

What controls the transition from fluvial regime to a debris-flow regime?

ETH zürich

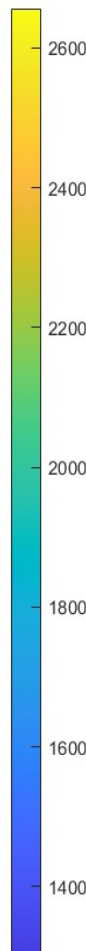
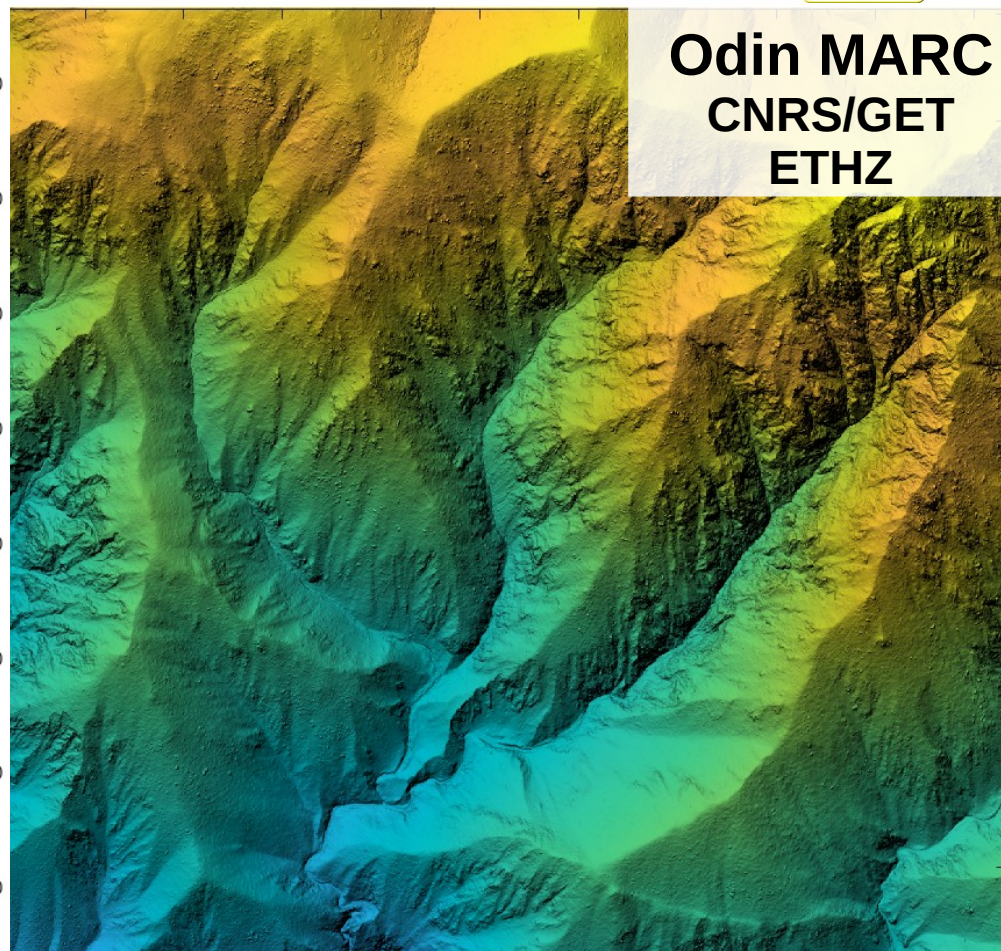
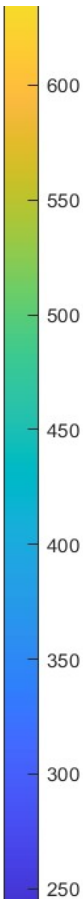
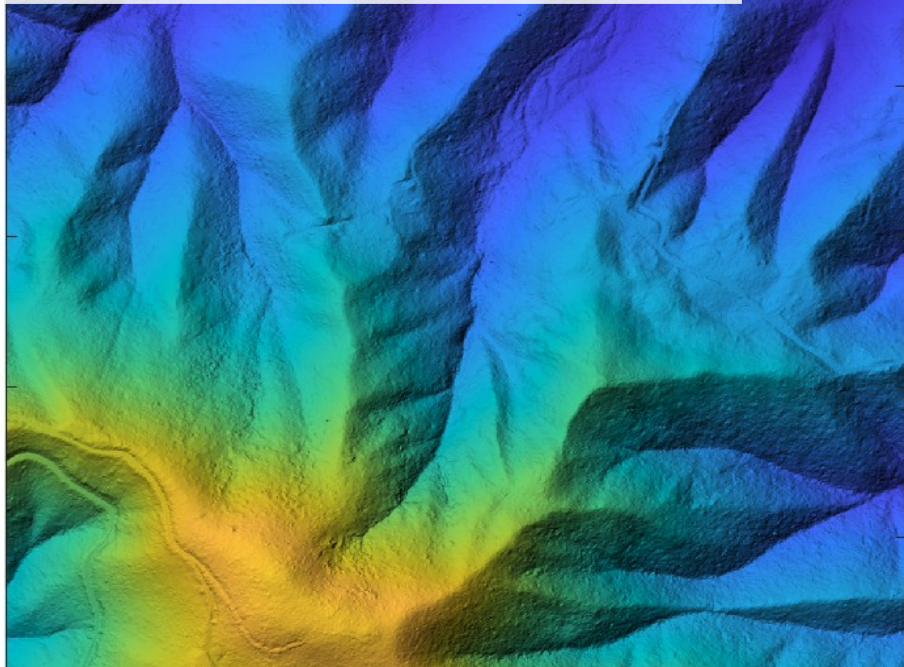


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CNRS/GET
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Fluvial scaling seems limited upstream

The widely used stream-power incision model state : $E=K A^m (dz/dx)^n$

Leading at steady-state to a slope area scaling:

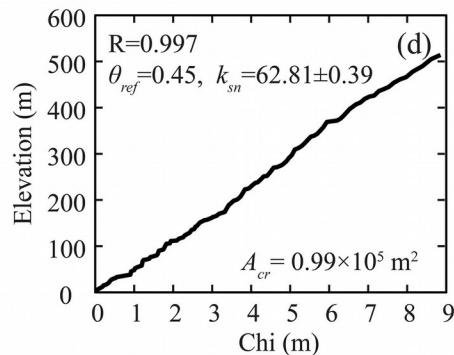
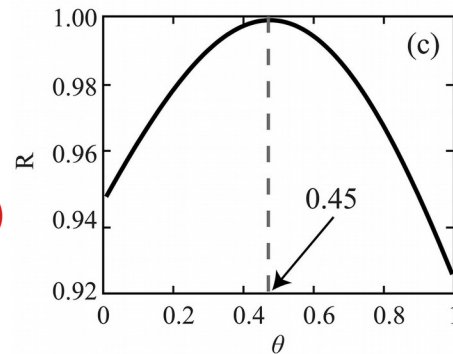
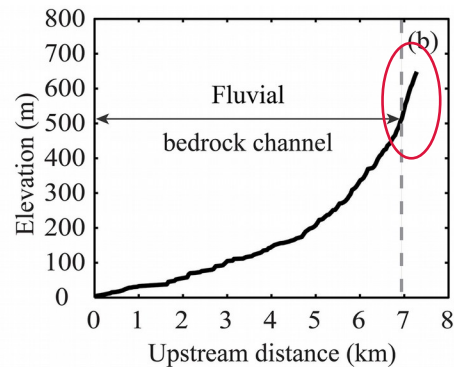
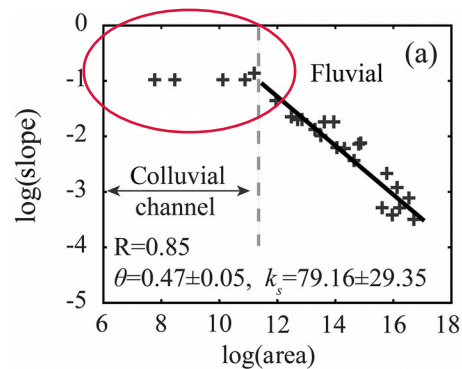
$$dz/dx = (U/K)^{1/n} A^{-\theta}$$

Or, in its integral form a proportionality between z and χ

$$z - z_0 = (U/K)^{1/n} \chi \text{ with } \chi = \int_0^x \left(\frac{A_o}{A(x')} \right)^\theta dx'$$

However, many upstream segments have constant slope. They are considered colluvial channel (DiBiase et al., 2012, Wang et al., 2017) or debris-flow channels (Stock and Dietrich 2003, Penserini et al., 2017)

