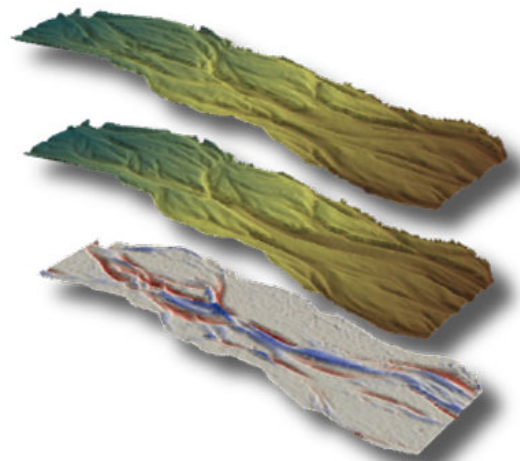


# PRINCIPLES OF TOPOGRAPHIC CHANGE DETECTION

$$\frac{\partial z}{\partial t}$$

GCD



**Utah State University**  
ECOGEOMORPHOLOGY & TOPOGRAPHIC ANALYSIS LABORATORY

CC BY JOE WHEATON



**NORTH ARROW RESEARCH**



**RIVERSCAPES CONSORTIUM**

# BY END OF HOUR

You should understand:

1. GCD techniques and how they are applied to monitoring rivers
2. How to account for unreliability uncertainties in DEMs
3. How to interpret DoDs

GCD = Geomorphic Change Detection

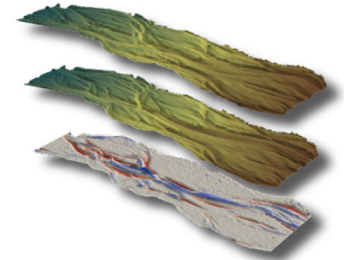
TCD = *Topographic* Change Detection



DoD  $\neq$



DoD = DEM of Difference =



# PRINCIPLES OF TOPOGRAPHIC CHANGE DETECTION

---

- At its heart TCD is a signal to noise problem
  - Best applied when signal is big and obvious and noise is negligible
  - Often applied when signal is small and obscured and noise is substantial
- Noise is estimated with error modelling & error propagation
- Apples to Apples Easiest
  - Orthogonality, Concurrency & Dimensional Divisibility
  - Allows this to be a simple subtraction problem with orthogonal rasters
  - Different survey methods okay if accounted for in error modelling
- Thresholding of changes allows separation of signals
  - Either discard or flag as 'do not trust' information below threshold
- Always start simple & conservative, and see if signal you are interested in is detectable. Invest in more complex methods if you believe signal is there, but is obscured...

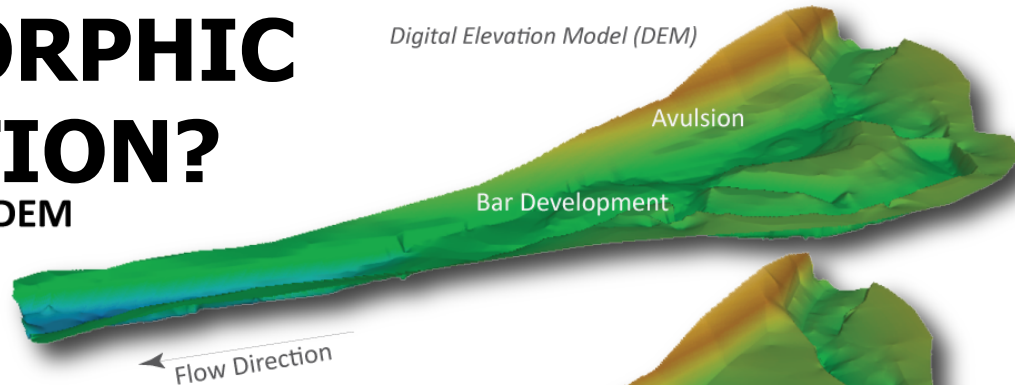


# WHAT IS GEOMORPHIC CHANGE DETECTION?

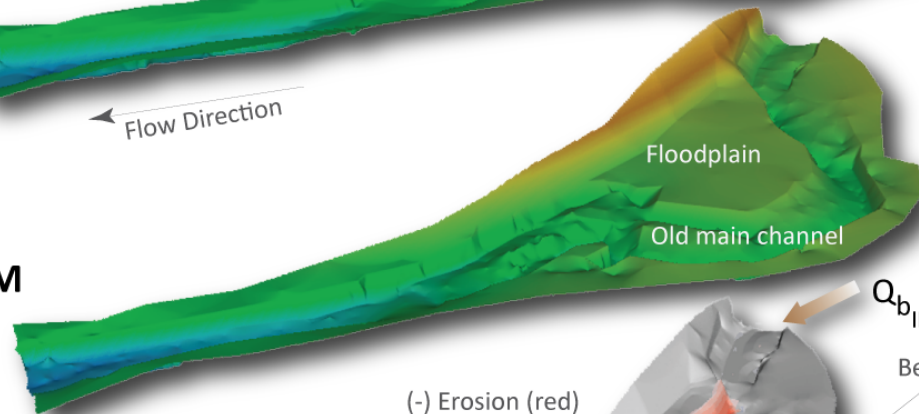
- Inferences about 'net' geomorphic changes resulting from erosion & deposition that are detectable despite noise...
- Inferences made with repeat topography... i.e.



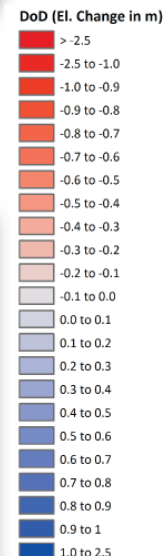
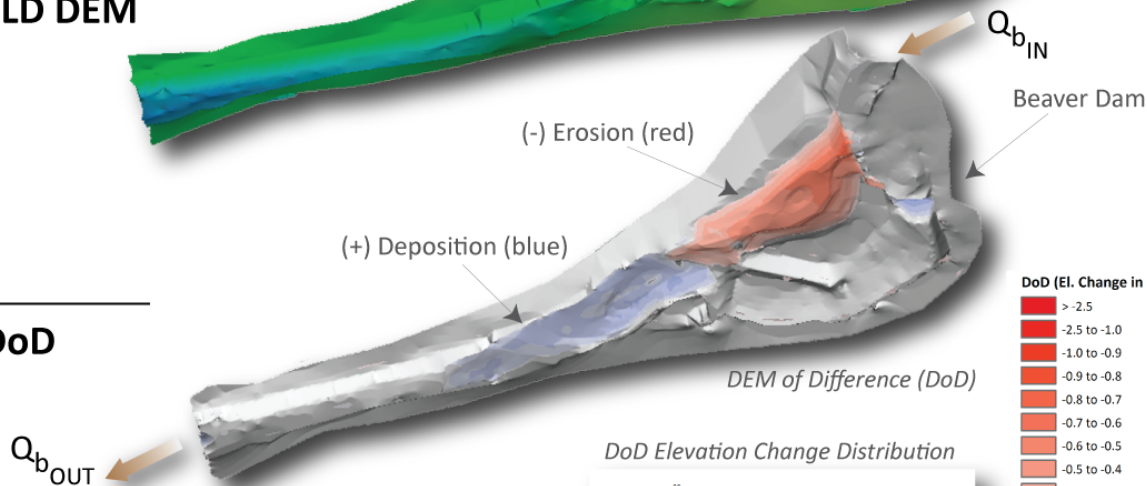
NEW DEM



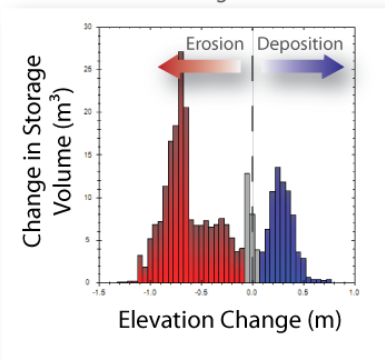
-OLD DEM



=DoD



DoD Elevation Change Distribution



$\Sigma V_{\text{Erosion}}$      $\Sigma V_{\text{Deposition}}$

Morphological Sediment Budget:

$$Q_{b_{IN}} - Q_{b_{OUT}} = \frac{\Delta V_{\text{DoD}}}{\Delta t}$$

Bedload Flux Difference    Change in Storage

$$\Delta V_{\text{DoD}} = \Sigma V_{\text{Deposition}} - \Sigma V_{\text{Erosion}}$$



# PRINCIPLES OF TOPOGRAPHIC CHANGE DETECTION

---

- At its heart TCD is a signal to noise problem
- **Noise is estimated with error modelling & error propagation**
- Apples to Apples Easiest
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- Always start simple & conservative, and see if signal you are interested in is detectable. Invest in more complex methods if you believe signal is there, but is obscured...



# IN A PERFECT WORLD...

- The signal (the change we're trying to detect) is much greater than our noise....

$$\frac{\partial z}{\partial t} \gg \delta(z)$$

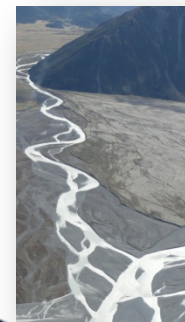
- In many instances, the noise is of similar magnitude to our noise...

$$\frac{\partial z}{\partial t} \approx \delta(z)$$

- Better in places where vertical changes are large!

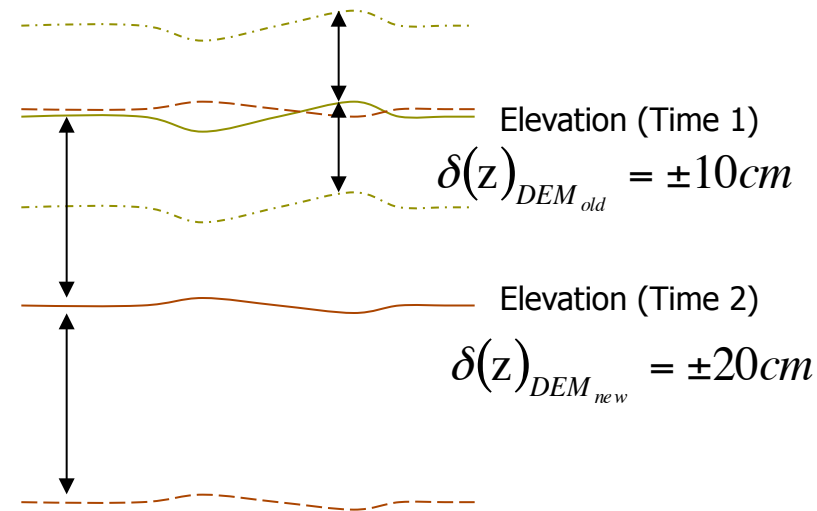


- LiDaR : +/- 10 to 25 cm (14 to 36 cm min LoD)
- Terrestrial Laser Scanning: +/- 0.5 to 4 cm (0.7 to 6 cm min LoD)



# ERROR PROPAGATION

- Distinguish those changes that are real from noise
- Use standard Error Propagation



$$\delta(z) = \sqrt{\left(\delta(z)_{DEM_{old}}\right)^2 + \left(\delta(z)_{DEM_{new}}\right)^2}$$

e.g.  $\delta(z) = \sqrt{(10)^2 + (20)^2} = 22.36$

$22.36 \text{ cm} \approx 8.8 \text{ in}$

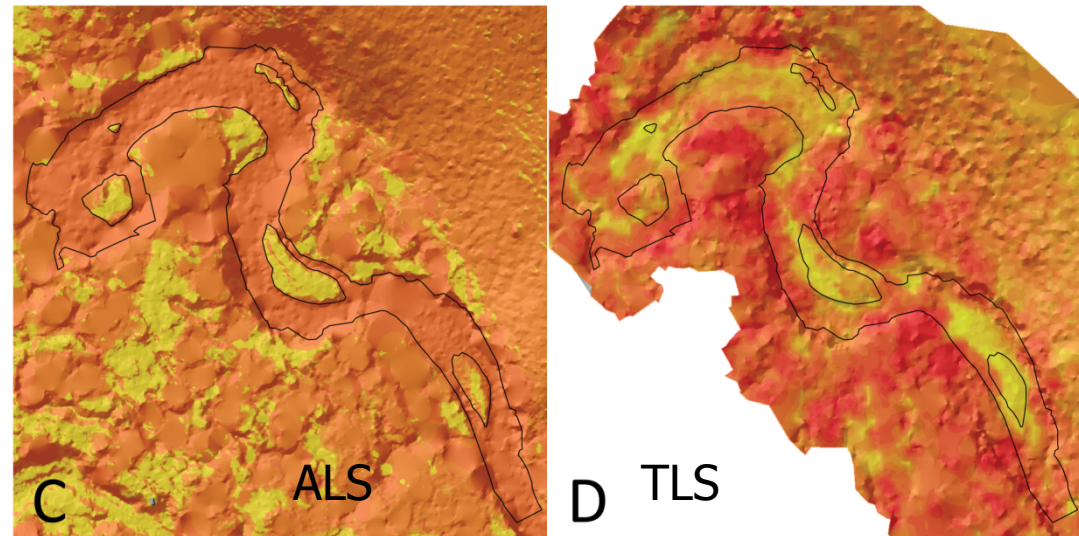
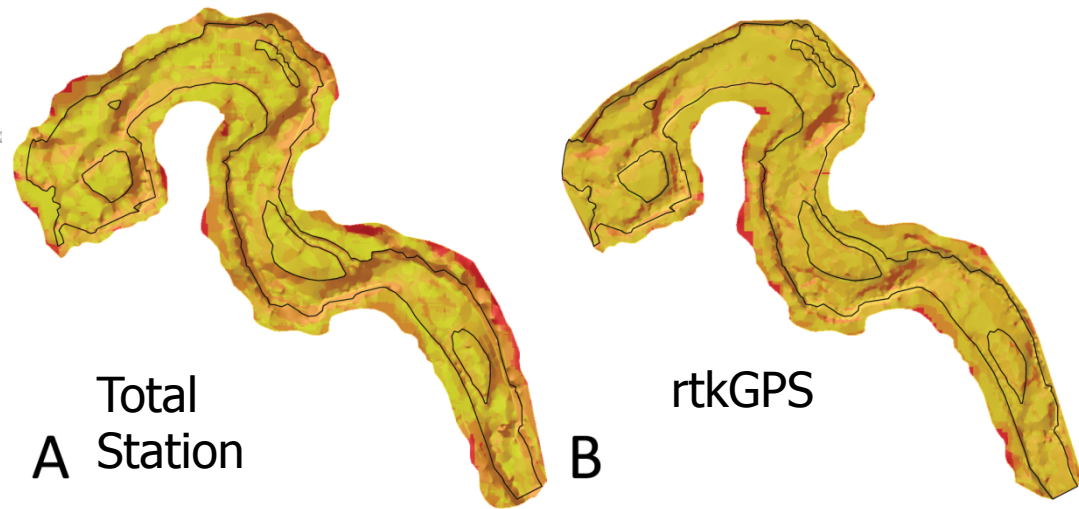
See

- Brasington et al (2000): *ESPL*
- Lane et al (2003): *ESPL*
- Brasington et al (2003): *Geomorphology*



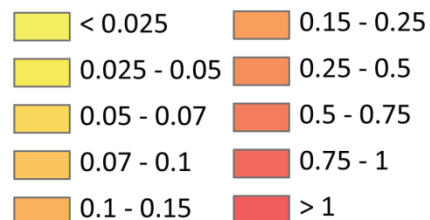
# EXAMPLES OF ERROR MODELS

- Greater extent on TLS & ALS
- ALS & TLS worthless in water
- ALS best on floodplain



FIS

Elev. uncertainty(m)



