Near-real-time Country-wide Estimation of Susceptibility and Settlement Exposure from Norwegian Mass Movements via Inter-graph Representation Learning

Joshua Dimasaka[1], Sakthy Selvakumaran[1], and Andrea Marinoni[1]

[1]Affiliation not available

February 28, 2024

Abstract

The increased occurrence of catastrophic events caused by climate change-induced mass movements affects human welfare and results in huge economic losses, making the development of early warning systems (EWSs) crucial to everyday decisions of local governments and communities. The state-of-the-art (SOTA) EWSs can only provide information on the level of direct danger of mass movement that each village is exposed to. This is the result of highly sensitive and coarse classifications and aggregated predictions at regional level, potentially leading to a poor perception of risk and inadequate local management plans. Also, this does not account for the indirect effects of mass movements on the local communities at social and economic levels, e.g., a town that can be cut out of the transportation and communication systems because of landslides blocking the roads around it is currently not considered by SOTA EWSs.

To overcome this issue, we developed a novel machine learning scheme that investigates the environmental (hydrological and geological) characteristics of mass movements and the connectivity information of formal settlements and road network data in terms of graph structures. In particular, we study the interaction of the probabilistic mass movement susceptibility (derived from the environmental properties by means of a supervised ensemble graph neural network) on the graph representing the road network connecting the formal settlements. As a result, we derive for each formal settlement a probability of being indirectly affected by mass movements (e.g., the probability to be isolated as a result of mass movements affecting their surroundings) by graph spectral clustering.

We tested this architecture (named Intergraph) on the Norwegian territory, taking advantage of over 68,000 incidents of reported mass movements since 1957. Our approach achieved an overall performance of 86.25% with the 2020 Gjerdrum quick clay incident as a demonstrated case study. With the intensifying effects of climate change, our study has opened an opportunity to develop solutions for adaptation and mitigation through a new holistic graphical perspective to assess various large-scale geospatial datasets of risk elements such as exposure, vulnerability, and hazard.

Plain-language Summary

Global early warning systems from mass movements have been increasingly important as the triggering rainfall patterns continue to intensify due to climate change. In particular, the Norwegian early warning systems for landslides and avalanches currently use a highly sensitive classification of danger reports that are presented at the county or village level of information, without any fine details needed to understand its potential implications on critical infrastructures such as transportation and communication systems. We developed a novel inter-graph framework that applies artificial intelligence to the interaction of various forms of graphical or relational connections such as (1) the spatial connectivity between road networks and settlements and (2) the proximity and similarity of mapped locations with different hydrological and geological variables, thereby producing near-real-time country-wide susceptibility maps and assessment of exposure level of all settlements in Norway. This study offers an alternative methodology to evaluate the widely-used disaster risk equation by explicitly modelling the interaction of these graphical or relational connections not only between exposure and susceptibility, but also between hazard, exposure, and vulnerability, for a holistic assessment of risk using geospatial datasets and artificial intelligence.

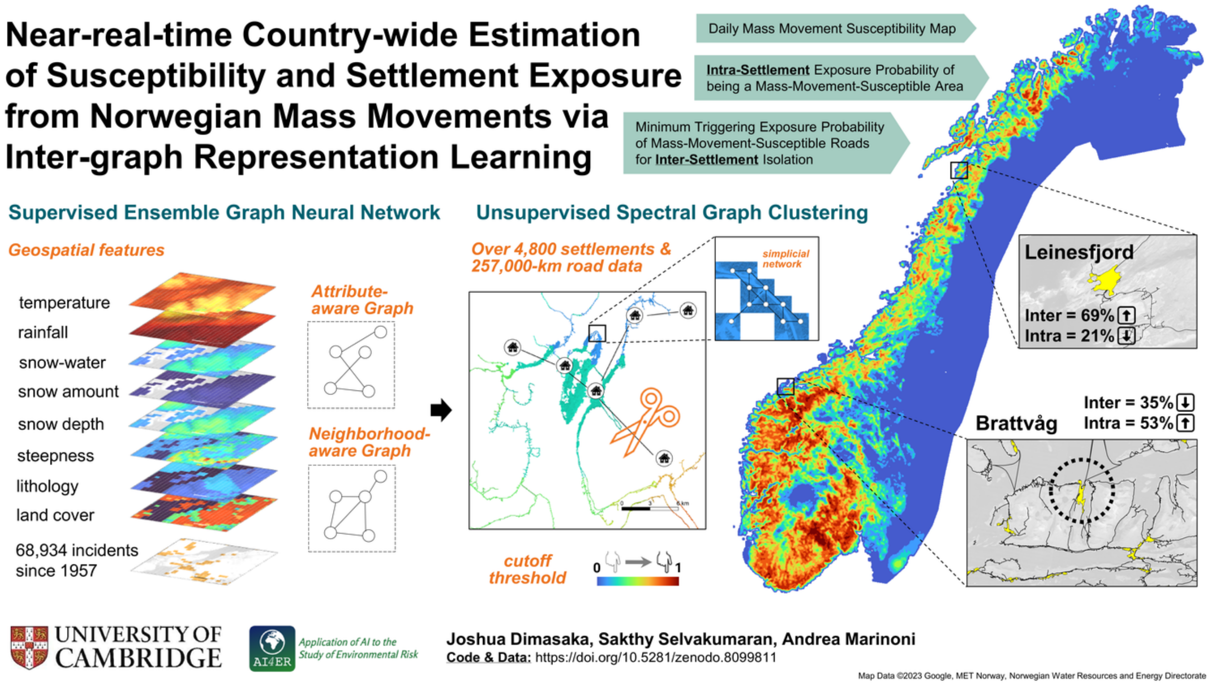


Figure 1: Graphical Abstract.

Rich media available at https://youtu.be/0u6MoxTm_8Y

Data and Code Availability

The complete set of data (40GB) and code are available in our publicly available **Zenodo** repository (Dimasaka, 2023). The code and its documentation are available in our **GitHub** repository.

References

Near-real-time Country-wide Estimation of Susceptibility and Settlement Exposure from Norwegian Mass Movements via Inter-graph Representation Learning. (2023). Zenodo. https://doi.org/10.5281/zenodo.8099812

Near-real-time Country-wide Estimation of Susceptibility and Settlement Exposure from Norwegian Mass Movements via Inter-graph Representation Learning

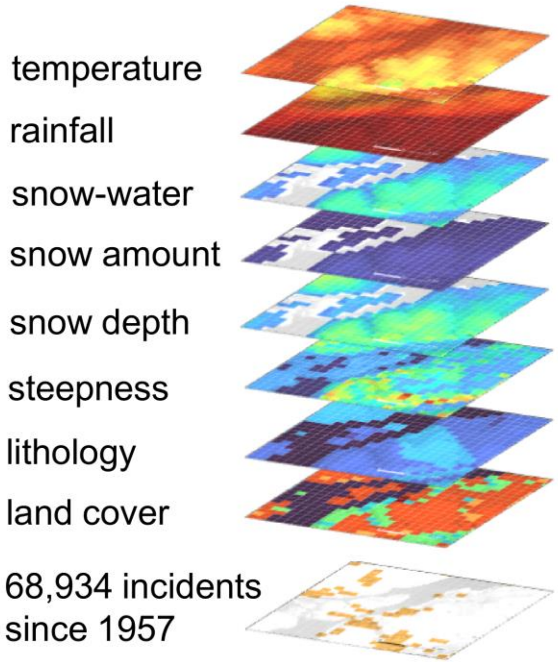
Daily Mass Movement Susceptibility Map

Intra-Settlement Exposure Probability of being a Mass-Movement-Susceptible Area

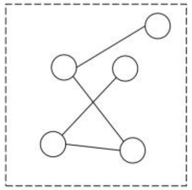
Minimum Triggering Exposure Probability of Mass-Movement-Susceptible Roads for **Inter-Settlement** Isolation

Supervised Ensemble Graph Neural Network

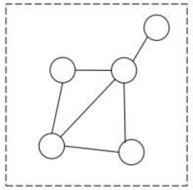
Geospatial features



Attribute-aware Graph

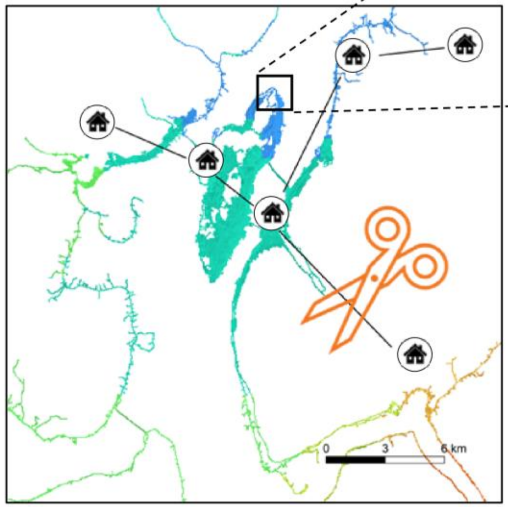


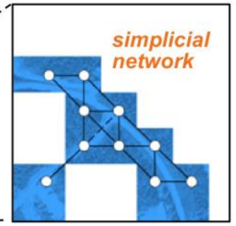
Neighborhood-aware Graph



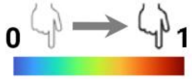
Unsupervised Spectral Graph Clustering

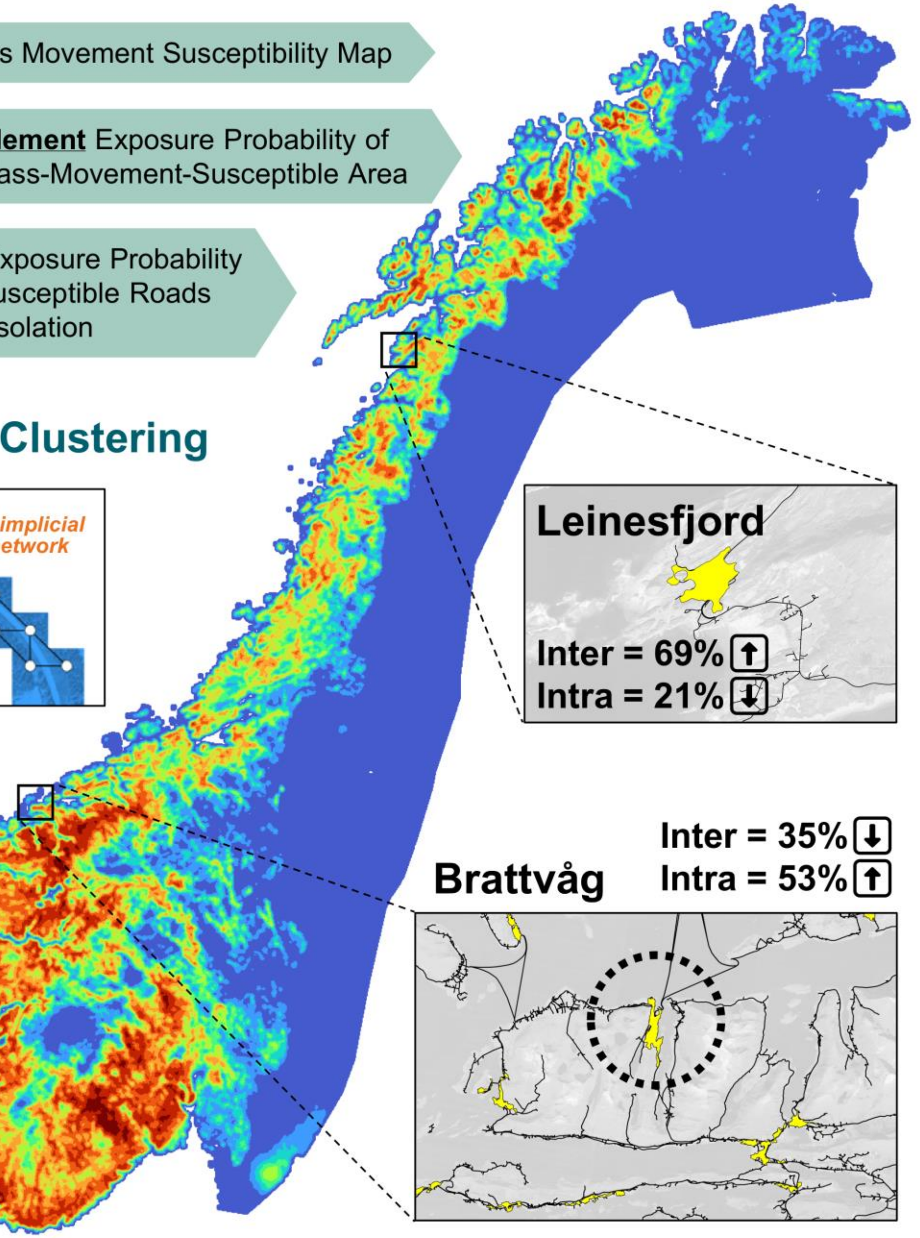
Over 4,800 settlements & 257,000-km road data





cutoff threshold





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AI4ER Application of AI to the Study of Environmental Risk

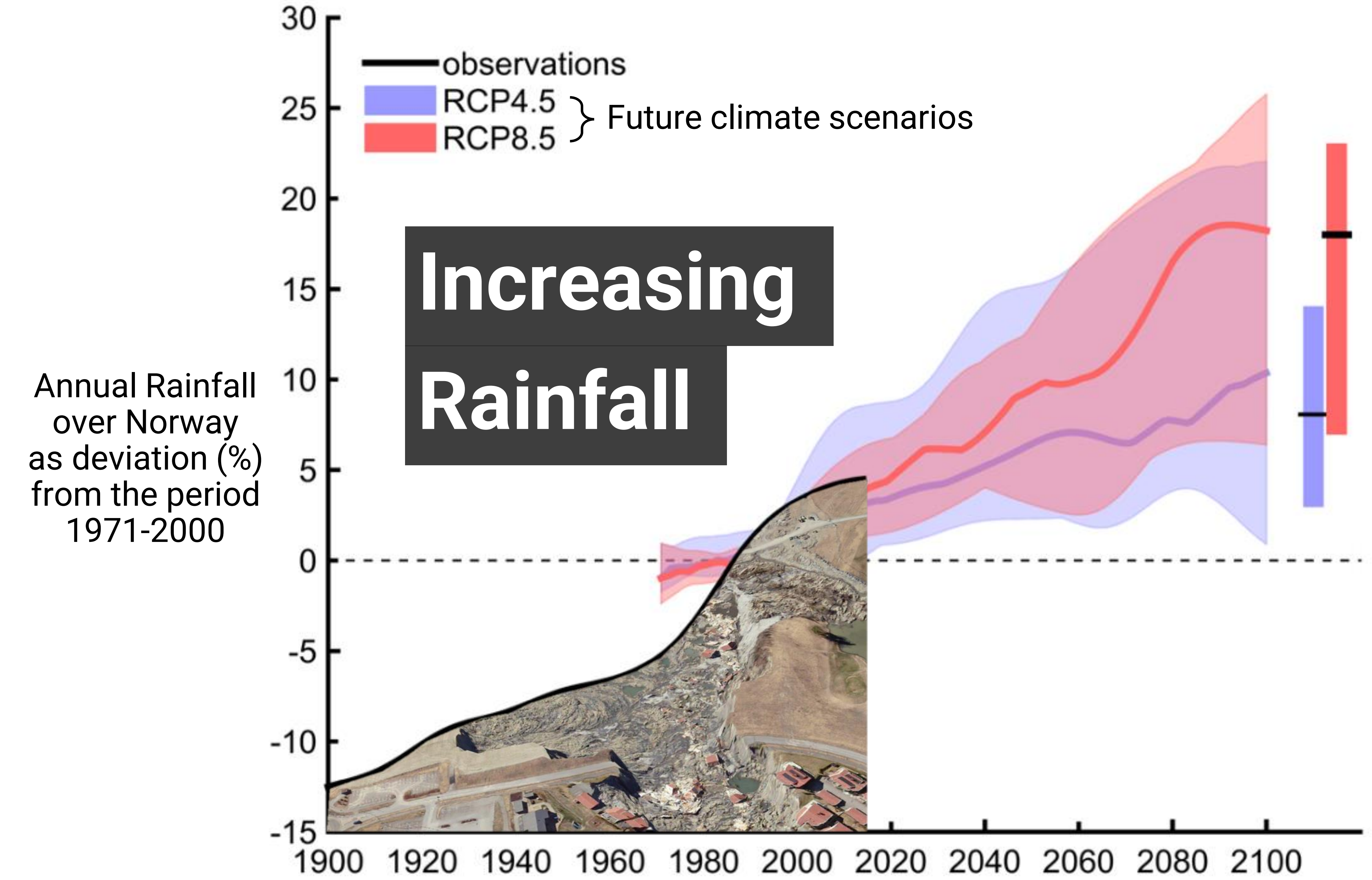
Joshua Dimasaka, Sakthy Selvakumaran, Andrea Marinoni

Code & Data: https://doi.org/10.5281/zenodo.8099811


Connecting
Ropes
Photo: Dhruv Suri

Connecting Roads

Photo: Fredrik Høgaas



Climate in Norway 2100

Challenge

Solution

1 Green	2 Yellow	3 Orange	4 Red
very low	*low*	*high*	*very high*

- **HIGHLY CONSERVATIVE ESTIMATES**
  Simple matrix-based approach with limited classes of susceptibility and daily rainfall intensity.

→ **Instead of four classes alone, what if we provide estimates with values from 0 to 100% with uncertainty?**

- **LIMITED REFINED INFORMATION**
  Too aggregated and no detailed information along road networks or within the vicinity of settlements.

→ **Instead of aggregated information, what if we extend the analysis at the detail of roads and settlements?**

- **LACK OF SPATIAL CORRELATION**
  Complex region-specific characteristics.