With,
A=Drainage area
K=Fluvial Erodibility
U=Uplift rate
 $\theta=m/n$ =concavity



An empirical hybrid model for channel erosion

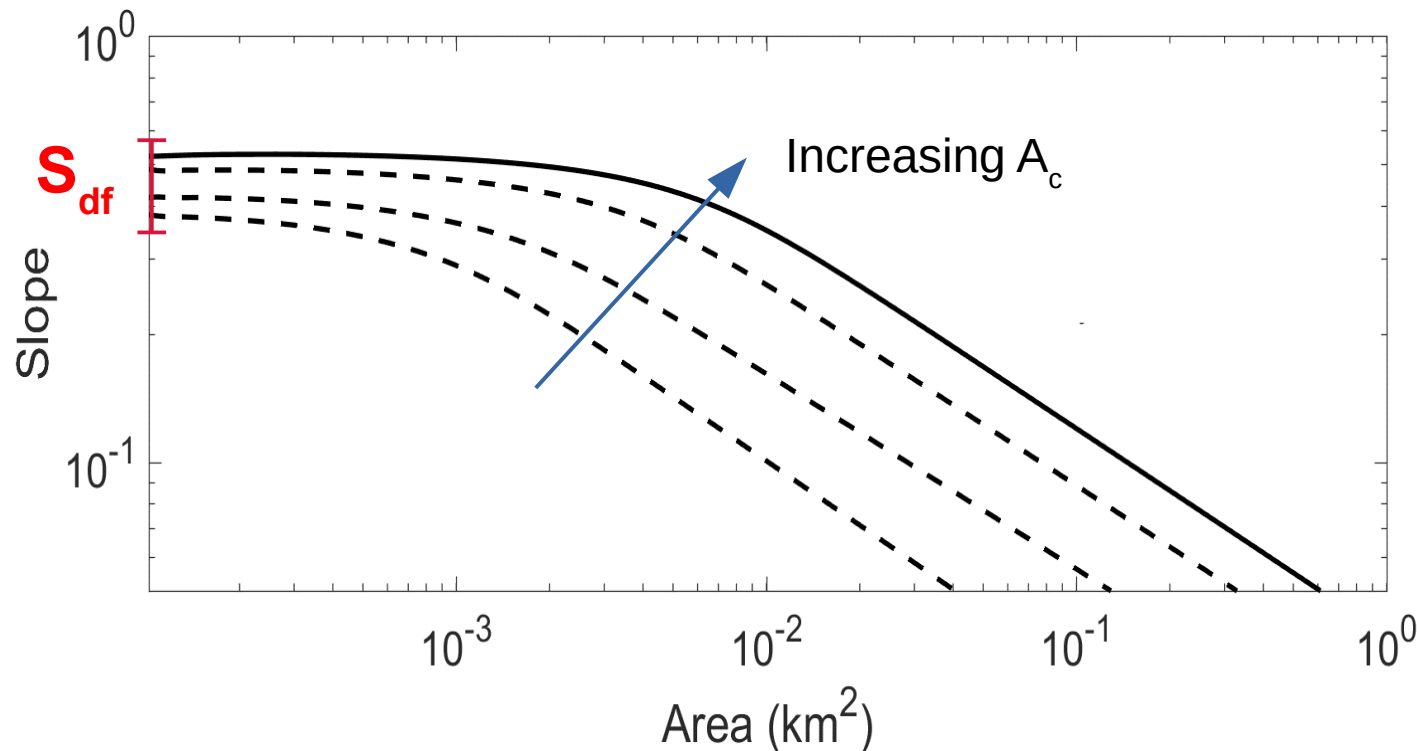
To describe the slope-area data going to a constant slope upstream, Stock and Dietrich, 2003 proposed a simple mathematical model, that can be rewritten as:

$$\frac{dz}{dx} = \frac{S_{df}}{1 + (A/A_c)^\theta}$$

What are typical values of S_{df} and A_c ?

How do they depend on erosion rates and hillslope processes ?

Penserini et al., 2017 suggested that A_c increase with erosion rates but not S_{df} ...



We analyzed the morphometry of >60 catchments with LIDAR DEM and average denudation constrained by ¹⁰Be.

Consistency of the hybrid model and SPIM: implications

$$\frac{dz}{dx} = \left(\frac{U}{K} \right)^{1/n} \frac{1}{A^\theta} \quad \text{Classic SPIM}$$

$$\frac{dz}{dx} = \frac{S_{df}}{1 + (A/A_c)^\theta} = \frac{S_{df} A_c^\theta}{A_c^\theta + A^\theta} \quad \text{Hybrid model}$$

For consistency the model should match for $A > A_c$. For a small catchment, where the maximum value is A_t (with $A_t > A_c$) we get:

$$\left(\frac{U}{K} \right)^{1/n} = S_{df} A_c^\theta \left(\frac{A_t^\theta}{A_t^\theta + A_c^\theta} \right)$$

And where $A \gg A_c$ (i.e., $A^\theta + A_c^\theta \sim A^\theta$), we obtain:

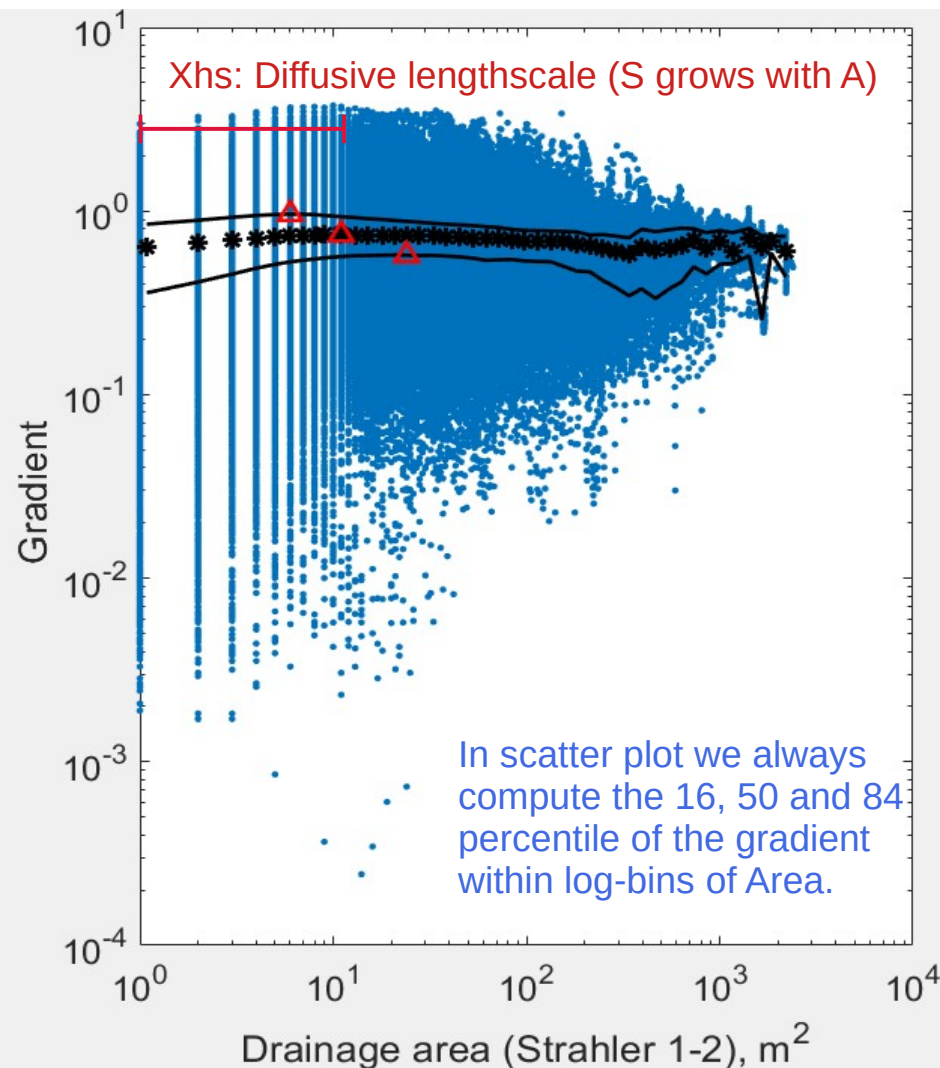
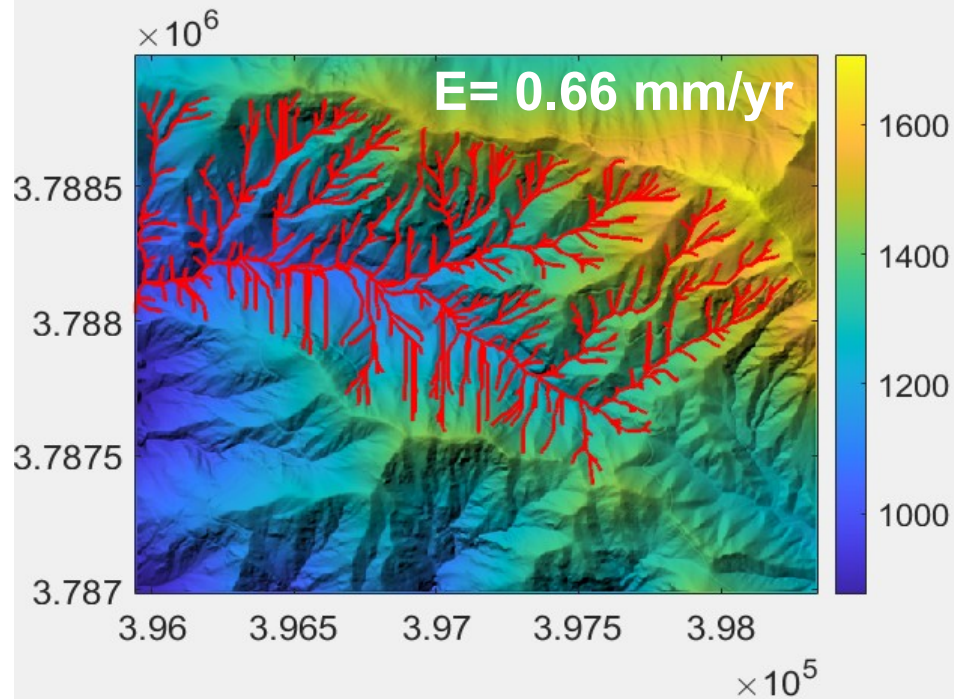
$$\left(\frac{U}{K} \right)^{1/n} \approx S_{df} A_c^\theta$$

