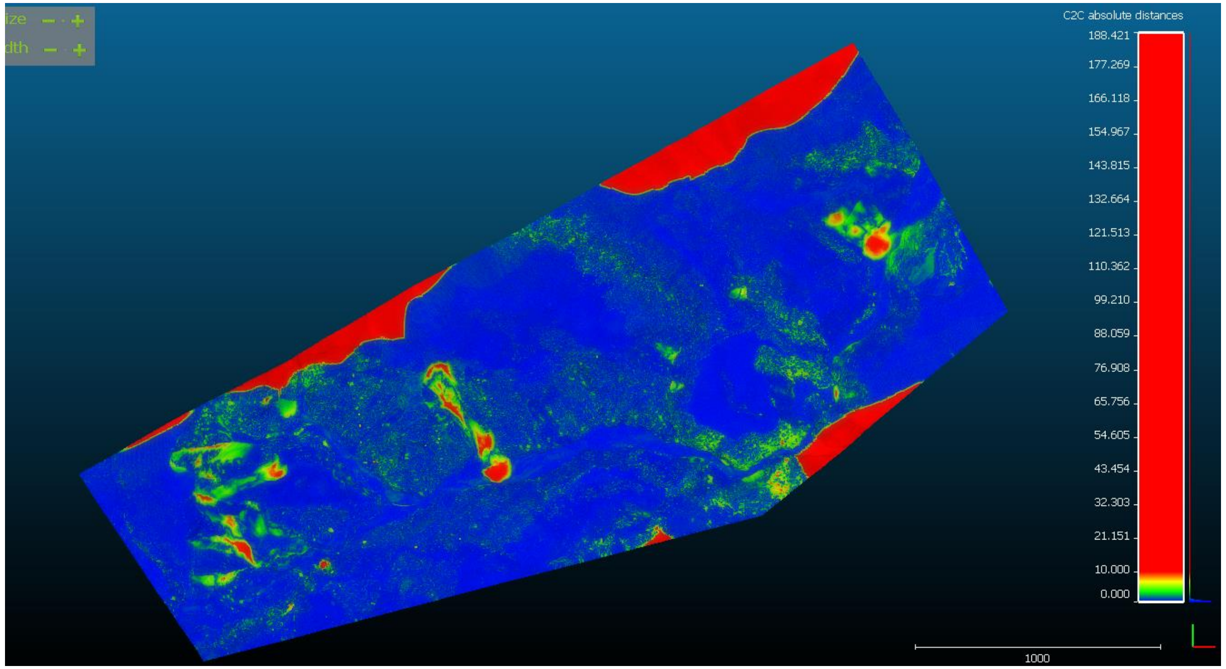
  → **Non-oriented measurement** : not necessarily the orthogonal distance between two surfaces. E.g. on a river bed, not generally the vertical distance → *overestimation of true distance*

  → **Non-signed measurement** : no difference between erosion and sedimentation
- **Highly sensitive to missing data**



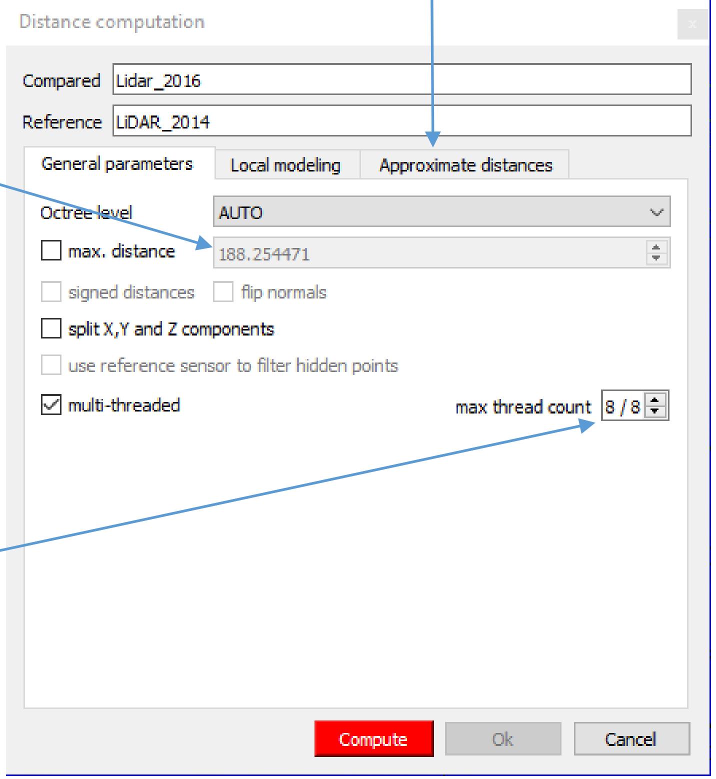
C2C distances in Cloudcompare

- Using the Kaikoura EQ dataset
  - Select C2C distance between 2016 and 2014, with 2014 as a reference (1st epoch)
  - Press COMPUTE
  - A new scalar field is created in the 2016 dataset



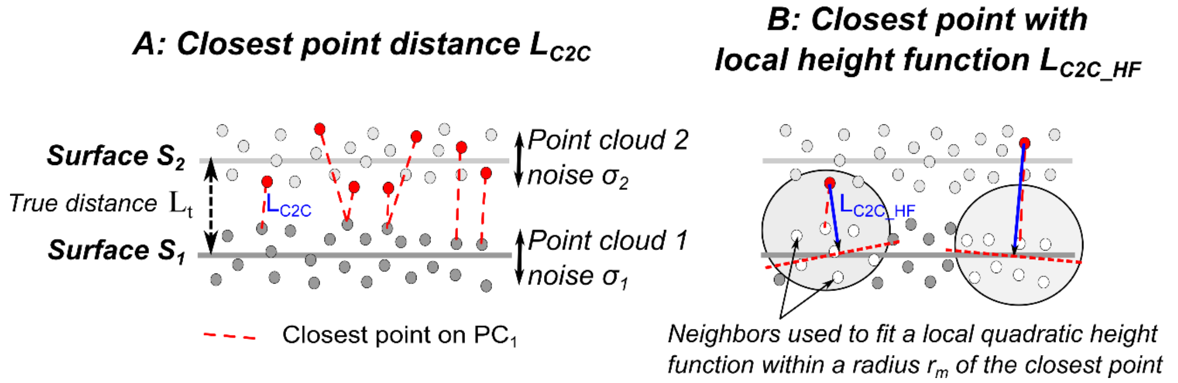
Some infos on very approximate measures. NOT TO BE USED

Very large value due to difference in LiDAR extents
→ can lead to very long computation time
→ can be lowered if necessary



This value depends on your CPY. On a very large dataset, leave at least 1 thread not used (7/8)

Improvements on C2C



From Lague et al., 2013

- Using a local model
  - Reduces the underestimation due to noise
  - Does not resolve the non-oriented issue
  - Does not yield a signed distance
- Using the vertical component of the distance vector
  - **Signed vertical distance** = erosion and sedimentation
  - Does not resolve the non-oriented issue
  - Is not accurate enough

Useful for quick & dirty exploration of data to evaluate where large vertical change occur

Recommandation on using C2C

Reference point cloud:

- Ideally the initial dataset
- But sometimes choosing a dataset with much larger point densities and less missing data yield better results

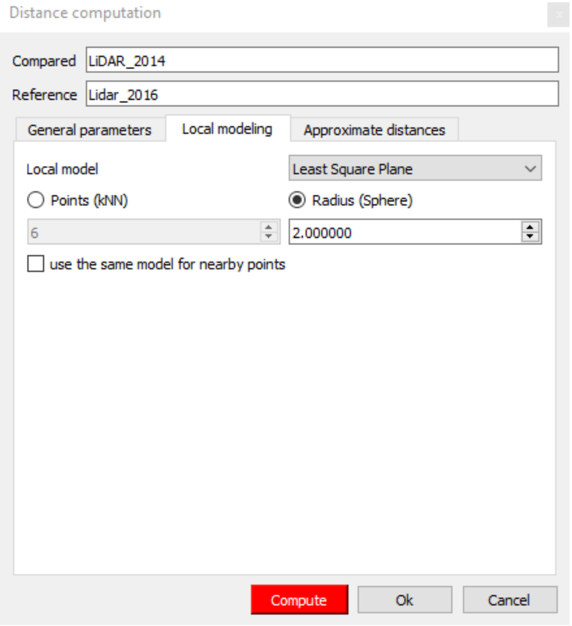
With cloudcompare:

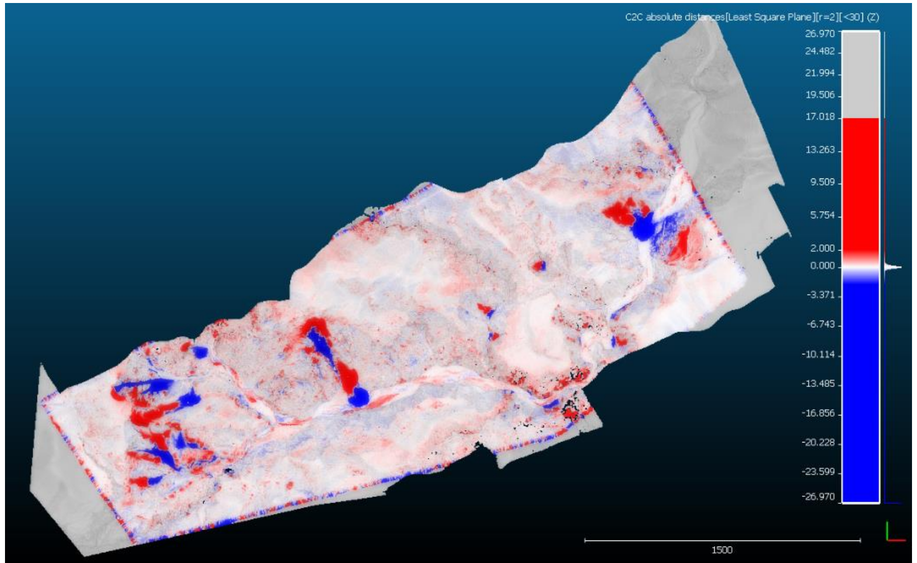
- Check the maximum distance before launching the calculation
- Can be imposed if using command line

Practical

Vertical C2C distances in Cloudcompare

- Using the Kaikoura EQ dataset
  - Select C2C distance between 2016 and 2014, with **2016 as a reference** (as it is the denser point cloud)
  - Tick the « split X,Y,Z components »
  - Set max_distance = 30 m
  - Select a local modeling : least square plane, 5 m radius
  - Press COMPUTE
  - 4 new scalar field are created on the 2014 dataset
  - Display the C2C absolute distance [<30] (Z) scalar field

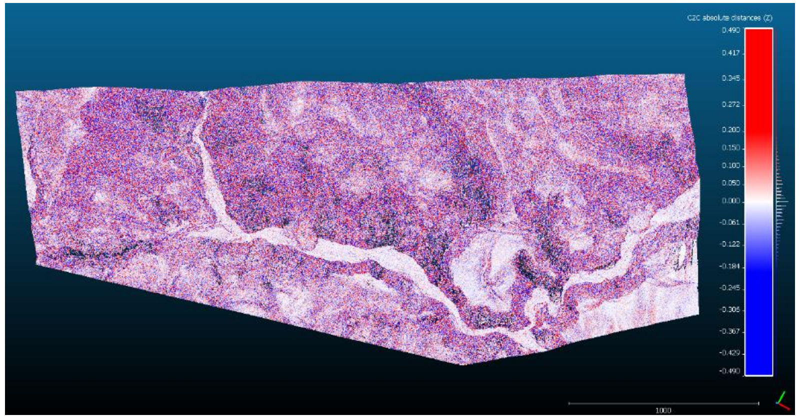


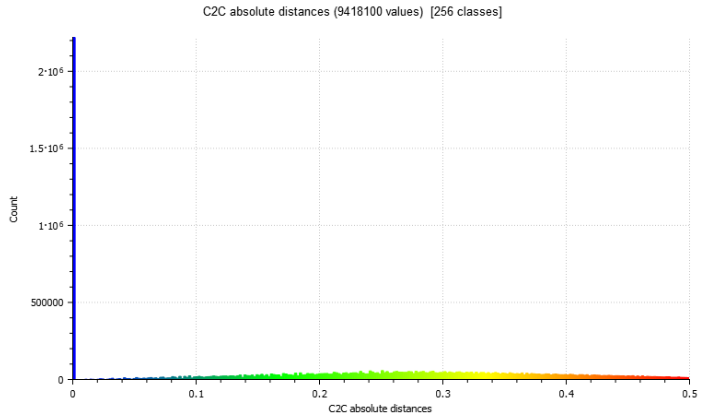


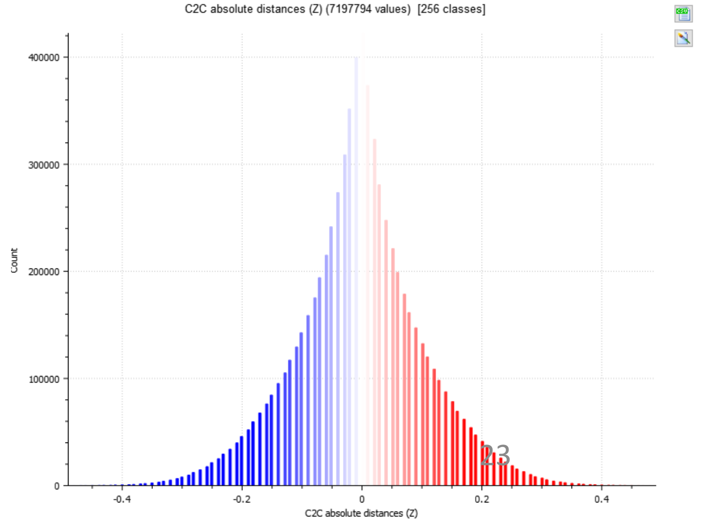
Tip: because we have inverted the reference, erosion appears as positive. To change that multiply by -1 in scalar arithmetics

SDDS test with C2C

- Perform a C2C without local modelling with the spatial subsampling as reference (with Z component)
- Display the histogram of absolute distances
  - Compute the mean of non-zero absolute distances
- Display the histogram of the vertical distance
  - Compute the std deviation of non zero absolute_distances_Z
  - Tricky question : why does the distribution appear discretized ?