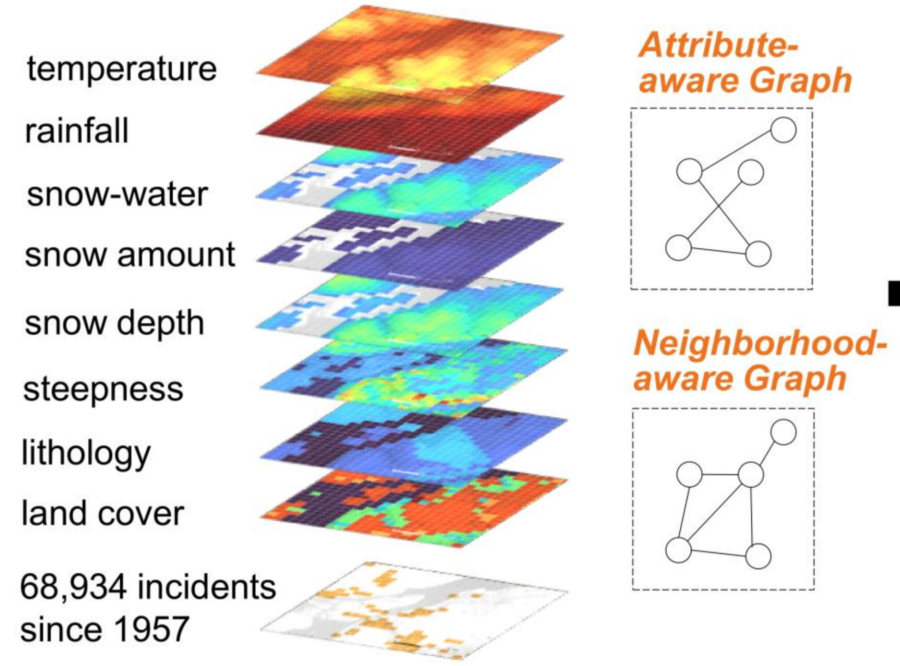
→ **Instead of no spatial correlation, what if we include it?**

Inter-graph Representation Learning

Near-real-time Country-wide Estimation of Susceptibility and Settlement Exposure from Norwegian Mass Movements via Inter-graph Representation Learning

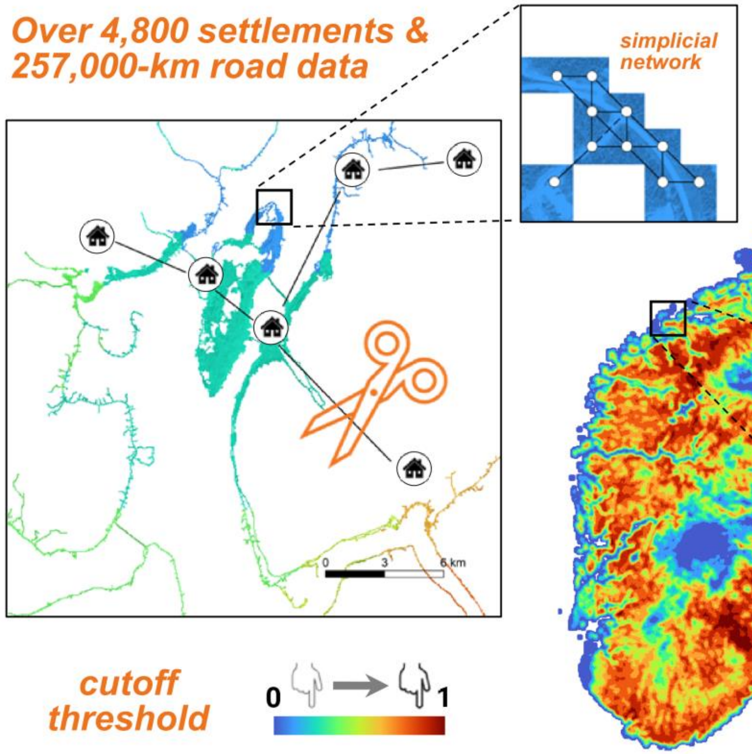
Supervised Ensemble Graph Neural Network

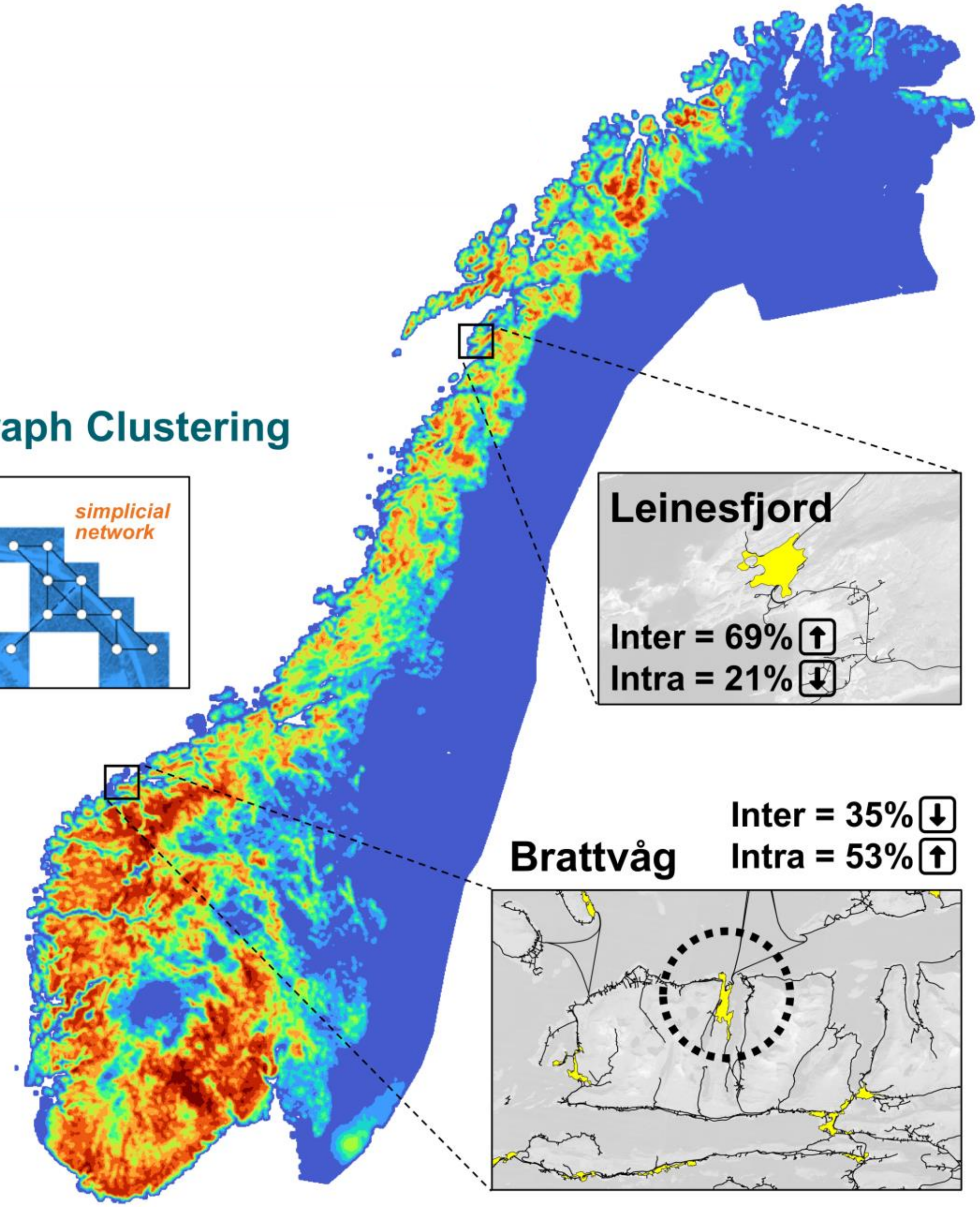
Geospatial features



Unsupervised Spectral Graph Clustering

Over 4,800 settlements & 257,000-km road data





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AI4ER Application of AI to the Study of Environmental Risk

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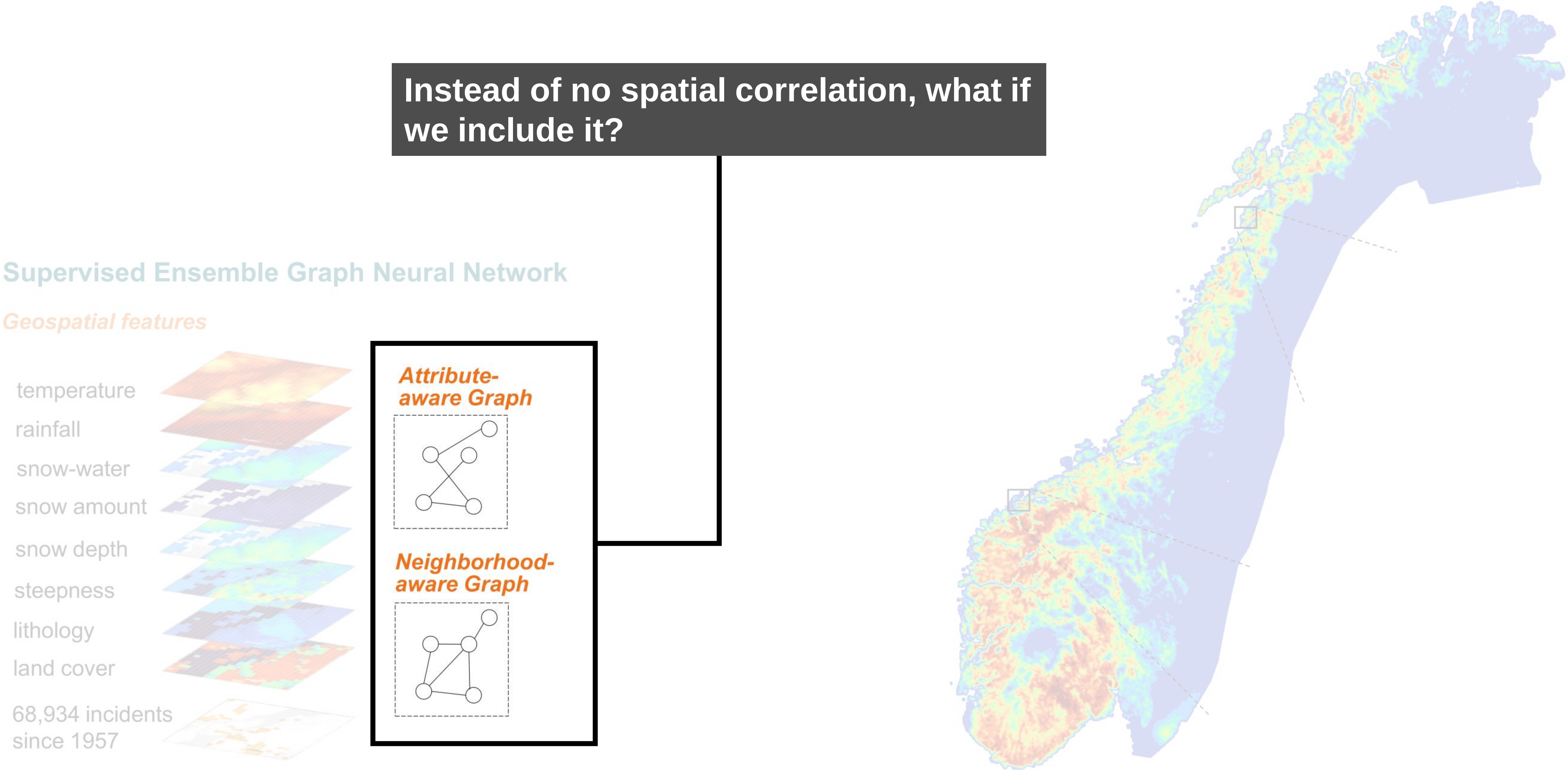
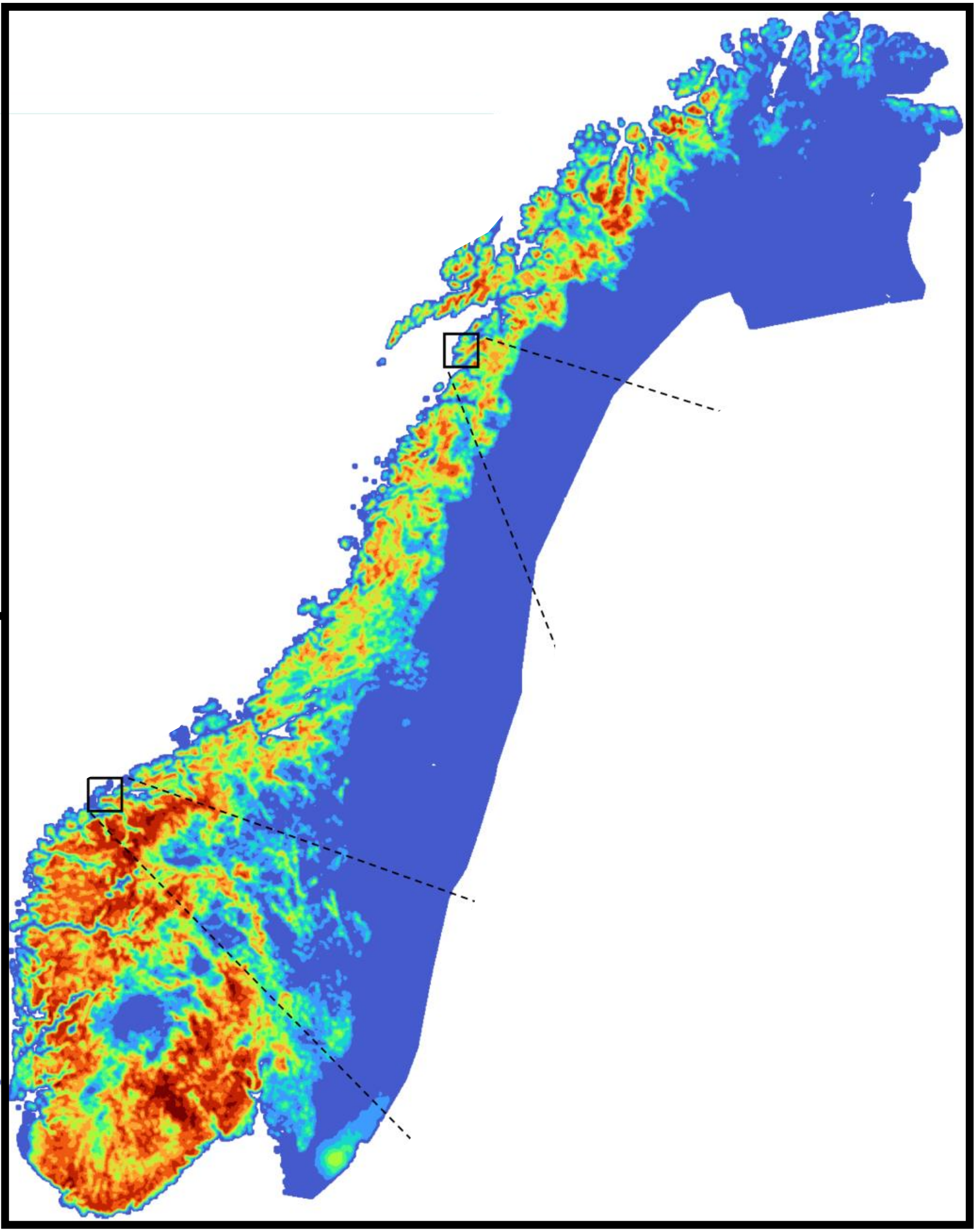
Code & Data: https://doi.org/10.5281/zenodo.8099811

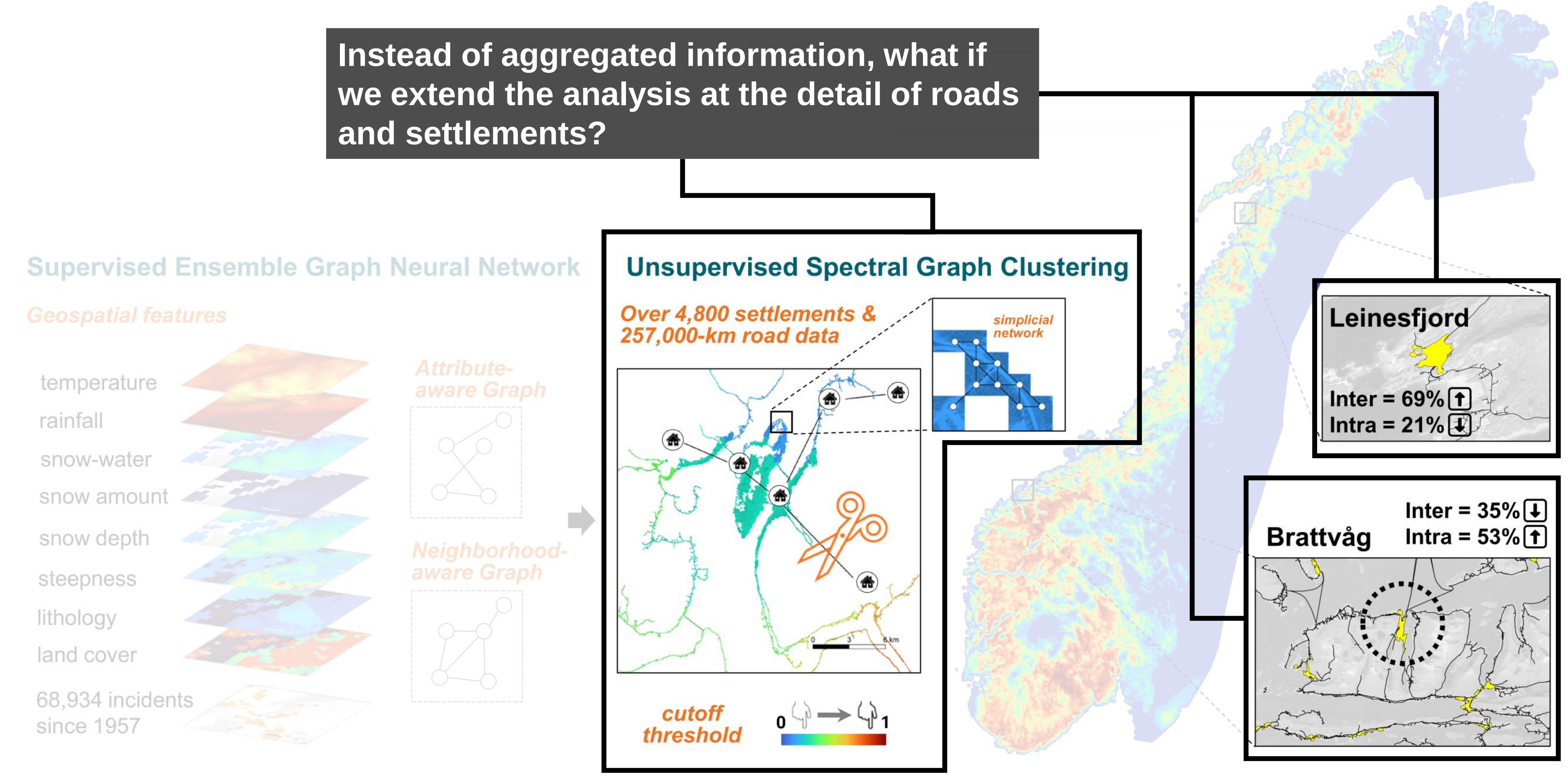
Instead of no spatial correlation, what if we include it?



Instead of four classes alone, what if we provide estimates with values from 0 to 100% with associated uncertainty?