Then note that the integral of the hybrid model yields a modified Chi definition
(Equivalent to Eq. 15 of Hergarten et al., 2016):

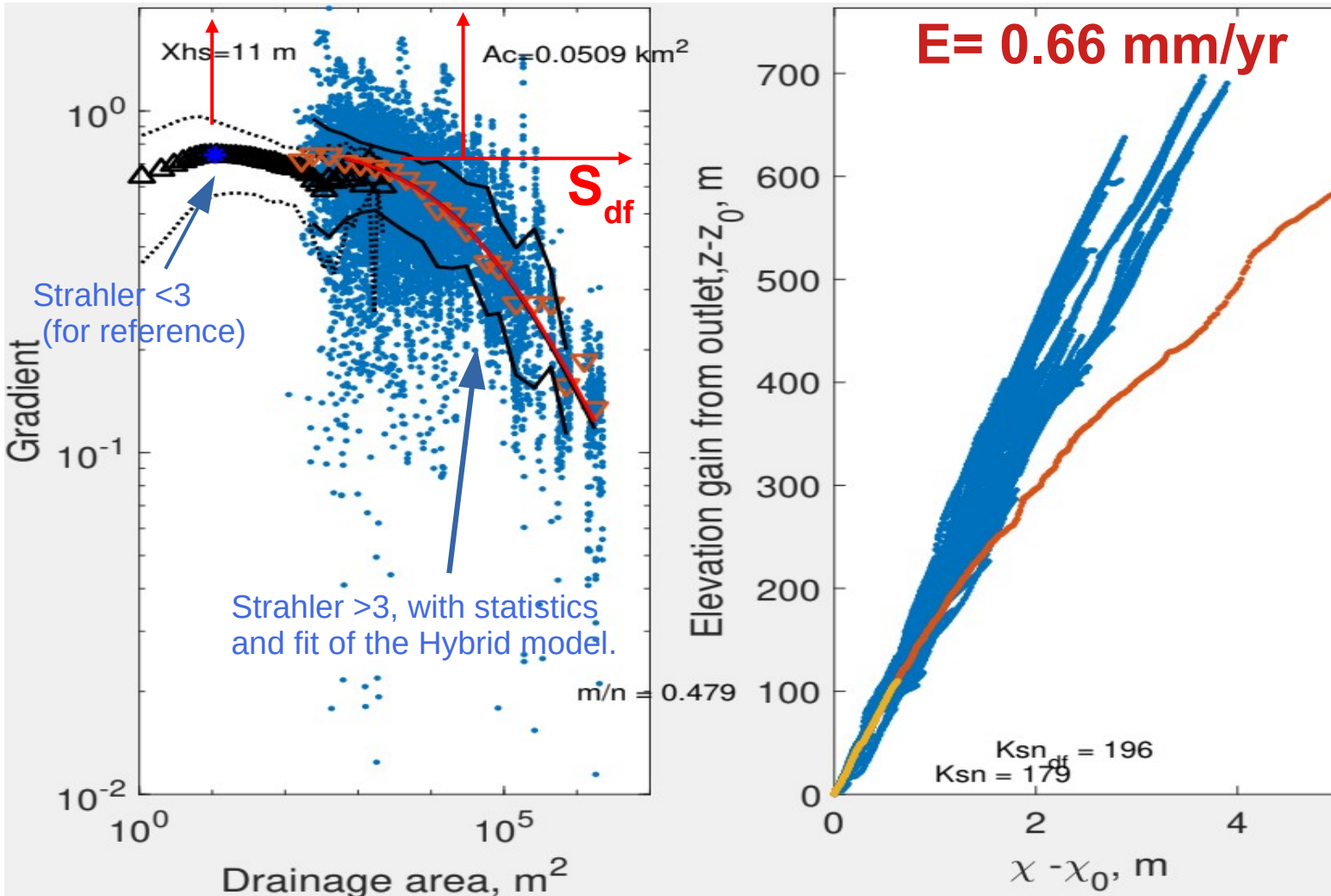
$$z - z_0 = S_{df} \frac{A_c^\theta}{A_0^\theta} \chi_{df} \approx \left(\frac{U}{K A_0^m} \right)^{1/n} \chi_{df} \quad \text{With:} \quad \chi_{df} = \int_0^x \left(\frac{A_o^\theta}{A(x')^\theta + A_c^\theta} \right) dx'$$

Extracting morphometry from LIDAR DEM: Ex 1

We use a D8 flow routing from the first pixel. Pixels with Strahler order < 3 are considered preliminary “hillslopes”, and the others “channels” (below in red).



Extracting morphometry from LIDAR DEM: Ex 1



We fit the slope-area median with the hybrid model and obtain A_c , S_{df} and θ .

We compute the fluvial steepness k_s as the slope of a Chi-Z plot.