0 10 20 30 40 50 Meters



From Bangen et al. (2014) *Geomorphology*  
DOI: 10.1016/j.geomorph.2013.10.010



# PRINCIPLES OF TOPOGRAPHIC CHANGE DETECTION

---

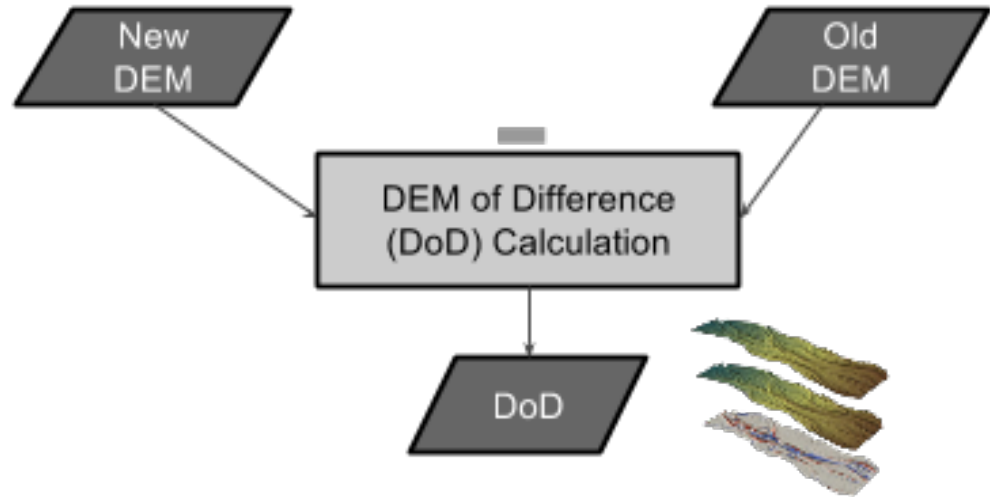
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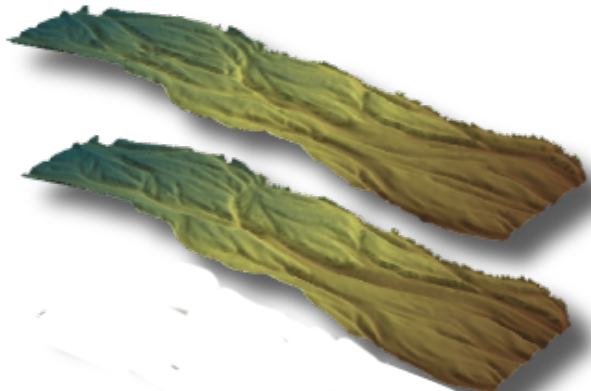
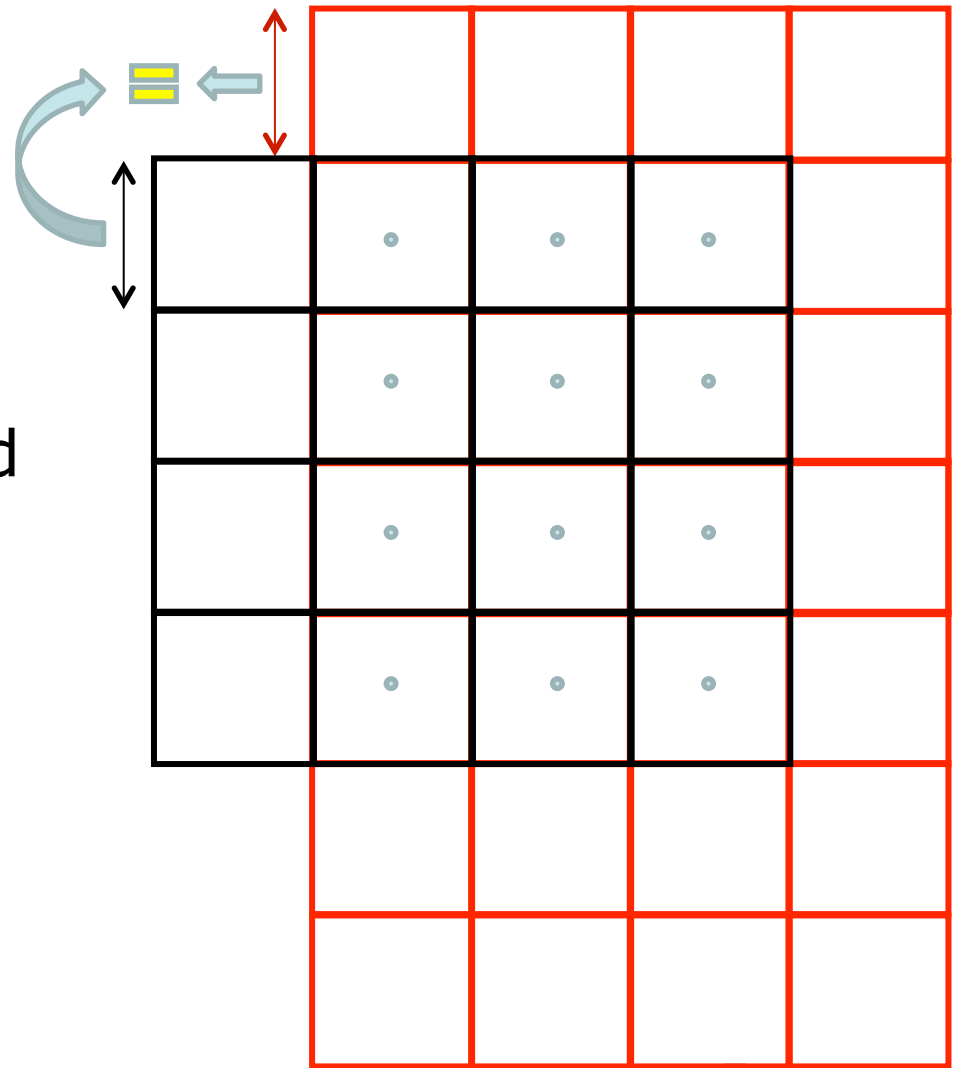
# 'SO... YOUR WHOLE CAREER IS A SIMPLE SUBTRACTION PROBLEM?'

- $DoD = DEM_{new} - DEM_{old}$



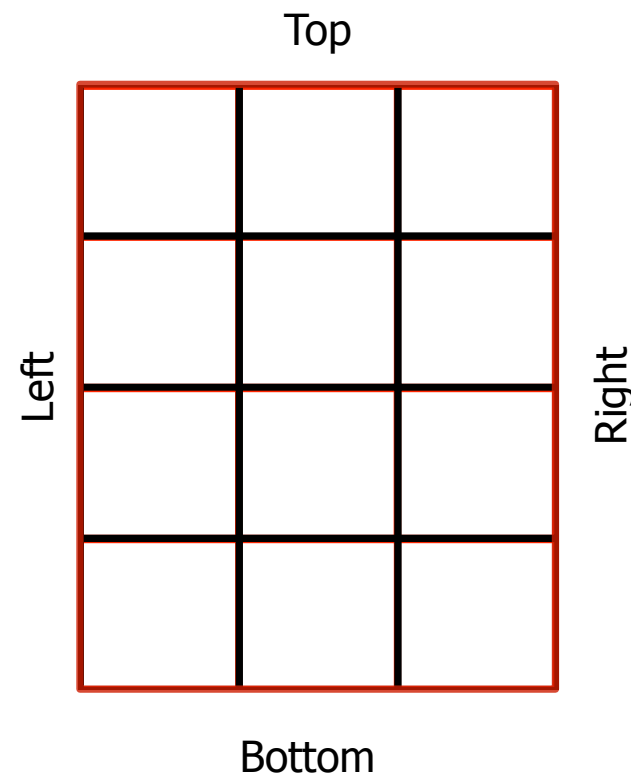
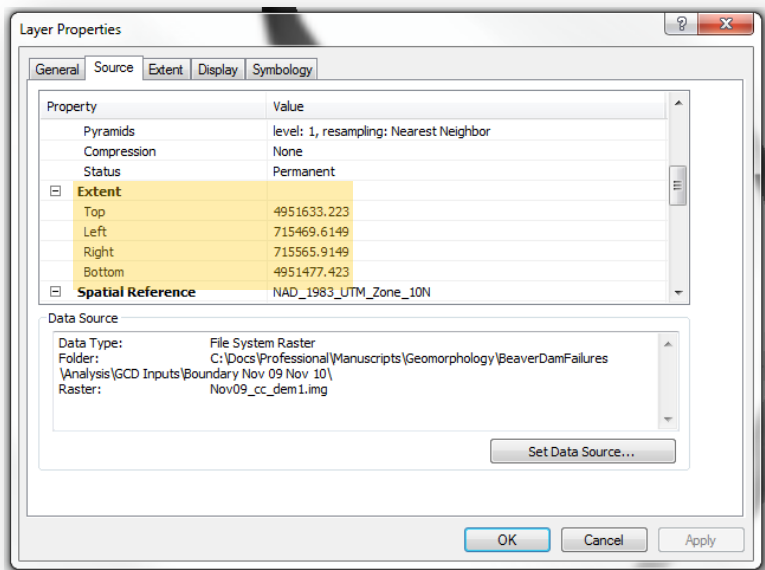
# ORTHOGONALITY

- Orthogonal rasters must:
  - Share exact same grid resolution
  - Share the exact same grid centers (i.e. aligned in both easting and northing)



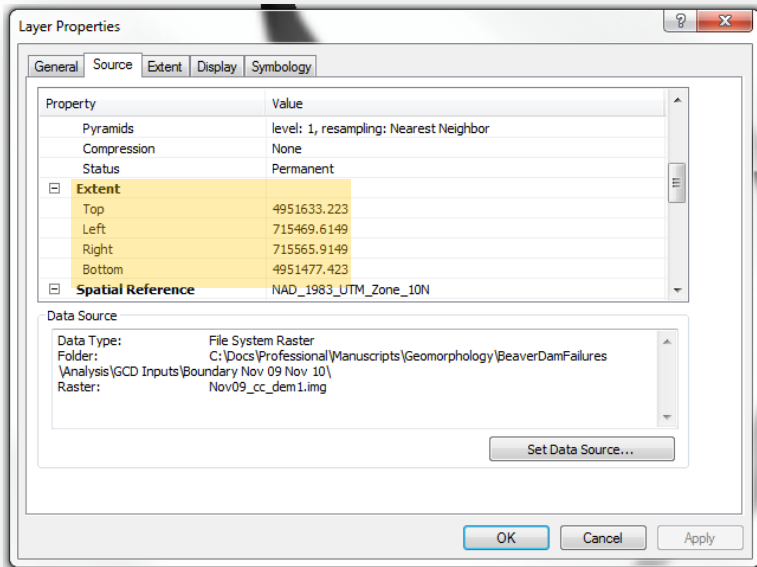
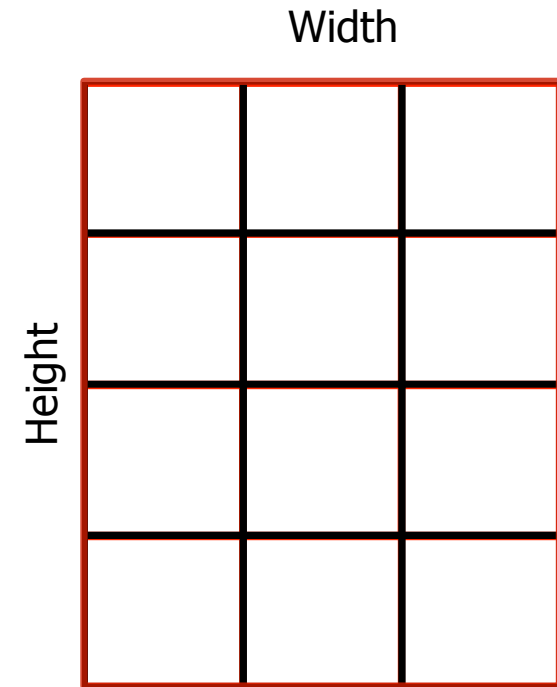
# CONCURRENCY

- Grids are orthogonal and:
  - Share *exact* same extents



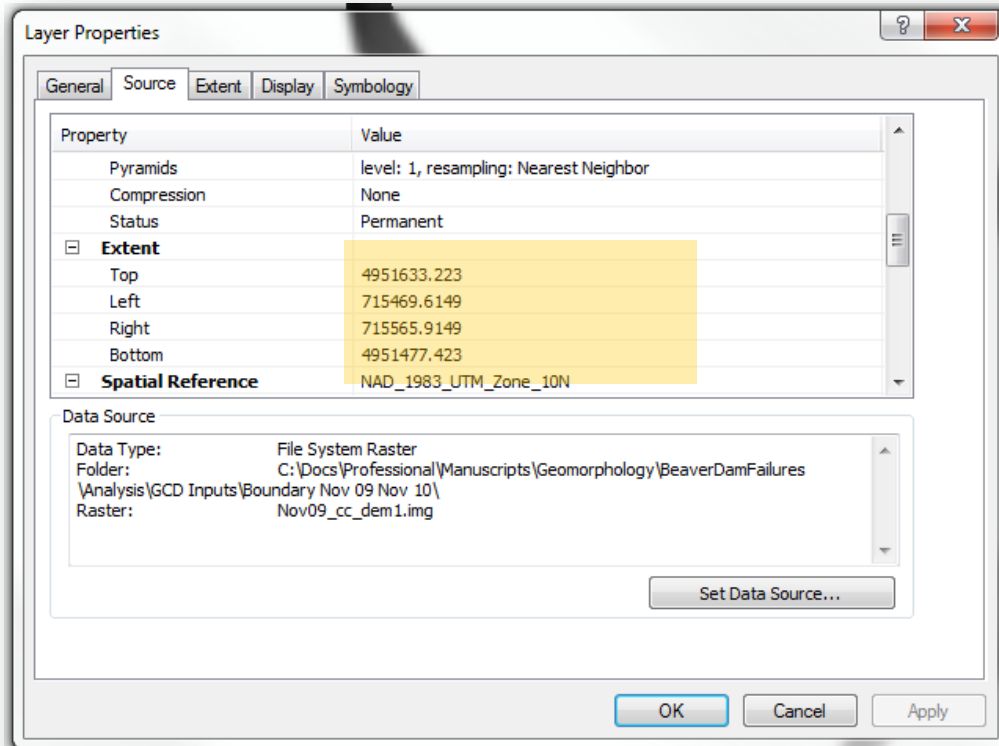
# DIMENSIONAL DIVISIBILITY

- Are width & height evenly divisible by cell resolution?
- If not:
  - Does cell resolution or number of rows and columns take the hit?



# INTERNAL DIVISIBILITY CONSISTENCY

- The corner coordinates must be evenly divisible by the cell resolution.



- More restrictive than dimensional divisibility, but gives rise to nice rounded extents
- Who cares?





# PRINCIPLES OF TOPOGRAPHIC CHANGE DETECTION

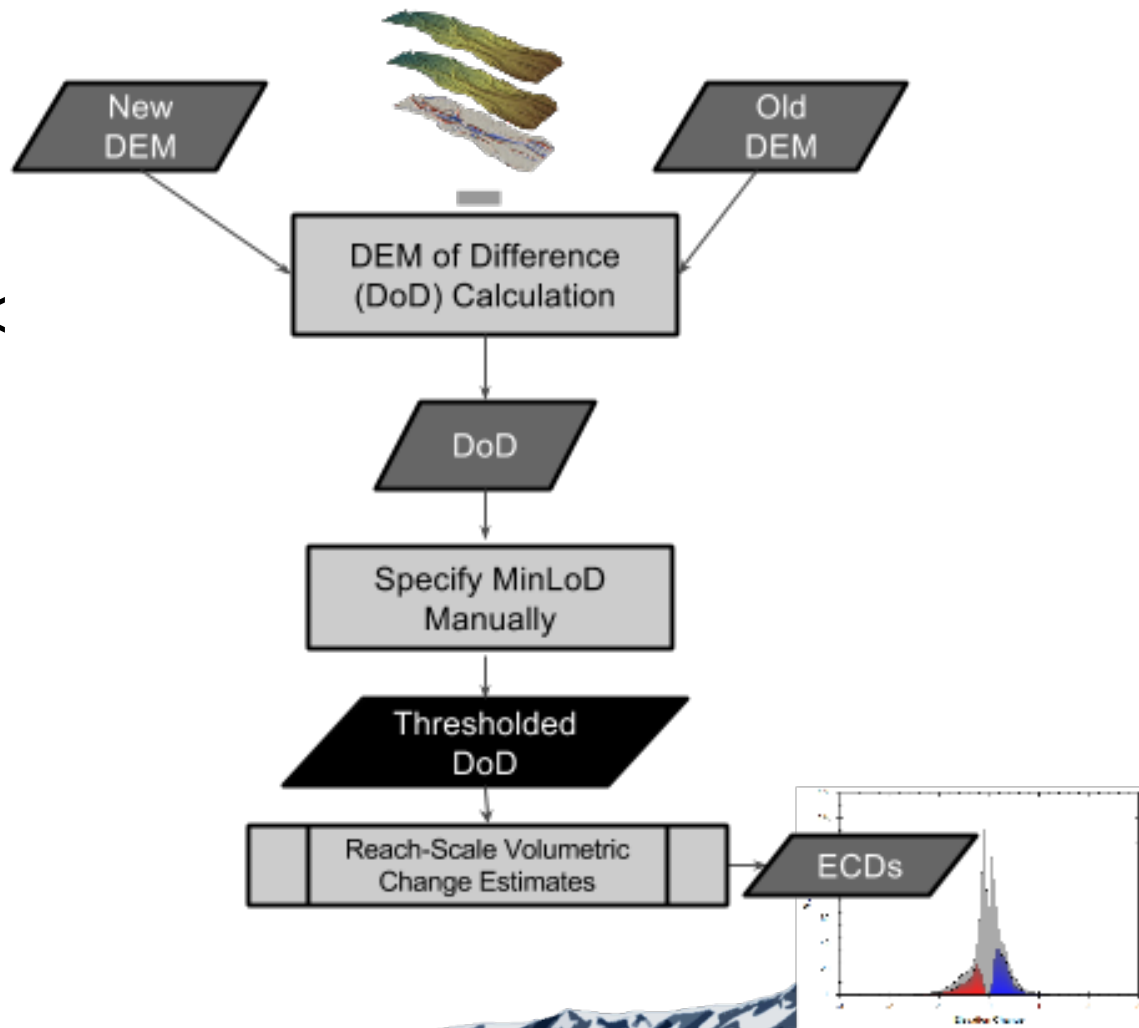
---

- At its heart TCD is a signal to noise problem
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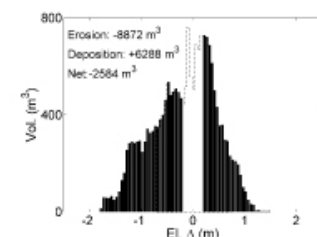
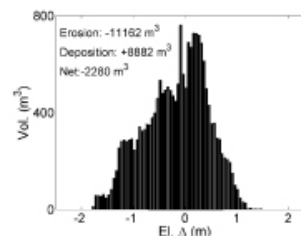
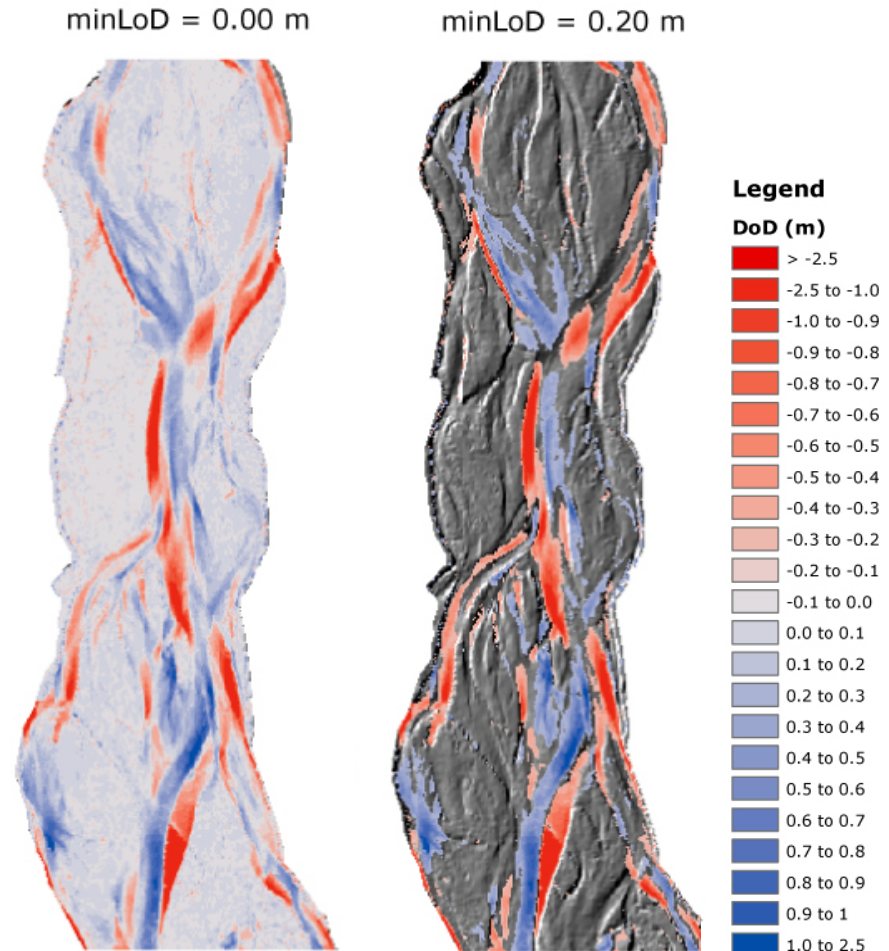
# WHAT WE'RE DOING TO SIMPLIFY SUBTRACTION PROBLEM

- Just specifying a minimum level of detection ( $\text{minLoD}$ )
- Throwing away  $\text{DoD} < \text{minLoD}$
- Calculating some summary statistics
- Multiplying cell by cell DoD by cell area to get volumes
- Looking at histograms of change (ECD)



# THRESHOLDING... APPLIED SPATIALLY

- Does not matter whether the  $\text{minLoD}$  is specified, or calculated from error propagation
- Just on a cell-by-cell basis!



