

The role of sensors in AI systems for dike monitoring.



3 Studies from 3 students ...
and a postdoc 😊

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Artificial Intelligence (AI), Machine learning (ML) and Deep learning

AI is ... the use of technologies to build machines and computers capable of mimicking human cognitive functions:

- Seeing
- Feeling
- Smelling
- Listening
- Reasoning
- Responding ...

Reinforced learning ...

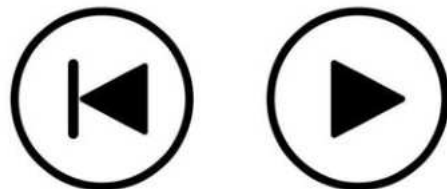
ML is ... a set of statistical (or not) databased learning algorithms for:

- Predicting
- Classifying
- Deciding
- Optimizing
- Augmenting
- Reducing
- Generalizing

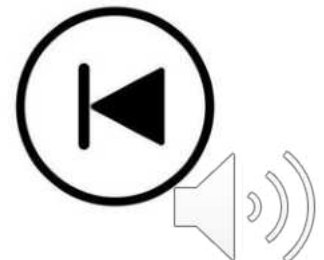
DL is ... one subset of ML methods based on ANN's with specific model architectures for:

- Predicting
- Classifying
- Deciding
- Optimizing
- Augmenting
- Reducing
- Generalizing

Sensors in AI
Are used during and after events.
(Predicting)



Sensors in ML/DL
are used before events.
(Training and Validation)



3500 Primary Dikes + 14000 Regional Dikes

Dikes are deteriorating faster due to climate change cycles (Flood and drought)

We need to monitor them more "densely" and frequently.

Its to much work if humans are best monitoring "devices".

We need sensors but they produce too much data.

2003



2021



FPH 15 June 2018



FPH 15 July 2018



3 Cases for 3 questions

a) Where to place pressure sensors to predict Backward Erosion Piping ?

Method: PCA



Manuel Wewer

b) Which dikes are more prone to develop drought induced cracks?

Method: (Random Forest) Decision Trees



Shaniel Chotkan

c) How to detect cracks with distributed temperature fiber optic sensors ?

Method: Convolutional encoders



Simone de Roos

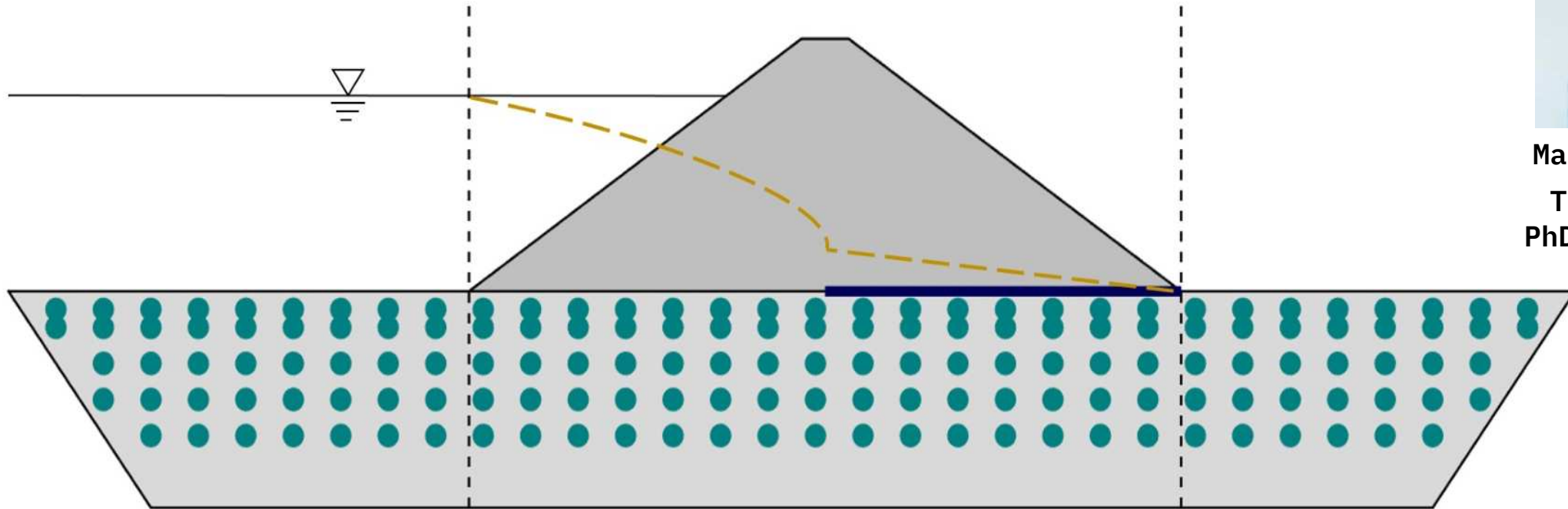


Leonardo Duarte

Case a: Where and how many pressure head (H_p) sensors to predict/monitor Backward Erosion Piping (BEP) ?



