



Introduction to modelling natural hazards

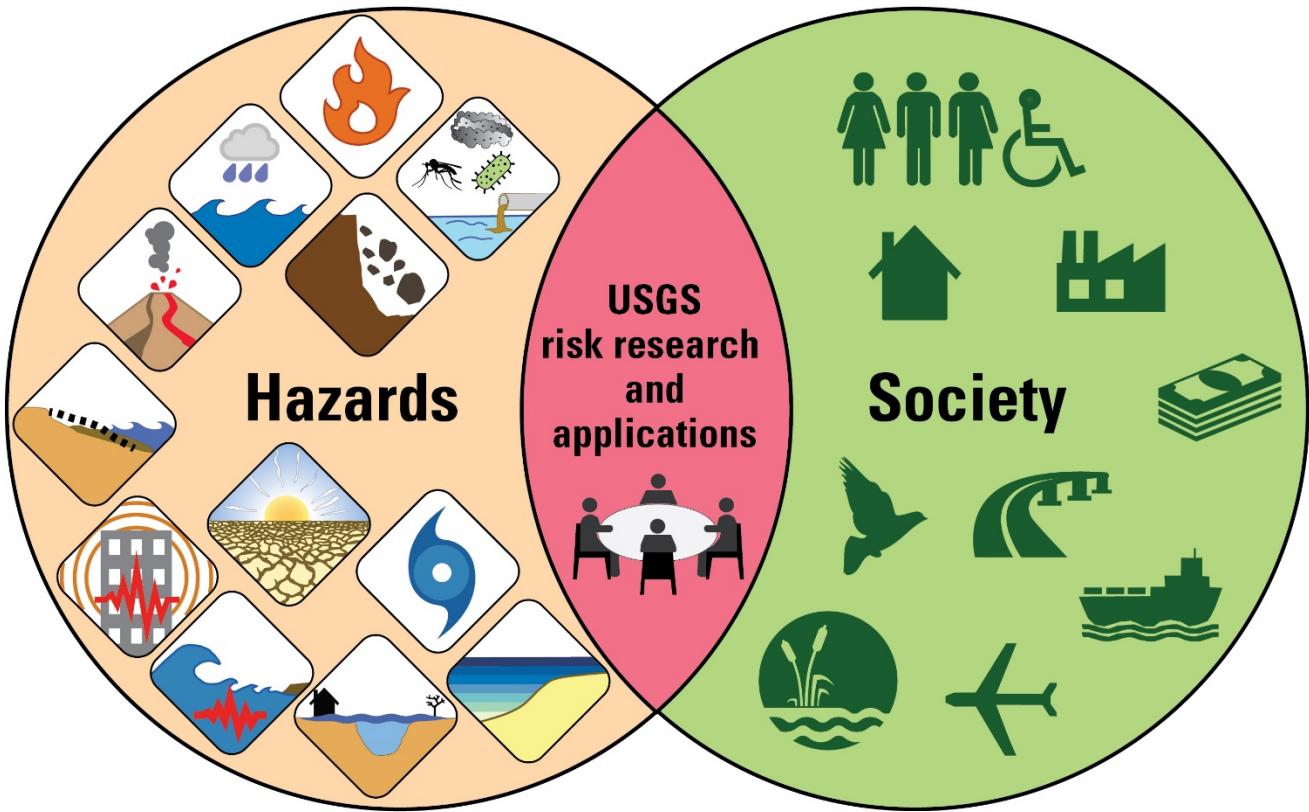
Helene (Petschko) Goetz
GIScience Jena

Learning objectives

After this lecture you will be able to ...

- Distinguish the term landslide susceptibility from hazard and risk
- Classify natural hazard modelling methods
- Describe the importance of ...
 - Input data (inventory, explanatory variables)
 - State of the art sampling designs within and outside of landslides
 - Modeling method (geo-statistical)
for the model result (map and performance measures)
- List model performance assessment methods
- Report the range of model uncertainty
- Design a geostatistical landslide susceptibility model (theoretically & practically after the workshop)

Natural hazards



Background

Every year naturally or anthropogenically triggered landslides cause damage on houses, linear infrastructure (roads, train tracks) or farmland

- worldwide but also in Austria (St. Lorenzen 2012; Feldbach & Lower Austria 2009; Gasen/Haslau 2005)
- not isolated events but spatially abundant

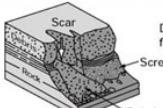
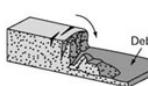
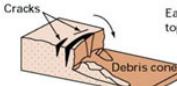
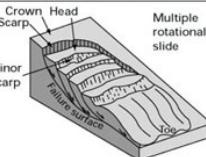
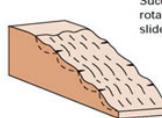
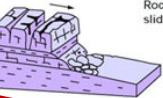
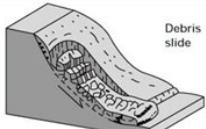
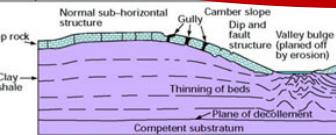
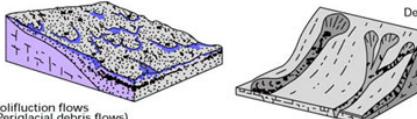
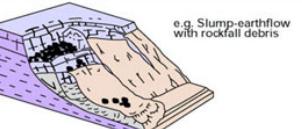


Motivation

- Gain knowledge on the **past** occurrence and distribution of **landslides**
- Detect possible **future affected areas/slopes** where more detailed analysis of the slope stability is necessary
- **Landslide susceptibility maps** as basis for well informed decisions of a municipality
 - Instead of reaction to events
avoidance of damage &
better preparedness to
possible landslide events



Landslide types

Material	ROCK	DEBRIS	EARTH
Movement type			
FALLS	 <p>Rock fall</p>	 <p>Debris fall</p>	 <p>Earth fall</p>
TOPPLES	 <p>Rock topple</p>	 <p>Debris topple</p>	 <p>Earth topple</p>
ROTATIONAL	 <p>Single rotational slide (slump)</p>	 <p>Crown Head Scarp Minor Scarp Failure surface</p> <p>Multiple rotational slide</p>	 <p>Successive rotational slides</p>
TRANSLATIONAL (PLANAR)	 <p>Rock slide</p>	 <p>Debris slide</p>	 <p>Earth slide</p>
SPREADS	 <p>Normal sub-horizontal structure Cap rock Clay shale Thinning of beds Plane of decollement Competent substratum</p> <p>Gully Camber slope Dip and fault structure Valley bulge (planed off by erosion) e.g. cambering and valley bulging</p>		
FLows	 <p>Solifluction flows (Periglacial debris flows)</p> <p>Debris flow</p>		
COMPLEX	 <p>e.g. Slump-earthflow with rockfall debris</p>		

Cruden & Varnes 1996

http://www.bgs.ac.uk/research/engineeringGeology/images/landslide_types_large.jpg

What is a landslide?

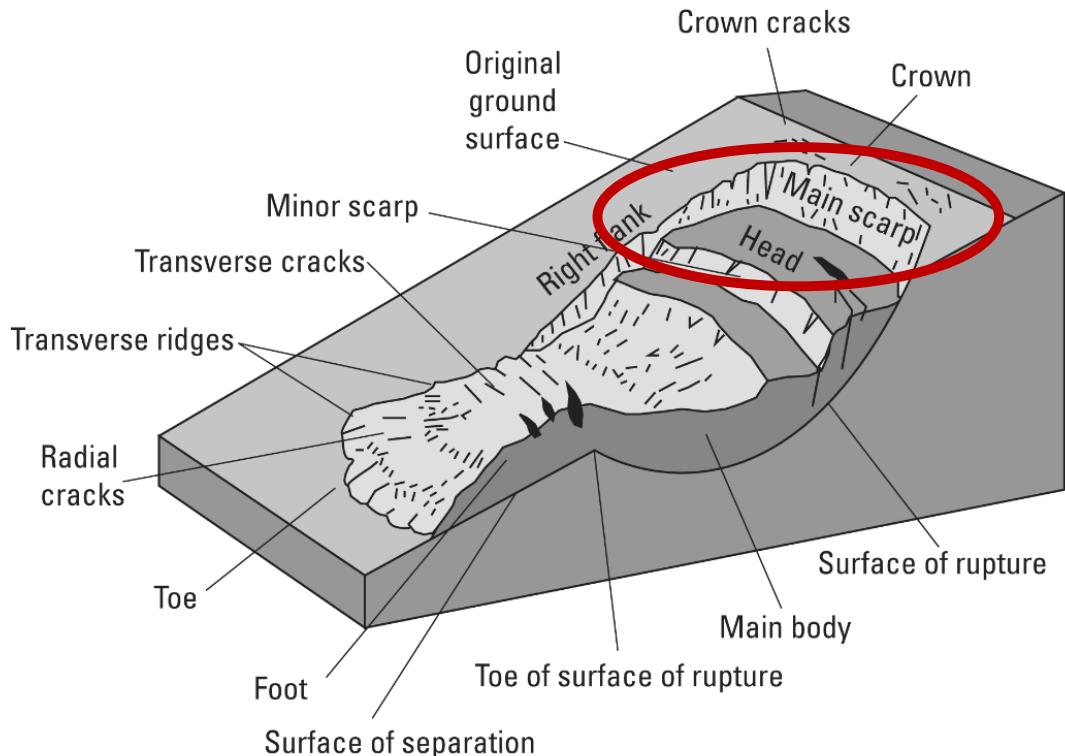


Figure 2. A simple illustration of a rotational landslide that has evolved into an earthflow. Image illustrates commonly used labels for the parts of a landslide (from Varnes, 1978, Reference 43).