# PRINCIPLES OF TOPOGRAPHIC CHANGE DETECTION

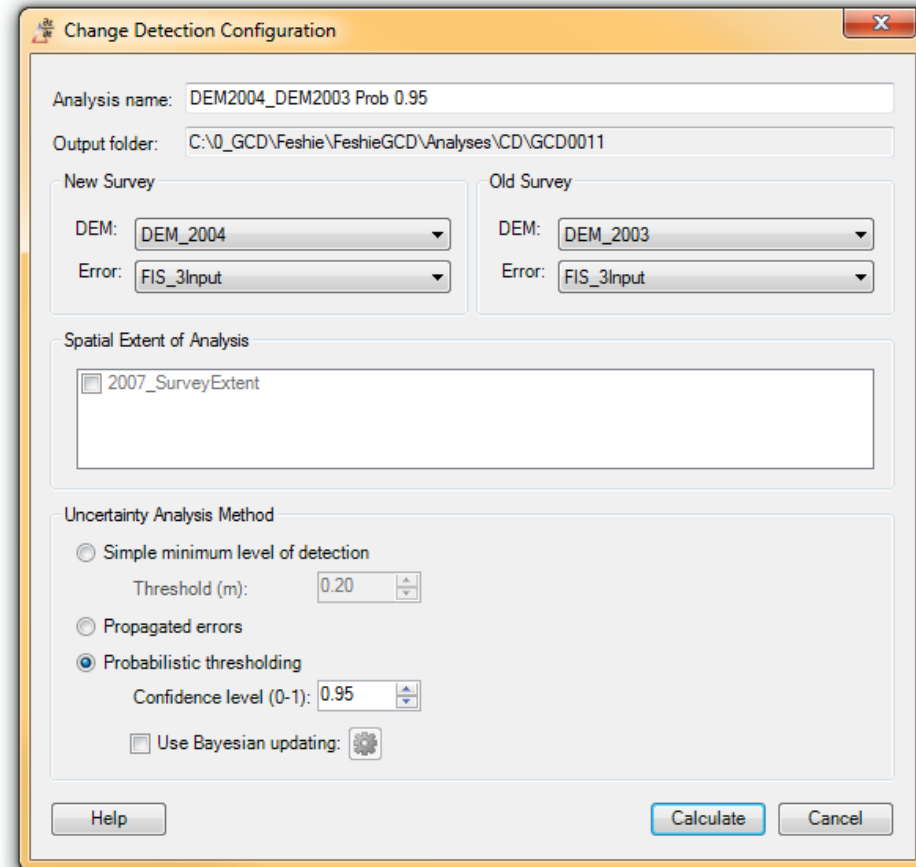
---

- At its heart TCD is a signal to noise problem
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# GCD THRESHOLDING

1. Simple defined  $\min$  LoD
2. Propagated Errors
3. Probabilistic Confidence Interval



The screenshot shows a software dialog box titled "Change Detection Configuration". It contains the following fields and options:

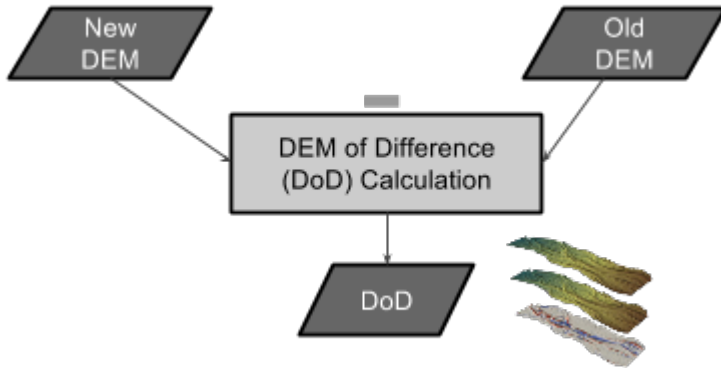
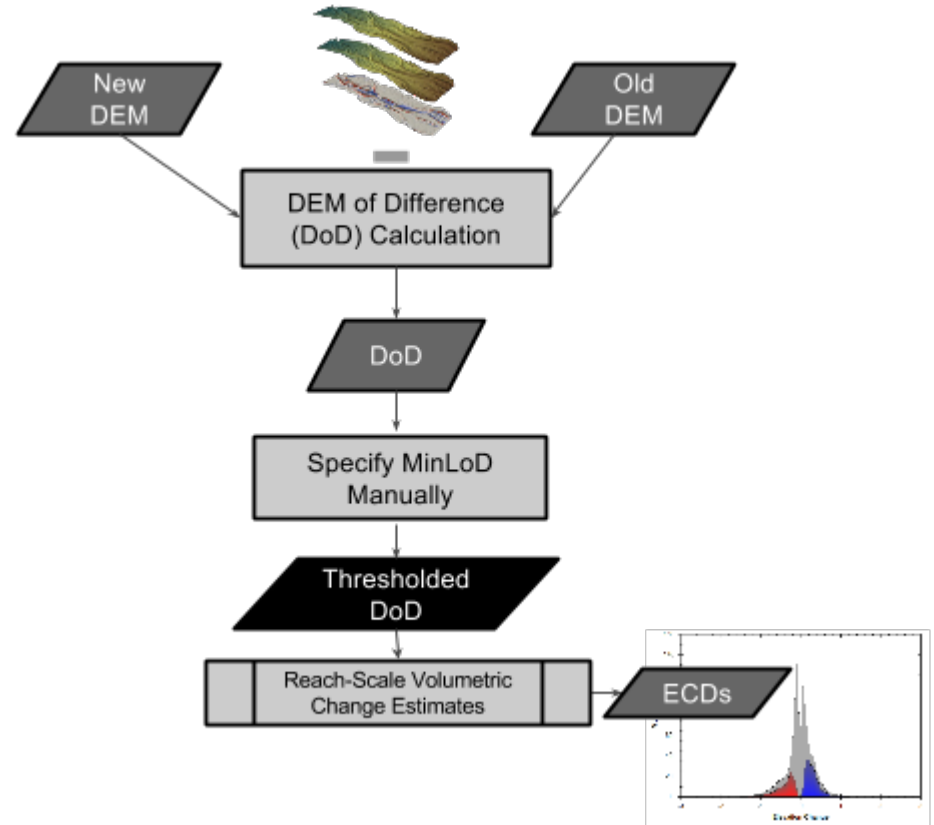
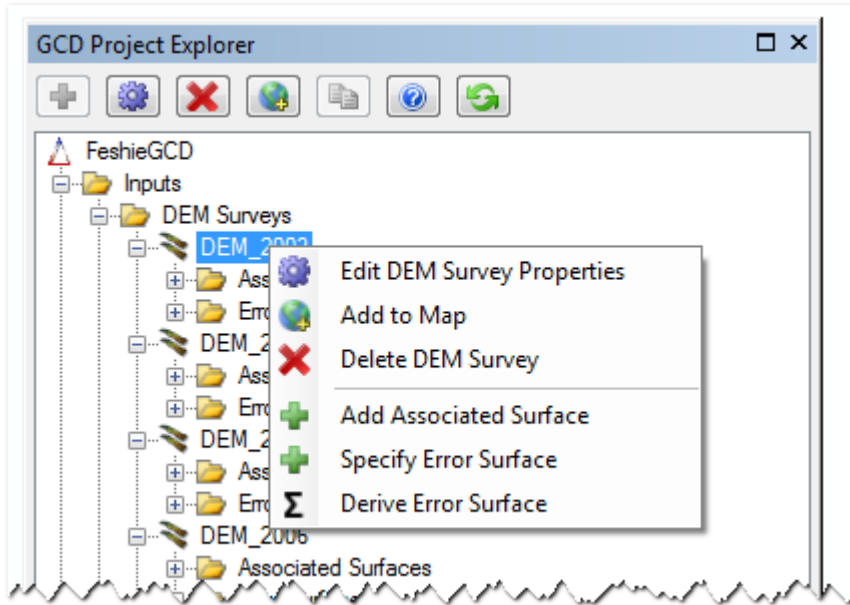
- Analysis name:** DEM2004\_DEM2003 Prob 0.95
- Output folder:** C:\0\_GCD\Feshie\FeshieGCD\Analyses\CD\GCD0011
- New Survey:** DEM: DEM\_2004, Error: FIS\_3Input
- Old Survey:** DEM: DEM\_2003, Error: FIS\_3Input
- Spatial Extent of Analysis:** A list box containing "2007\_SurveyExtent" with a checked checkbox.
- Uncertainty Analysis Method:**
  - Simple minimum level of detection (Threshold (m): 0.20)
  - Propagated errors
  - Probabilistic thresholding (Confidence level (0-1): 0.95)
  - Use Bayesian updating: [gear icon]

Buttons at the bottom: Help, Calculate, Cancel.





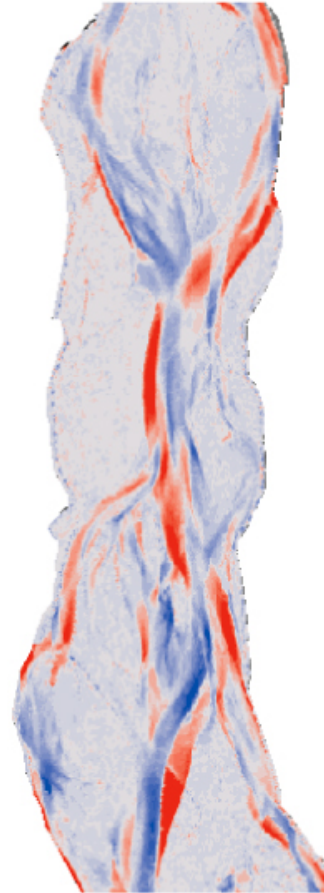
# ALL WE DID IN PREVIOUS EXERCISE...



# APPLICATION OF A $\text{minLoD}$

- You take original DoD, and remove all changes  $\leq \text{minLoD}$
- For example +/- 20 cm

minLoD = 0.00 m

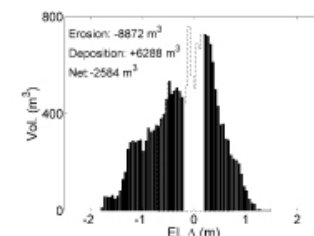
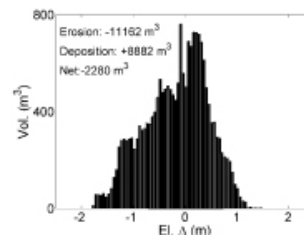


minLoD = 0.20 m



## Legend

### DoD (m)



# VARYING <sub>min</sub> LoD THRESHOLDS



minLoD = 0.00 m

minLoD = 0.05 m

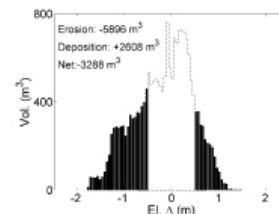
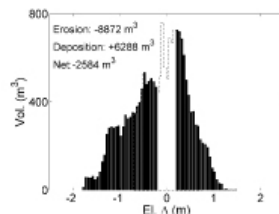
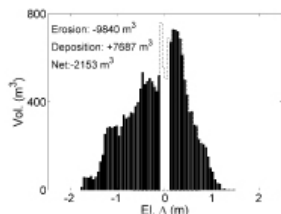
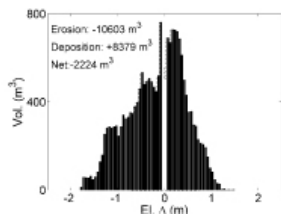
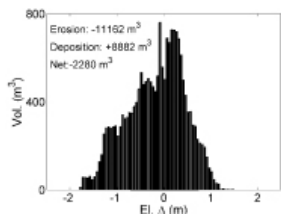
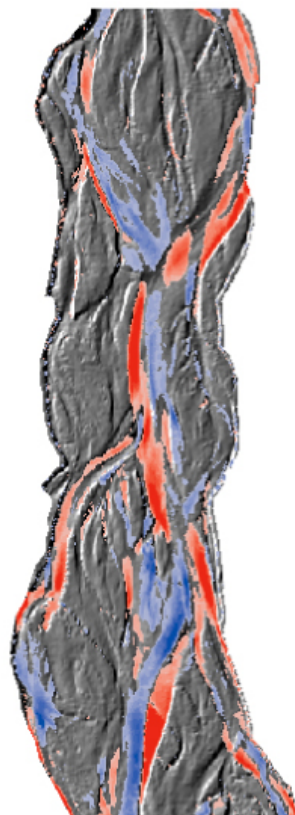
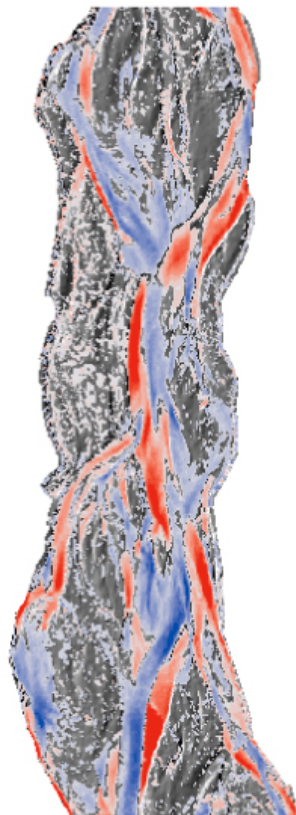
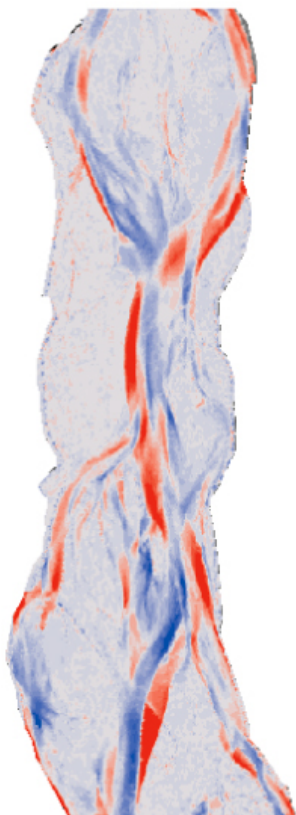
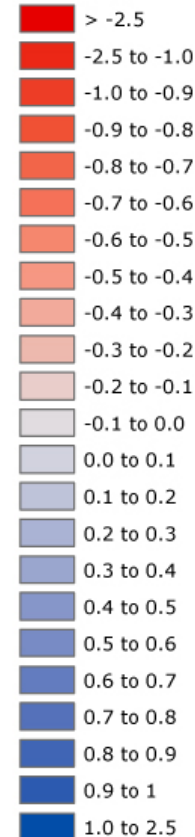
minLoD = 0.10 m

minLoD = 0.20 m

minLoD = 0.50 m

**Legend**

**DoD (m)**



© Wheaton 2008

# EXERCISE: VARYING <sub>MIN</sub>LOD

---

C:\0\_GCD\Excercises\G\_Thresholding

1. Start new ArcMap Document
2. Create new GCD Project called 'Feshie\_Threshold' in I
3. Load 2 DEMs provided as surveys
4. Do Change Detections with following minLoDs:
  - 0 cm, 5 cm, 10 cm, 20 cm, 50 cm
5. Compare the outputs (maps, summaries, elevation change distributions)...





