Towards satellite based deep-seated landslide nowcasting

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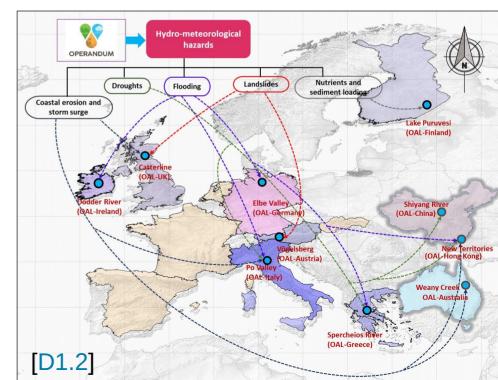
ESA Living Planet Symposium '22, Bonn





Context

- H2020 OPERANDUM project: Nature based solutions for hydrometeorological hazards
- 'Open Air Laboratories'
 - Optimize design
 - Monitor effect





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Vögelsberg: a deep-seated landslide

- Near Innsbruck, Austria
- Progressive damage, to roads, houses, etc.

- Hydromet. controlled
- 4-5 cm/year
- Two distinct deformation patterns/regions

Pfeiffer, et al. "Spatio-temporal assessment [...]: The Vögelsberg landslide in Tyrol (Austria)." https://doi.org/10.1002/esp.5129



[Pfeiffer & Zieher, ÖAW]



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Model/monitoring requirements

- A priori assess effect of preventive measures
- Keep model on up-to-date, including changing climate
- Classification is insufficient (always active)







Where to start?

- Flexibility is a necessity Intervention is a break in landslide dynamics Quickly adapt to this change
- 2) Preferably based on remote sensing data as generic as possible



3) Upscaling: regional application/monitoring

Resemblance to early warning systems early warning, based on deformation only, is impossible

Approach

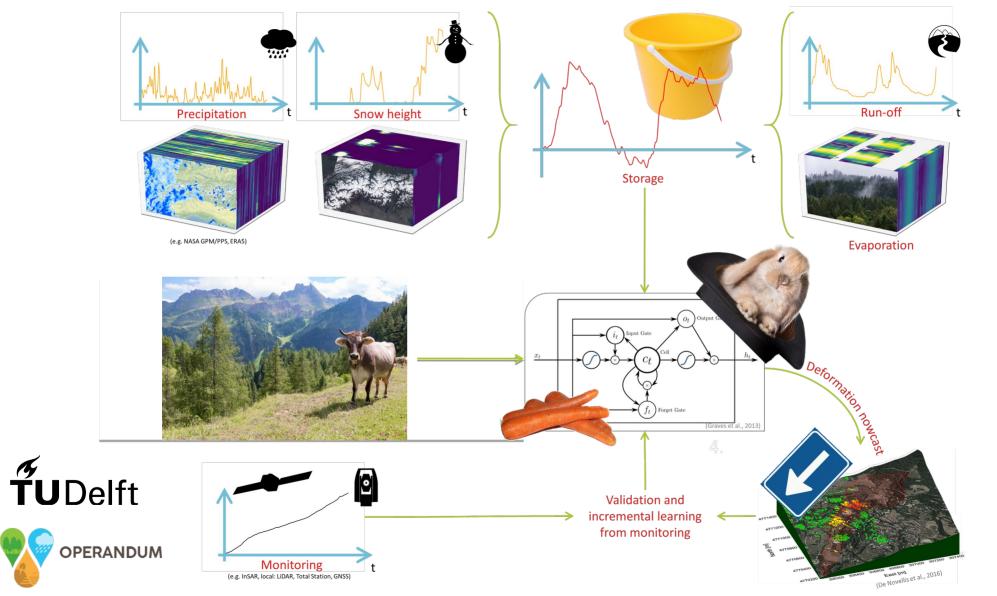
- Extensive literature study: machine learning!
- Conclusion
 - Multiple, successful studies based on local data
 - Sufficient remote sensing data available





van Natijne et al. "Machine Learning: new potential for local and regional deep-seated landslide nowcasting" https://doi.org/10.3390/s20051425





Ingredient: deformation data

- Planned: deformation measurements from InSAR
 - Technology not as mature as expected
 - However: Alpine terrain not necessarily problematic

(a) (b)

• Alternative: 5 years of local deformation measurements





Zieher et al. "Integrated Monitoring of a Slowly Moving Landslide [...]" https://doi.org/10.1109/IGARSS47720.2021.9553324

van Natijne et al. "World-wide InSAR sensitivity index for landslide deformation tracking" In press at the International Journal of Applied Earth Observation and Geoinformation

Ingredient: hydro.-met. conditions

	Variable	Source
	Deformation	Local (ATS)
1.	Precipitation	ERA5
2.	Precipitation	GPM
3.	Snow water equivalent	ERA5
4.	Snow melt	ERA5
5.	Soil moisture	SMAP
6.	Soil moisture	GLEAM
7.	Soil moisture	ERA5
8.	Evaporation	GLEAM
9.	Air temperature	ERA5

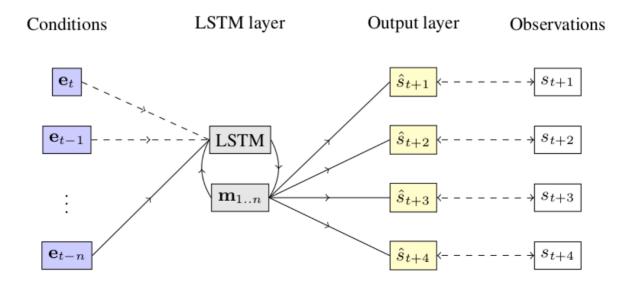






Model

- Simple, shallow, neural network (TensorFlow)
- Long-short term memory, resembles a bucket model Three memory cells, 32-day history
- 2×4 output neurons (one per region, per day)