Supervised **Ensemble** Graph **Neural Network**




Instead of aggregated information, what if we extend the analysis at the detail of roads and settlements?
Supervised Ensemble Graph Neural Network
Geospatial features
temperature
rainfall
snow-water
snow amount
snow depth
steepness
lithology
land cover
68,934 incidents since 1957
Attribute-aware Graph
Neighborhood-aware Graph
Unsupervised Spectral Graph Clustering
Over 4,800 settlements & 257,000-km road data
simplicial network
cutoff threshold
0
1
Leinesfjord
Inter = 69%
Intra = 21%
Brattvåg
Inter = 35%
Intra = 53%

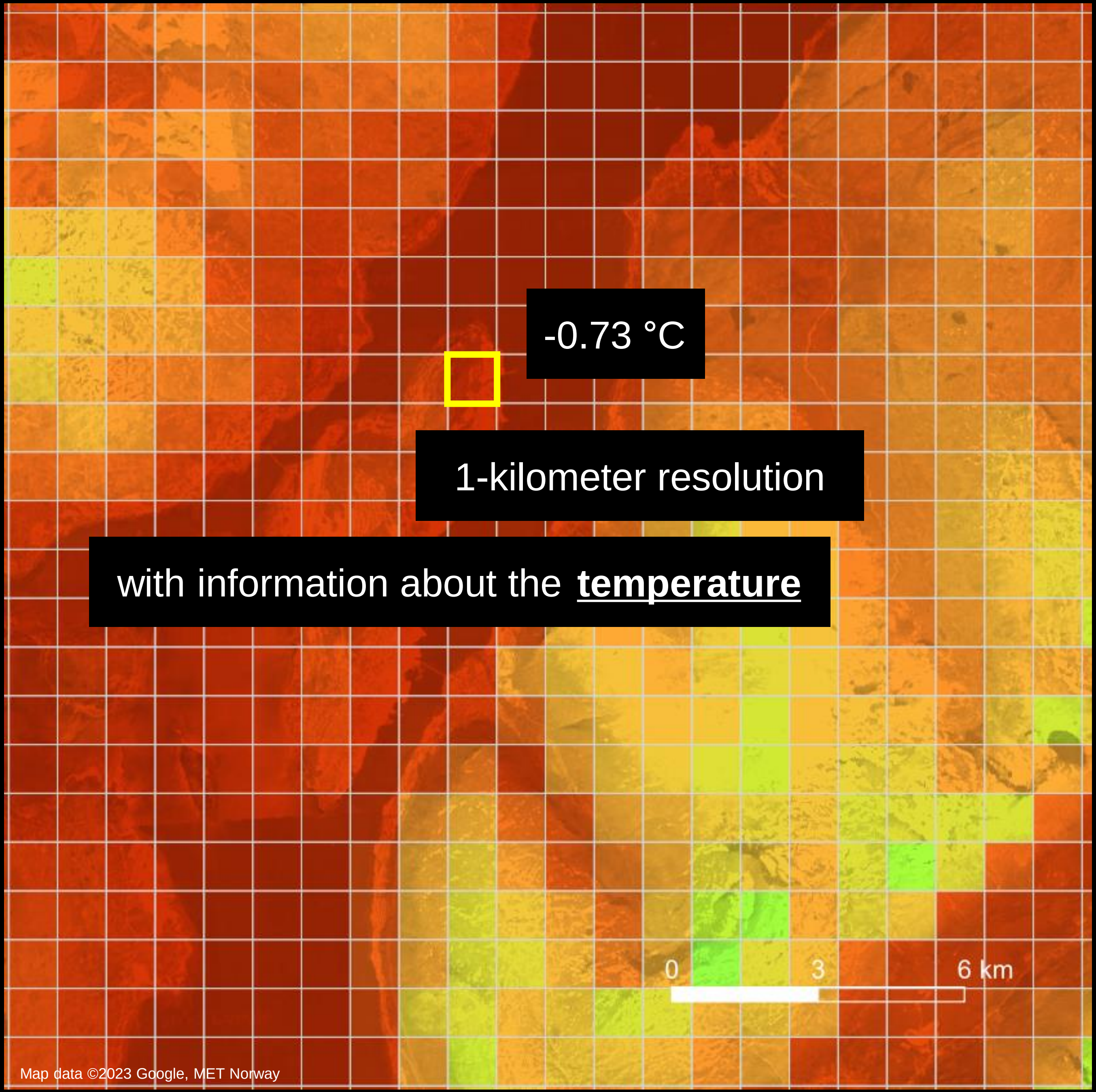

0
200
400 km
Map data ©2023 Google

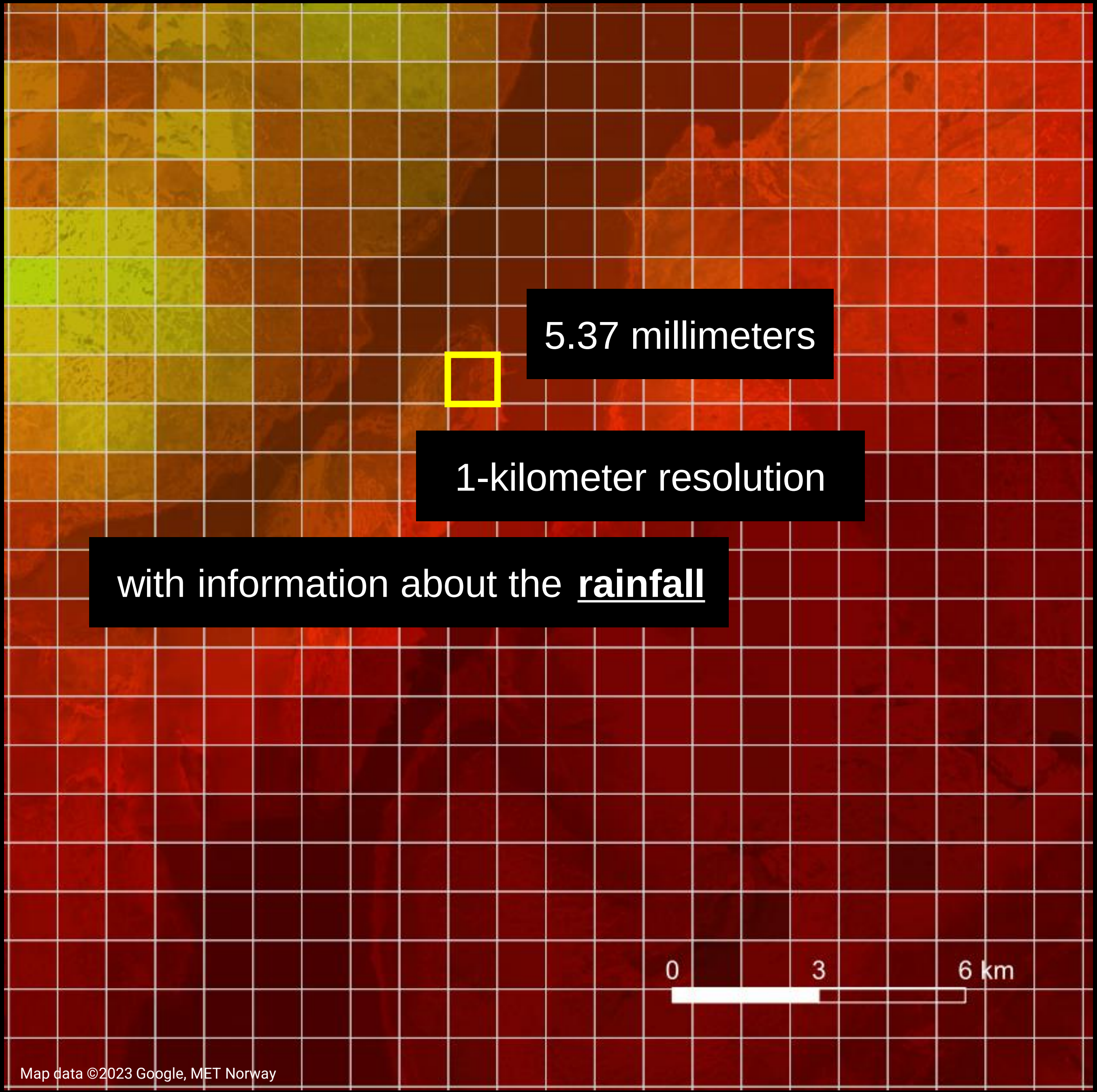

0
200
400 km
Map data ©2023 Google, GADM

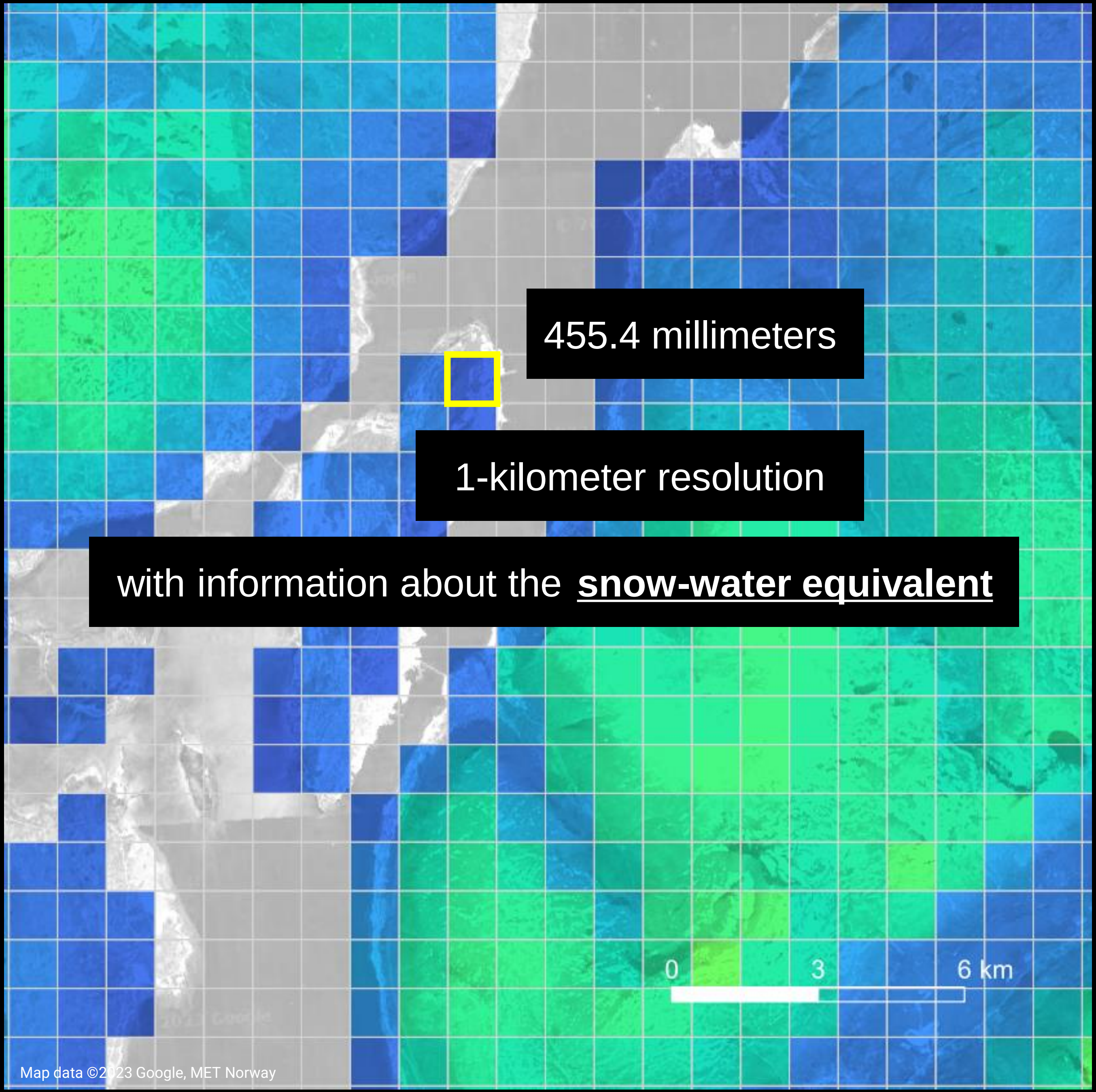

0
3
6 km
Map data ©2023 Google

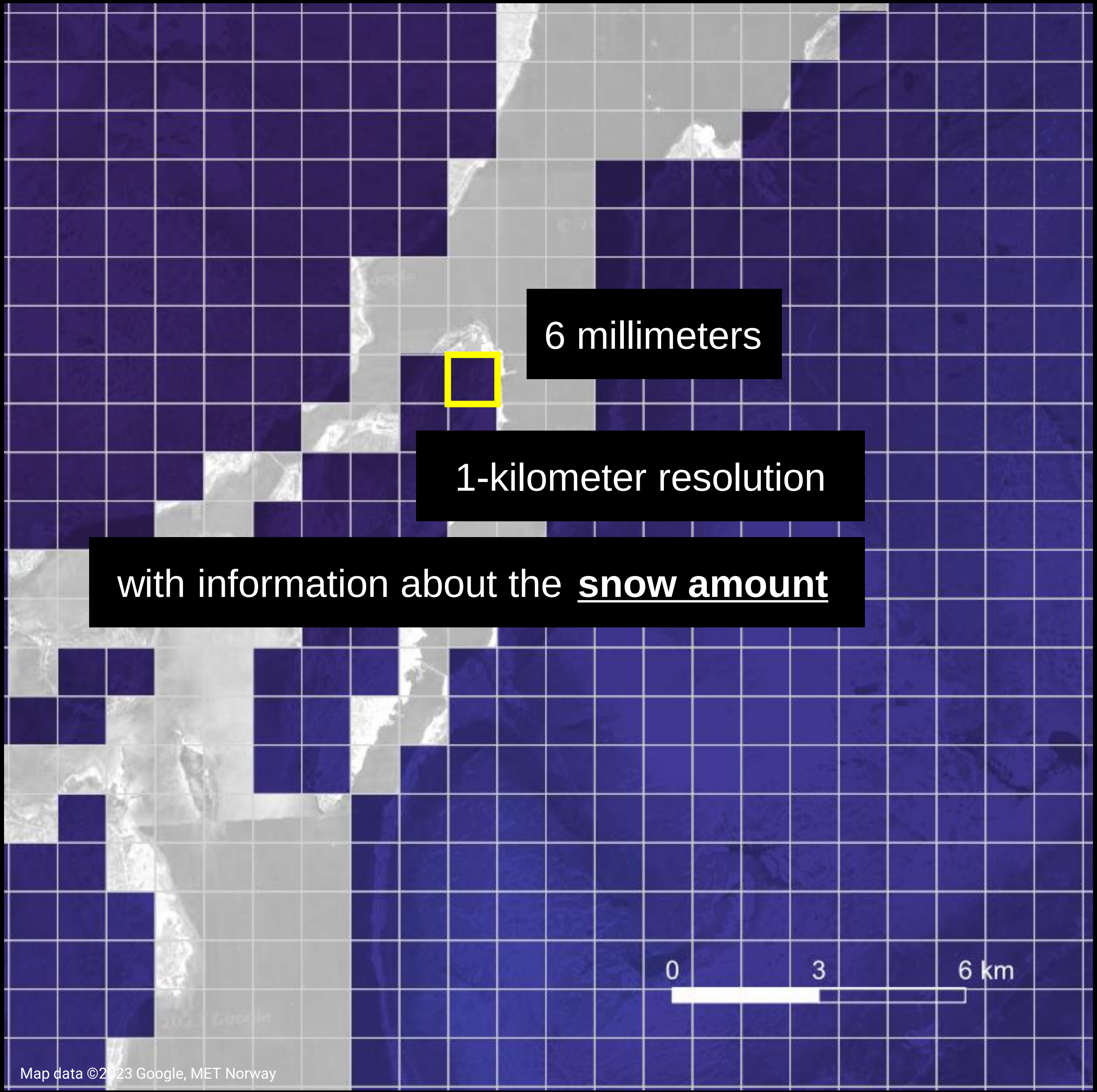

City of Tromsø
0
3
6 km
Map data ©2023 Google

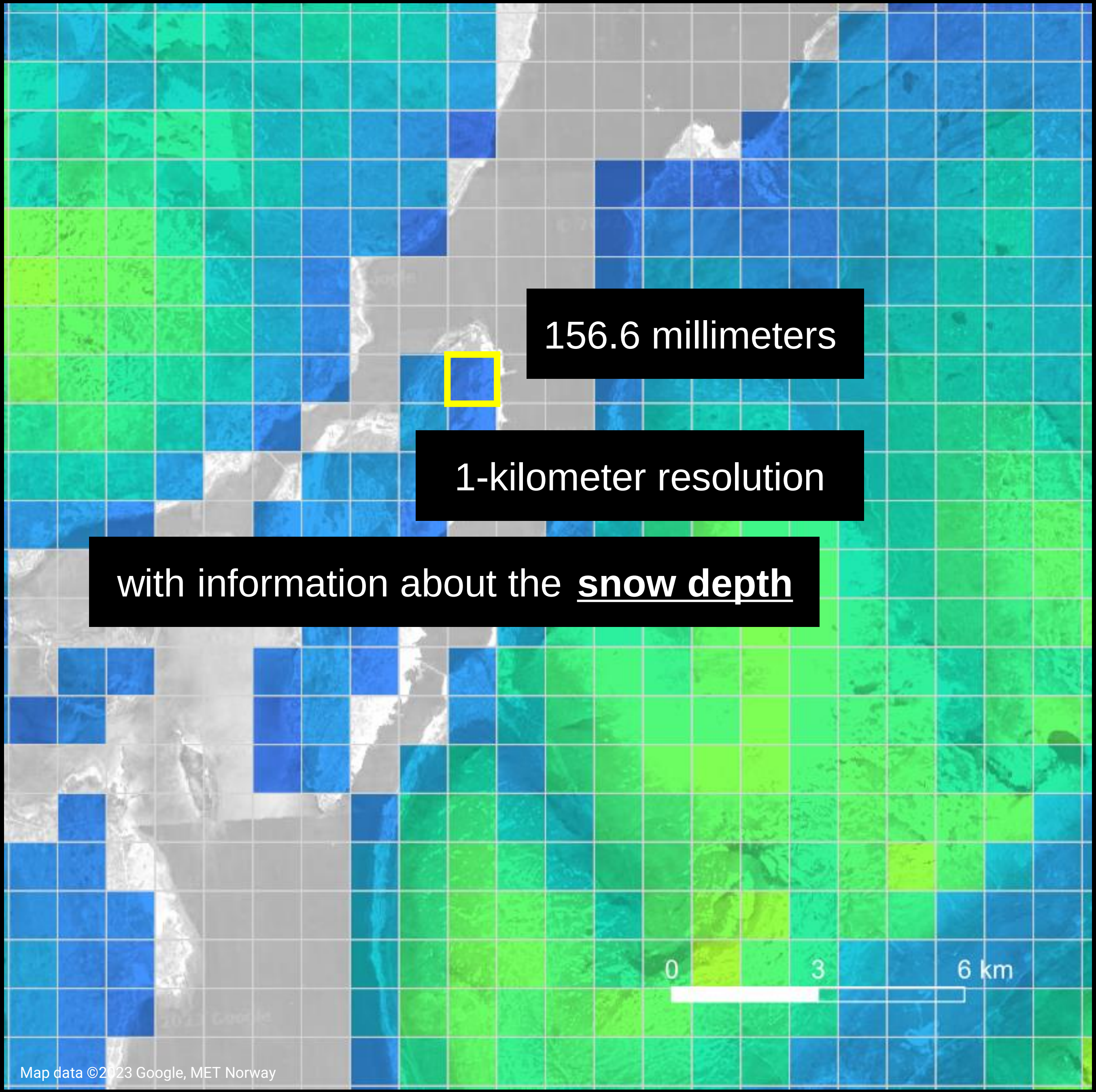

1-kilometer resolution
0
3
6 km
Map data ©2023 Google

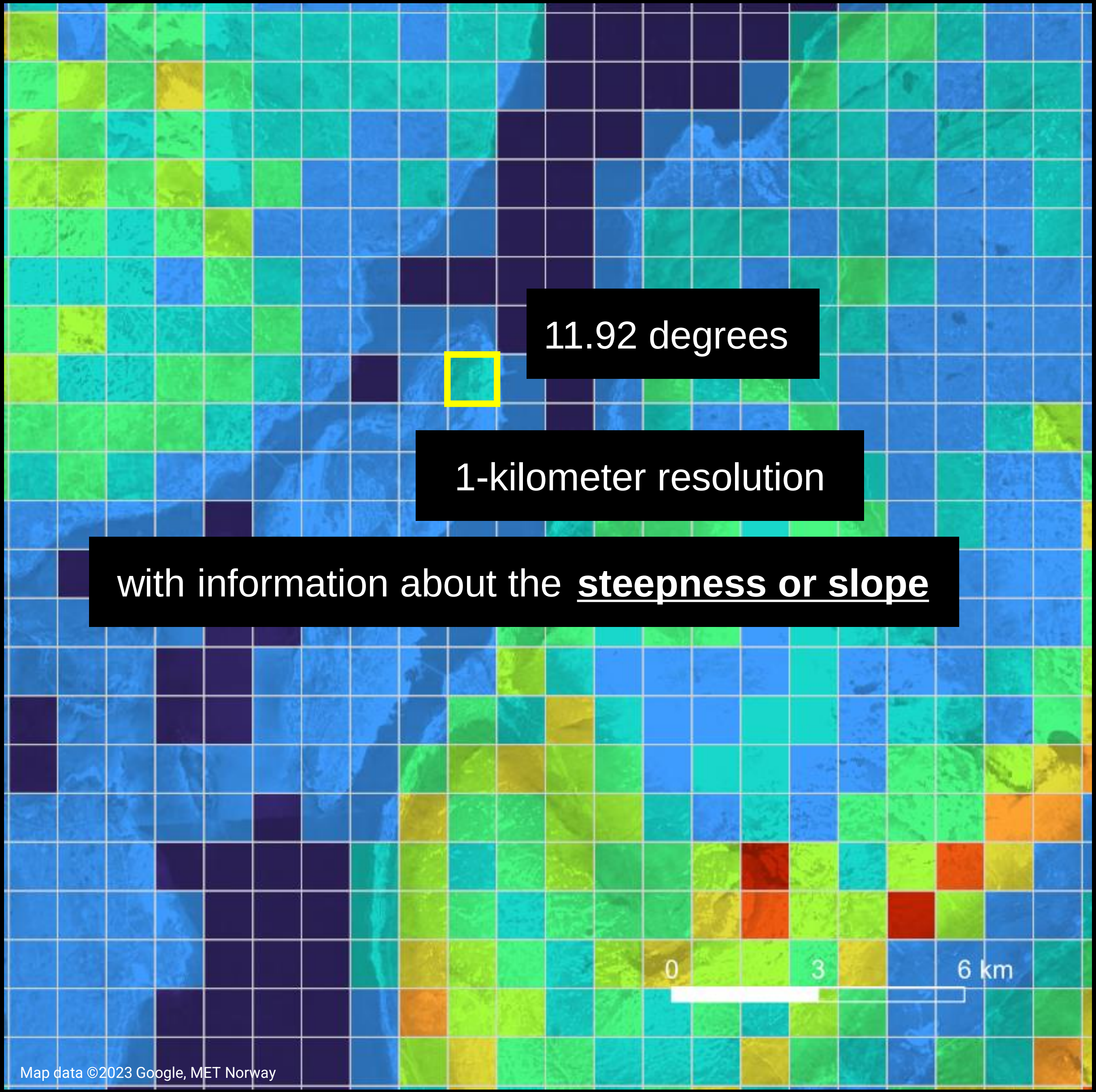

-0.73 °C
1-kilometer resolution
with information about the **temperature**
0
3
6 km
Map data ©2023 Google, MET Norway