# GCD THRESHOLDING

1. Simple defined  $\min$  LoD
- 2. Propagated Errors**
3. Probabilistic Confidence Interval

Change Detection Configuration

Analysis name: DEM2004\_DEM2003 Prob 0.95

Output folder: C:\0\_GCD\Feshie\FeshieGCD\Analyses\CD\GCD0011

New Survey

DEM: DEM\_2004

Error: FIS\_3Input

Old Survey

DEM: DEM\_2003

Error: FIS\_3Input

Spatial Extent of Analysis

2007\_SurveyExtent

Uncertainty Analysis Method

Simple minimum level of detection

Threshold (m): 0.20

Propagated errors

Probabilistic thresholding

Confidence level (0-1): 0.95

Use Bayesian updating:

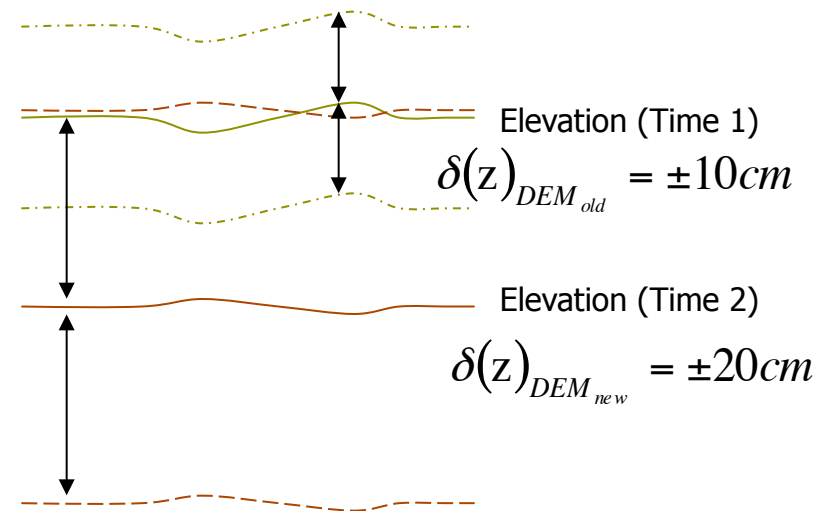
Help Calculate Cancel





# MIN LoD USING ERROR PROPAGATION

- Distinguish those changes that are real from noise
- Use standard Error Propagation
- DEM Errors can vary temporally and spatially



$$\delta(z) = \sqrt{\left(\delta(z)_{DEM_{old}}\right)^2 + \left(\delta(z)_{DEM_{new}}\right)^2}$$

e.g.  $\delta(z) = \sqrt{(10)^2 + (20)^2} = 22.36$

$22.36 \text{ cm} \approx 8.8 \text{ in}$

See

- Brasington et al (2000): *ESPL*
- Lane et al (2003): *ESPL*
- Brasington et al (2003): *Geomorphology*



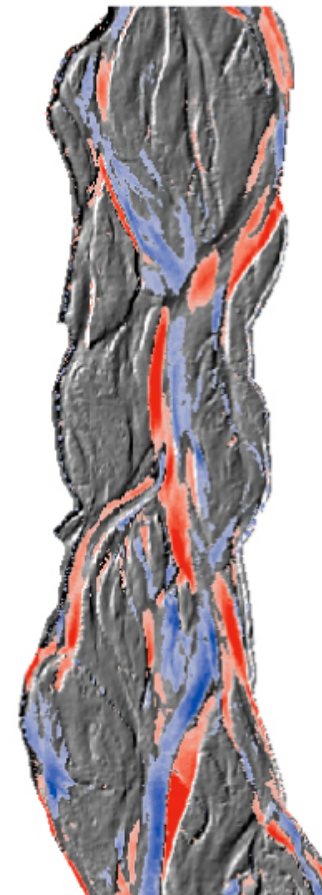
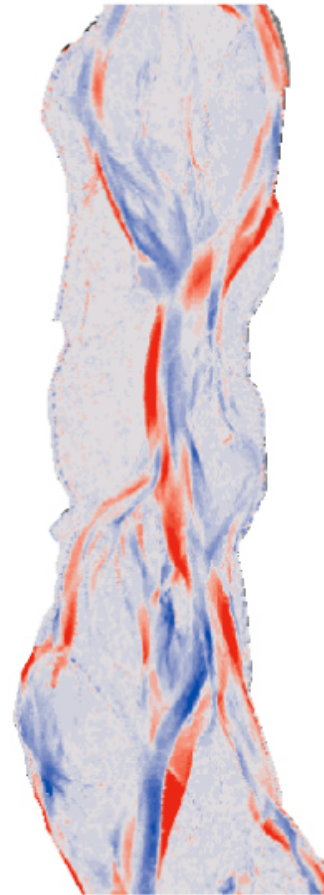
# ERROR PROPAGATION GETS APPLIED

## SAME WAY AS $\text{minLoD}$

- Does not matter whether the  $\text{minLoD}$  is specified, or calculated from error propagation
- Just on a cell-by-cell basis!
- In background a perror grid is produced

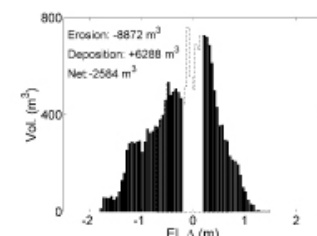
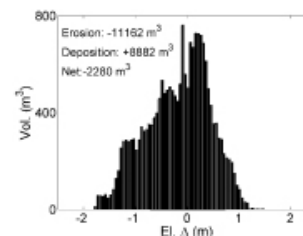
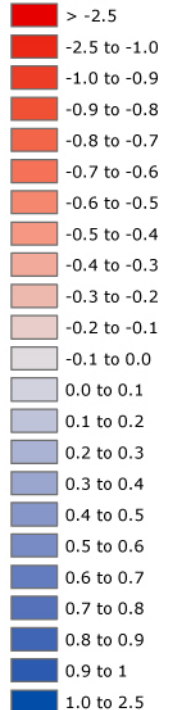
$\text{minLoD} = 0.00 \text{ m}$

$\text{minLoD} = 0.20 \text{ m}$



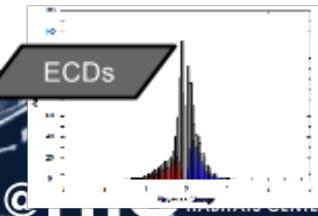
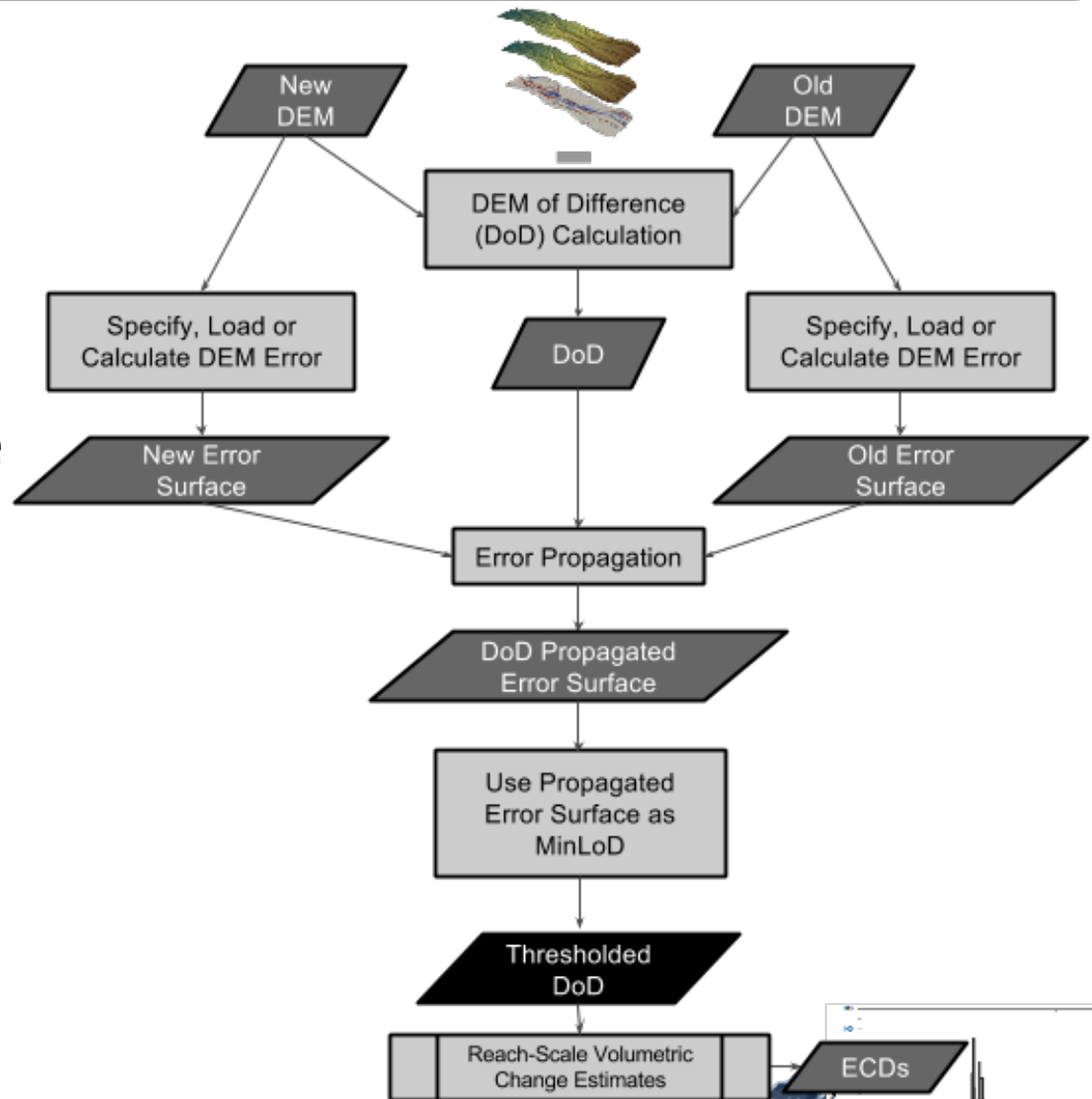
### Legend

#### DoD (m)



# OUR REVISED WORKFLOW: PROPAGATED

- Just *come up with* separate estimates of error for  $DEM_{new}$  &  $DEM_{old}$  & propagate using square root of the sum of the square of the errors in quadrature...





# WHAT ARE TYPICAL ERRORS?

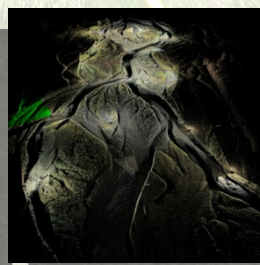
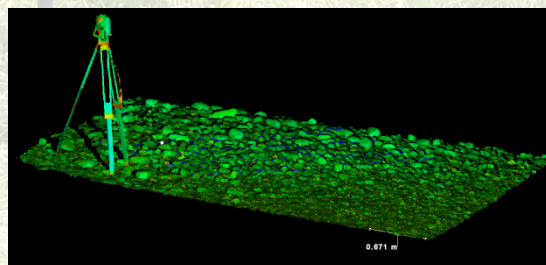
## Remotely Sensed or Aerial Surveys

- LiDaR : **+/- 12 to 25 cm**
- Aerial Photogrammetry : **+/- 10 to 15 cm**



## Ground-Based Surveys

- Total Station Surveys : **+/- 2 to 10 cm**
- GPS: : **+/- 3 to 12 cm**
- Terrestrial Laser Scanning: **+/- 0.5 to 4 cm**





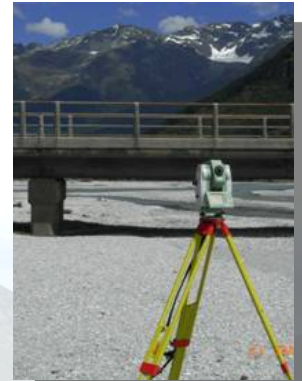
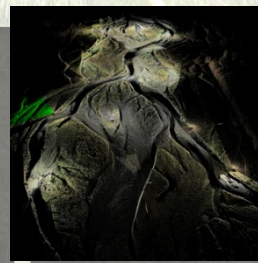
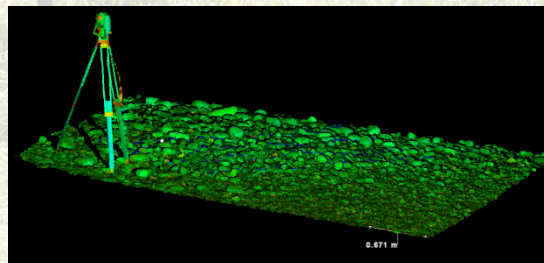
# SO WHAT WOULD PROPAGATED ERRORS BE?

## Remotely Sensed or Aerial Surveys

- LiDaR : **+/- 12 to 25 cm** (17 to 36 cm  $\text{min LoD}$ )
- Aerial Photogrammetry : **+/- 10 to 15 cm** (14 to 22 cm  $\text{min LoD}$ )

## Ground-Based Surveys

- Total Station Surveys : **+/- 2 to 10 cm** (3 to 14 cm  $\text{min LoD}$ )
- GPS: : **+/- 3 to 12 cm** (4 to 17 cm  $\text{min LoD}$ )
- Terrestrial Laser Scanning: **+/- 0.5 to 4 cm** (0.7 to 6 cm  $\text{min LoD}$ )



# EXERCISE: PROPAGATED ERROR

---

C:\0\_GCD\Excercises\G\_Thresholding

1. In Same ArcMap Document
2. Go to each DEM Survey, and derive spatially uniform error surface for rtkGPS
3. Do Change Detections with Propagated Error
4. Compare the outputs (maps, summaries, elevation change distributions)...





# GCD THRESHOLDING

1. Simple defined  $\min$  LoD
2. Propagated Errors
- 3. Probabilistic Confidence Interval**

The screenshot shows a software dialog box titled "Change Detection Configuration". It contains the following fields and options:

- Analysis name:** DEM2004\_DEM2003 Prob 0.95
- Output folder:** C:\0\_GCD\Feshie\FeshieGCD\Analyses\CD\GCD0011
- New Survey:** DEM: DEM\_2004, Error: FIS\_3Input
- Old Survey:** DEM: DEM\_2003, Error: FIS\_3Input
- Spatial Extent of Analysis:** A list box containing "2007\_SurveyExtent" with a checked checkbox.
- Uncertainty Analysis Method:** Three radio buttons: "Simple minimum level of detection" (unselected), "Propagated errors" (unselected), and "Probabilistic thresholding" (selected).
  - Under "Simple minimum level of detection": Threshold (m): 0.20
  - Under "Probabilistic thresholding": Confidence level (0-1): 0.95
  - Under "Use Bayesian updating": A checked checkbox with a gear icon.

Buttons at the bottom: Help, Calculate, Cancel.



# HOW COULD I REPRESENT AS PROBABILITY?

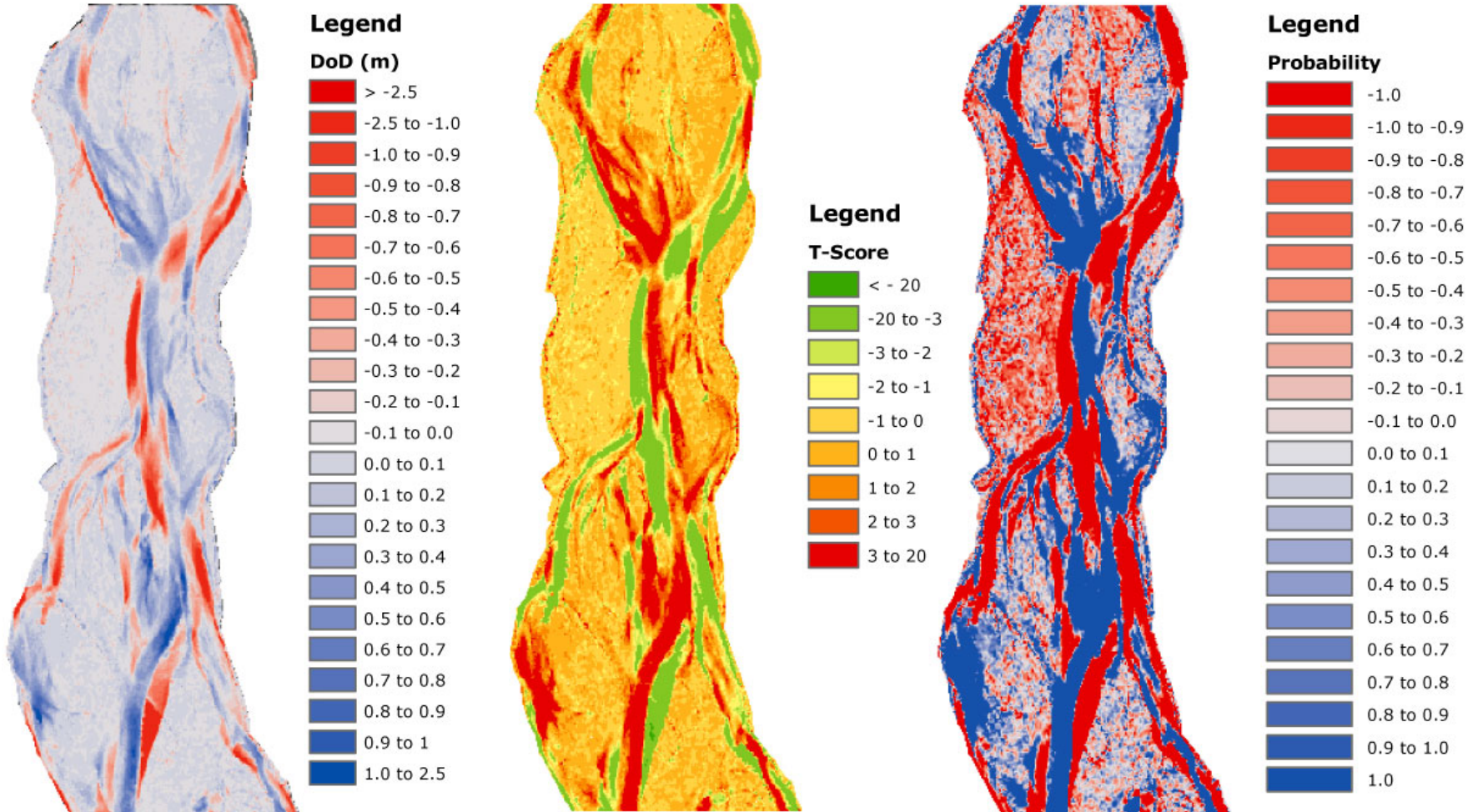
- Using inferential statistics, we'll calculate a t-score
- $\sigma_{DoD}$  is the characteristic uncertainty
  - In this case  $\sigma_{DoD} = \min \text{LoD}$
- Just the ratio of actual change to  $\min \text{LoD}$  change
- Assuming two-tailed test, t is significant at:
  - 68% confidence limit when  $t = 1$
  - 95% confidence limit when  $t = 1.96$

$$t = \frac{|z_{DEM_{new}} - z_{DEM_{old}}|}{\sigma_{DoD}}$$



# PROBABILITY THAT CHANGE IS REAL

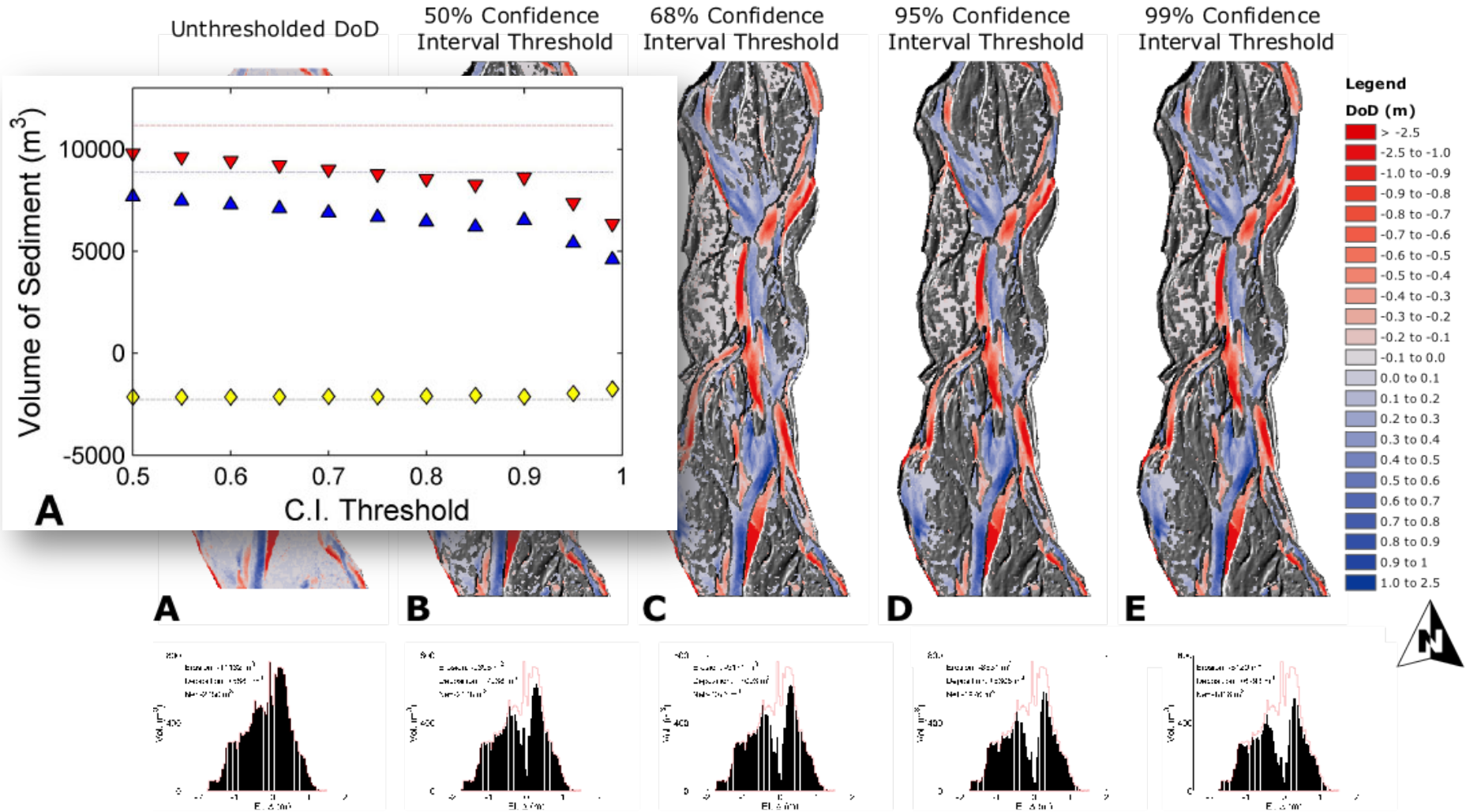
Original DoD → Propagated DoD Uncertainty → Calculated T-Score → Converted Probability



