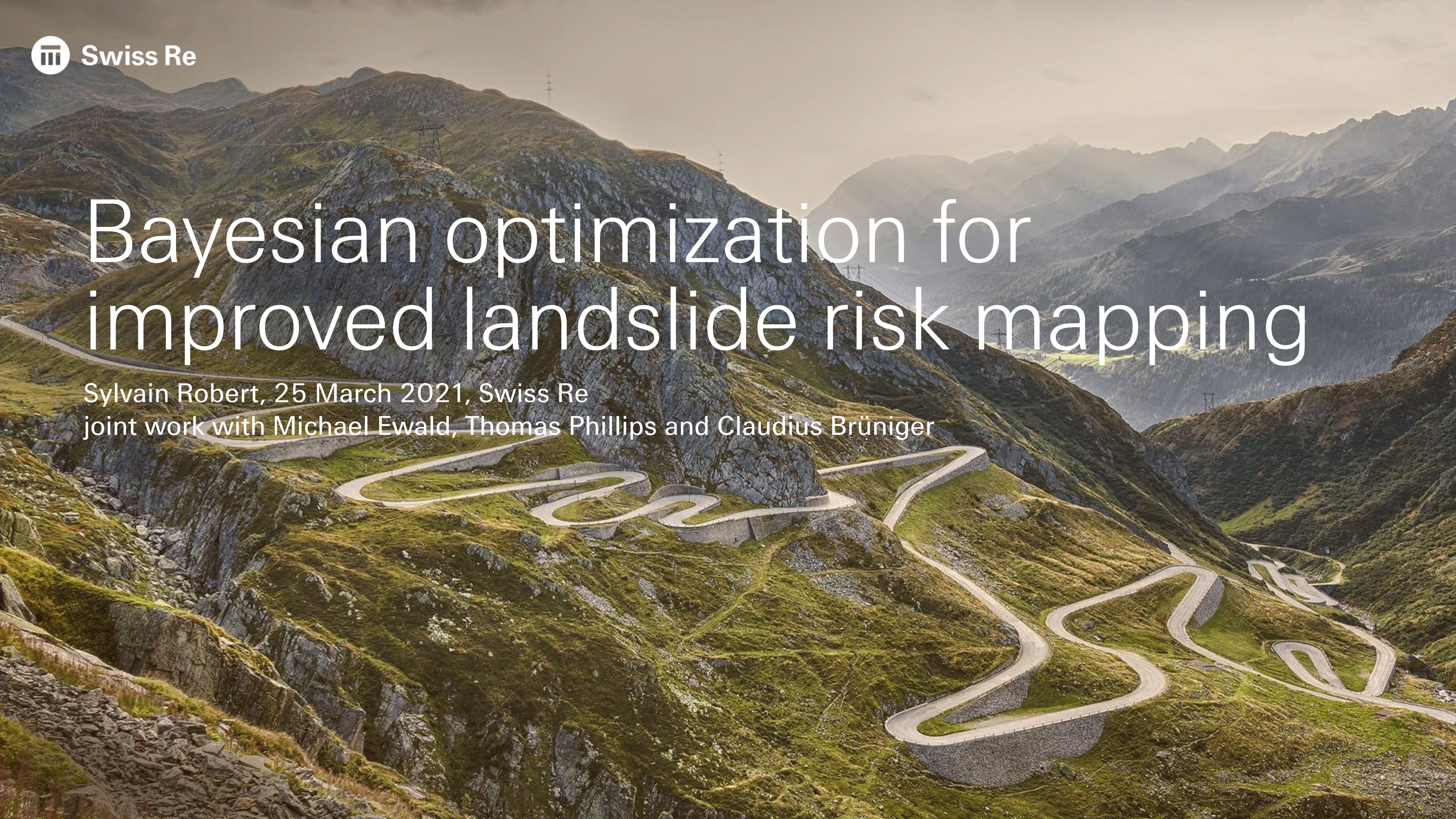
Swiss Re



# Bayesian optimization for improved landslide risk mapping

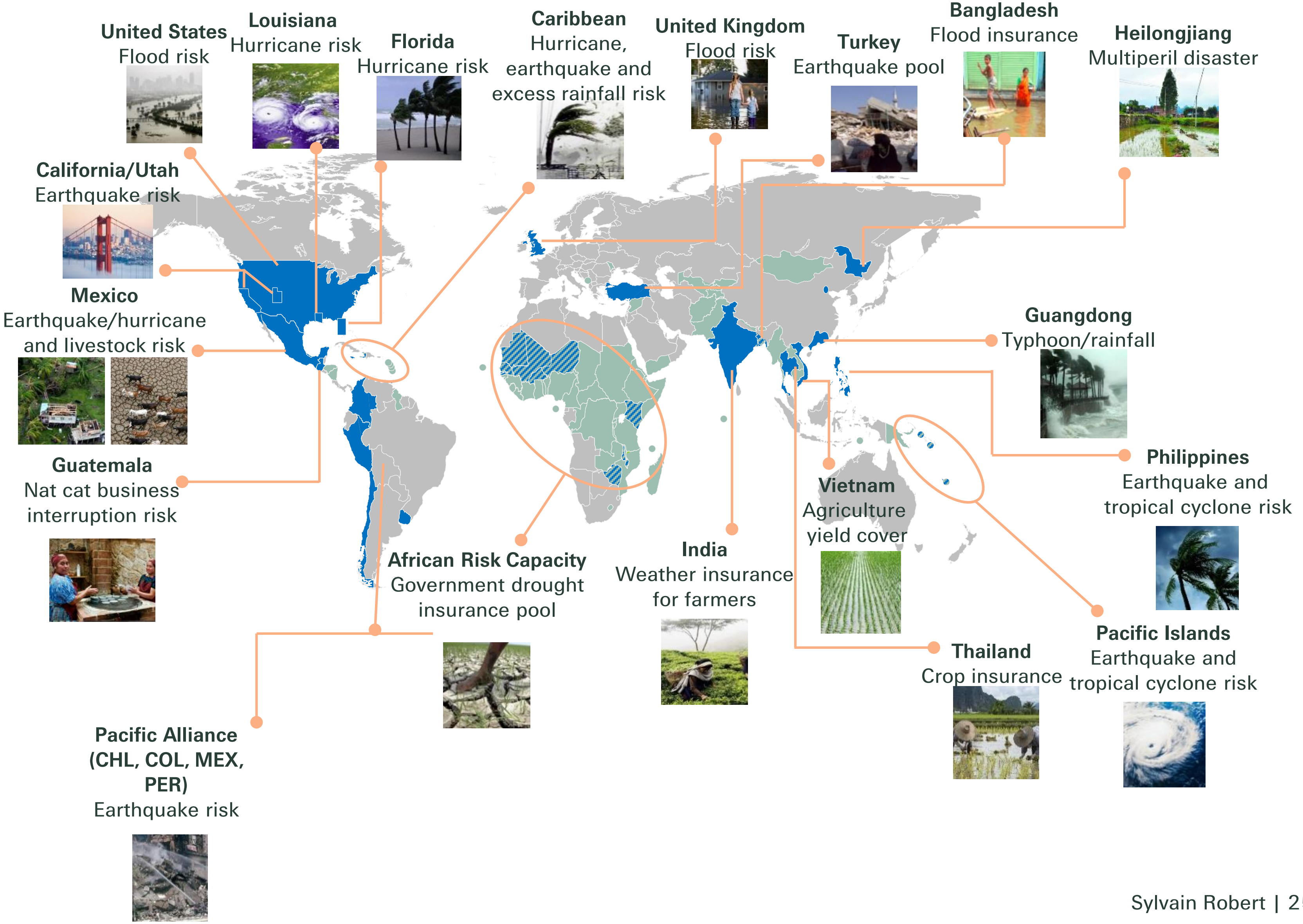
Sylvain Robert, 25 March 2021, Swiss Re
joint work with Michael Ewald, Thomas Phillips and Claudius Brüniger

