LiDAR Based Analysis of a Degraded Fault Scarp in Hector Mine, California.

Xiao Zhang[1], Kenneth W Hudnut[2], Craig L Glennie[1], Frank Sousa[3], Joann M Stock[3] and Sinan O Akciz[4]

MOTIVATION

- Determination of k, mass diffusivity of fault scarps, is normally estimated using traditional survey methods (for example profile elevations of a line perpendicular to the scarp at each location). These methods require significant field work, but also tend to introduce significant variations due to the varying quality of input observations.
- LiDAR (light detection and ranging) offers great potential to precisely document and rigorously determine morphologic degradation of fault scarps. [Renard et al., 2006] first used modern TLS imaging of a fault surface and [Brodsky et al., 2011] calculated evolution of fault-surface roughness using TLS data. [Hilley et al., 2010] used DEM's to estimate scarp profiles and landform evolution as well, but much remains to be done.
- In order to automate mass diffusivity calculations we need to evaluate different approaches to estimating k from airborne laser scanning data.

BACKGROUND

- The Mw 7.1 right-lateral strike-slip Hector Mine earthquake occurred on 10/16/1999 and generated an approximately 48 km long surface rupture: the Lavic Lake fault and the central section of the Bullion fault and smaller fault ruptures on minor strands were involved, with main strand rupture characterized by maximum strike slip of 5.25 ±0.85 m [Treiman, 2002].
- Since this is a remote and sparsely populated area of the Mojave Desert, southern California, it is favorable for fault scarp degradation studies because there is little interference from vegetation or human activity.

Fig. 1 Hector Mine surface rupture after 1999 earthquake in southern California. (Photo by Katherine Kendrick, U.S. Geological Survey)

RESEARCH OBJECTIVE

- Temporally spaced ALS (Airborne Laser Scanning) is used to evaluate the rate of degradation of the Hector Mine fault scarp near Twenty-nine Palms, CA.
- Comparison of four different profile based methods for mass diffusivity estimation and one semi-automatic extraction procedure for selectively assessing fault scarp degradation.

TEST DATASETS

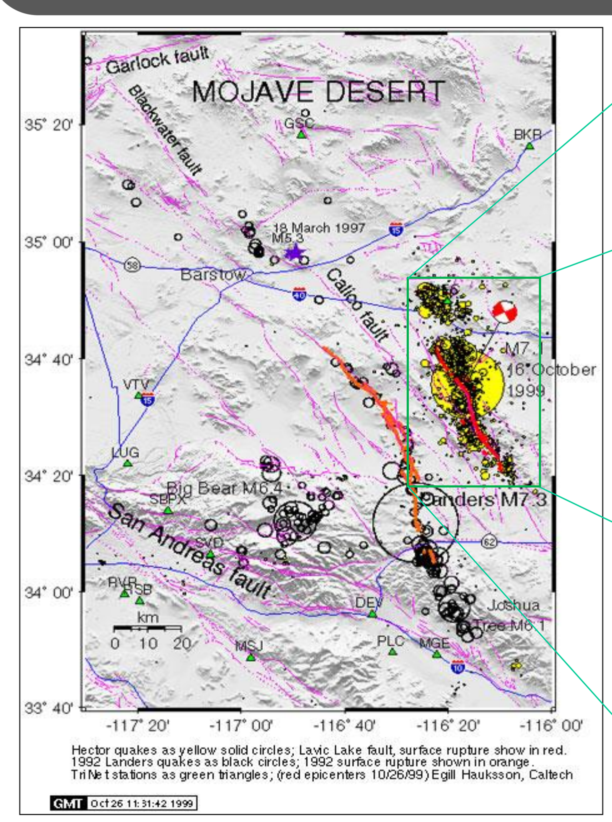

Fig. 2 M7.1 Hector Mine Earthquake of 16 October 1999 (http://www.data.scec.org/significant/hectormine1999.html)