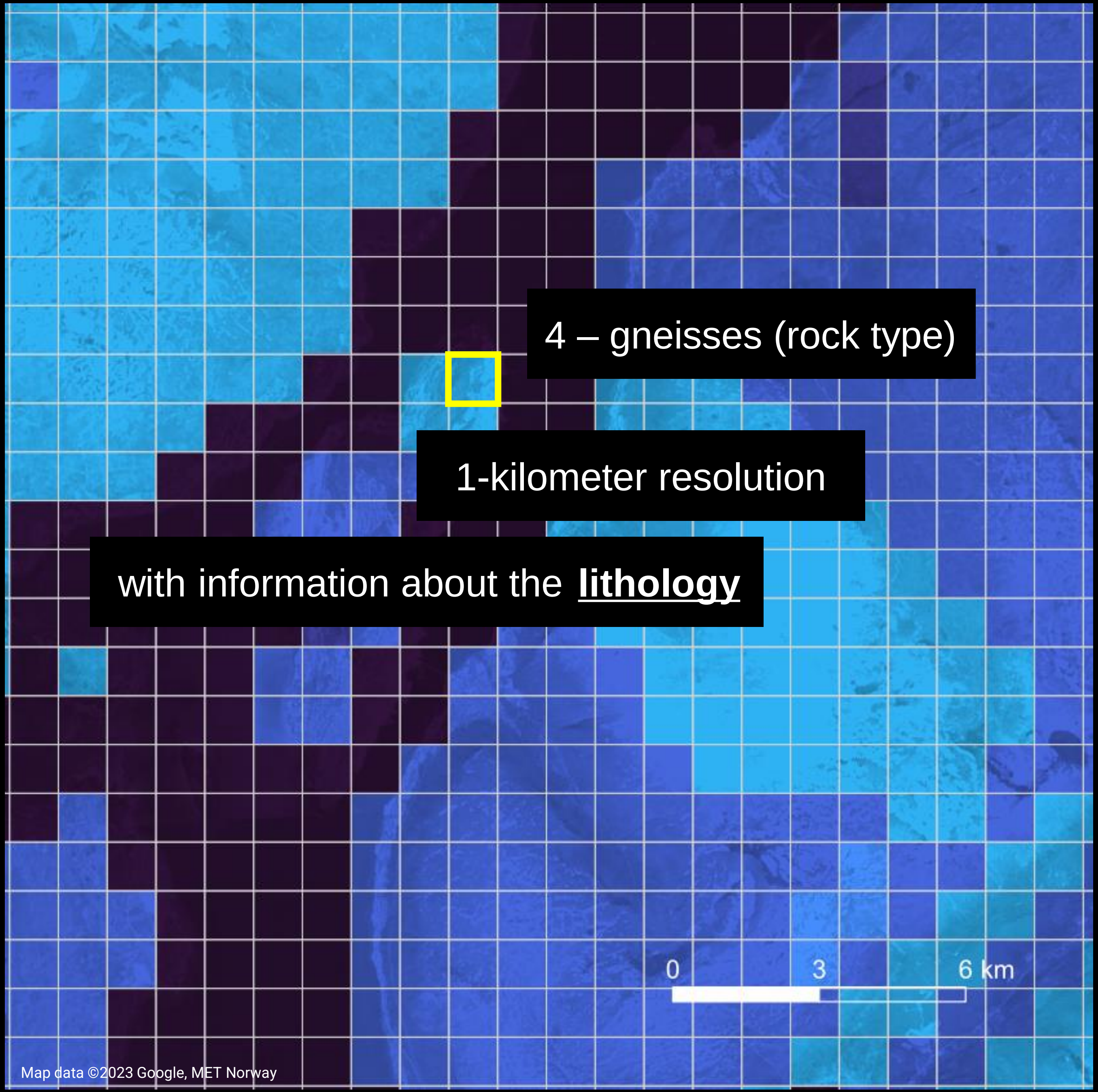

5.37 millimeters
1-kilometer resolution
with information about the **rainfall**
0
3
6 km
Map data ©2023 Google, MET Norway

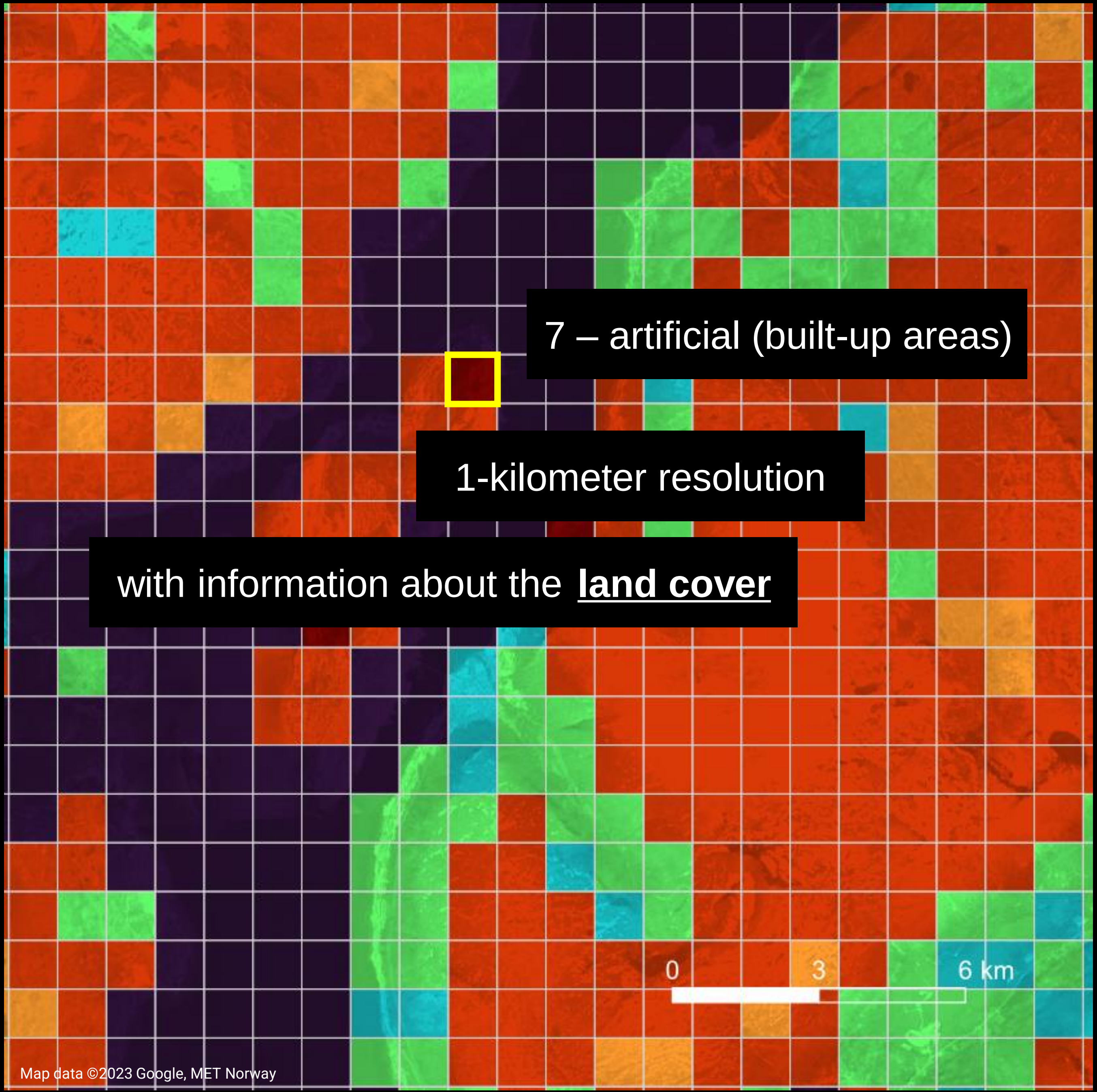

455.4 millimeters
1-kilometer resolution
with information about the **snow-water equivalent**
0
3
6 km
Map data ©2023 Google, MET Norway

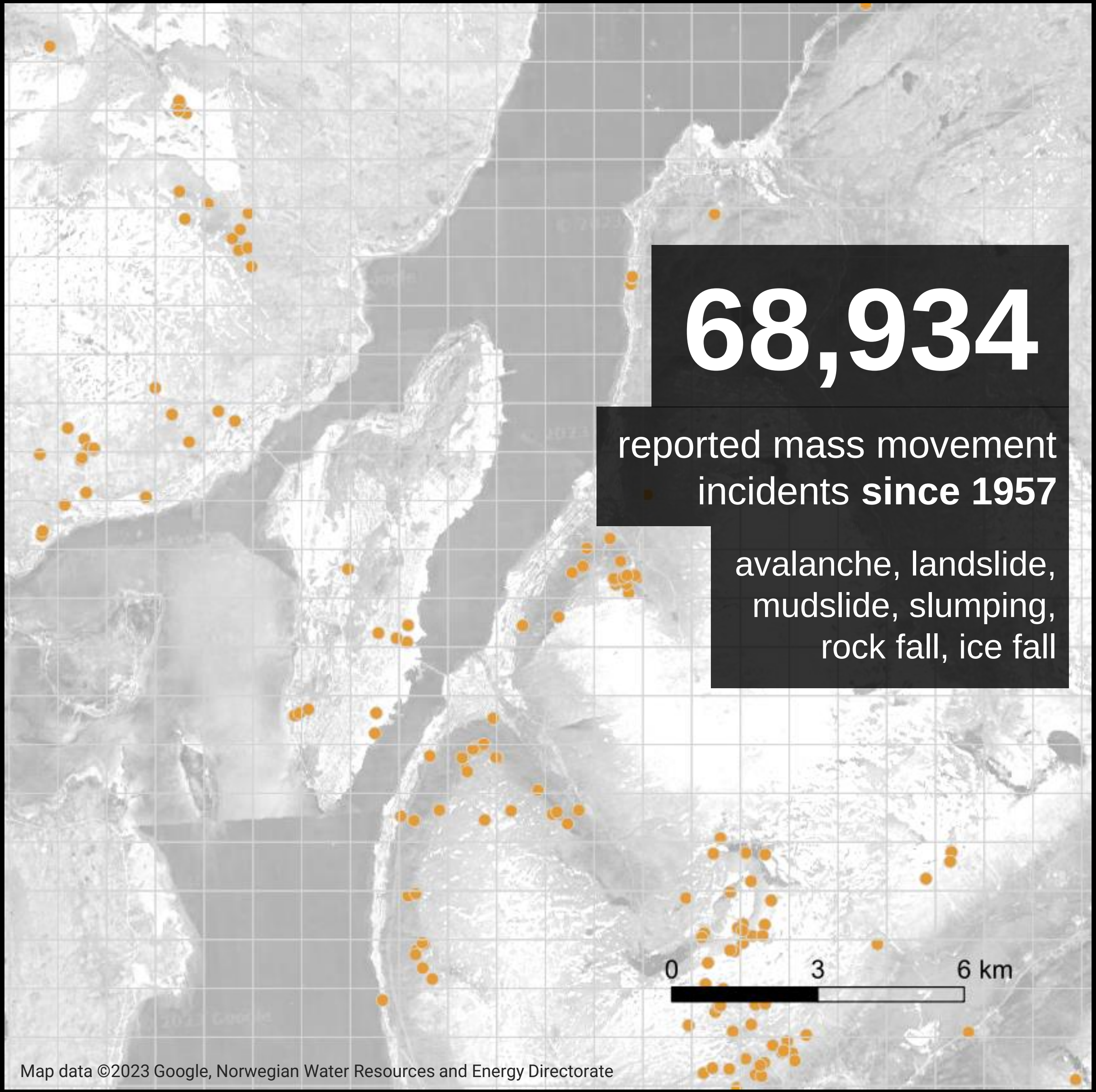

6 millimeters
1-kilometer resolution
with information about the **snow amount**
0
3
6 km
Map data ©2023 Google, MET Norway


156.6 millimeters
1-kilometer resolution
with information about the **snow depth**
0
3
6 km
Map data ©2023 Google, MET Norway


11.92 degrees
1-kilometer resolution
with information about the **steepness or slope**
0
3
6 km
Map data ©2023 Google, MET Norway


4 – gneisses (rock type)
1-kilometer resolution
with information about the **lithology**
0
3
6 km
Map data ©2023 Google, MET Norway

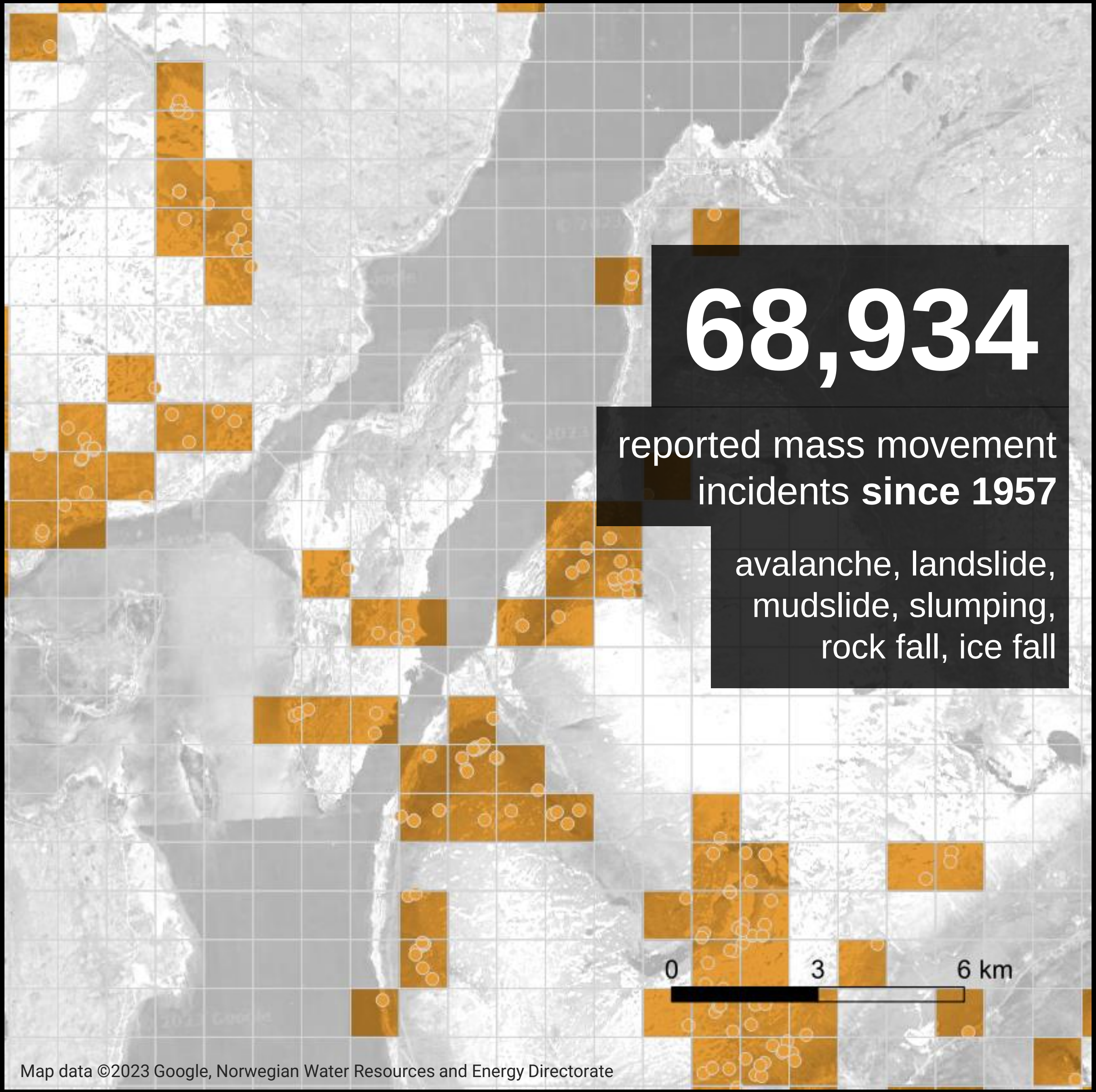

7 – artificial (built-up areas)
1-kilometer resolution
with information about the **land cover**
0
3
6 km
Map data ©2023 Google, MET Norway



68,934

reported mass movement incidents **since 1957**

avalanche, landslide, mudslide, slumping, rock fall, ice fall


68,934
reported mass movement incidents **since 1957**
avalanche, landslide, mudslide, slumping, rock fall, ice fall
0
3
6 km
Map data ©2023 Google, Norwegian Water Resources and Energy Directorate


0
3
6 km
Map data ©2023 Google


0
200
400 km
Map data ©2023 Google


508,182
points to cover
the entire map of Norway
0
200
400 km
Map data ©2023 Google, GADM

Dataset

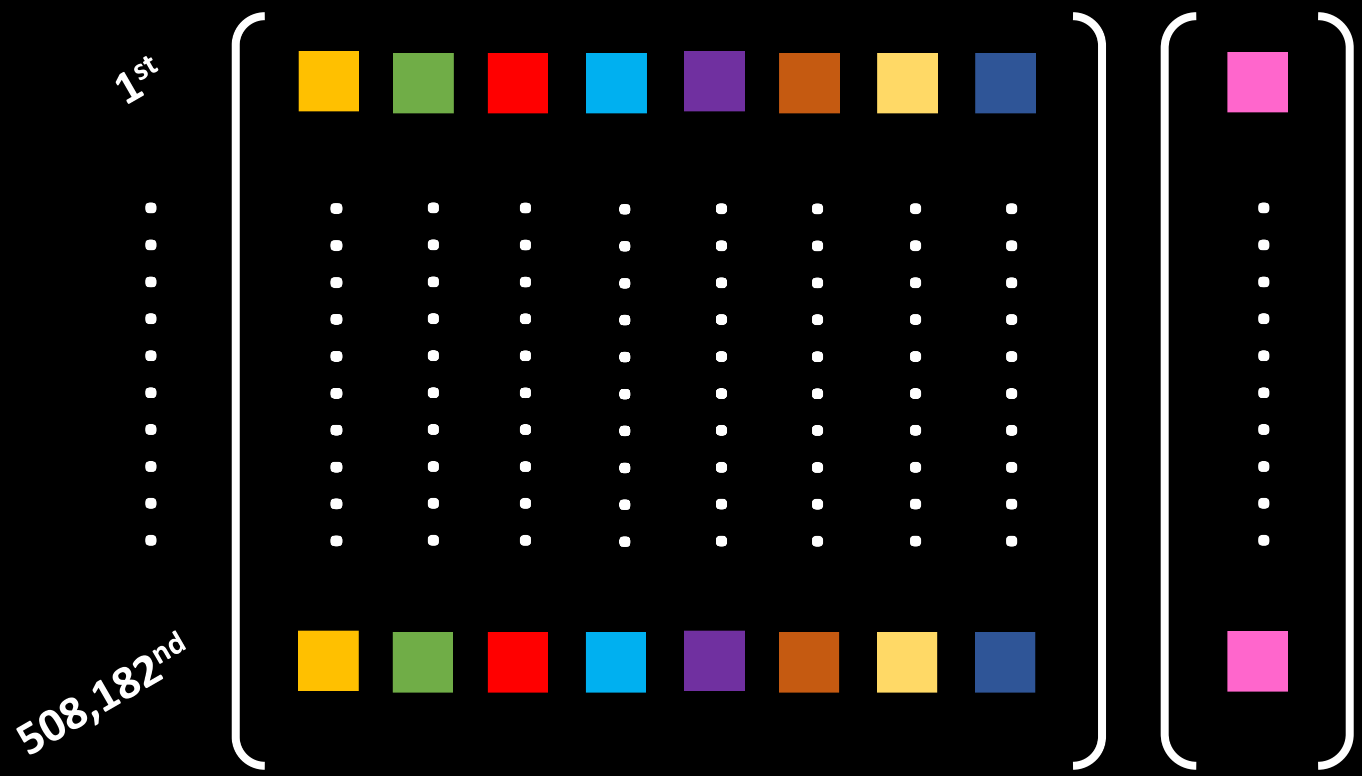
Dataset

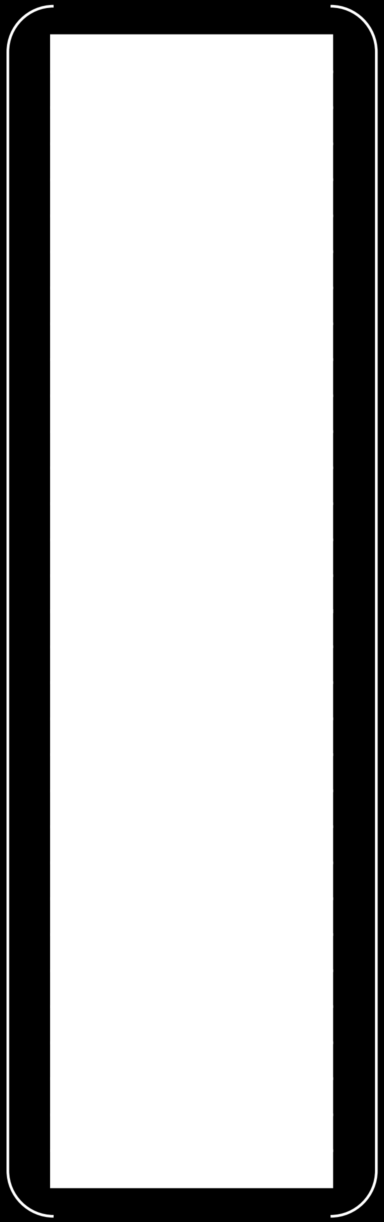
- temperature
- rainfall
- snow-water equivalent
- snow amount
- snow depth
- slope
- rock type
- land cover
- occurrence of mass movement

