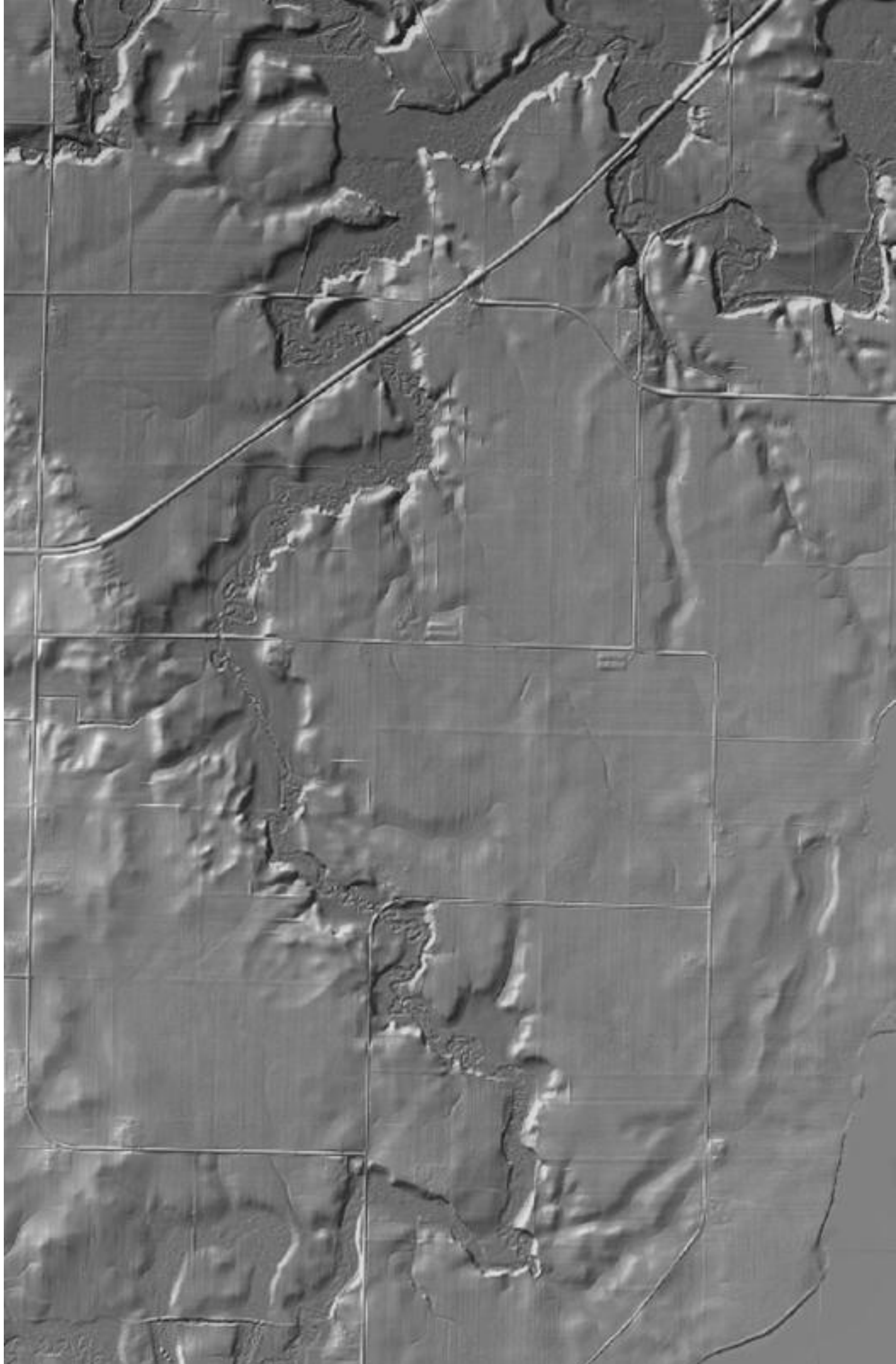
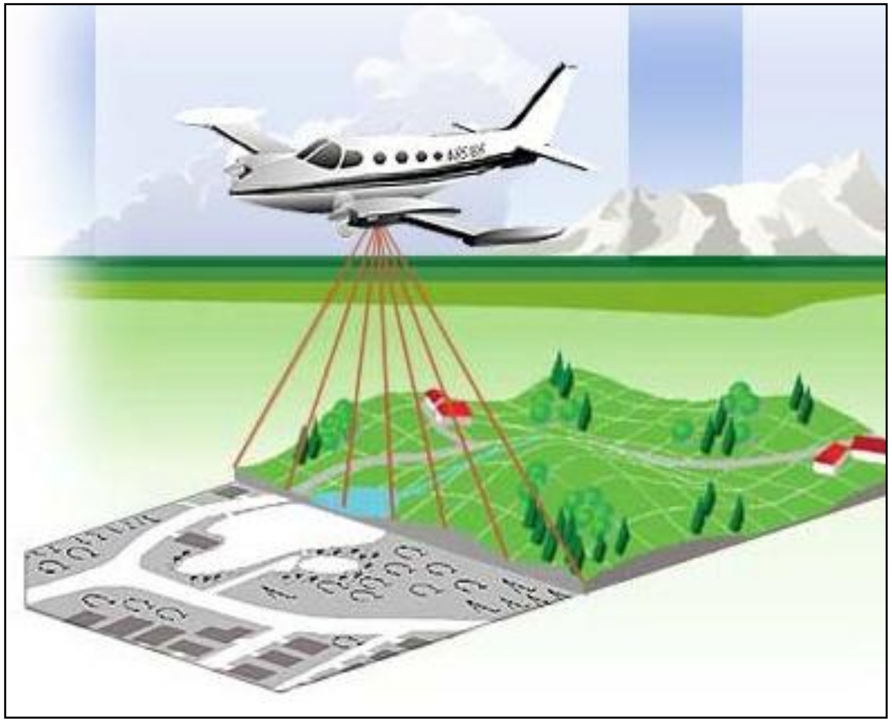
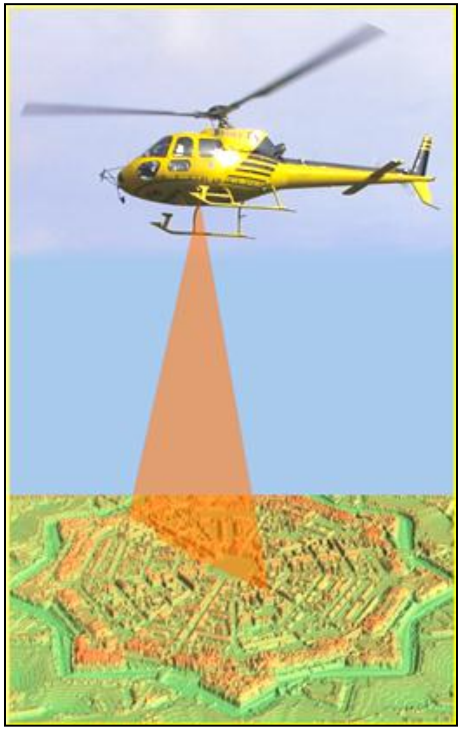
Lidar data in water resources applications

Paola Passalacqua

CE 374K Lecture, April 5th, 2012

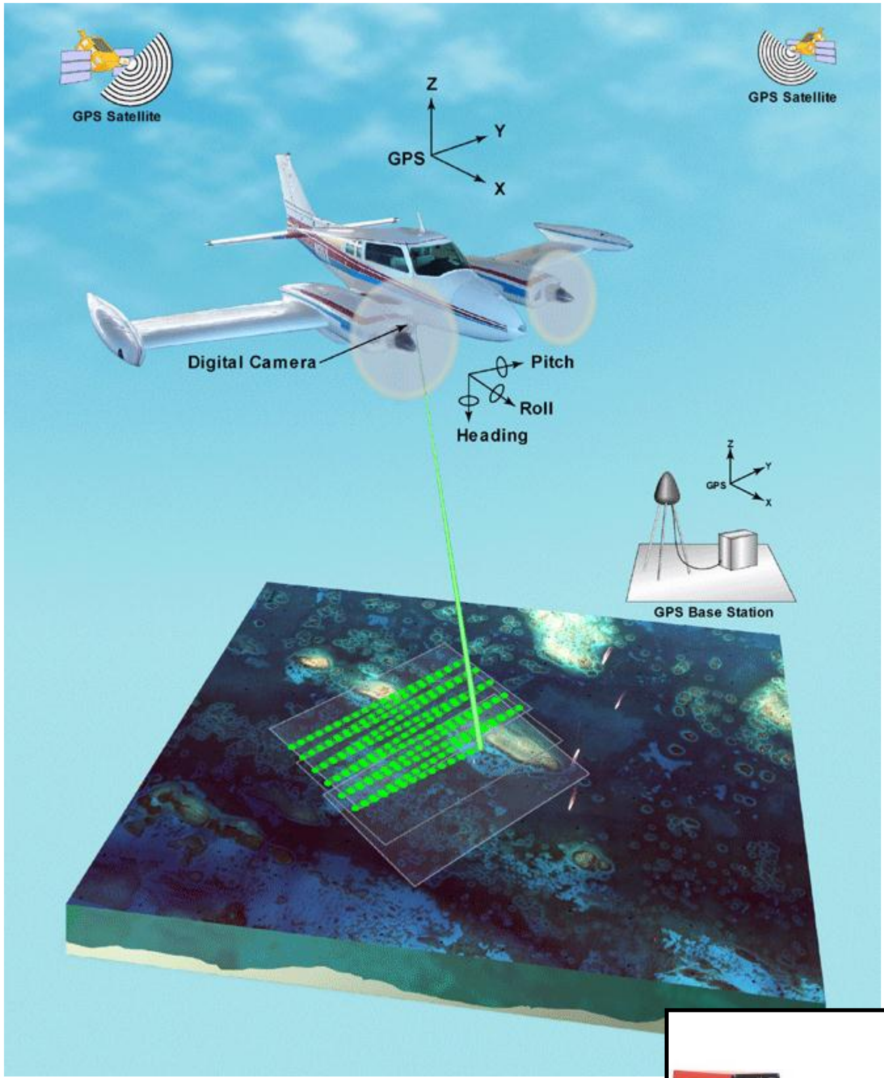


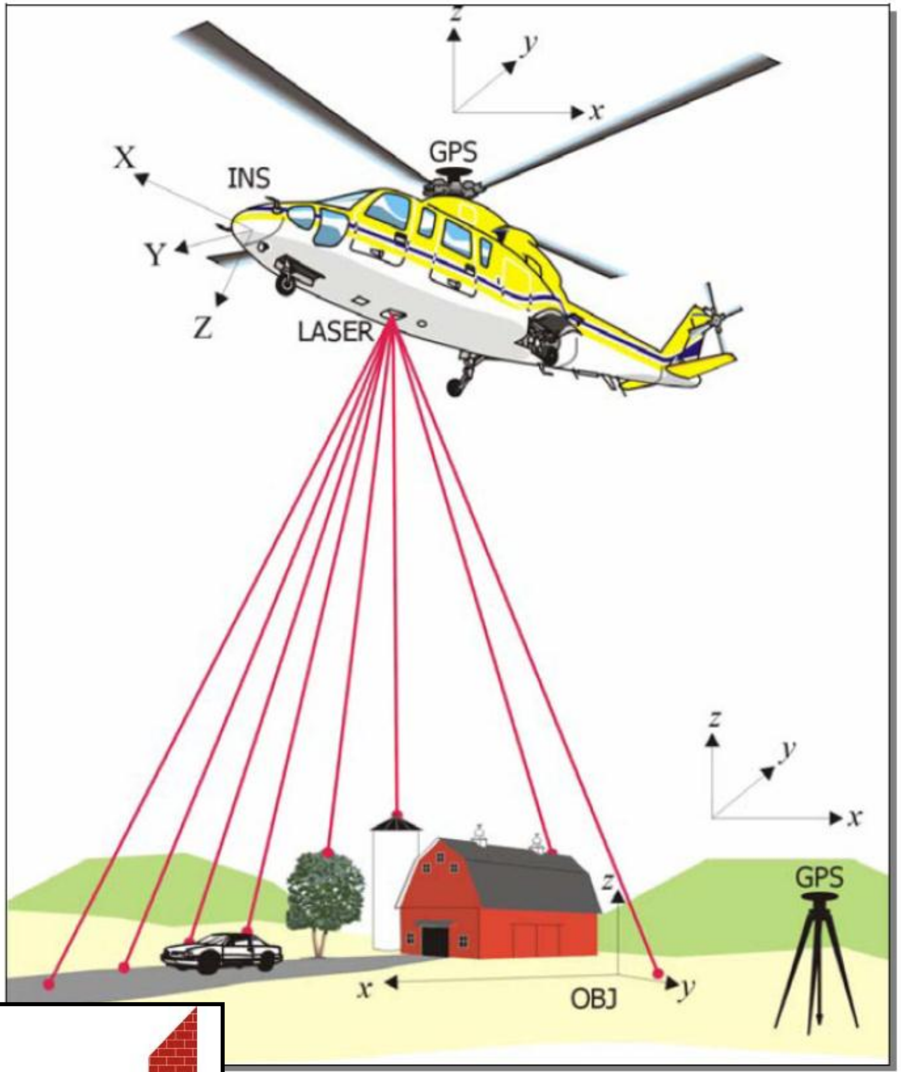
Airborne Lidar

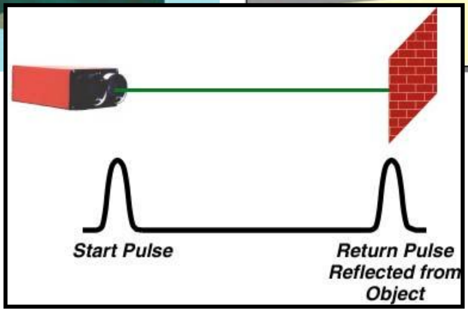




Airborne laser altimetry technology (LiDAR, Light Detection And Ranging) provides high-resolution topographical data, which can significantly contribute to a better representation of land surface. A valuable characteristic of this technology, which marks advantages over the traditional topographic survey techniques, is the capability to derive a high-resolution Digital Terrain Model (DTM) from the last pulse LiDAR data by filtering the vegetation points (Slatton et al., 2007).

Slide courtesy of Dr. Paolo Tarolli, University of Padova, Italy







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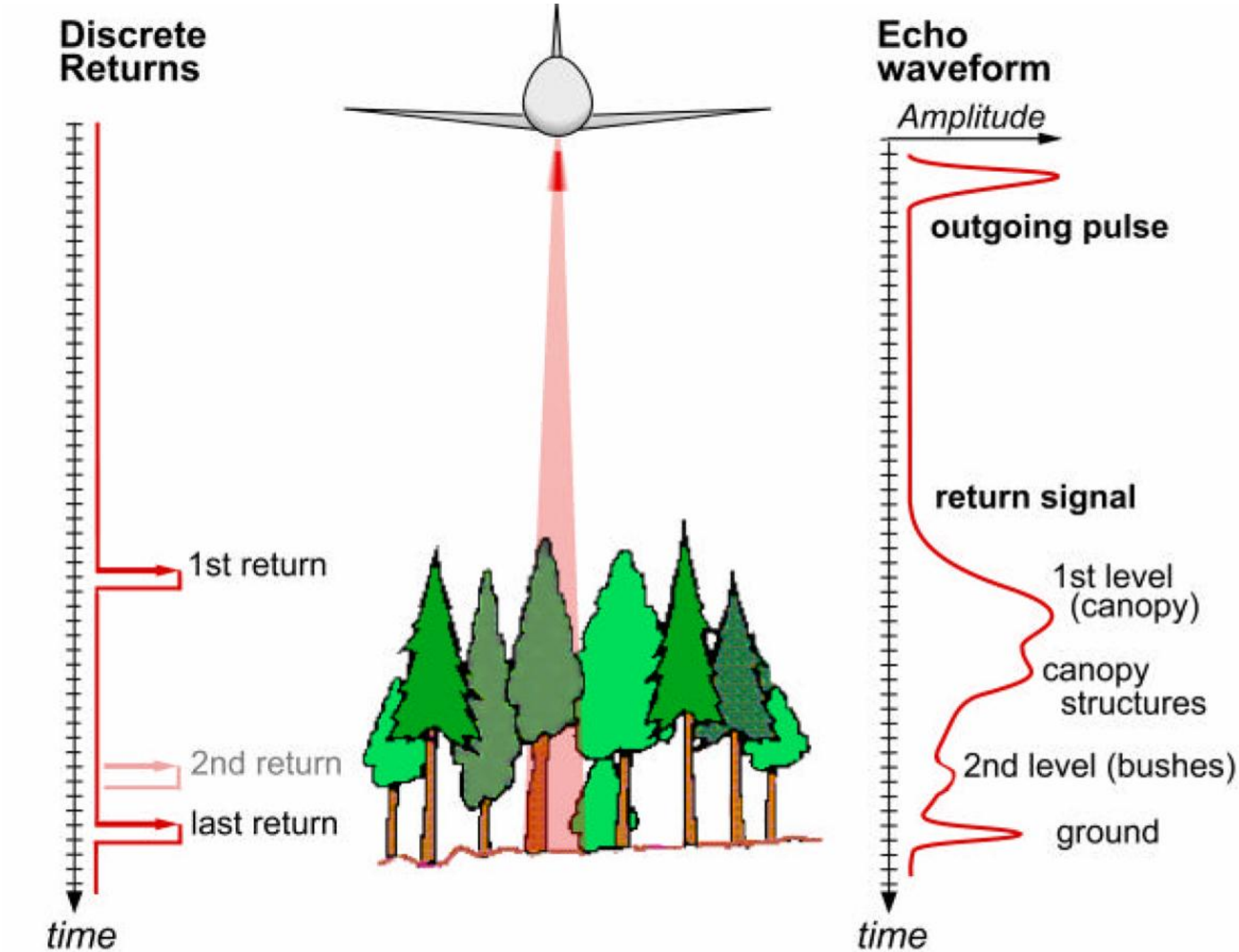
x,y,z