Manuel Wewer
TU Dresden
PhD Candidate



1. Scenario: Sensor placements in the entire aquifer
2. Scenario: Sensor placements at the sides of the dike

We proposed a time dependent physically based BEP model

A transient backward erosion piping model based on laminar flow transport equations. Wewer, M., Aguilar-López, J. P., Kok, M., & Bogaard, T. (2021). Computers and Geotechnics, 132, 103992



1. Ijkdiik Experiment 2009

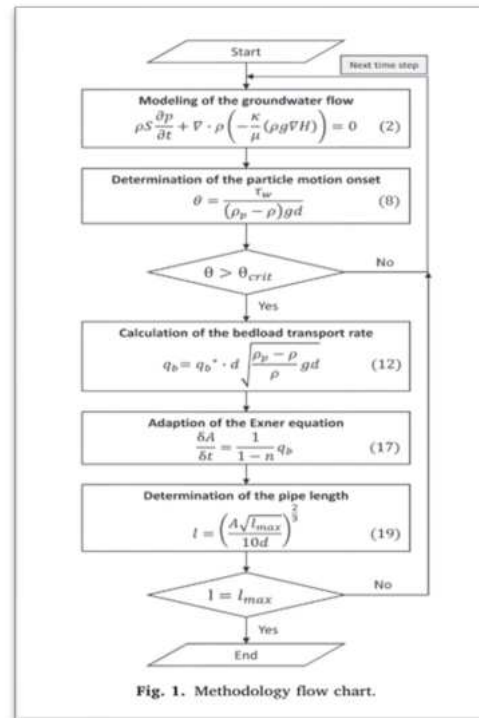
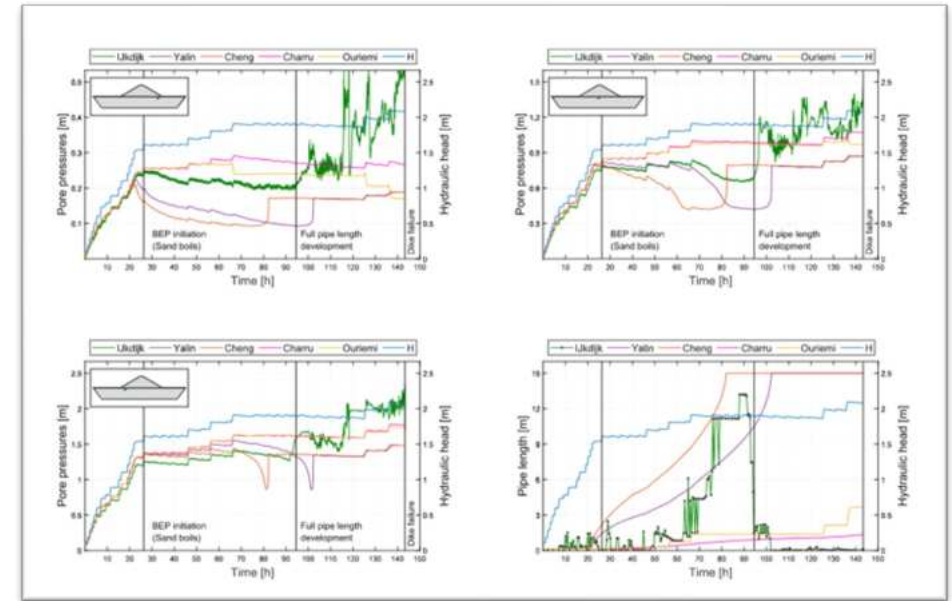


Fig. 1. Methodology flow chart.

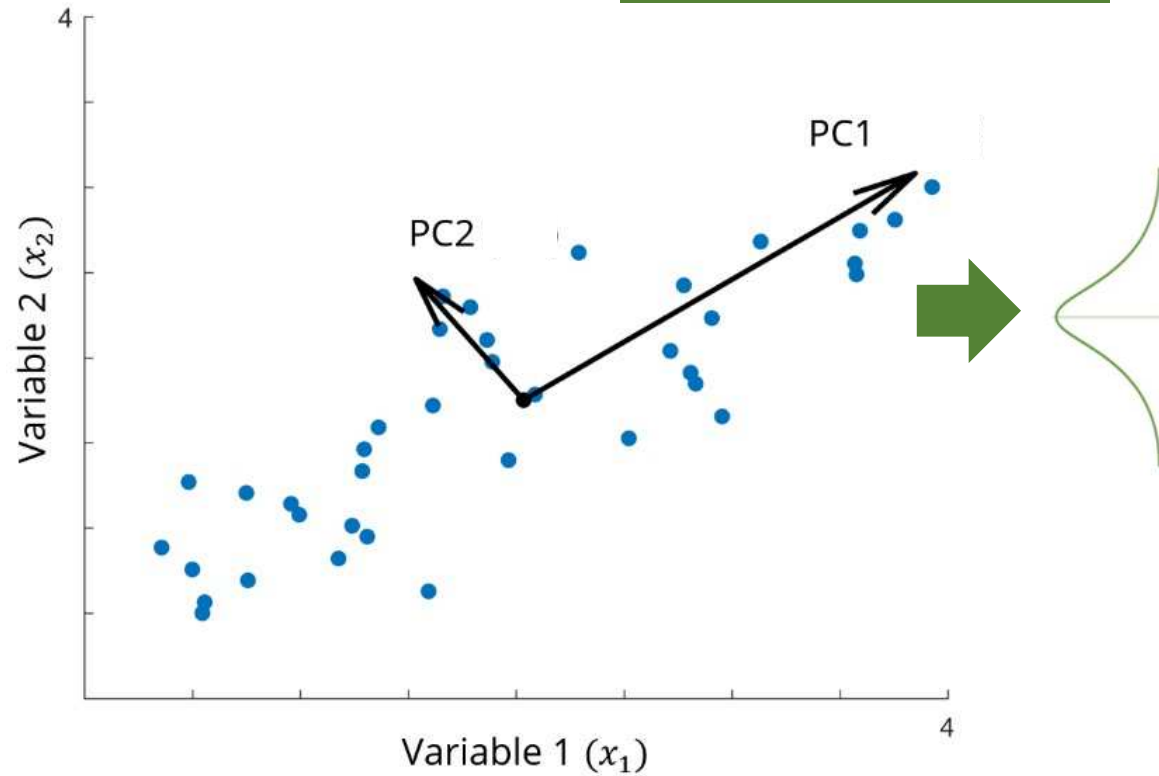
2. FEM model + Laminar sediment transport equations