© Wheaton (2008)

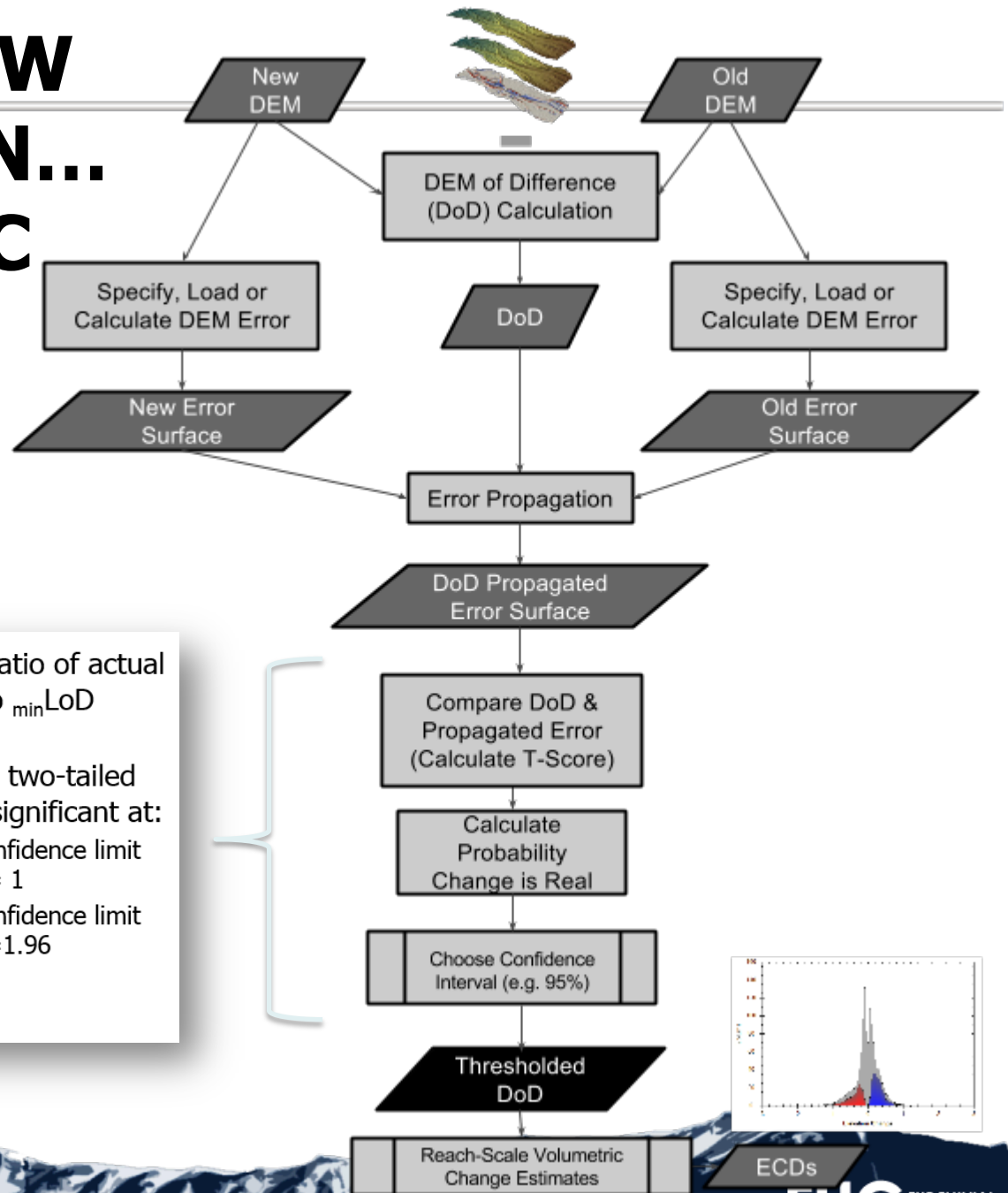
Even when  $\min$  LoD is spatially constant, probability varies in space... why?

# SENSITIVITY OF THRESHOLD?



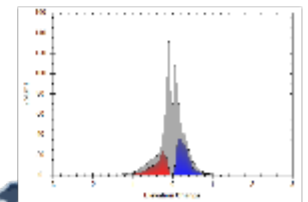


# OUR WORKFLOW REVISED AGAIN... PROBABILISTIC



- Using inferential statistics, we'll calculate a t-score
- $\sigma_{DoD}$  is the characteristic uncertainty
  - In this case  $\sigma_{DoD} = \frac{\min LoD}{t}$
- Just the ratio of actual change to  $\min LoD$  change
- Assuming two-tailed test, t is significant at:
  - 68% confidence limit when  $t = 1$
  - 95% confidence limit when  $t = 1.96$

$$t = \frac{|Z_{DEM_{new}} - Z_{DEM_{old}}|}{\sigma_{DoD}}$$



# EXERCISE: VARYING PROB.

---

C:\0\_GCD\Excercises\G\_Thresholding

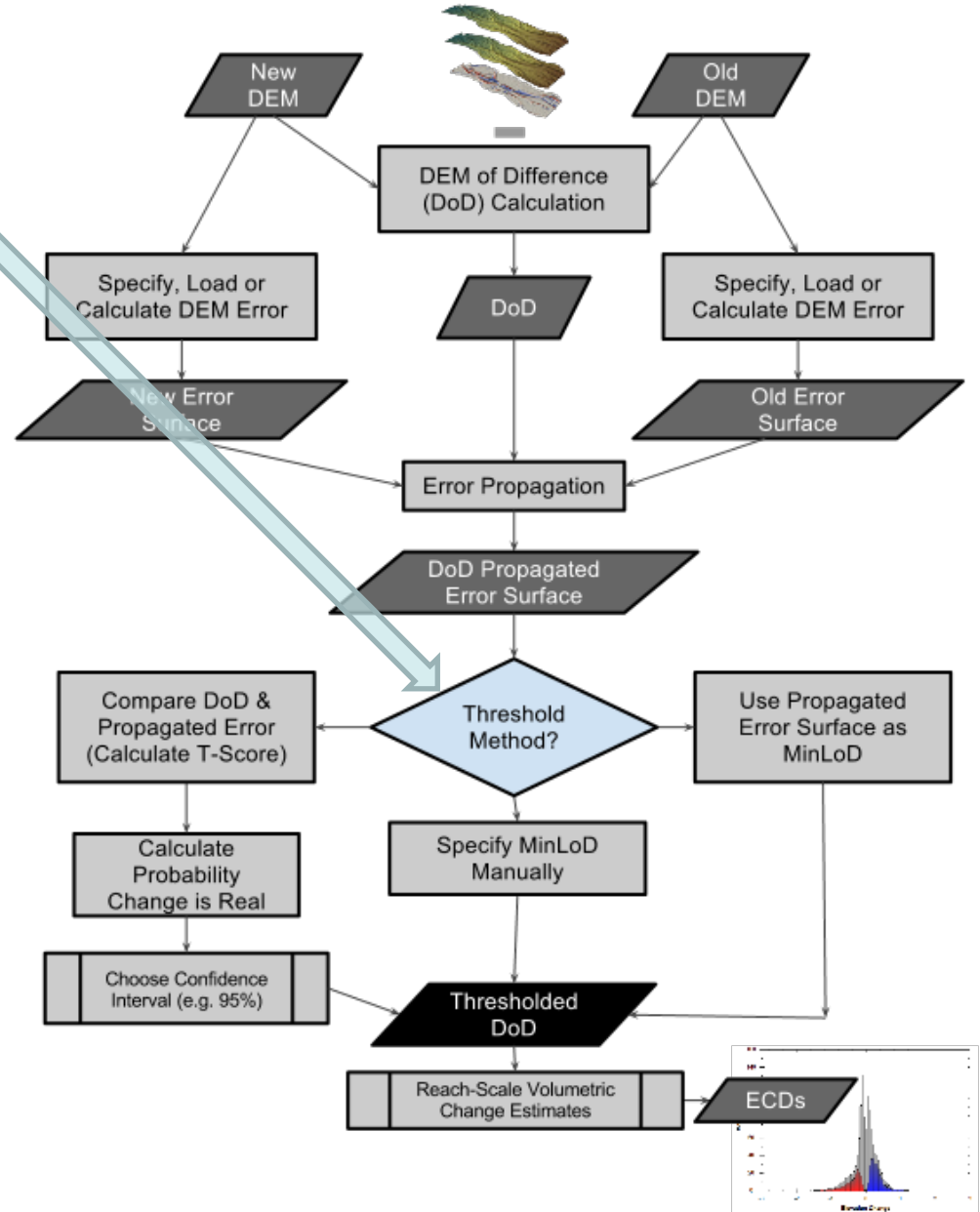
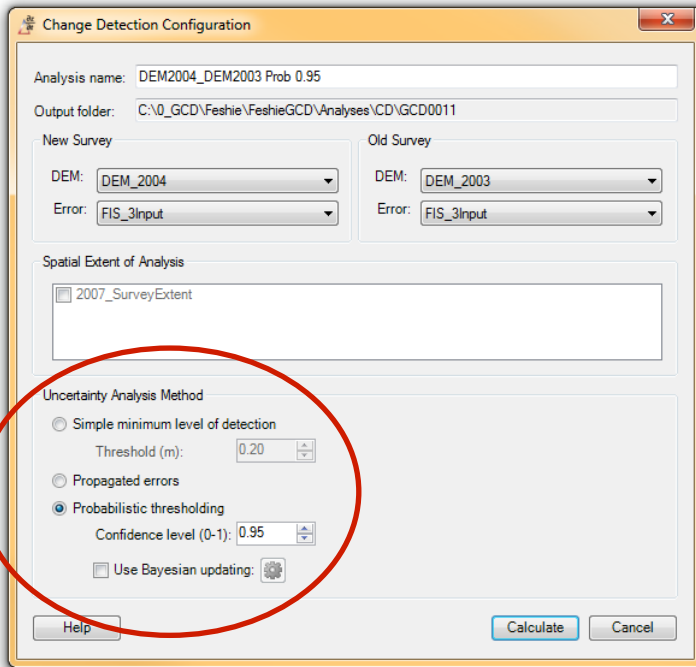
1. In Same ArcMap Document
2. Do Change Detections with Propagated Error for following probabilities:
  1. 99%, 95%, 90%, 80%, 66% and 50%
3. Compare the outputs (maps, summaries, elevation change distributions)...





# WHERE DOES THIS FIT IN GCD?

- Choosing the Threshold Method is a choice:



# PRINCIPLES OF TOPOGRAPHIC CHANGE DETECTION

---

- At its heart TCD is a signal to noise problem
- Noise is estimated with error modelling & error propagation
- Apples to Apples Easiest
- Thresholding of changes allows separation of signals
- Always start simple & conservative, and see if signal you are interested in is detectable. **Invest in more complex methods if you believe signal is there, but is obscured...**



# FUZZY ERROR MODELLING ...



## How important is DEM uncertainty in impacting our ability to detect geomorphic change?

EARTH SURFACE PROCESSES AND LANDFORMS  
 Earth Surf. Process. Landforms 35, 136–156 (2010)  
 Copyright © 2009 John Wiley & Sons, Ltd.  
 Published online 10 December 2009 in Wiley InterScience  
 (www.interscience.wiley.com) DOI: 10.1002/esp.1886

### Accounting for uncertainty in DEMs from repeat topographic surveys: improved sediment budgets

Joseph M. Wheaton<sup>1</sup>, James Braington<sup>2</sup>, Stephen E. Darby<sup>3</sup> and David A. Sear<sup>4</sup>  
<sup>1</sup> Department of Watershed Sciences, Utah State University, 5210 Old Main Hill, NR 210, Logan, UT 84322, USA  
<sup>2</sup> Institute of Geography & Earth Sciences, Aberystwyth University, Aberystwyth, SY23 3DB, UK  
<sup>3</sup> Institute of Geography & Earth Sciences, Southampton, Highfield, Southampton, SO17 1BJ, UK  
<sup>4</sup> School of Geography, University of Southampton, Highfield, Southampton, SO17 1BJ, UK

Received 22 September 2008; Revised 26 June 2009; Accepted 6 July 2009  
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 E-mail: Joe.Wheaton@usu.edu

ESPL  
 Earth Surface Processes and Landforms

**ABSTRACT:** Repeat topographic surveys are increasingly becoming more affordable, and possible at higher spatial resolutions and over greater spatial extents. Digital elevation models (DEMs) built from such surveys can be used to produce DEM of Difference (DoD) maps and estimate the net change in storage terms for morphological sediment budgets. While these products are extremely useful for monitoring and geomorphic interpretation, data and model uncertainties render them prone to misinterpretation. Two new methods are presented, which allow for more robust and spatially variable estimation of DEM uncertainties and propagate these forward to evaluate the consequences for estimates of geomorphic change. The first relies on a fuzzy inference system to estimate the spatial variability of elevation uncertainty in individual DEMs while the second approach modifies this estimate on the basis of the spatial coherence of erosion and deposition units. Both techniques allow for probabilistic representation of uncertainty on a cell-by-cell basis and thresholding of the sediment budget at a user-specified confidence interval. The application of these new techniques is illustrated with 5 years of high resolution survey data from a 1 km long braided reach of the River Feshie in the Highlands of Scotland. The reach was found to be consistently degradational, with between 370 and 1970 m<sup>3</sup> of net erosion per annum, despite the fact that spatially, deposition covered more surface area than erosion. In the two wetter periods with in the Highlands of Scotland, the uncertainty analysis thresholded at a 95% confidence interval resulted in a larger percentage per annum, despite the fact that spatially, deposition covered more surface area than erosion. In the two wetter periods with in the Highlands of Scotland, the uncertainty analysis thresholded at a 95% confidence interval resulted in a larger percentage per annum, despite the fact that spatially, deposition covered more surface area than erosion. In the two wetter periods with in the Highlands of Scotland, the uncertainty analysis thresholded at a 95% confidence interval resulted in a larger percentage per annum, despite the fact that spatially, deposition covered more surface area than erosion.

