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Relevance of morphometric predictors and completeness of inventories in earthquake-induced landslide susceptibility

Never Stand Still

School of Civil and Environmental Engineering

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Background

- The Gorkha Earthquake 2015 event triggered thousands of landslides in the central Nepal Himalayas.

    Mainshock: April 25, 2015 (7.8)

    Biggest aftershock: May 12, 2015 (7.3)

- Nearly 25, 000 landslides were reported by different researchers.
- 14 out of 77 districts were several affected.

Landslides in Sindhupalchowk and Rasuwa districts

Landslide Risk Management ≡ Landslide susceptibility, hazard and risk zoning

Shano et al., 2020; Australian Geomechanics Society Landslide Zoning Working Group, 2007

Landslide susceptibility, therefore, is defined as the chance of occurrence of landslide in a geographic location for a given set of environmental factors.

Landslide Hazard is defined as:

$H(v,t)=T(v,t)U(v,t)S(v,t)$

where,

v =set of environmental conditions or landslide causative factors

t = time.

T(v,t) = Time dependence (e.g. frequency)

U(v,t)= the measure of landslide magnitude

S(v,t) = landslide susceptibility .

Roback and others (2017)

Map data of landslides triggered by the 25 April 2015 Mw 7.8 Gorkha, Nepal earthquake

Gnyawali and others (2016)

Earthquake Induced Landslides triggered by 25 April 2015 Gorkha Earthquake, Mw 7.8, Nepal

Geomorphic and geologic controls of geohazards induced by Nepal's 2015 Gorkha earthquake

J. S. KARGEL, G. J. LEONARD, D. H. SHUGAR, U. K. HARITASHYA, A. BEVINGTON, E. J. FIELDING, K. FUJITA, M. GEERTSEMA, E. S. MILES, [...] N. YOUNG +55 authors
Authors Info & Affiliations

SCIENCE • 8 Jan 2016 • Vol 351, Issue 6269 • DOI: 10.1126/science.aac8353

Published: 28 March 2018

Assessment of co-seismic landslide susceptibility using LR and ANCOVA in Barpak region, Nepal

Suchita Shrestha, Tae-Seob Kang & Jung Chang Choi

Journal of Earth System Science **127**, Article number: 38 (2018) | Cite this article

261 Accesses | **10** Citations | Metrics

Zhang and others (2016)

Characteristics of landslides in Koshi River Basin, Central Himalaya

Published: 25 October 2016

Landslide susceptibility assessment of the region affected by the 25 April 2015 Gorkha earthquake of Nepal

Amar Deep Regmi, Megh Raj Dhital, Jian-qiang Zhang, Li-jun Su & Xiao-qing Chen

Journal of Mountain Science **13**, 1941–1957 (2016) | Cite this article

508 Accesses | **30** Citations | Metrics

Short report | Open Access | Published: 05 April 2017

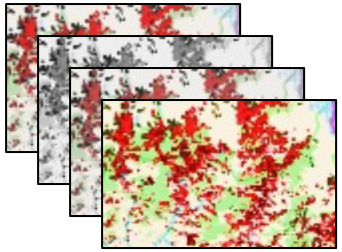
Landslide damage along Araniko highway and Pasang Lhamu highway and regional assessment of landslide hazard related to the Gorkha, Nepal earthquake of 25 April 2015

Chong Xu, Yingying Tian, Bengang Zhou, Hongliu Ran & Gaohu Lyu

Geoenvironmental Disasters **4**, Article number: 14 (2017) | Cite this article

2978 Accesses | **16** Citations | Metrics

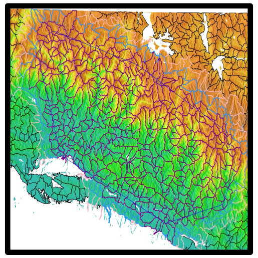
Methodological framework

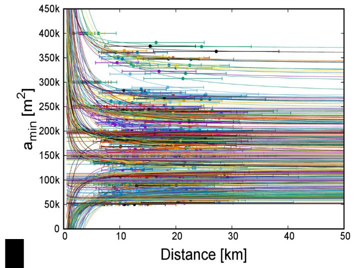


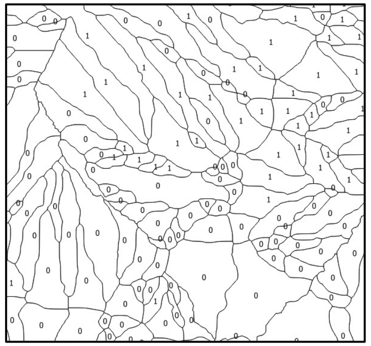
Collection of inventories

Delineation of slope units (SU)