Natural hazard maps

Inventory (Points, Polygons)



Susceptibility map



Hazard map



Exposure map or elements at risk

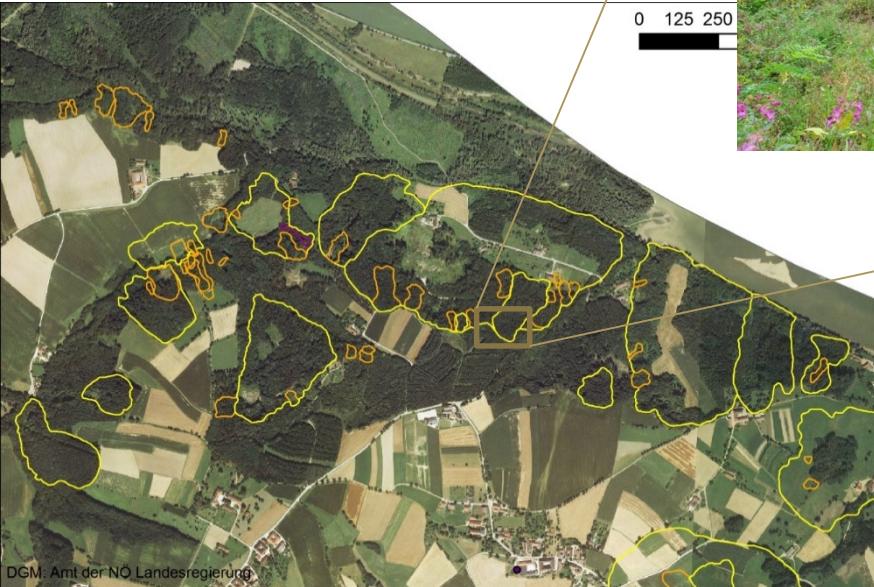


Risk map $R = f(H_i, V_i)$

Landslide inventories

- The most important data
- WHERE have landslides occurred historically
- Ideally complete inventory – NEVER the case
→ at least representative inventories necessary
- Different mapping methods: (Guzzetti et al. 2012)
 - Mapping in the field: topographic map, GPS, Laser-distancemeasurements combined with GPS
 - Desktop mapping: orthophotos, satellite imagery, stereoscopic interpretation of satellite imagery, high resolution DTMs

Landslide inventories LiDAR DTM based



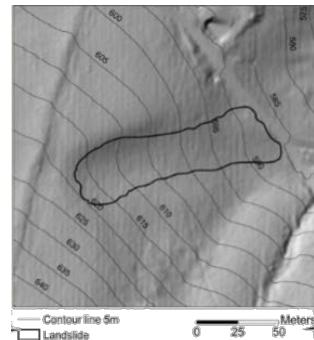
Bias in input data and modelling results

Inventory:

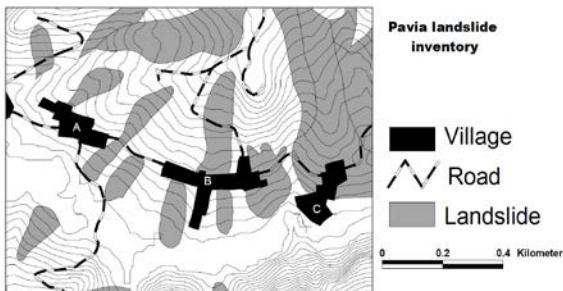
- Completeness of the landslide inventory varies depending on
 - source: archive, search of news reports, mapping on LiDAR DTM, mapping on orthophotos
 - Mapping team

Explanatory variables:

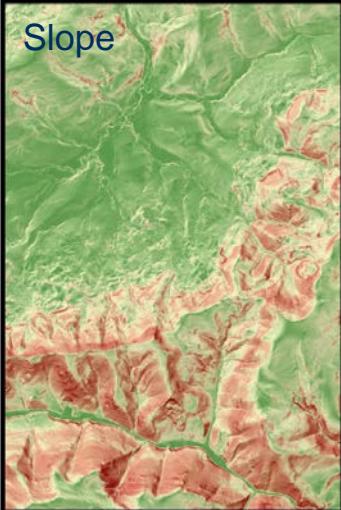
- Match of landslide occurrence conditions with explanatory variables (e.g. landuse)



Perugia landslide inventory



Slope



Northness

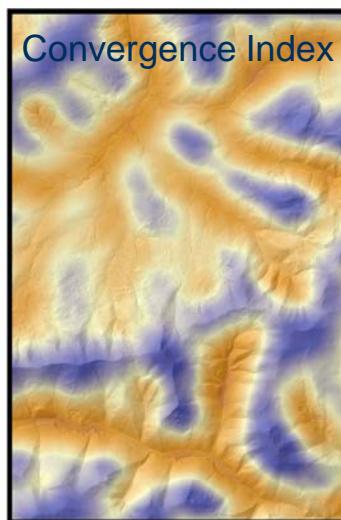


Curvature

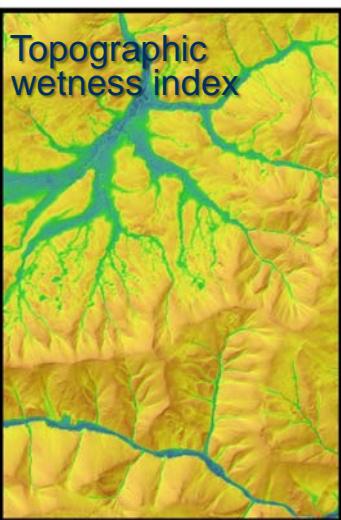


Explanatory Variables (examples)

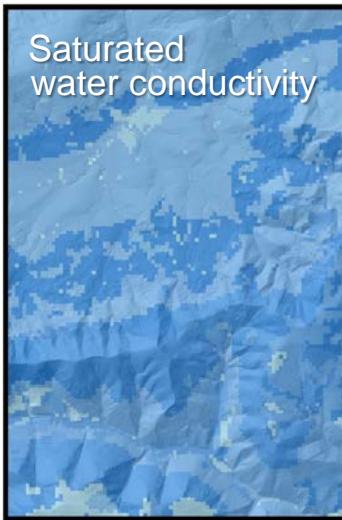
Convergence Index



Topographic wetness index



Saturated water conductivity



Kilometer

A horizontal scale bar with tick marks at 0, 0.6, 1.2, 1.8, and 2.4 kilometers.

Landslide susceptibility ...

[...] is the likelihood of a landslide occurring in an area on the basis of local terrain conditions” (Brabb, 1984)

[...] is the probability of spatial occurrence of slope failures, given a set of geo-environmental conditions.” (Guzzetti, 2005)

→ Frequency and magnitude of the landslides remain unknown!

Landslide susceptibility maps (LSM) can be implemented in spatial planning.