Red: Chi for trunk channel

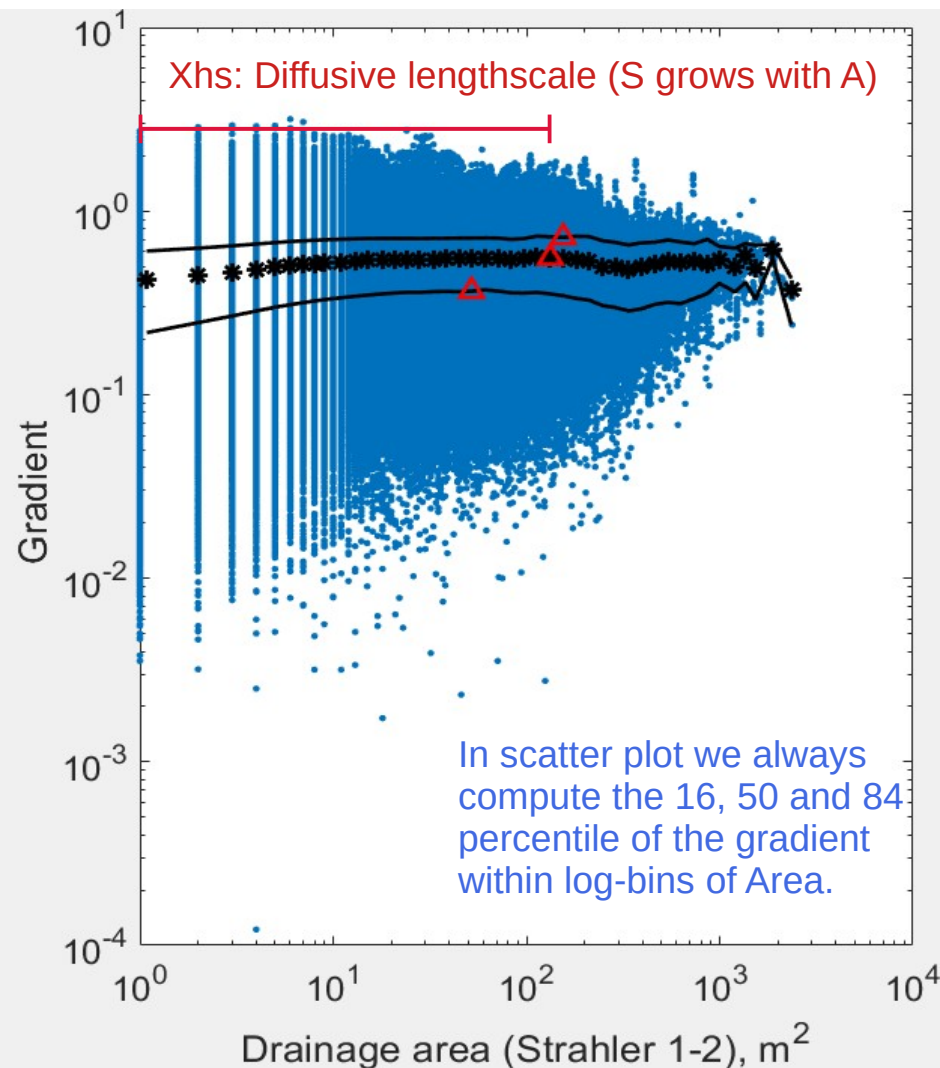
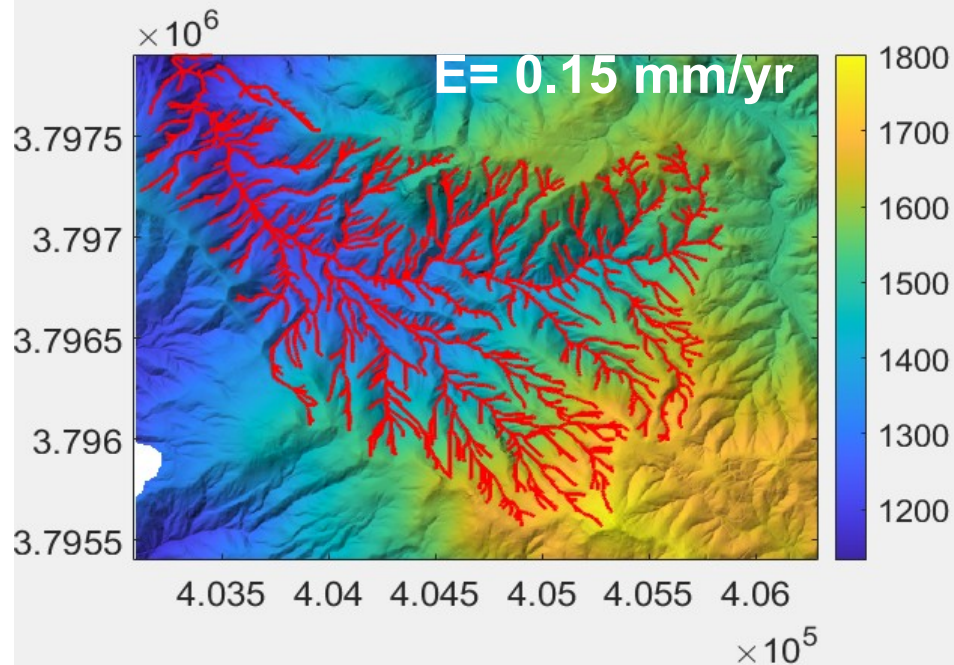
Yellow: idem but where $A > 0.66A_t$, A_t the max of A .

Blue: Chi_df (slide 4) for trunk and tributaries.

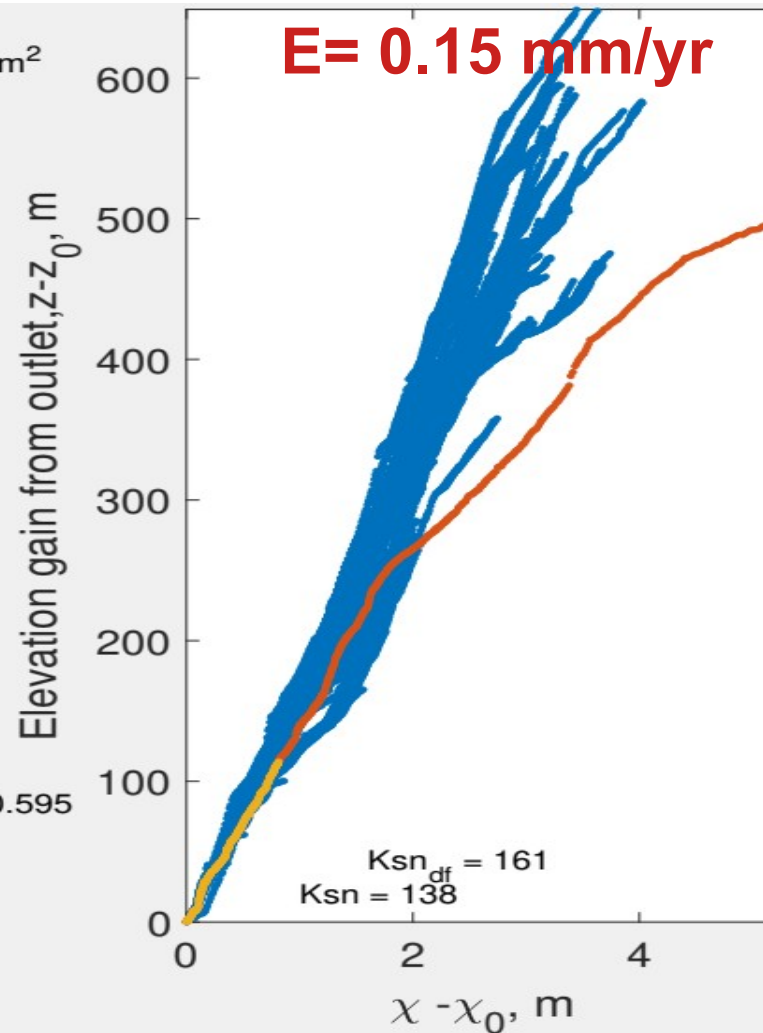
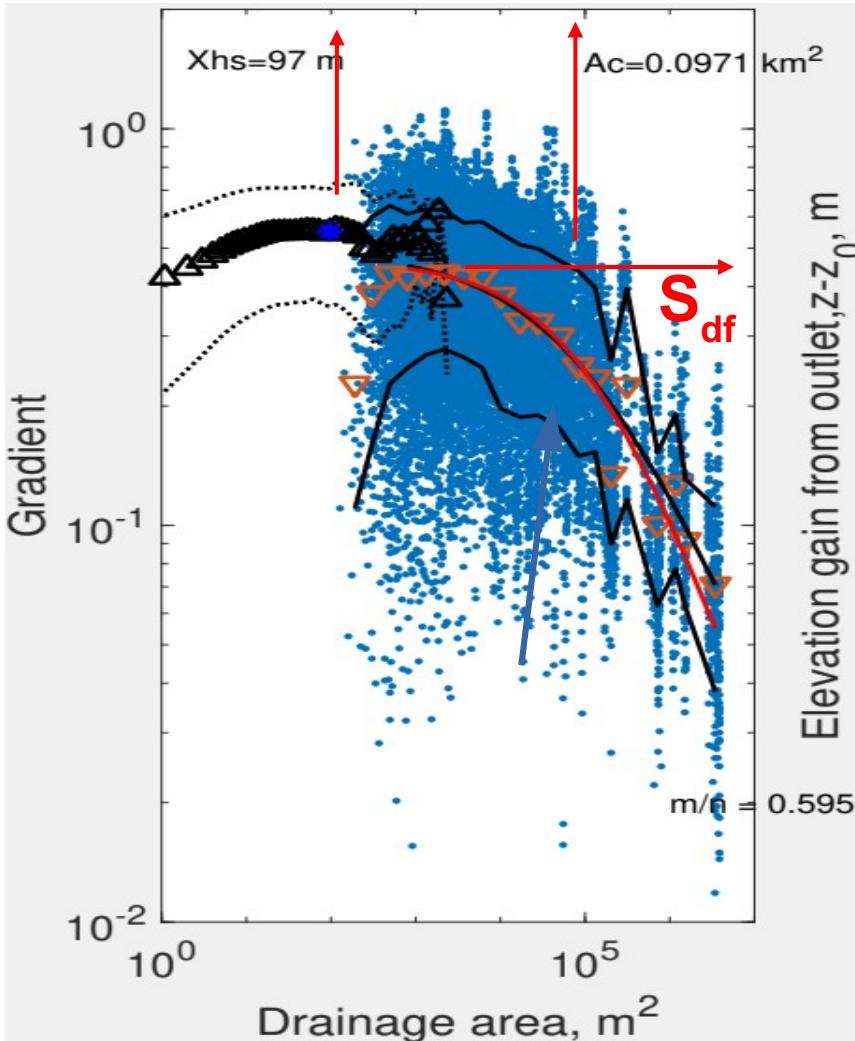
k_s and k_{sdf} is extracted from yellow and blue curves, respectively. Note their similar values.