# Outline

- Business context
- Methodology
- Results
- Conclusions

# Business context

# Swiss Re is a major reinsurer of natural catastrophe events

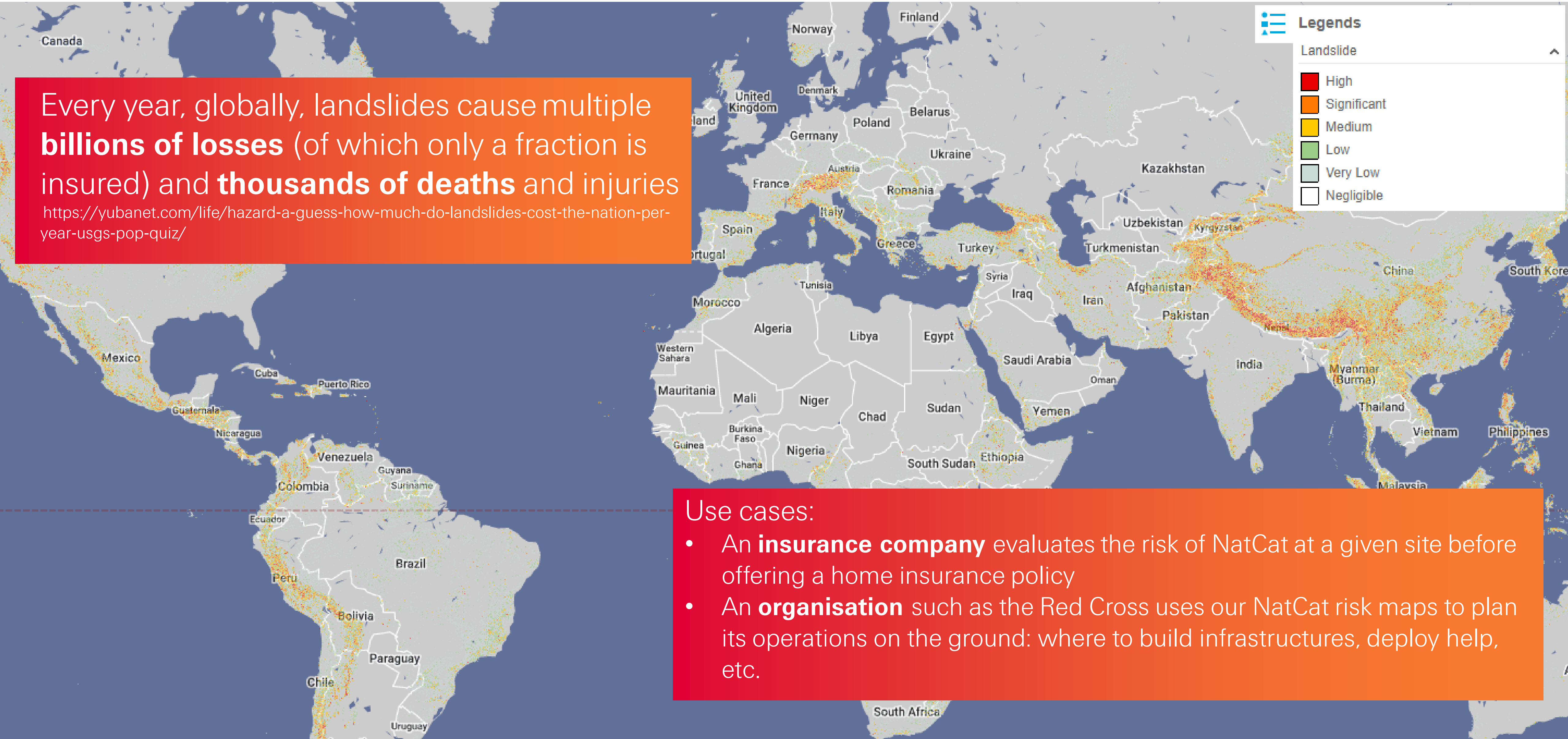


# Over 50 % of Nat Cat losses came from secondary perils in 2017 and 2018...


... still “secondary”?

# Landslide risks mapping in CatNet®

Every year, globally, landslides cause multiple **billions of losses** (of which only a fraction is insured) and **thousands of deaths** and injuries
https://yubanet.com/life/hazard-a-guess-how-much-do-landslides-cost-the-nation-per-year-usgs-pop-quiz/




Use cases:

- An **insurance company** evaluates the risk of NatCat at a given site before offering a home insurance policy
- An **organisation** such as the Red Cross uses our NatCat risk maps to plan its operations on the ground: where to build infrastructures, deploy help, etc.

# Methodology

# Landslide risk mapping for insurance

We make a distinction between two types of landslide risks:

- The **susceptibility risk** is the risk of a landslide starting at a given location
- The **runout risk** is the risk of a location to be hit by a landslide

For insurance (and risk management) purpose, the runout risk is the most important! Usually houses are not built on slopes, but at the bottom…