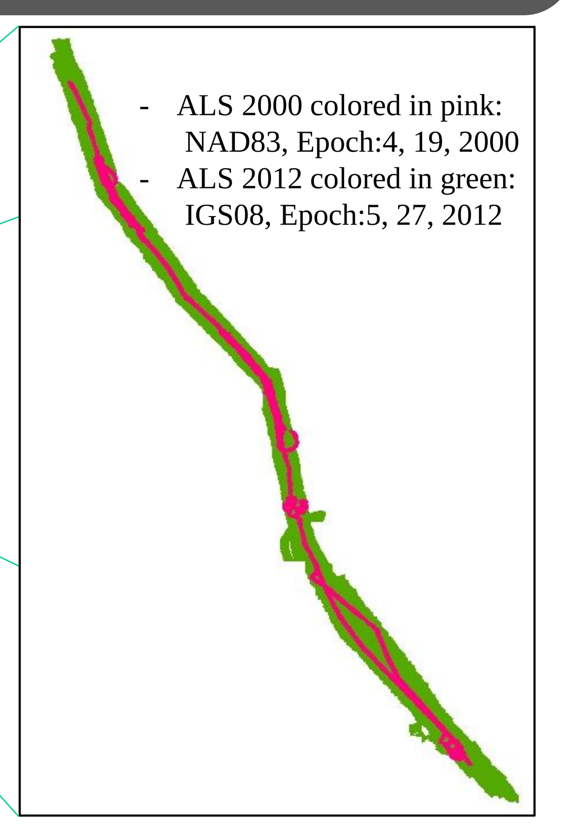

Fig. 3 ALS Datasets Coverage

DATA PROCESSING

- A common Datum is required for the two datasets. Datum shift and differential Geoid model applied to the 2000 ALS dataset.
- Residual differences determined with the Iterative Closest Point [Besl and McKay, 1992] algorithm to account for uncertainty in datum for 2000 ALS.
- LiDAR filtering was performed for ground classification and outlier removal.
- Smoothing of ground model and generation of surface model was also performed.

DIFFUSION MODEL

The rate of downslope transfer of surface debris Q, is assumed to be proportional to the local slope, given by the linear diffusion equation [Andrews and Hanks, 1985] :

$$Q = -k\,\frac{dU}{dx} \qquad (1)$$

Here U is the vertical elevation, x is horizontal distance (positive upslope) and k is the mass diffusivity. The conservation of mass in cross section yields the condition:

$$\frac{\partial U}{\partial t} = \frac{\partial V}{\partial x} = k\,\frac{\partial^2 U}{\partial x^2} \qquad (2)$$

METHODS

FINITE DIFFERENCE

For $i = 1: N$

$$Z_i(t2) = Z_i(t1) + \lambda\,(Z_{i+1} - 2Z_i + Z_{i-1}) \qquad (3)$$

$$\lambda = k\,\frac{dt}{dx^2} \qquad (4)$$

To minimize the RMS difference of observed model and calculated model:

$$RMS = \sqrt{\frac{\sum_{i=1}^{N}\left(Z_i(observed) - Zi(model)\right)^2}{N}} \qquad (5)$$

A least squares nonlinear estimation method is applied to iterate the process until a minimum RMS threshold is met. This method introduces finite interval errors.

SHAPE LAGRANGE MODELING (SLM)

Maximum scarp slope $tg\theta$ is considered to be the key geometric parameter.

If there is constant mass diffusivity, then (3) (4) derived as follows:

$$For\ \alpha = 90,\quad tg\,\theta = \frac{a}{\sqrt{\pi\tau}} + b \qquad (6)$$

$$For\ \alpha \neq 90,\quad tg\,\theta = (tg\alpha - b)\,erf\left[\frac{a}{2\sqrt{\pi\tau(tg\alpha - b)}}\right] + b \qquad (7)$$

where the initial scarp slope is $tg\alpha$, α being the angle of repose of the material. The product of the numerical age by the mass diffusivity constant *kt* may then be estimated directly from one scarp using equation (4). Measurement of the regional slope *b*, half scarp offset *a*, and maximum scarp slope $tg\,\theta$ may then be performed. [*Colman and Watson*, 1983]

$$k\tau = \frac{d^2}{4\pi}\left[\frac{1}{(tg\theta - b)^2} - \frac{1}{(tg\alpha - b)^2}\right] \qquad (8)$$

$$k\Delta\tau = k(\tau_2 - \tau_1) = \frac{d^2}{4\pi}\left[\frac{1}{(tg\theta_2 - b_2)^2} - \frac{1}{(tg\theta_1 - b_1)^2}\right] \qquad (9)$$

ERF (GAUSS ERROR FUNCTION) MODEL

For $\alpha = 90^o$

$$U_{syn}(x,\ t) = a\,erf\left(\frac{x}{2\sqrt{k\tau}}\right) \qquad (10)$$

For $\alpha \neq 90^o$

$$U_{syn}(x,\ t) = a\left[erf\left(\frac{x - acotg\alpha}{2\sqrt{k\tau}}\right) + erf\left(\frac{x + acotg\alpha}{2\sqrt{k\tau}}\right)\right] + a\int_{-acotg\alpha}^{acotg\alpha} x'\,tg\alpha\,e^{-\frac{(x-x')}{4k\tau}}\,dx' \qquad (11)$$