© Canli, 2012



© Montafon, 2010

Theoretical background Susceptibility modelling

Uniformitarianism:

“The past is the key to the future” (Hutton, Lyell)

→ used in statistical modelling methods:

Past location of landslides used to predict
future location

Principles of slope instability:

Shear stress/shear strength (Coloumb, Terzaghi)

Stability states and destabilizing factors (Crozier, 1986)

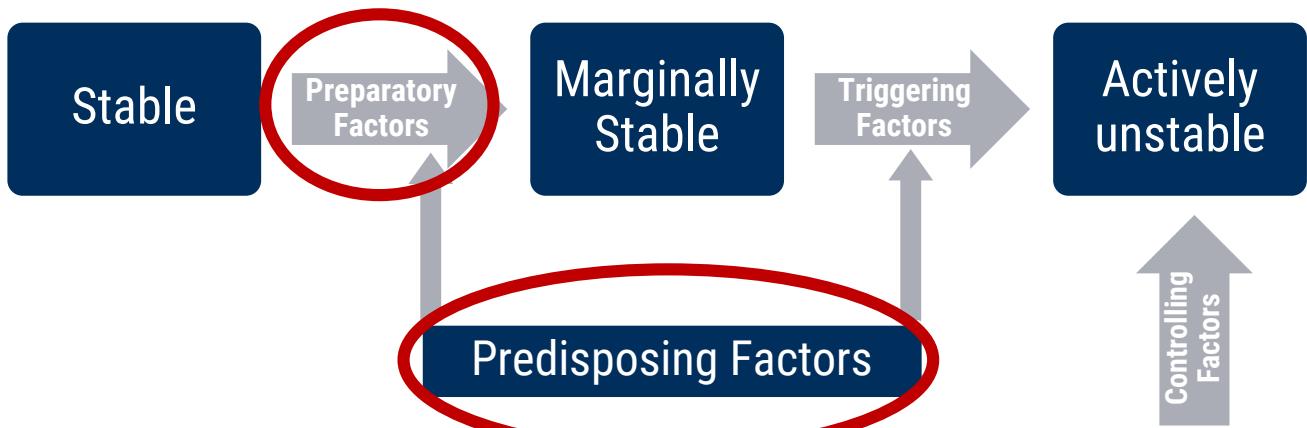
→ gives basic concept for identification of “geomorphologically relevant”
variables

Theoretical background Susceptibility modelling

Mass Movement Theory –

Stability states and destabilizing factors (based on Crozier, 1986)

Margin of Stability



Statistical landslide susceptibility modelling

"All models are wrong, but some are useful..." (Box, 1979)

- Heuristic methods
 - Expert opinion (weighting of variables), Index method
 - Geo-statistical methods of spatial modelling
 - **representative** knowledge on the location of landslides and the extent of landslide free areas in the past necessary
 - Physically-based methods
 - Soil mechanics, hydrological properties of the subsurface need to be determined to calculate shear stress/strength of the material under different conditions
-
- Regional**
(country,
province,
municipality)
to local
(slope)
Global?
- Local (slope)
to
Regional

Modelling steps – your way to a susceptibility map

Data collection, landslide mapping (response variable), Datenaufbereitung (explanatory variables)



Sample (Point(s) in landslide (value 1) and points outside landslides (value 0) with a 1:1 ratio); extract values of explanatory variables to points



Generalised additive **modell** to predict where landslides are 0 – 100 % probable



Model performance assessment (spatial cross validation)



Transfer of the prediction to all raster cells; Classification in **landslide susceptibility classes** for the **landslide susceptibility map**



Statistical landslide susceptibility modelling

- Weights of Evidence
- Logistic Regression

Traditional methods

- Generalised Additive Models

Mix providing non-linearity

- Artificial Neuronal Networks
- Support Vector Machines
- Regression trees or random forest

Machine learning methods

(Brenning 2005, 2008)

—

Statistical landslide susceptibility modelling

- Linear logistic regression (response variable $y = (0|1)$)

$$\log \frac{p(y_i | x_{i1}, \dots, x_{ip})}{1 - p(y_i | x_{i1}, \dots, x_{ip})} = \beta_0 + x_{i1}\beta_1 + \dots + x_{ip}\beta_p$$

- Generalised additive modell (response variable $y=(0|1)$)

$$\log \frac{p(y_i | x_{i1}, \dots, x_{ip})}{1 - p(y_i | x_{i1}, \dots, x_{ip})} = \beta_0 + f_1(x_{i1}) + \dots + f_p(x_{ip})$$

Statistical landslide susceptibility modelling

Generalized additive models (GAM)

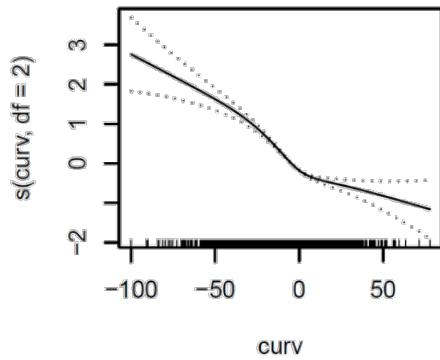
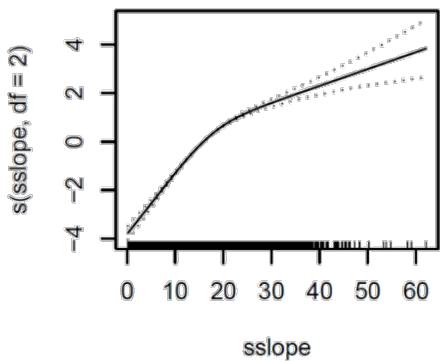
(Hastie & Tibshirani 1990, Brenning 2008, Goetz 2011)

Comparable to logistic regression

BUT: GAM includes nonlinearities
in the relationship between
explanatory and response variable

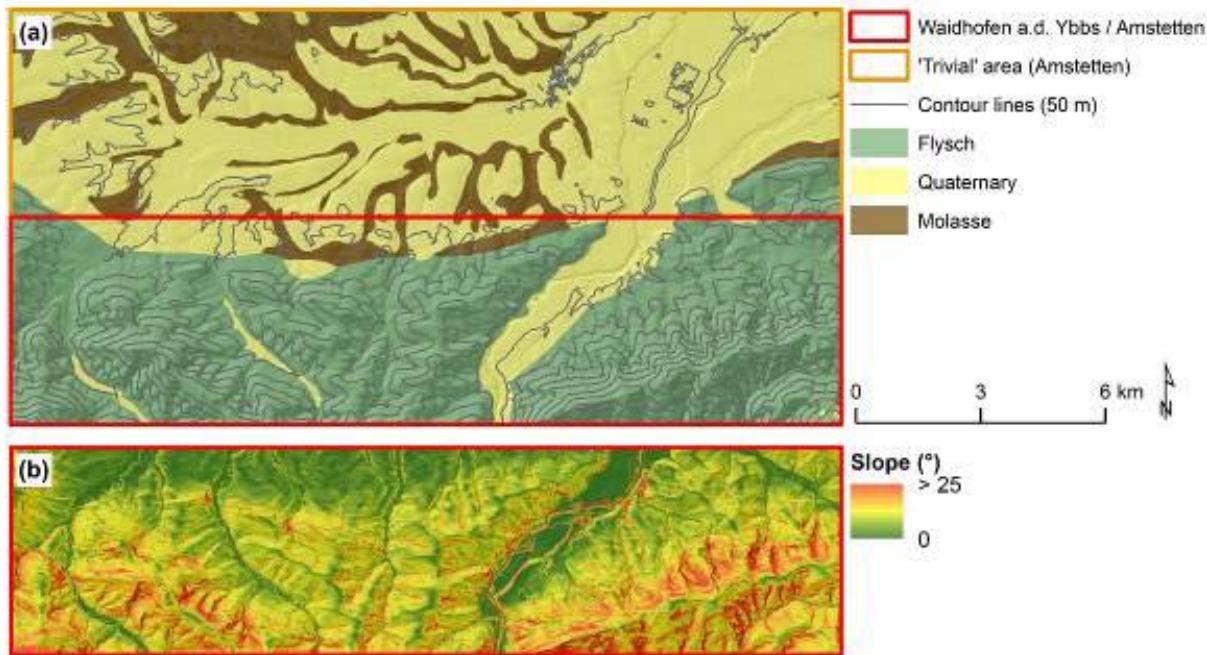
Model design:

- Random sampling of points within and outside of landslides (1:1)
- Stepwise variable selection
- Cell size 10 m x 10 m



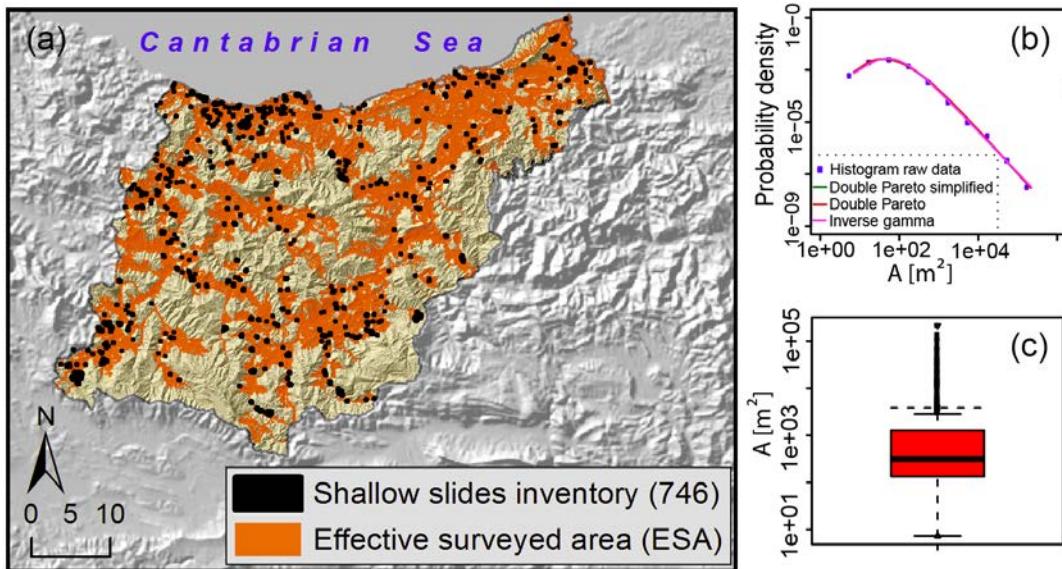
Sampling design stable areas (outside of landslides)