High susceptibility risk

High runout risk

La Conchita – 1995 – California
Source: R.L. Schuster/U.S. Geological Survey

# From landslide susceptibility to landslide runout

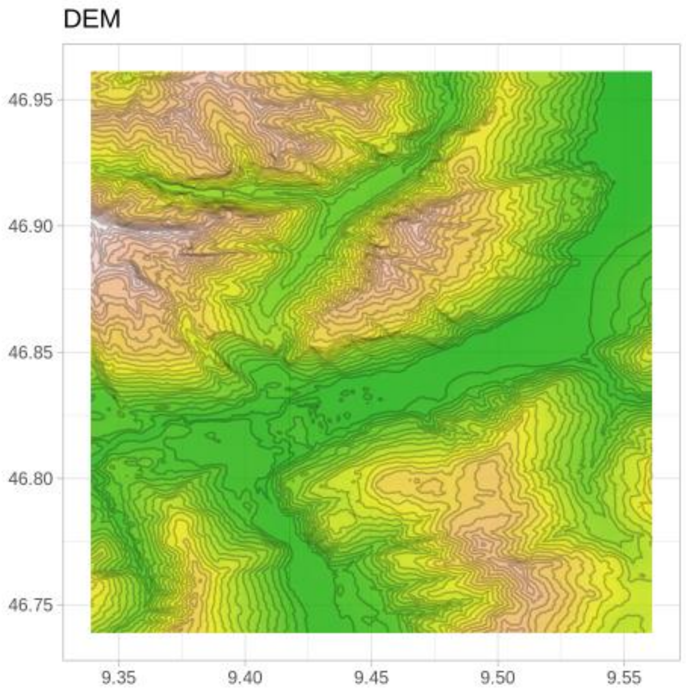
## Susceptibility risk mapping

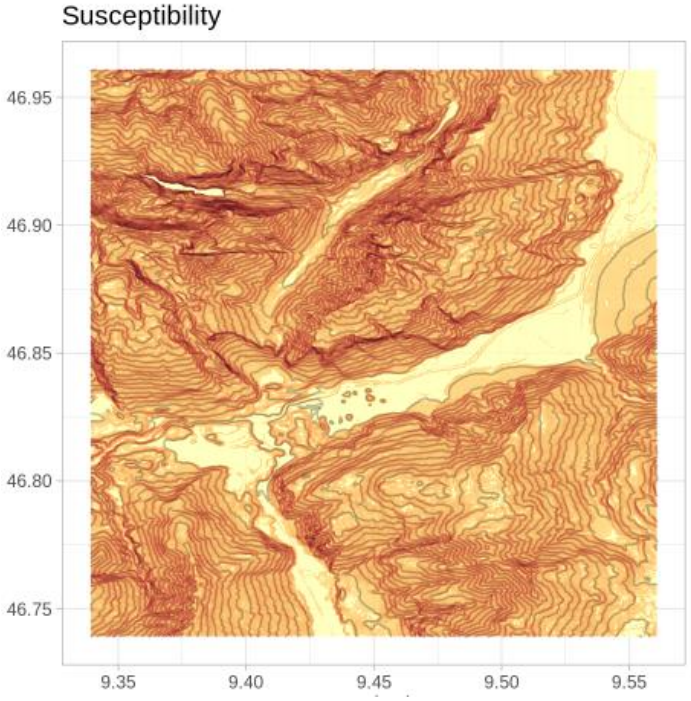
(previous work done by Emanuel Bueechi)

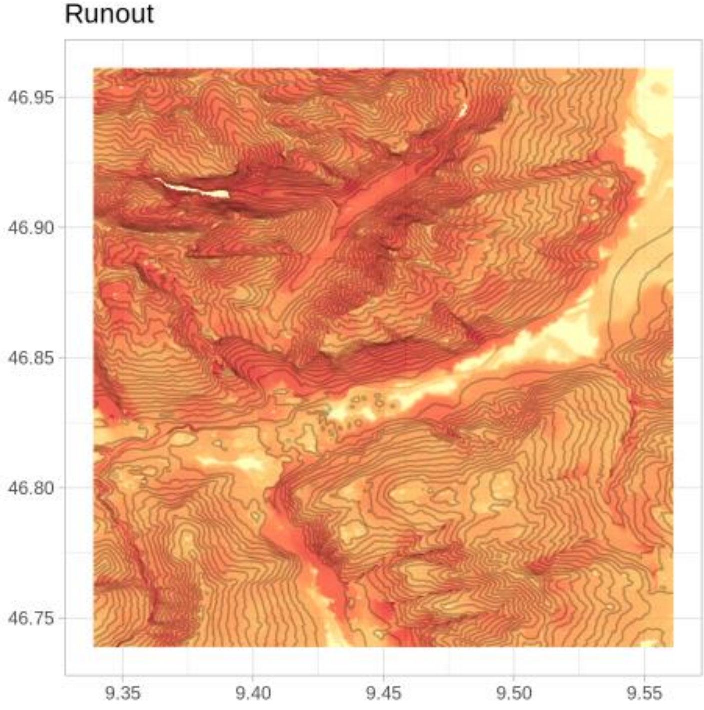
$$\text{Susceptibility} = \text{f(slope, geology, earthquake risk, rainfall risk)}$$

## Runout risk mapping

new approach based on a simplified dynamical model of runout flow



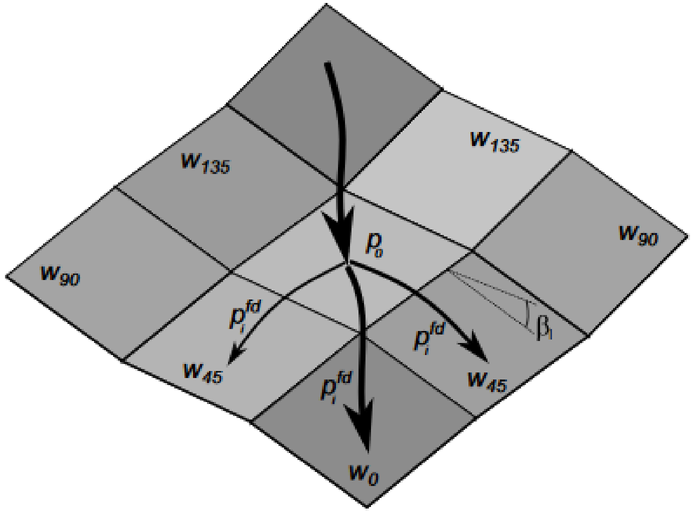
# Simplified runout model

Ideally we would use a physical model of runout flow. But...

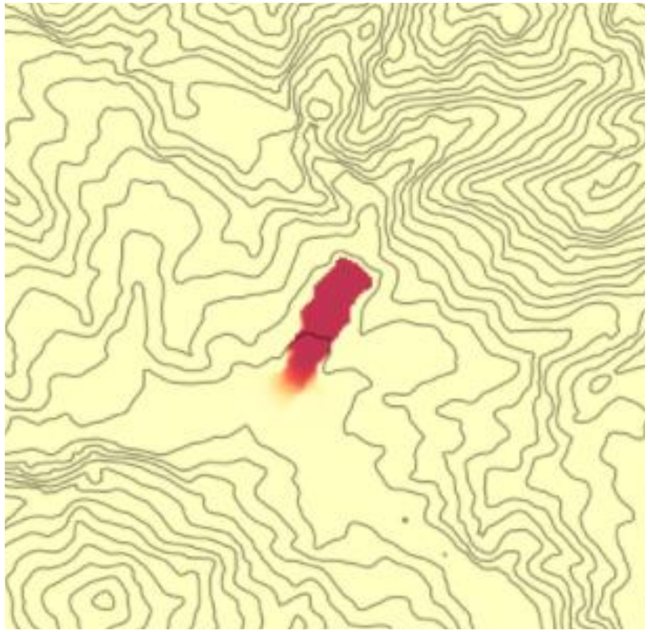
- expensive to compute
- accurate input required (DEM, soil depth, detachment areas, etc.)

Solution:

- start from our susceptibility map
- propagate the risk downhill, taking into account the slope and possible momentum
- iterate for many steps



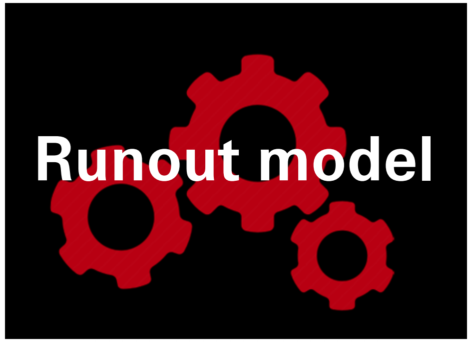

Spreading of susceptibility values to neighbouring cells
Source: Horton et al. Nat. Hazards Earth Syst. Sci 2013



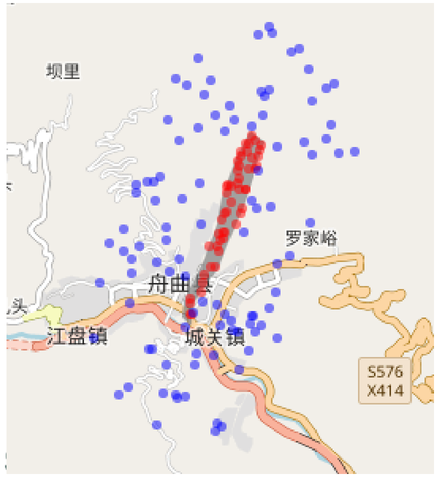
# Model training: an optimization problem

amount of flow, dispersion rate, momentum strength, overflow threshold, slope factor, etc.