For each set of parameters *(b, a, kτ)* the synthetic profile U_{syn} is sampled at the data points abscesses $(X_i)_{1<i<N}$ and the standard deviation *SD(b, a, kτ)* between synthetic points and measured points is evaluated.

$$SD(b, a, k\tau) = \left[\frac{1}{N}\sum_{i=1}^{N}\left(U_i - U_{syn}(X_i)\right)^2\right]^{\frac{1}{2}} \qquad (12)$$

The geometric parameters derived from a scarp profile are regional slope b, half scarp offset a=d/2, and kτ. The diffusion age thus takes into account the width of the scarp slope distribution and the global shape of the scarp profile, and not only the maximum scarp-slope.

Again,

$$k\Delta\tau = k\tau_2 - k\tau_1 \qquad (13)$$

GAUSSIAN MODEL OF 1ST DERIVATIVE

Gaussian erosional model, using a least squares fit of measured profiles to synthetic profiles, adjusting the parameters a, b, α, and τ, in order to retrieve an evaluation of the uncertainty [Avouac, 1993] .

Erosion is modelled by convolution with a Gaussian curve with variance $2k\tau$. The analytical expression of the synthetic profiles is given by:

$$U(x,t) = E(x,[t_0,t]) * 2aH(x)] + bx \qquad (14)$$

$$E(x,[t_0,t]) = \frac{1}{2a}\left[\frac{\partial U(x,t)}{\partial x} - b\right] \qquad (15)$$

This approach does not rely on the diffusion model; the degradation coefficient is defined with a dimension of length squared as follows:

$$E(x,[t_0,t]) = \frac{1}{\sqrt{2\pi\sigma^2}}\,e^{-\frac{x^2}{2\sigma^2}} \qquad (16)$$