Dataset

Feature and Label Vectors

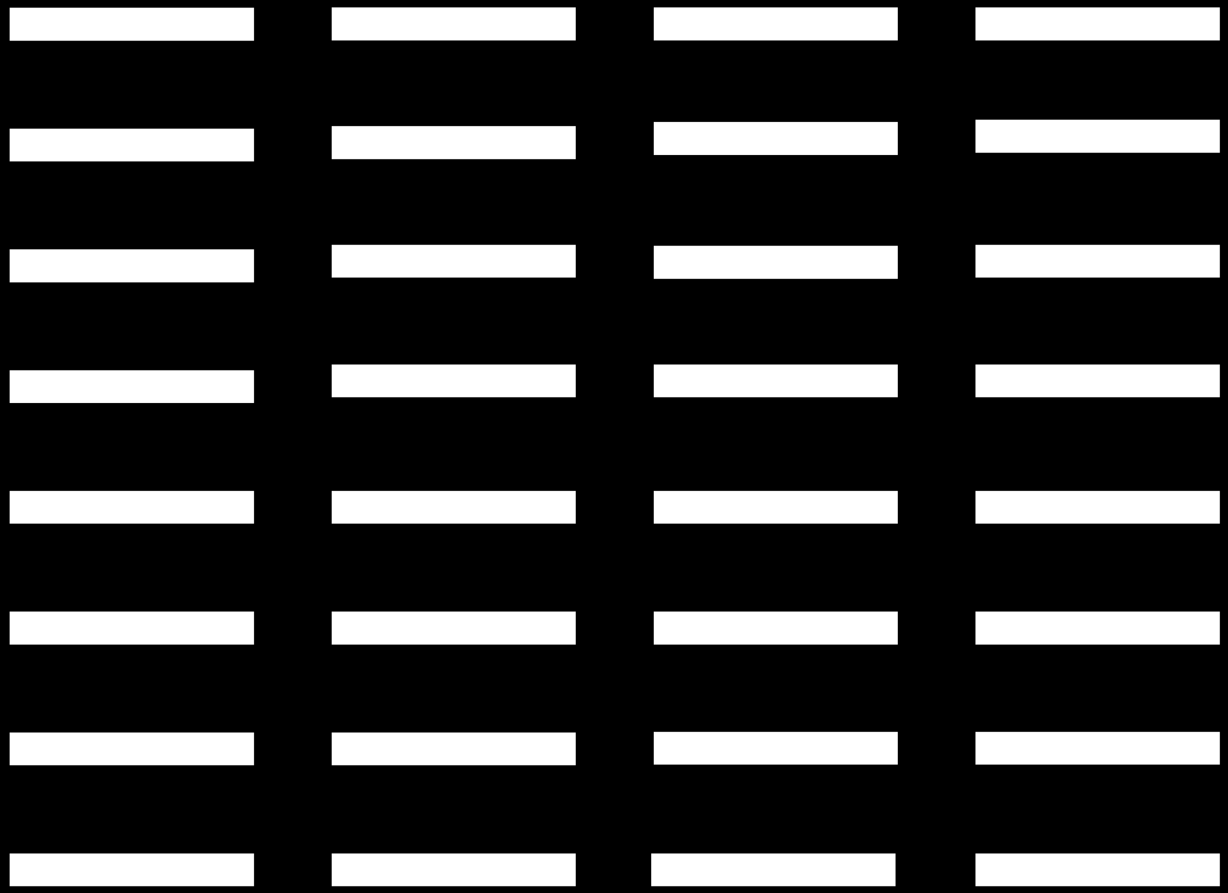
Feature and Label Vectors



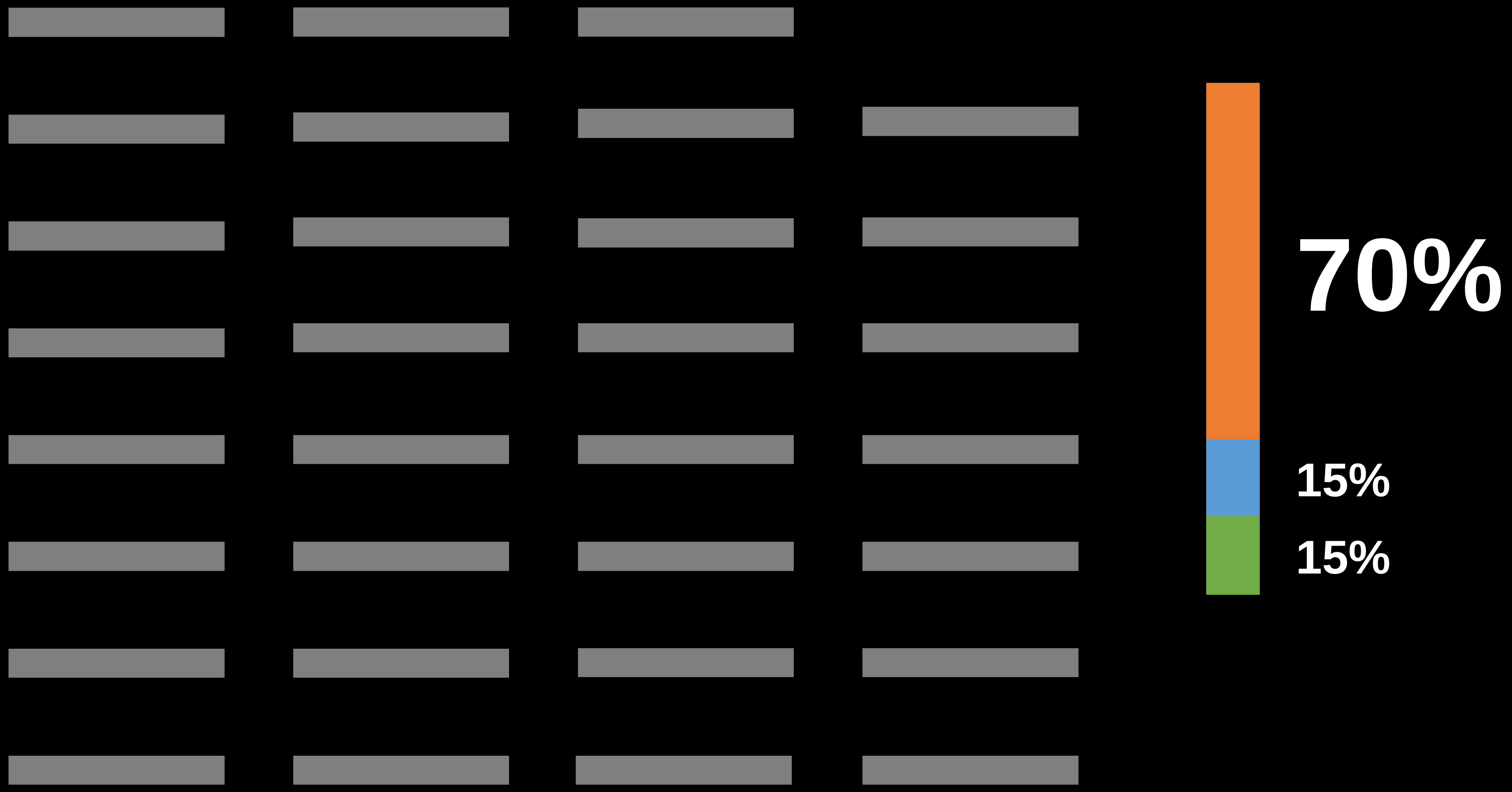


Very Tall Vector

Randomly subdivide into
32 smaller datasets



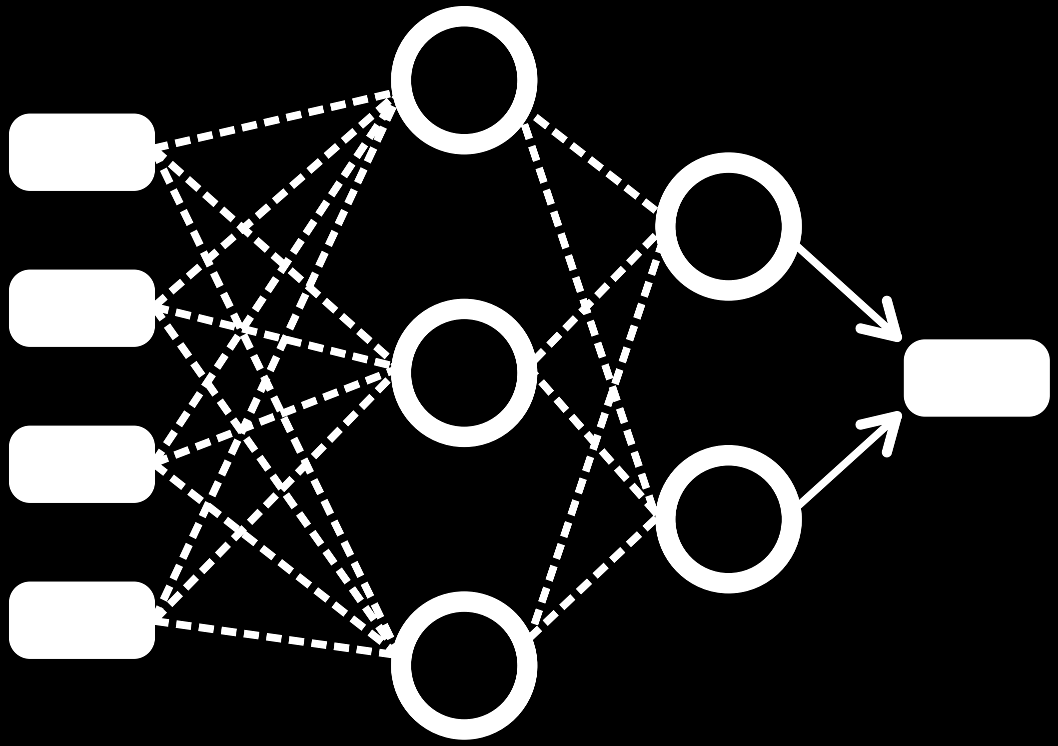
Each smaller dataset is split into training/validation/testing samples.



Each with own trained machine learning

Icon by Christensen (2019)

Each machine learning model is a graph neural network

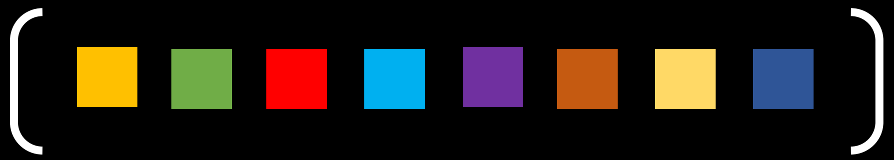


Icon by Christensen (2019)

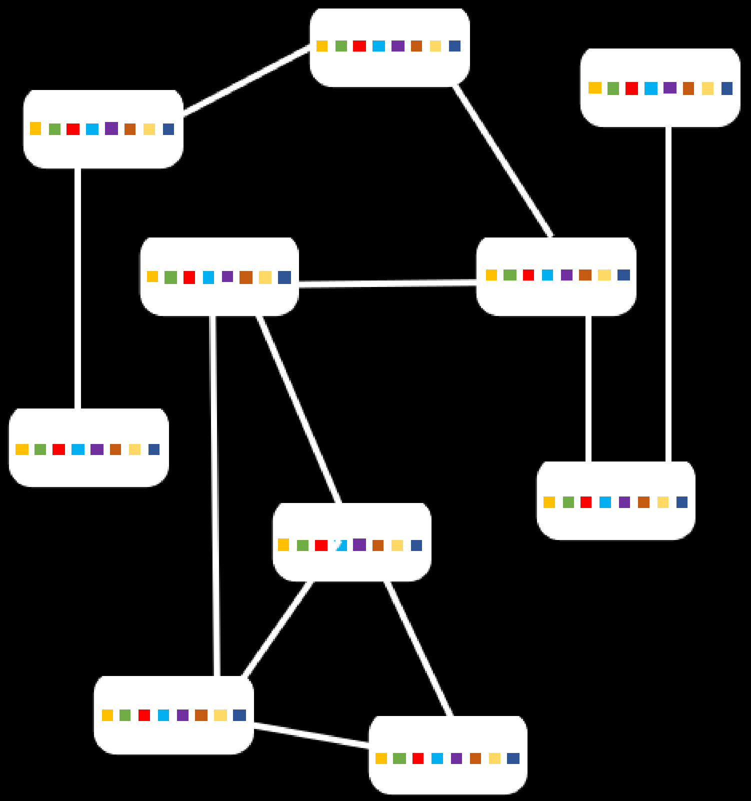
What is our graph?
Recall, each point ( ) has

1. Latitude and Longitude
(neighborhood)

2. Feature Vector
(attribute)



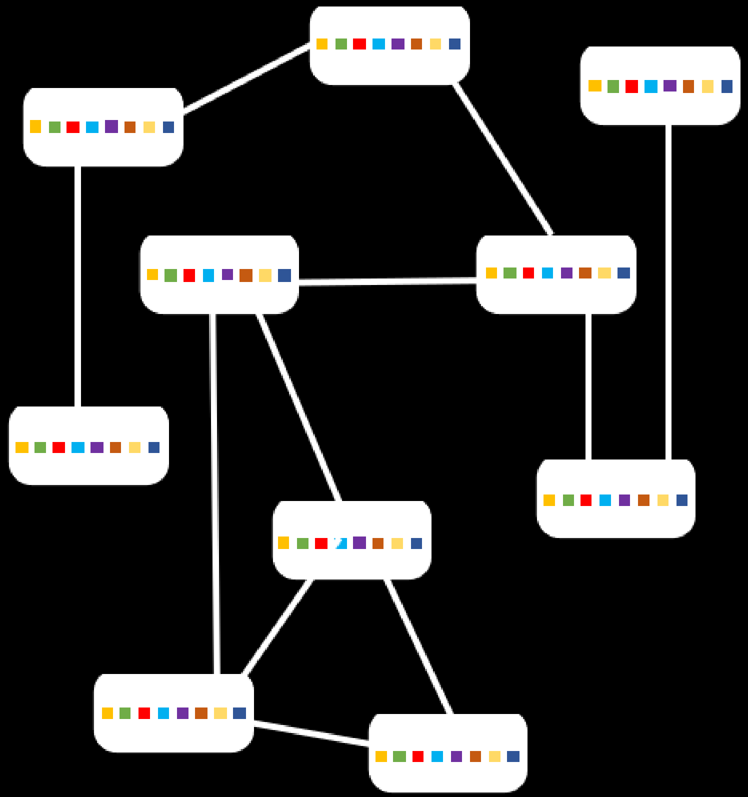
Imagine 10 samples of



neighborhood-aware graph

If they are close to each other *(say 12km-radius),* we build a connection.

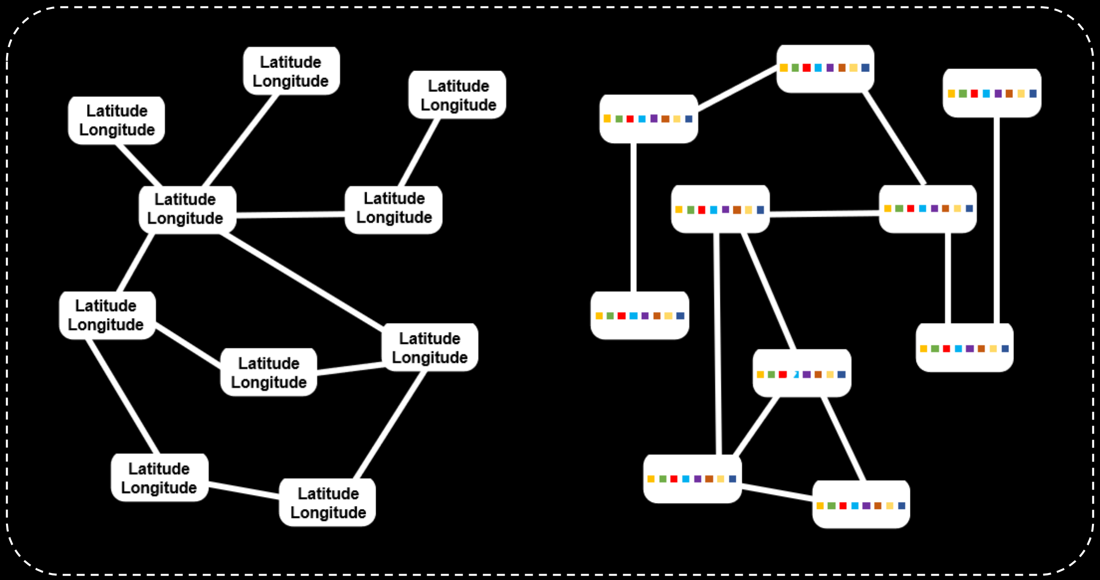
Imagine the same 10 samples of

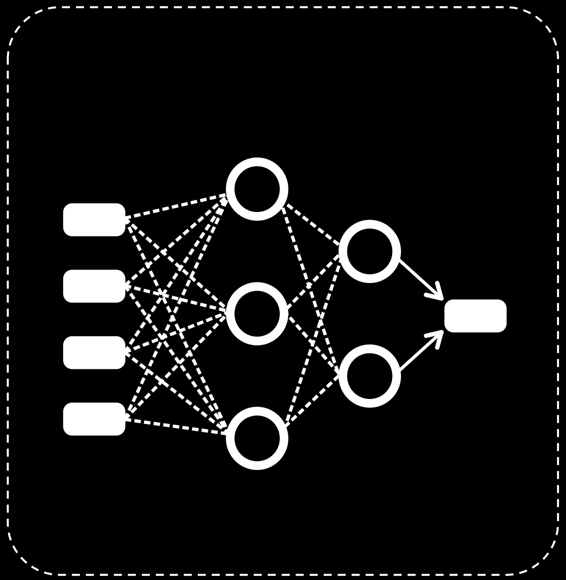


attribute-aware graph

If their feature vectors are similar (say cosine similarity of lithology, steepness, and land cover), we build a connection.