Extracting morphometry from LIDAR DEM: Ex 2

We use a D8 flow routing from the first pixel. Pixels with Strahler order < 3 are considered preliminary “hillslopes”, and the others “channels” (below in red).



Extracting morphometry from LIDAR DEM: Ex 2



We fit the slope-area median with the hybrid model and obtain A_c , S_{df} and θ .

We compute the fluvial steepness k_s as the slope of a Chi-Z plot.

Red: Chi for trunk channel

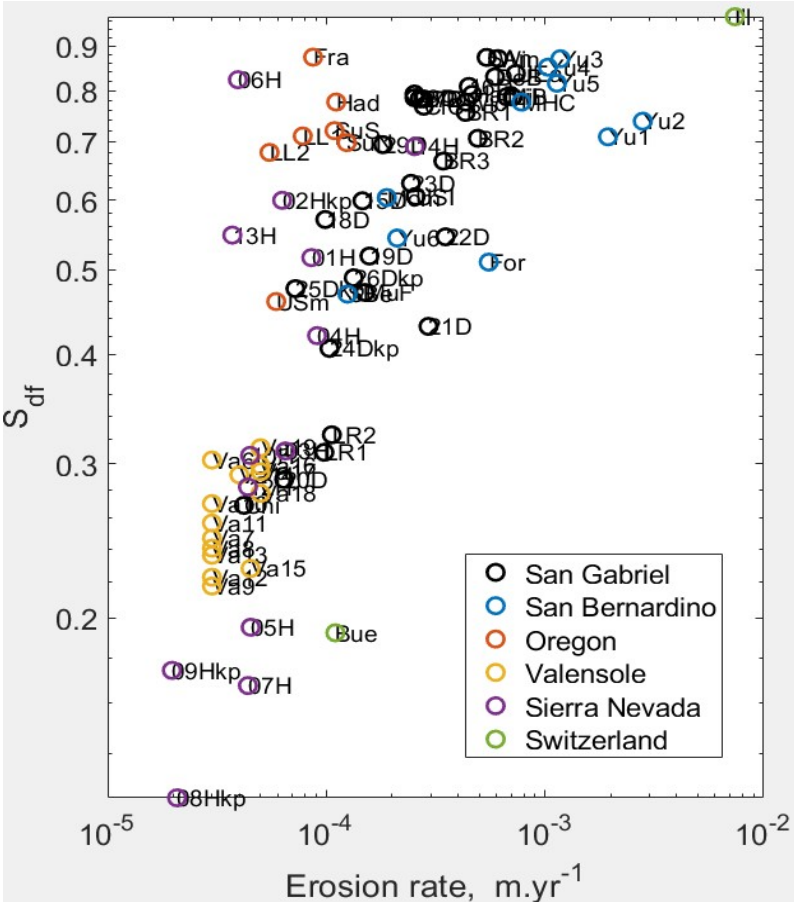
Yellow: idem but where $A > 0.66 A_t$, A_t the max of A .

Blue: Chi_df (slide 4) for trunk and tributaries.

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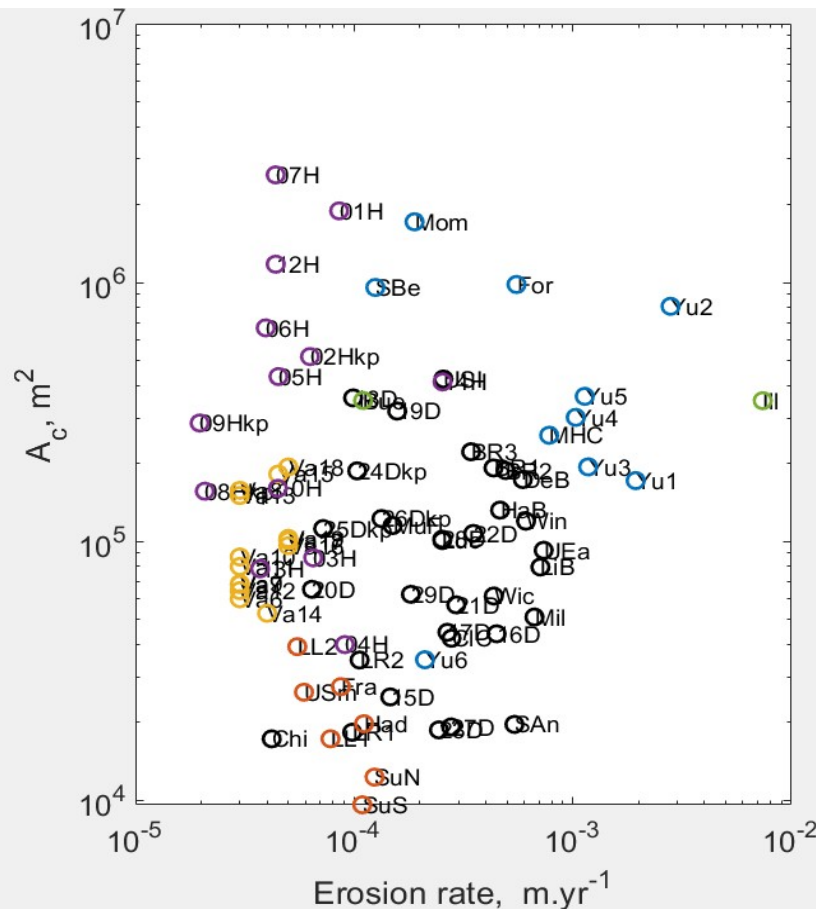
Summary of debris-flows (DF) parameters vs erosion:

1) S_{df} seems to increase with E with saturation near 0.8-1...



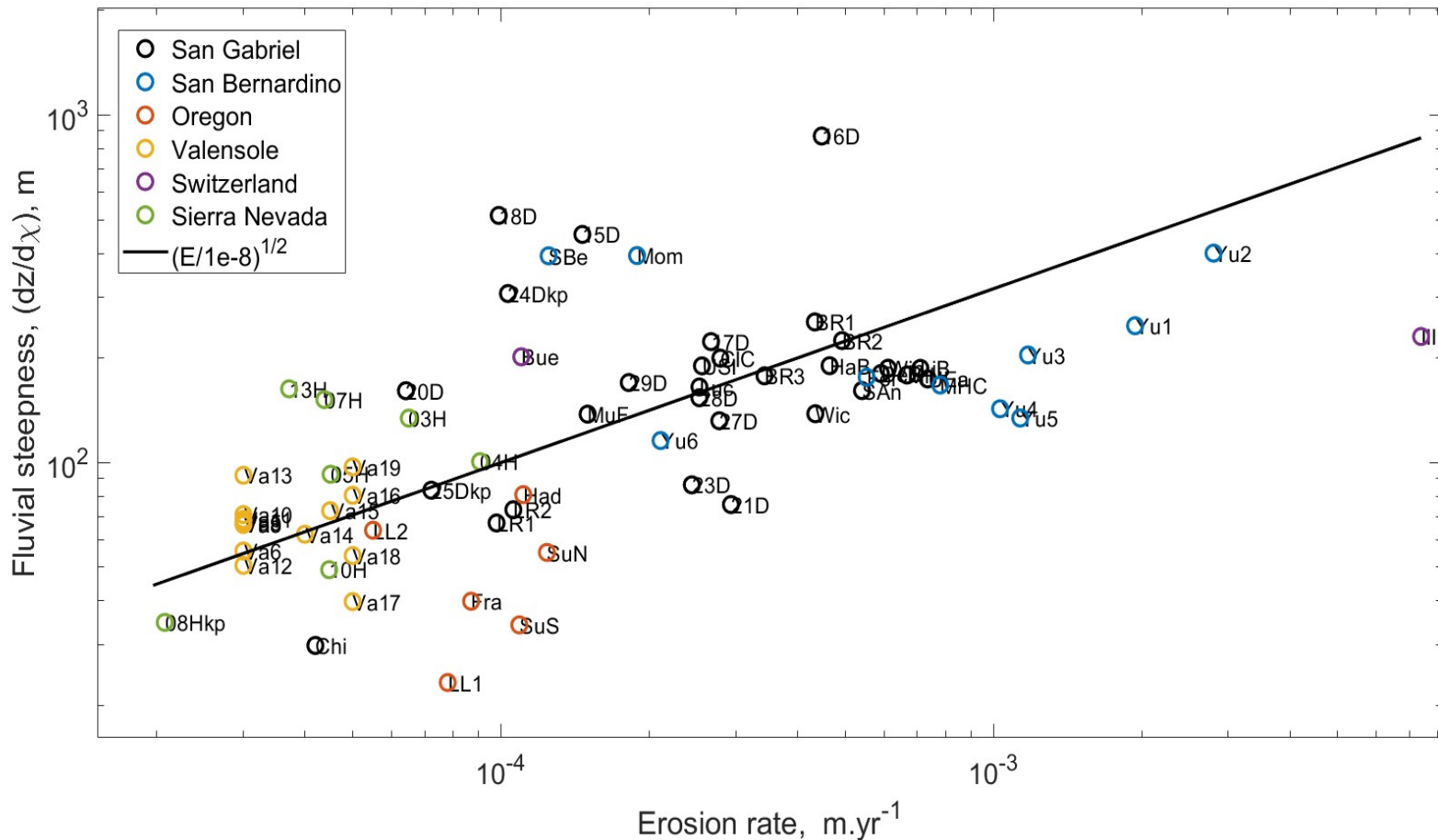
2) S_{df} can be pretty low ~ 0.2 (10°)
But not inconsistent with DF angle of arrest.