Plan

1. **Type of distance measurements**
    1. Feature based change detection
    2. **Featureless distance measurement**
        1. Difference of DEM
        2. Cloud to cloud
        3. M3C2 distance
            a) Algorithm and choice of parameters
            b) Benefits of 3D differencing vs vertical differencing
            c) Worflow for an equivalent Difference of DEM with M3C2
            d) Working with complex TLS data

2. **Dealing with uncertainties**
    1. Components of uncertainty in 3D point cloud change detection
        1. Positional uncertainty
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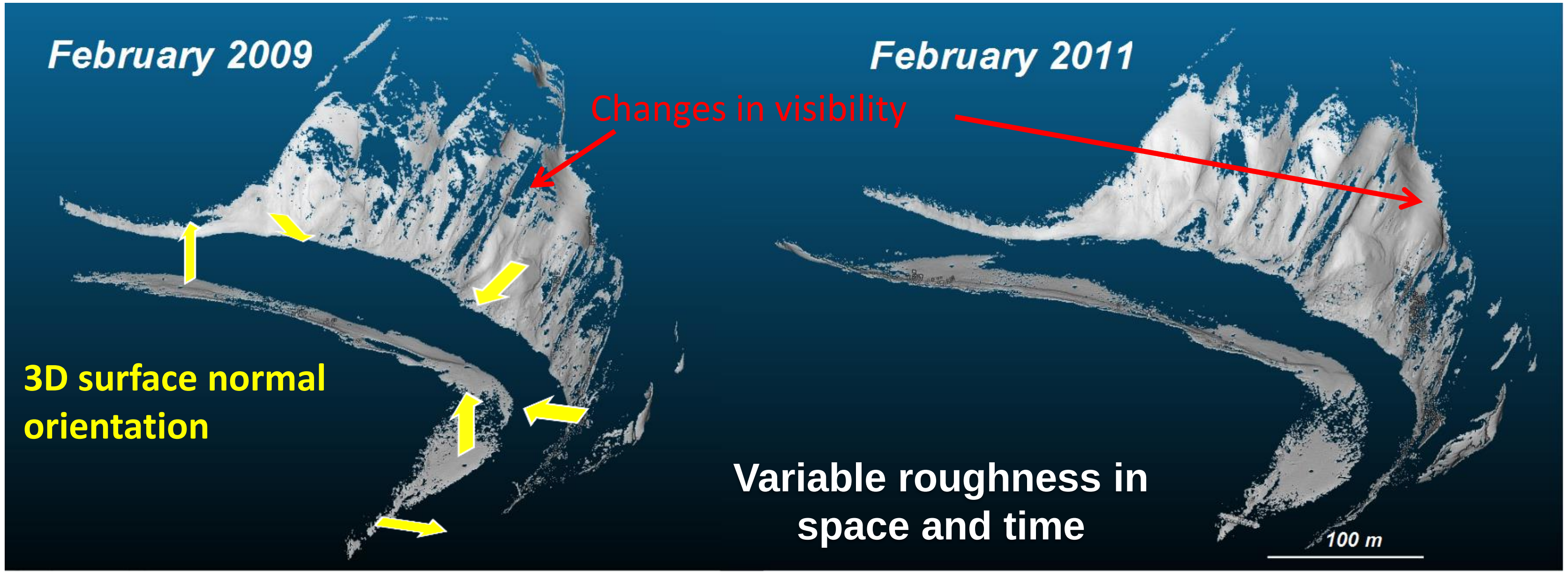
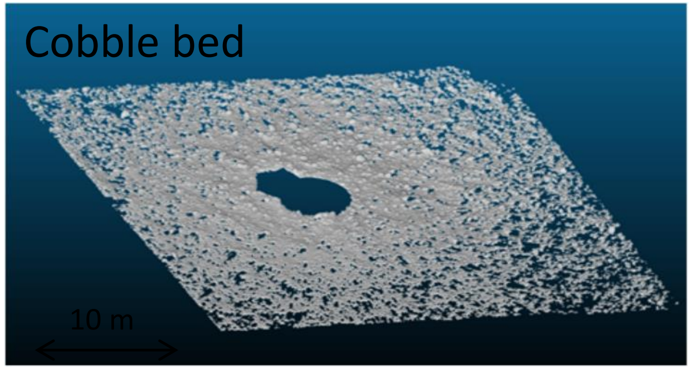
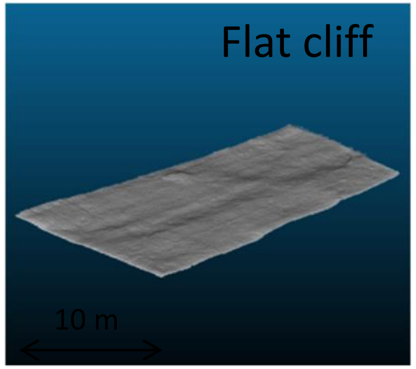
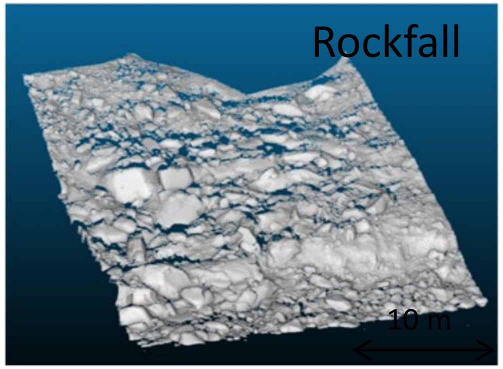
Multiscale Model to Model Cloud Comparison (M3C2), Lague et al. 2012

Rangitikei river, New-Zealand





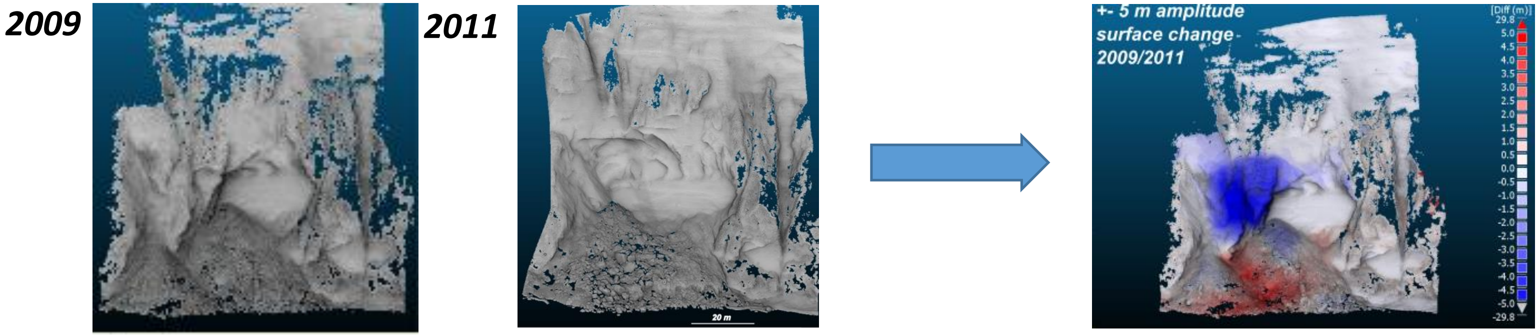


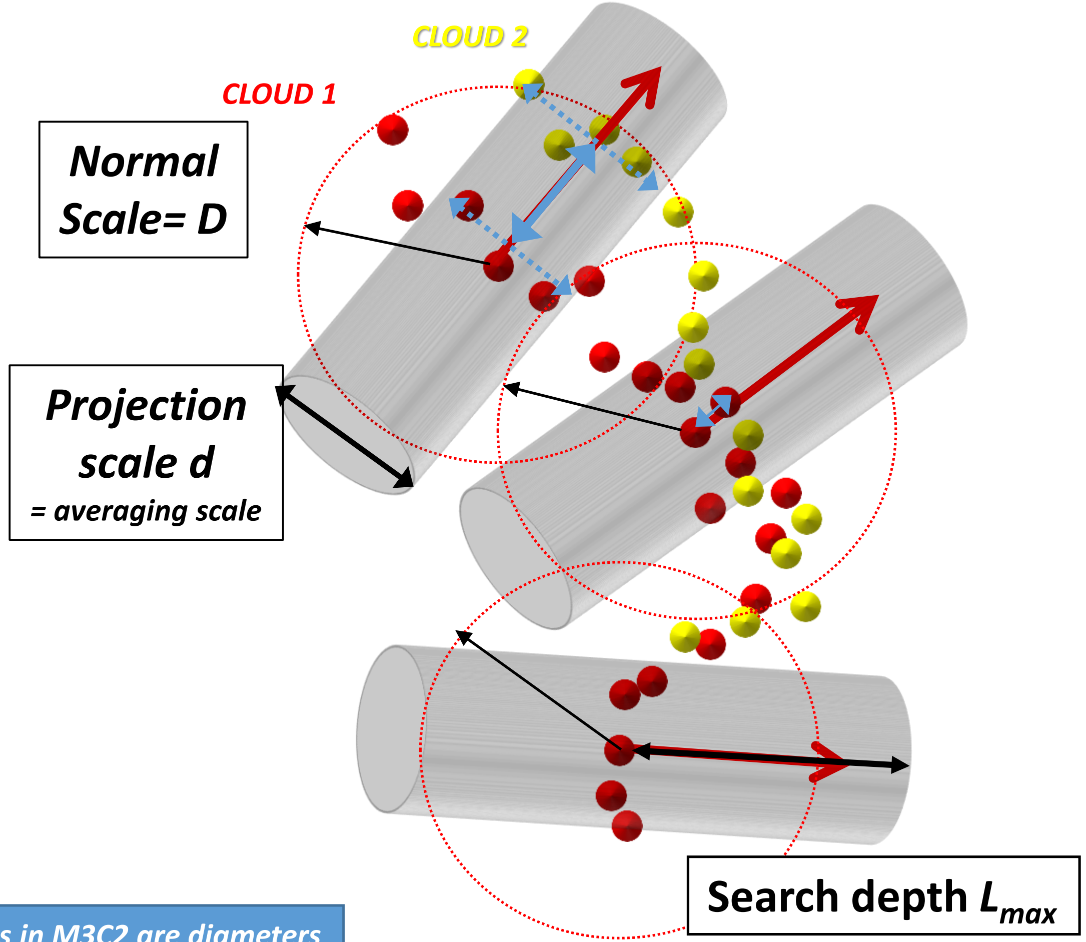


Elements of M3C2

1. A way to compute distances
2. A model of uncertainty to compute a confidence interval for each distance accounting

M3C2: 3D point cloud differencing *(Lague et al., 2013)*





1: Normal direction calculation on cloud 1 at scale D

→ **Oriented difference**

2: Cylinder of diameter d (projection scale)

- ***Average position of each*** *PC within the cylinder*
- **M3C2 Distance = distance between the two average position along the normal direction**

3: Local confidence interval calculation using

→ **Local cloud roughness**

→ **Local point density**

→ **Global registration**

4: Distance smaller than confidence interval

→ **statistically not significant**

5: Length of the cylinder = L_{max}. If no intercept with other cloud

→ **no calculation**

→ **no need to trim the data**

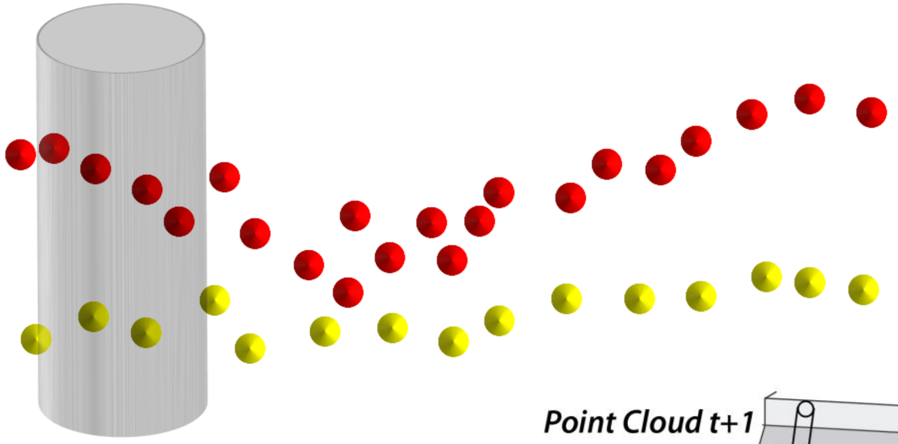
Tip : scales in M3C2 are diameters

M3C2 options

Option 1: **Vertical mode**

→ **no normal calculation** → Faster

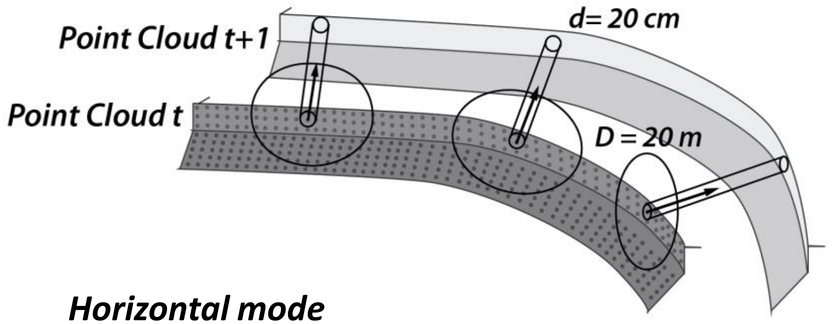
Nickname : vertical-M3C2



Option 2: **Horizontal normals**

⟶ **Bank or cliff retreat**

⟶ No need to rotate the data



Horizontal mode

Automatically tracks bank orientation

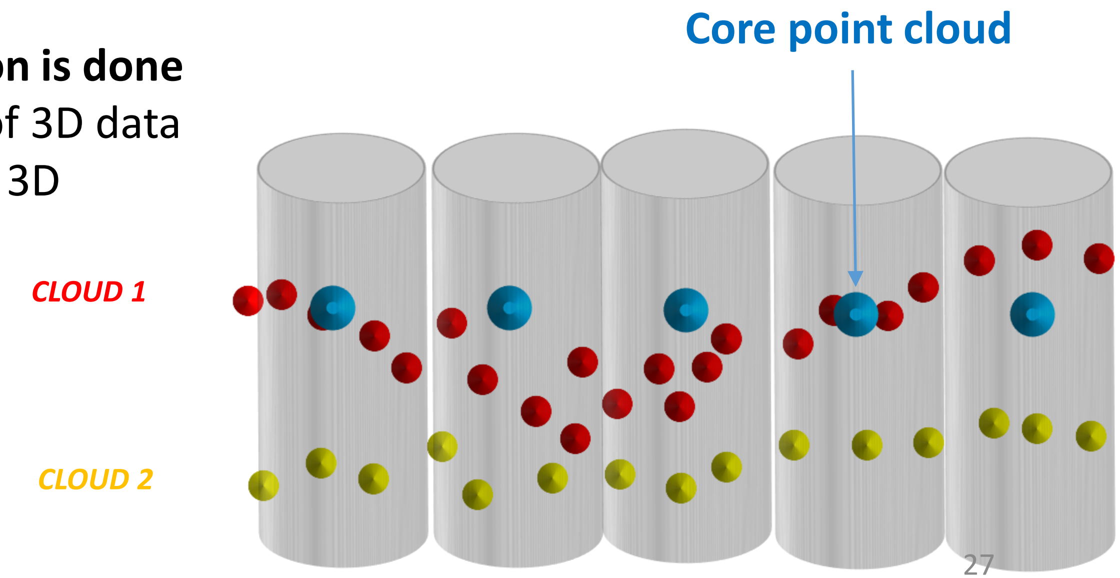
Option 3: **CORE POINTS**

- **Subset of points of arbitrary geometry on which the calculation is done**
  - → Grid of core points solve the sampling irregularity issue of 3D data
  - → Spatial resampling of the data with minimum distance in 3D
- **But uses the RAW DATA for underlying calculation**
  - ***Mean point position, point density, local roughness***