Alvioli et al., 2016, 2020

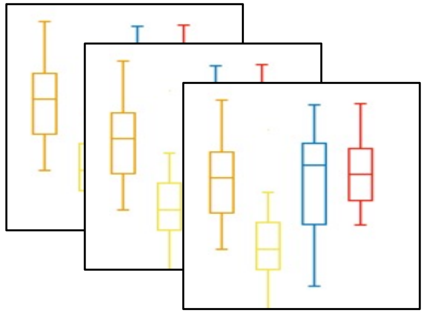






Characterization of slope units

Selection of the causative factors

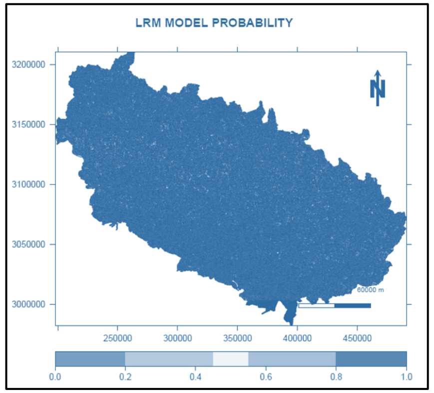


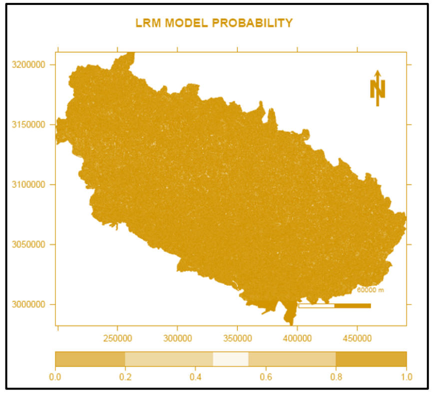
Type	Independent variables	GRASS GIS module/Reference
Dynamic	PGA	
Dynamic	PGV	
Dynamic	MMI	
Static	Slope	r.slope.aspect
Static	Topographic Wetness Index (TWI)	r.topidx
Static	Vector Ruggedness Measure (VRM)	r.vector.ruggedness
Static	Local relief	r.neighbors
Static	Landform classes	r.geomorphon
Static	Plan curvature	r.slope.aspect
Static	Profile curvature	r.slope.aspect

We obtained descriptive statistics and run a χ-square test to calculate the p-values for all independent variables in 20 runs.

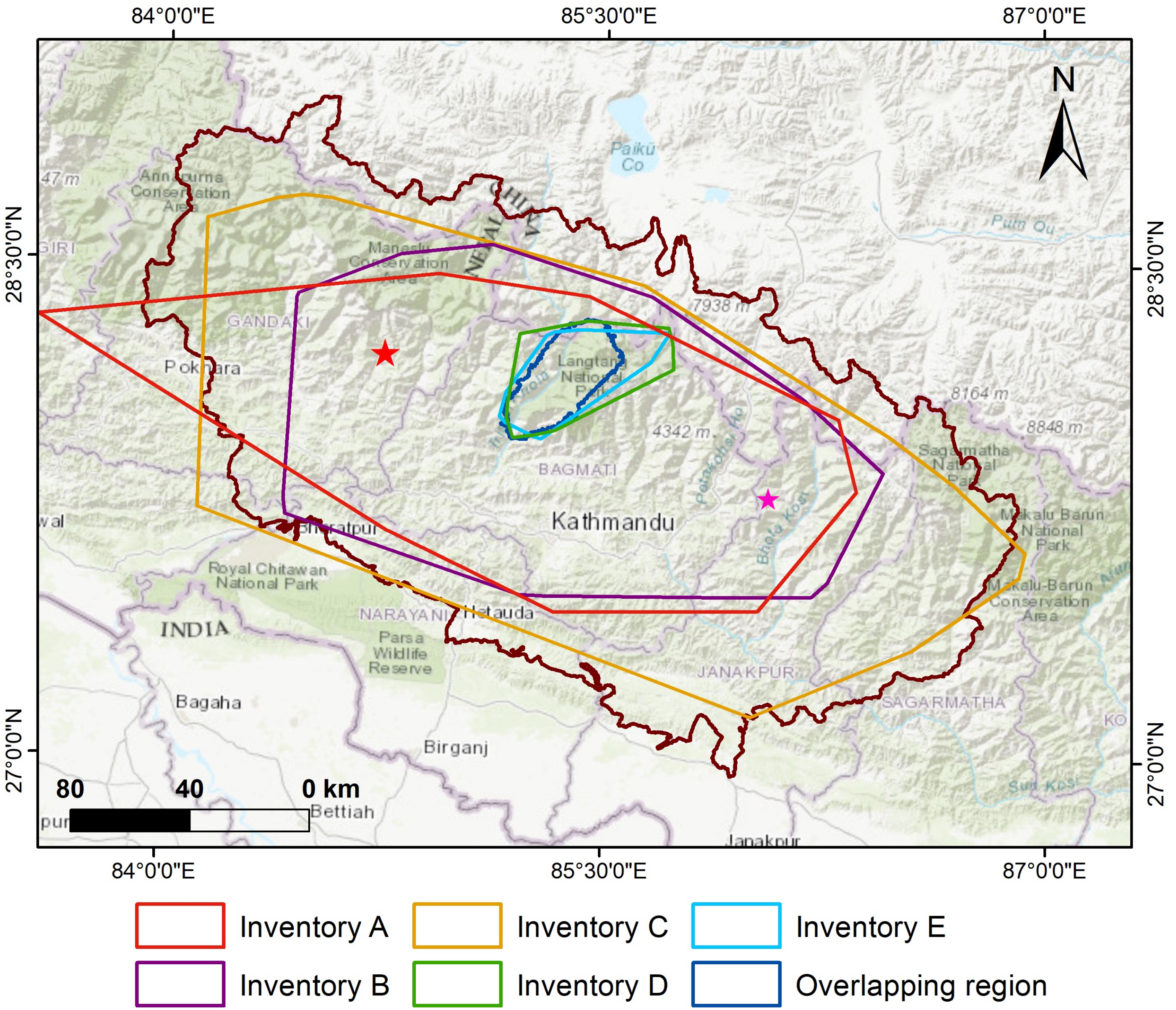
We selected variables that have straightforward interpretation in terms of their effect on landslides.