Train the neural network while the outputs respect the two graphs





Neighborhood-aware graph

Attribute-aware graph

Neural Network

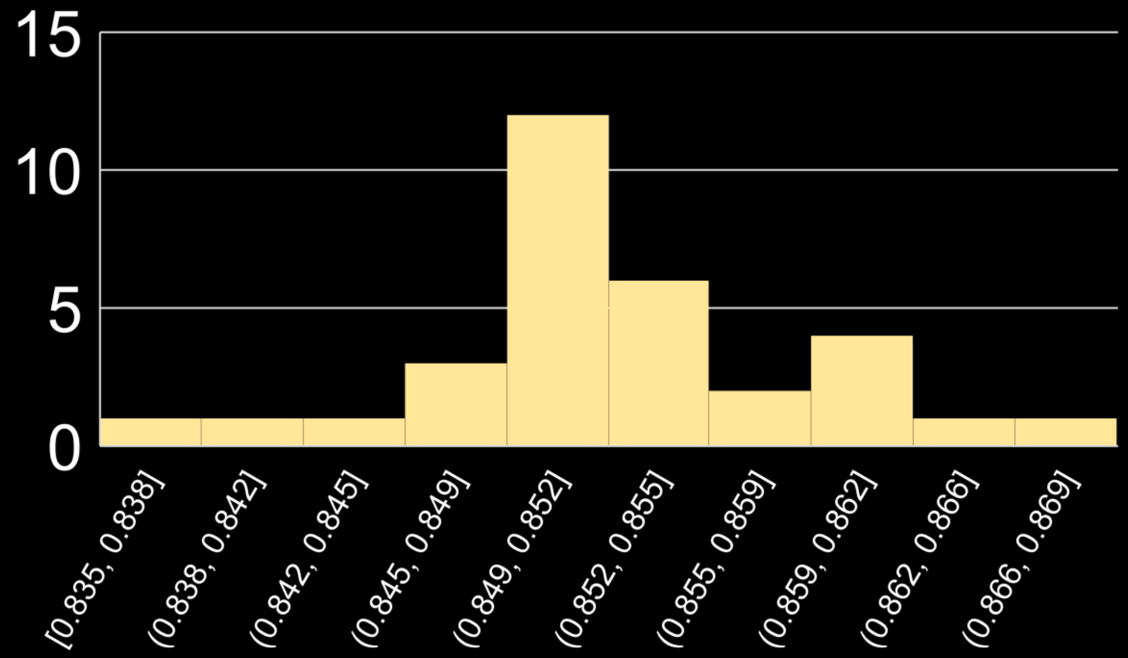
Icon by Christensen (2019)

once trained, the ensemble of 32 models predict the probability of mass movement

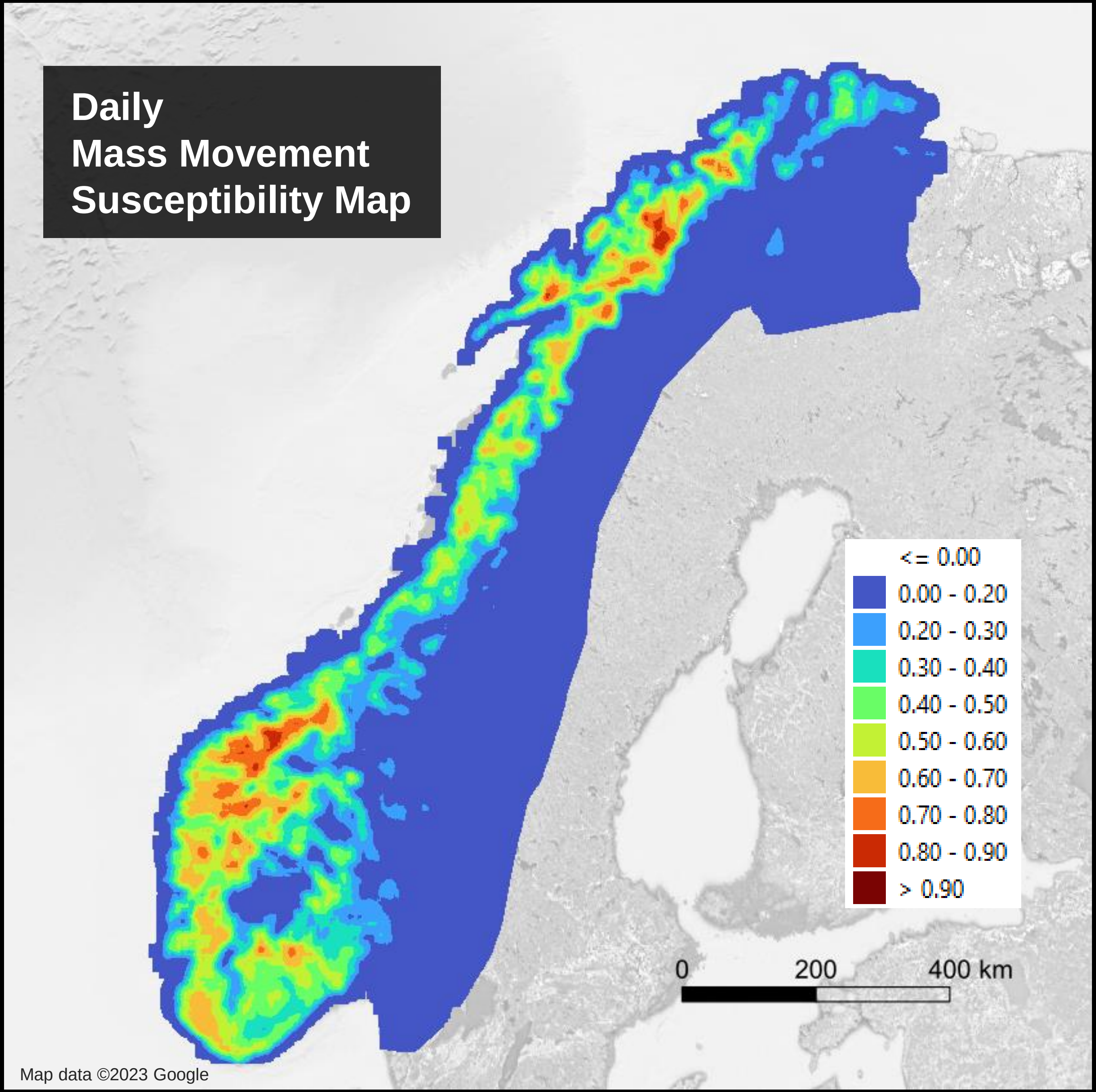
0.851	0.850	0.862	0.855
0.849	0.855	0.855	0.835
0.848	0.849	0.860	0.869
0.852	0.855	0.865	0.859
0.856	0.849	0.848	0.847
0.854	0.849	0.850	0.851
0.861	0.857	0.850	0.855
0.845	0.849	0.840	0.848

aggregating the predictions

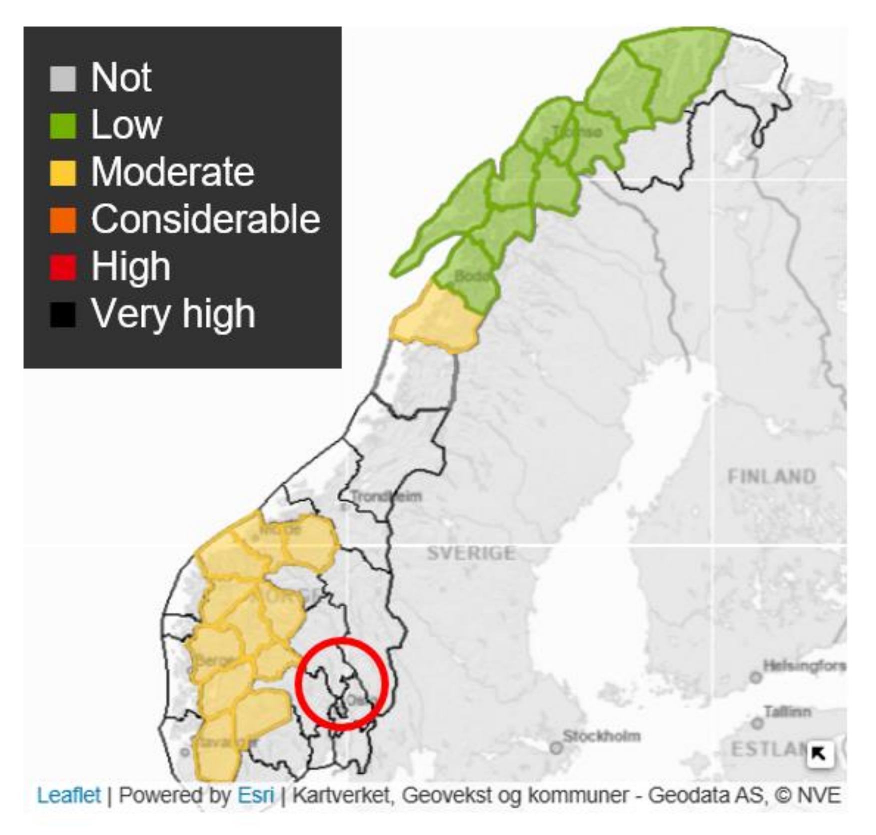
Average = 0.853 ± 0.007



Daily Mass Movement Susceptibility Map



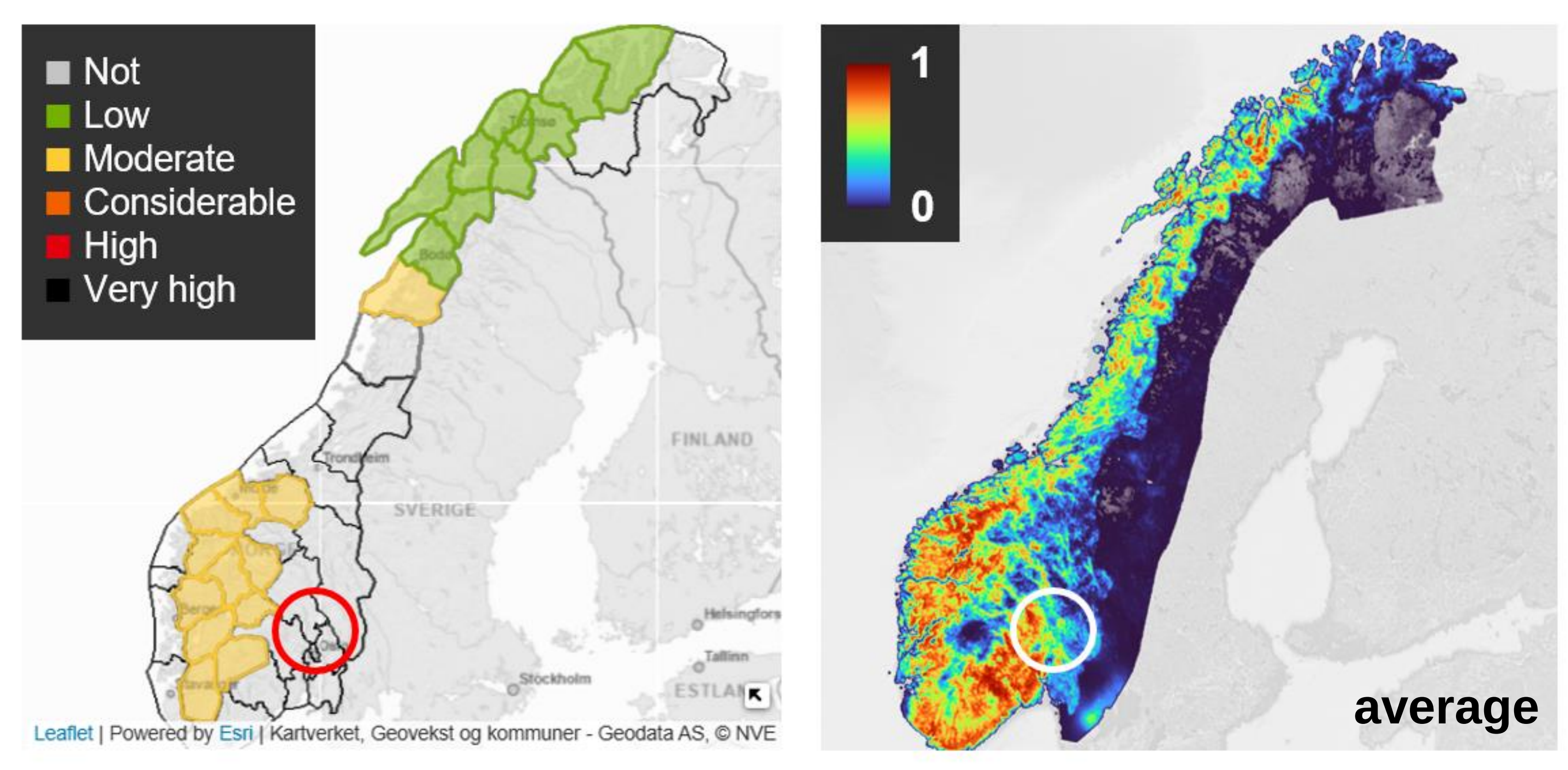
2020 Gjerdrum Mass Movement Incident

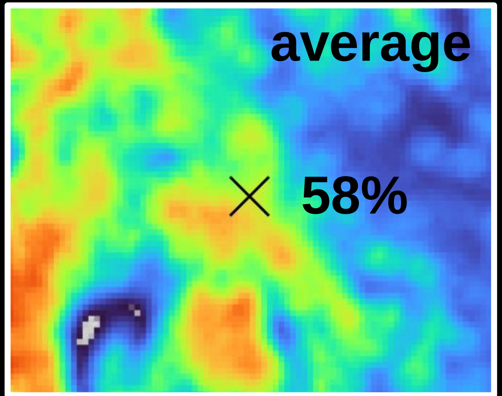


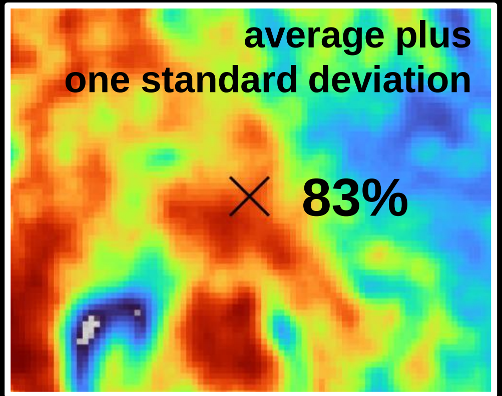
avalanche: no danger
landslides: low warning