$$k\tau = \frac{\sigma^2}{2} \qquad (17)$$

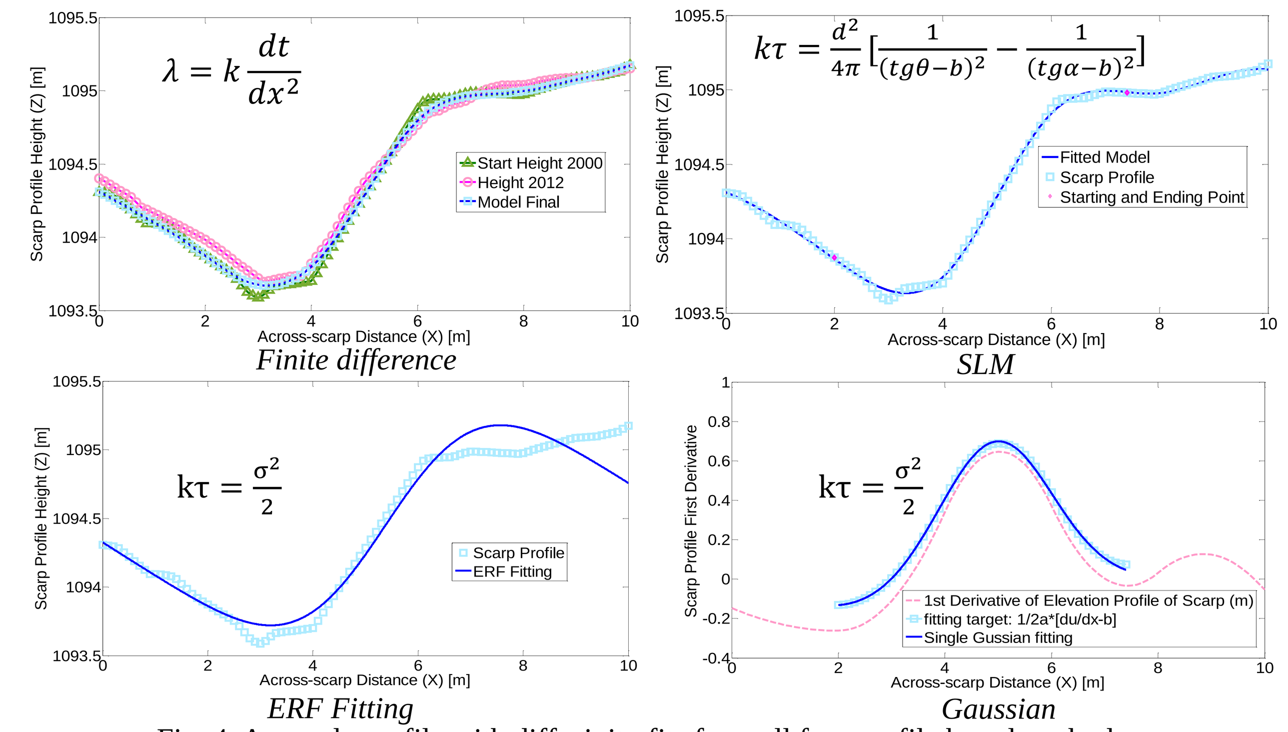

Fig. 4 A sample profile with diffusivity fits from all four profile based methods.

Figure note: Numerical artifacts exist in all methods; the irregularities are not related to the degradation of the scarp:

1) Finite Difference can mitigate the artifacts because it doesn't assume a particular profile model and thereby guarantees forward direction estimation.
2) SLM and ERF (error function) fitting are both single profile estimation techniques and therefore may suffer from far-field topographic irregularities.
3) Small irregularities in the slope distribution far from the scarp mid-height point, can adversely effect the results from ERF fitting.
4) The Gaussian method locates singular points to constrain artifacts but at the expense of losing important details and biases the trend of the first derivative.

SEMI-AUTOMATIC EXTRACTION

Using a high resolution digital elevation surface generated from point clouds, the directional second derivative (directional curvature) of best fitting profiles (with predefined step distance) across the major fault scarp is calculated using an approach similar to [*Hilley et al.*, 2010], along with an examination of RMSE of fit to identify areas containing fault and/or scarp-like topography.

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RESULTS

ANALYSIS OF TOPOGRAPHIC SWATH ALONG THE HECTOR MINE FAULT

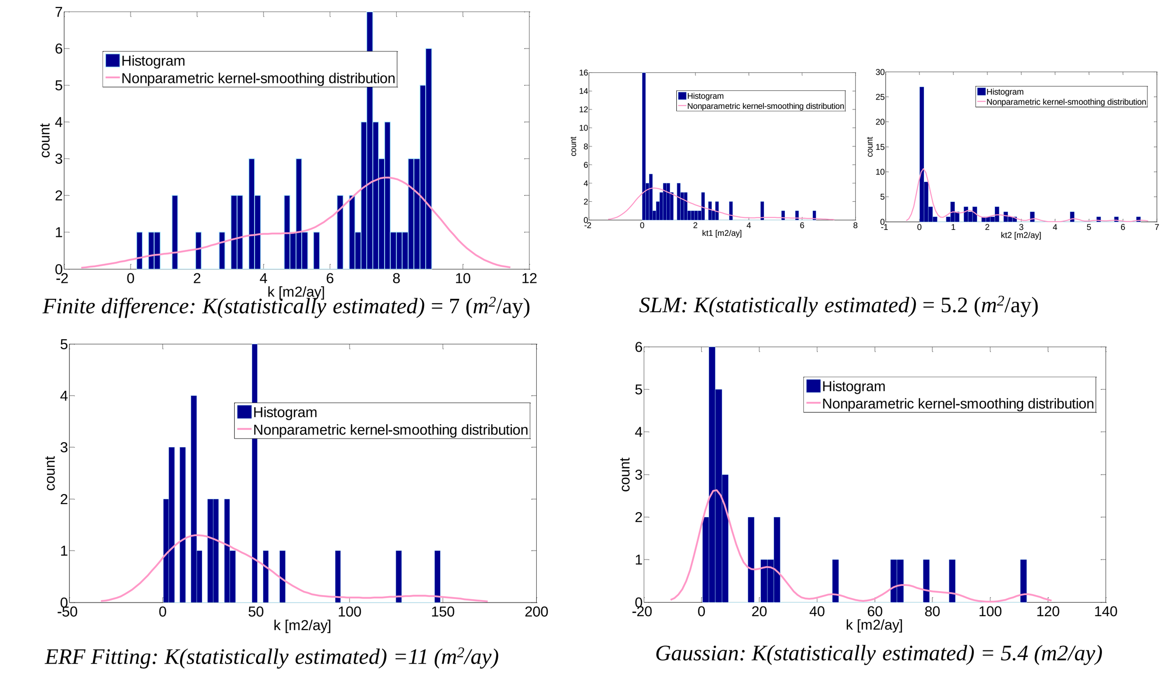

Figure 5 Histogram plots and Kernel density estimation of k values for 71 representative profiles.