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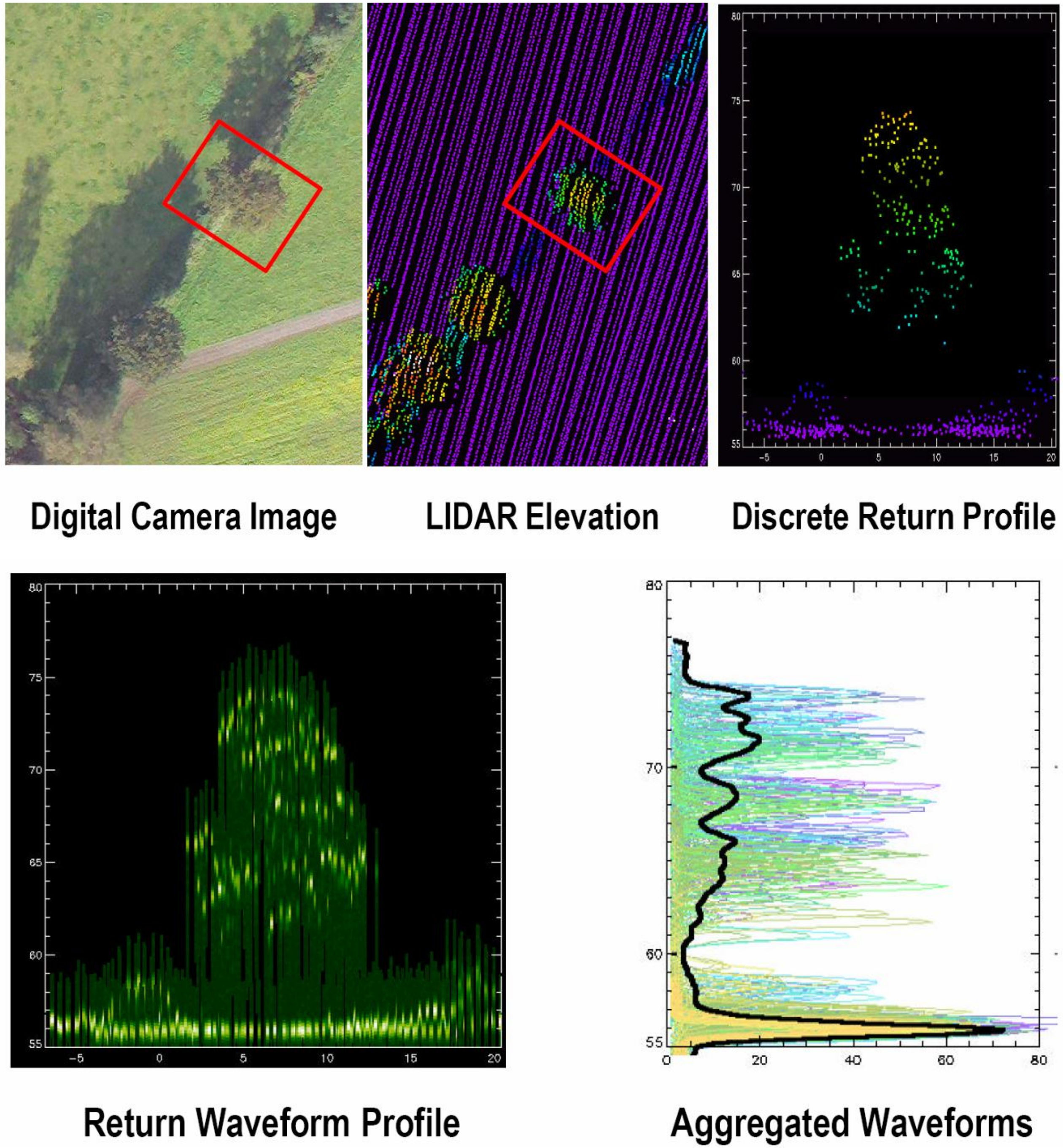
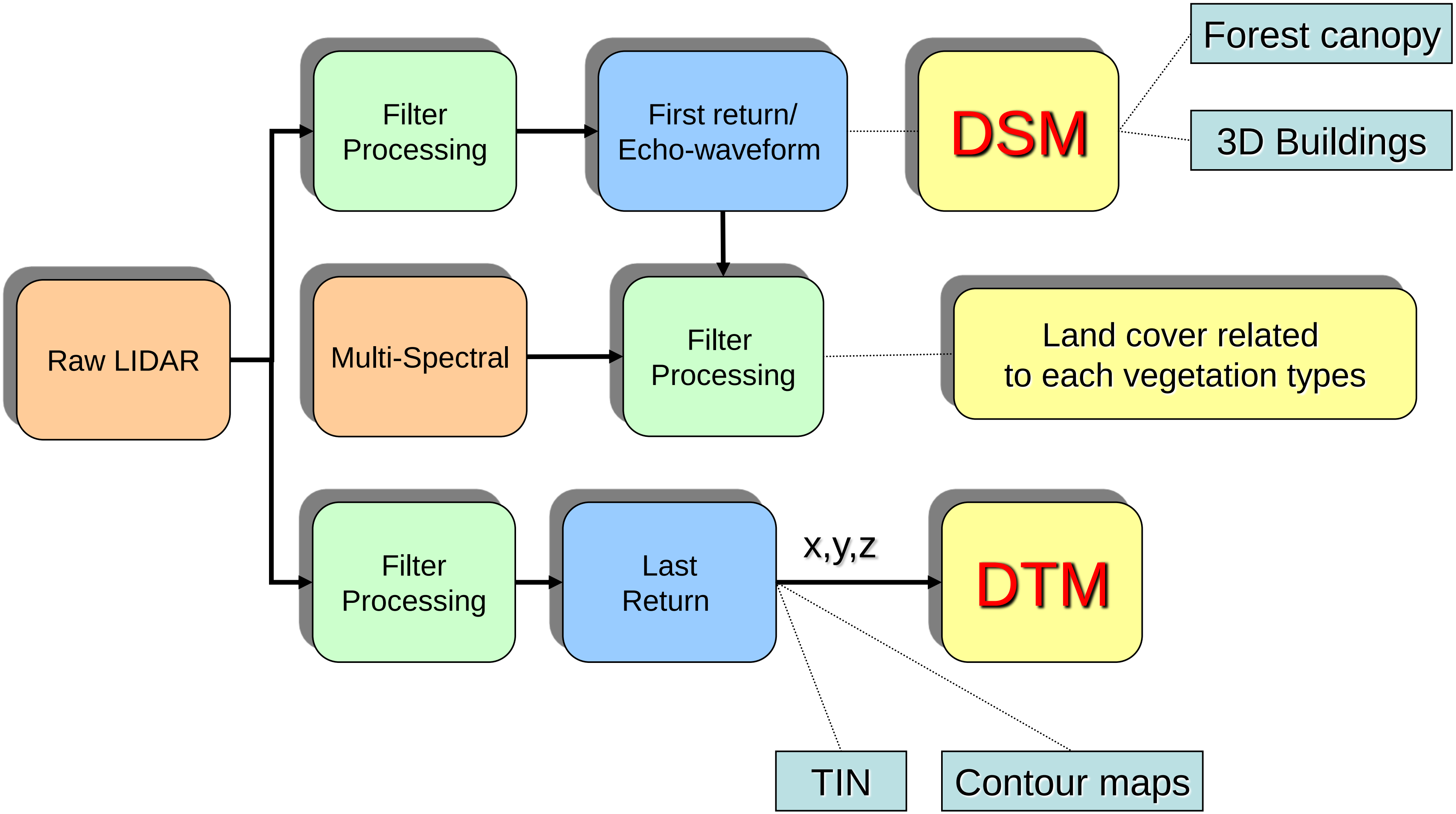


x,y,z (point)

Slide courtesy of Dr. Paolo Tarolli, University of Padova, Italy



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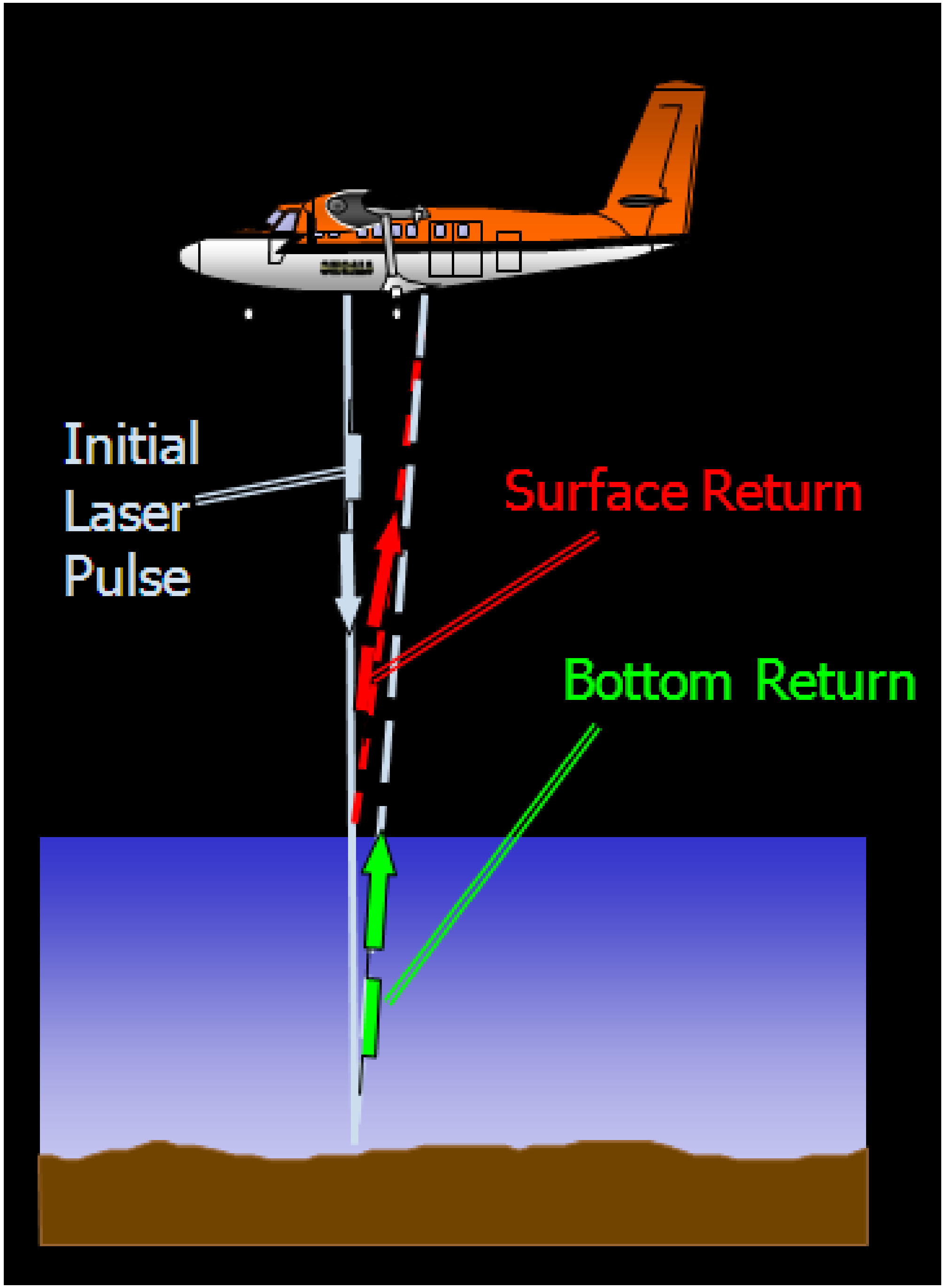


Topographic Lidar

λ = 1064 nm

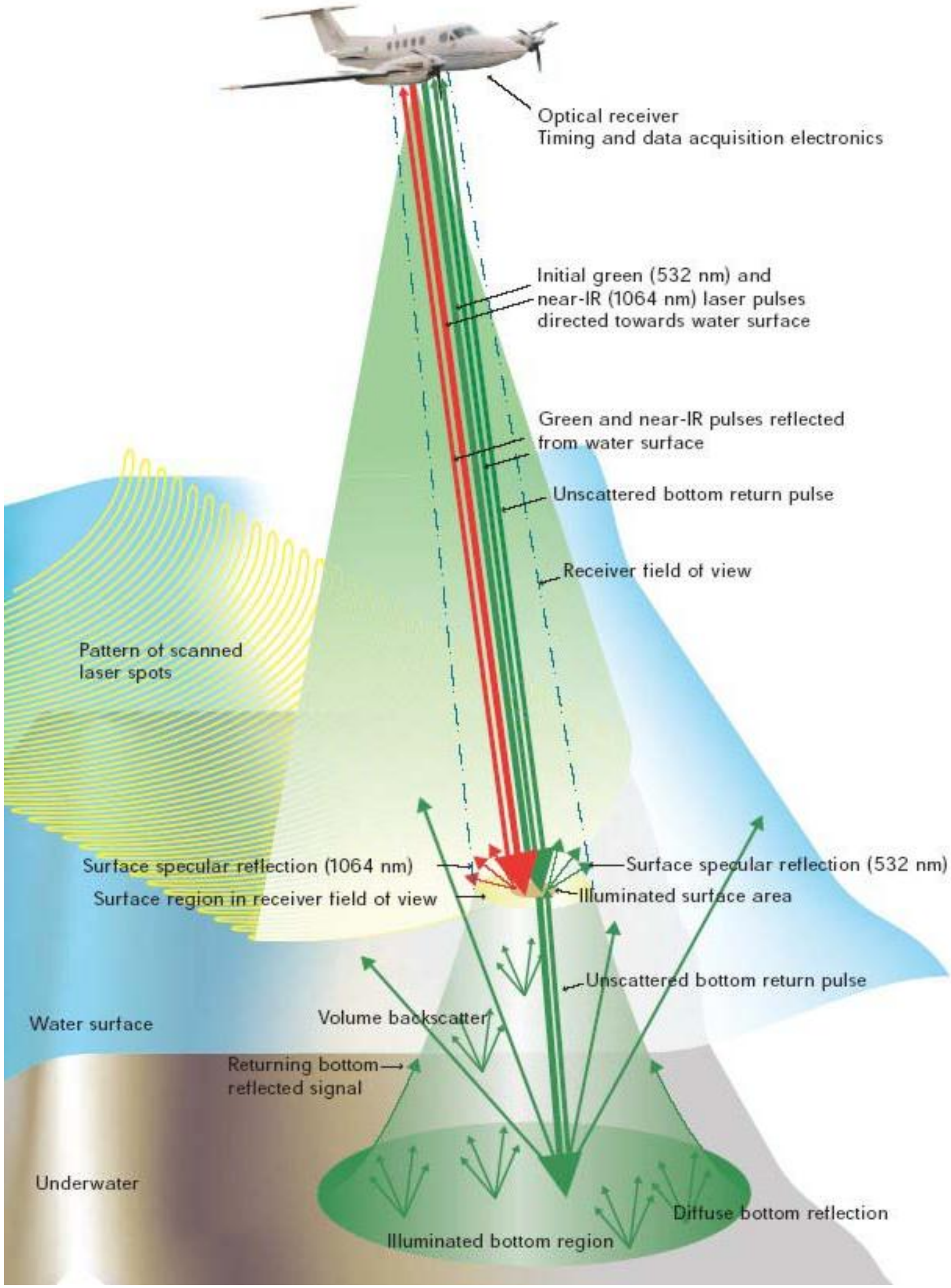
Green LiDAR

λ = 532 nm + λ =1064 nm

It is important to remember that the deep water surfaces normally do not reflect the signal: however this is not true in case of presence of floating sediments or when using bathymetric lidar. The bathymetric lidar, that is based on the same principles as topographic lidar, emits laser beams in two wavelengths: an infrared (1064 nm) and a green one (532 nm). The infrared wavelength is reflected on the water surface, while the green one penetrates the water and is reflected by the bottom surface or other objects in the water. Due to this reason the bathymetric lidar is also called green lidar.

Slide courtesy of Dr. Paolo Tarolli, University of Padova, Italy

Fonte: www.optech.ca



During optimal environment condition, when the water is clear, the green lidar survey may reach 50 m water depth with an horizontal accuracy of ±2.5 m, and vertical accuracy of ±0.25 m. This technology is growing fast, and some of the first applications in rivers are coming out (Hilldale and Raff, 2008; McKean et al., 2009).