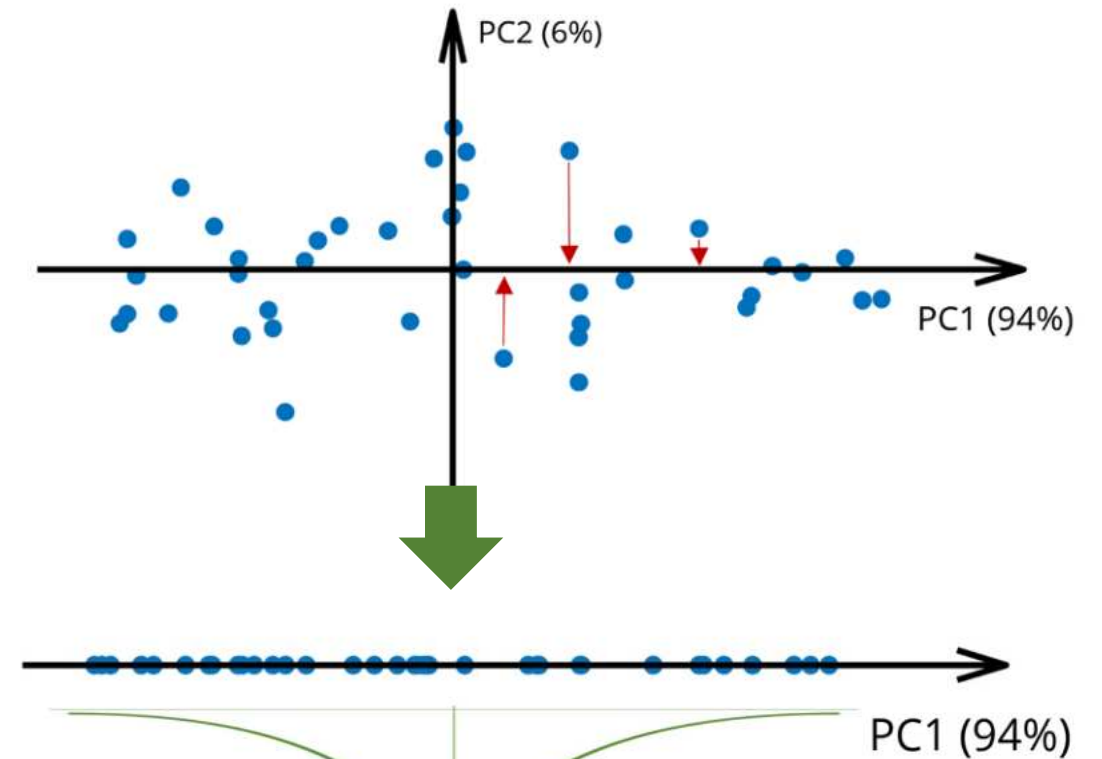
3. Piping erosion progression in time (Pore Pressure estimations)

We implemented an ML Method: Principal Component Analysis (PCA)

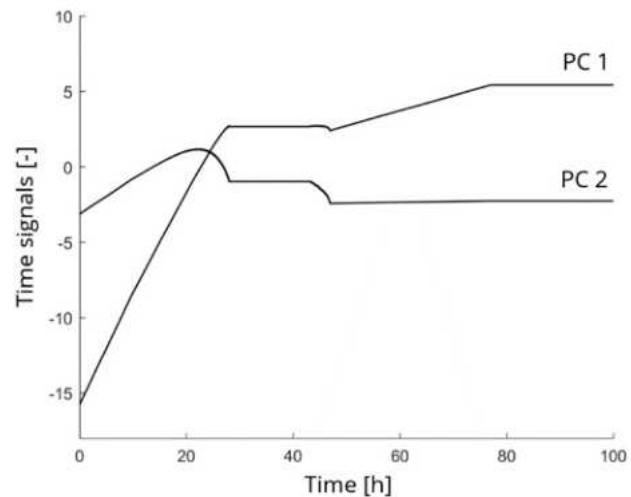
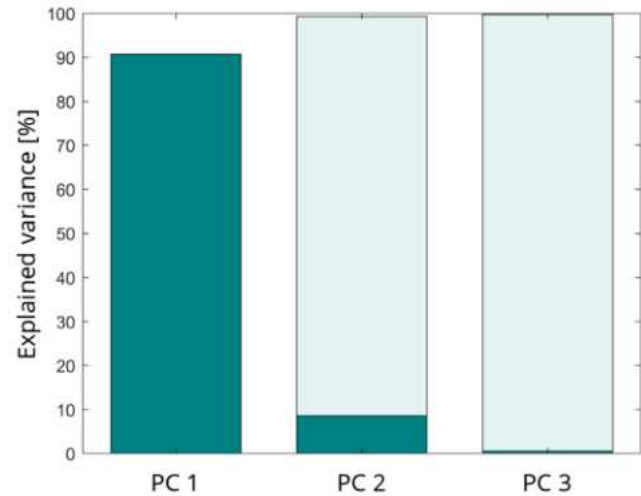
Original Data