- Avoid sampling in “trivial areas” (Steger et al. 2017)



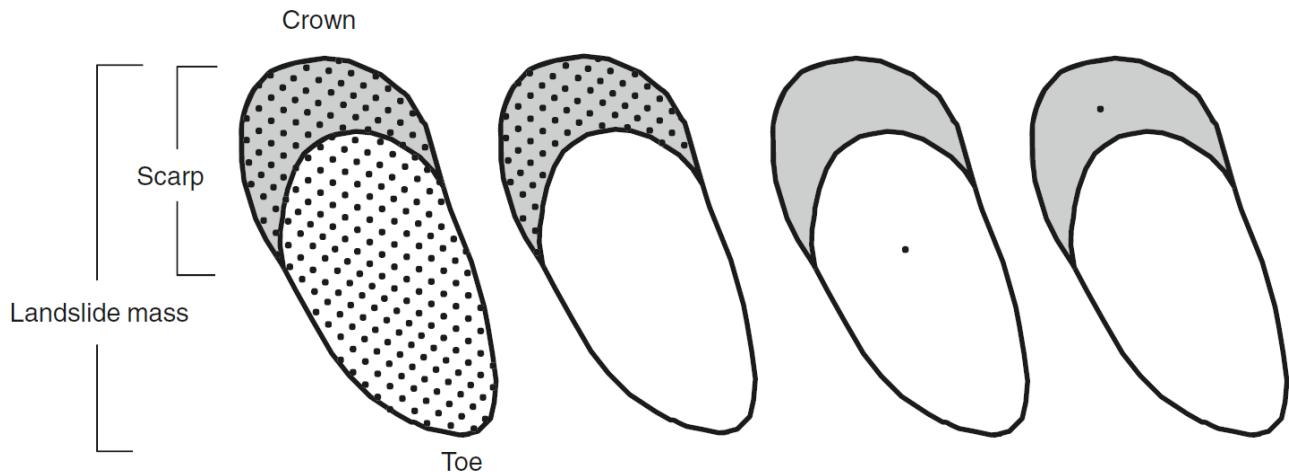
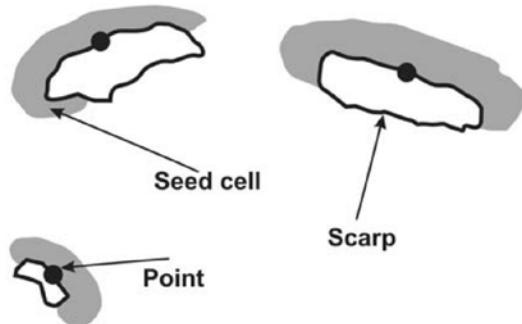
Sampling design stable areas (outside of landslides)

- Know where landslides were mapped (and where not; e.g. definition of visible area from the mapped landslides after Bornaetxea et al. 2018)



Sampling design within landslides

- Scarp, body, entire polygon, seed cell
- One point, multiple points per area
- Centroid or center of mass, highest point random point(s)



Assessment of the quality of susceptibility maps

(Spatial) transferability of model...

... is the ability to fit a model in one training area / point sample and apply it to a test area / point sample which has comparable geo-environmental conditions

How good does my model fit to “new” landslides?

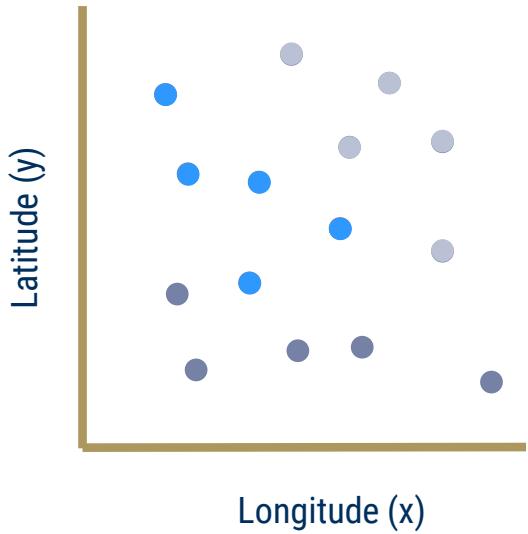
→ k -fold cross-validation



Why do we need to validate?

Common approach

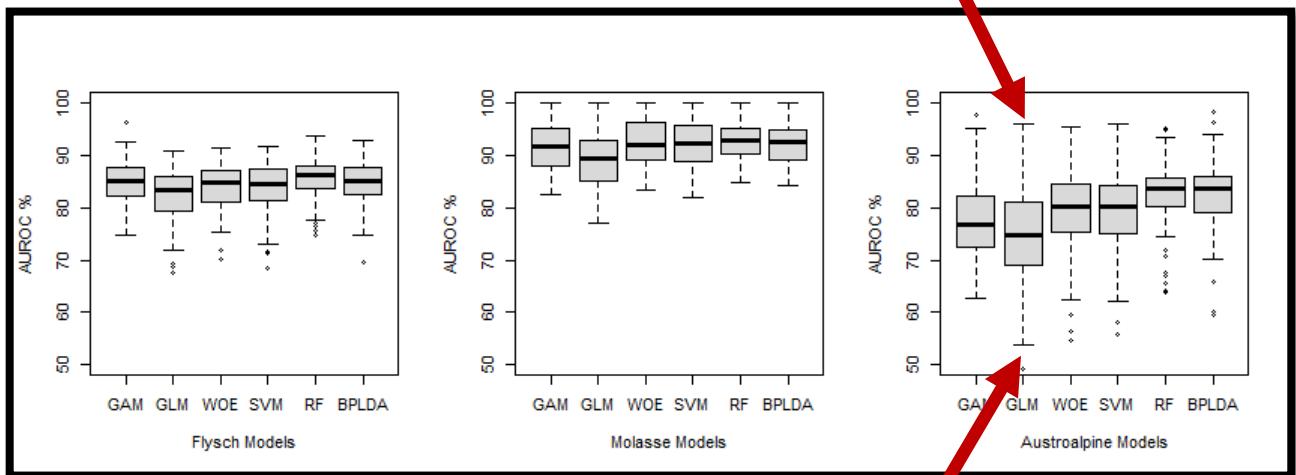
- Holdout method
- k -fold cross-validation



Do you feel lucky?

Is your model really good, or is it just by chance?

Performance measure



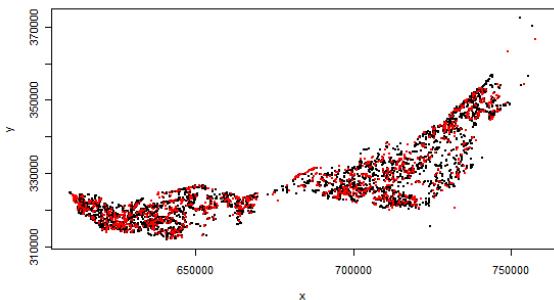
53% to 96% AUROC

Repeated k -fold cross-validation

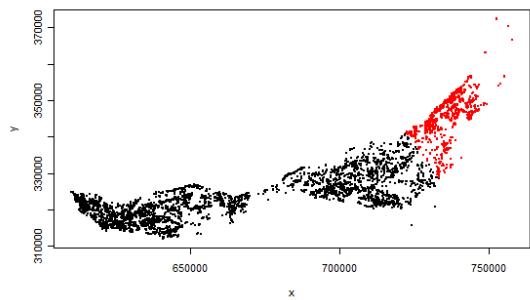
Calculation and comparison of area under the receiver operating characteristic curve (AUROC) values (0-1)