We run logistic regression in LAND-SE software to obtain Landslide susceptibility maps (LSMs).





Comparing LSMs



Published inventories

Inventory A: 2,645

Inventory B: 17,638

Inventory C: 24,915

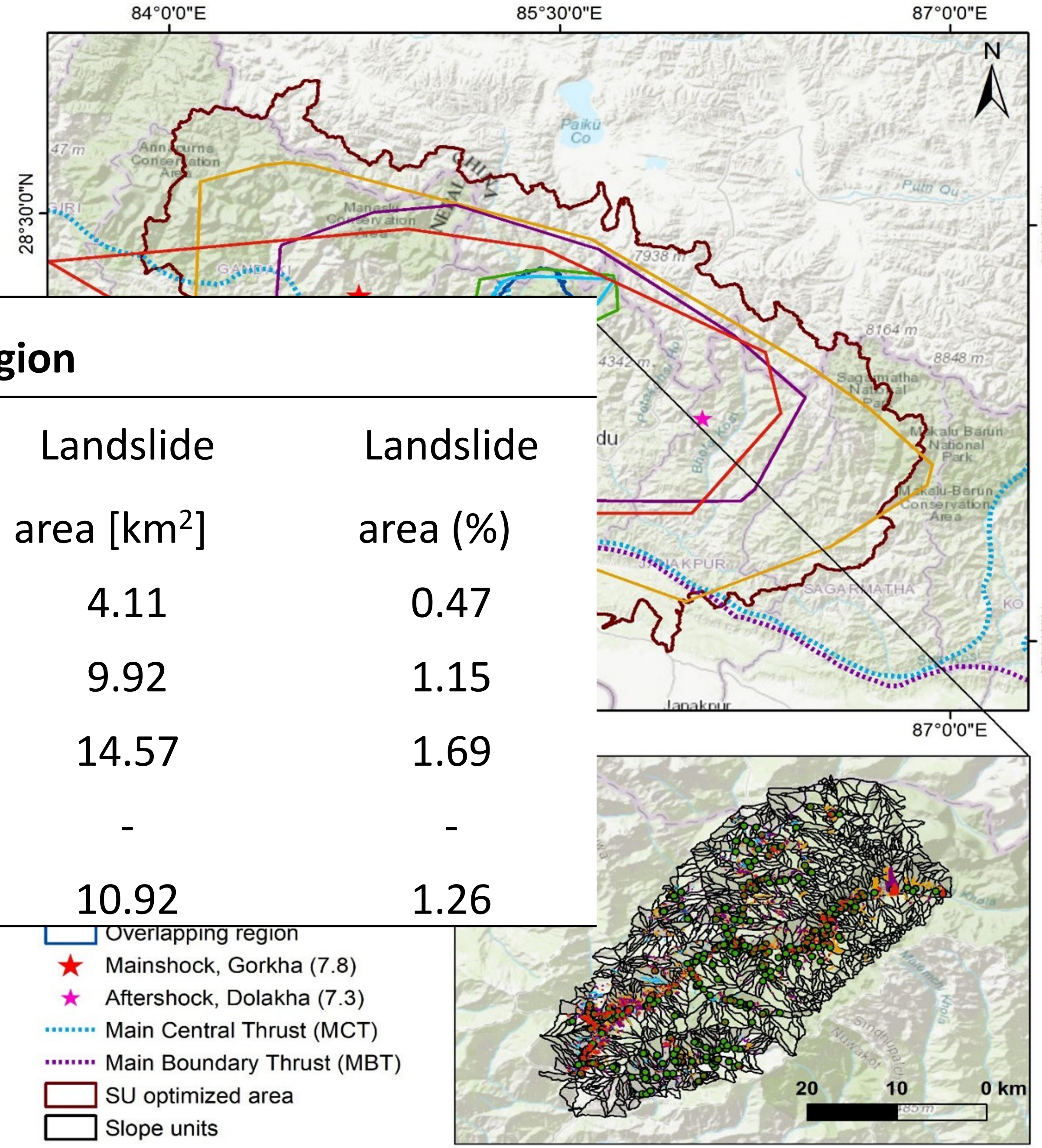
Inventory D: 4,312

Inventory E: 1,416

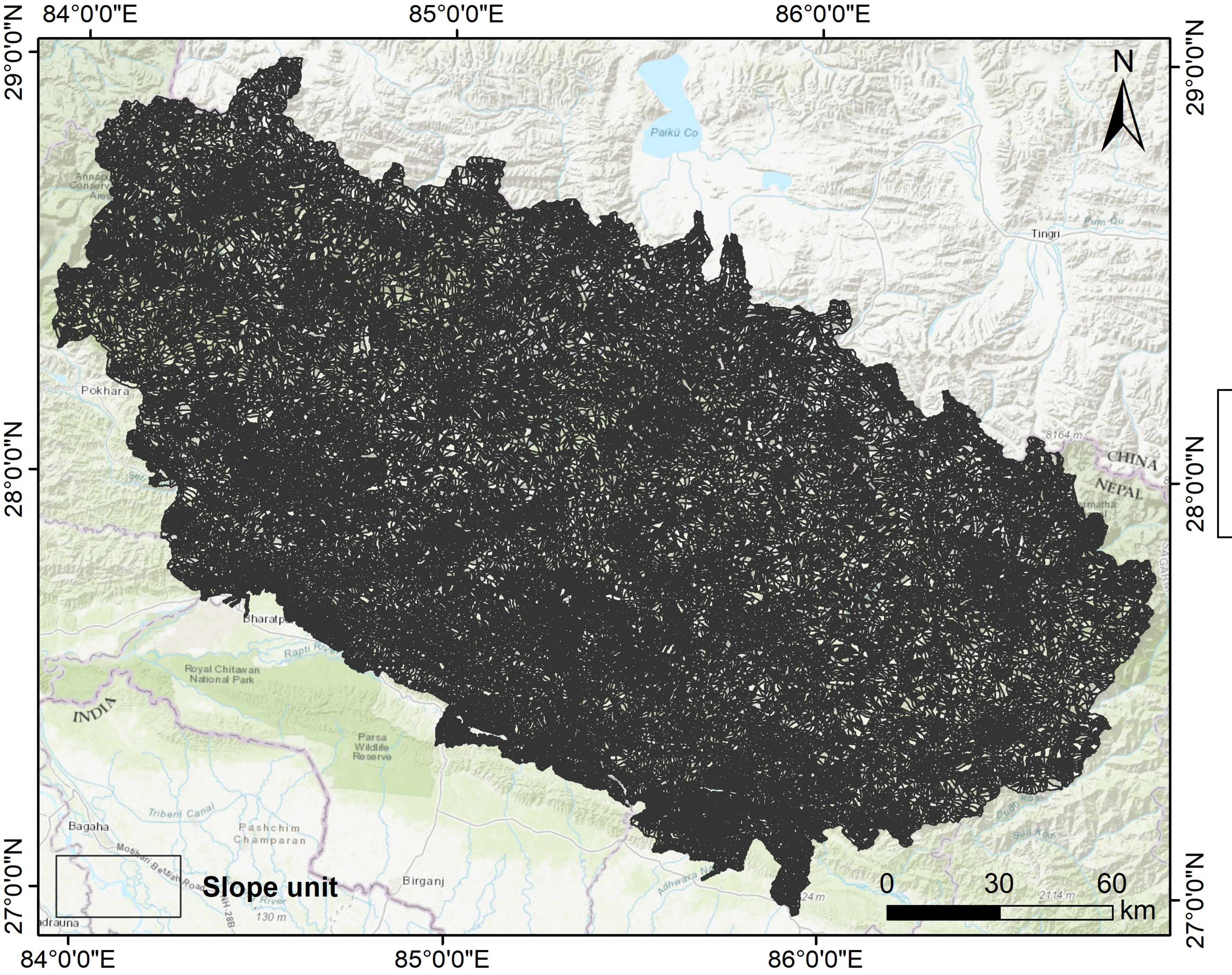
Zhang et al., 2016 (A), Gnyawali and Adhikari, 2017 (B), Roback et al., 2017 (C), Kargel et al. (2016), Pokharel and Thapa, 2019 (E)

Comparison of landslide susceptibility maps

Details of overlapping region				
Inventory	Number of Landslides	Number of Unstable SUs	Landslide area [km^2]	Landslide area (%)
A	2075	198	4.11	0.47
B	1,780	143	9.92	1.15
C	2,118	132	14.57	1.69
D	371	204	-	-
E	359	74	10.92	1.26