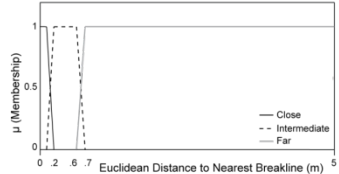
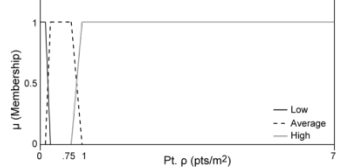
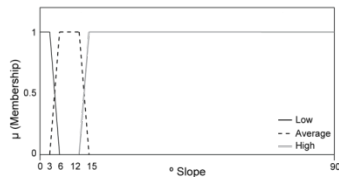
**KEYWORDS:** DEM of Difference (DoD); fluvial geomorphology; morphological method; morphological sediment budgeting; River Feshie; fuzzy inference system

#### Introduction

With recent advances in ground-based, boat-based and remotely-sensed surveying technologies, the rapid acquisition of topographic data is now possible at spatial resolutions and extents previously unimaginable (Lane and Chandler, 2001; Adams and Fontal, 2008; Notebaert et al., 2008). These advances make monitoring geomorphic changes and estimating sediment budgets through repeat topographic surveys and the application of the morphological method (Church and Ashmore, 1998) a tractable, affordable approach for monitoring applications in both research and practice. In fluvial geomorphology, the morphological approach has been used as an alternative to measuring sediment transport directly and has historically been applied primarily to repeat surveys of river plan form, cross-sections and/or longitudinal profiles

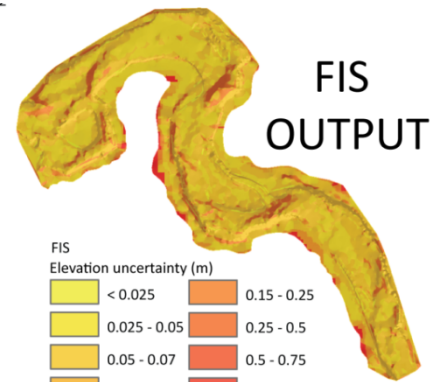
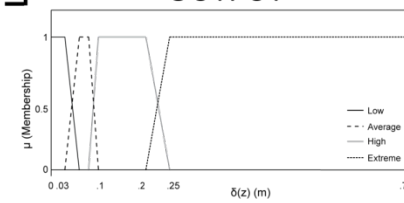
(Illwaco and Passmore, 2002; Lane, 1998). However, from the early 1990s (Lane et al., 1994), the morphological method has been expanded to include the use of repeat topographic surveys from which digital elevation models (DEMs) could be constructed and differenced to produce DEMs of Difference (DoDs). This paper focuses exclusively on the 2D application of the morphological method using DoDs. The morphological method has already received considerable attention (Lane et al., 1994; Milne and Sear, 1997; Braington et al., 2000; Lane, 1998; Lane et al., 2003). Diving this interest has been the basic question that, given the uncertainty inherent in individual DEMs, is it possible to distinguish real geomorphic changes from noise? Repeat surveys using rGPS (Braington et al., 2000), total stations (Milne and Sear, 1997), aerial photogrammetry (Winterbottom and Gilvar, 1997; Winterbottom et al., 2001), multi-beam echosounding (Caldor and Mayer,

#### INPUTS



**FUZZY INFERENCE SYSTEM**  
 Type: Mamandi  
 And Method: Min  
 Or Method: Max  
 Implication: Min  
 Aggregation: Max  
 Defuzz Method: Centroid

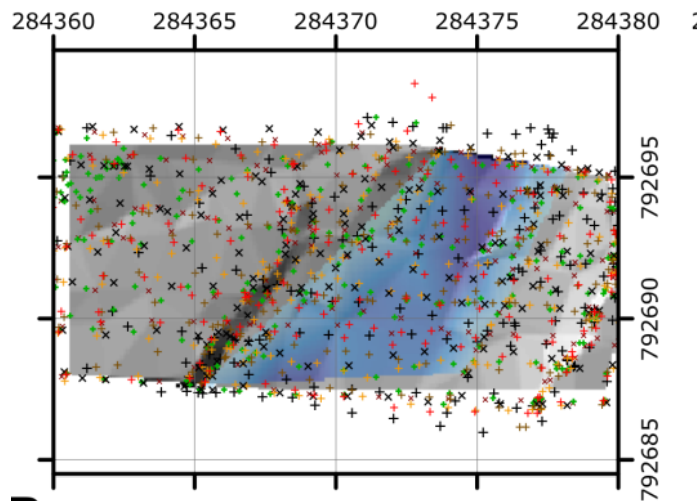
#### OUTPUT



From  
 DOI: 10.1002/esp.1886

# A SIMPLE TWO RULE FUZZY INFERENCE SYSTEM...

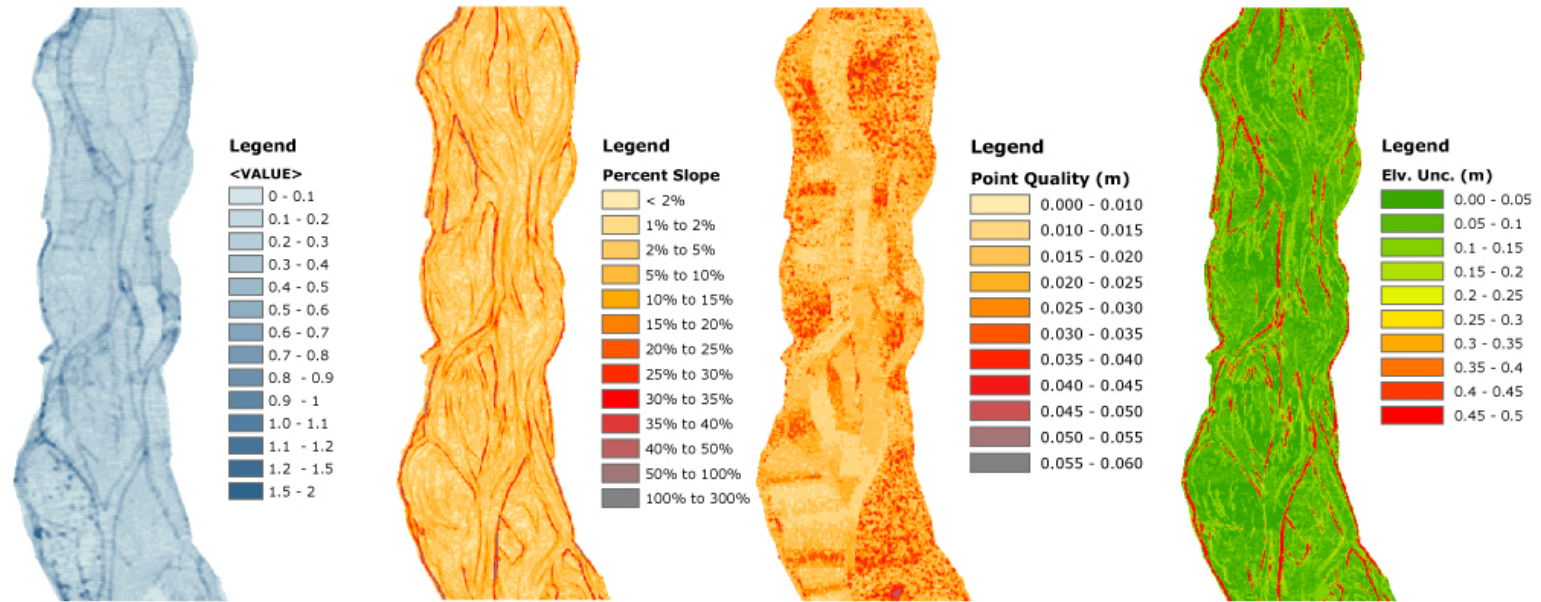
- Given a point cloud
- Relationship between topographic complexity (slope) and sampling (point density)



Rule:	Inputs		Output
	Slope %	Pt. $\rho$ m/pts <sup>2</sup>	$\delta(z)$ m
1	Low	Low	Average
2	Low	Medium	Low
3	Low	High	Low
4	Medium	Low	High
5	Medium	Medium	High
6	Medium	High	Average
7	High	Low	Extreme
8	High	Medium	High
9	High	High	High

B

# SPATIALLY VARIABLE ERROR MODELLING



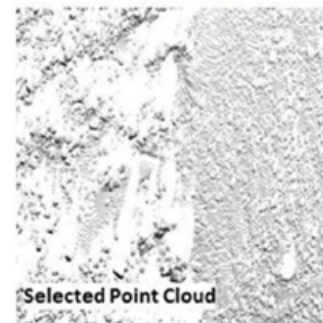
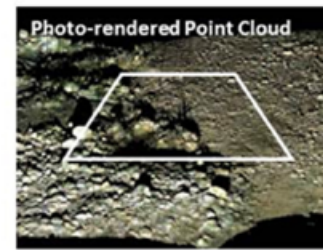
FIS Input 1 (Point Density) + FIS Input 2 (Slope) + FIS Input 3 (GPS Quality) = FIS Surface (El. Unc (m))

- Readily tractable now!
- FIS, needs to be minimally survey method specific and output should be locally calibrated



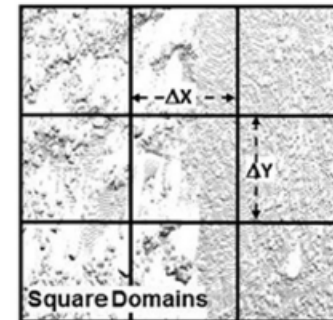
# STATISTICAL METHODS

- **Topographic Point Cloud Analysis Toolkit (ToPCAT; formerly PC-Tools)**
- Look at statistical estimates of variance for elevation
  - Absolute Zmin & Zmax
  - Zmean
  - range
  - stdev - The absolute  $\sigma$
  - sk - Skew
  - n - Count of number of points in cell (i.e. point density)

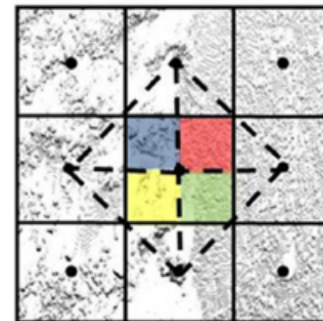


## ToPCAT Topographic Point Cloud Analysis Toolkit

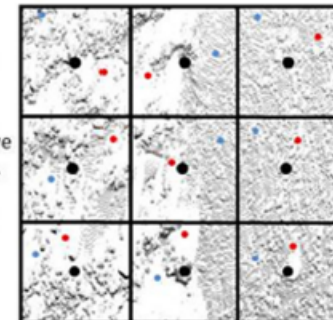
STAGE 1  
Sort laser scan  
points into  
regular grid



STAGE 2  
Sort points in each cell  
and calculate  
elevation statistics



STAGE 3  
Fit local tessellation  
across cardinal  
neighbours and  
detrend points relative  
to this set of planes.  
Derive detrended  
elevation statistics



OUTPUT 2

(c) Centroid ●

- Detrended Minimum(z)
- Detrended Maximum(z)
- Detrended Kurtosis(z)
- Detrended Skewness(z)
- Detrended Std. Deviation(z)

OUTPUT 1

(a) Centroid ●

- Minimum(z)
- Maximum(z)
- Kurtosis(z)
- Skewness(z)
- Std. Deviation(z)
- n. Obs.

(b) Precise location

- Minimum (z) ●
- Maximum (z) ●

Files written out

See: Brasington, J., Vericat, D., Rychkov, I., 2012. Modeling river bed morphological roughness, and surface sedimentology using high resolution terrestrial laser scanning. Water Resources Research 48. DOI: [10.1029/2012wr012223](https://doi.org/10.1029/2012wr012223).





# DETRENDED STD. DEV RELATES TO ROUGHNESS

- Simple empirical relationship to convert detrended  $\sigma$  to grain size & roughness...

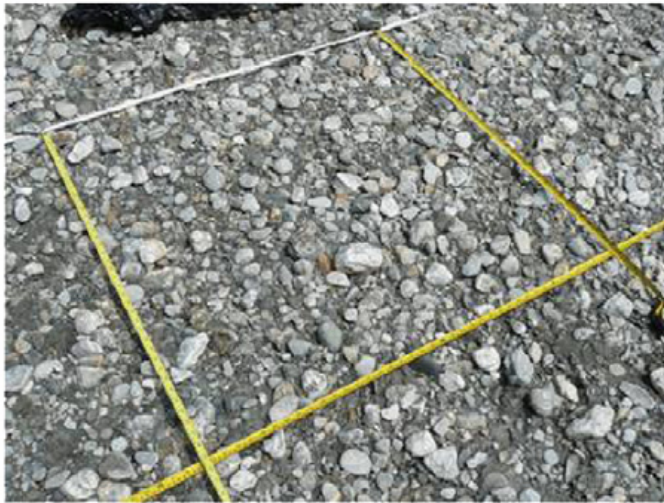
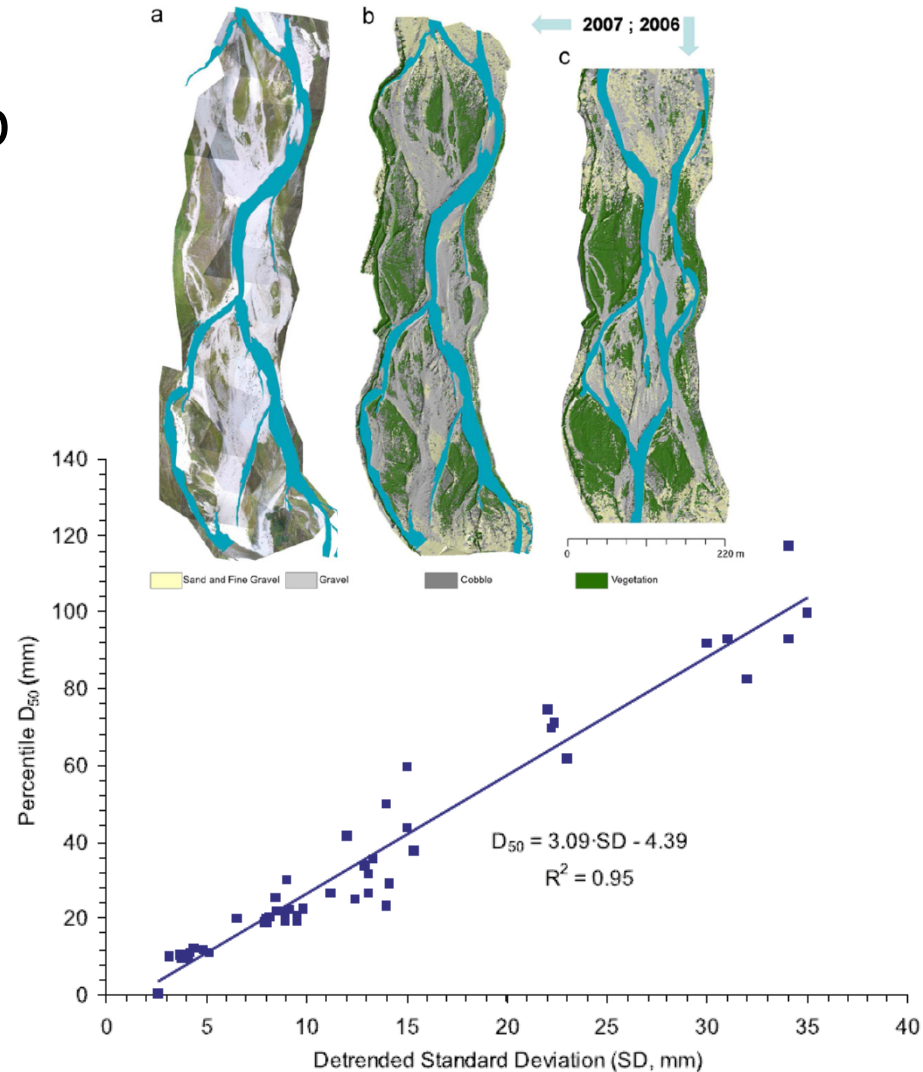


Fig. 3. Measuring patch-scale grain size distribution median ( $D_{50}$ ) by method of pebble counts.

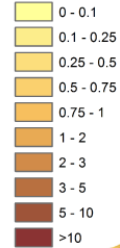


# IF ROUGHNESS IS LIMITING...

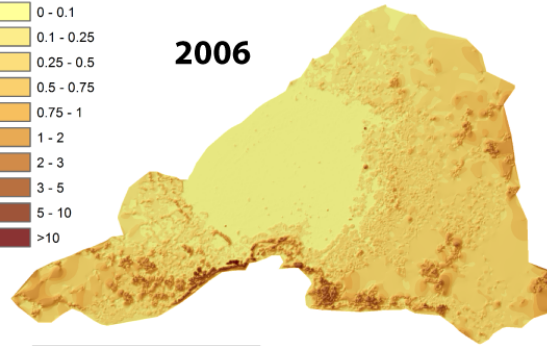
- Roughness itself can be used as an error model for some point clouds



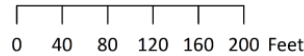
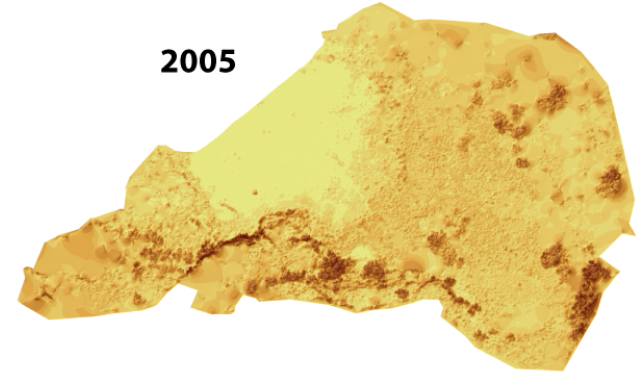
Roughness Height (ft)



2006

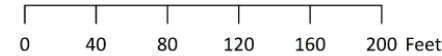
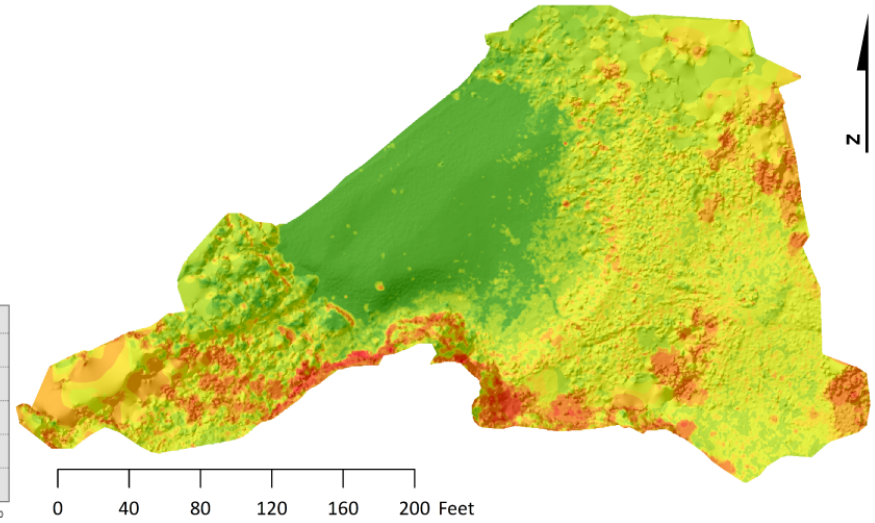
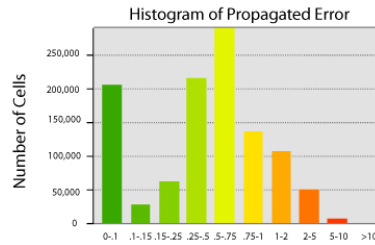
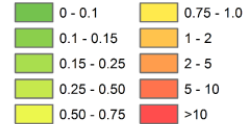


2005



Propagated Error (Roughness)

Elevation Uncertainty (ft)



- Use roughness as proxy for error...