© NTB/AFP via GETTY Images

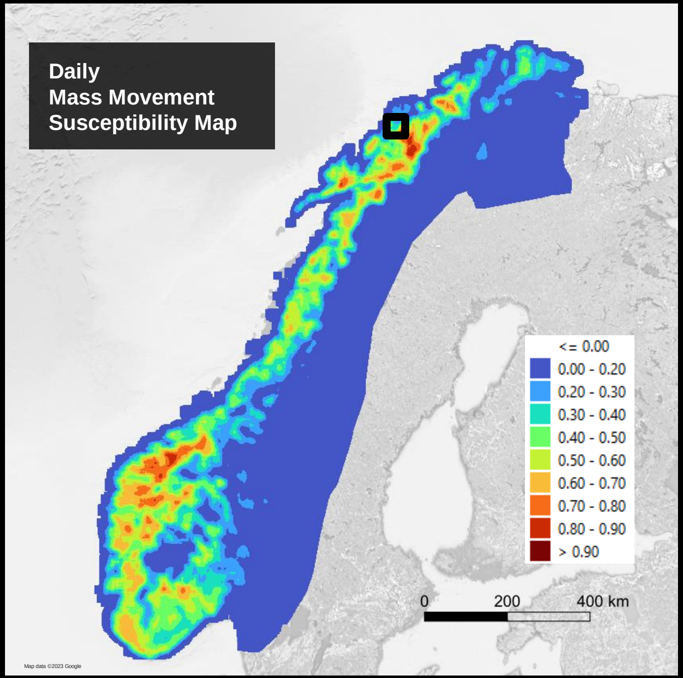
2020 Gjerdrum Mass Movement Incident

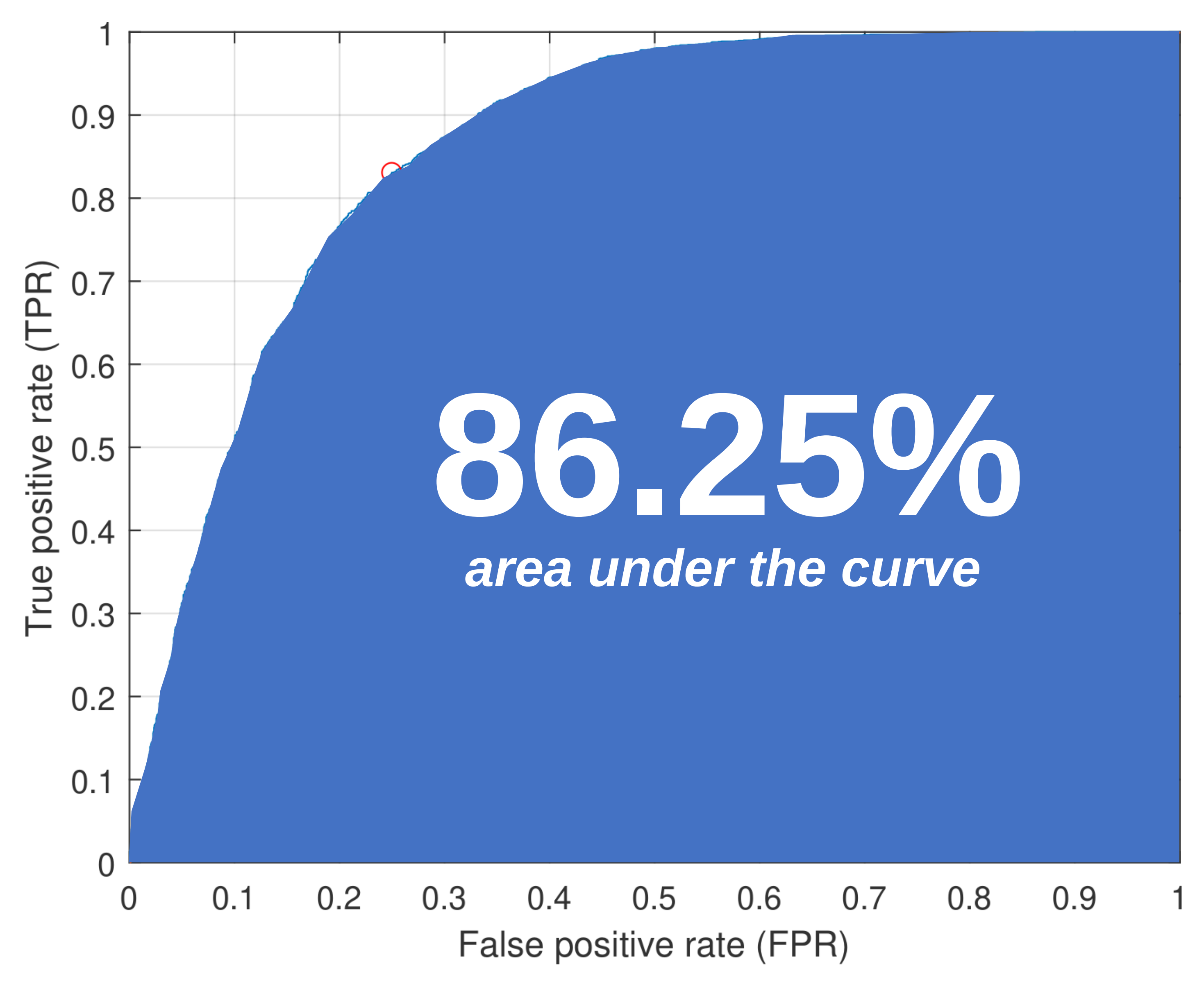


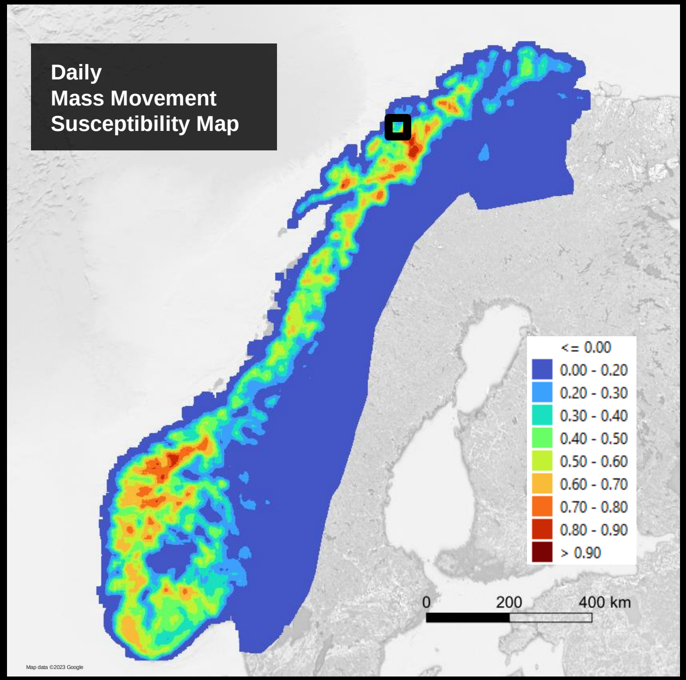




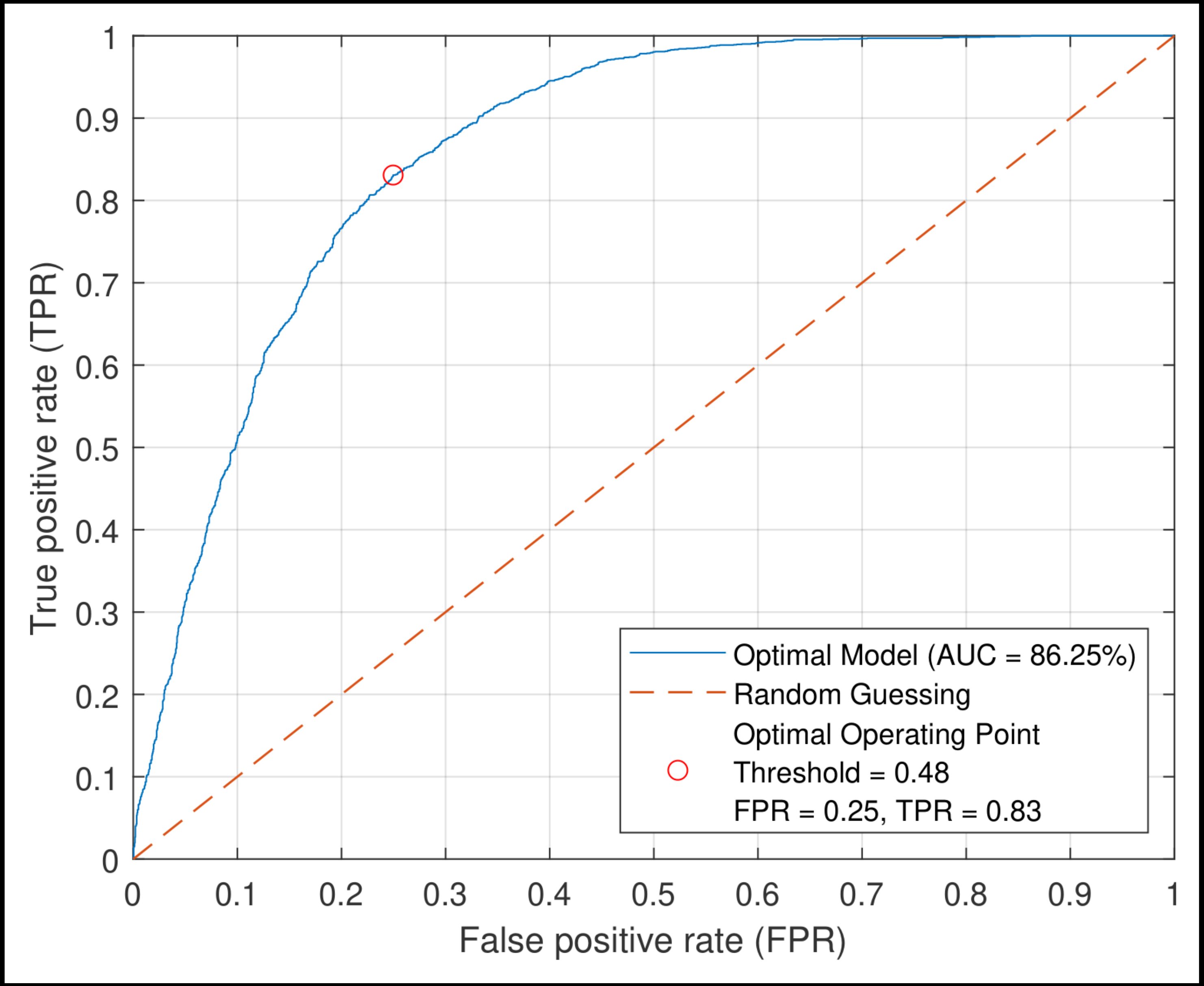
avalanche: no danger
landslides: low warning


Daily
Mass Movement
Susceptibility Map
<= 0.00
0.00 - 0.20
0.20 - 0.30
0.30 - 0.40
0.40 - 0.50
0.50 - 0.60
0.60 - 0.70
0.70 - 0.80
0.80 - 0.90
> 0.90
0
200
400 km

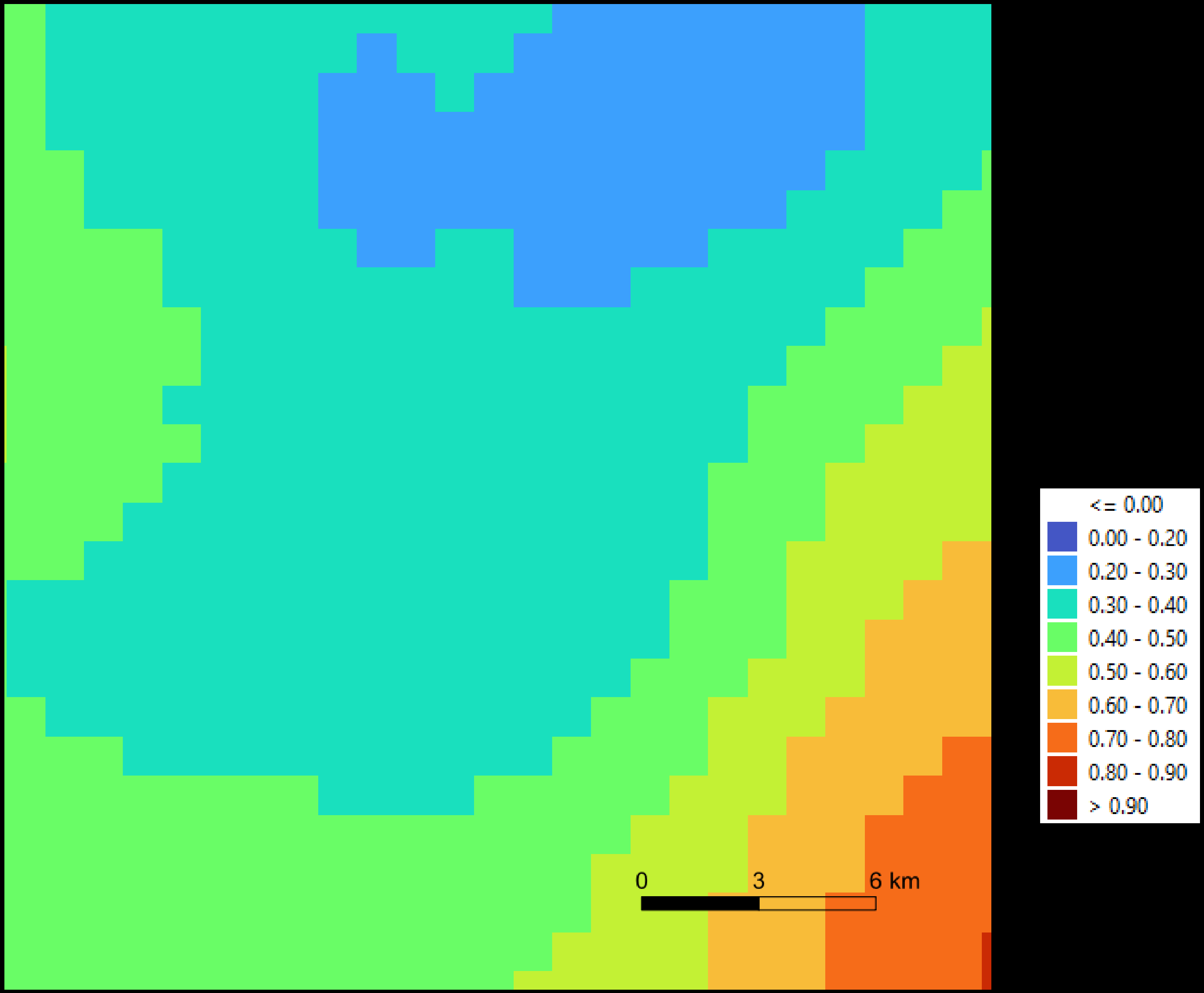

86.25%
area under the curve
True positive rate (TPR)
False positive rate (FPR)
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1

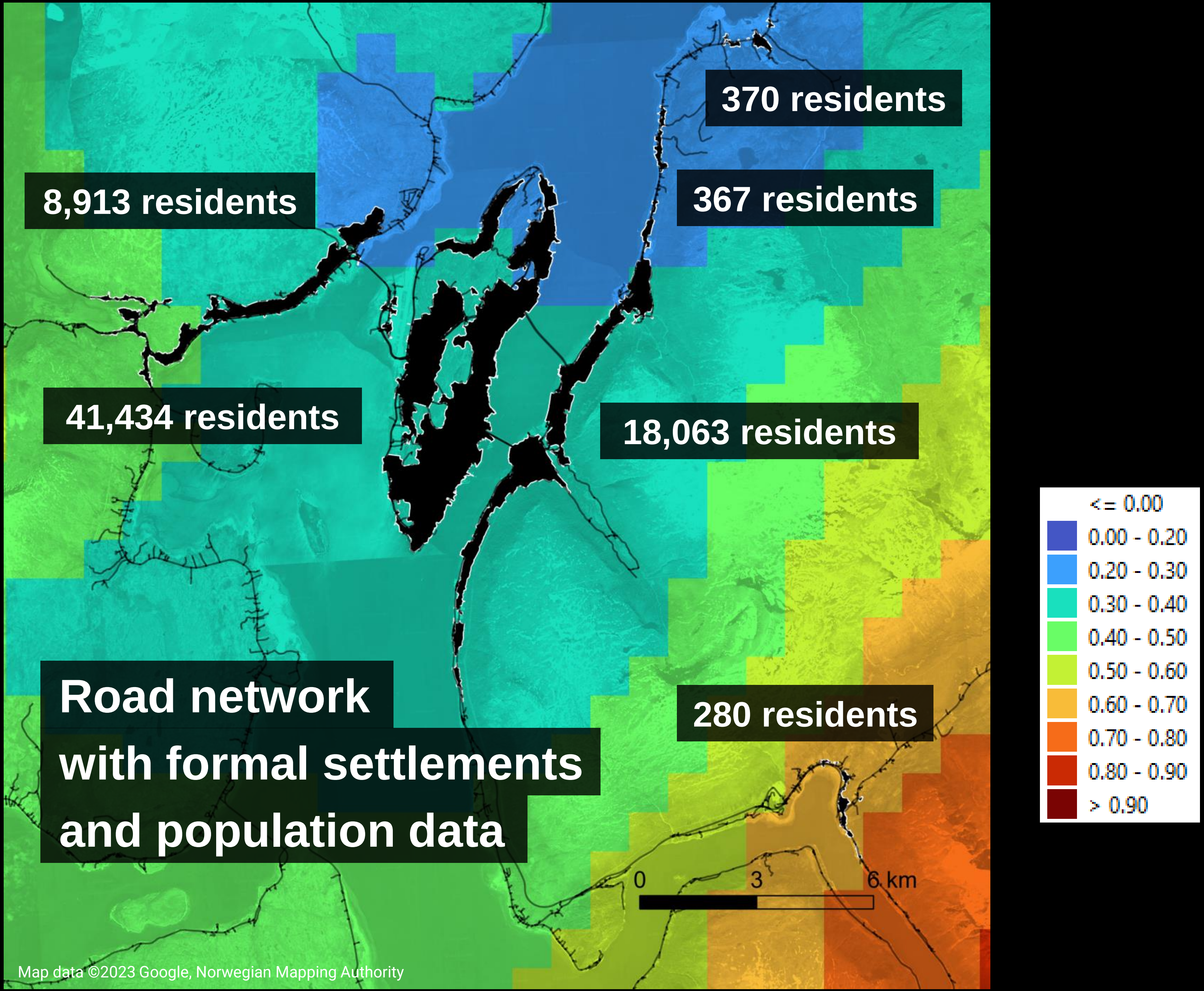


Daily
Mass Movement
Susceptibility Map
<= 0.00
0.00 - 0.20
0.20 - 0.30
0.30 - 0.40
0.40 - 0.50
0.50 - 0.60
0.60 - 0.70
0.70 - 0.80
0.80 - 0.90
> 0.90
0
200
400 km

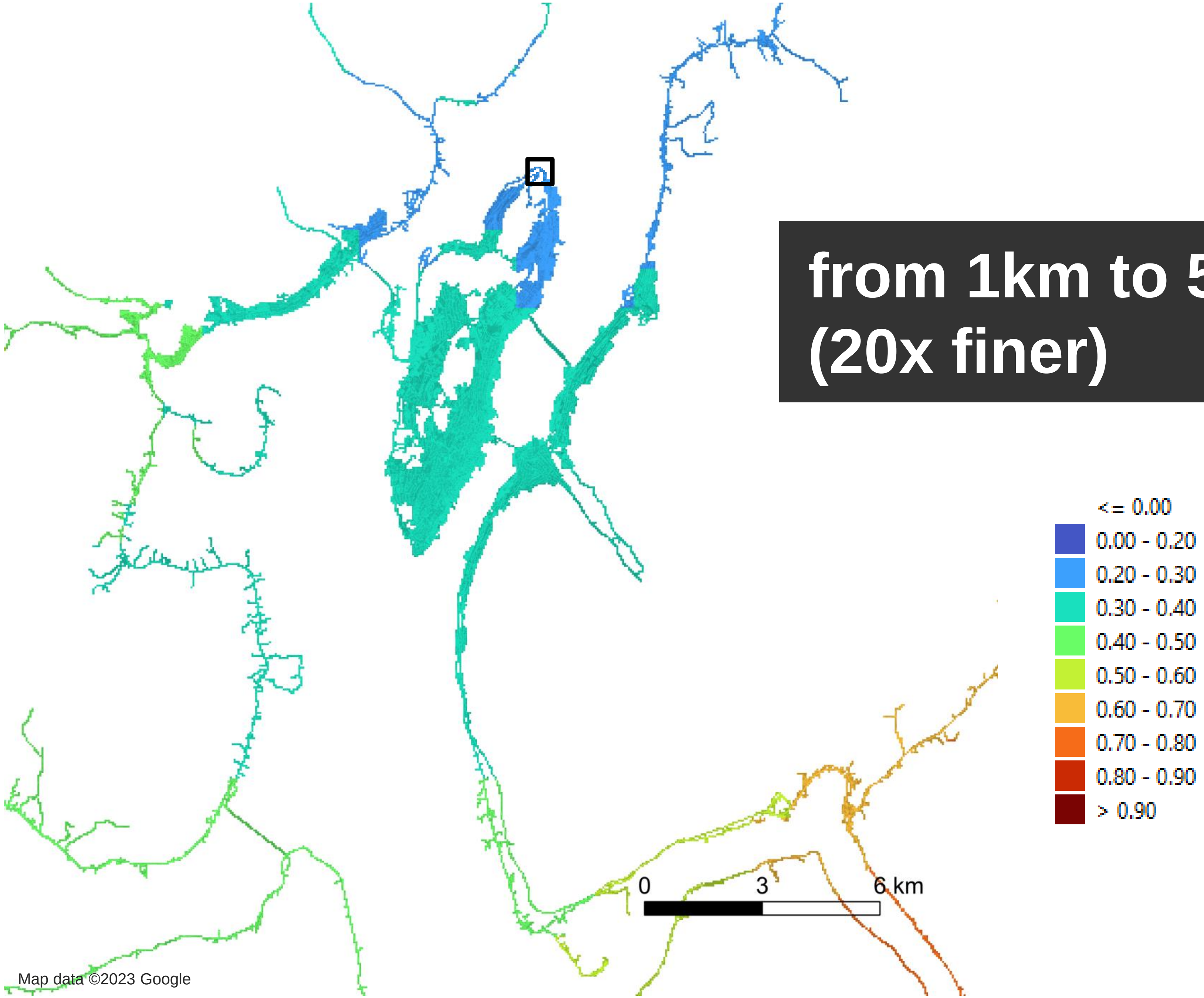


True positive rate (TPR)
False positive rate (FPR)
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
Optimal Model (AUC = 86.25%)
Random Guessing
Optimal Operating Point
Threshold = 0.48
FPR = 0.25, TPR = 0.83


<= 0.00
0.00 - 0.20
0.20 - 0.30
0.30 - 0.40
0.40 - 0.50
0.50 - 0.60
0.60 - 0.70
0.70 - 0.80
0.80 - 0.90
> 0.90
0
3
6 km

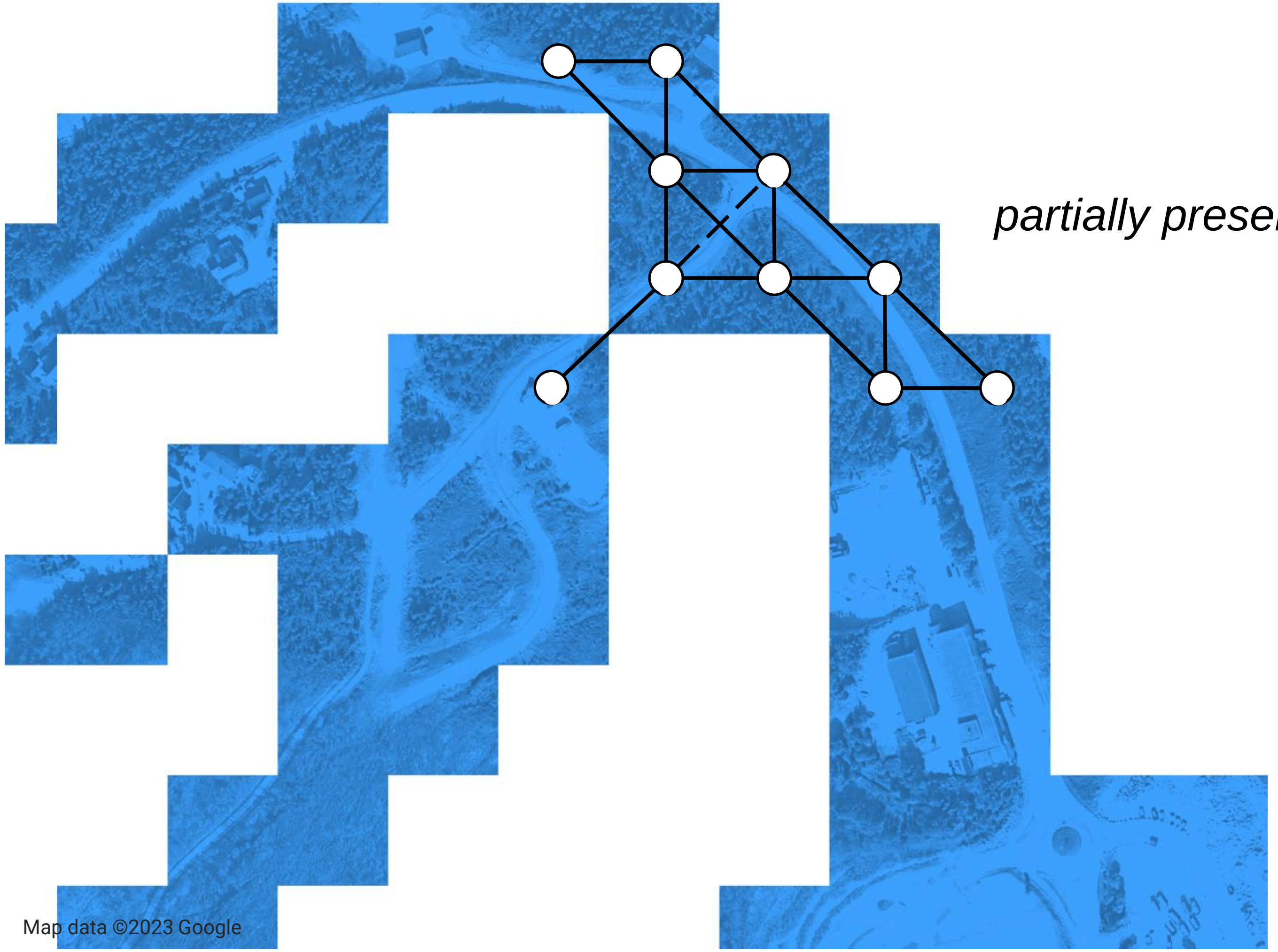

370 residents
367 residents
8,913 residents
41,434 residents
18,063 residents
280 residents
Road network
with formal settlements
and population data
0
3
6 km
Map data ©2023 Google, Norwegian Mapping Authority
<= 0.00
0.00 - 0.20
0.20 - 0.30
0.30 - 0.40
0.40 - 0.50
0.50 - 0.60
0.60 - 0.70
0.70 - 0.80
0.80 - 0.90
> 0.90

from 1km to 50m (20x finer)