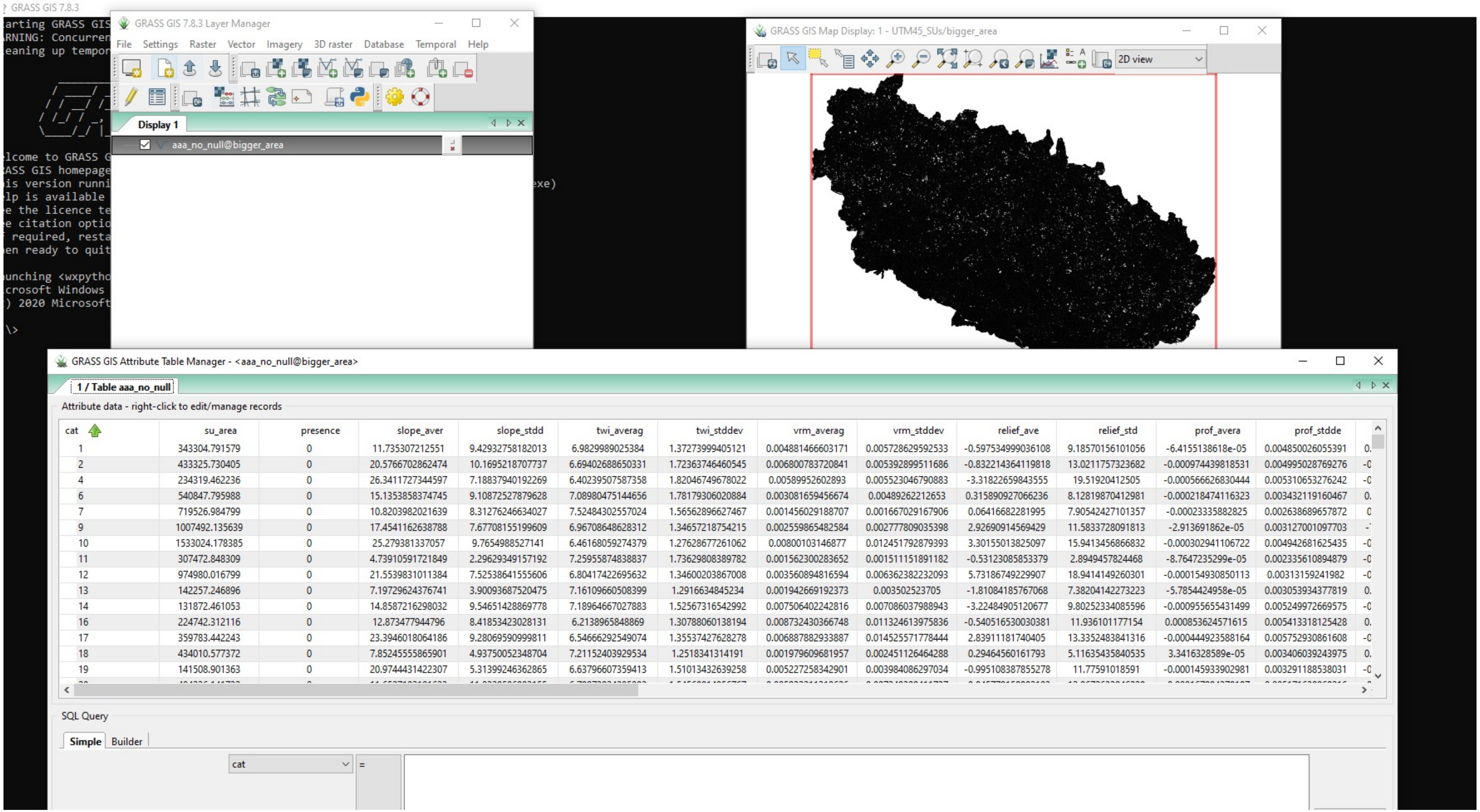


Slope unit delineation



Total number: 91,947
Total area area: 35,153.80 sq. km
Av. Area: 0.38 sq. km

Alvioli et al., 2016, 2020



GRASS GIS: https://grass.osgeo.org/documentation/

Significance independent factors

How we trained the LR model?

Check for the smallest number between stable and unstable SUs among all inventories

74 unstable SUs (Inventory E)