# 4 'CLASSICS' IN YOUNG FIELD OF RASTER GCD

- Lane SN, Chandler JH and Richards KS. 1994. Developments in Monitoring and Modeling Small-Scale River Bed Topography. *Earth Surface Processes and Landforms*. 19(4): 349-368. DOI: [10.1002/esp.3290190406](https://doi.org/10.1002/esp.3290190406).
- McLean DG and Church M. 1999. Sediment transport along lower Fraser River - 2. Estimates based on the long-term gravel budget. *Water Resources Research*. 35(8): 2549-2559.
- Lane SN, Westaway RM and Hicks DM. 2003. Estimation of erosion and deposition volumes in a large, gravel-bed, braided river using synoptic remote sensing. *Earth Surface Processes and Landforms*. 28(3): 249-271. DOI: [10.1002/esp.483](https://doi.org/10.1002/esp.483).
- Brasington J, Langham J and Rumsby B. 2003. Methodological sensitivity of morphometric estimates of coarse fluvial sediment transport. *Geomorphology*. 53(3-4): 299-316. DOI: [10.1016/S0169-555X\(02\)00320-3](https://doi.org/10.1016/S0169-555X(02)00320-3)

EARTH SURFACE PROCESSES AND LANDFORMS, VOL. 19, 349-368 (1994)

## DEVELOPMENTS IN MONITORING AND MODELLING SMALL-SCALE RIVER BED TOPOGRAPHY

*Earth Surface Processes and Landforms*  
*Earth Surf. Process. Landforms* 28, 249-271 (2003)  
Published online in Wiley InterScience (www.interscience.wiley.com). DOI: 10.1002/esp.483

## ESTIMATION OF EROSION AND DEPOSITION VOLUMES IN A LARGE, GRAVEL-BED, BRAIDED RIVER USING SYNOPTIC REMOTE SENSING



Available online at [www.sciencedirect.com](http://www.sciencedirect.com)

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*Geomorphology* 53 (2003) 299–316

GEOMORPHOLOGY

[www.elsevier.com/locate/geomorph](http://www.elsevier.com/locate/geomorph)

## Methodological sensitivity of morphometric estimates of coarse fluvial sediment transport

James Brasington<sup>a,\*</sup>, Joe Langham<sup>b</sup>, Barbara Rumsby<sup>b</sup>

<sup>a</sup>Department of Geography, University of Cambridge, Downing Place, Cambridge CB2 3EN, UK  
<sup>b</sup>Department of Geography, University of Hull, Cottingham Road, HU6 7RX, UK

Received 11 October 2001; received in revised form 26 September 2002; accepted 4 October 2002

### Abstract

The estimation of fluvial sediment transport rate from measurements of morphological change has received growing recent interest. The arrival of the 'morphological method' reflects continuing concern over traditional methods of rate determination but also the availability of new survey methods capable of high-precision, high-resolution topographic monitoring. Remote sensing of river channels through aerial digital photogrammetry is a potentially attractive alternative to labour intensive ground surveys. However, while photogrammetry presents the opportunity to acquire survey data over large areas, data precision and accuracy, particularly in the vertical dimension are lower than in traditional ground survey methods. This paper presents results of recent research in which digital elevation models (DEMs) have been developed for a reach of a large braided gravel-bed river in Scotland using both digital photogrammetry and high-resolution RTK, GPS ground surveys. A statistical level of change detection is assessed by comparing surfaces with independent check points. The methodological sensitivity of the annual channel sediment budget (1999–2000) to the threshold is presented. Results suggest that while the remote survey methods employed here can be used to develop qualitatively convincing, moderate precision DEMs of channel topography which lead to important information losses. Tests at a 95% confidence interval for change detection show that over 60% of channel deposition and 40% of erosion may be obscured by the lower level of precision associated with photogrammetric monitoring when compared to ground survey measurements. This bias reflects the difficulty of detecting the topographic signature of widespread, but shallow deposition on bar tops.

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Keywords: Braided river; DEM; Photogrammetry; GPS; Sediment transport

### 1. Introduction

The relationship between river channel form and process is one of sensitive mutual adjustment in

which river morphology is both a control and consequence of fluvial processes. The significance of this interaction requires that a central aspect of modern river science and engineering is the detailed specification of channel topography. This requirement has been emphasized by recent interest in the prediction of flood-wave propagation, floodplain inundation and overbank sedimentation through proc-

\* Corresponding author. Tel.: +44-1223-339966; fax: +44-1223-333392.

E-mail address: [jb10076@cam.ac.uk](mailto:jb10076@cam.ac.uk) (J. Brasington).

0169-555X/03/\$ - see front matter © 2003 Elsevier Science B.V. All rights reserved.  
doi:10.1016/S0169-555X(02)00320-3

# TWO TIME DEPENDENT ESTIMATES OF ERROR... PROPAGATED INTO EACH OTHER

- Why are error models different?
- Propagated error used to compare against DoD and calculate T-Score...

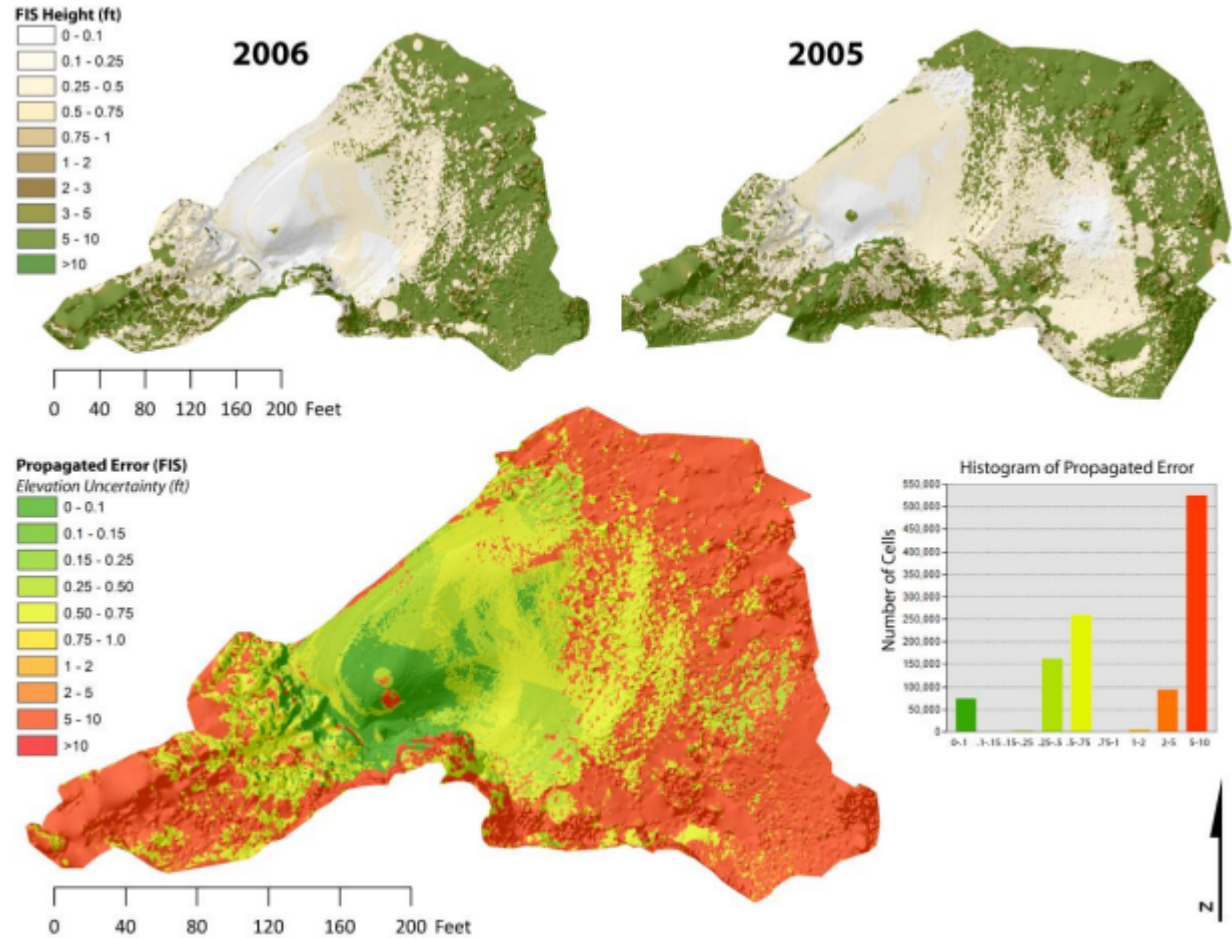


Figure S1 -- Propagated error surface produced from 2006 and 2005 FIS rasters for China Bar.

From [Leary et al. \(2012\)](#)



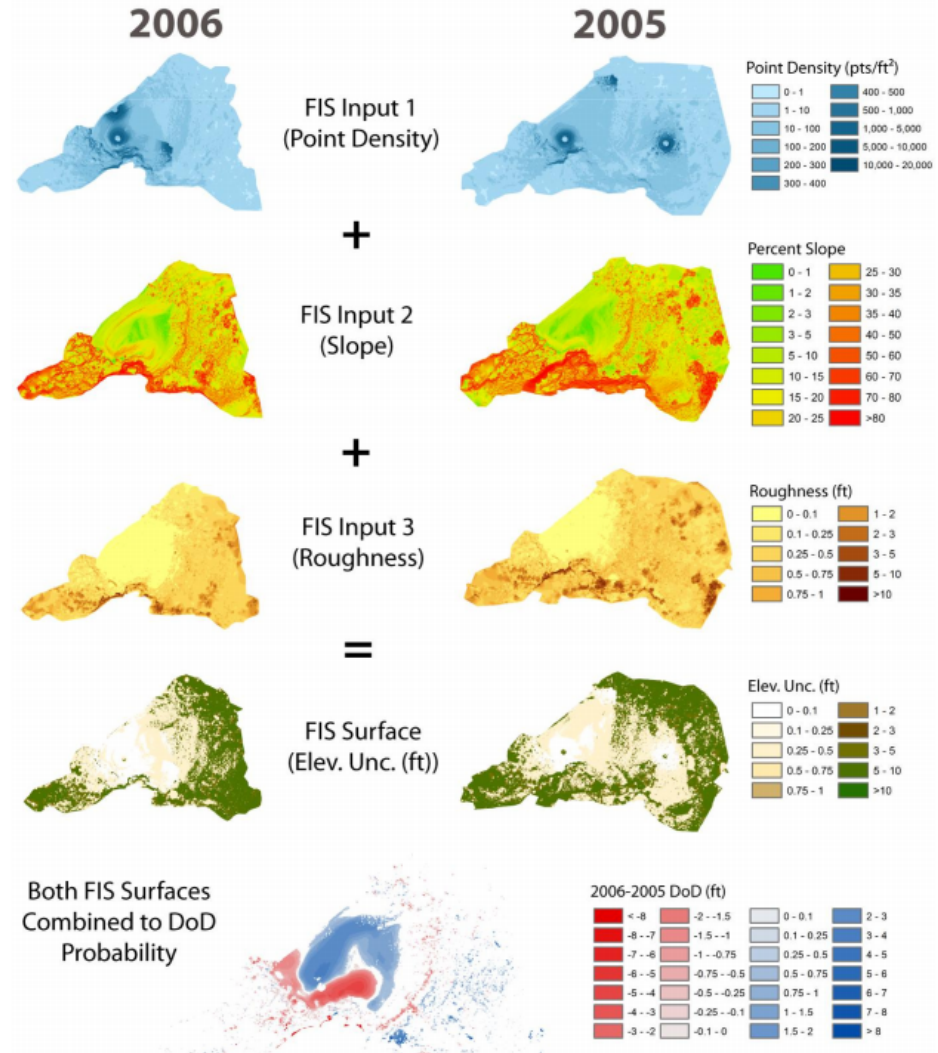
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HABITATS CENTER

# EXAMPLE OF HOW TO GET THERE...

Rule	Inputs→			Output Elevation Uncertainty
	Slope	Point Density	Roughness	
1	Low	Sparse	Smooth (sand)	Average
2	Low	Medium	Smooth (sand)	Average
3	Low	Dense	Smooth (sand)	Low
4	Medium	Sparse	Smooth (sand)	High
5	Medium	Medium	Smooth (sand)	Average
6	Medium	Dense	Smooth (sand)	Low
7	High	Sparse	Smooth (sand)	High
8	High	Medium	Smooth (sand)	Average
9	High	Dense	Smooth (sand)	Average
10	Low	Sparse	Rough (Gravel/Cobble)	High
11	Low	Medium	Rough (Gravel/Cobble)	Average
12	Low	Dense	Rough (Gravel/Cobble)	Average
13	Medium	Sparse	Rough (Gravel/Cobble)	Extreme
14	Medium	Medium	Rough (Gravel/Cobble)	High
15	Medium	Dense	Rough (Gravel/Cobble)	Average
16	High	Sparse	Rough (Gravel/Cobble)	Extreme
17	High	Medium	Rough (Gravel/Cobble)	High
18	High	Dense	Rough (Gravel/Cobble)	Average
19	Low	Sparse	Very Rough (Boulder/Veg)	Extreme
20	Low	Medium	Very Rough (Boulder/Veg)	Extreme
21	Low	Dense	Very Rough (Boulder/Veg)	High
22	Medium	Sparse	Very Rough (Boulder/Veg)	Extreme
23	Medium	Medium	Very Rough (Boulder/Veg)	Extreme
24	Medium	Dense	Very Rough (Boulder/Veg)	High
25	High	Sparse	Very Rough (Boulder/Veg)	Extreme
26	High	Medium	Very Rough (Boulder/Veg)	Extreme
27	High	Dense	Very Rough (Boulder/Veg)	Extreme



From [Leary et al. \(2012\)](#)



Utah State University  
ECOLOGICAL HYDROLOGY & TOPOGRAPHIC ANALYSIS LABORATORY

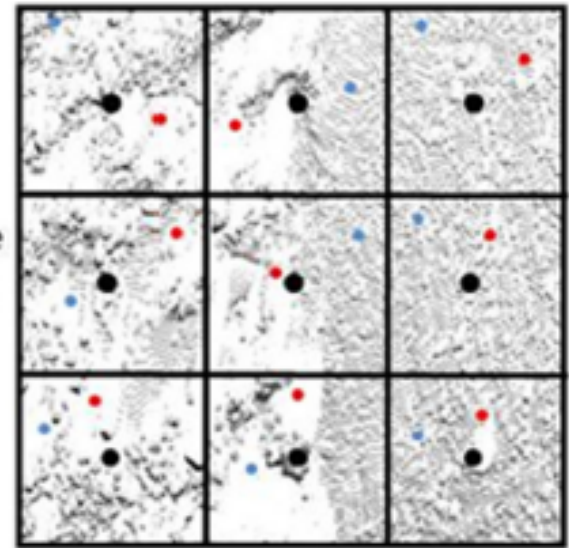


THE FLUVIAL HABITATS CENTER



# DECIMATION of BIG POINT CLOUDS...

- **Topographic Point Cloud Analysis Toolkit (ToPCAT;** formerly PC-Tools)
- Can be used to go from 1000's to 10,000's of points per square meter to 1 to 10...
- Absolute zMin can be extracted in a window of defined size... That can be used to model elevation



OUTPUT 1



- (a) Centroid ●
- Minimum(z)
  - Maximum(z)
  - Kurtosis(z)
  - Skewness(z)
  - Std. Deviation(z)
  - *n.* Obs.

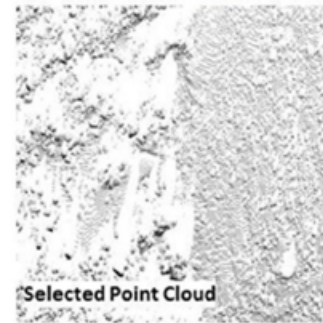
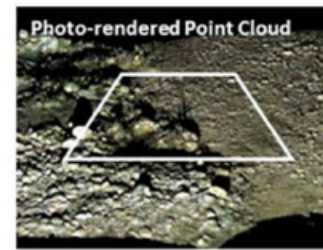
- (b) Precise location:
- Minimum (z) ●
  - Maximum (z) ●

See: Brasington, J., Vericat, D., Rychkov, I., 2012. Modeling river bed morphology, roughness, and surface sedimentology using high resolution terrestrial laser scanning. Water Resources Research 48. DOI: [10.1029/2012wr012223](https://doi.org/10.1029/2012wr012223).



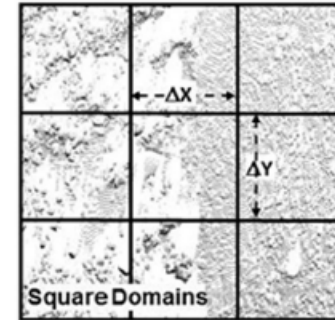
# POINT CLOUD STATS

- **Topographic Point Cloud Analysis Toolkit (ToPCAT; formerly PC-Tools)**
- Look at statistical estimates of variance for elevation
  - Absolute  $Z_{\min}$  &  $Z_{\max}$
  - $Z_{\text{mean}}$
  - range
  - stdev - The absolute  $\sigma$
  - sk - Skew
  - n - Count of number of points in cell (i.e. point density)



## ToPCAT Topographic Point Cloud Analysis Toolkit

STAGE 1  
Sort laser scan  
points into  
regular grid



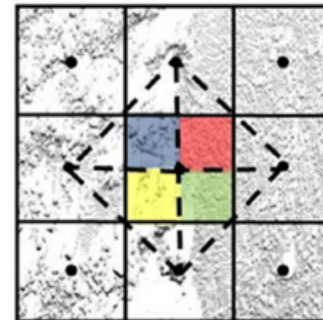
STAGE 2

Sort points in each cell  
and calculate  
elevation statistics



STAGE 3

Fit local tessellation  
across cardinal  
neighbours and  
detrond points relative  
to this set of planes.  
Derive detronded  
elevation statistics



OUTPUT 2

- (c) Centroid ●
- Detronded Minimum(z)
  - Detronded Maximum(z)
  - Detronded Kurtosis(z)
  - Detronded Skewness(z)
  - Detronded Std. Deviation(z)

OUTPUT 1

- (a) Centroid ●
- Minimum(z)
  - Maximum(z)
  - Kurtosis(z)
  - Skewness(z)
  - Std. Deviation(z)
  - n. Obs.
- (b) Precise location:
- Minimum (z) ●
  - Maximum (z) ●



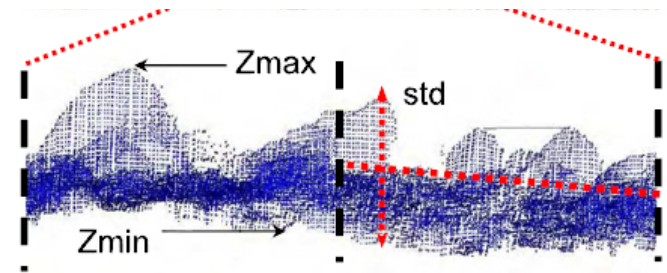
Files written out

See: Brasington, J., Vericat, D., Rychkov, I., 2012. Modeling river bed morphol roughness, and surface sedimentology using high resolution terrestrial laser scanning. Water Resources Research 48. DOI: [10.1029/2012wr012223](https://doi.org/10.1029/2012wr012223).