3) Unclear for A_c .



→ However we saw (slide 4) that $S_{df} A_c$ scales with U/K .
What about variability in K ?

Steepness against erosion: we expect $k_s = (E/K)^{1/n}$



^{10}Be Erosion rates:

S. Gab: DiBiase et al., 2010, 2012

S. Ber: Binnie et al., 2007

Oregon: Penserini et al., 2017,

Valensole: Godard et al., 2020

Switzerland

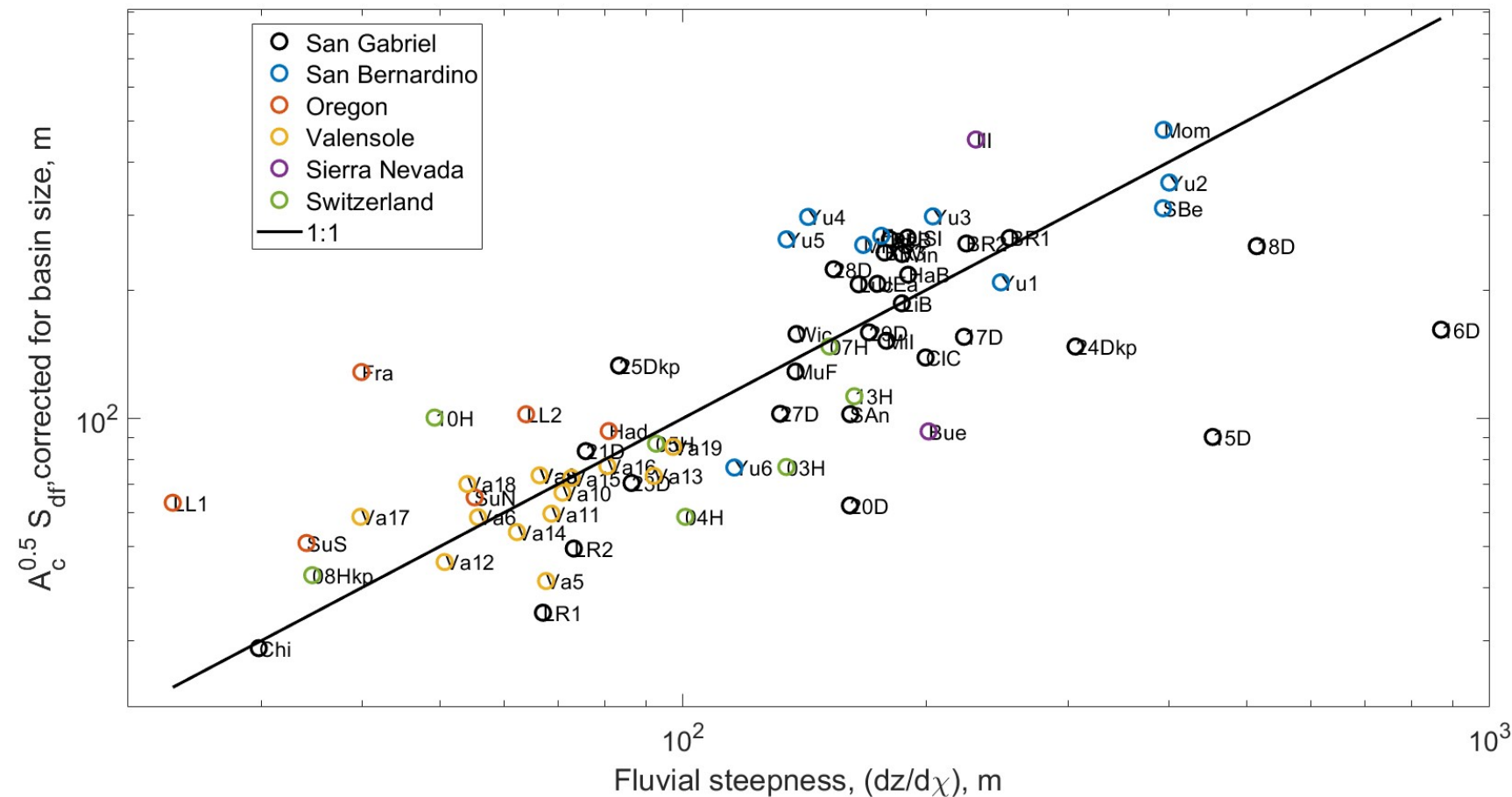
Sierra Nev.: Hurst et al., 2012.

→ Global n rather near 2 than 1. In any case K is quite variable...

→ Let's compare A_c to steepness...

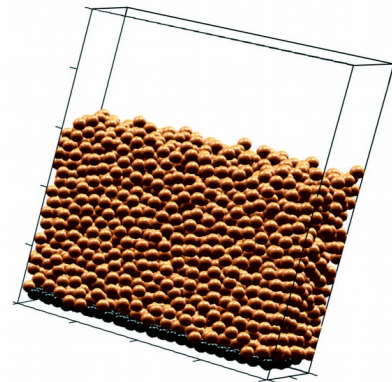
Debris-flow steepness match fluvial steepness

So knowing k_s and S_{df} we can find A_c ! But what controls S_{df} ?



Debris-flow mechanics from granular model

(courtesy S. McCoy/ L. McGuire)



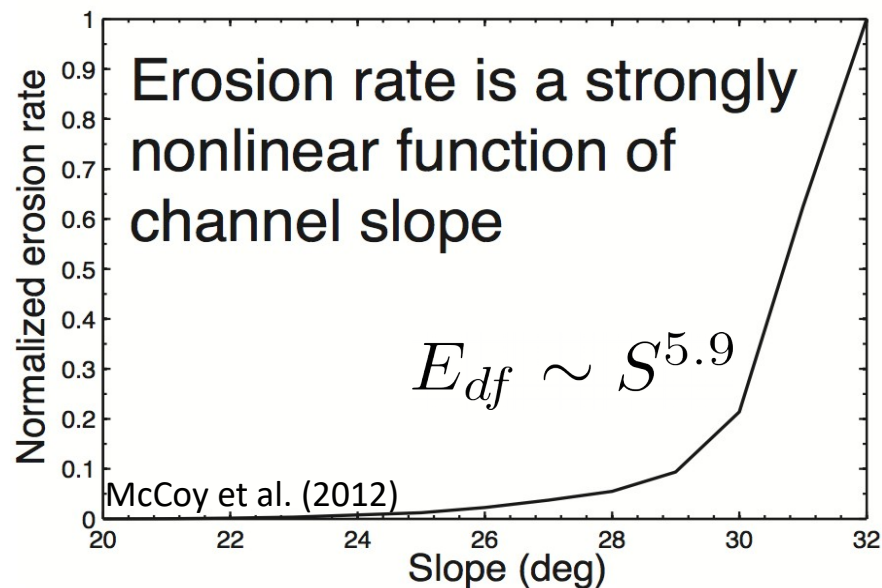
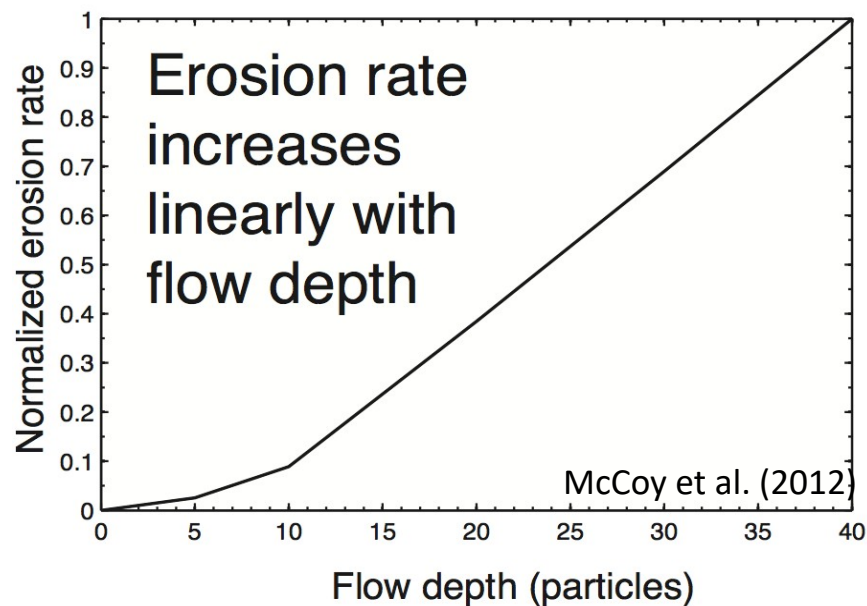
Debris flow
Erosion rate