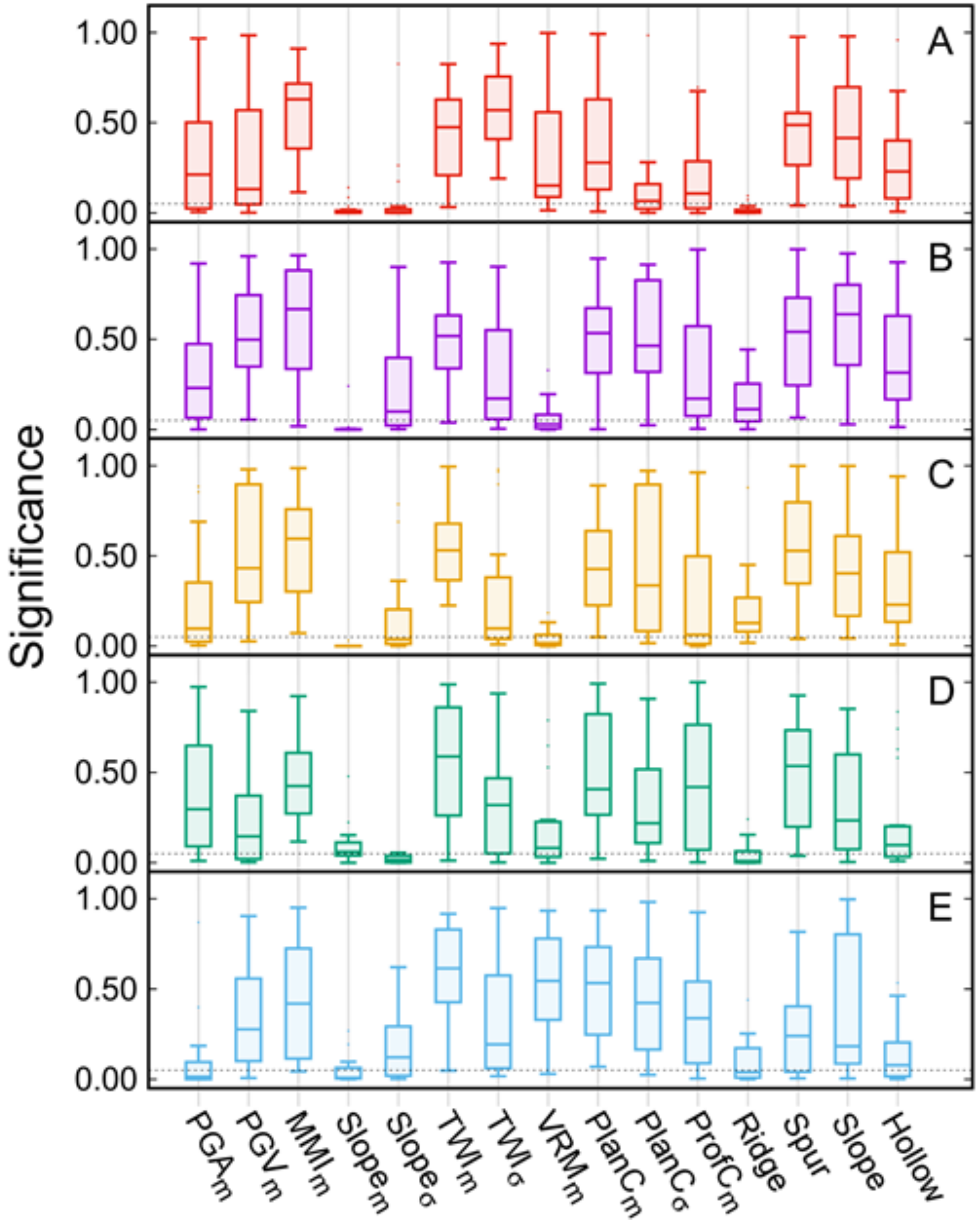
75% of 74 unstable SUs and equal number of stable SUs