# HOW IT WORKS...

- Locally detrended stats, relative to a best-fit plane surface through the point cloud
- $Z_{\text{mean\_det}}$ ,  $\text{stdev\_det}$ ,  $\text{sk\_det}$ ,  $k_{\text{det}}$



<http://code.google.com/p/point-cloud-tools/>

66

I. Rychkov et al. / Computers & Geosciences 42 (2012) 64–70

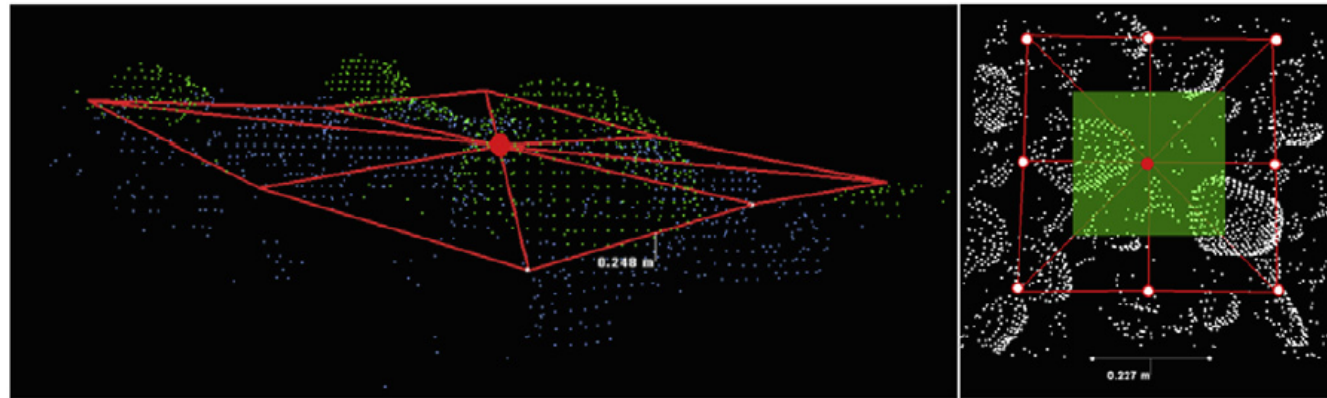


Fig. 2. Triangular mesh laid over grid cells. Green mask represents the current cell. Vertices can be central elevations, centroids or points of minimum elevations. Vertices from neighboring cells are connected by red lines. 3D (left image) and top (right image) views. The facets of the mesh give the local ground slopes. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

See: Rychkov I, Brasington J and Vericat D (2012). DOI: 10.1016/j.cageo.2012.02.011



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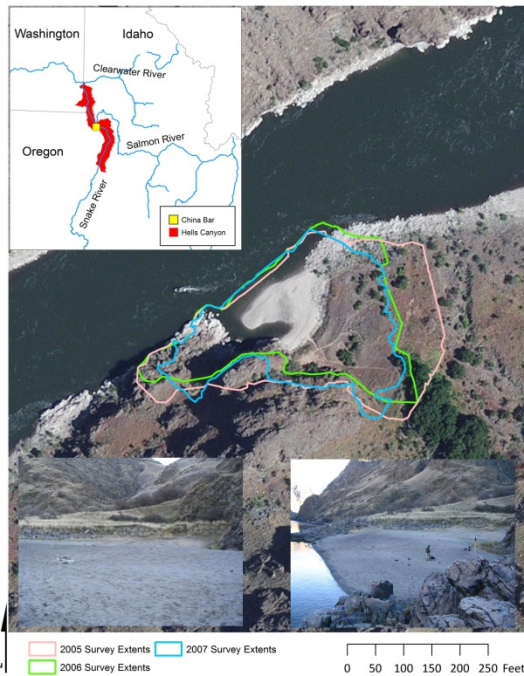
@FHC

THE FLUVIAL  
HABITATS CENTER

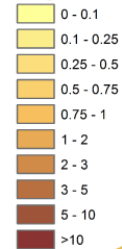


# A SANDBAR EXAMPLE...

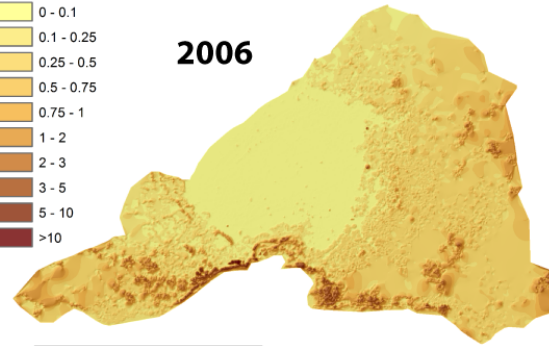
- Roughness changes through time



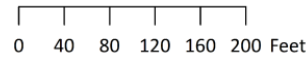
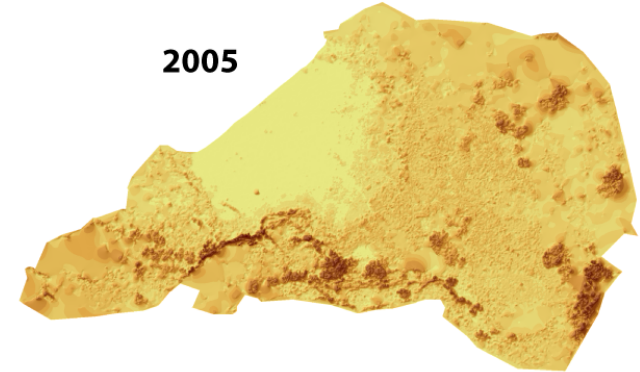
Roughness Height (ft)



2006

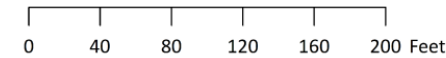
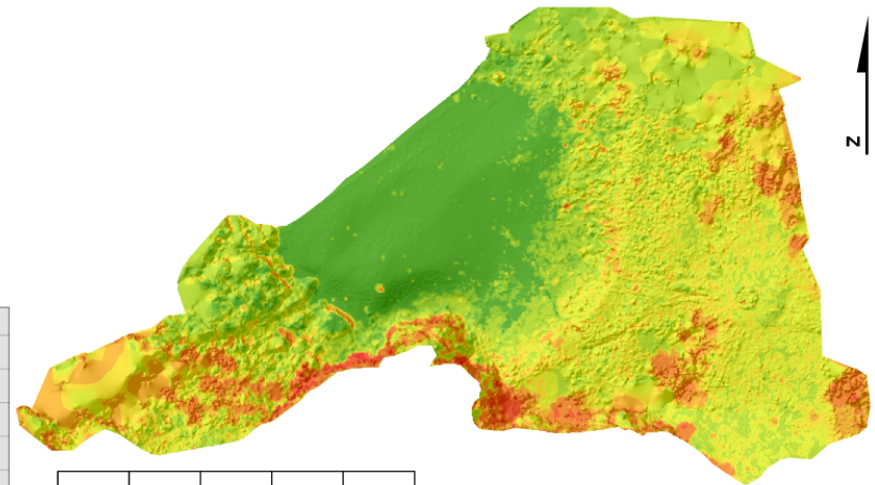
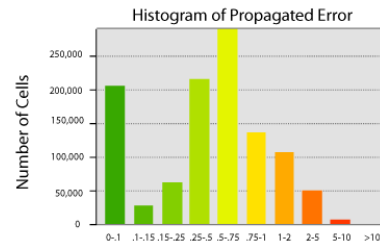
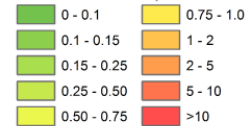


2005



Propagated Error (Roughness)

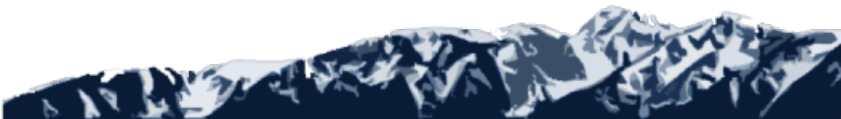
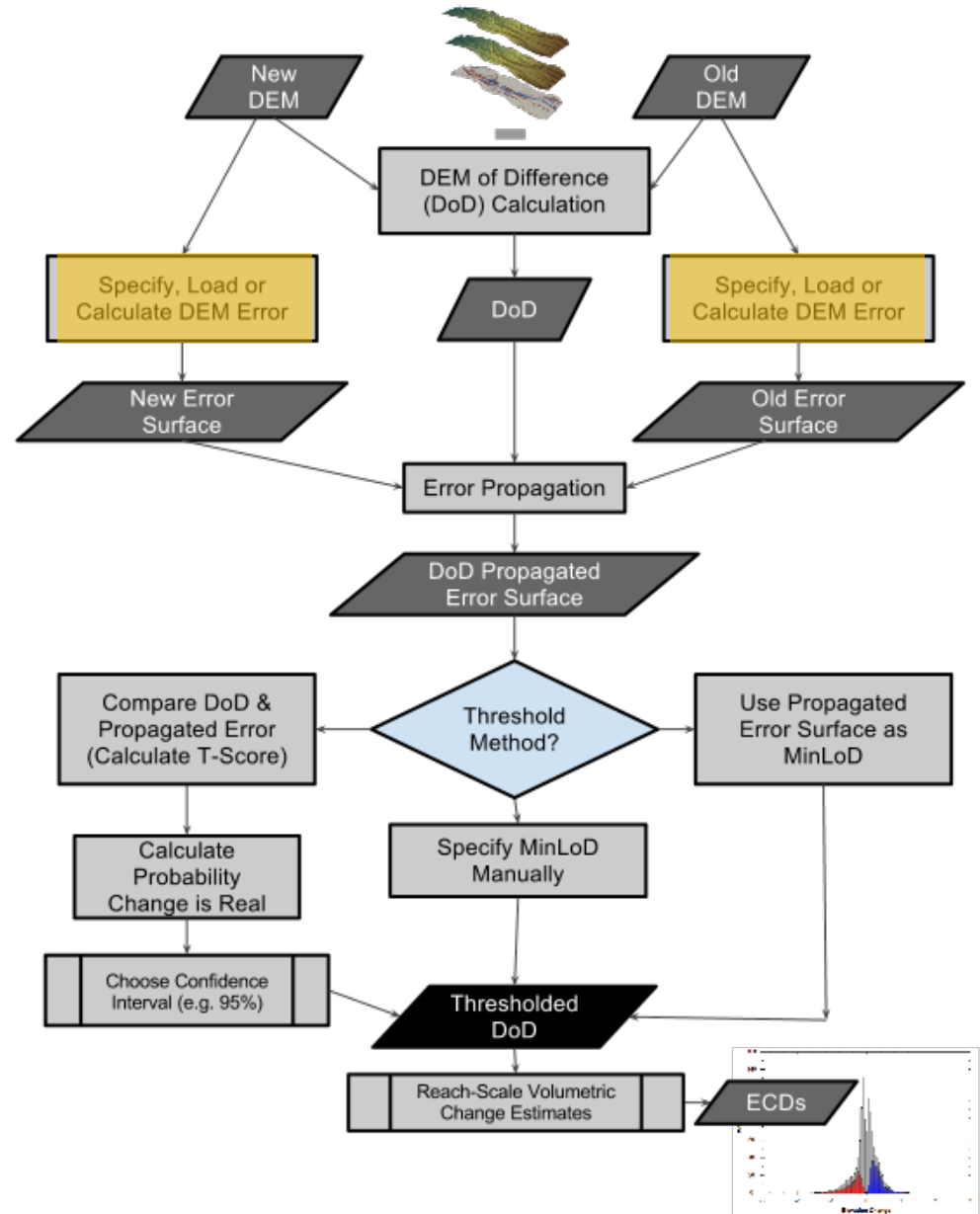
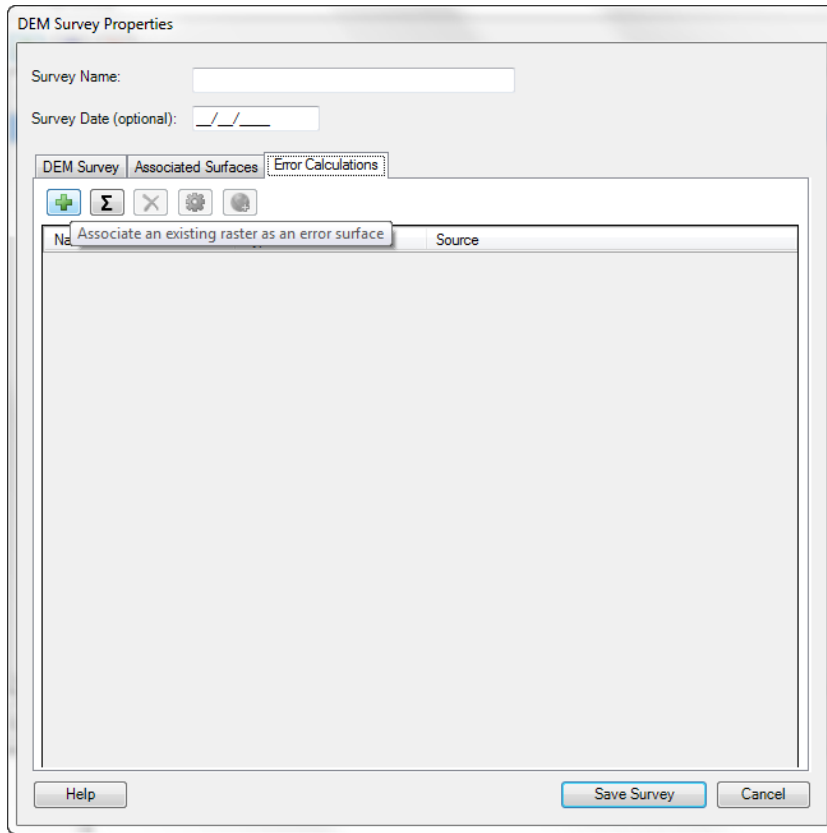
Elevation Uncertainty (ft)



- Use detrended standard deviation as proxy for roughness and/or error...

# ADD ROUGHNESS AS ERROR SURFACE

- New DEM Error
- Old DEM Error





# ALTERNATIVES... PySESA

- PySESA – Python program for spatially explicit spectral analysis

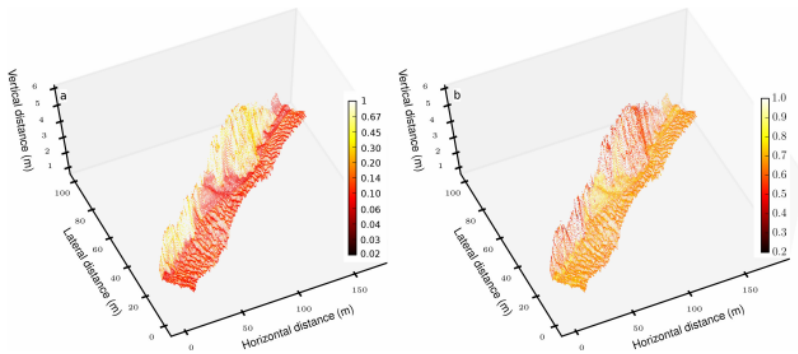


Figure 8: The point cloud shown in Figure 7a, decimated to a  $0.25 \times 0.25$ m regular grid by the PySESA program, and colour-coded by: a) spectral root-mean-square variation in amplitude,  $\sigma$  (m); and b) spectral strength  $\omega_2$  ( $\text{m}^4$ ).

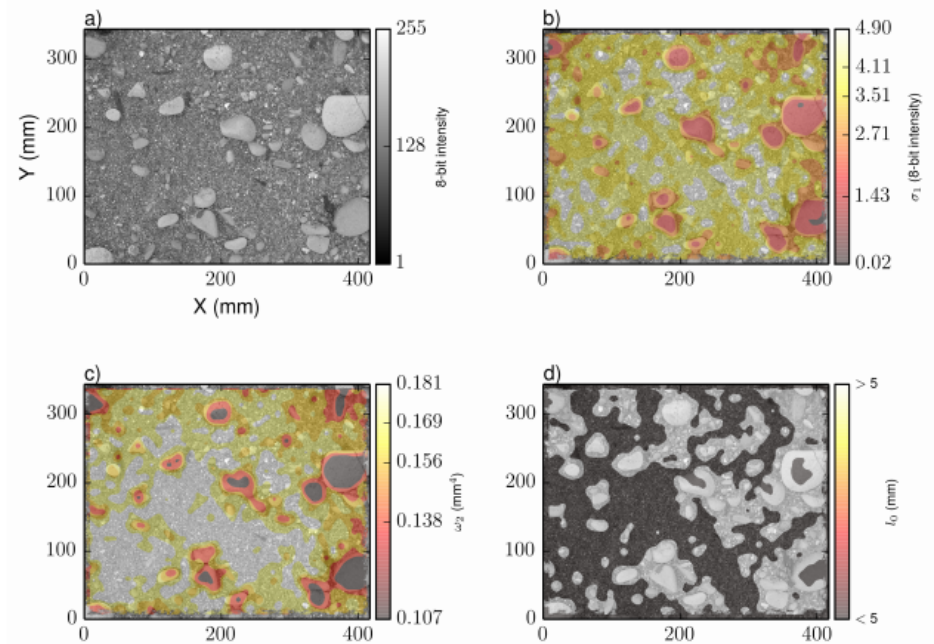


Figure 10: a) 8-bit grayscale intensity image of coarse sand, gravel and pebbles; b) grayscale image overlain by contour map of spectral RMS amplitude,  $\sigma_1$  (equation 15); c) grayscale image overlain by contour map of spectral strength,  $\omega_2$  (equation 12); and d) grayscale image overlain by binary map of where integral lengthscale,  $l_0$  (equation 11) is < (dark) and >5 (light) mm.

PySESA Website: <https://dbuscombe-usgs.github.io/pysesas/index.html>

PySESA Source code: <https://github.com/dbuscombe-usgs/pysesas>

From Dan Buscombe  
(USGS GCMRC)