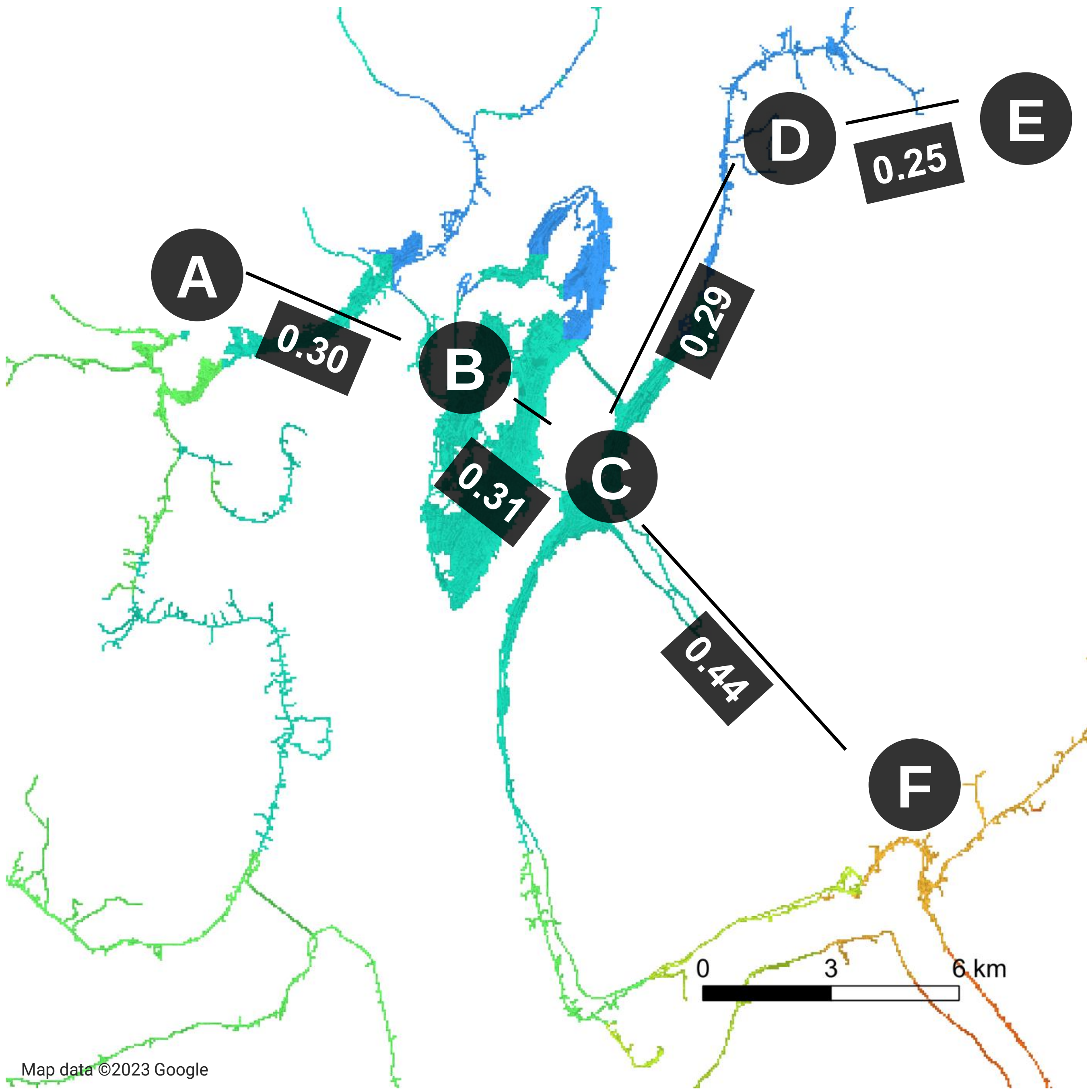


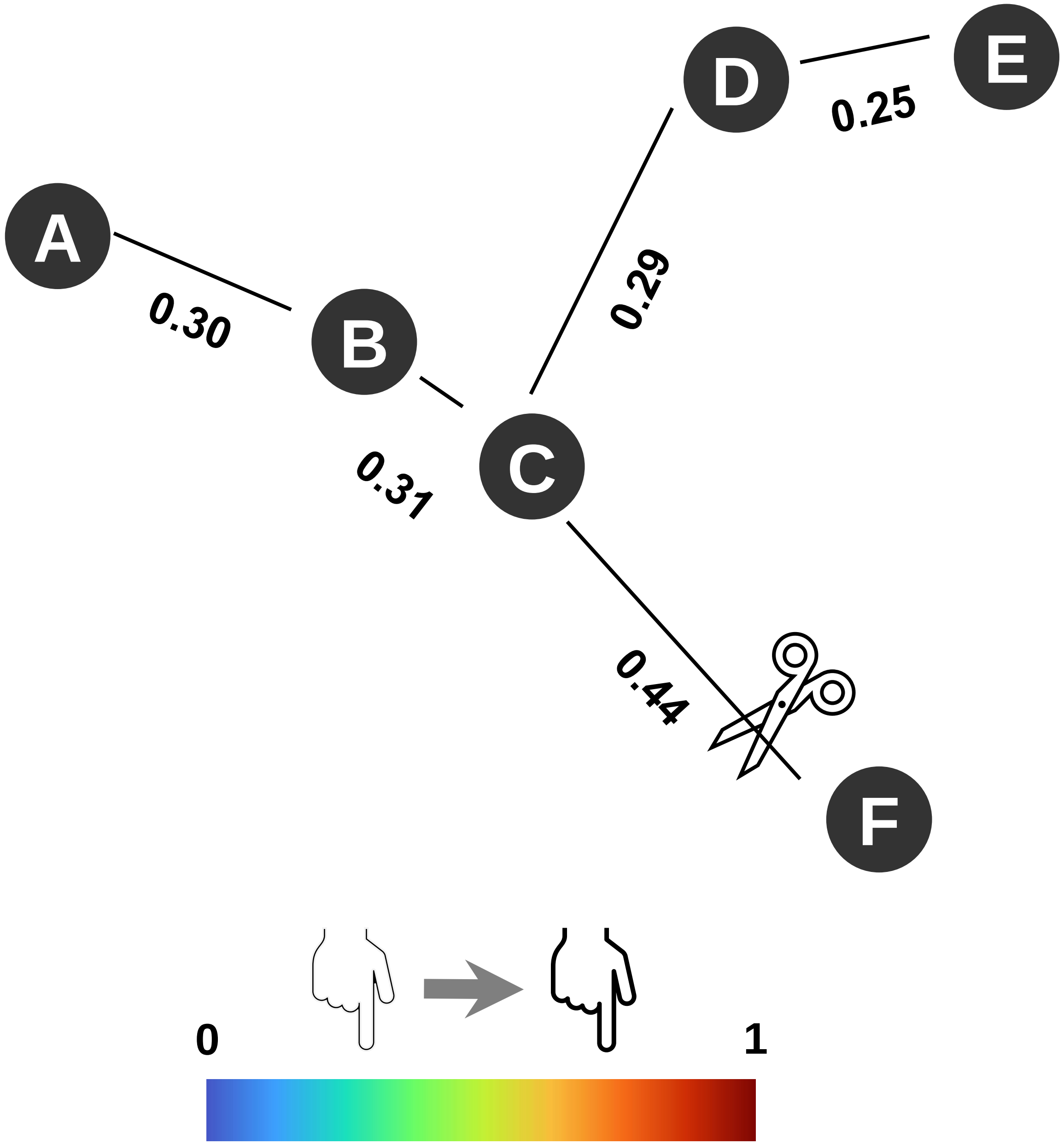
simplicial networks

shortest path



partially presented


A
B
C
D
E
F
0.30
0.31
0.29
0.25
0.44
0
3
6 km
Map data ©2023 Google



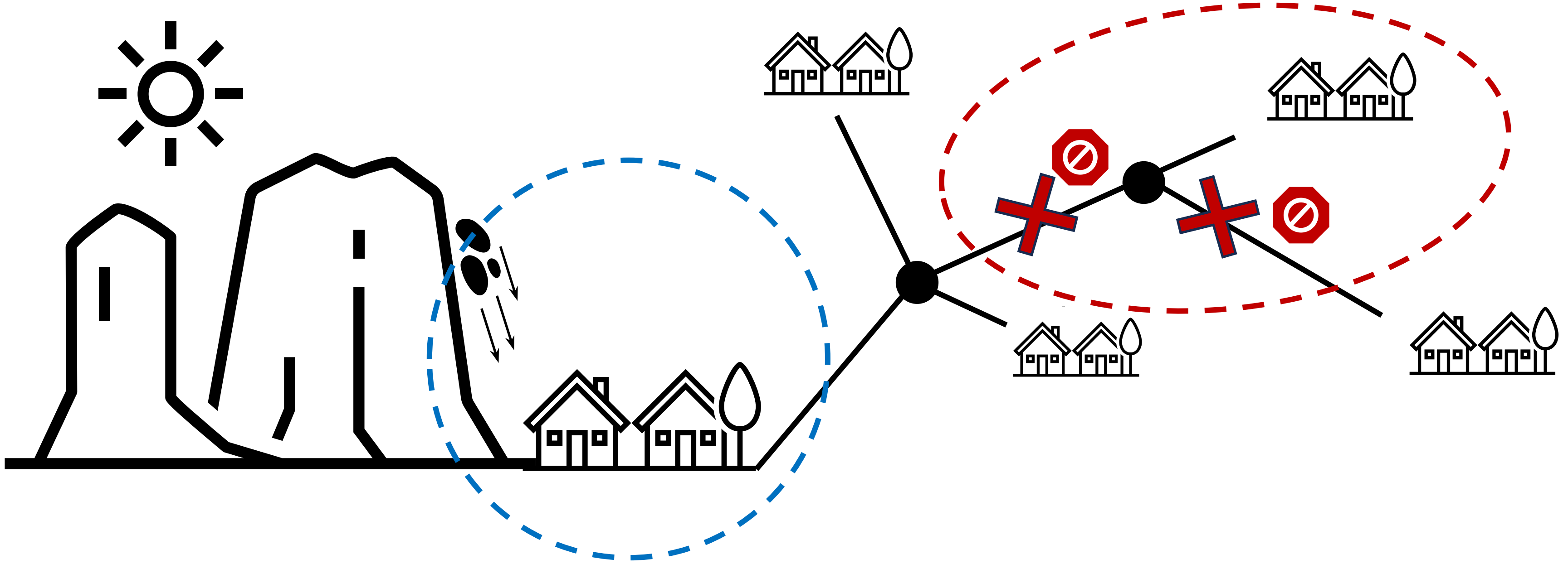
Iteratively increase the cutoff susceptibility threshold [0,1] to "cut" the edge (i.e., road)

Perform spectral graph clustering using the Laplacian transformation

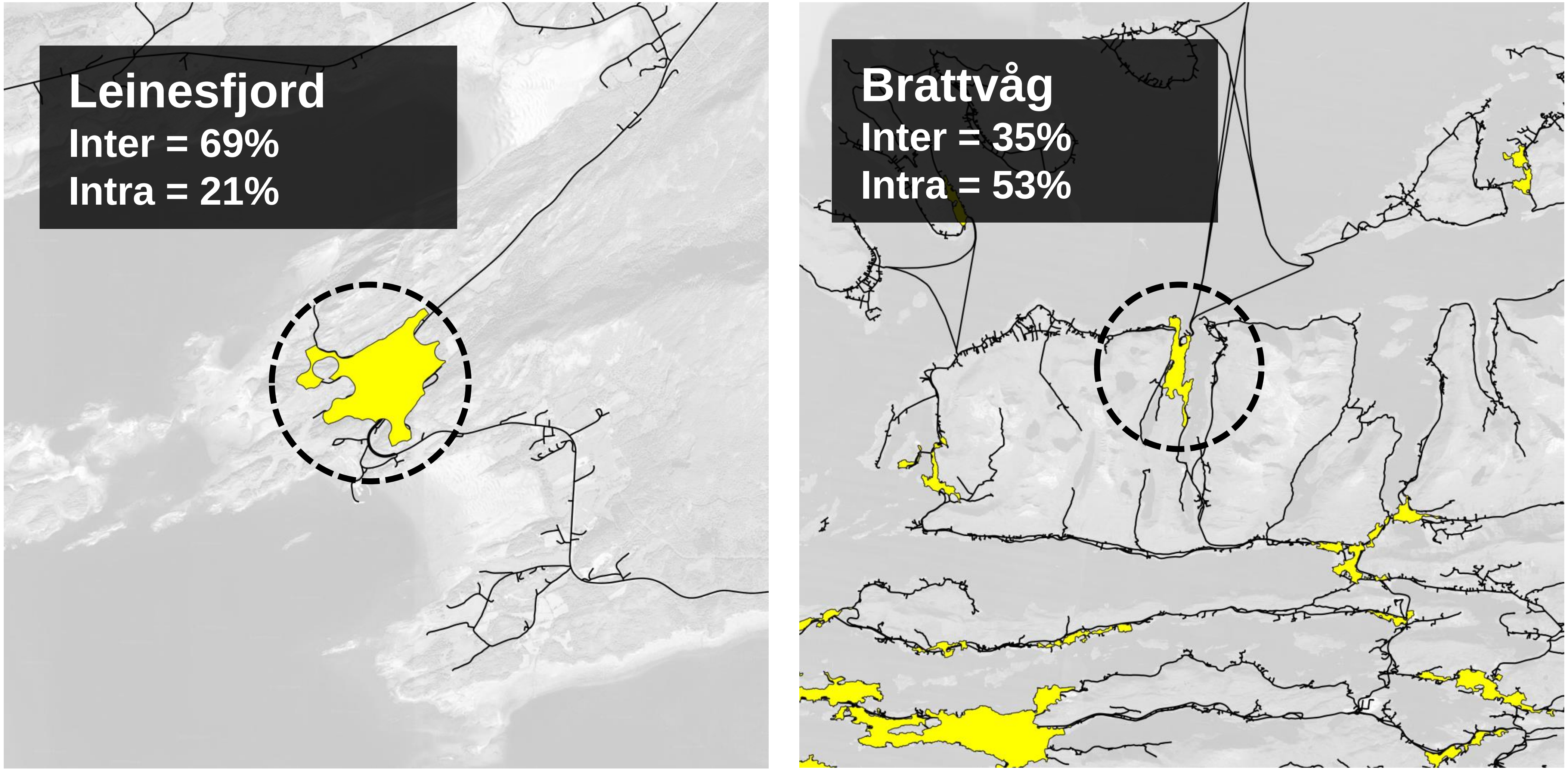
Extract the lowest cutoff value that results in the isolation of a settlement from the graph

lowest cutoff value

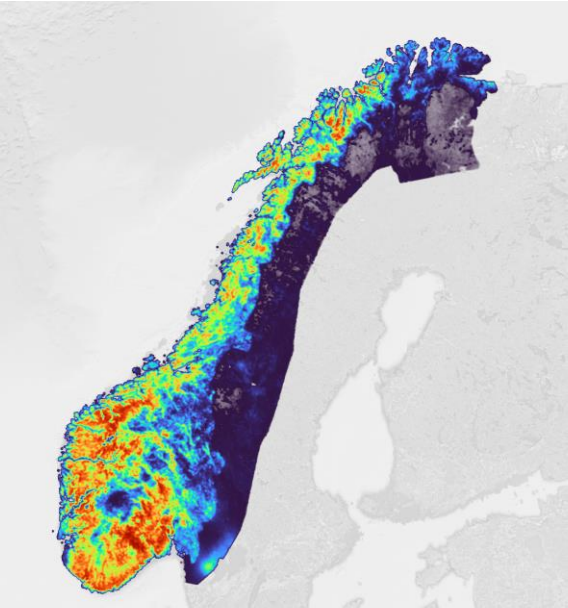
Minimum Triggering Exposure Probability
of Mass-Movement-Susceptible Roads for
<u>Inter-Settlement</u> Isolation

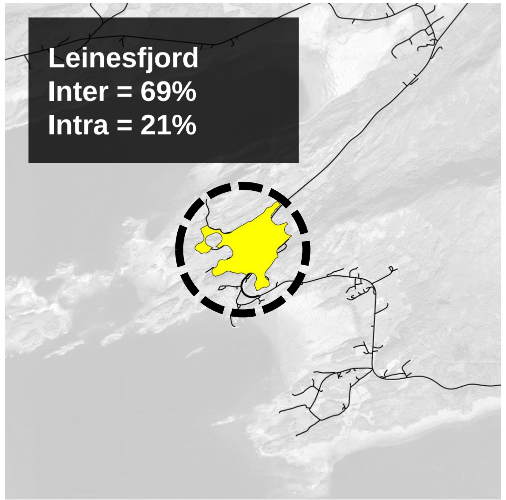


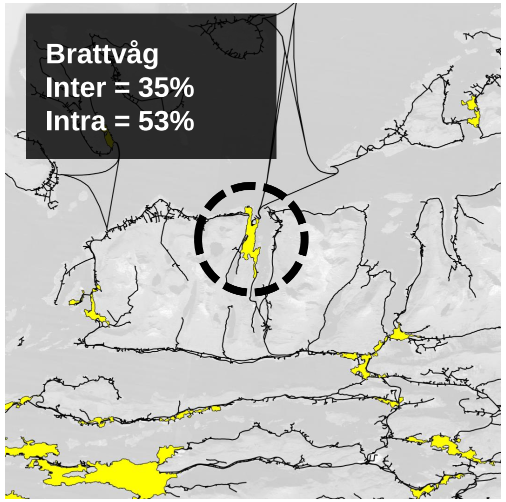
<u>Intra-Settlement</u> Exposure Probability of
Being a Mass-Movement-Susceptible Area



Map Data ©2023 Google







Map Data ©2023 Google

Table A.5: 190 settlements or villages in Oslo-Viken.

Village	Intra	Inter	Population
Askgrenda	82.73%	82.30%	522
Askim	21.03%	20.73%	14651
Aulifeltet	25.02%	25.33%	2,875
Aursmoen	15.40%	15.92%	3493
Berger	57.26%	58.43%	1110
Bjertnestunet	9.50%	9.65%	415