→ **Faster**

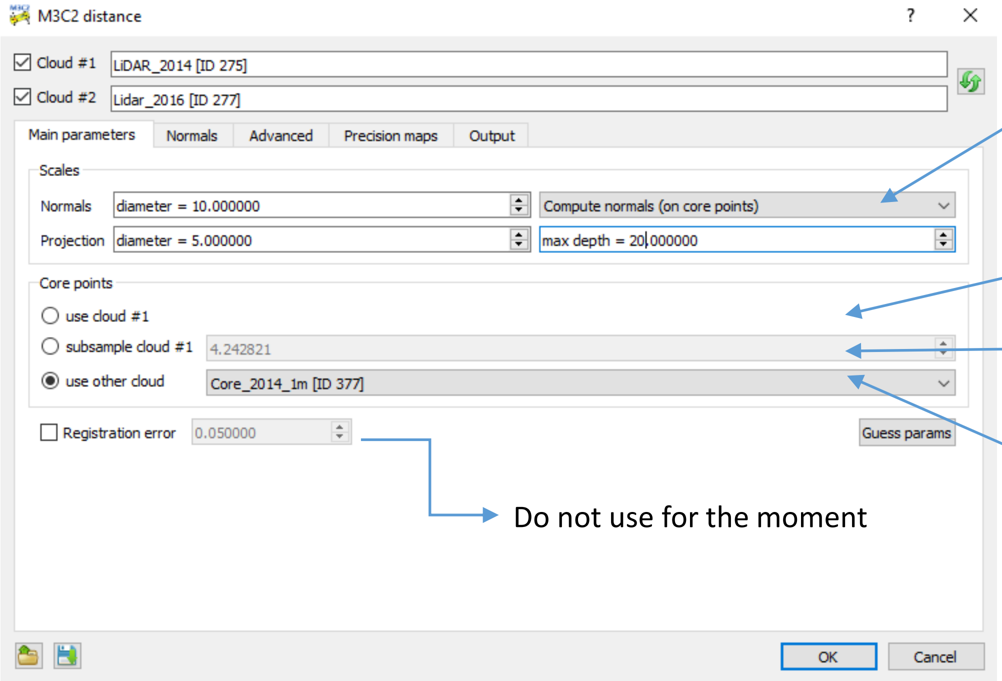
→ **Generate calculation**

→ **Can be used for volume calculation**



ALS data
M3C2 on the Kaikoura EQ dataset

- Create a raster from the 2014 dataset with 1 m step → core_2014_1m
- Select the 2014 and 2016 data and launch M3C2
- Fill the parameters as follow :



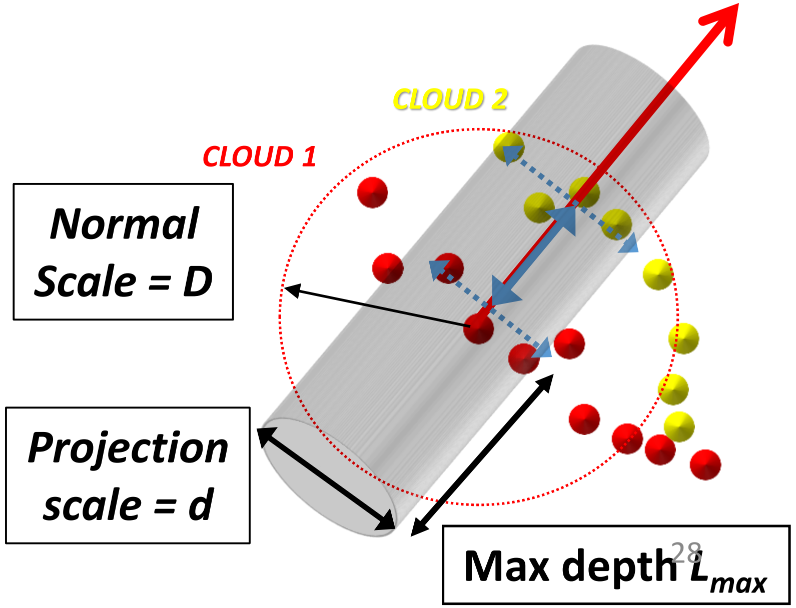
Tip : if the core_point already has normals, you can directly use them for faster processing

Calculation on all the points of cloud # 1

On the fly minimum distance sub-sampling

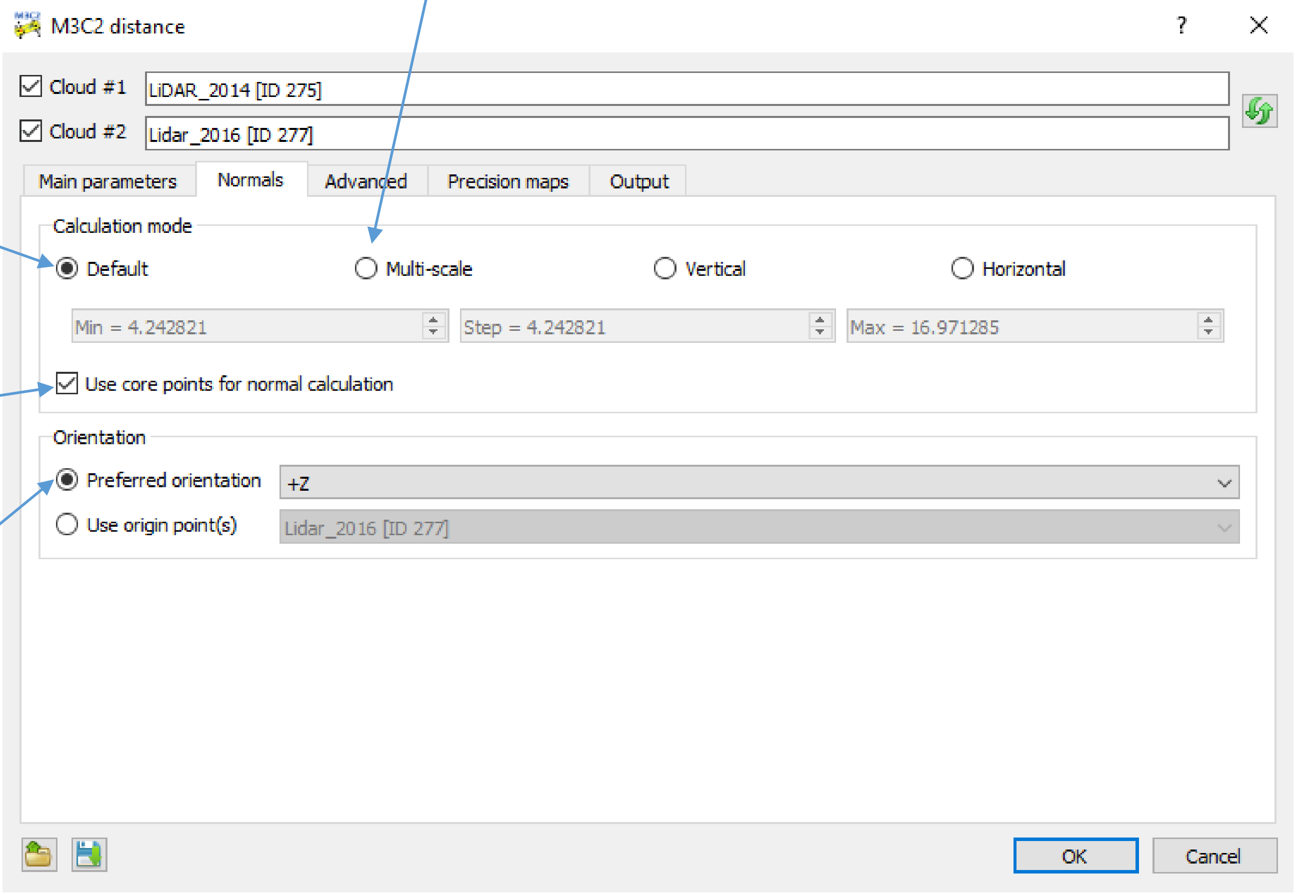
A specific core point cloud that you have created

Do not use for the moment



Normals

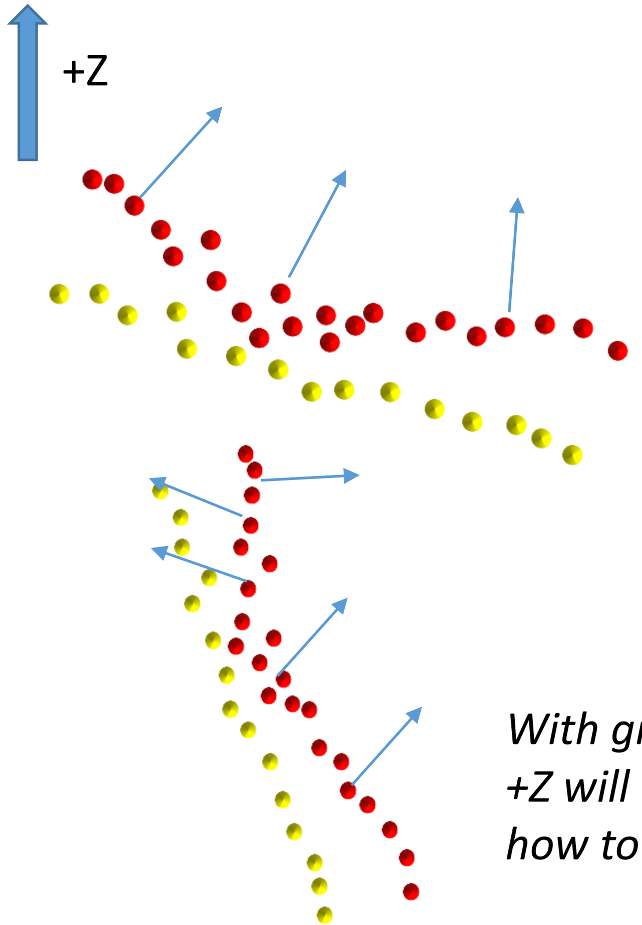
3D multi-scale
(will be explained later)



3D normal at a constant scale (default mode)

Faster calculation as there are less points than cloud #1

Because we are using ALS we can directly use +Z (i.e., the sky)

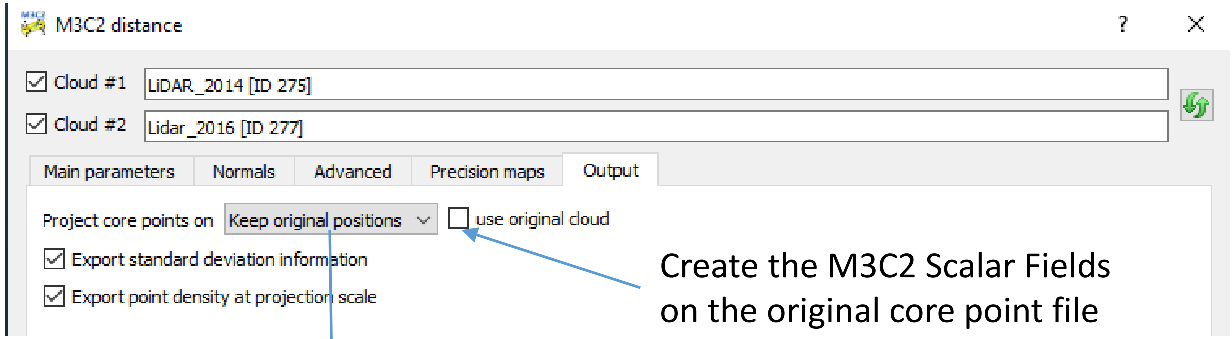


With ground-based 3D data (e.g., TLS) with overhanging parts using +Z will be incorrect (flipping of sign of the M3C2_distance). We'll see how to deal with these limits using an « origin points file »

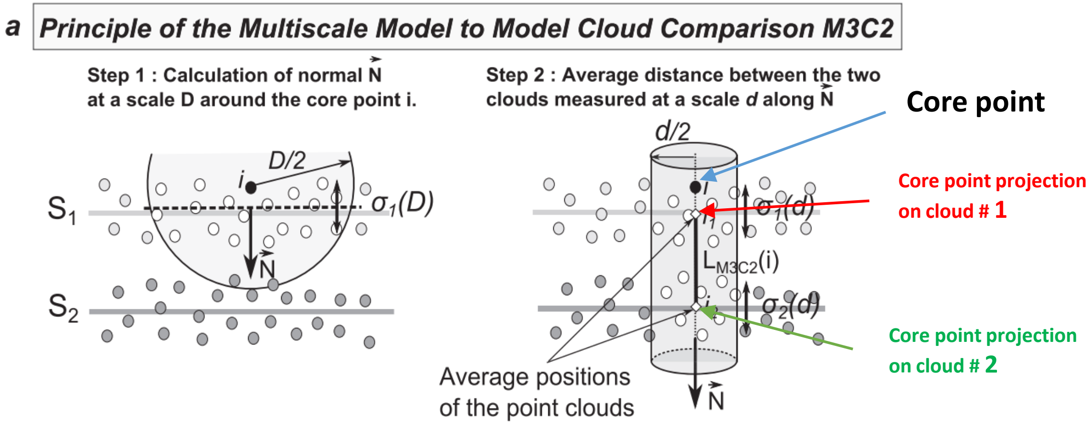
Practical M3C2

Output

Typical configuration



Create the M3C2 Scalar Fields on the original core point file



Lague et al., 2013

Create a copy of the core point file (without all the scalars of the core point file) with the M3C2 Scalar Fields

Other options (advanced use):

Project core points on « cloud #1 »

- Create a new point cloud corresponding to the average position of cloud #1 around each core point
- Records the M3C2 scalar fields on it

Tip : this will generate a smoothed version of cloud #1. I recommend to use it only if you really know what you're doing !

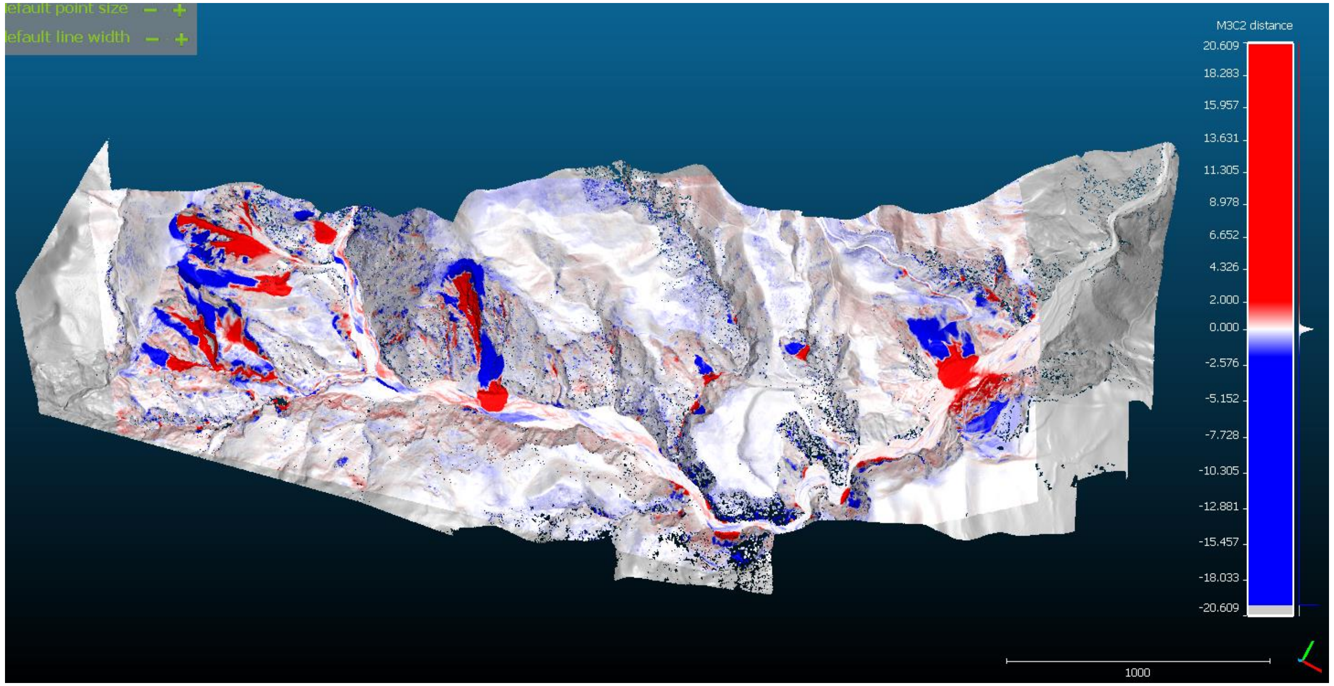
Project core points on « cloud #2 »

- Create a new point cloud corresponding to the average position of cloud #2 around each core point
- Records the M3C2 scalar fields on it

Tip : this will generate a smoothed version of cloud #2. I recommend to use it only if you really know what you're doing !