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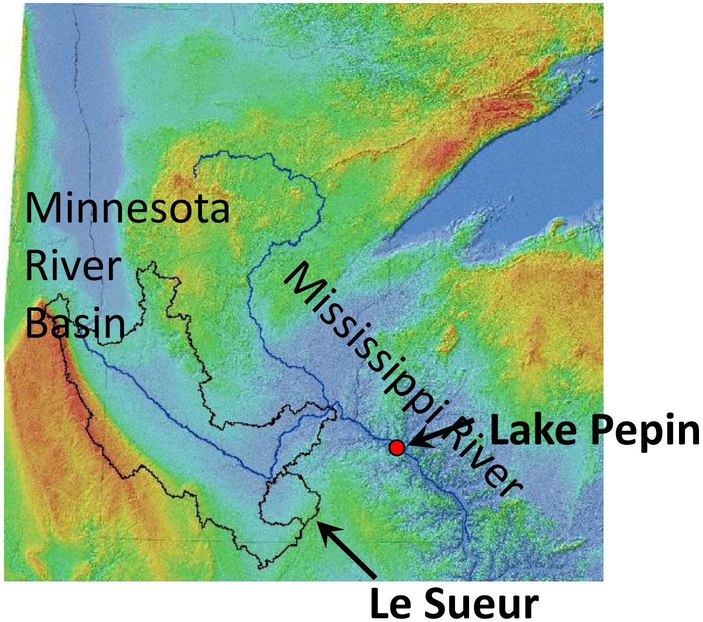
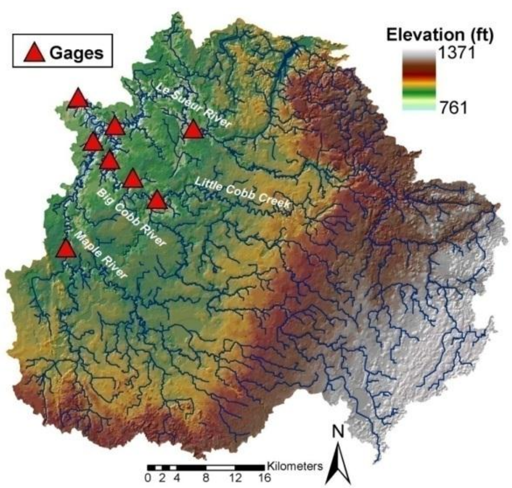
Example 1: Le Sueur River basin





Le Sueur River located in south-central Minnesota, covers an area of 2880 km^2 (87% row-crop agriculture)

Provides ~ 24%-30% of the TSS entering the Minnesota River

Minnesota River major source of sediment for Lake Pepin (~85% of TSS load)

Turbidity and related nutrients levels of Lake Pepin are far in excess of EPA standards

State of Minnesota required to determine the sources of pollution and take management and policy actions

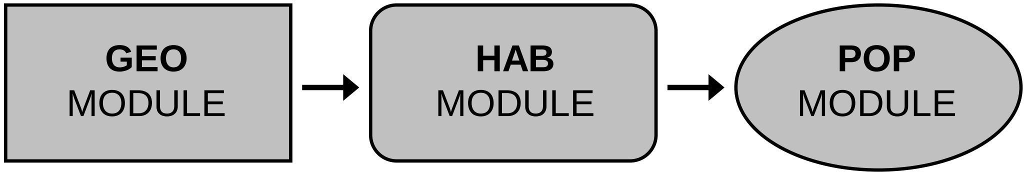
NCED Research

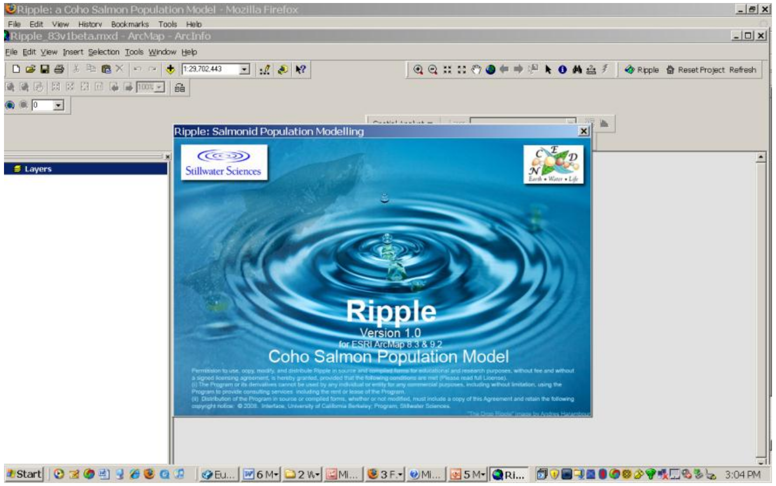
Example 2: Limiting factors analysis of Coho salmon

River networks produce a highly structured pattern of process and morphology downstream.

This structure can be exploited to predict habitat and carrying capacity of species throughout the watershed.

Ripple: spatially explicit model that links quantitatively topography, habitat carrying capacity and population dynamics for an entire watershed.





GEO module: uses DEM to compute local slope and drainage area

NCED Research

From specific examples to the large picture

Hydrologic and sediment modeling need detailed information of basin geomorphological characteristics; channel form relevant to floods.

Input basin geomorphological characteristics to determine habitat limitations.

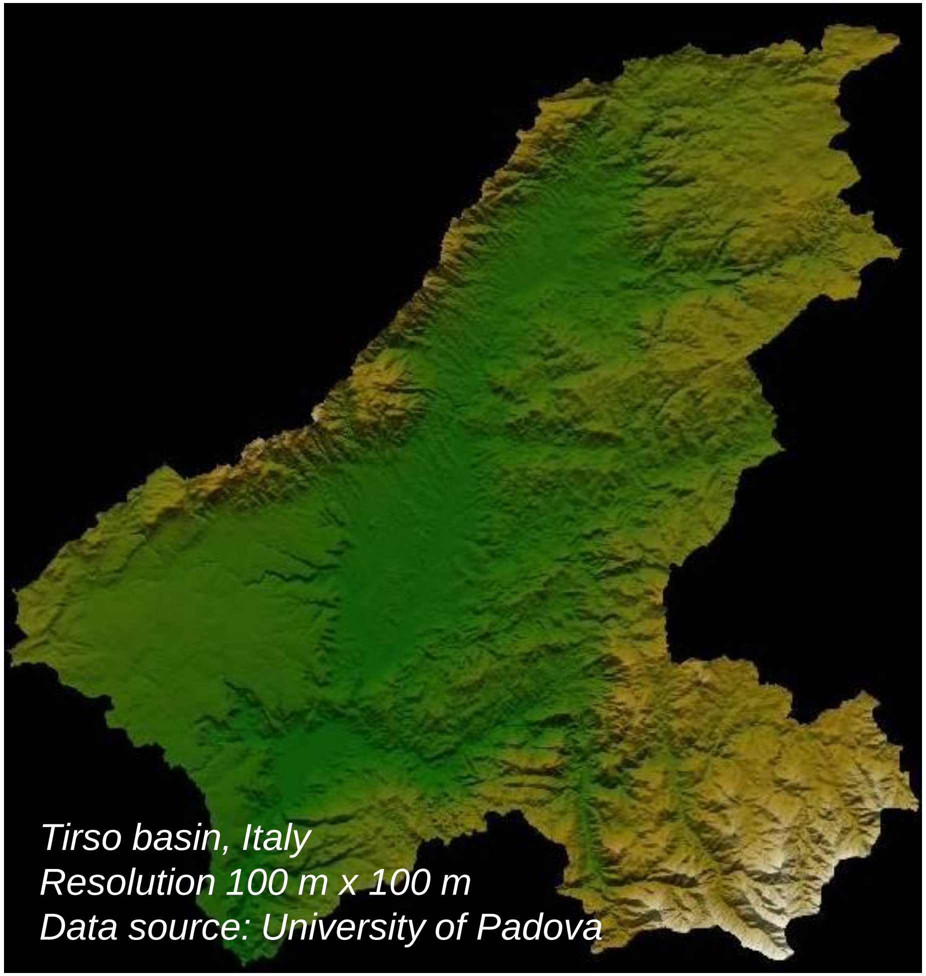
Spatial-temporal patterns of extreme floods f(drainage area, slope, stream morphology….); spatial analysis of channel properties as related to extreme events.

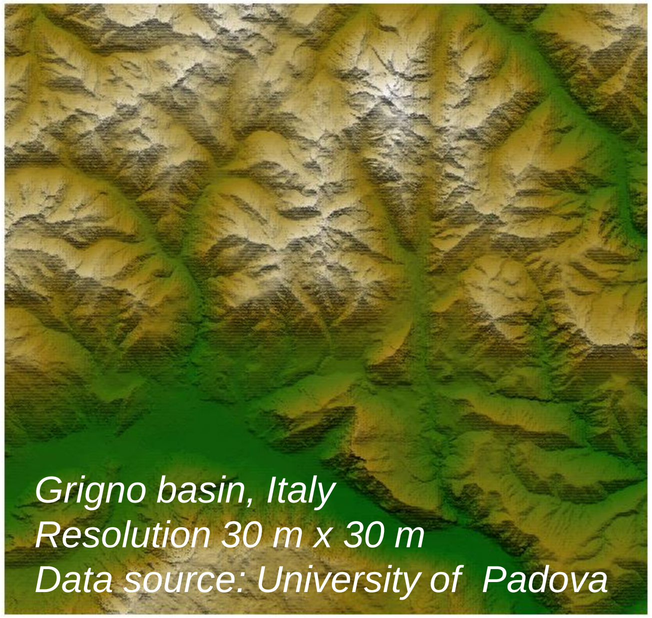
Effect of climate variability on floods and consequently on channel morphology.

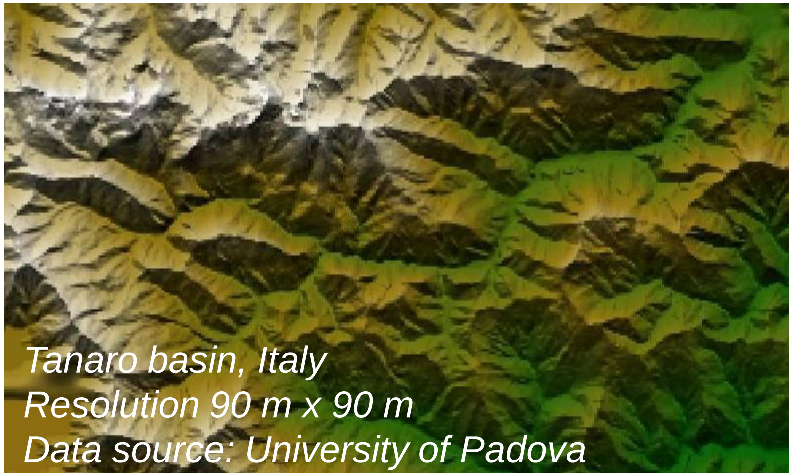
Need to understand channel form deeply

Digital elevation data

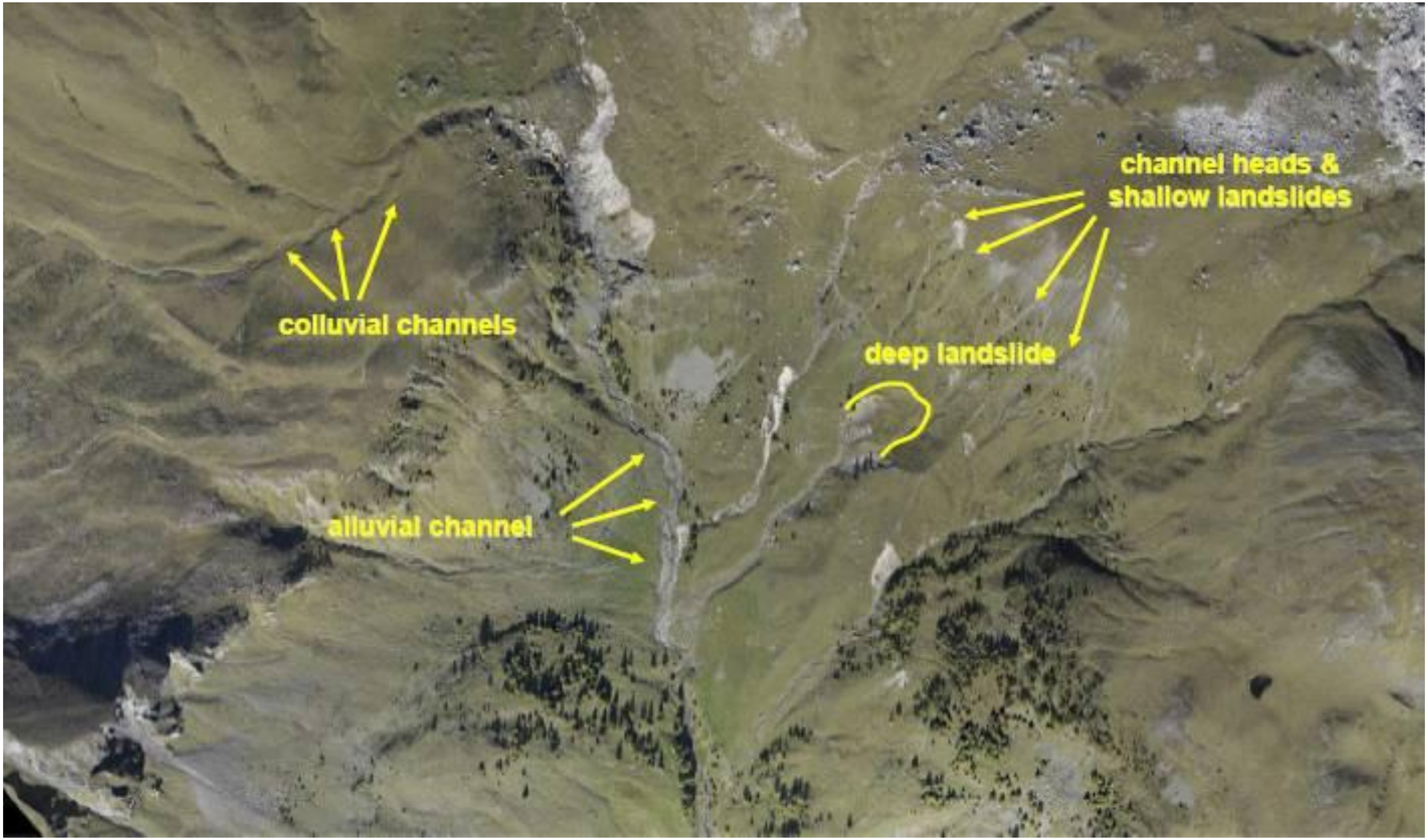
Data resolution available until recently 30-100 m.







Rio Cordon basin, Selva di Cadore, Italy



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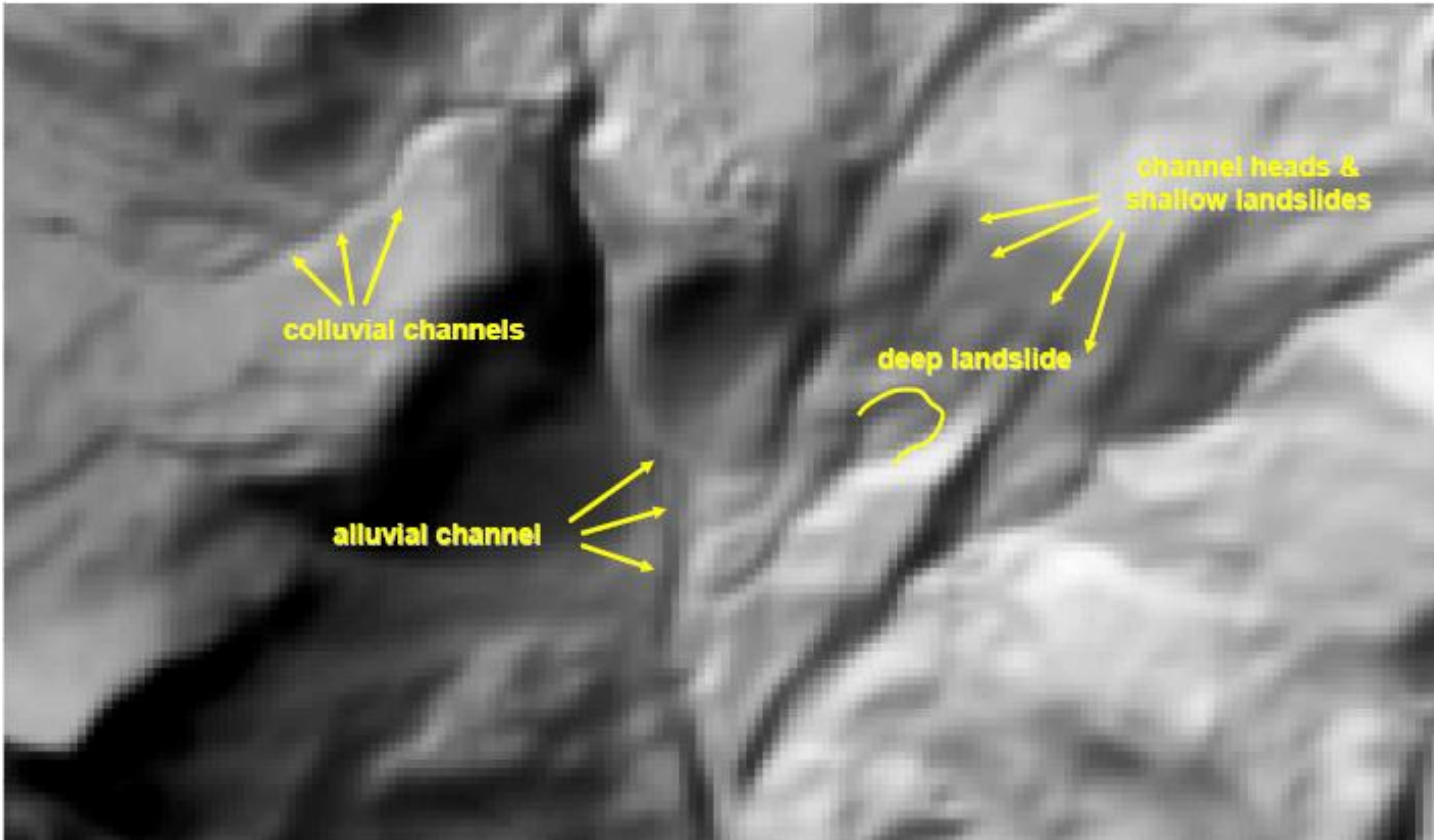
The role of data resolution