5-fold validation: $k-1$ folds to train the model, 1 fold to test the model

Random partitioning



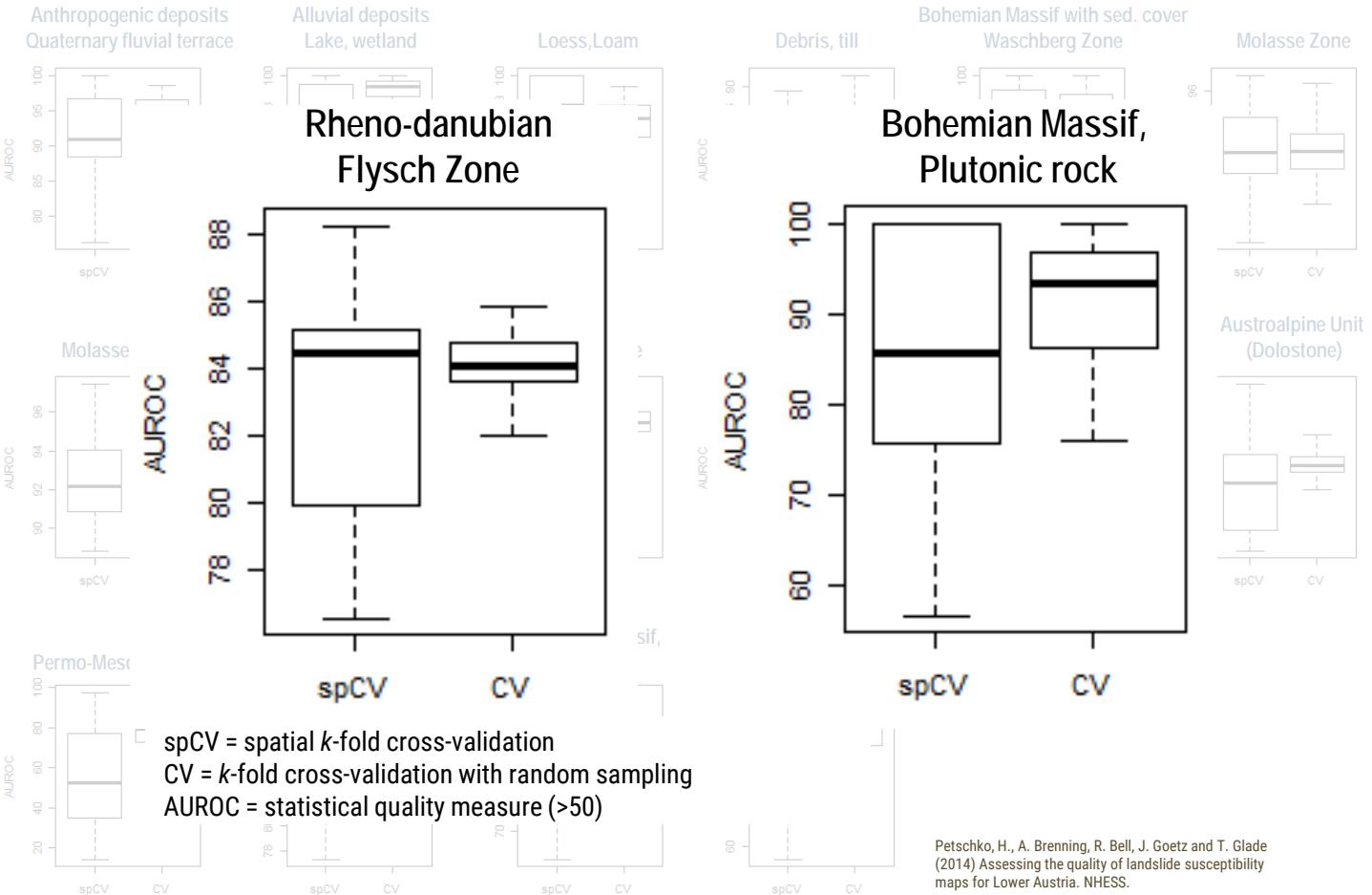
Spatial partitioning



20 repetitions = 100 model (GAM) runs

(Brenning 2005, Brenning 2012)

(Spatial) transferability



Bias in input data and **modelling results**

Artefacts due to

- bias in input data (inventory, explanatory variables) → geomorphic plausibility
- Sampling design (within and outside of landslide samples)
- Modelling method

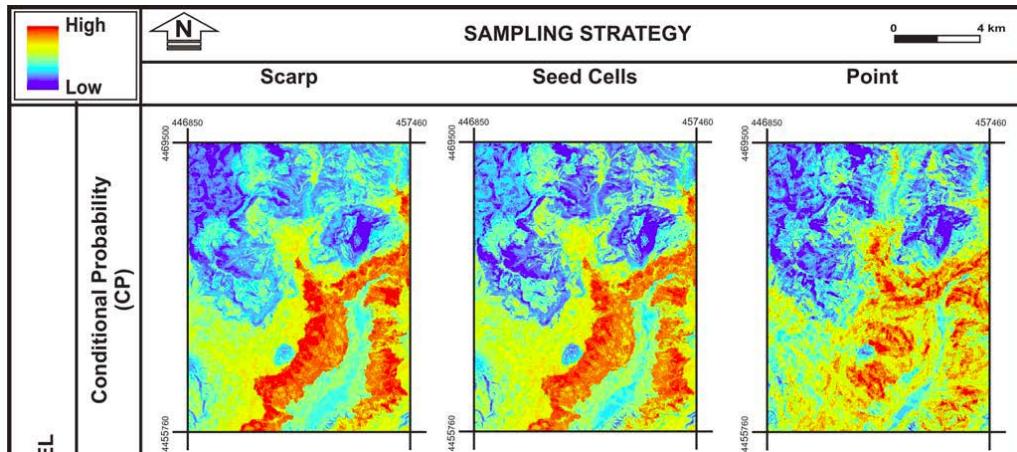
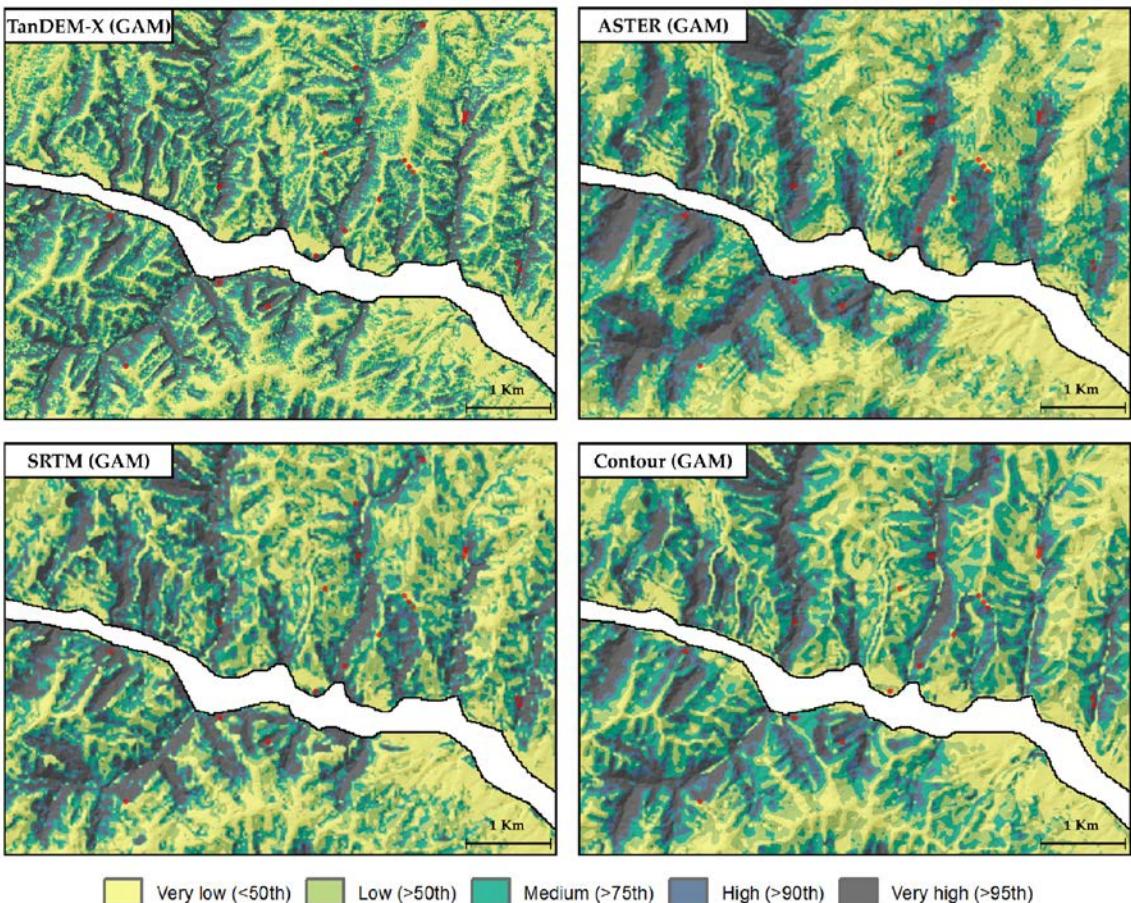
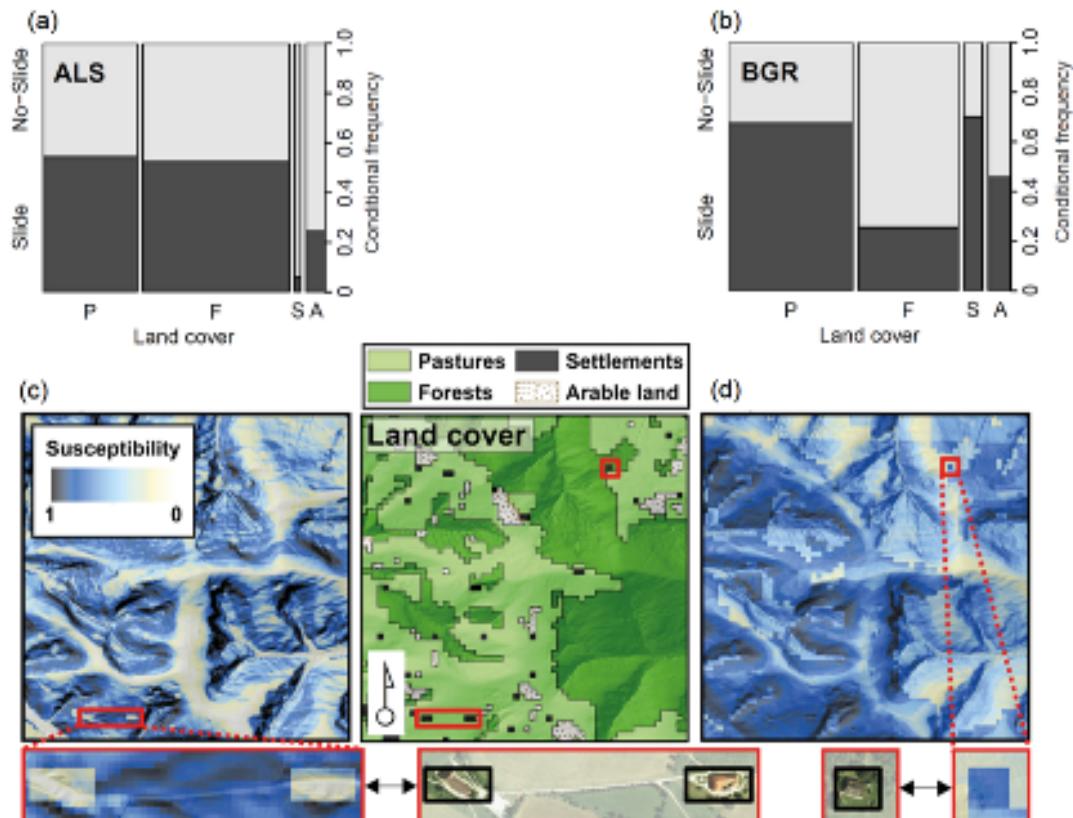