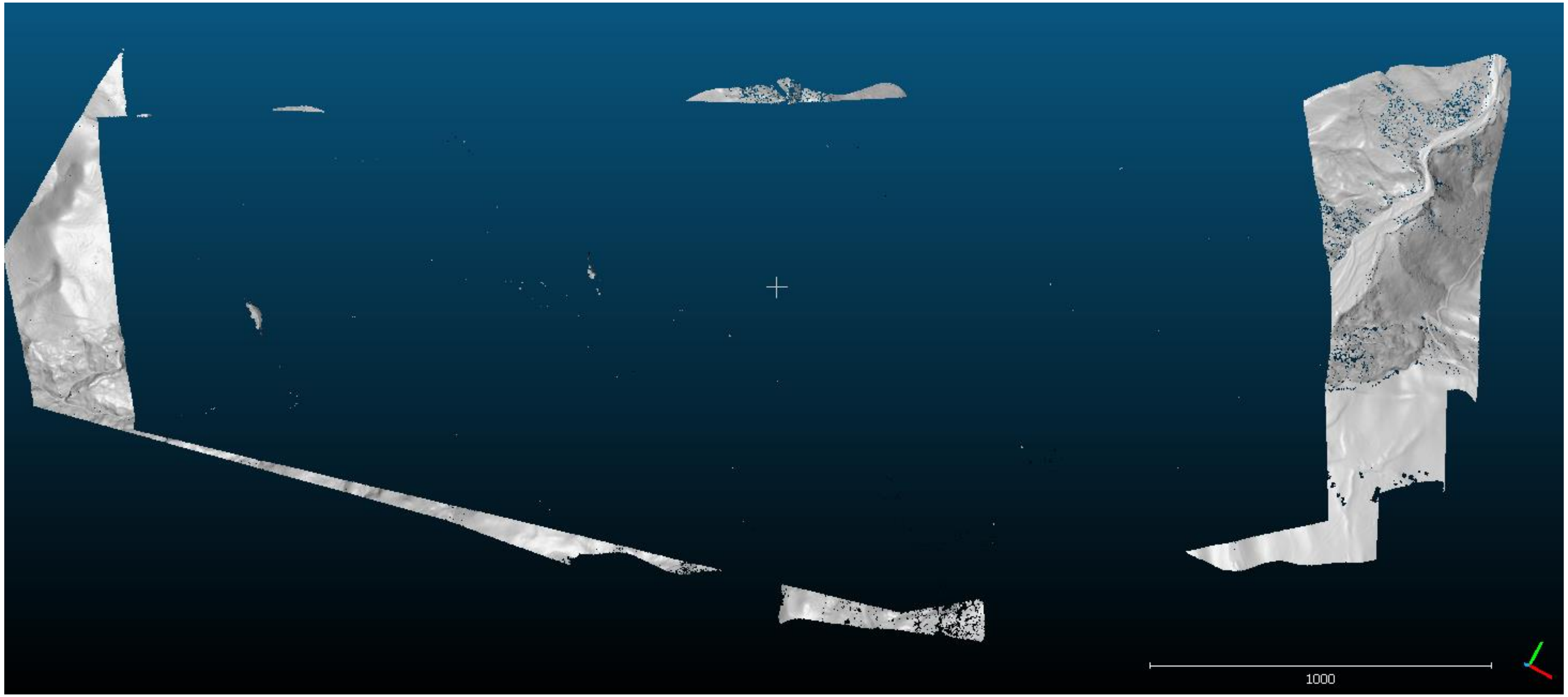
Result

- The output of M3C2 now has normals
- 7 new scalar fields :
  - **M3C2 distance**: signed 3D distance (grey = no intercept with cloud # 2)
  - **Distance uncertainty at 95% confidence:** spatially variable *(will be explained later)*
  - **Significant change (boolean):** **1= M3C2_distance≥distance_uncertainty**; **0= M3C2_distance<distance_uncertainty**
  - **Npoints_cloud1** (resp 2) = nb pts intercepted by the projection cylinder in cloud #1 (resp cloud #2)
  - **Std_cloud1** (resp 2) = detrended roughness at the projection scale of cloud #1 (resp cloud #2)



Inspection of M3C2 field

- Split the M3C2 _distance field in values, and NaN (min-max without changing anything)
- Inspect the NaN values

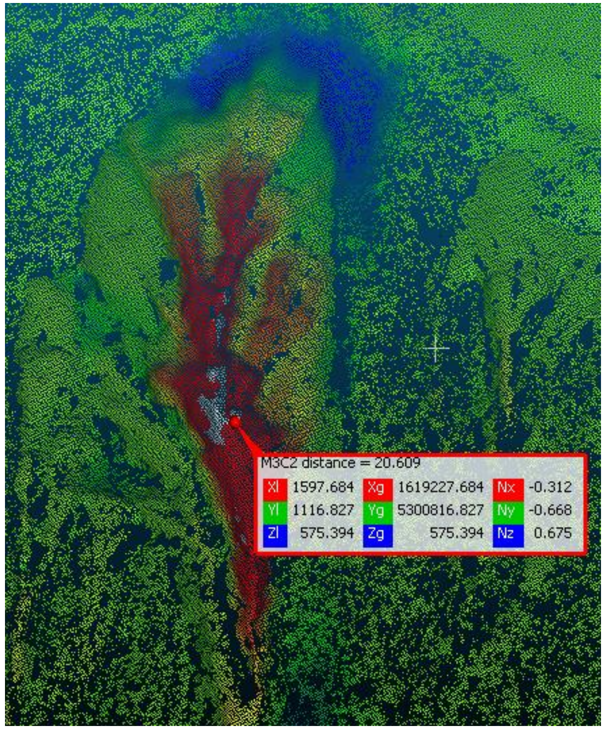


Why an M3C2 distance is not computed everywhere ?

Missing M3C2 distances: solutions

- On the non-overlapping data, there are no correspondence in cloud #2 → **expected behaviour, no need to trim the data !**
- **Inside the overlapping area 3 possible causes:**
  - **The maximum depth is not large enough**
    - **Increase the maximum depth**
  - **Data is locally missing in one of the cloud**
    - e.g., below a tree, or due to water (full NIR absorption)
    - Normal behaviour
  - **M3C2_distance is frequently not calculated**
    - **The projection scale is too small**

Typical case of max depth not large enough



On this dataset 40 m would be needed

Choosing the projection scale d

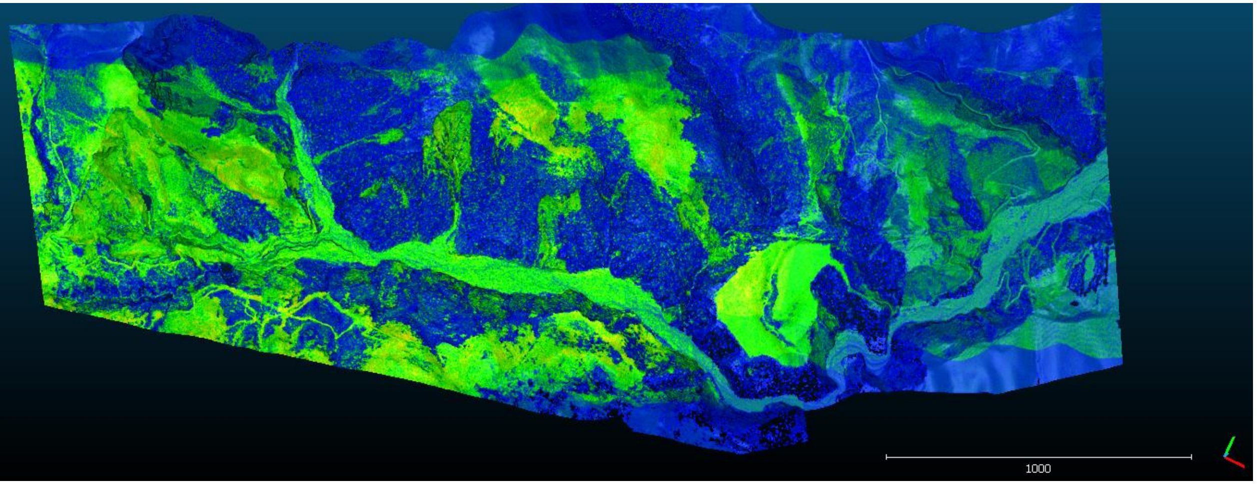
- M3C2 « averages » the point cloud to :
  - Obtain a more **accurate estimate of the mean position** of the implicit surface (e.g., averaging random noise)
  - Evaluate local parameters of the uncertainty model: nb points, standard deviation
- The optimal projection scale is thus a balance between :
  - **d large enough to have enough points** on both clouds to compute a robust uncertainty model (typically ~ 20 pts) $\longrightarrow$ **function of point clouds densities**
  - **d small enough to resolve sharp spatial variations in M3C2 distances** (i.e., avoiding a too large smoothing effect)

Choose d such that you have at least ~ 20 pts on the point cloud with the smallest point density

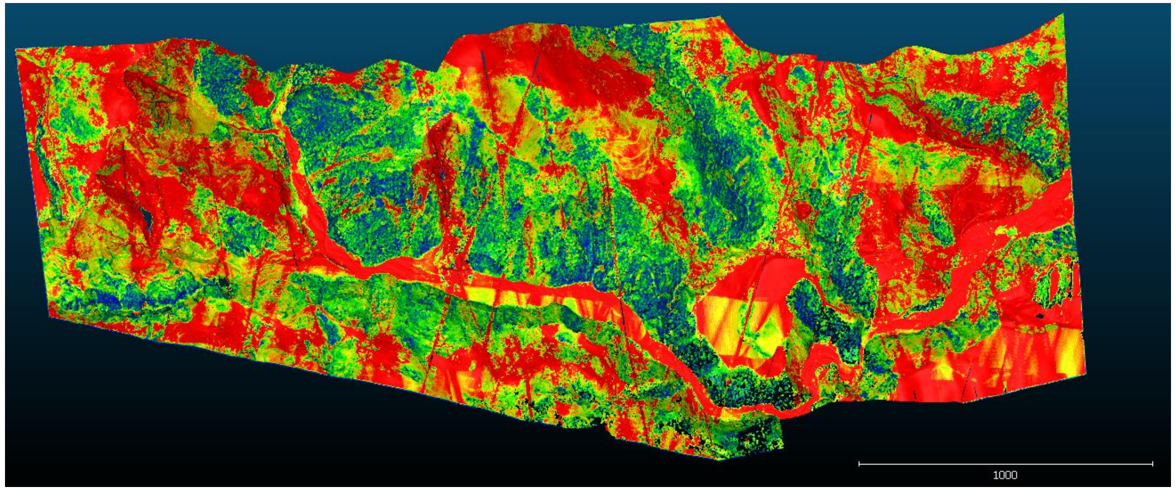
e.g., discussion in Lague et al. 2013 and Bernard et al., 2021

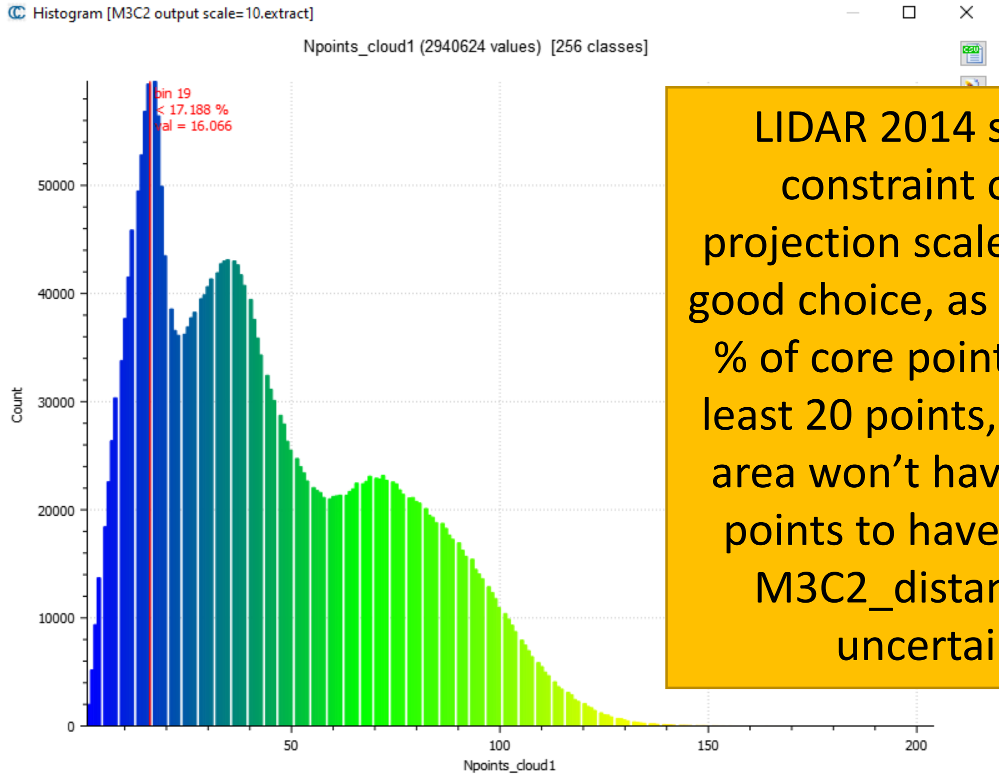
Practical M3C2 : choosing the projection scale