DTM 10x10 m



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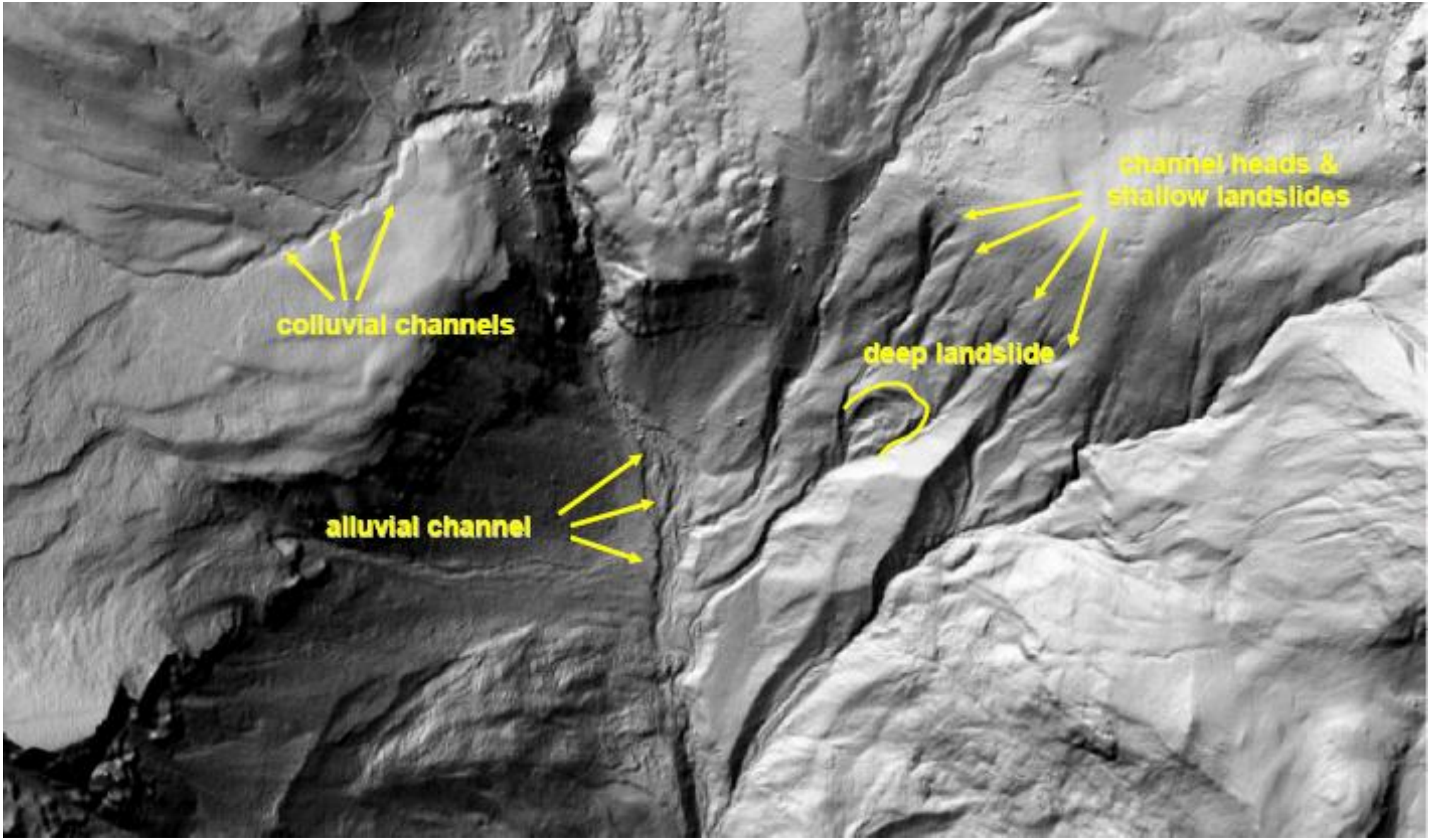
The role of data resolution

DTM 1x1 m



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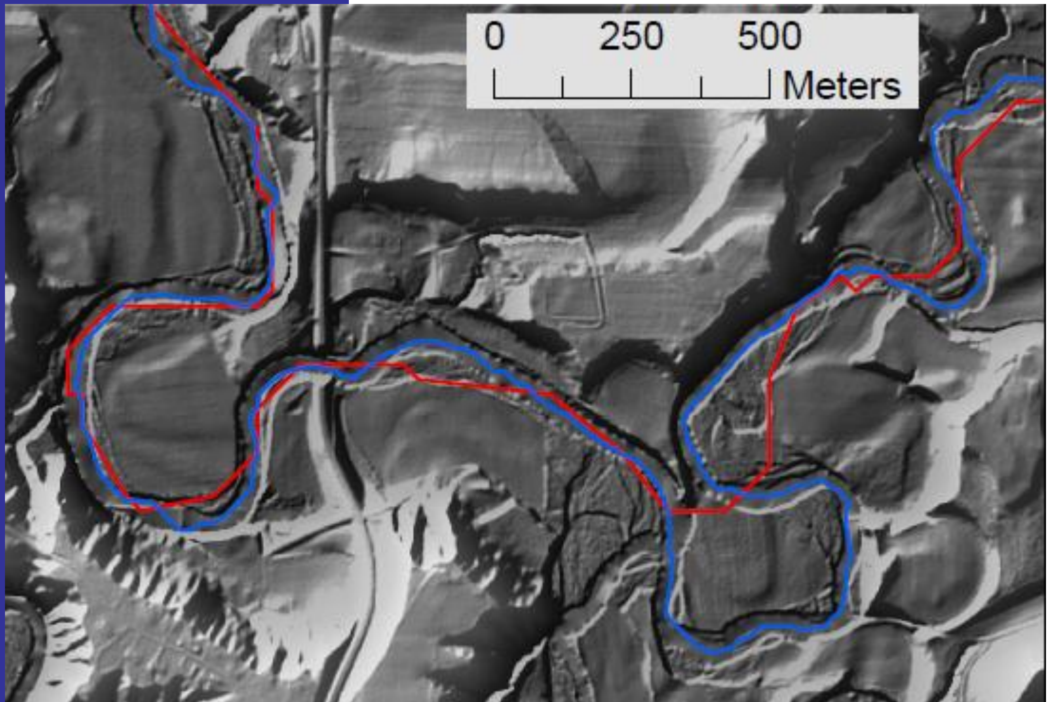
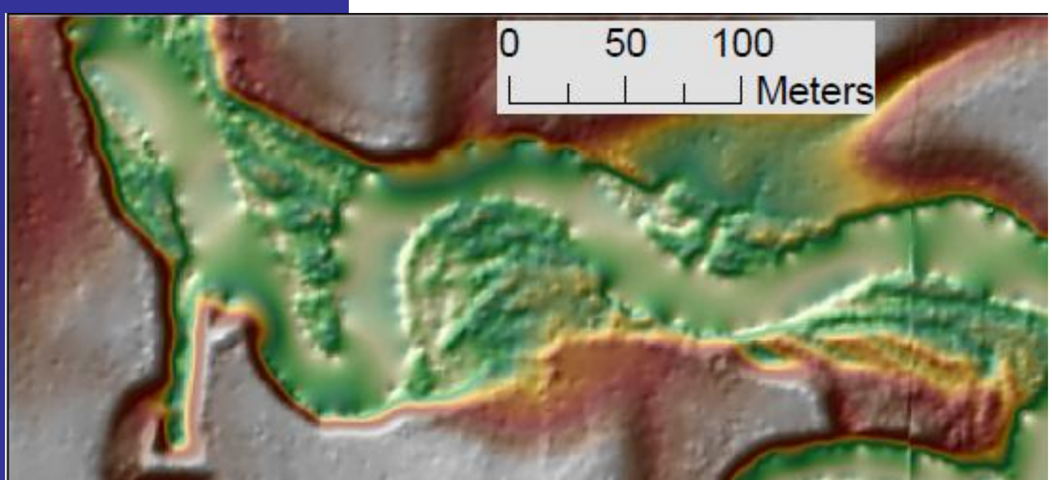
Challenges in geomorphic feature extraction

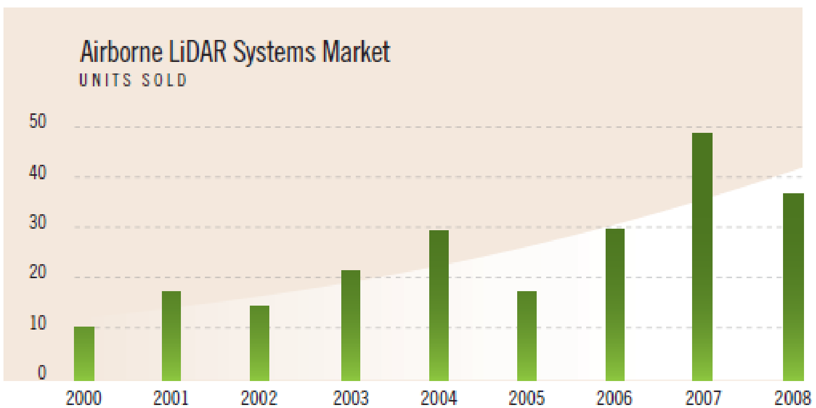




- Channel initiation
- Identification of accurate centerline
- Presence of roads and bridges
- Artificial drainage ditches
- Small signal to noise ratio
- Identification of channel banks
- Measurement of bluffs

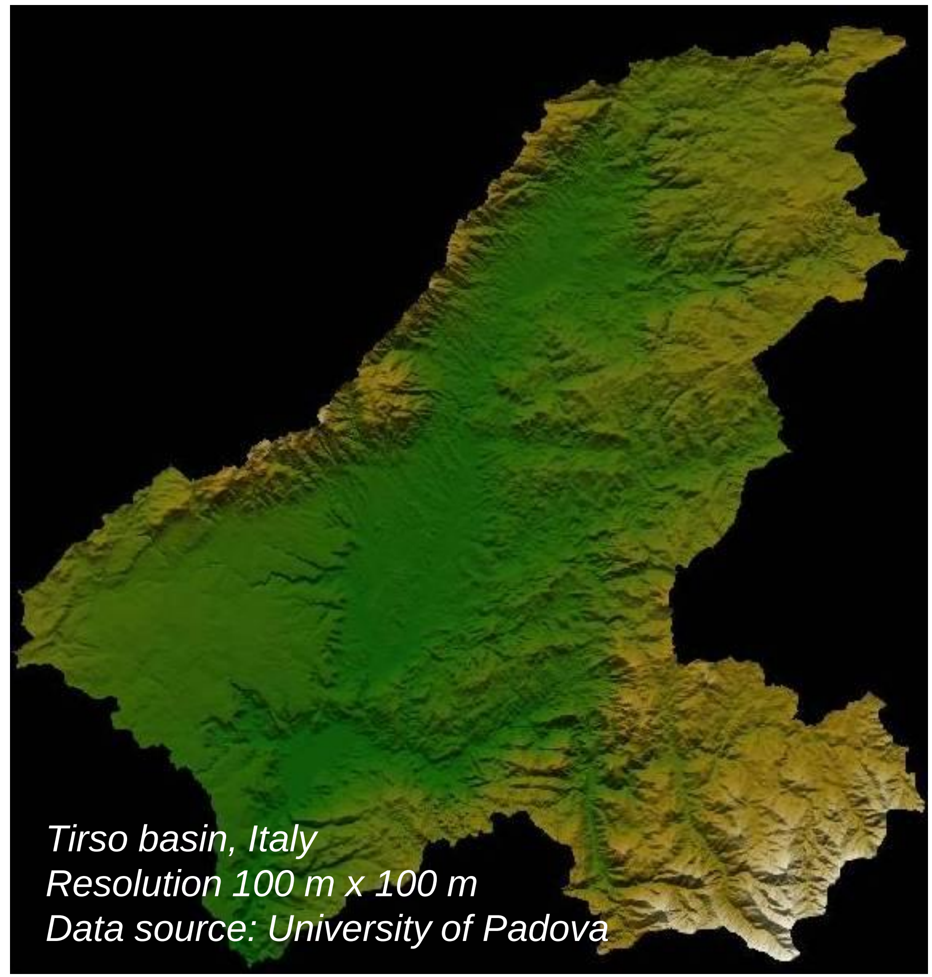
How do we extract this information?

Methodologies available for determining channel initiation from DTMs often include a threshold on drainage area, or a combination of area and slope.



"The LiDAR market is growing all around the world, but LiDAR handling software is not and there is a void in LiDAR processing software."
Richard Vincent –Virtual Geomatics

Data from Leica Geosystems



GeoNet: NCED toolbox for channel network extraction

GeoNet 2.0

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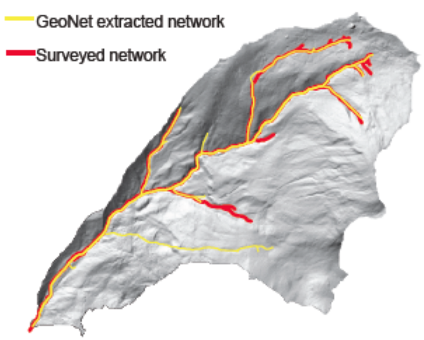
Welcome to GeoNet 2.0

GeoNet 2.0 is a MatLab-based computational tool for the automatic extraction of channel networks and geomorphic features from lidar data. It is the newest version of GeoNet, following GeoNet 1.0 and GeoNet 1.0.1. GeoNet 2.0 has been sustantially re-coded, but the basic idea behind the tool remains the same.

GeoNet combines nonlinear filtering for data preprocessing and cost minimization principles for feature extraction. The use of nonlinear filtering achieves noise removal in low gradient areas and edge enhancement in high gradient areas, i.e., near feature boundaries. After preprocessing, GeoNet extracts channels as geodesics—lines that minimize a cost function based on fundamental geomorphic characteristics of channels such as flow accumulation and curvature.



GeoNet extraction of the Rio Col Duro river basin in the Eastern Italian Alps and comparison to the surveyed network (results obtained with GeoNet 1.0.1) [Passalacqua, Tarolli and Foufoula-Georgiou, WRR, 2010].

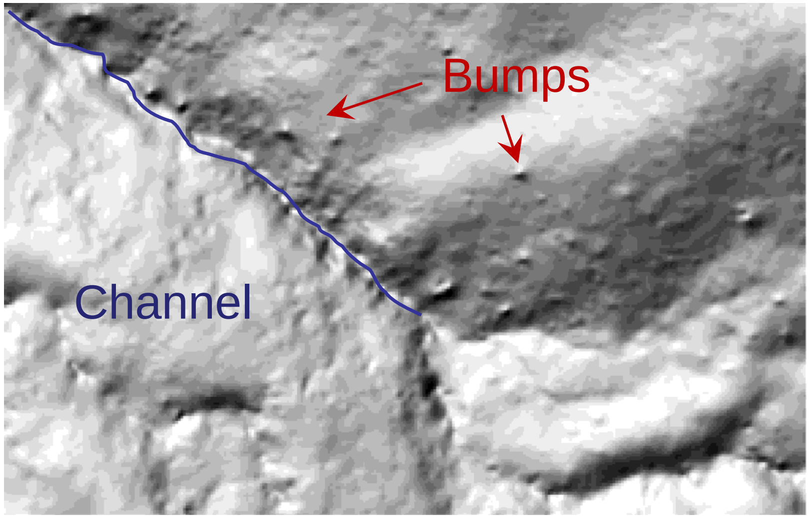
Subpages (2): Acknowledgments Contributors

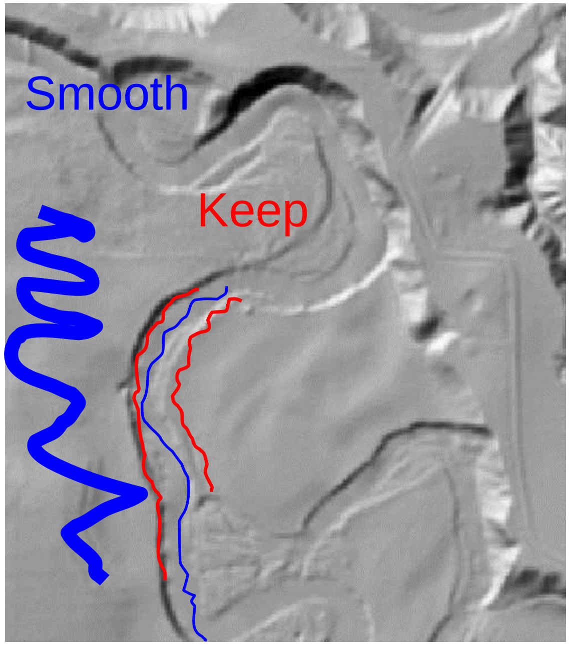
GeoNet: Nonlinear filtering

1. **Nonlinear filtering:** Enhance features of interest, while smoothing small scale features. Perona and Malik [1990]

$$\partial_t h(x,y,t) = \nabla \cdot \left(c(x,y,t) \nabla h \right)$$

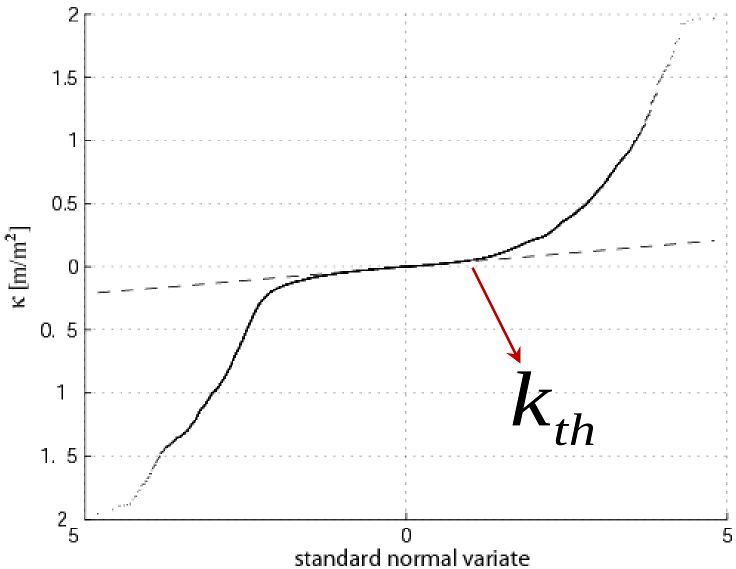
$$c = \frac{1}{1 + \left(|\nabla h| / \lambda \right)^2}$$

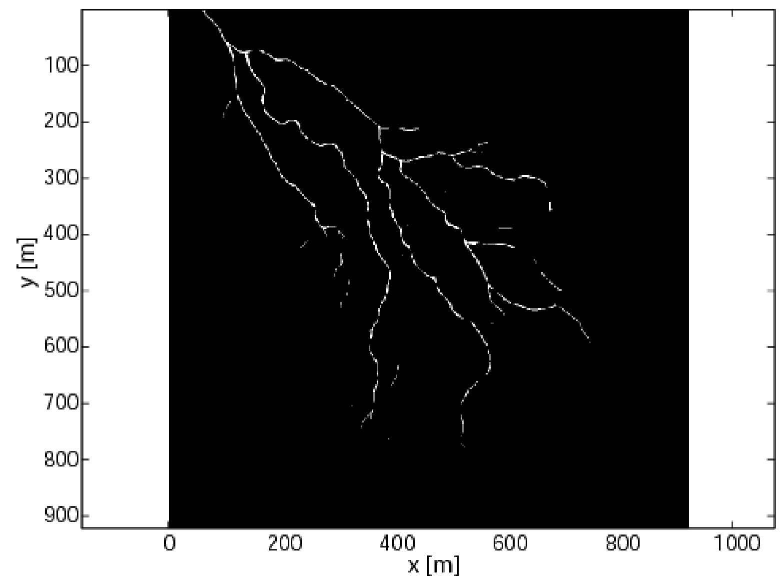




GeoNet: Statistical signature of geomorphic transitions

2. **Skeleton of likely channelized pixels:** Set of pixels with curvature above threshold, identified from quantile-quantile plot of curvature.