Figure from Yilmaz I (2010) The effect of the sampling strategies on the landslide susceptibility mapping by conditional probability and artificial neural networks. Environ Earth Sci 60:505–519



..: Classified landslide susceptibility maps at slope scale for each DEM, generated through GLM and GAM. Red points indicate previous landslides.

Geomorphic plausibility of resulting map



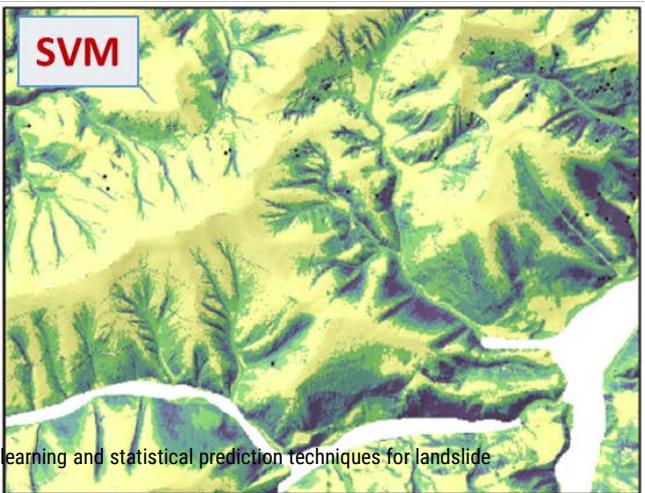
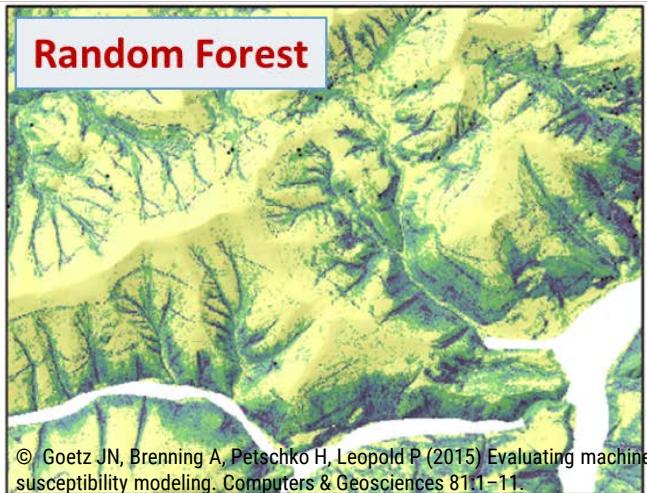
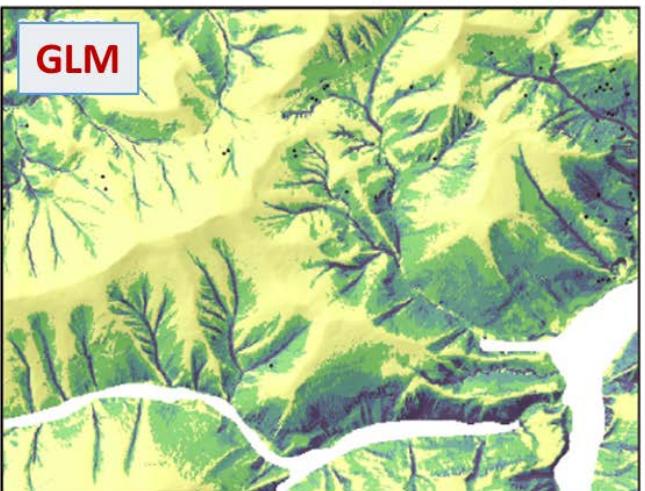
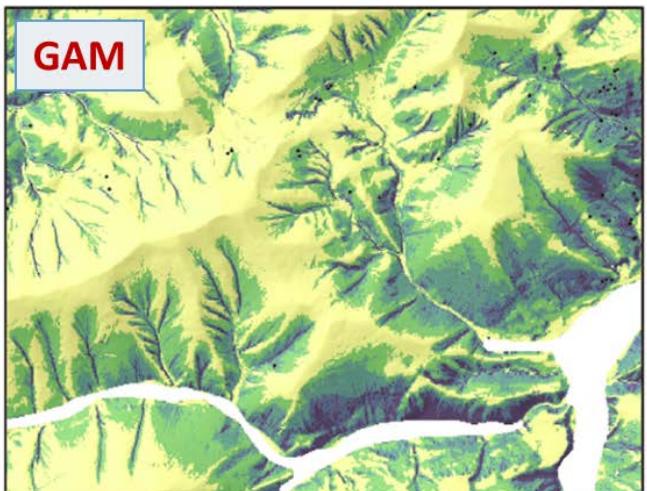
Landslide susceptibility index (Percentile) - AUSTROALPINE

Very low (<50th) Low (>50th) Medium (>75th) High (>90th) Very high (>95th)