Parameters θ




Score = f(θ, x)




Data x

**Optimization problem**

find $\theta^{opt} = \text{argmax } f(\theta, x)$

**Assumptions about f(θ, x)**

- expensive to compute (e.g. simulate runout on all target points)
- non-differentiable
- relatively "smooth" as a function of θ

# Bayesian optimization in a nutshell

1. Place a **Gaussian process** prior on $f(\theta)$
2. Observe $f(\theta)$ at a set of initial points $\theta$: typical experimental design, grid search or random.
3. for $n < N$:
   i. update the **posterior** distribution of $f(\theta)$ given all observations so far
   ii. pick a new $\theta^n$ that maximizes the **acquisition function** over the posterior distribution
   iii. evaluate objective function at candidate point: $f(\theta^n)$
4. Return the optimal $\theta^n$

**Gaussian process**: distribution over a space of function (defined by a mean function and a kernel)

**Posterior distribution:** specified by new mean function and covariance after having observed data

**Acquisition function**: controls the trade-off between exploration and exploitation. Examples are “expected improvements” or “upper confidence bound” (based on confidence intervals and optimism).

# Bayesian optimization in a nutshell

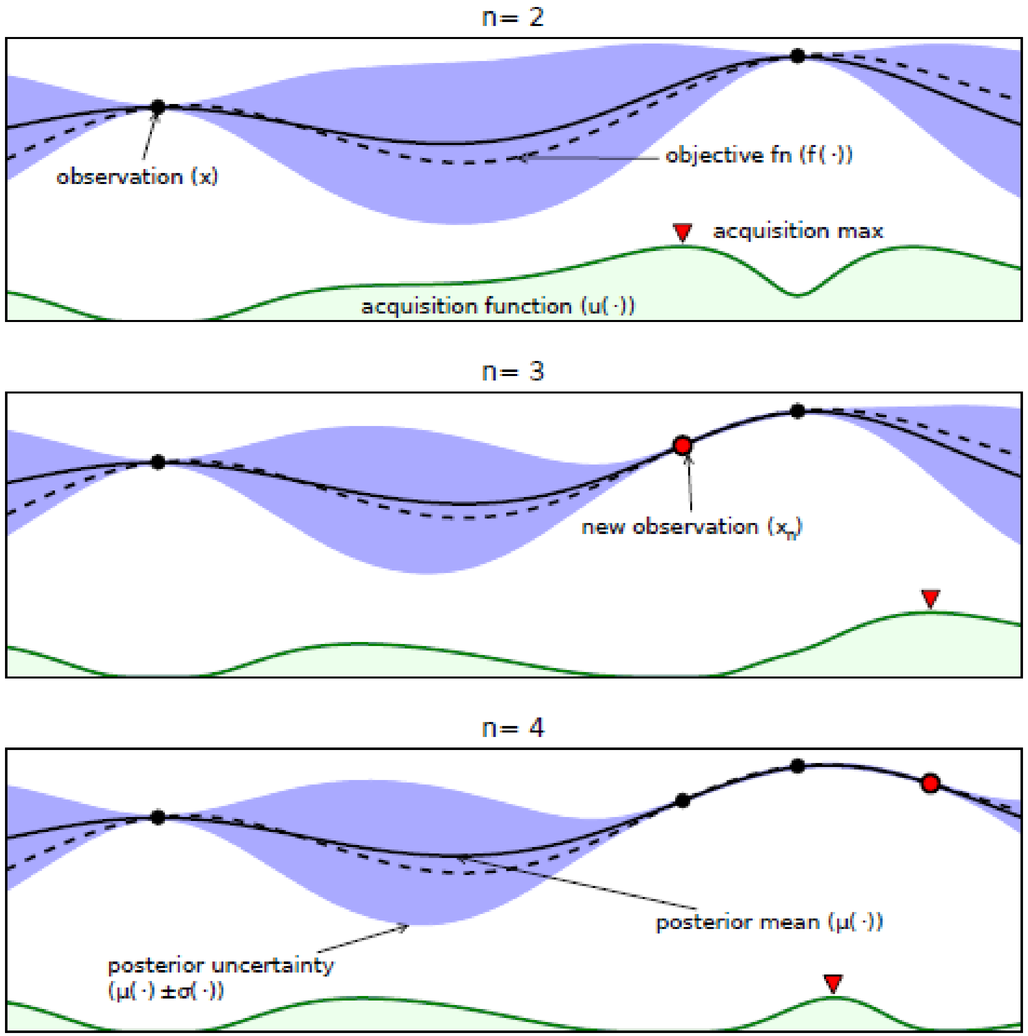
**Dotted black**: objective function (truth)

**Solid black**: posterior mean of f(θ)

**Purple**: posterior confidence bands of f(θ)

**Green**: acquisition function,

We see that the acquisition function is high either due to a high mean (exploitation) or to a high uncertainty (exploration). The algorithm explore possibly interesting regions (optimism) and focuses more and more on the region of highest score with iterations.



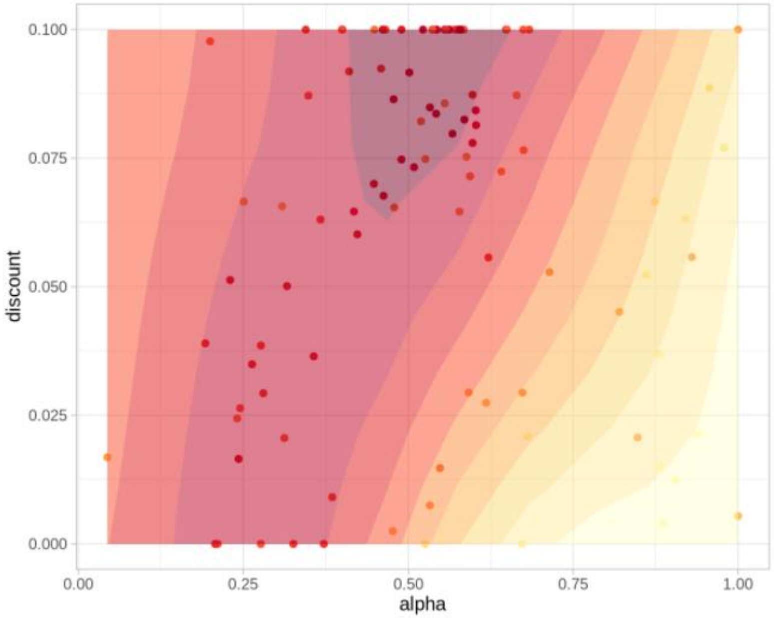

Source: Shahriari et al. IEEE 2016

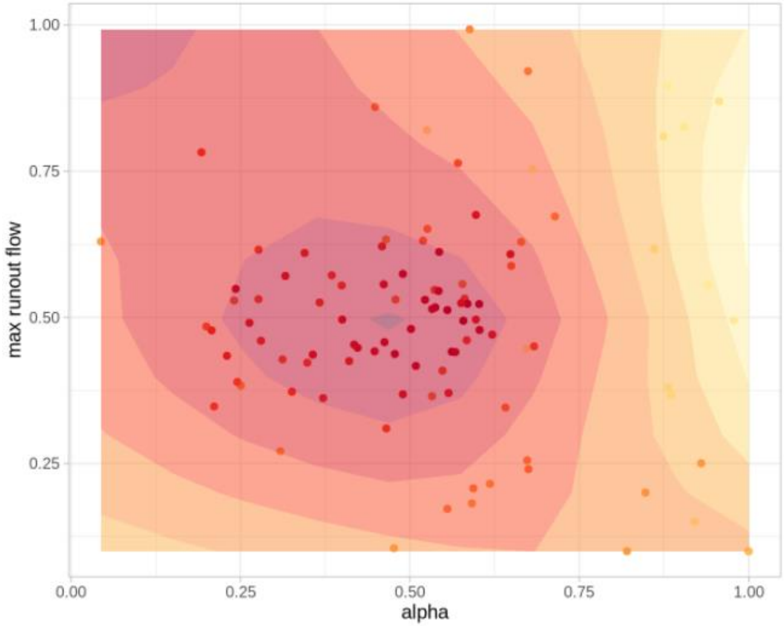
# Bayesian optimization for our runout model