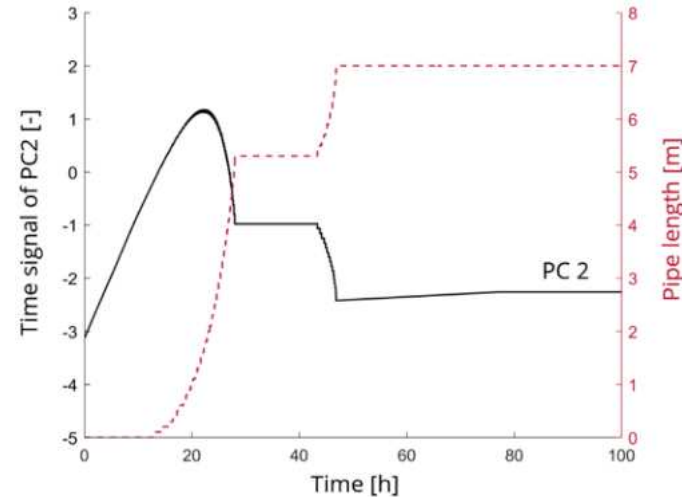
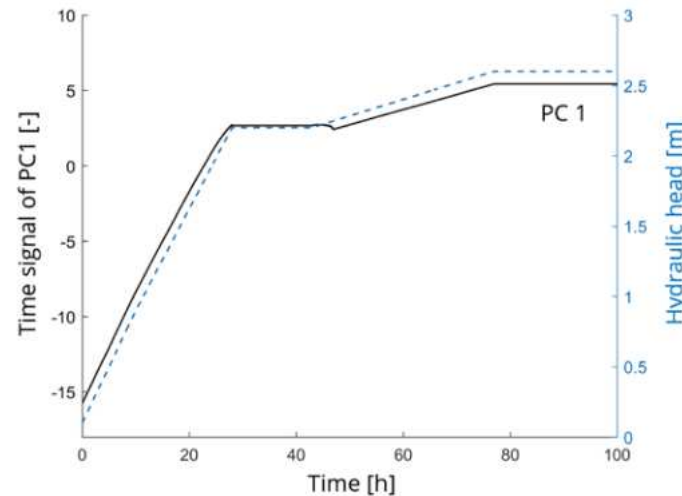
Transformed Data



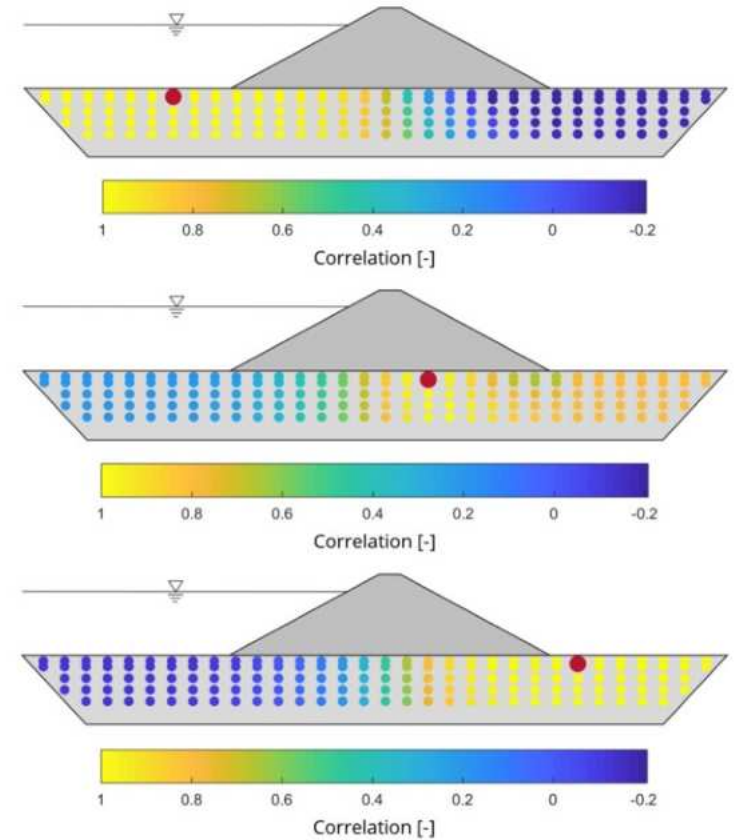
These are the main components and interesting findings 😊