Landslide initiation point

1,000

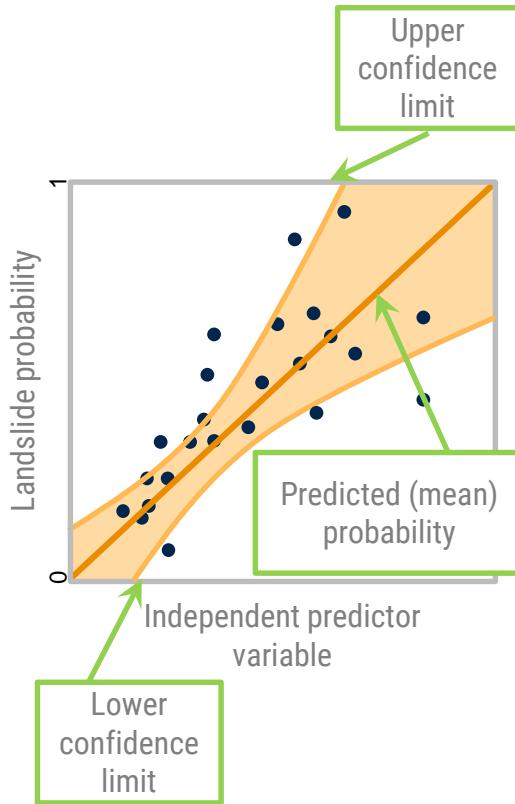
Meters



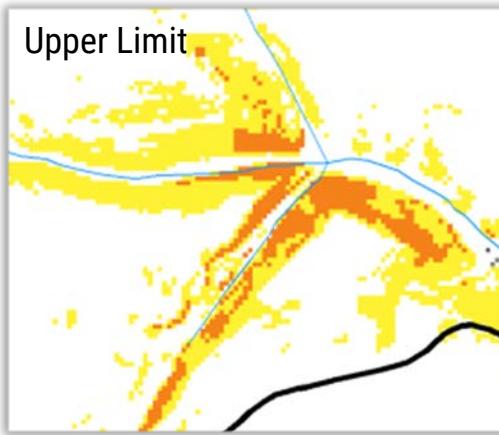
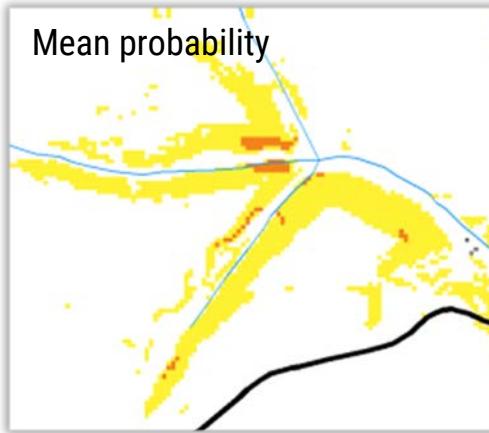
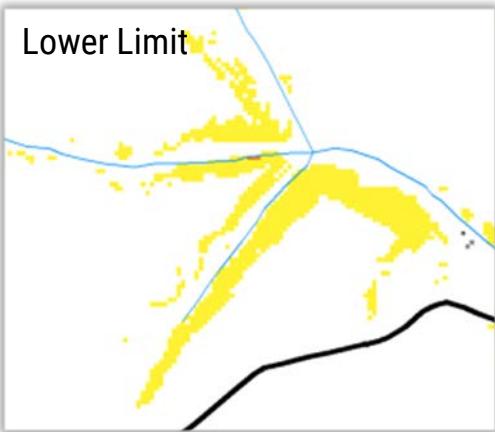
Model uncertainty and its influence on classified susceptibility maps

Estimate approximate 95% confidence limits

- Standard error of the prediction for each raster cell
- Calculated estimated 95% upper and lower confidence limits using the standard error
- Classified landslide susceptibility map using probability threshold values from "original" predicted (mean) probability map
 - three landslide susceptibility maps



Model uncertainty and its influence on classified susceptibility maps

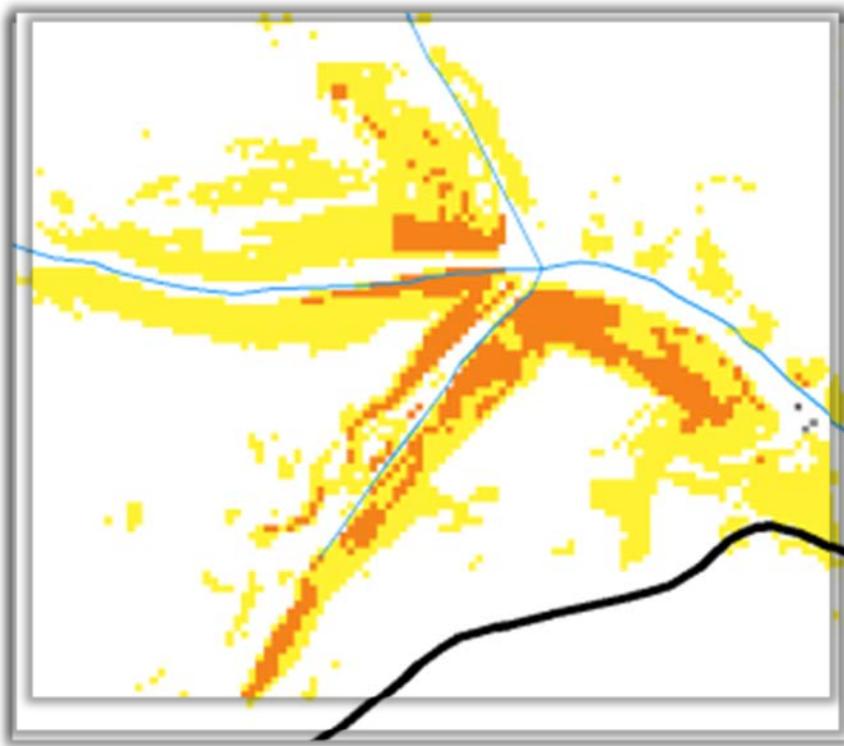


95% Confidence interval

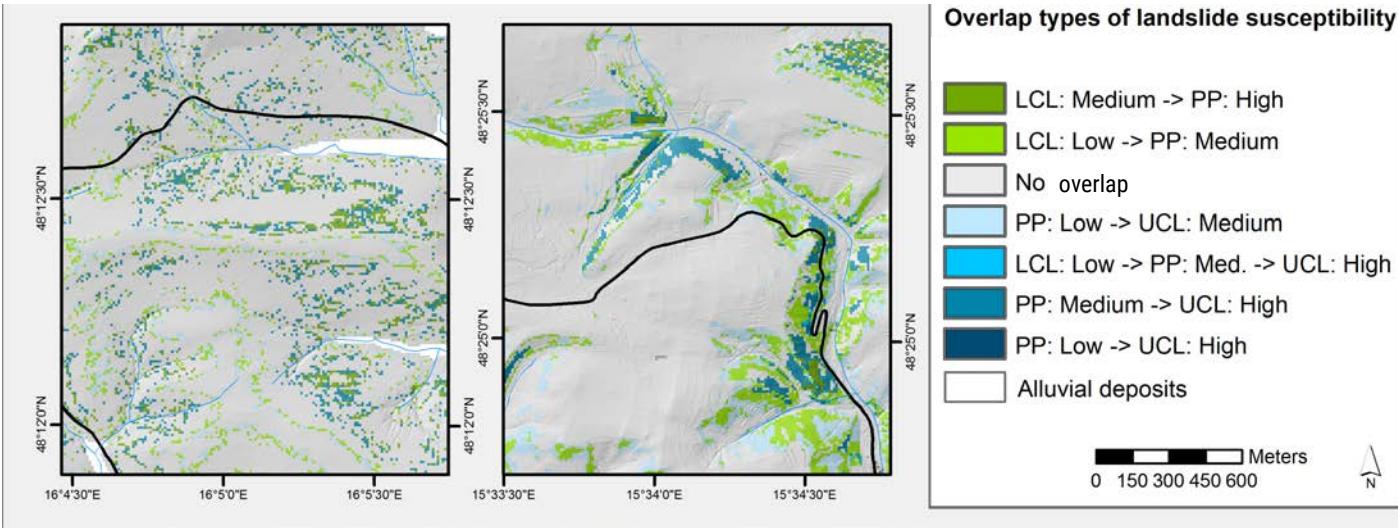
White = Low landslide probability
Yellow = medium landslide prob.
Orange = high landslide prob.

1 Pixel = 10m

Model uncertainty and its influence on classified susceptibility maps



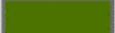
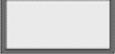
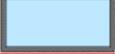
Model uncertainty and its influence on classified susceptibility maps



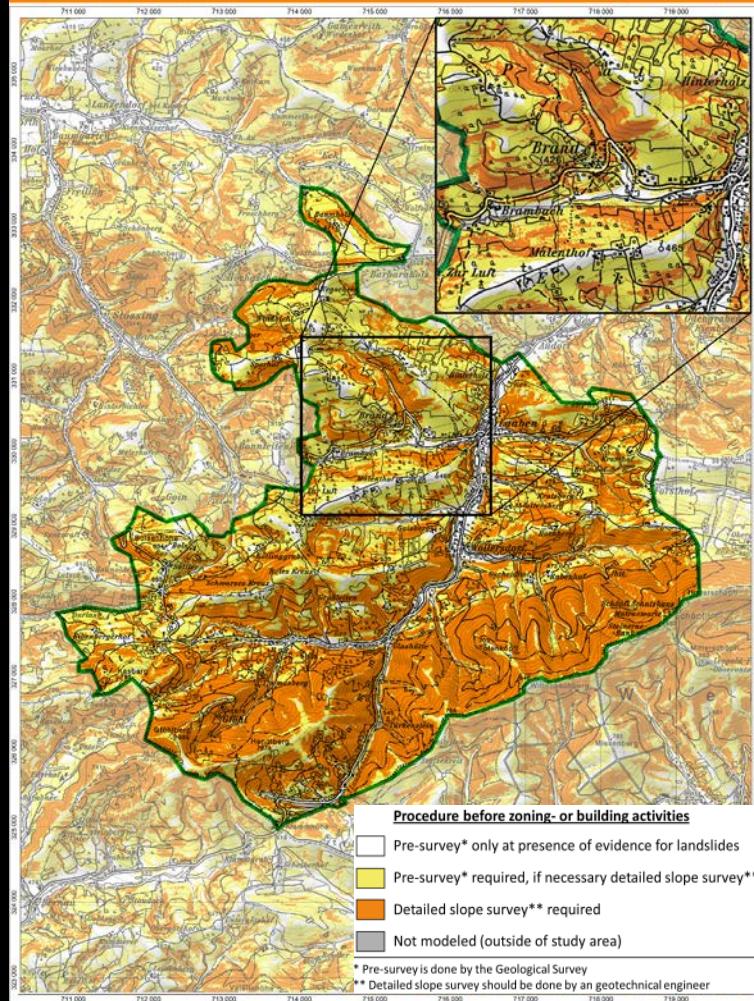
LCL: Lower confidence interval limit
PP: Predicted mean probability
UCL: Upper confidence interval limit