Parameter space:

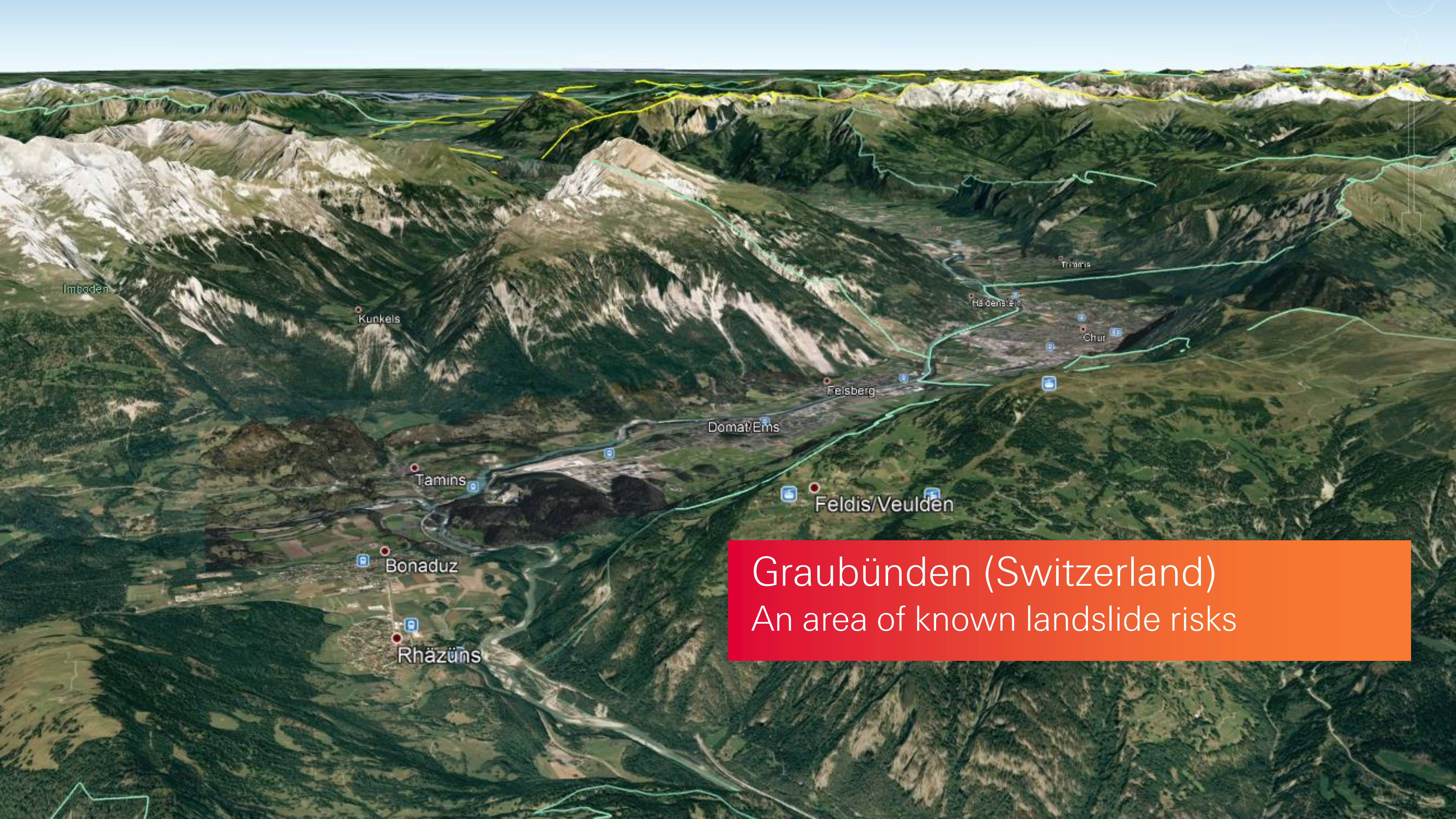
amount of flow (alpha), dispersion rate (discount), momentum strength, max runout flow, slope factor, etc.

Slices of the estimated f(θ) and sampled points
Remark: red gradient indicates the score