2014 Lidar Nbpoints

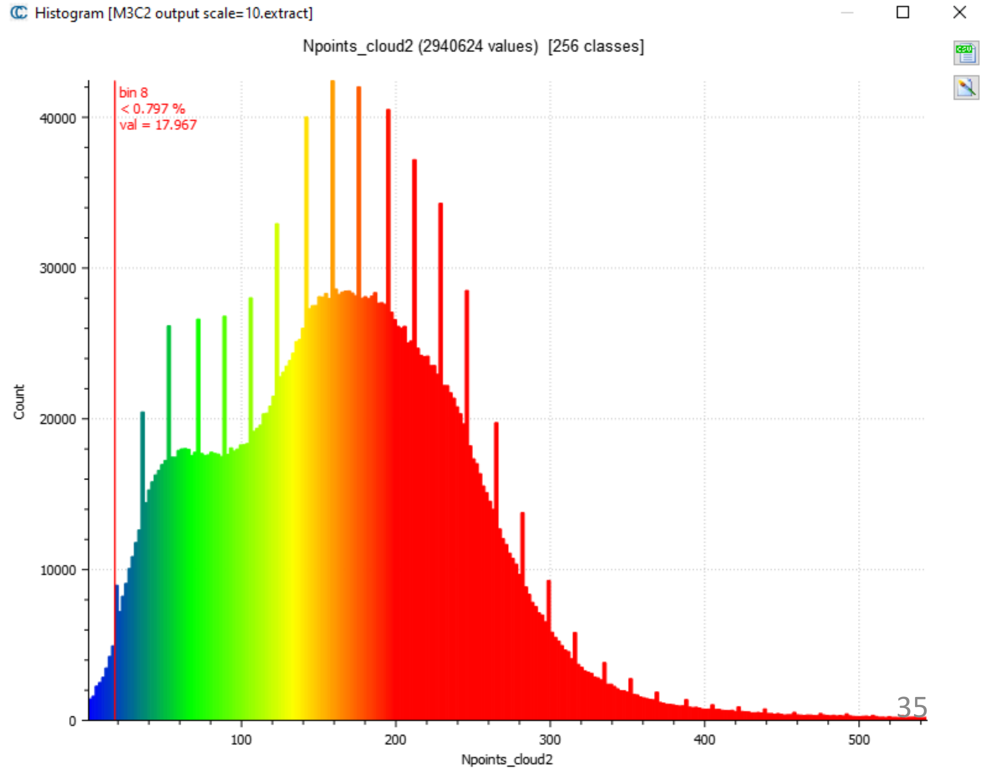


2016 Lidar Nbpoints



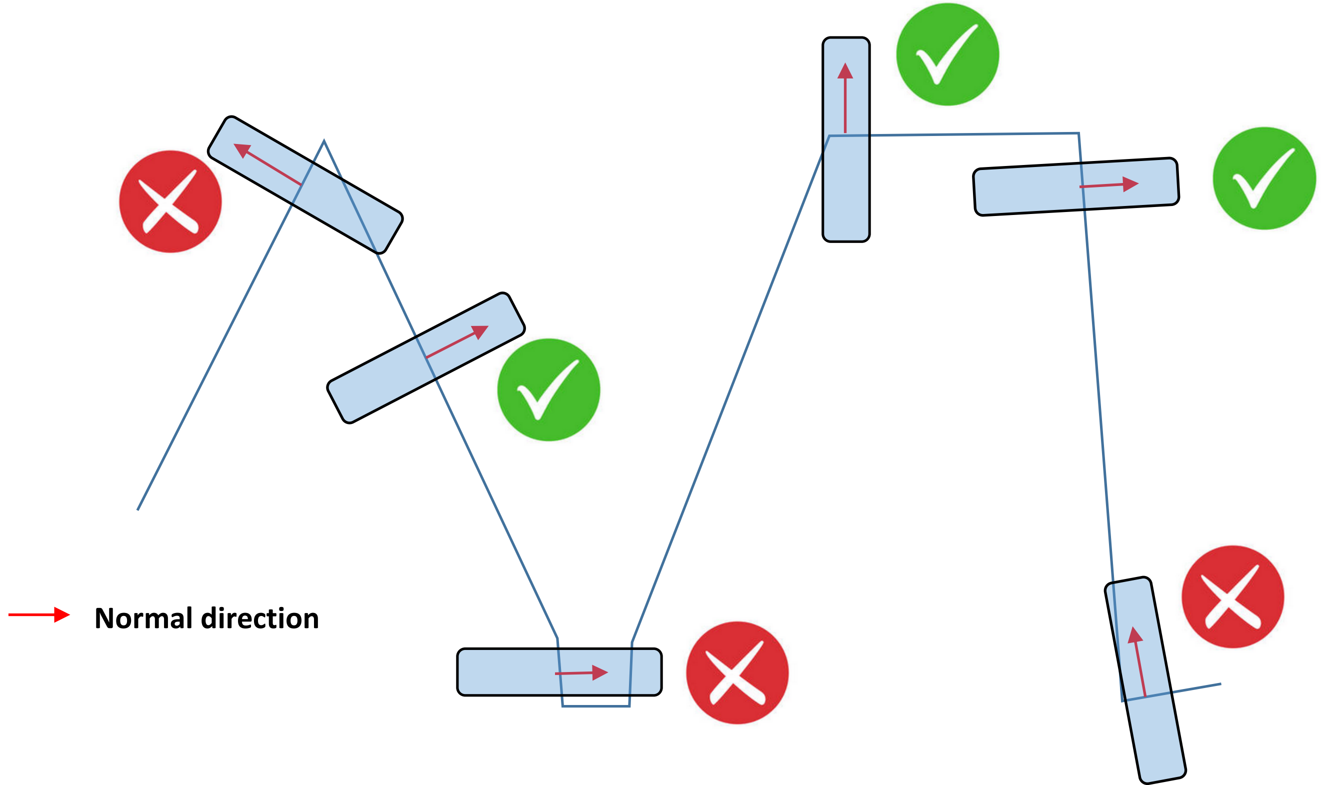


LIDAR 2014 sets the constraint on the projection scale. 5 m is a good choice, as roughly 80 % of core points have at least 20 points, but some area won't have enough points to have a robust M3C2_distance and uncertainty



Choosing the max depth

- Large enough to intercept the two point clouds = f(max topographic change)
- Vertical-M3C2: can be very large, but the larger the longer the calculation
- **Standard 3D M3C2: be careful of double intercepts : cylinder crossing the same cloud twice : incorrect distance measurement**



- **Use the smallest max depth possible to avoid double intercepts**
- Inspect your data !
- Use a SDDS test to evaluate the problem
- **New version of M3C2 using a progressive cylinder search currently in beta testing !**
- **Tip:** the multiscale normal tend to favor this issue, while a constant large normal reduces it (at the expense of accurate distance measurement)

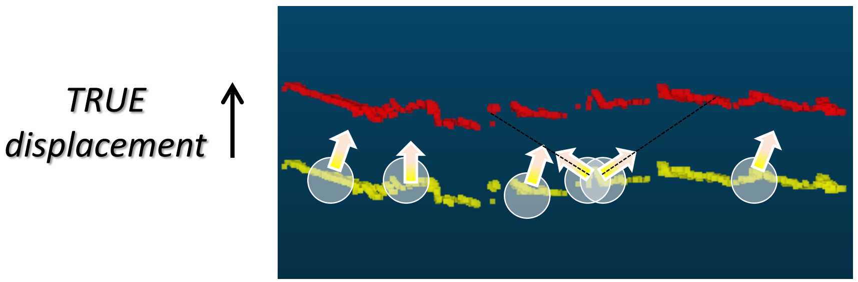
Illustrating double intercepts

- **Kaikoura 2016 EQ Lidar dataset**
  - Create a raster of core points with 2 m spacing -> core_2 m
  - Use subsample versions « 2016_sub0.5 » and « 2016_rand »
  - 3D-M3C2 with core_2m normal scale = 10 m, proj scale = 5 m, **depth = 40 m**
  - Rename the M3C2_distance in M3C2_distance_40m
  - 3D-M3C2 with the previous M3C2_result as core points, with normal scale = 10 m, proj scale = 5 m and **depth = 2 m (on output, tick the box use original cloud)**
  - **Using scalar arithmetics compare M3C2_distance_40m and M3C2_distance at 2m depth**
  - **Highlight where there are differences**

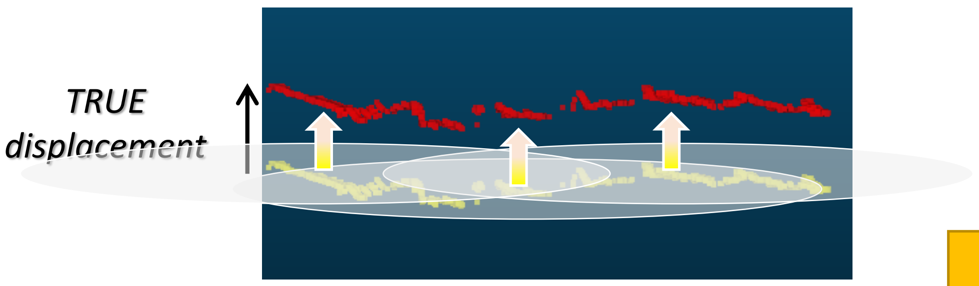
Choosing the normal scale D in M3C2

- Computing normal on rough surfaces is an extremely complex problem !
- D should be **small enough to track the changes of the topography**
- D should be **large enough to not « flicker » due to noise**
- The smaller is D, the faster is the computation of normals

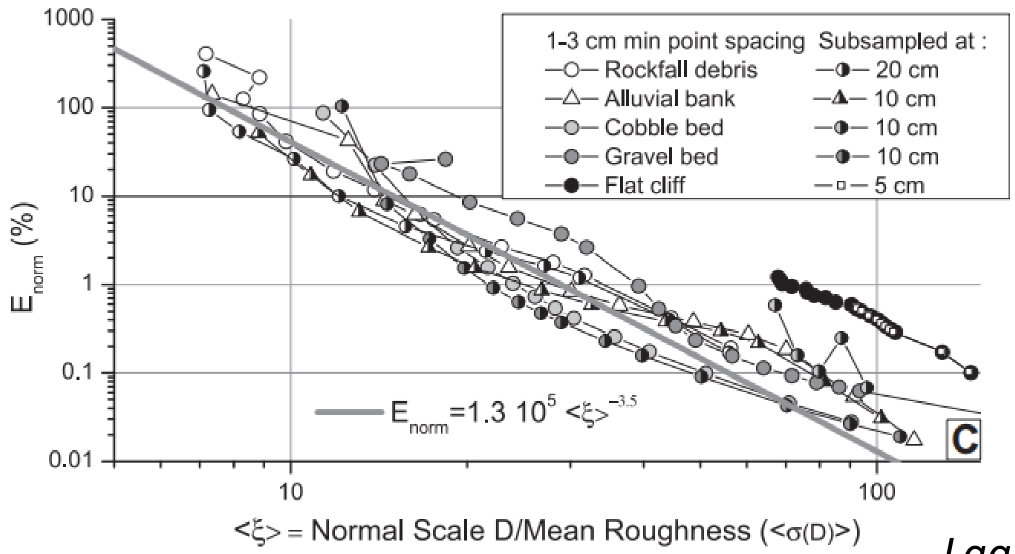
Small scale compared to rougness characteristics



Large scale compared to rougness characteristics



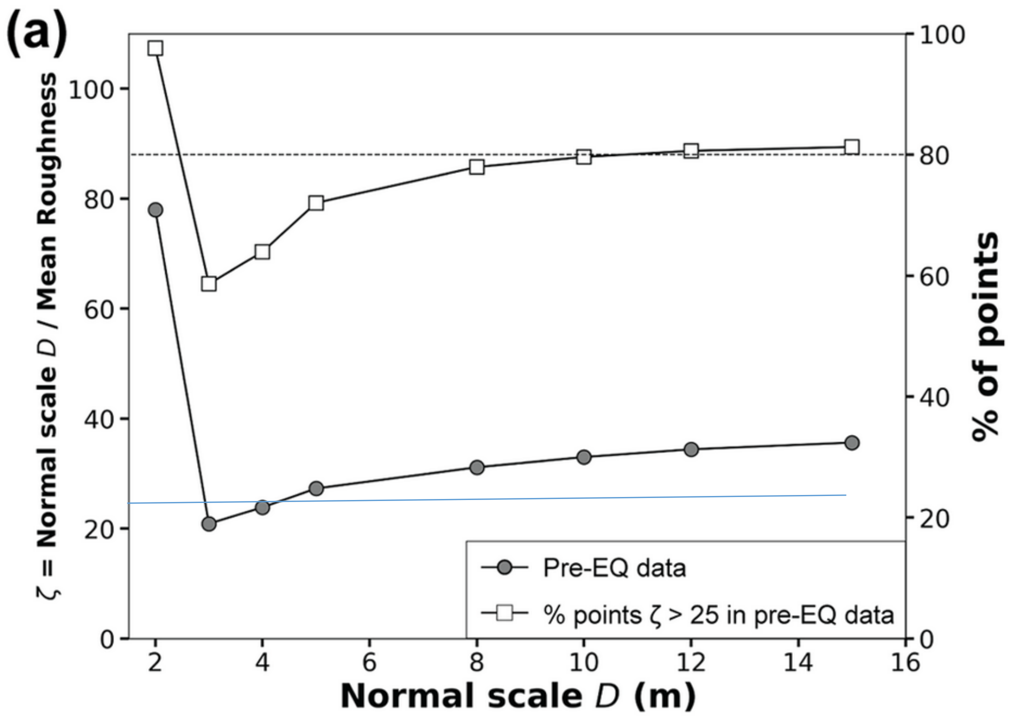
Attempt in Lague et al., 2013 to define an objective function by comparing the **distance estimation error E_{norm}** and **normal scale/roughness**



Lague et al., 2013

Choose the smallest Dn such that
Normal Scale D_N > ~ 25 roughness(D_N)

Choosing the normal scale D, Kaikoura EQ



Bernard et al., esurf, 2021

- No simple a priori prediction as roughness is scale dependent
  - *Roughness needs to be calculated at all scales (no automated way (yet) in M3C2)*
- Bernard et al., esurf, 2021 : Using the pre-EQ with the lowest point density, **a normal scale of 10 m allows for ~80% of the points to validate ζ > 25**

For a given type of data (ALS, TLS,…), the normal scale is generally not depending a lot on point density but on the roughness properties of the landscape :
ALS : 10-20 m seems a good range but further exploration of this parameter is needed

What about the multiscale approach ? (the first M in M3C2)

- Developped as an attempt to automatically find the optimal scale
- Compute the normal at various scales and choose the scale at which the surface **appears flatter**

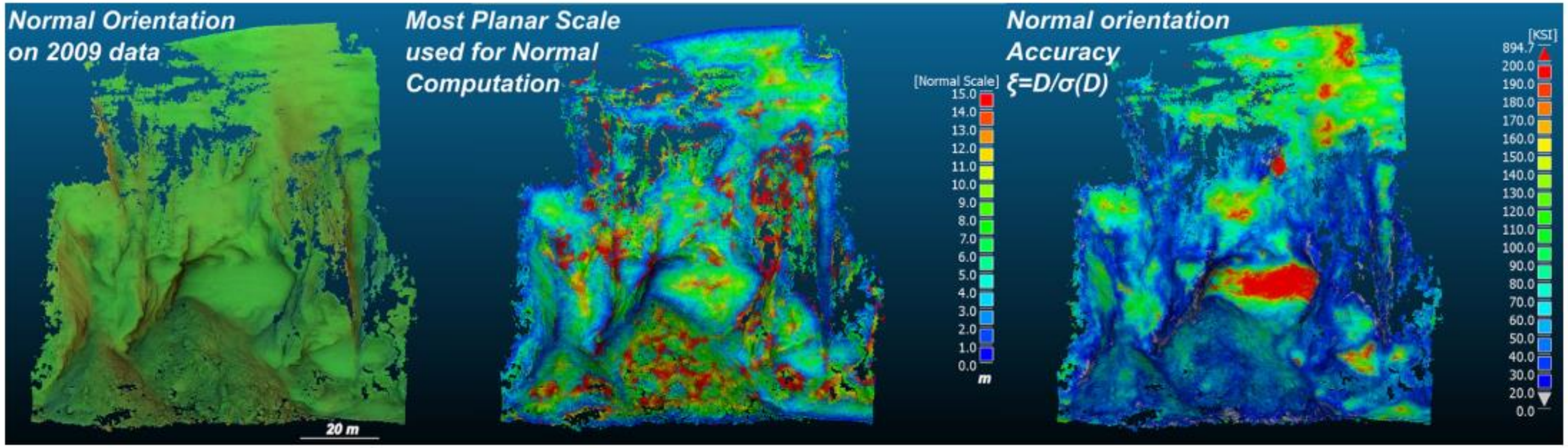


Fig. 7. Normal calculation with automatic selection of the most planar scale on the rockfall area (Fig. 1). Normal orientation is defined in a Hue Saturation Value colour wheel. ξ is an indicator of normal orientation accuracy given by Eq. (4): when $\xi \geqslant 20$ error on distance calculation between two clouds due to the normal orientation inaccuracy is lower than ~2%. Points in grey correspond to $\xi < 20$.