Model uncertainty and its influence on classified susceptibility maps

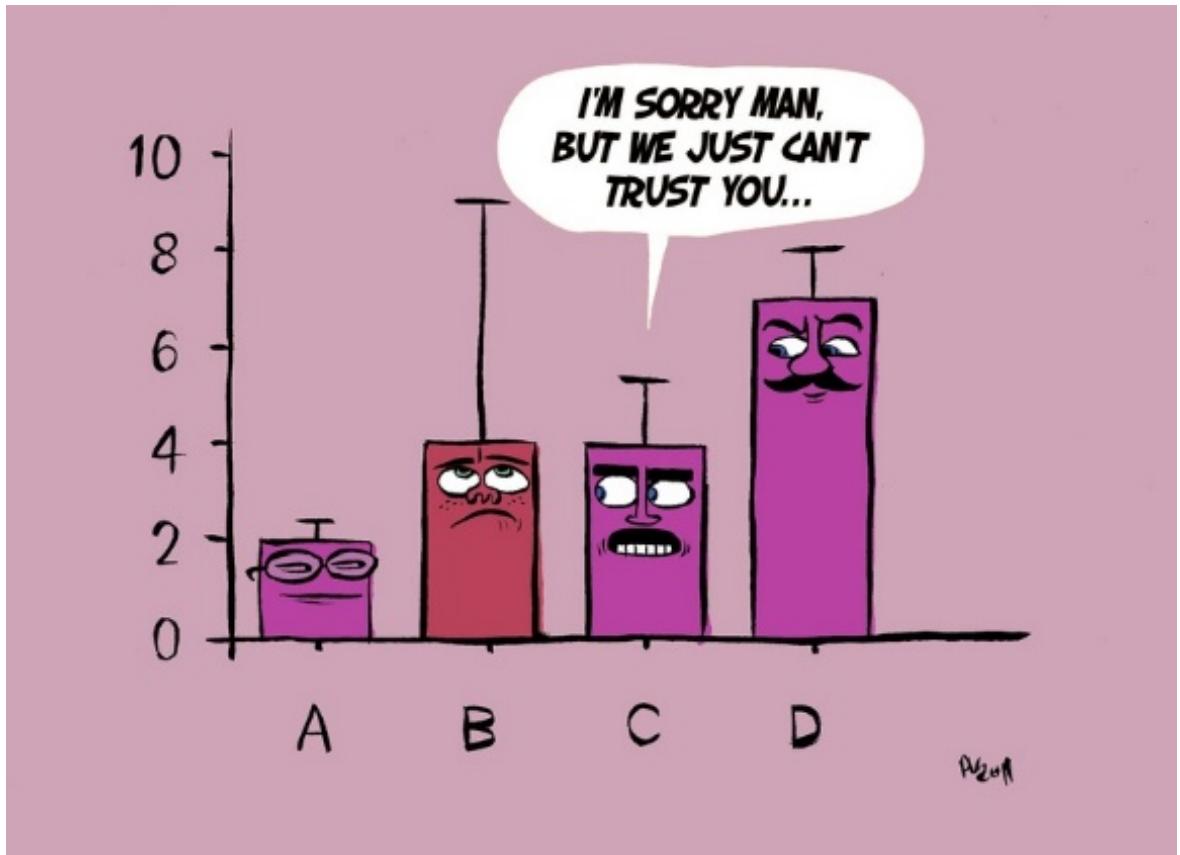
Percent of raster cells

	LCL: Low → PP: High	0.02
	LCL: Medium → PP: High	2.00
	LCL: Low → PP: Medium	5.00
	No change	85.00
	PP: Low → UCL: Medium	6.00
	LCL: Low → PP: Medium → UCL: High	0.40
	PP: Medium → UCL: High	2.00
	PP: Low → UCL: High	0.03





Lessons Learnt





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Thank you!

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Materials:
daad_summerschool/2_day/4_ps/nat_haz/



Landslide research @ GIScience

Topics

- **Predictive geostatistical landslide susceptibility modelling** to create landslide susceptibility maps for spatial planning purposes
- **Estimating the importance of predisposing and triggering factors** of landslides (distance to highways, climate change, land use change, topography,...) with geostatistical models
- Improving model comparisons using **advanced model performance assessments**
- Increasing the **understanding of model uncertainties** of statistical landslide susceptibility models

Current Projects

- LaCCiLUC „Network for Environmental Modeling of Earth Surface Processes: Landslide Hazards in the Context of Climate and Land Use Change“**

BMBF (03/2017 – 02/2019).

PI: GIScience FSU Jena

Partner: codematrix GmbH, Institute of Geography der Romanian Academy and Department of Geography, University of Vienna.

- EASICLIM „Eastern Alpine Slope Instabilities under Climate Change“**

Austrian Climate Research Programme – ACRP (04/2017 – 03/2019).

PI: Wegener Center for Climate and Global Change, University Graz

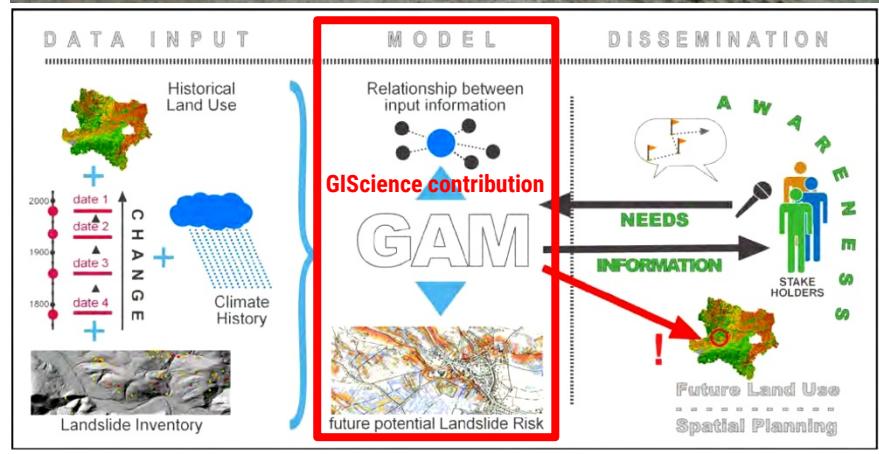
Partner: JOANNEUM RESEARCH, AIT, GIScience FSU Jena

- ILLAS „Integrating Land use Legacies in Landslide Risk Assessment to support Spatial Planning“**

ACRP (04/2017 – 03/2020).

PI: AIT Austrian Institute of Technology

Partner: JOANNEUM RESEARCH, GIScience FSU Jena, Institute of Social Ecology (SEC) BOKU





Methods and Geocomputation in R

- Spatial Statistical Modelling (Generalized Linear Model (logistic regression), Generalized Additive Models)
- Machine Learning (Boosting, Random Forest, Support Vector Machine)
- Model performance assessment: **spatial k-fold cross validation** (implementation of R software extension *sperrorest*)
- Developed R packages
 - RSAGA (using SAGA GIS within R)
 - RQGIS (using QGIS within R)
 - Parallelized spatial error estimation and variable importance assessment (*sperrorest*)
 - odds ratio calculation (*oddsratio*)



Study areas

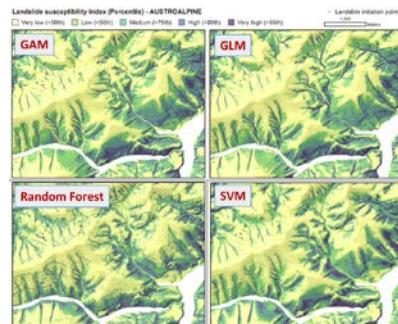
- Vancouver Island (Canada)
- Southern Ecuador
- Lower Austria
- Paldau (Styria, Austria)
- Romanian sub-Carpathians



Recent Publications

Landslide susceptibility modelling

- Steger S, Brenning A, Bell R, Glade T (2017) **The influence of systematically incomplete shallow landslide inventories on statistical susceptibility models and suggestions for improvements.** Landslides
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