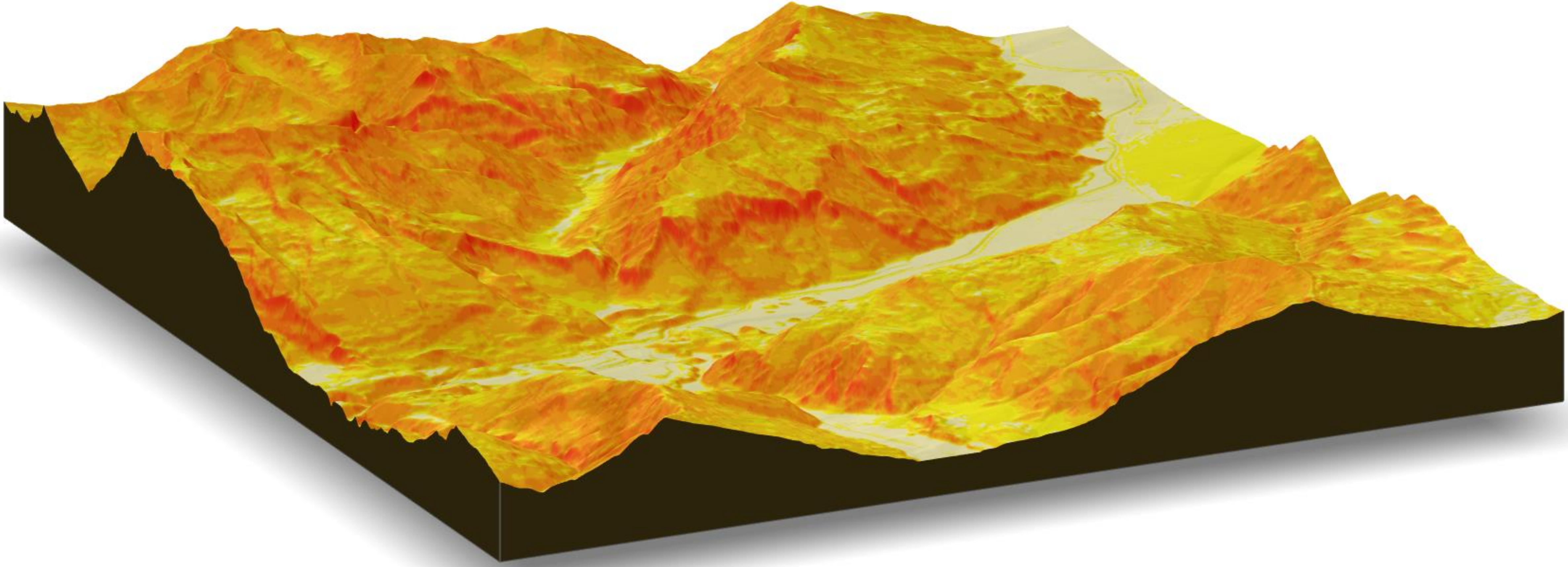
# Results



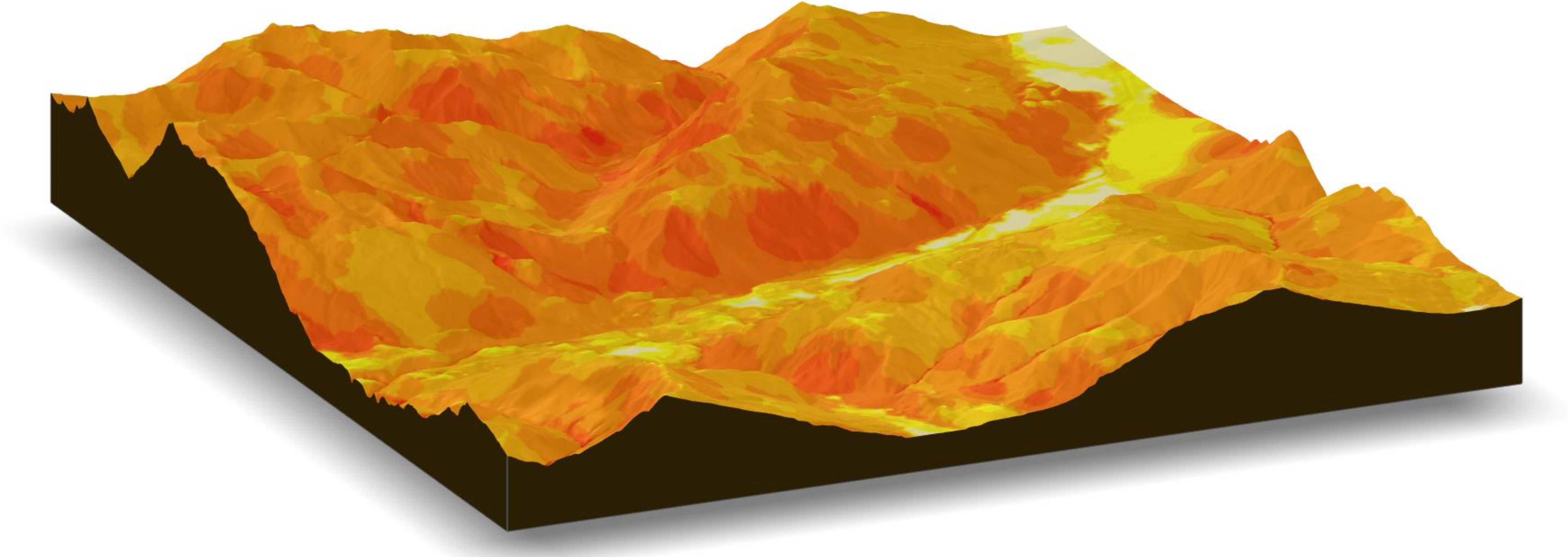

# Graubünden (Switzerland)

An area of known landslide risks

# Susceptibility



# Runout




# Sichuan (China) - 2017

source: https://blogs.agu.org/landslideblog/2017/06/25/xinmo-1/

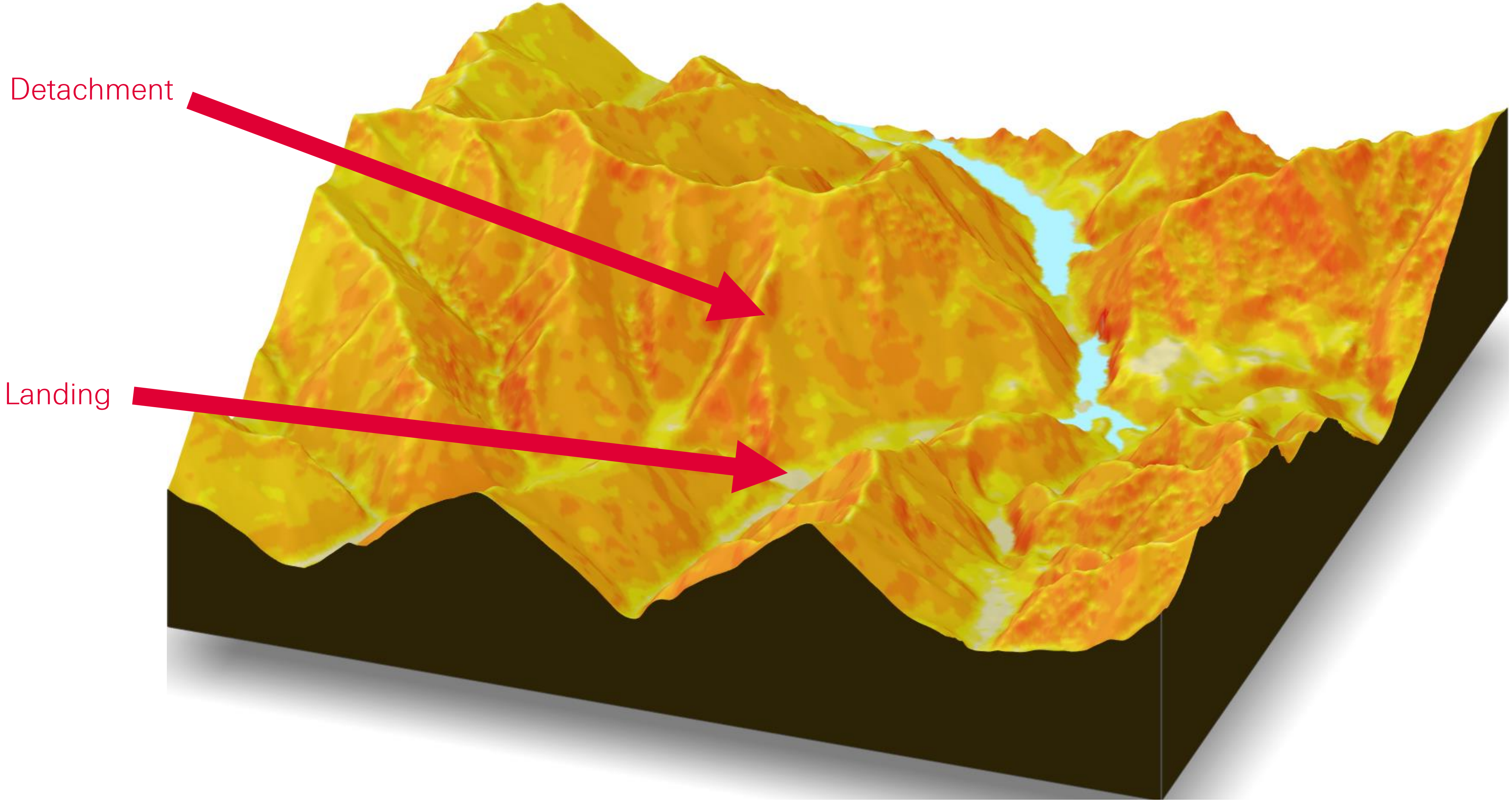
40 houses destroyed, more than10 people killed