Semi-automatic extraction is implemented using elevation surface generated from our point clouds by a natural neighborhood gridding method with resolution of 0.1 m. The directional curvature of best fitting 20 m profiles (step distance of 0.2 m) across the major fault scarp (colored in green in Figure.6) is calculated along with RMSE of fit.

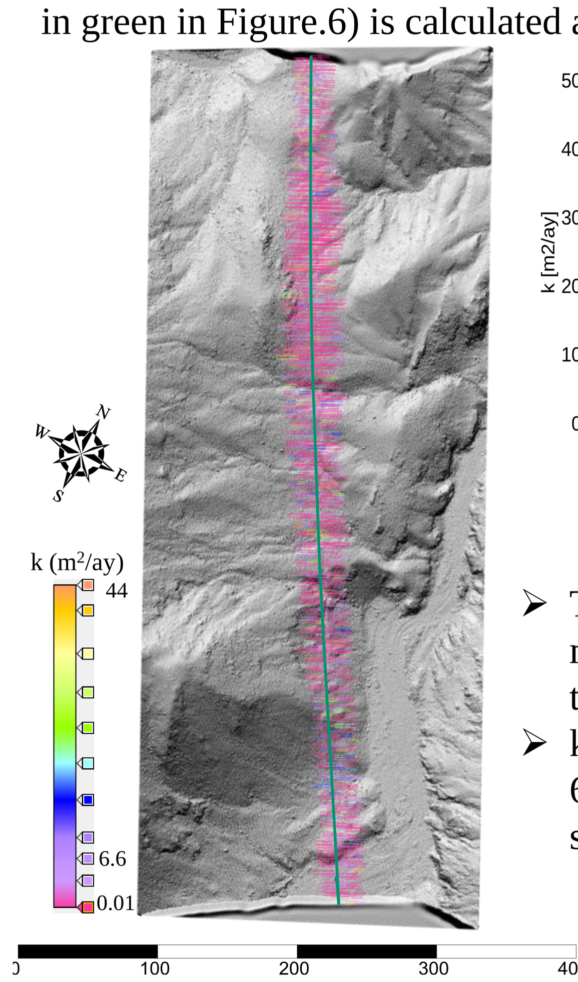

Figure 6. Location of profiles with best fitting error functions

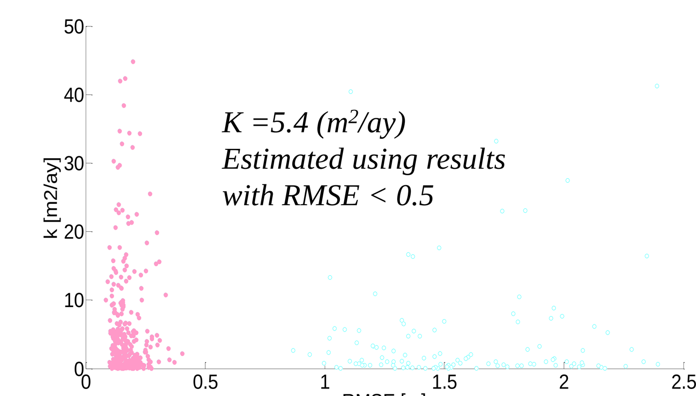

Figure 7 Scatter plot of RMSE of fitting vs. k

- Threshold of RMSE is set to be 0.5, magenta points in Figure.7 are below this threshold and used to estimate k.
- k estimates are color coded in Figure. 6. The profiles used for calculation are scaled proportionally using RMSE.

CONCLUSIONS

- LiDAR allows repeated documentation of fault scarp degradation over areas of interest.
- Finite Difference shows the best consistency among all of the profile fitting methods we studied; assessed using manually scrutinized sample profiles.
- Final k estimation using our semi-automatic topography analysis with best fitting degraded fault scarps is 5.4 m^2/ay.
- Short time span (12 years) between ALS observations appears to make estimation of mass diffusivity difficult. Longer temporal spacing is likely required for more consistent estimates.
- Future work will investigate a 3D approach to estimate k value using repeat-pass LiDAR.

[1]National Center for Airborne Laser Mapping, Houston, TX, United States, [2]USGS Pasadena Field Office, Pasadena, CA, United States, [3]California Institute of Technology, Pasadena, CA, United States, [4]Univ California Los Angeles, Los Angeles, CA, United States