Pros:

It better captures variations in normal orientation near edges, but appears more important for TLS than ALS

Cons:

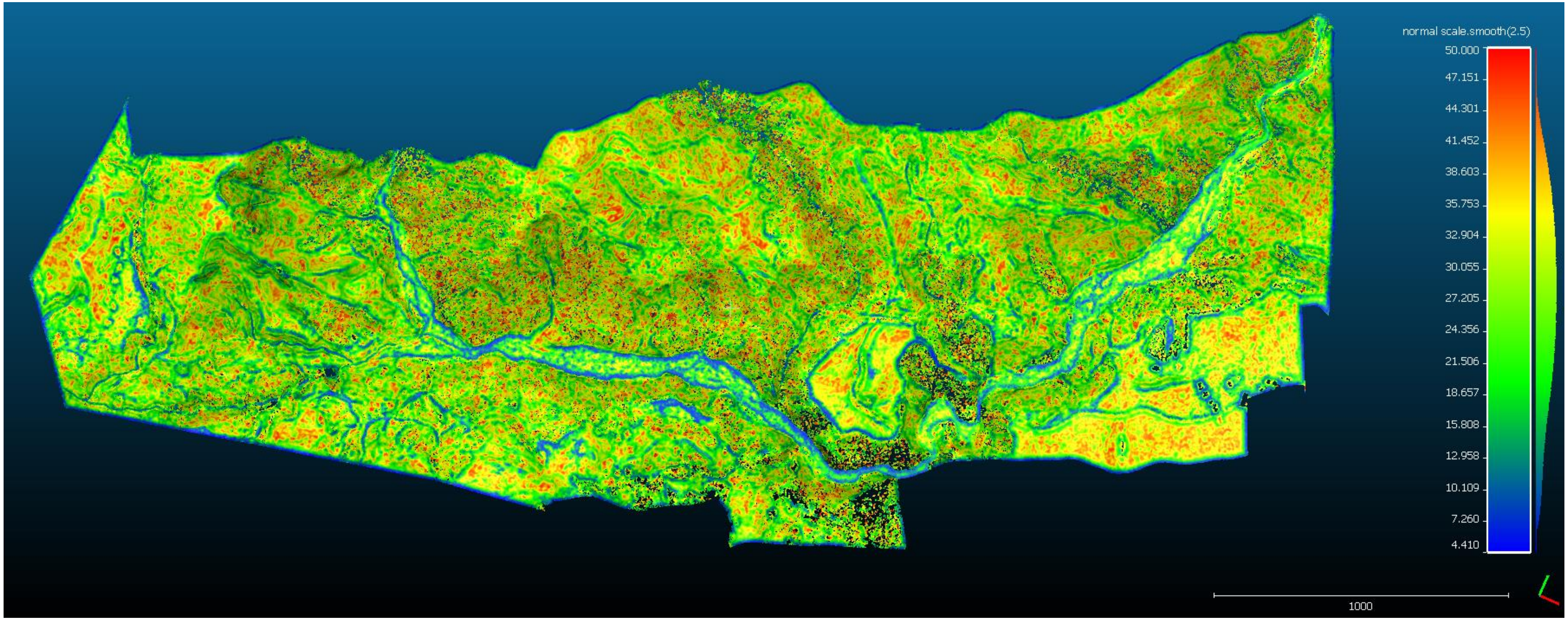
It is super long, especially as we increase the largest scale -> **in practive I barely use it, or with a limited range of scale**

It can create very large local variations which may not be desirable for data interpretation

It remains to be systematically tested in more environments than Lague et al., 2013, especially for ALS

Application to the Kaikoura ALS lidar data

Multiscale approach from 4 to 50 m with 2 m step. M3C2 creates a new scalar field called « normal scale »
Result smoothed at 2.5 m radius



High curvature areas (channel banks, ridges…) yield small normal scales -> 4-10 m
Flat areas yield very large ones, typically 20-50 m : for these surfaces, using a 10 m scale does not change the normal vector, but significantly speed up calculation

Plan

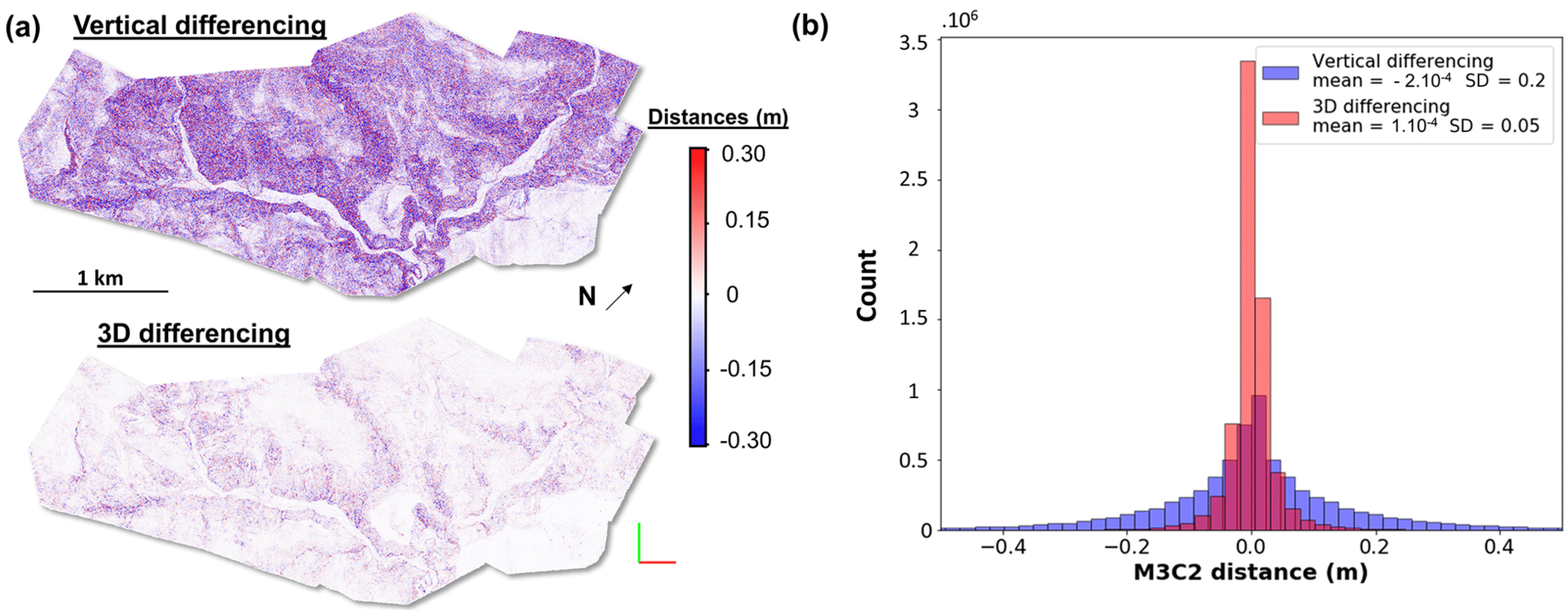
1. **Type of distance measurements**
    1. Feature based change detection
    2. **Featureless distance measurement**
        1. Difference of DEM
        2. Cloud to cloud
        3. M3C2 distance
            a) Algorithm and choice of parameters
            b) Benefits of 3D differencing vs vertical differencing
            c) Worflow for an equivalent Difference of DEM with M3C2
            d) Working with complex TLS data

2. **Dealing with uncertainties**
    1. Components of uncertainty in 3D point cloud change detection
        1. Positional uncertainty
        2. Registration uncertainty
        3. Roughness uncertainty
    2. Background on uncertainties
    3. Examples

The impact of 3D differencing vs vertical differencing

- **SDDS test : Same Data Differing Sampling test** (Lague et al., 2013)
- **Kaikoura 2016 EQ Lidar dataset**
  - Create a raster of core points with 2 m spacing -> core_2 m
  - Subsample with 0.5 m min distance -> 2016_sub0.5
  - Subsample randomly to have ~ 9.5 million points -> 2016_rand
  - Vertical-M3C2 with projection scale = 5 m, depth = 3m
    - Compute std of M3C2_distances
    - Optionnal: you can perform a 2.5 volume calculation on 2016_sub0.5 and 2016_rand
  - 3D-M3C2 with normal scale = 10 m, proj scale = 5 m, depth = 3 m
    - Compute std of M3C2_distances
  - Compare the two maps with similar saturation

Benefit of 3D differencing vs vertical differencing



From Bernard et al., 2021

Increased ability to detect change on steep slopes

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Alternatives to Difference of DEM directly on point clouds

(e.g. Wagner et al., GRL, 2017)

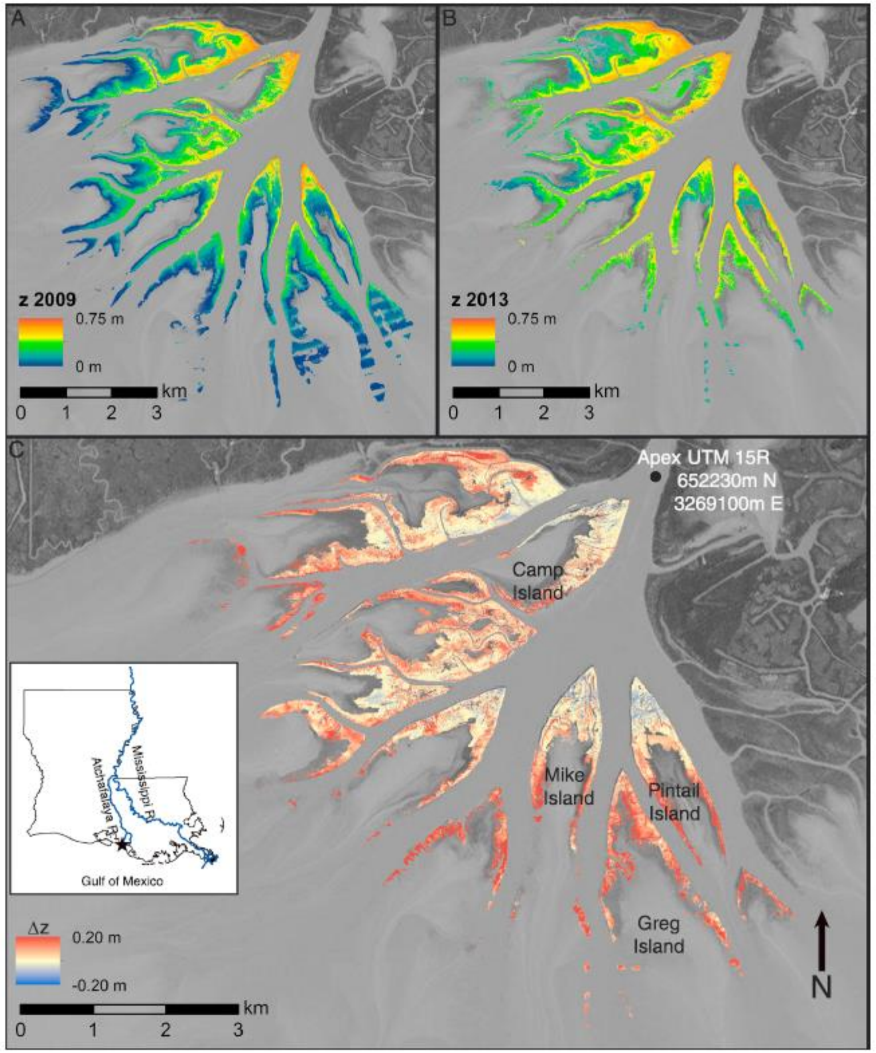
1. Create a regular grid of point clouds with step dx
2. Vertical-M3C2 with a projection scale > $\sqrt{2}dx$ to ensure entire sampling of the surface

   $\rightarrow$ **Grid of vertical distances** where it can be calculated : no computation where there is no corresponding data (i.e. wetted channels)

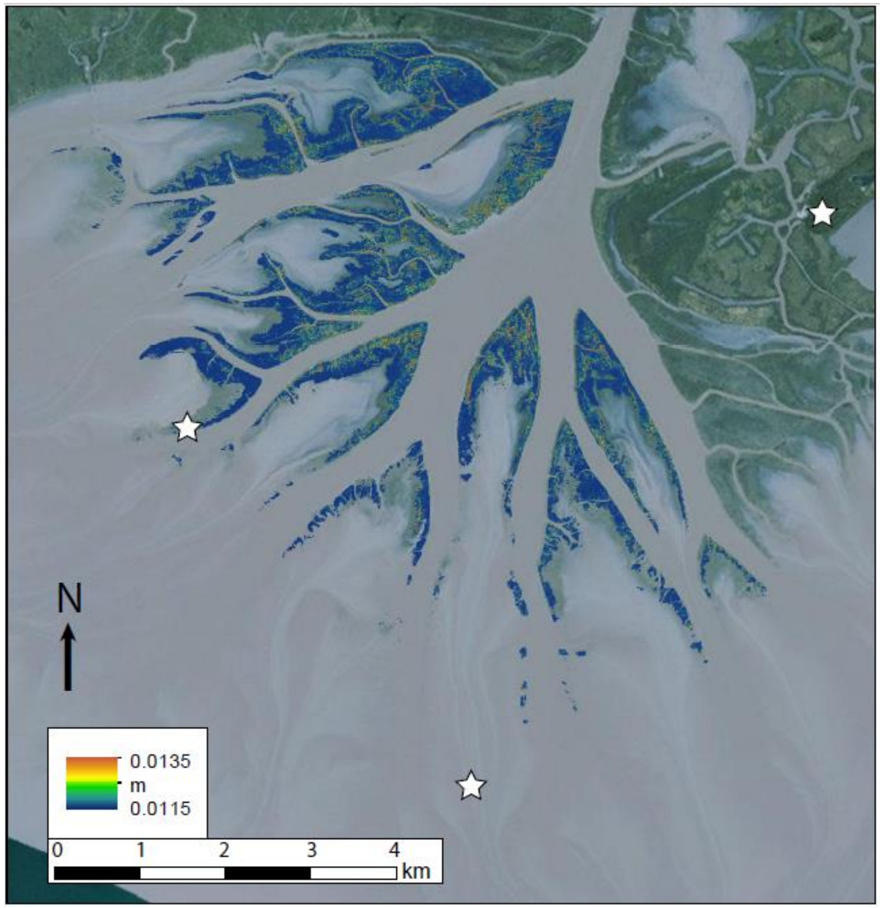
   $\rightarrow$ **Grid of spatially variable confidence intervals**
3. Interpolate the grid of vertical distances if needed
4. Compute volume and volume uncertainty