Volume eroded
by impact

Impact
frequency

Impact intensity

$$= E_{df} = V_i I_f = k_{df} I_i I_f \quad (\text{e.g. Sklar and Dietrich, 2004})$$



Implications of granular model scaling:

$$E_{df} \propto H_{df} \left(\frac{dz}{dx} \right)^{n_{df}}, \text{ with } n_{df} \sim 5-6, \text{ and } H_{df} \text{ the DF flow height, proportional to initial volume, } V_i.$$

Further the long term erosion will depend on DF frequency, yielding: $E_{df} \propto F_{df} V_i \left(\frac{dz}{dx} \right)^{n_{df}}$

At steady-state $U = E_{df}$ and the $F_{df} V_i$ should be proportional to the sediment flux equal to $U A_{hs}$.

Assuming $A_{hs} = w_c X_{hs}^2$ we obtain: $U = E_{df} \propto U X_{hs}^2 \left(\frac{dz}{dx} \right)^{n_{df}}$

And therefore: $S_{df} \propto X_{hs}^{-2/n_{df}}$

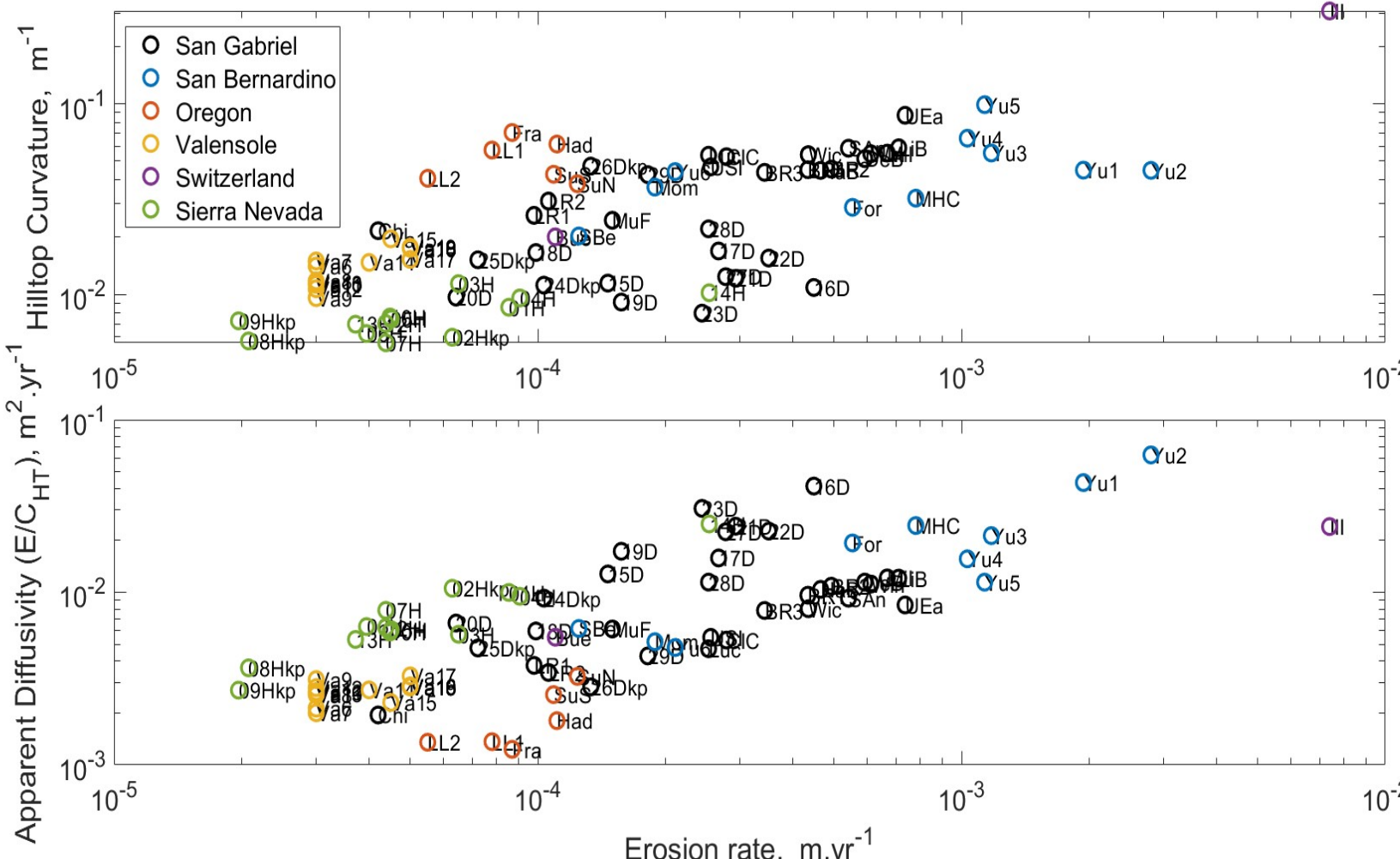
Can we validate this scaling ? What control X_{hs} ? If we assume a simple diffusive hillslope that ends when its gradient is reaching S_{df} , (i.e., $S_{df} = U X_{hs} / D$) we obtain :

$$S_{df} \propto \left(\frac{U}{D} \right)^{\frac{2}{(n_{df}+2)}}$$

$$X_{hs} \propto \left(\frac{D}{U} \right)^{\frac{n_{df}}{(n_{df}+2)}}$$

→ We also need to constrain D! For example by extracting hilltop curvature.