block road and river

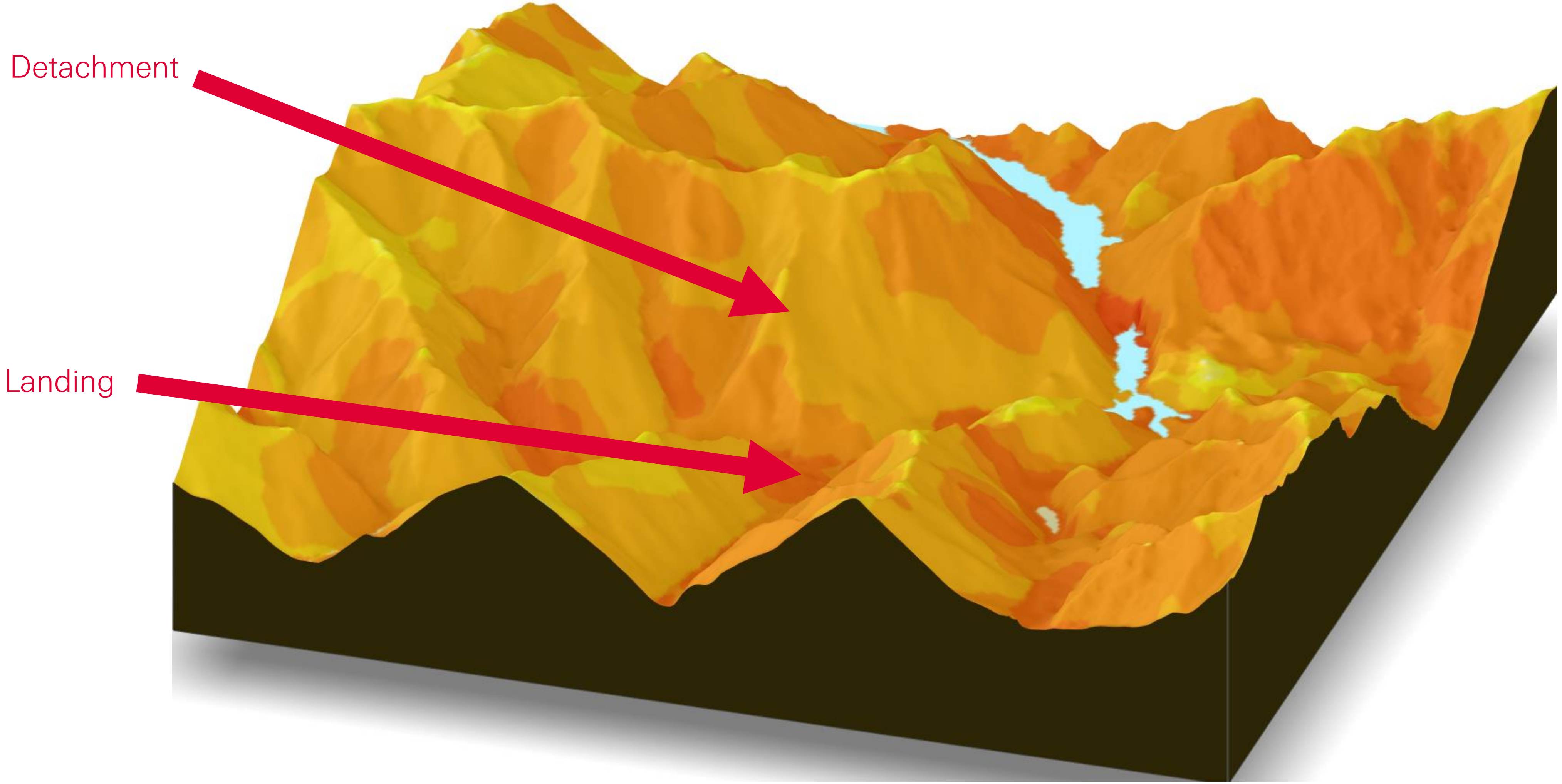
runout distance: 2600m

# Sichuan landslide footprint

# Susceptibility map
## Underestimate the risk on the road and habitations below the slope



# Runout map
## Much better risk estimation at the bottom of the slope



# Mount Meager (Canada) - 2010

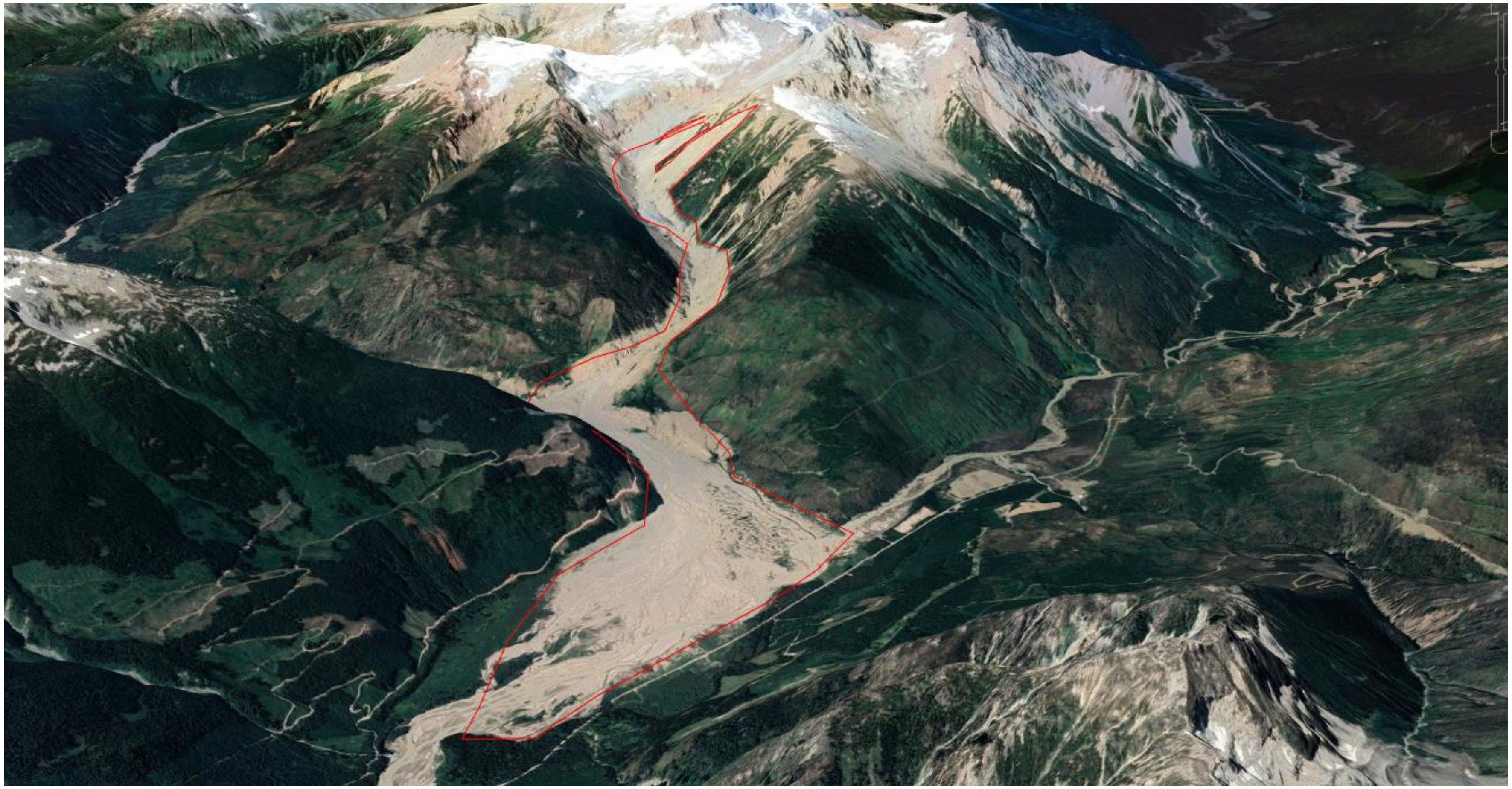
source: https://thetyee.ca/News/2010/08/12/MeagerLandslide/