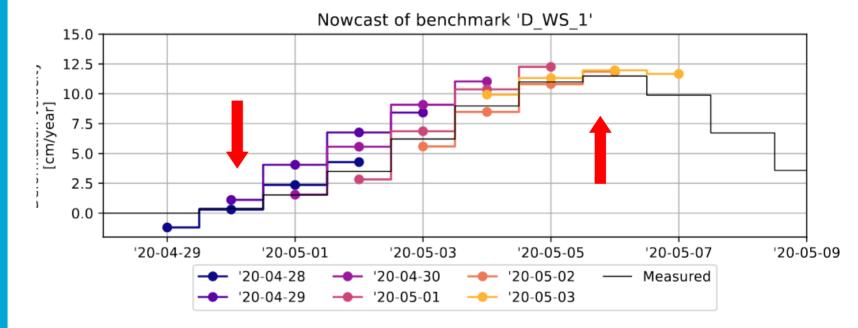


Desired output

OPERANDUM

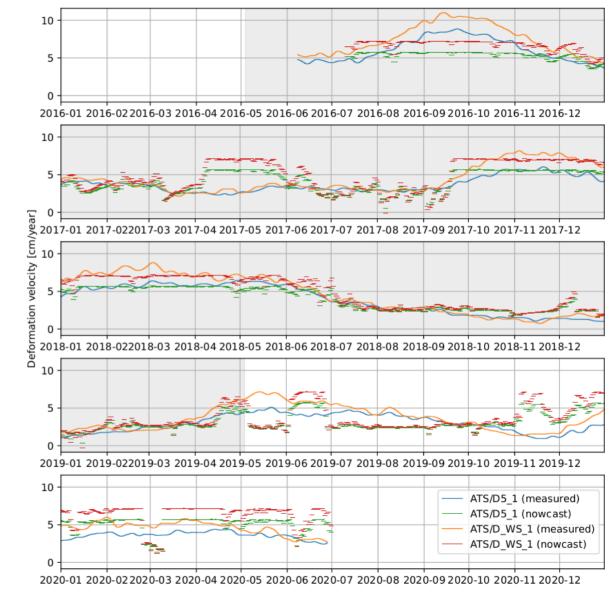
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• Deformation velocity estimate, four days ahead



Demonstrates 'understanding' of slope process

Results

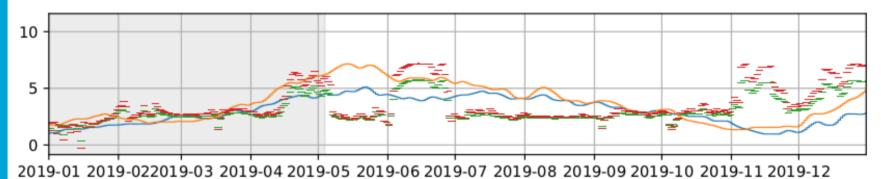




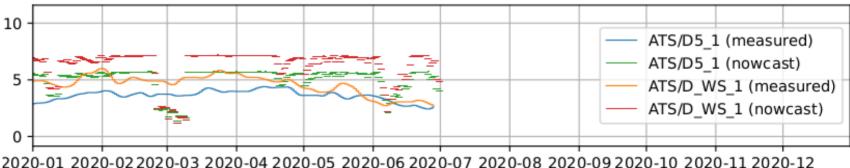


Results

• A very 'expensive' mean?..

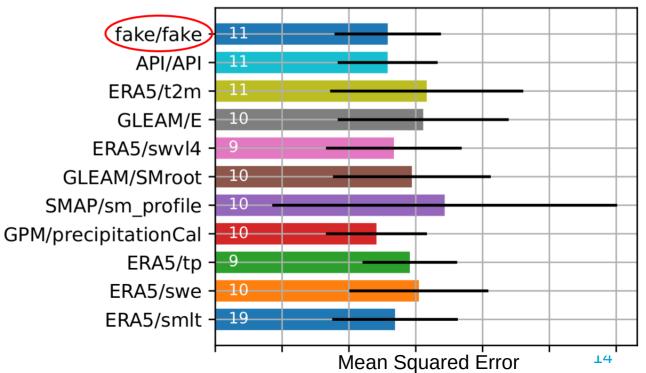






The (not so) magicians hat

• 3 million model combinations/variations



1 variable (n = 120)





Challenges and opportunities

- 1) High frequency input, slow response
- 2) Biased input and deformation signals No-negative deformation/precipitation
- 3) Unsatisfactory error metric
- 4) Limited length of time series (5 years \approx 1500 samples) No clear reoccurrence (e.g. hydrological year)



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- 5) Limited availability of *operational* satellite RS
- 6) Successes in literature stay true to the process

Further constraints forced the system to desired solution at the cost of flexibility

Conclusion

- ML deformation velocity prediction was too ambitious Especially with further reduction of dynamics, due to mitigation measures
- Second experiment: stronger signal, direct response





Machine learning will **not** tell you anything you did not already know. However, it will tell you **faster**, and is therefore an important ingredient in **upscaling**

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