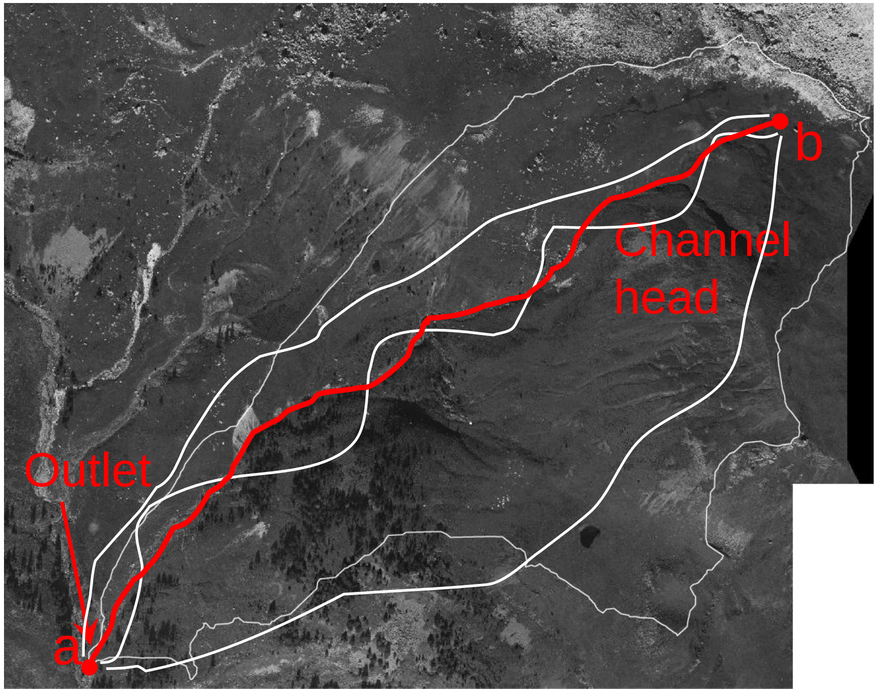
The deviation of the pdf from Gaussian can be interpreted as transition from hillslope to valley [Lashermes et al,. 2007].

Channel extraction: geodesics

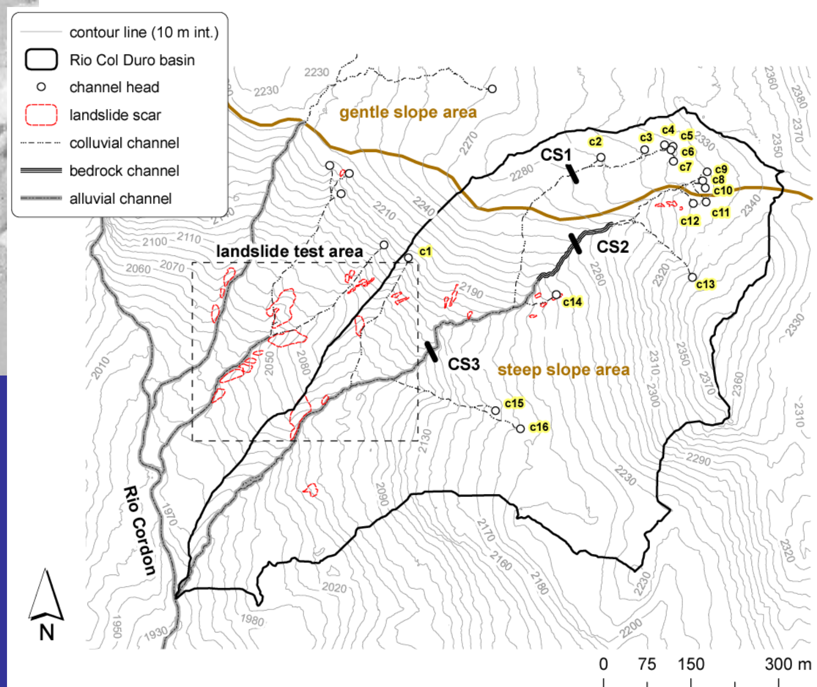
2. **Geodesic minimization:** Channels are extracted as paths of minimum cost

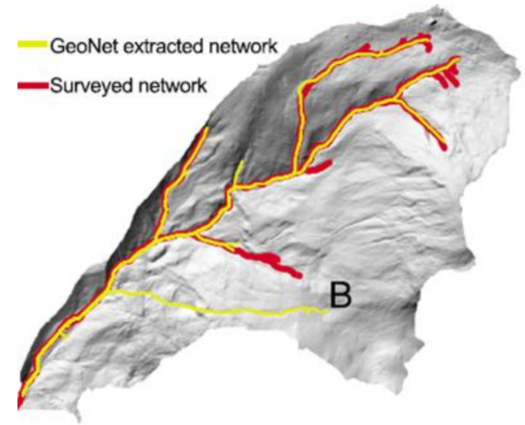
The *cost function* ψ represents the cost of traveling between point a and point b in terms of a function of area (A), slope (S), curvature (κ) and skeleton (Skel):

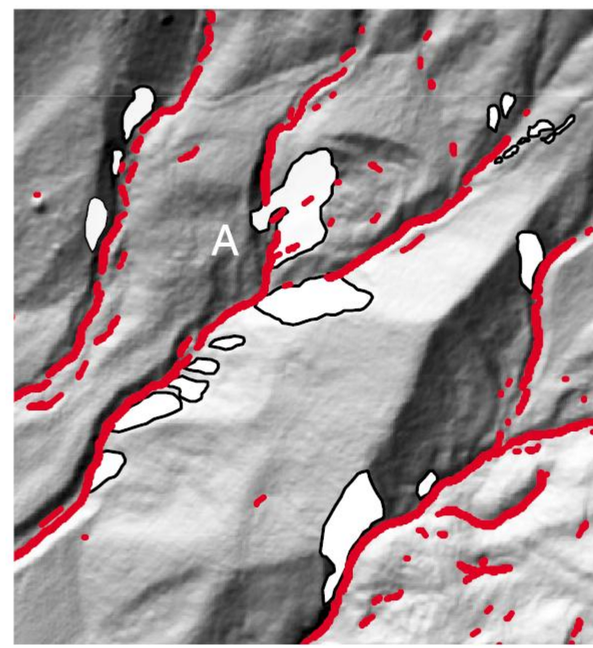
$$\psi = \frac{1}{f(A, S, \kappa, Skel)} \quad e.g., \frac{1}{\alpha \cdot A + \delta \cdot \kappa}$$



Channel initiation and channel disruptions

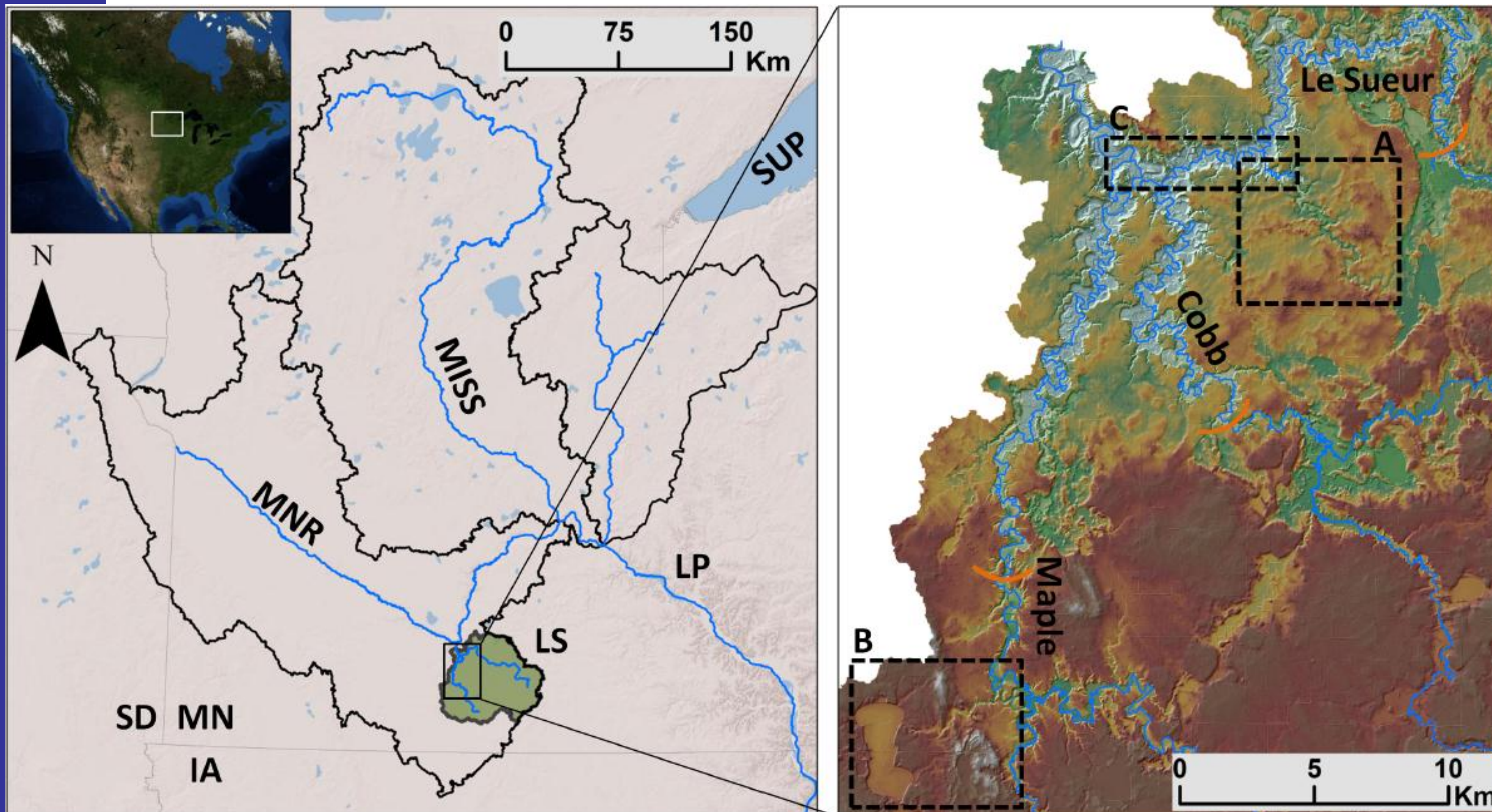






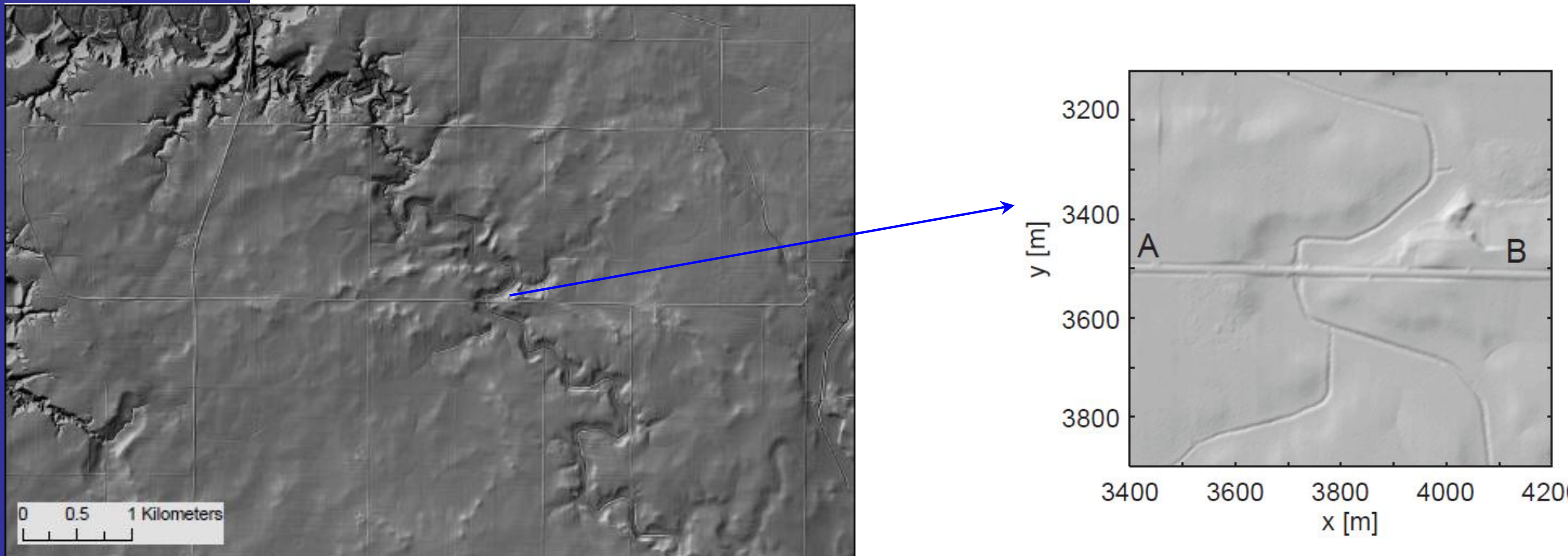
Passalacqua, P., P. Tarolli, and E. Foufoula-Georgiou, Water Resour. Res, 2010