Illustration on the Kaikoura ALS Data

Example of DoD workflow with M3C2



Uncertainty map combining roughness and registration effects



(Wagner, Lague, Morhig, Passalacqua, Shaw, Moffett, GRL, 2017)

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Practical on TLS survey of the Rangitikei cliff Complex data

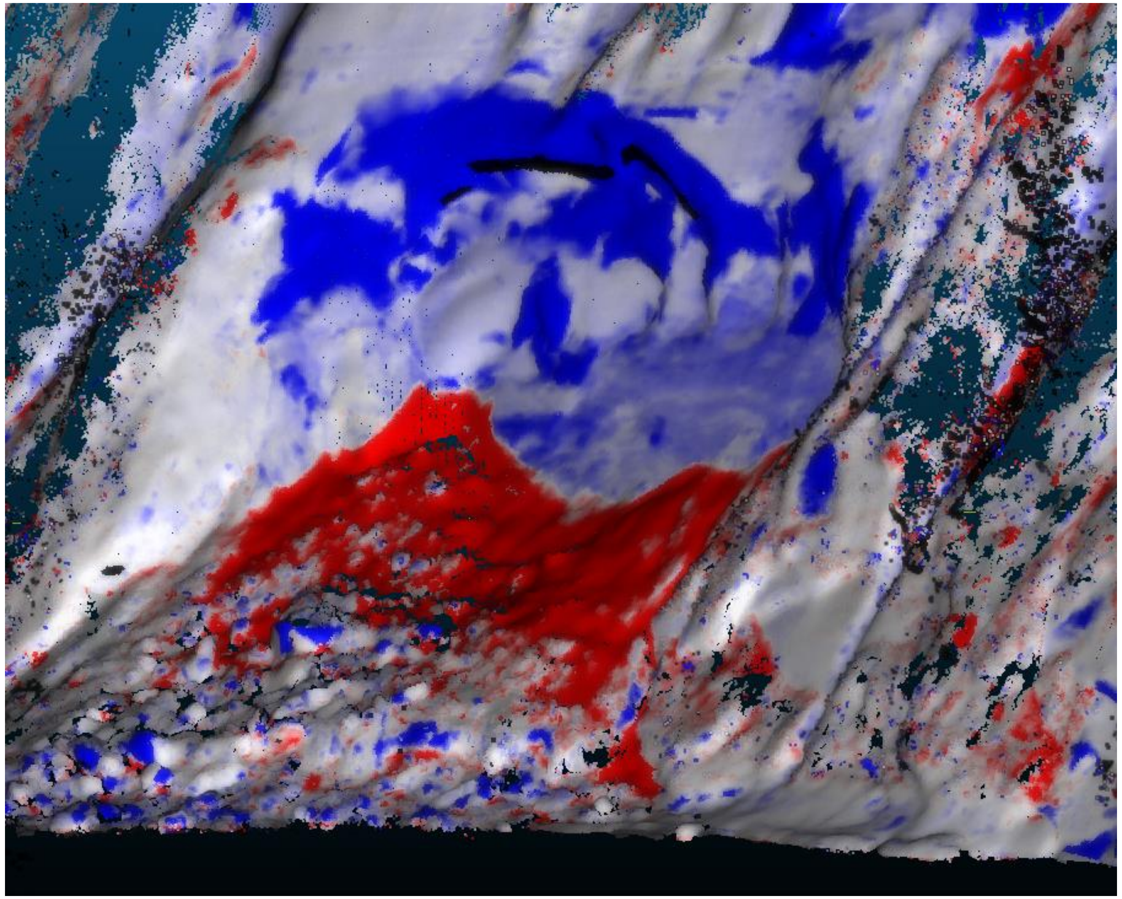
- Load the TLS_Mangarere_Rangitikei.bin file
- C2C with 2011 data as the reference
  - *What do you observe ?*
- Core points creation for M3C2 calculation
  - *Which dataset would be best to create the core points ?*
  - *Create core points from spatial subsampling at 5 cm*
- Perform M3C2 with the parameters of your choice
  - *What do you observe ?*

Suggested parameters for the Rangitikei cliff TLS survey

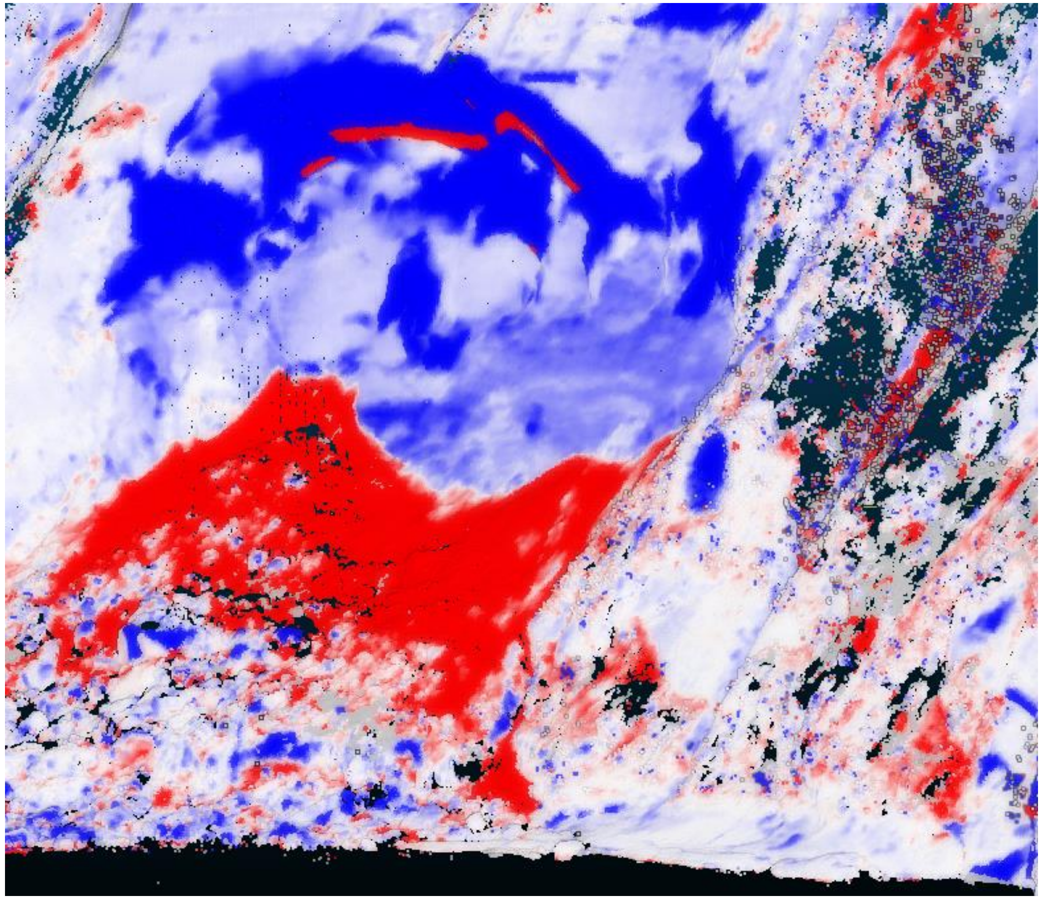
- Following Lague et al., 2013
  - **Core points = 5-10 cm** (could be less with higher resolution TLS)
  - **Normal scale ~ 10 m:**
    - To capture large scale normal fluctuations and capture average change on rockfall deposits
    - Could be lower to capture change on individual blocs/overhangs
  - **Projection scale ~ 0.5 m -> could be less with higher resolution TLS**

- Try an M3C2 with a normal scale of 2 m

Example of normal orientation issue when using +Z option on overhanging parts



With normals « on », appears black



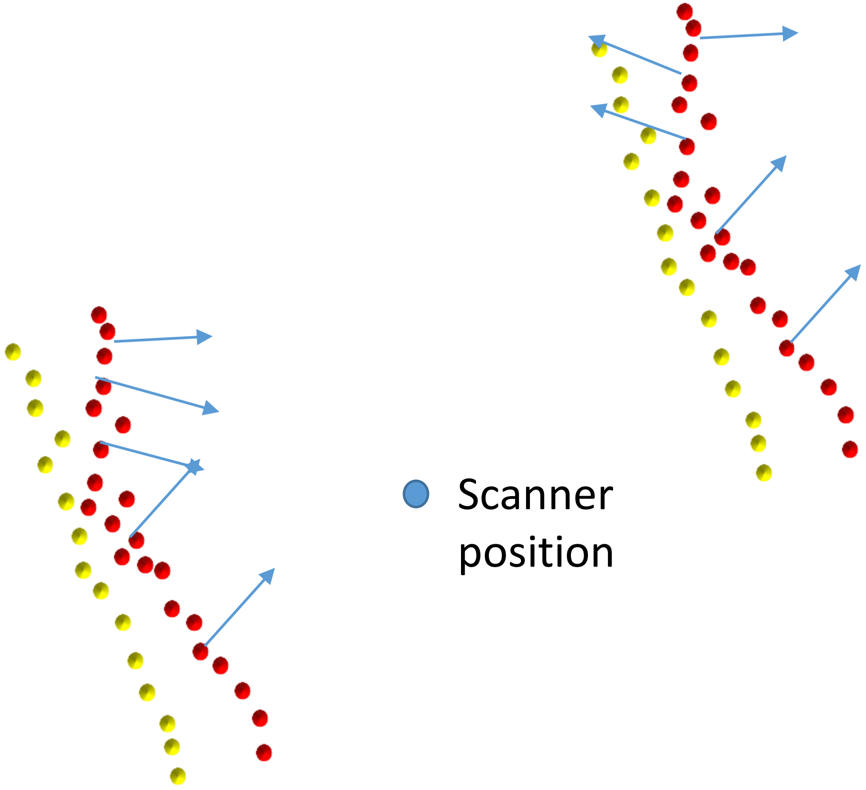
With normals « off », appears as locally inverted change

Dealing with normal orientation issues

Extremely complex to deal with !

Solutions:

- **With M3C2** : provide a series of position towards which orienting the data
  - *Fails for very complex surfaces*
- Try to reorient normals within Cloudcompare or Meshlab
  - *Very time consuming, not guaranteed*
- Cut your core points in several bits, rotate them towards the +Z, compute the normals, and rotate back. Merge them back
  - **Gives a core point file with correctly oriented normals**



Practical on Rangitikei

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Components of uncertainties

1. **Position uncertainty of points within a given point cloud**
   - Dependent on the survey technique
   - Can generally be assumed an uncorrelated random error = **can be reduced by averaging**
   - Complex dependency with range and incidence angle that are difficult to account for

2. **Registration uncertainty within and between surveys**
   - Dependent on the survey technique TLS, ALS, SFM
   - **Is a systematic error that cannot be reduced by averaging**
   - **Is generally assumed uniform and isotropic, but IS NEVER UNIFORM**
     - Slight misalignment of flight lines or TLS surveys
   - **Extremely complex to have a spatially explicit registration error in TLS or ALS**
   - Not always easy to evaluate

3. **Surface roughness related errors**
   - Independent of the survey technique
   - Even if rough surface does not change, a change will be measured between two point clouds taken at different times owing to the difference of sampling **(cf SDDS test)**
   - Spatially variable

Lague et al., 2013

+ Errors related to ground classification !

Quick & dirty reminder on statistics

Uncorrelated random error

- Standard error of the mean of **n** observations from a population of standard deviation **σ**

$$SE = \frac{\sigma}{\sqrt{n}}$$

- Hyp : the SE on the mean position of the surface characterized by n points from a **fixed** LiDAR with a ranging error **σ (precision or repeatability)**
  - **TLS : σ ~ 1 mm. 1OO pts gives SE ~ 0.1 mm**
  - **ALS : σ ~ 10 mm. 50 pts gives SE ~ 3.1 mm**

Systematic error

- An uncertainty that cannot be reduced by averaging samples
  - E.g.: accuracy of a LiDAR system (= bias)
  - A registration error between two dataset

Propagation of errors

- Two values $X \pm SE_x$, $Y \pm SE_y$, the uncertainty of the linear combination of X and Y is :

$$SE_{X+Y} = \sqrt{SE_x^2 + SE_y^2 + 2rSE_xSE_y}$$

with r the correlation coefficient between SE_x and SE_y

- If X and Y are **perfectly random**, r=0

$$SE_{X+Y} = \sqrt{SE_x^2 + SE_y^2}$$

- If X and Y are **perfectly correlated**

$$SE_{X+Y} = SE_x + SE_y$$

See Anderson, ESPL, 2019 for a study in the context of DoD

Hypothesis behind the M3C2 uncertainty model

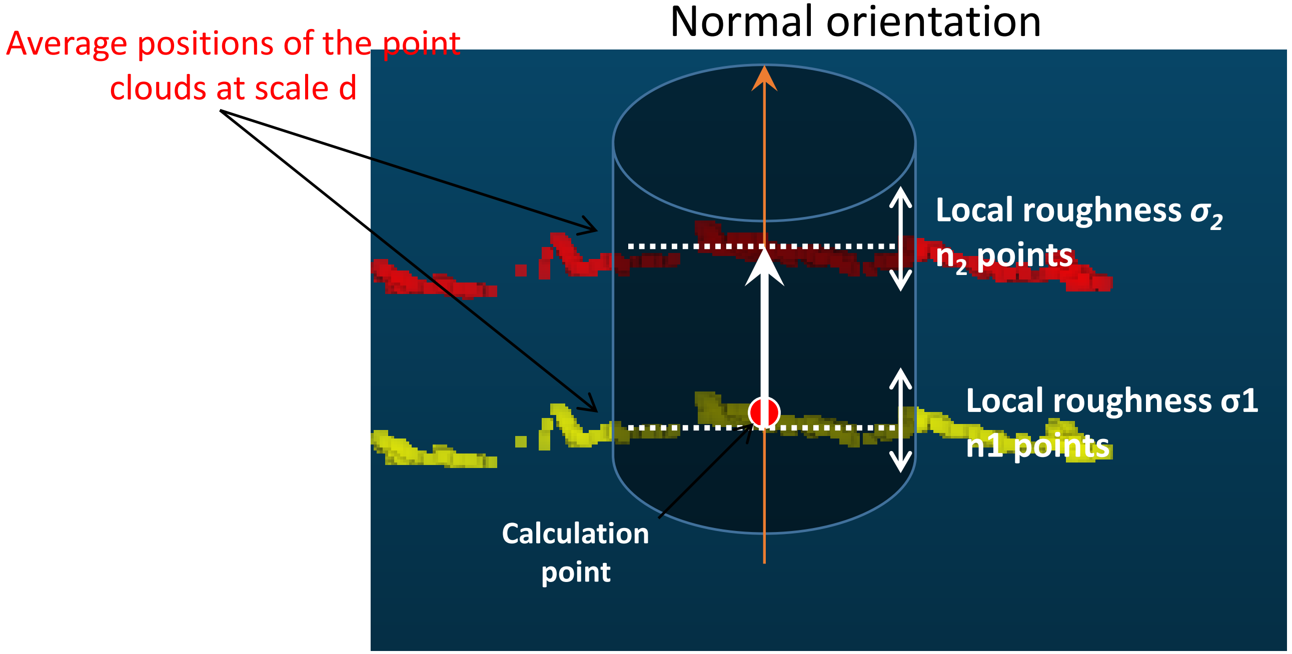
SE$_{pc}$ = Combined Standard Error associated to the point cloud position uncertainties and roughness

Hyp: **Point cloud roughness can be considered an uncorrelated random noise :**

- **True if the surface is flat**: point cloud roughness is the ranging noise
- **Debatable if the surface is rough**: a grabel bed is not a random surface

Hyp 2: **Two successive surveys are uncorelated**

- True if the surface is flat
- Debatable if the surface is rough and has not changed !