Estimation of Hilltop curvature and diffusivity



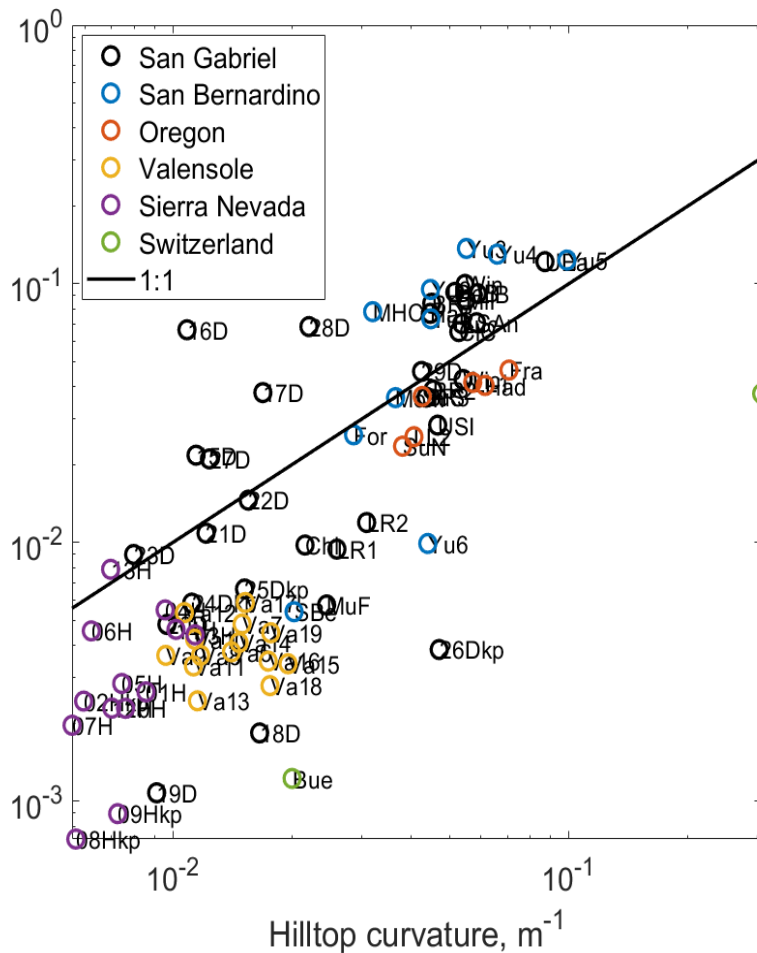
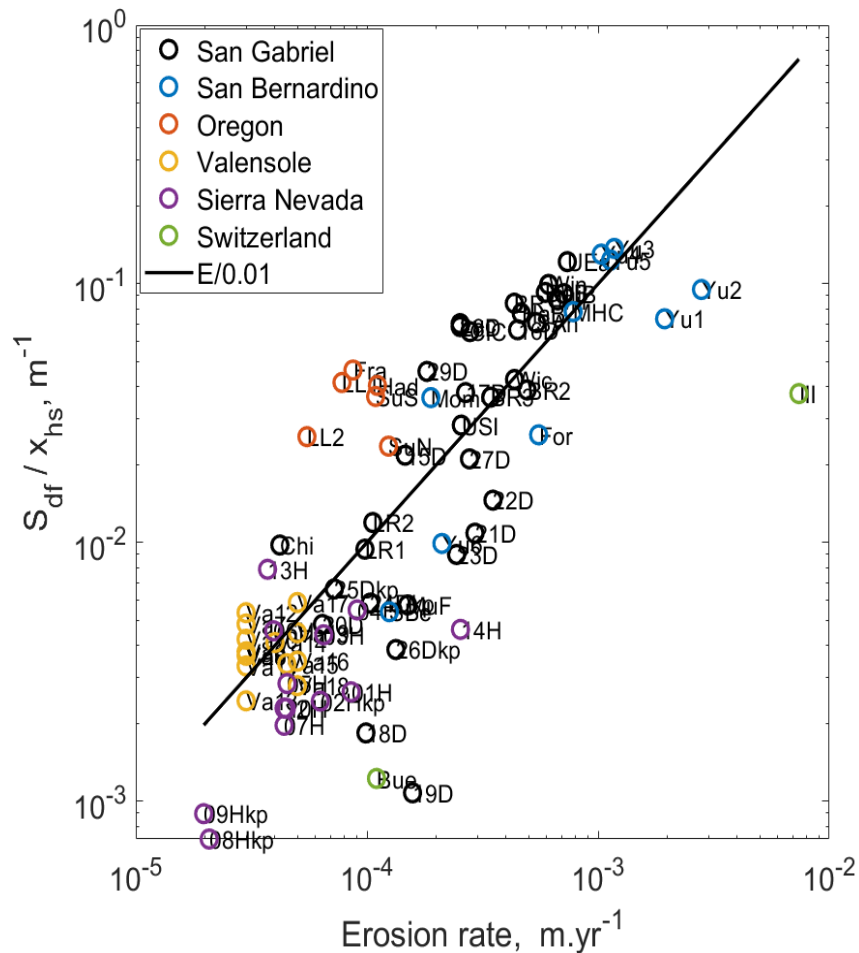
We implement a method similar to the one proposed by Hurst et al., 2012.

However CHT
seems to increase
sublinearly with E.

And thus D to increase with E.

Hillslope length and maximum slope:

Diffusion theory : $S_{hs} = U/D \times$; $U/D = C_{HT}$. **Is $\max(S_{hs})=S_{df}$?** \rightarrow matches better E/0.01 than C_{ht}



Is the apparent increase in diffusion an artifact ?

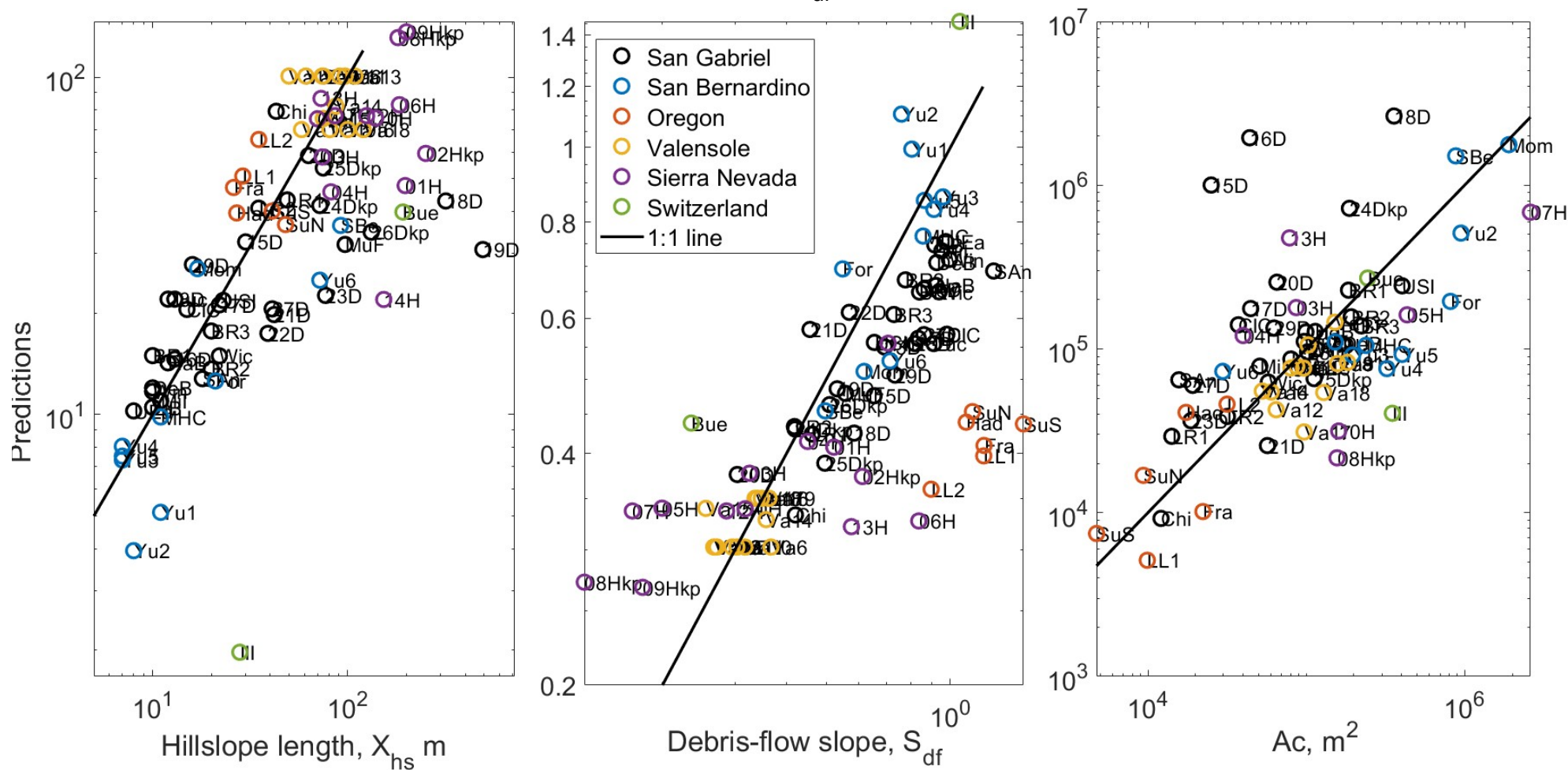
Or U/D is different
of C_{HT} , ?

because of soil
depth variations ?

Anyway we next assume $D=0.01$ to try to predict X_{hs} , S_{df} and A_c .

Predictions based on global parameters

Variable : E, K ; Fixed : $D=0.01$; $n=2$; $m=1$; $n_{df}=5$; Hacks constant. Eq. On slide 4 and 13.



Conclusions:

With LIDAR and ^{10}Be data we constrained relations between erosion rate E , fluvial erodibility K , hillslope diffusivity D and debris flow parameters A_c and S_{df} . Our major findings are:

→ Fluvial network systematically overprinted by DF upstream of 0.5-5 km². The upstream limit of SPIM can be found based on A_c , when knowing S_{df} and the steepness.

As a result a DF-corrected version of χ is proposed and validated (as in Hergarten et al., 2016).

→ We found S_{df} between 0.2 and 0.9, varying with E but also with the length of diffusive hillslopes, X_{hs} . Although it does not match perfectly with our estimate of D based on curvature, the assumption that hillslopes are diffusive and end where their gradient reach S_{df} is fair.

→ The (bidirectional) coupling of X_{hs} and S_{df} means that, knowing U , D and DF mechanics constant allow to predict X_{hs} and S_{df} . Then knowing fluvial steepness, A_c can be found and a profile from divide to the fluvial domain can be fully predicted.

Future work : → Include variable m/n (in this presentation we fixed $m/n=0.5$, often but not always matching the best-fit to the data...)

→ Better understand the relations between E , D and C_{ht} .

→ Implement the predictions into the numerical model DAC (Divide And Capture).