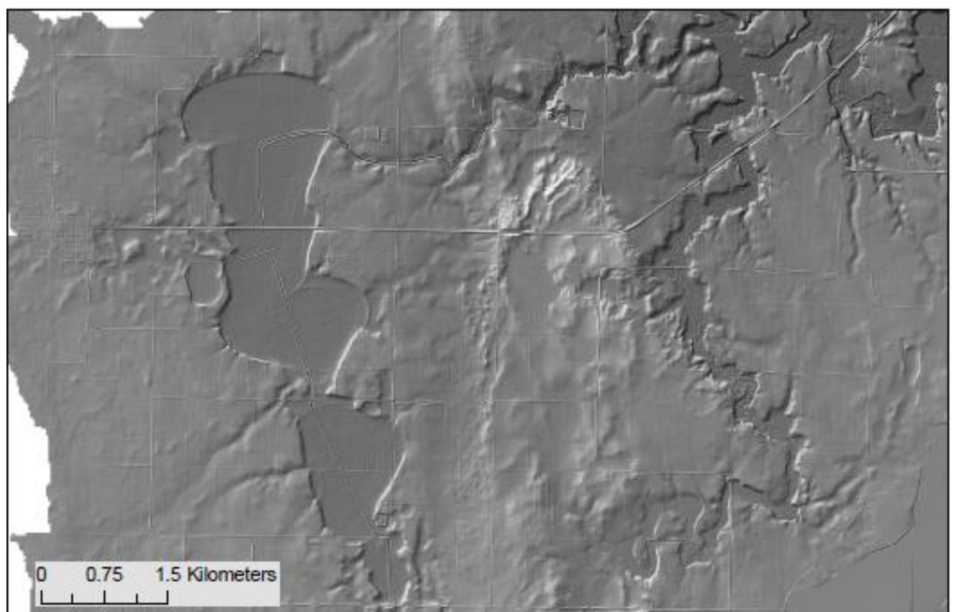
Flat lands and channel morphology



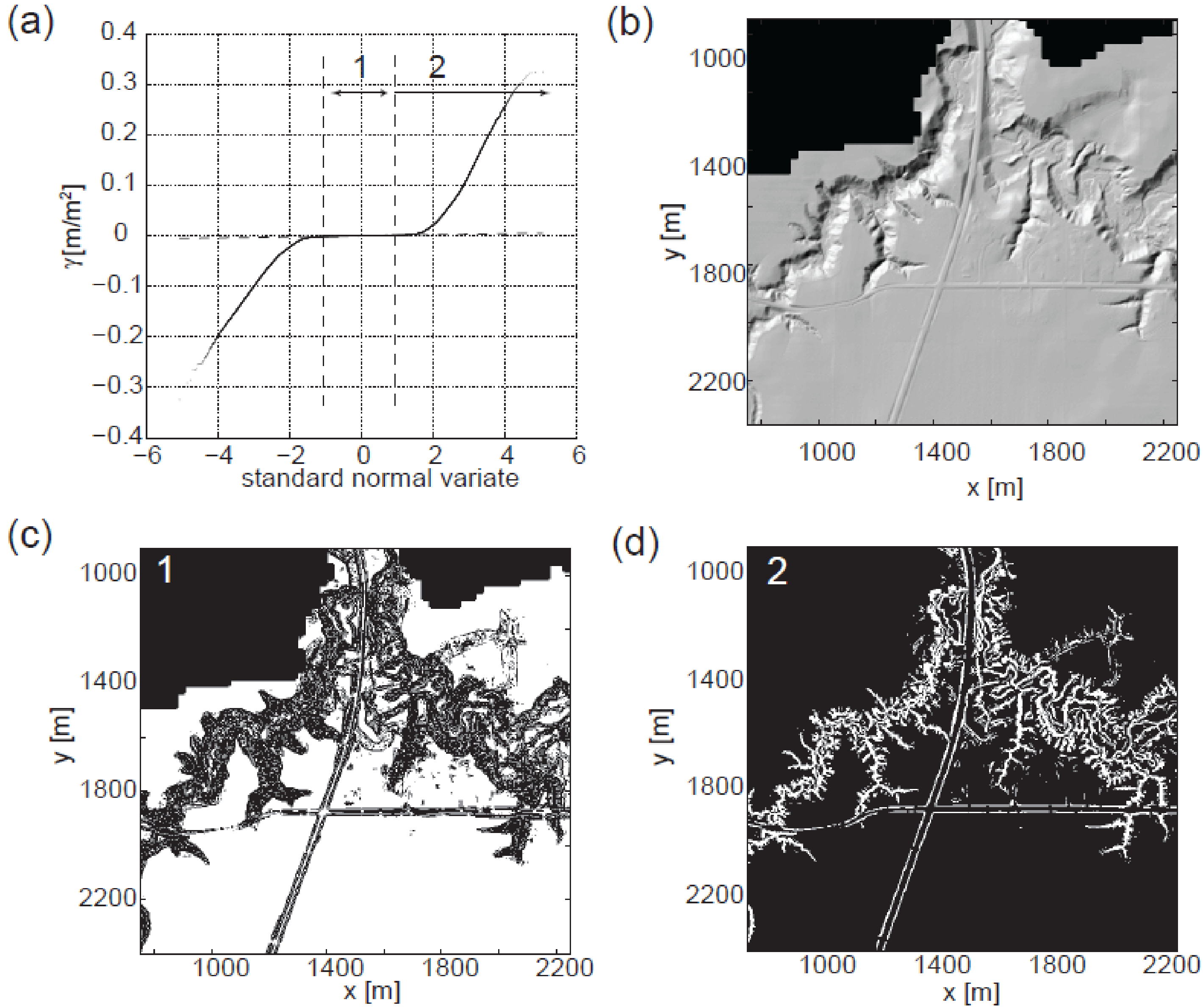
- Le Sueur River major source of sediment to the Minnesota River.
- Both listed as impaired for turbidity by USEPA.
- Need to identify sediment sources

Roads and ditches





Identification of likely channelized pixels in engineered landscapes

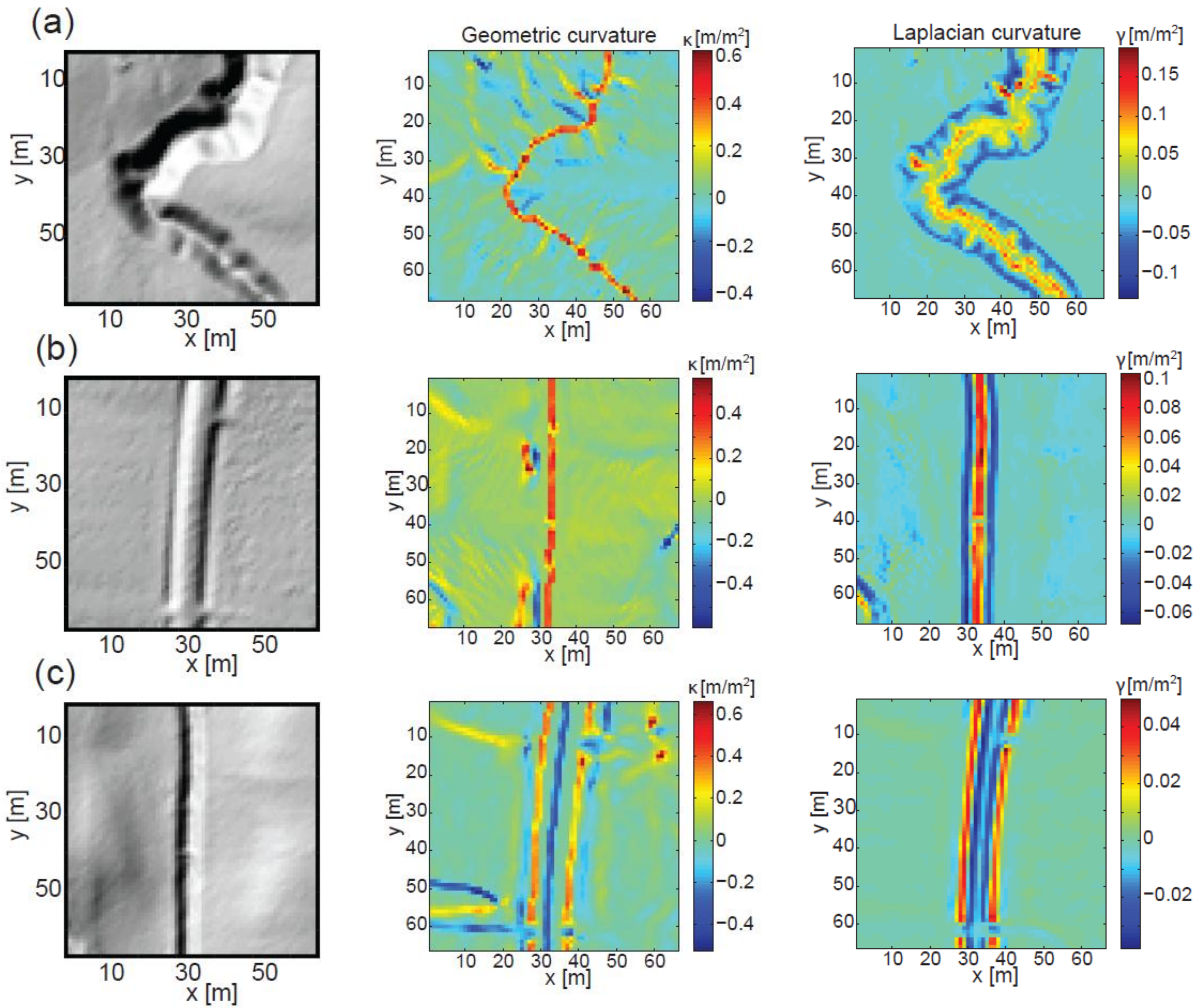


Passalacqua, P., P. Belmont, and E. Foufoula-Georgiou, Water Resour. Res., 2012

Curvature analysis to distinguish channels and roads

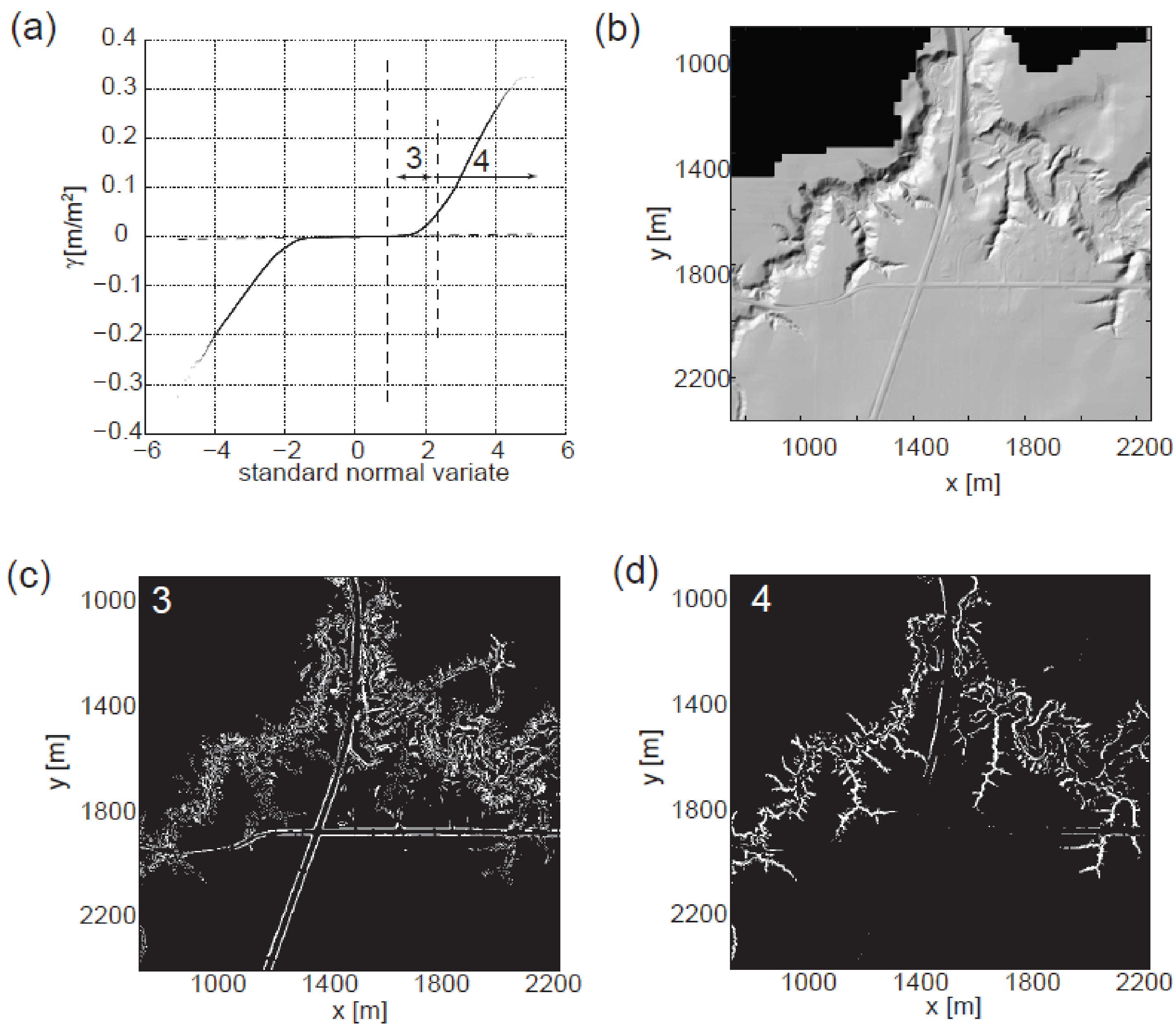
$$\kappa = \nabla \cdot \left(\frac{\nabla h}{|\nabla h|} \right)$$

$$\gamma = \nabla^2 h$$



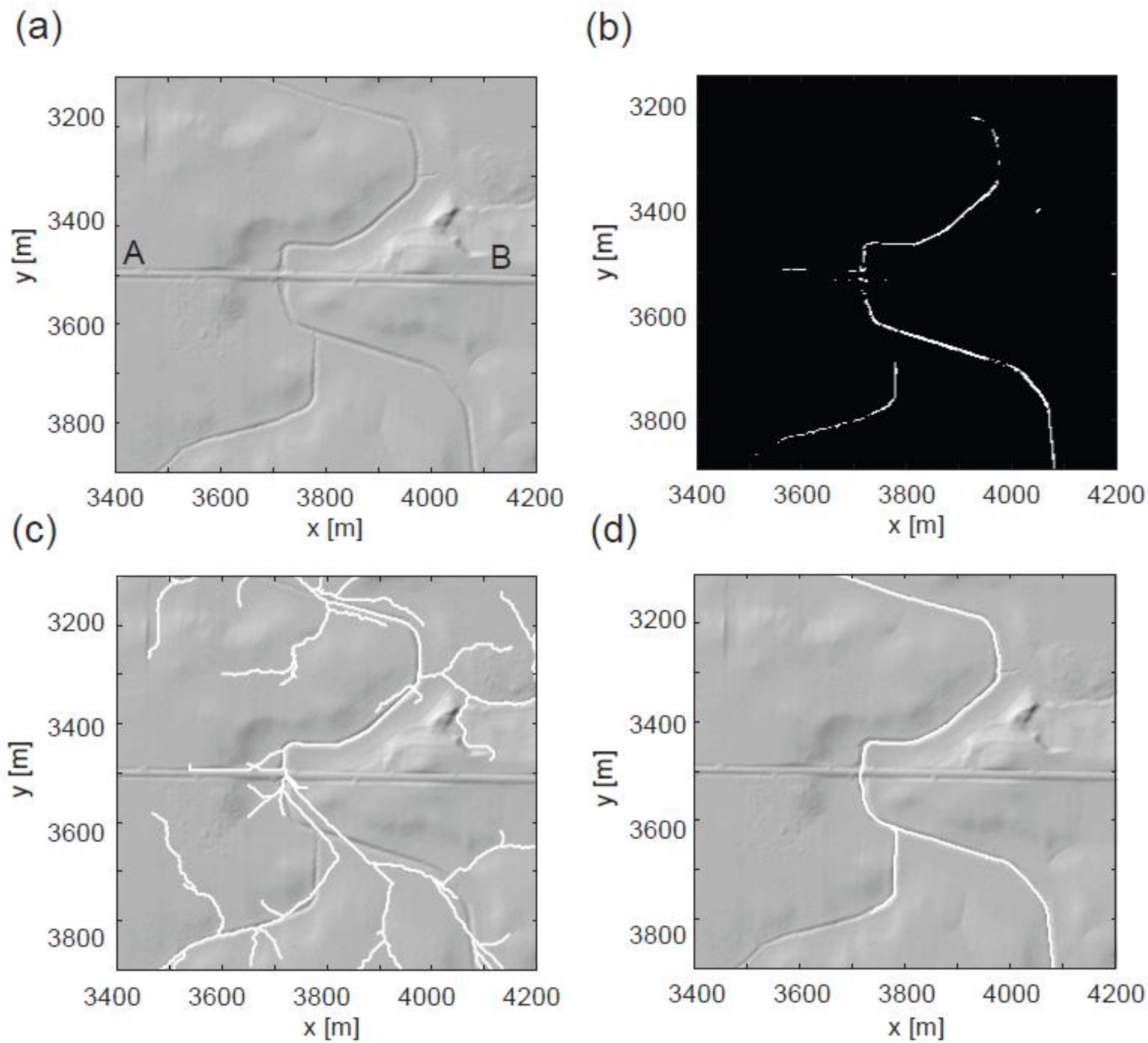
Passalacqua, P., P. Belmont, and E. Foufoula-Georgiou, Water Resour. Res., 2012

Differentiating natural versus artificial features



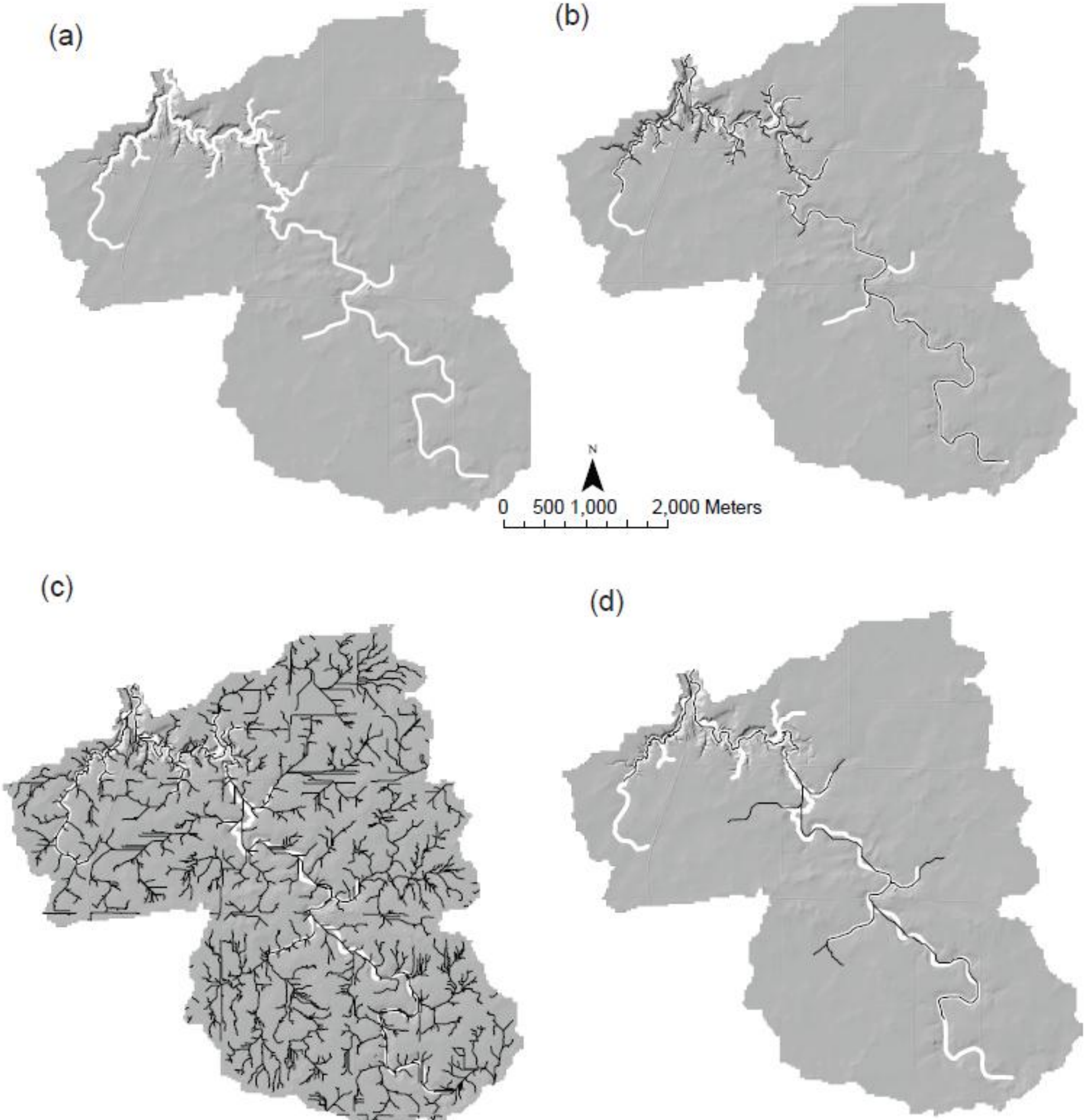
Passalacqua, P., P. Belmont, and E. Foufoula-Georgiou, Water Resour. Res., 2012