20 iterations

Implementation of glm() function for 20 training samples

χ-square test to calculate p-values

20 dataset

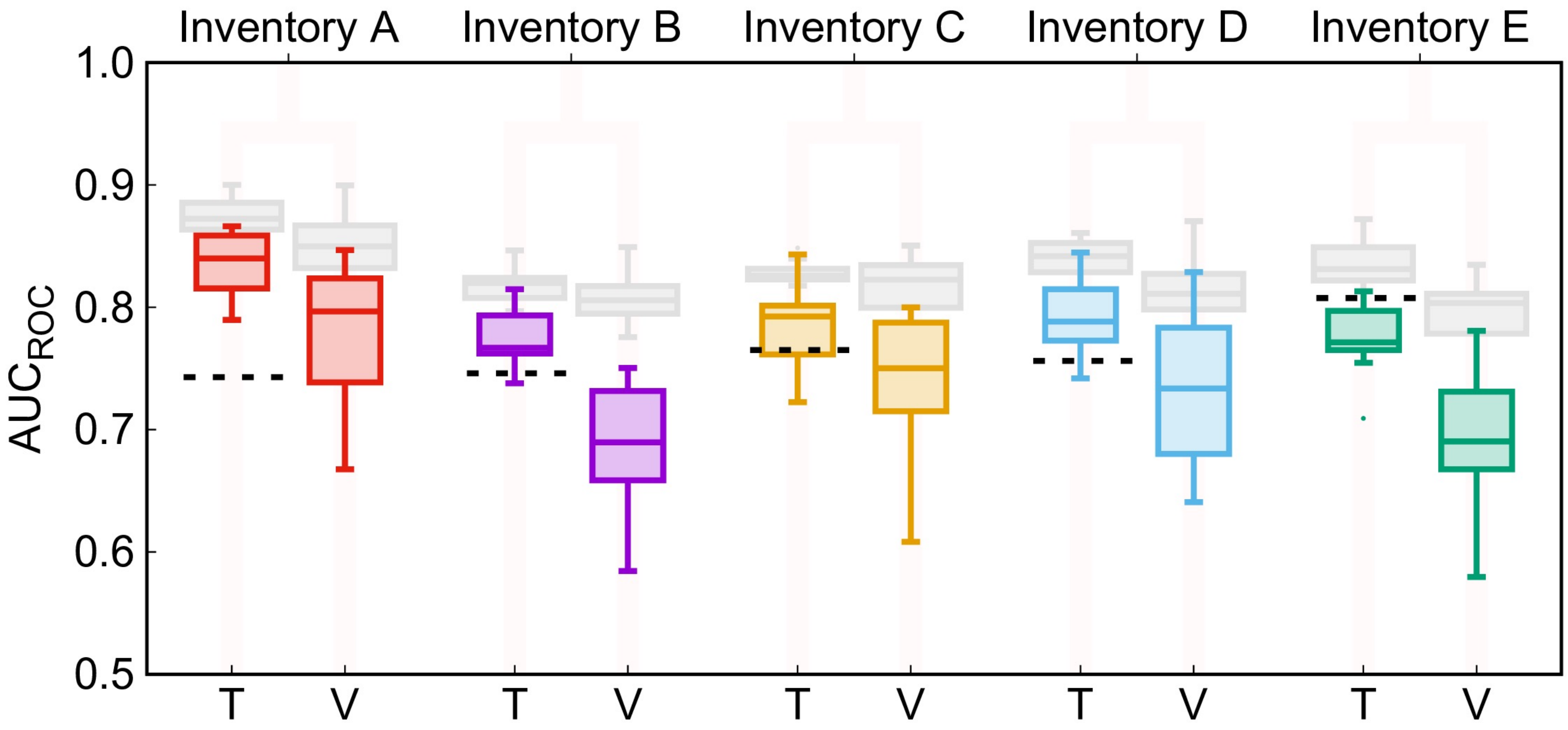


Pair-wise validation

		Validated by Inventory				
		A	B	C	D	E
Trained with Inventory	A	**0.78±0.03**	0.80±0.03	0.82±0.03	0.82±0.04	0.80±0.02
	B	0.83±0.03	**0.74±0.01**	0.80±0.03	0.71±0.02	0.80±0.03
	C	0.83±0.02	0.77±0.02	**0.74±0.03**	0.77±0.02	0.79±0.02
	D	0.88±0.03	0.81±0.03	0.81±0.03	**0.71±0.03**	0.80±0.03
	E	0.83±0.03	0.78±0.03	0.80±0.03	0.78±0.03	**0.77±0.02**

The table presents the mean with one standard deviation confidence level for the AUC_{ROC} obtained from each testing/validating pair, with 20-fold random selection.

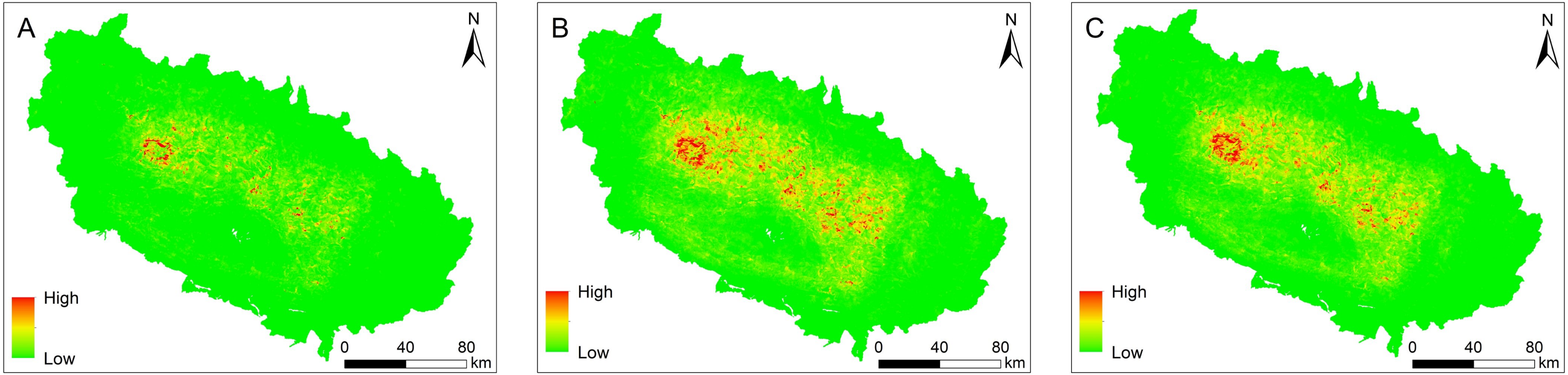
Performance of LSMs



Colored: 70% of stable or unstable SU as training

Grey: Smallest of stable or unstable as training

Dot: All SU



- We used LAND-SE software (Rossi and Reichenbach,2016) to generate LSM.