infrastructures destroyed, 0 people killed

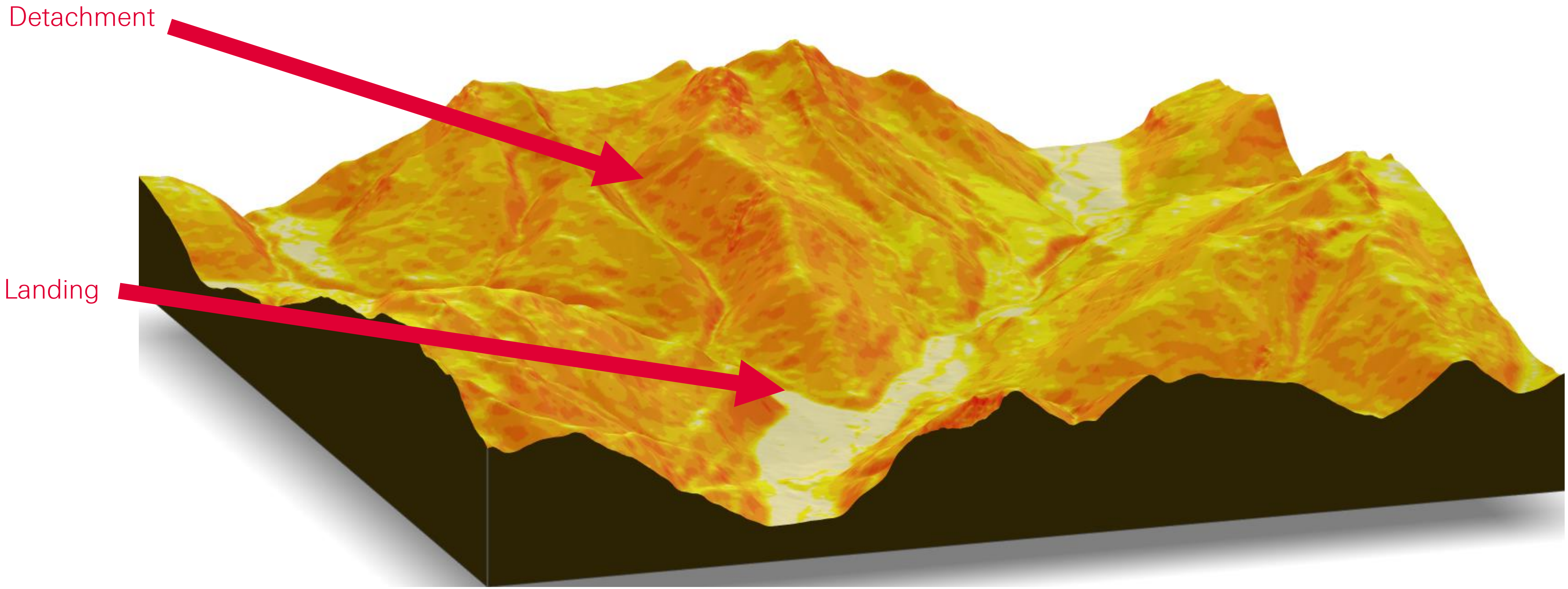
block road and river

runout distance: >7km!

# Meager (Canada) landslide footprint

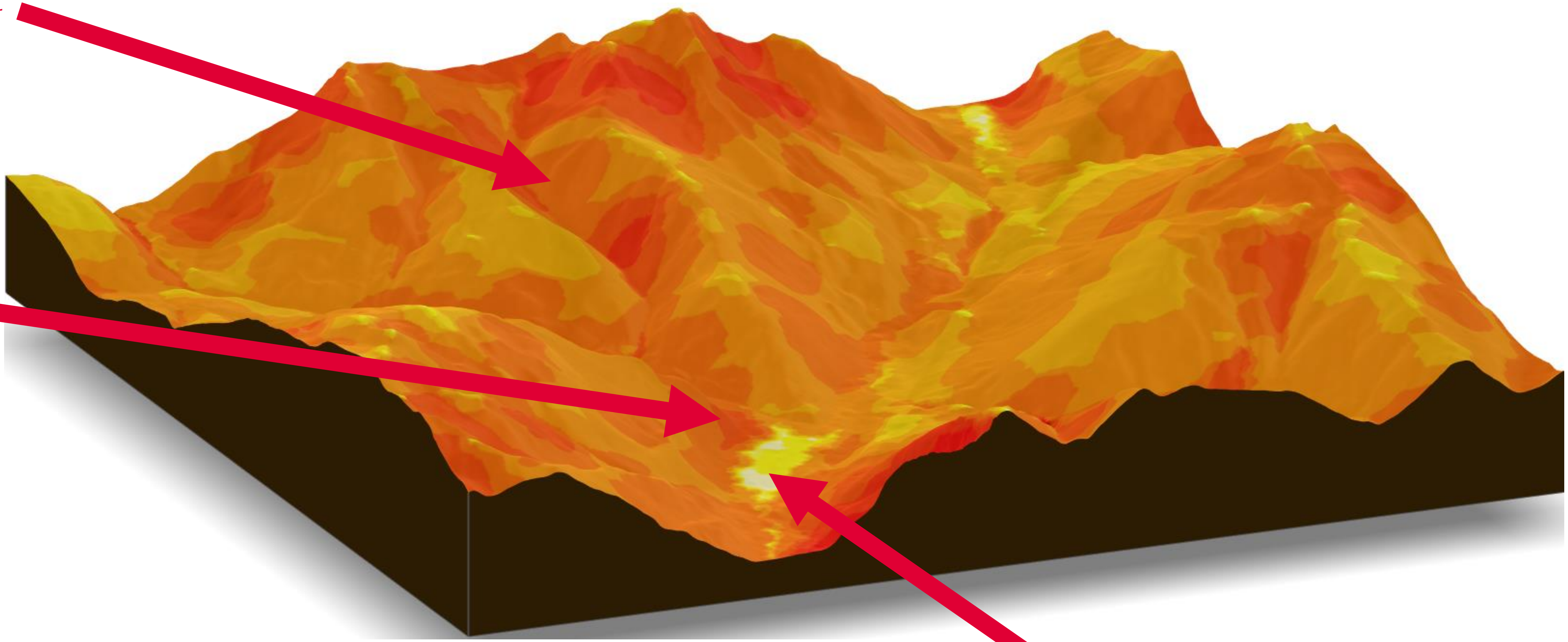


# Susceptibility map
## Underestimate the risk in the valley below



# Runout map

## Better estimation of risk downhill, but doesn't go as far as the actual landslide



# Conclusions

# Summary

## New runout model

- landslide susceptibility risk is not enough for insurance
- new runout model with simplified landslide dynamics

## Bayesian Optimization

- map the problem as an optimization (derivative-free)
- learn model parameters using data

## Landslide risks mapping

- global coverage
- susceptibility and runout risks
- resolution 30m x 30m

# Legal notice