Channel network extraction and bridge crossings



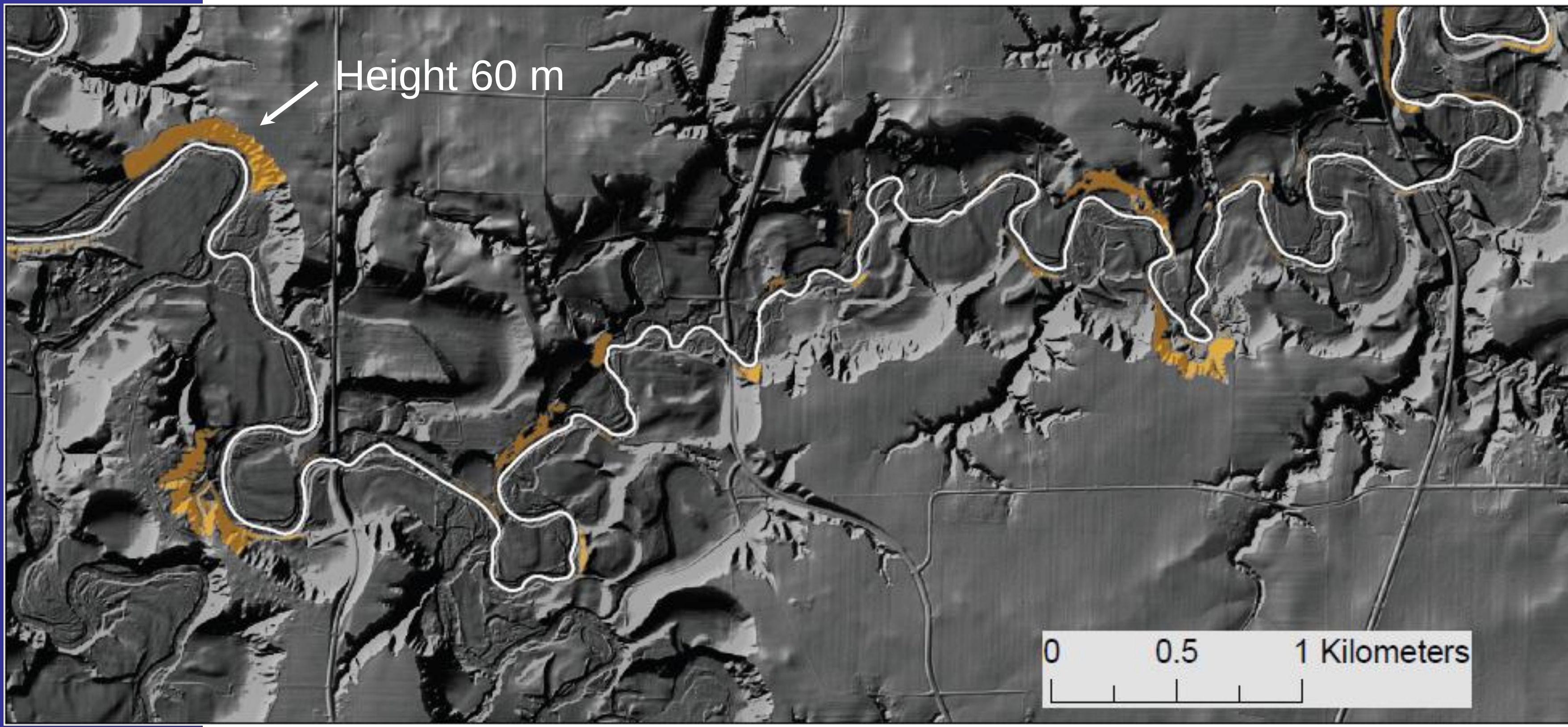
Passalacqua, P., P. Belmont, and E. Foufoula-Georgiou, Water Resour. Res., 2012

Channel network extraction and area threshold



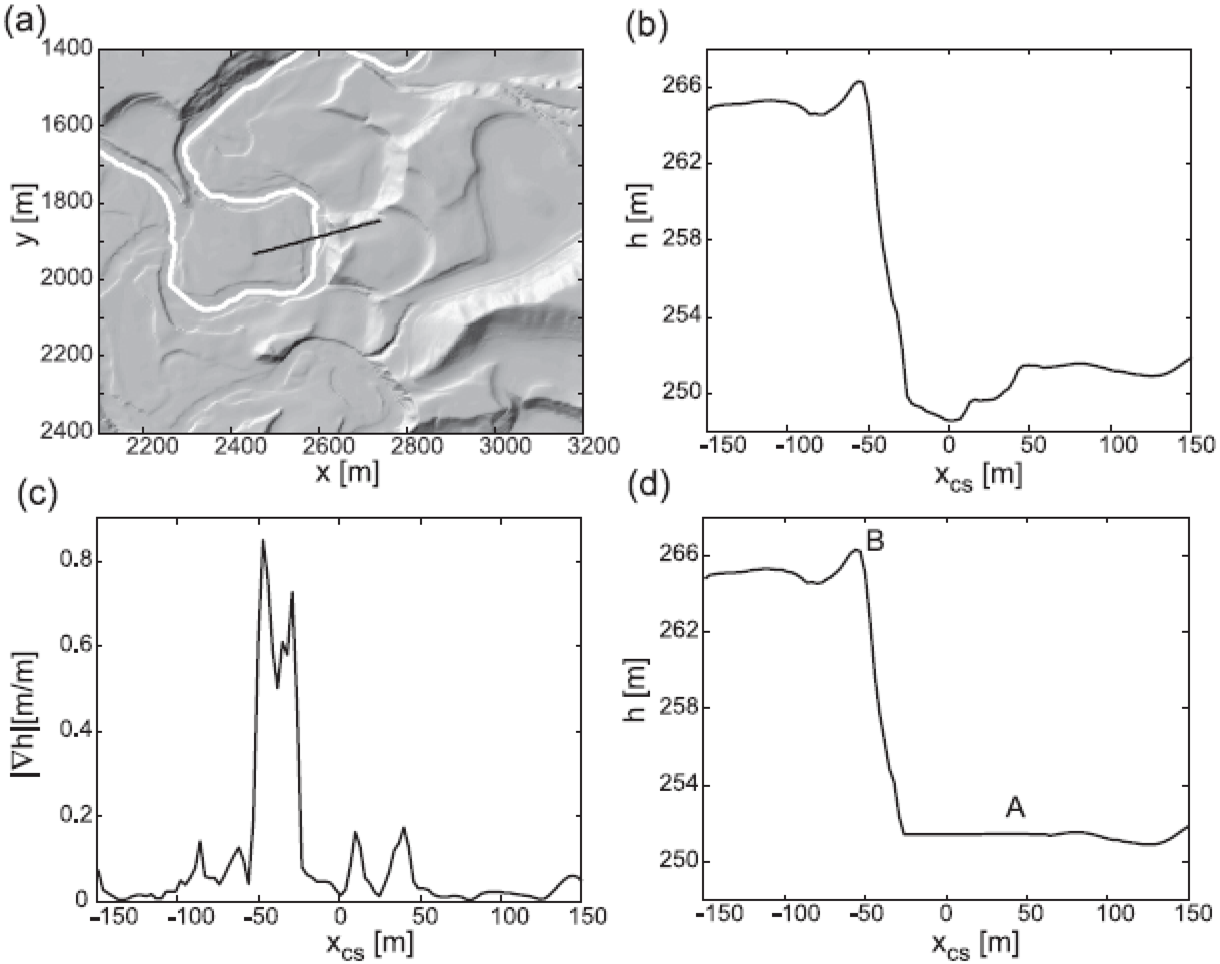
Passalacqua, P., P. Belmont, and E. Foufoula-Georgiou, Water Resour. Res., 2012

Automatic extraction of channel morphology



- Automatic extraction of channel cross-section
- Detection of bank location
- Identification of geomorphic bankfull water surface elevation
- Measurements of channel width and of bank and bluff height

Automatic extraction of channel morphology

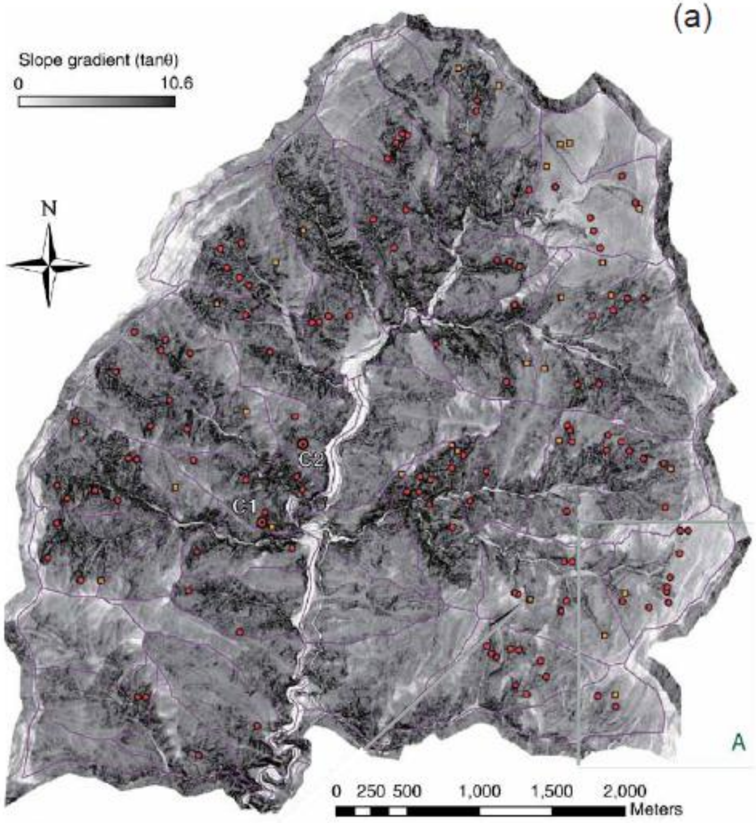


Source: P. Belmont

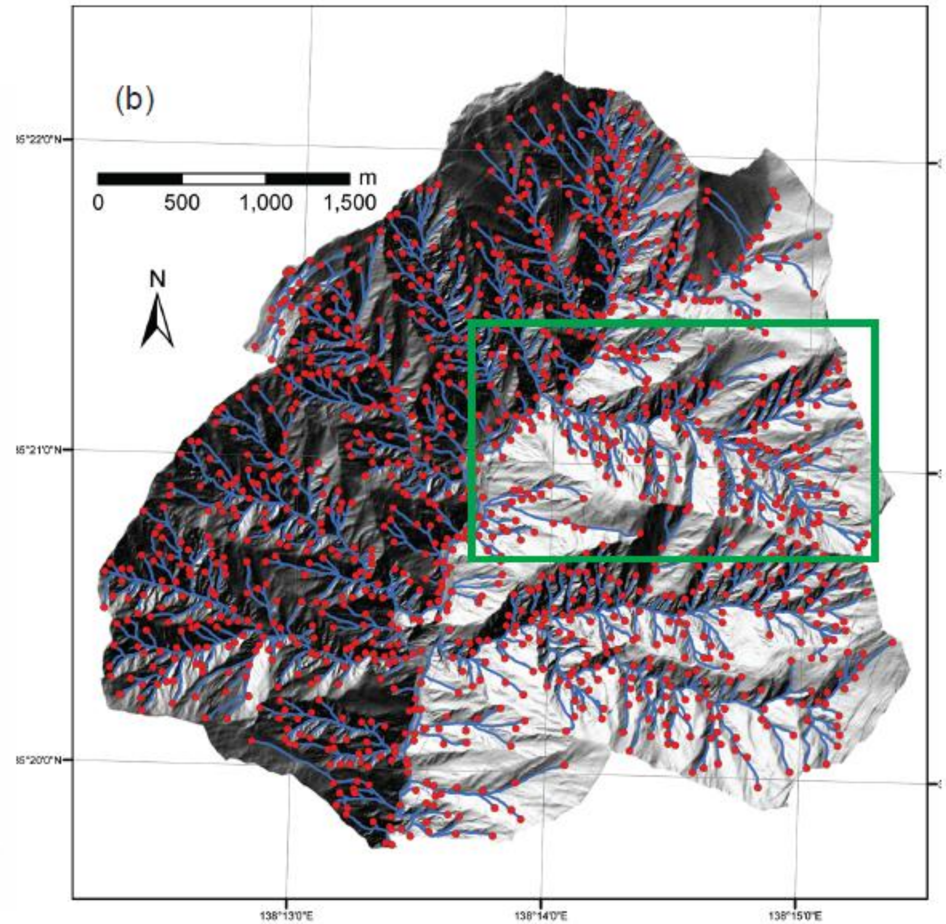
Source: C. Jennings

Passalacqua, P., P. Belmont, and E. Foufoula-Georgiou, Water Resour. Res., 2012

Codependence of vegetation and drainage density

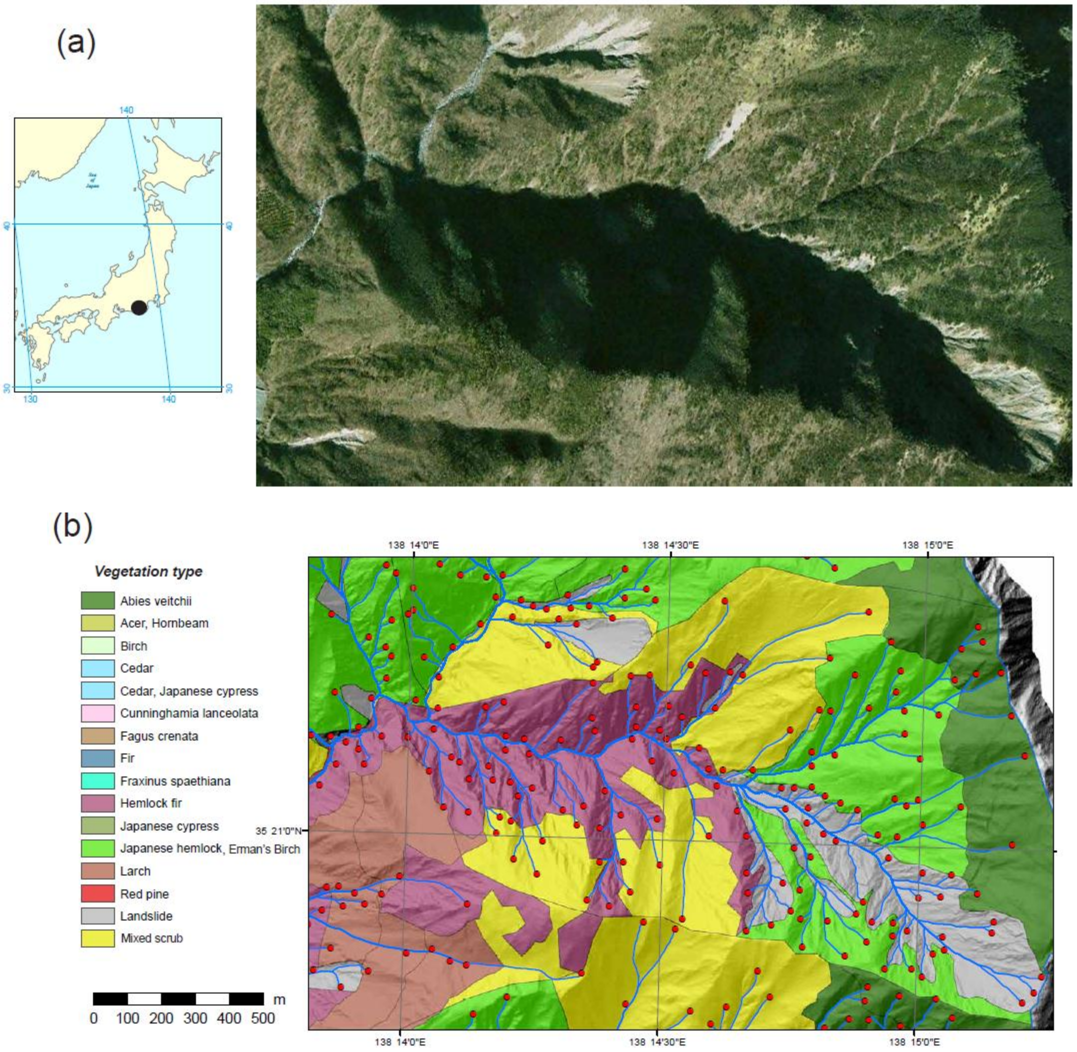


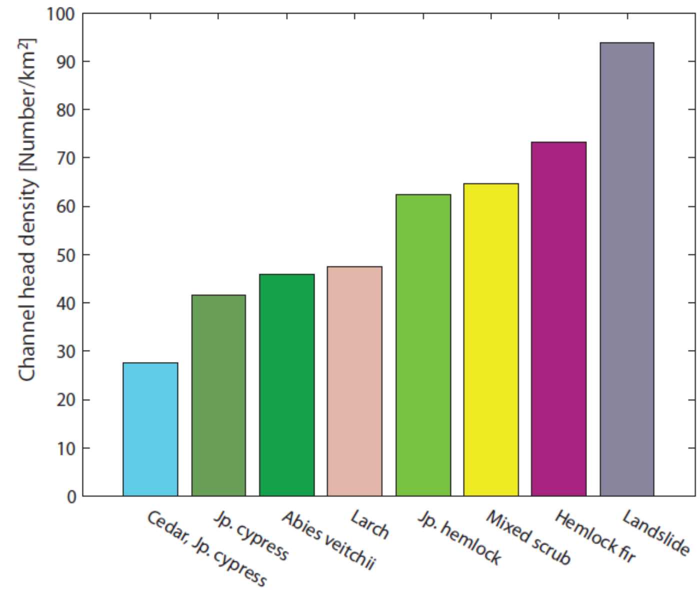
Field mapped channel heads on slope gradient map (Imaizumi et al. [2010]).