- Each SU is characterized by Landslide susceptibility index (LSI).

- The higher value of LSI indicates higher susceptibility.

Inventories	Mean	S.D
A	0.013	0.037
B	0.045	0.094
C	0.057	0.105

Conclusions

1. Reliability and interpretation of landslide susceptibility maps are influenced by the differences in the significance of the predictors.

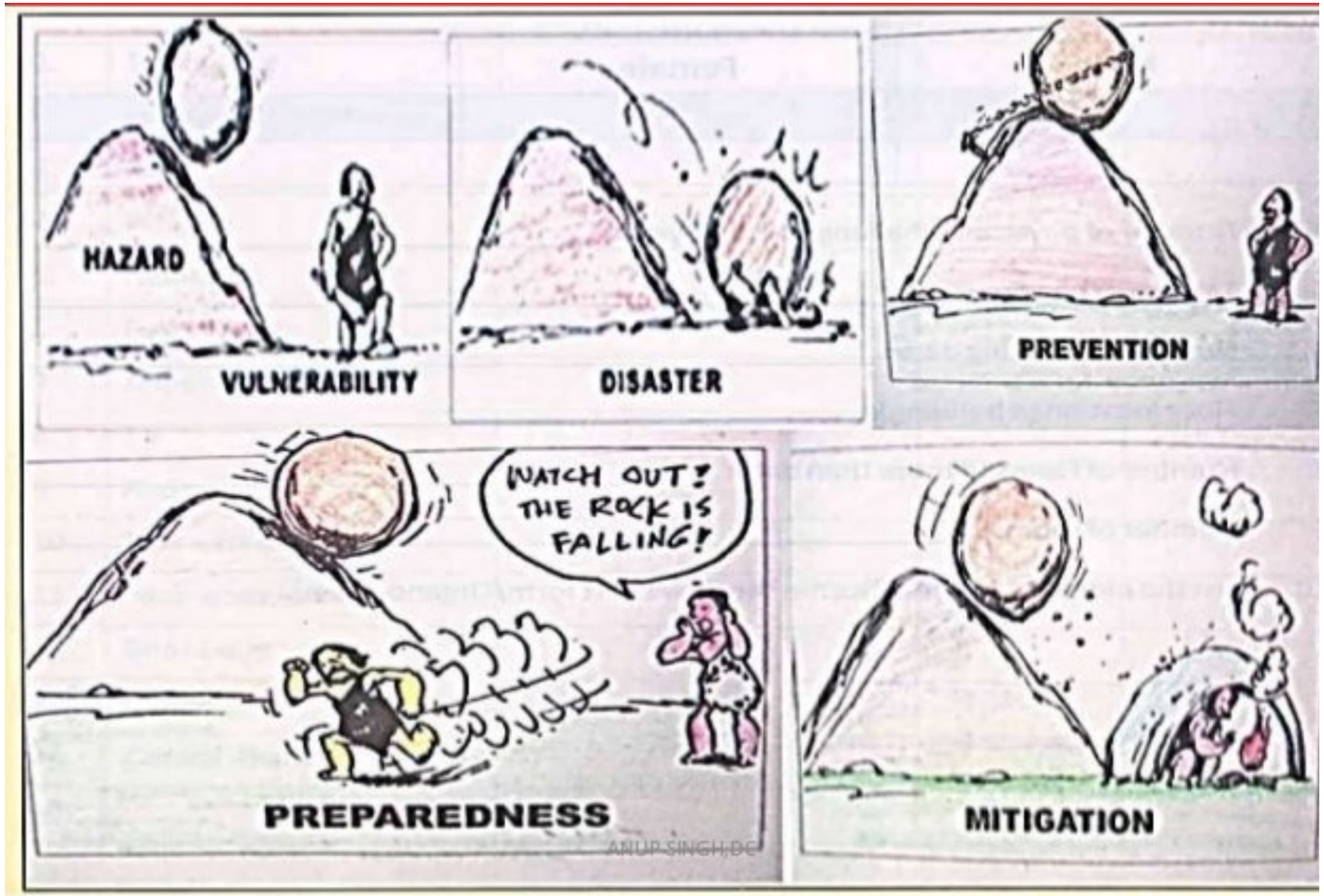
2. The values of AUC_{ROC} calculated from the different LSMs adopting different sampling techniques were also shown to have different average values and variability. All these points further exhibit that preparation of a landslide inventory is a subjective process.

3. The values of AUC_{ROC} calculated from the different LSMs adopting different sampling techniques were also shown to have different average values and variability. All these points further exhibit that preparation of a landslide inventory is a subjective process. Henceforth, the derived LSMs are subjective as well and depend on many factors.

Significant outcomes

(1) SU will be available on http://geomorphology.irpi.cnr.it/tools/slope-units

(2) We have a paper close to be accepted in a high-rank journal.



Source: https://www.slideshare.net/anupsingh3363/hvrc-analysis-for-school-safety

Thank you