1. We Determine PCA's in time



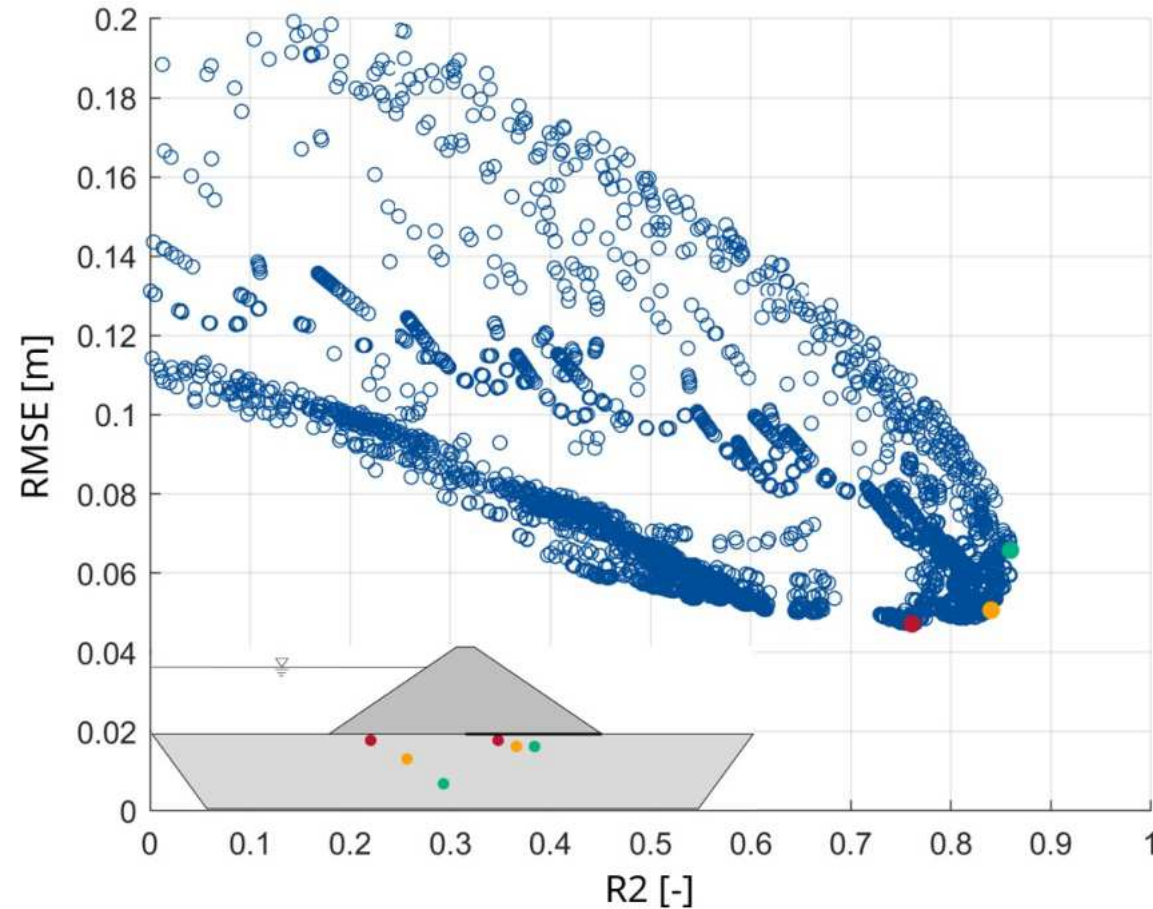
2. PCA's vs BEP



3. We make a Correlation analysis of Hp Vs PCA



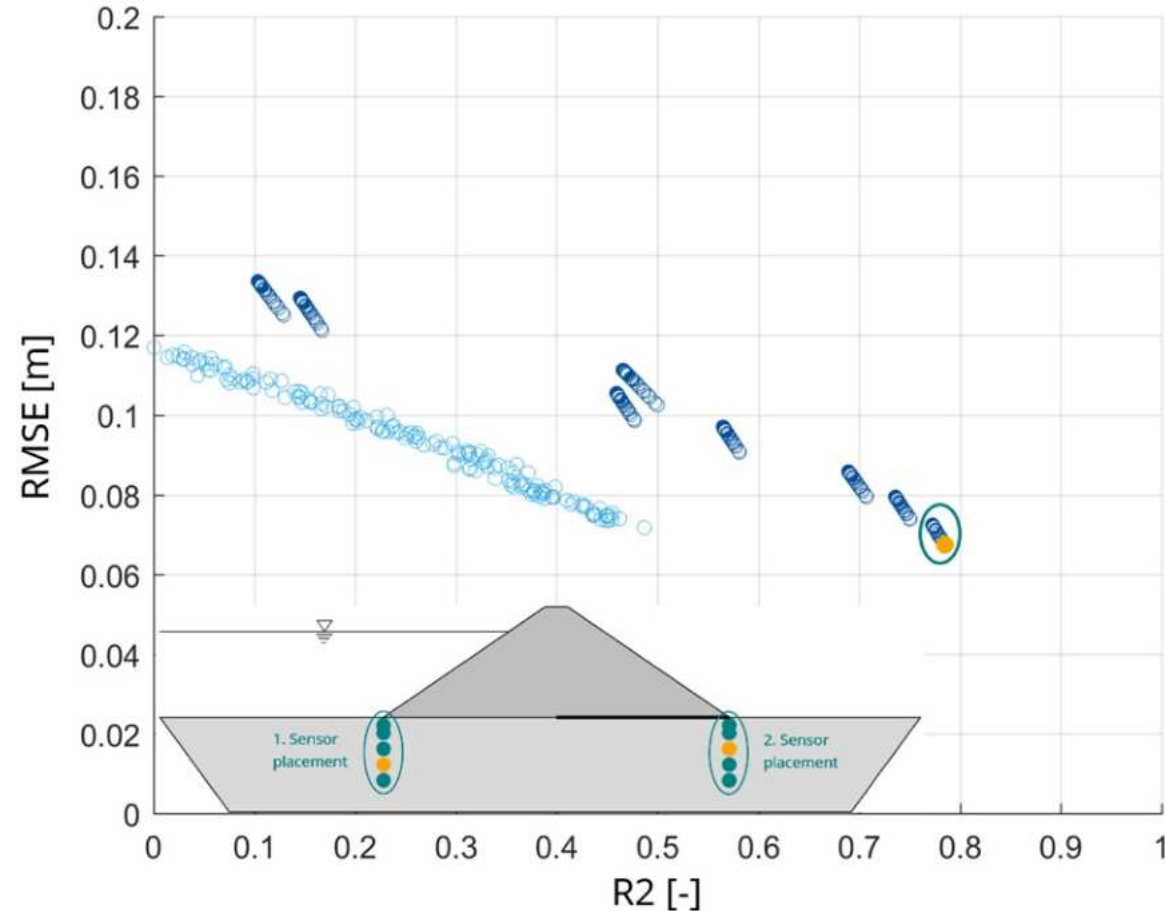
Results: Scenario 1



For each scenario we determined 3 multi-objective optimizations based on a Pareto front of 2 dimensions.