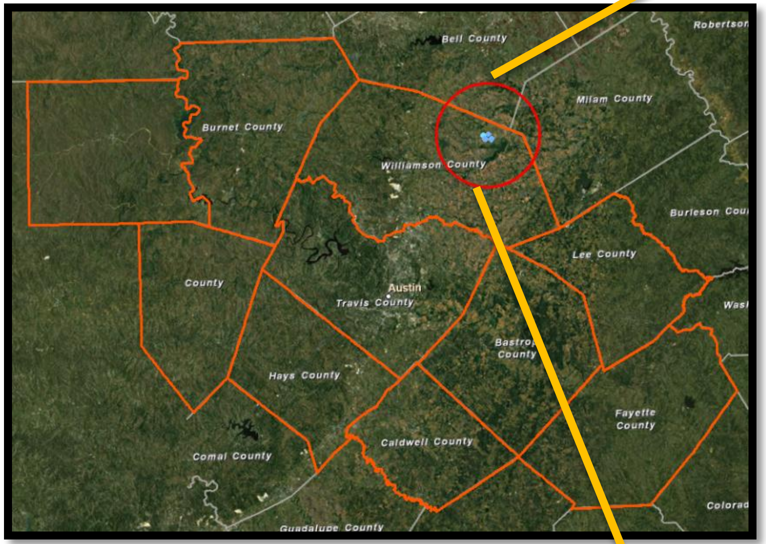
GeoNet drainage delineation.

Codependence of vegetation and drainage density





Study Area

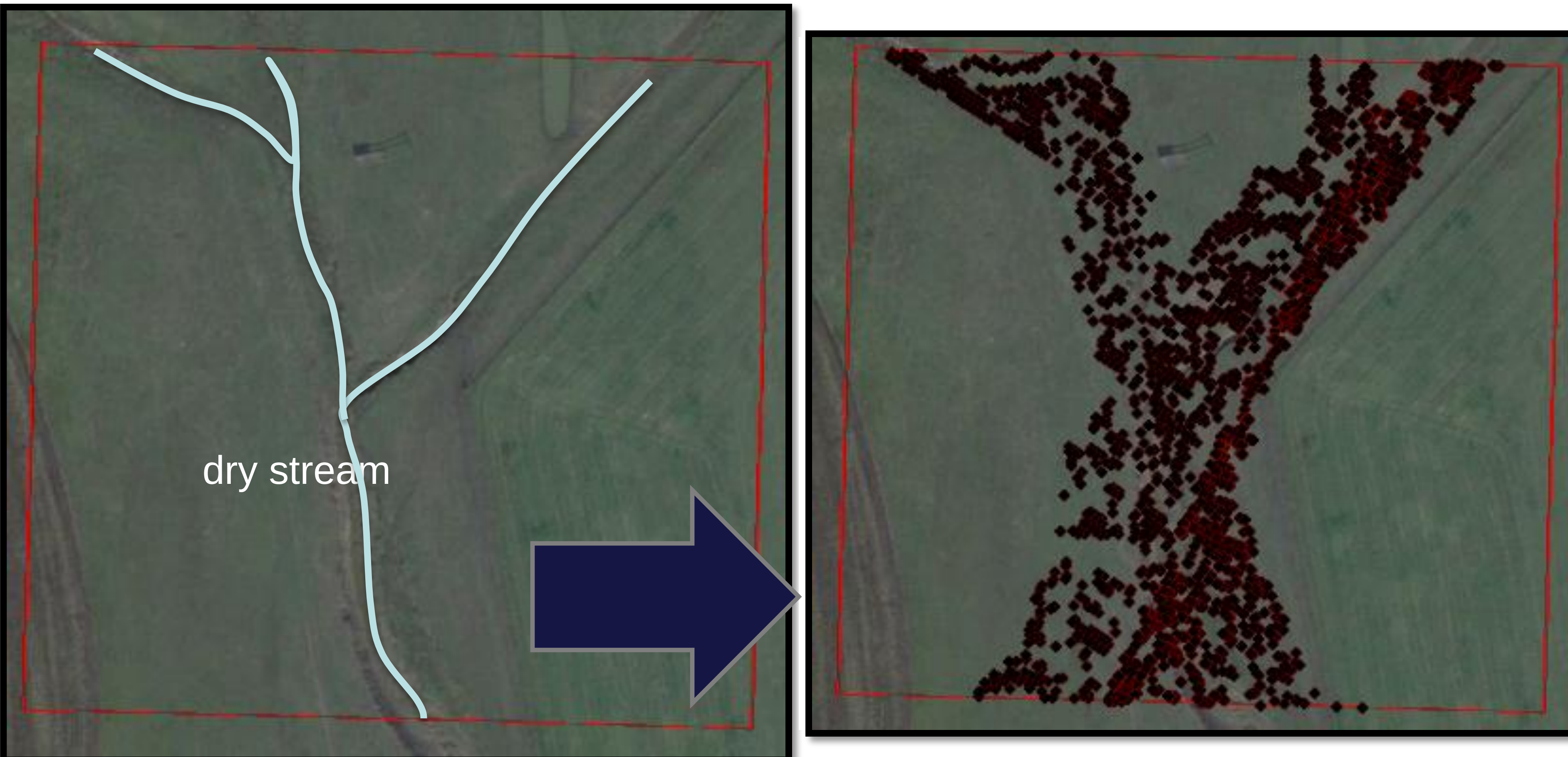


Six test sites were studied for testing the methodology.
The data for the test sites was obtained from TNRIS

Slide courtesy of Harish Sangireddy, UT Austin

Site 1 results

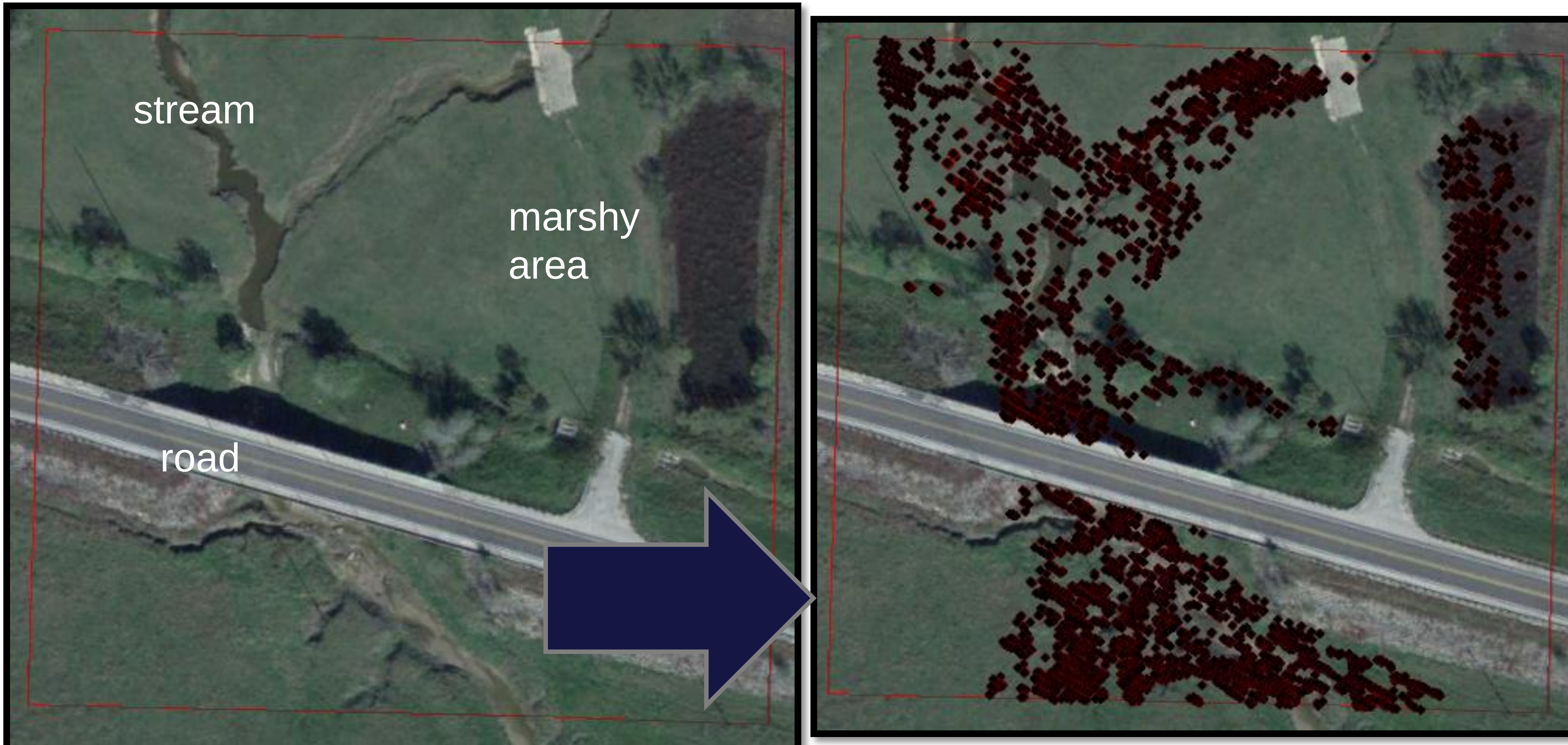
The site has only streams and surrounding farmlands



Slide courtesy of Harish Sangireddy, UT Austin

Site 2 results

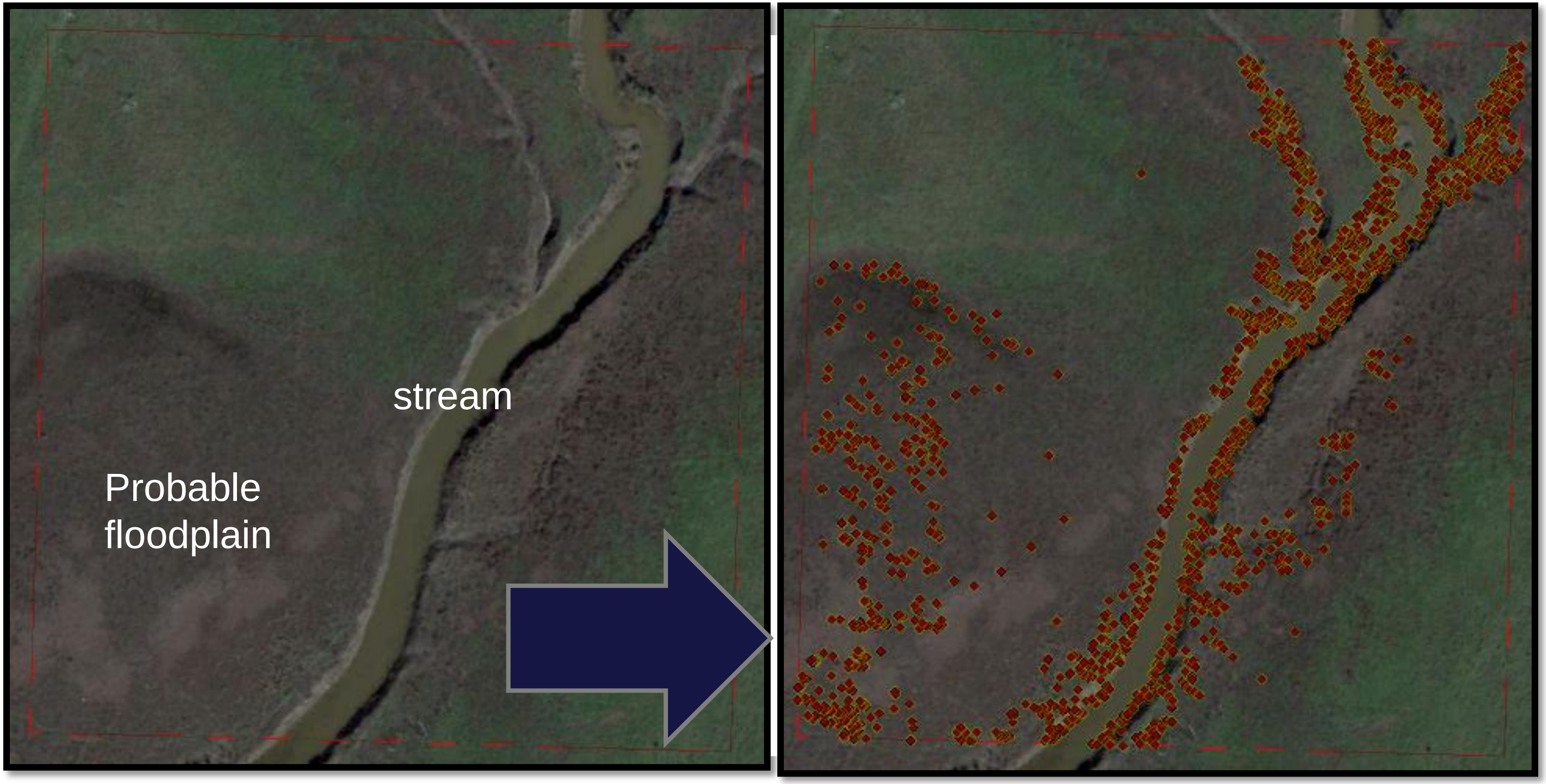
Site has roads, streams, marshy areas, small culvert and drains by the roadside



Slide courtesy of Harish Sangireddy, UT Austin

Site 6 results

Detects points around the water gaps and maps the geometry of stream properly



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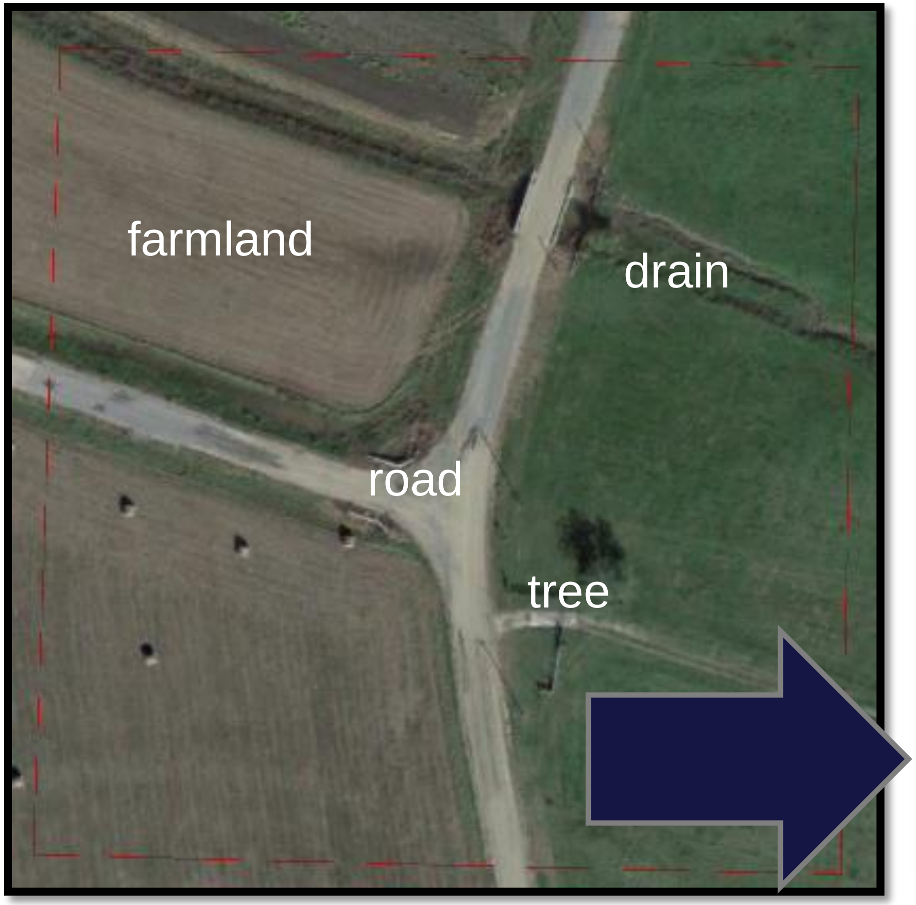
Limitations

When the elevation difference is very small in the region, the model identifies all low lying areas as water surfaces



Site 5

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Acknowledgements

Work supported by:
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NSF EAR-0835789
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Collaborators:
Tien Do Trung, Colin Stark, Guillermo Sapiro, Bill Dietrich, Efi Foufoula-Georgiou, Nachiket Gokhale, Paolo Tarolli, Patrick Belmont , Harish Sangireddy, David Maidment