Combined standard error of the two surveys at projection scale *d*

$$SE_{PC} = \sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}$$

Hypothesis behind the M3C2 uncertainty model

reg *= registration error model between the two point clouds*

Hyp 1: The registration error *reg* between the two point clouds is spatially uniform and isotropic

Hyp 2: *reg* and SE_{pc} are supposed fully correlated : sum of the standard error (conservative assumption)

$$SE_{tot} = \sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}} + reg$$

From the standard error we build a confidence interval at 95%:

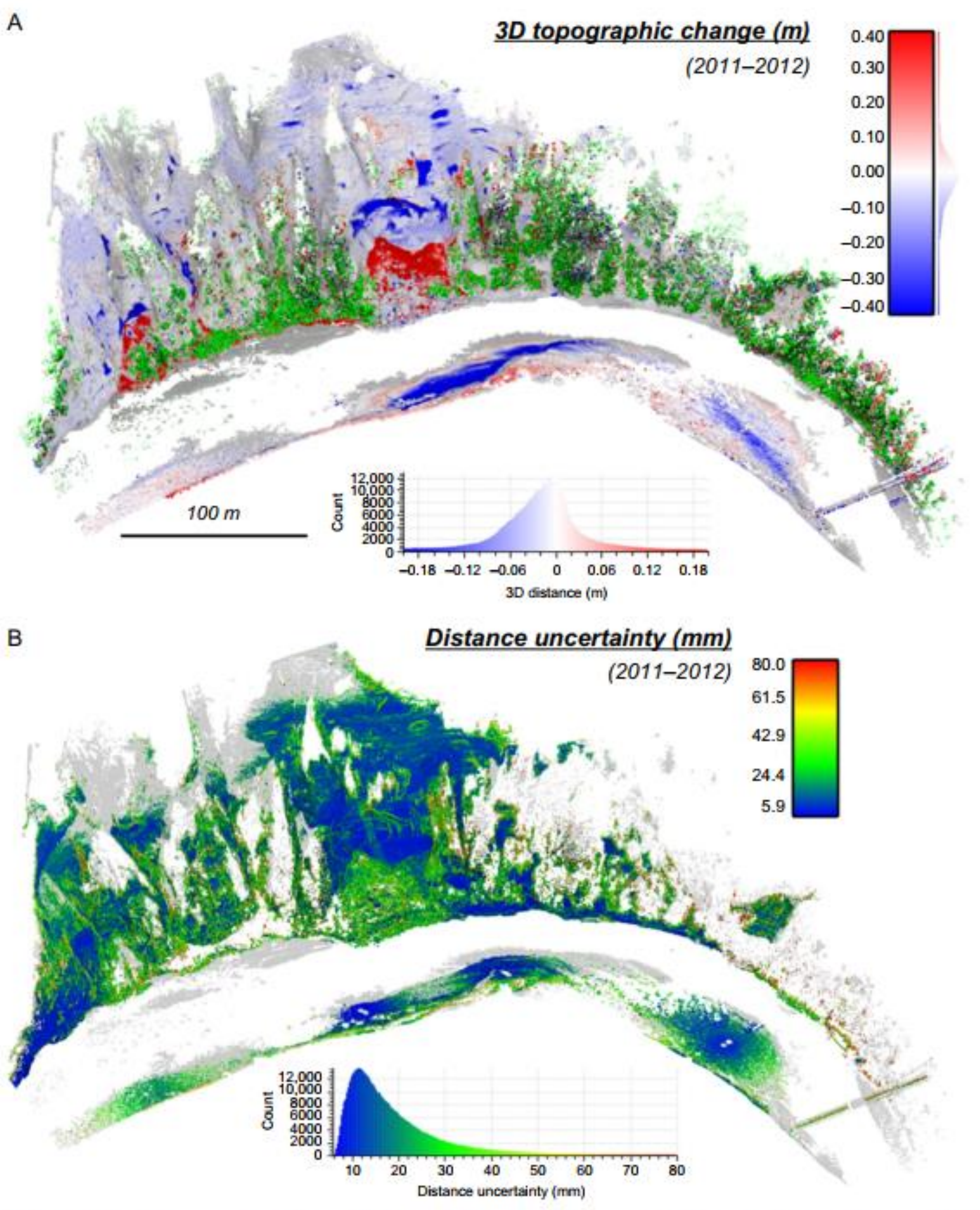
Point cloud roughness at scale d

$$\boxed{LoD_{95\%} = 1.96\left(\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}} + reg\right)}$$

Registration error

Point cloud density at scale d

More advanced model when n1 and n2 < 20 in Bernard et al., 2021



Statistically significant change when **Dist_M3C2 > LoD95%**

How to define the registration error ?

- Super tricky !!
- TLS, Lague et al., 2013 :
  - With fixed target : mean error on fixed target position between surveys (~ 3 mm)
  - With GNSS target : combined error accounting for GNSS accuracy (i.e., 1 cm per survey, then reg = $\sqrt{2}$ cm
- ALS, Bernard et al., 2021 :
  - Standard deviation of M3C2 distances on stable areas (after ICP on stable areas)
- ALS, Wagner et al., 2017 :
  - Standard error from 3 buildings (after removing vertical bias)
- …

For SFM

Creates at local uncertainty model based on multiple SFM reconstruction.

M3C2-PM version in CloudCompare

3-D uncertainty-based topographic change detection with structure-from-motion photogrammetry: precision maps for ground control and directly georeferenced surveys

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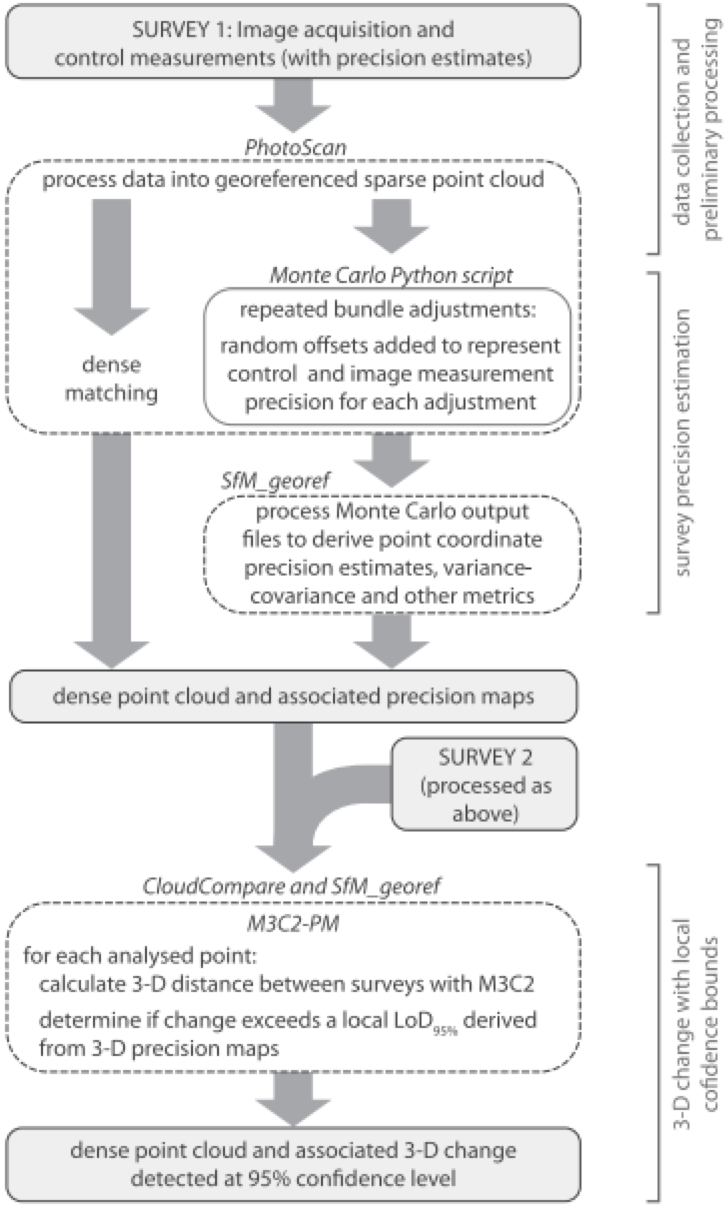
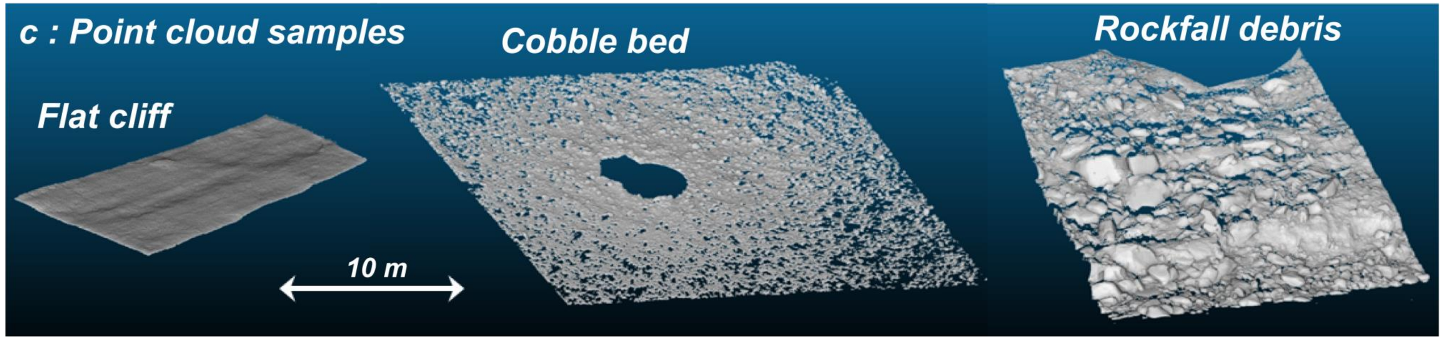
Received 19 November 2016; Revised 6 February 2017; Accepted 9 February 2017



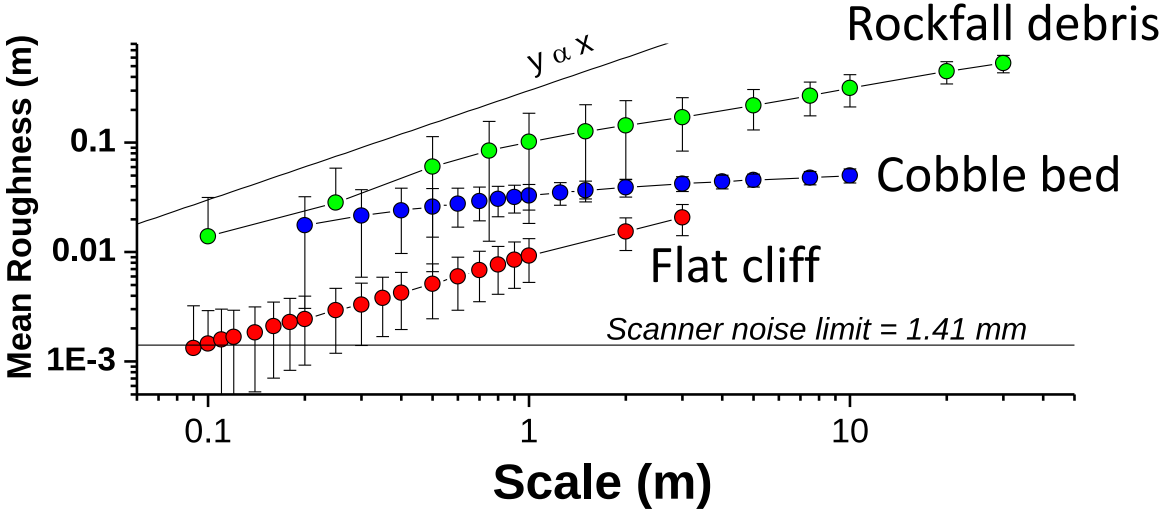
Evaluation of the uncertainty budget in TLS

- Explore the values of standard deviation, point density and distance uncertainty, assuming reg=0 mm
- When is

Self-affinity of rough natural surfaces and consequences



Roughness = detrented point cloud deviation



Consequences for :

• reduction of uncertainty by spatial averaging is limited

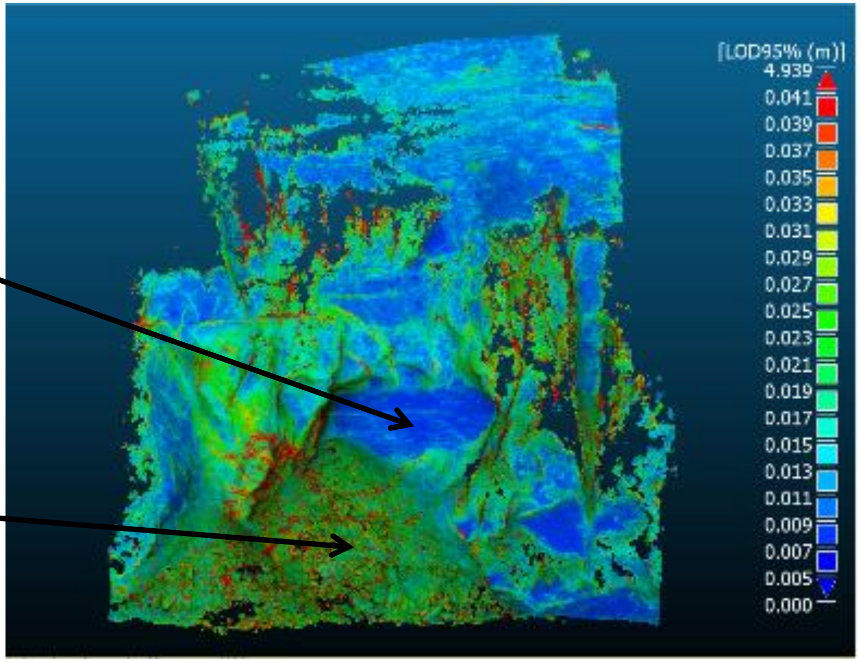
(Lague et al., 2013, ISPRS journal)

Total budget for level of change detection (LoD) at 95 % confidence (Leica Scanstation 2 or C10)

Lague et al., ISPRS journal, 2013

1. Registration error between 2 surveys : **~ 4 - 6 mm**
2. Scanner noise : 1.41/√n -> 0 mm by spatial averaging
3. Surface roughness effects (d=0.5 m):
   - **Flat rock : 0.5 – 5 mm**
   - **Gravel bed : 1- 30 mm**
   - **Rockfall debris : 5-260 mm**

3D map of confidence interval



Best case : ±4 mm

Set by registration error

Debris: ~ 4 cm

Set by surface roughness

Detecting flight line overlap errors in ALS

- Extract lines using the point_ID
- 3D M3C2 on the 2 extracted lines :
  - What do you observe ?
- Select a registration error of your choice and recompute 3D-M3C2 between 2014 and 2016
  - Check the significant change field of M3C2.