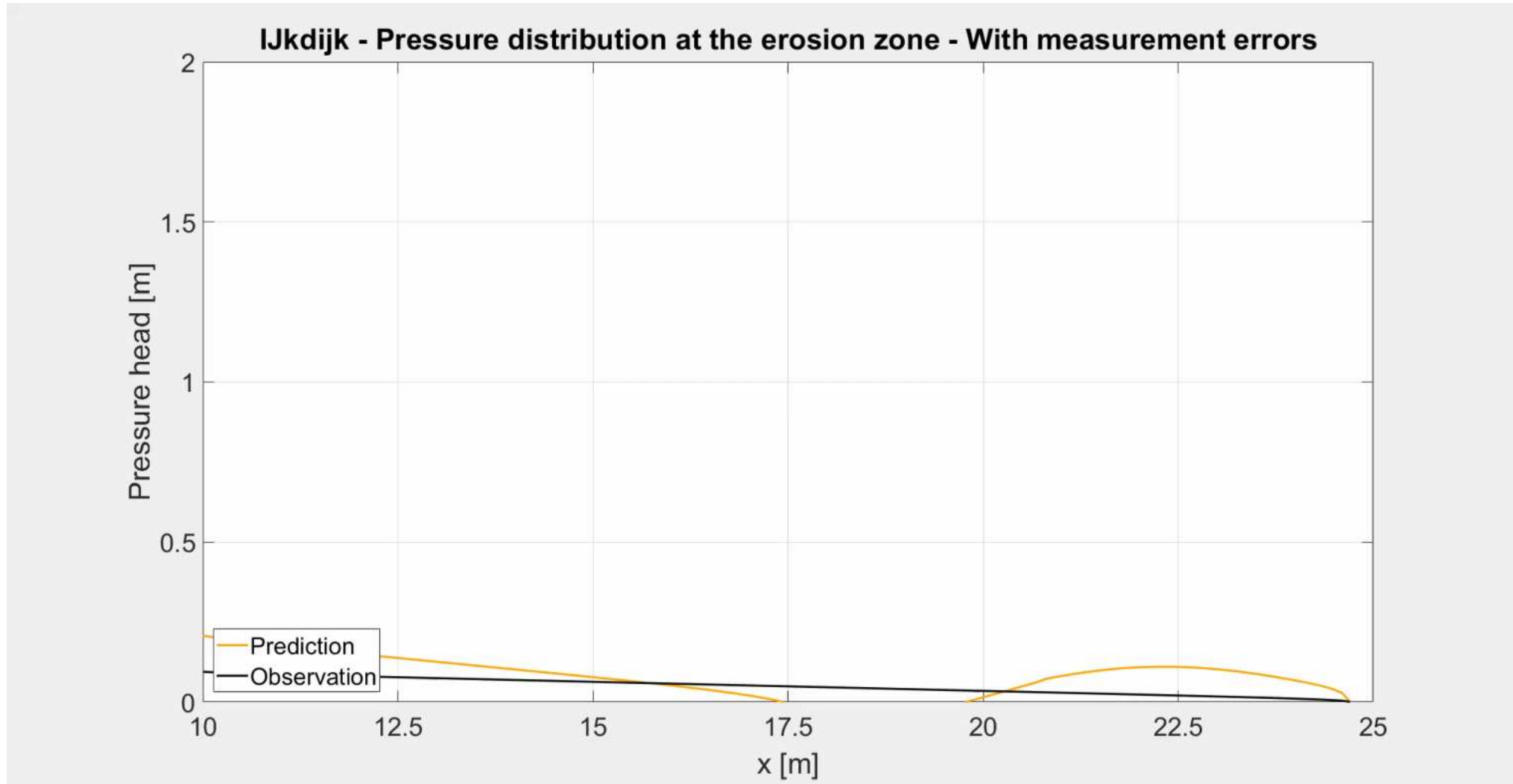
Results: Scenario 2



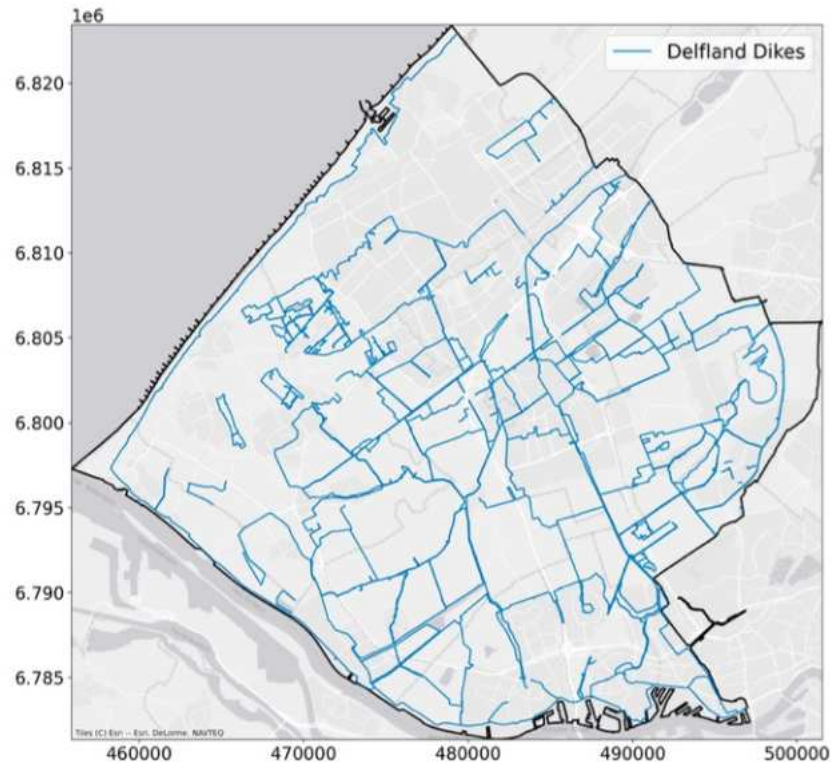
Please note that the best locations are not necessarily the most Superficial ones.



PCA vs Actual BEP-FEM



Case b: Which dikes are more prone to develop drought induced cracks?



Shaniel Chotkan
Royal Haskoning
DHV

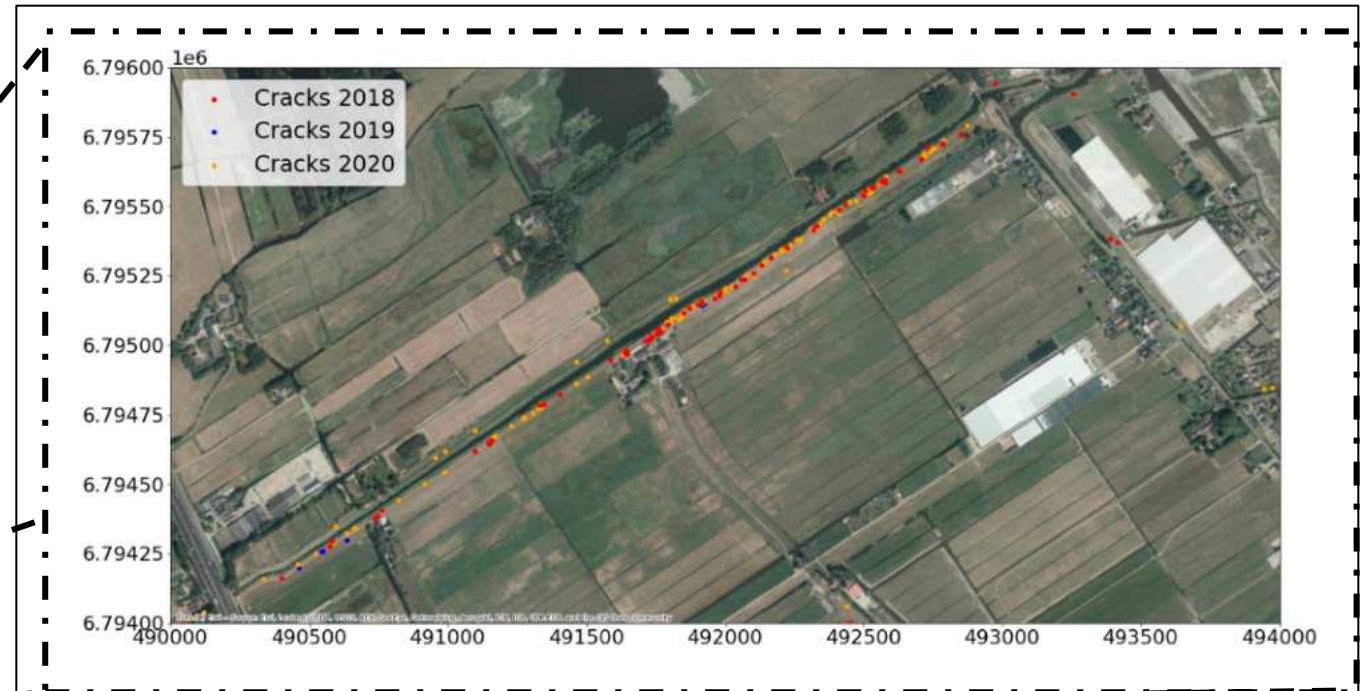
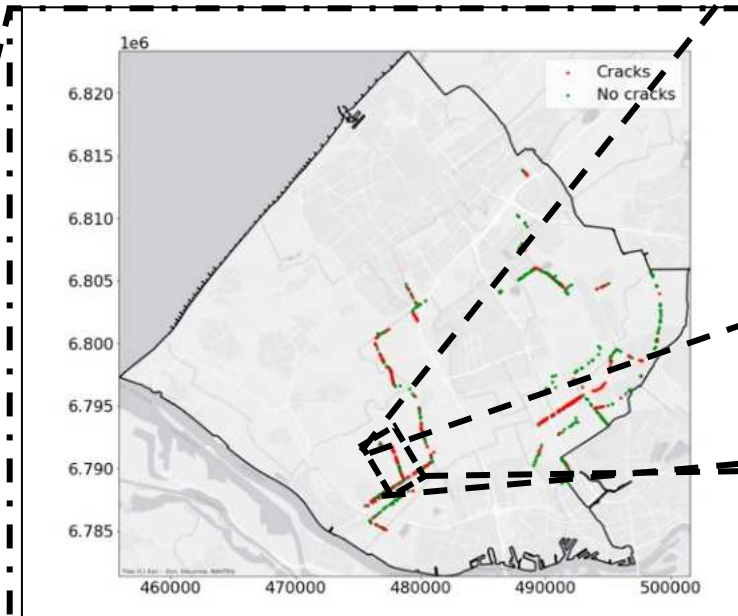
Let's use PROXY variables to try to predict observations !

" Predicting drought-induced cracks in dikes with artificial intelligence " MSc Thesis Shaniel Chotkan (2021) - TU Delft

Chotkan, Shaniel, et al. "A data-driven method for identifying drought-induced crack-prone levees based on decision trees." Sustainability 14.11 (2022): 6820.



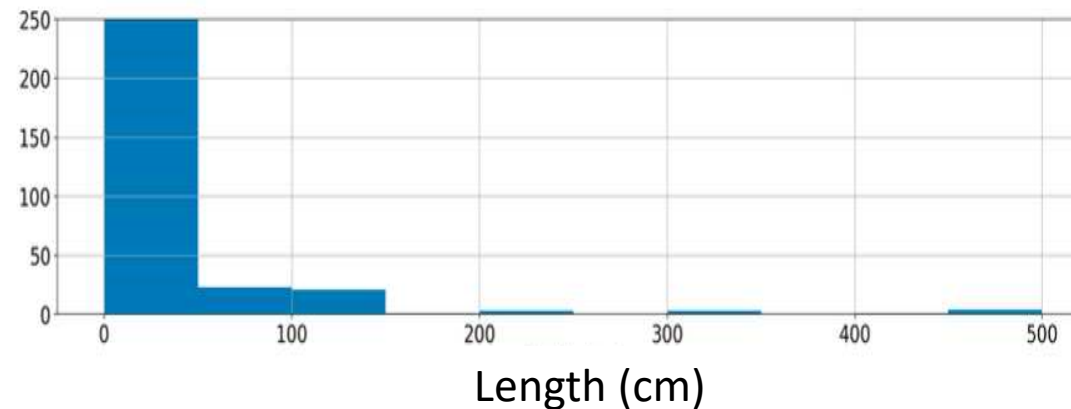
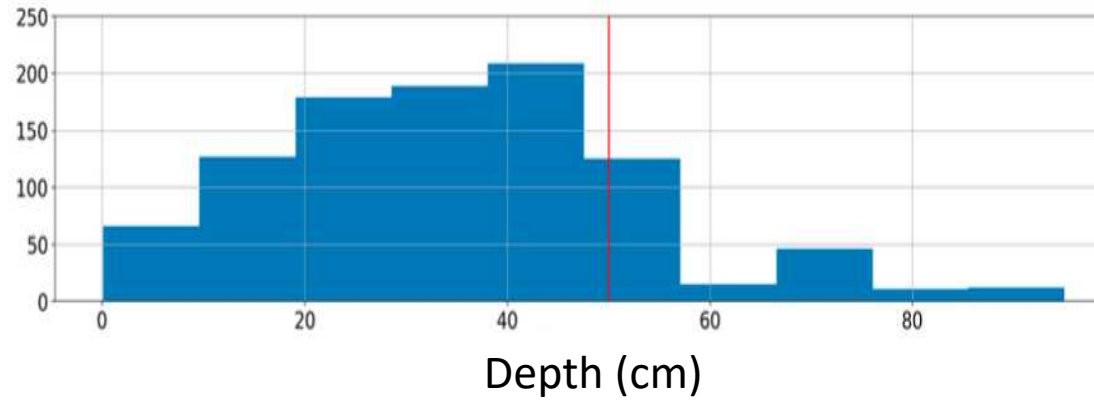
We analyzed the inspections and crack location between 2018-2021



Today you had one and next year you don't !

What data do we (Delfland) have ?

Attribute	Description
ObjectID	The characteristic number of the specific observation. This attribute is used to identify elements.
Dijkvak	Delfland has multiple manners in which they divide their dike sections. One of them is splitting up the drought sensitive dikes in parts of 100 meters. These sections are then labeled again, resulting in this attribute.
Typekering	The type of dike. In this case of the scope of this thesis this will always be a regional levee.
Locaties schade	The location on the dike where the observation is situated. This may for example be on the crest but also on the whole dike body.
Parameter	The specific type of observation. Examples are subsidence and cracks.
Lengte	The length of the crack in meters.
Breedte	The width of the crack in meters.
Diepte	The depth of the crack in meters.
Patroon	This attribute indicates whether multiple observation parameters are present on the specified coordinates or a single one.
Richting	The orientation of the observation in the case of a crack. This feature was not accounted for in all of 2019.
Datum observatie	The date at which the parameter is observed.

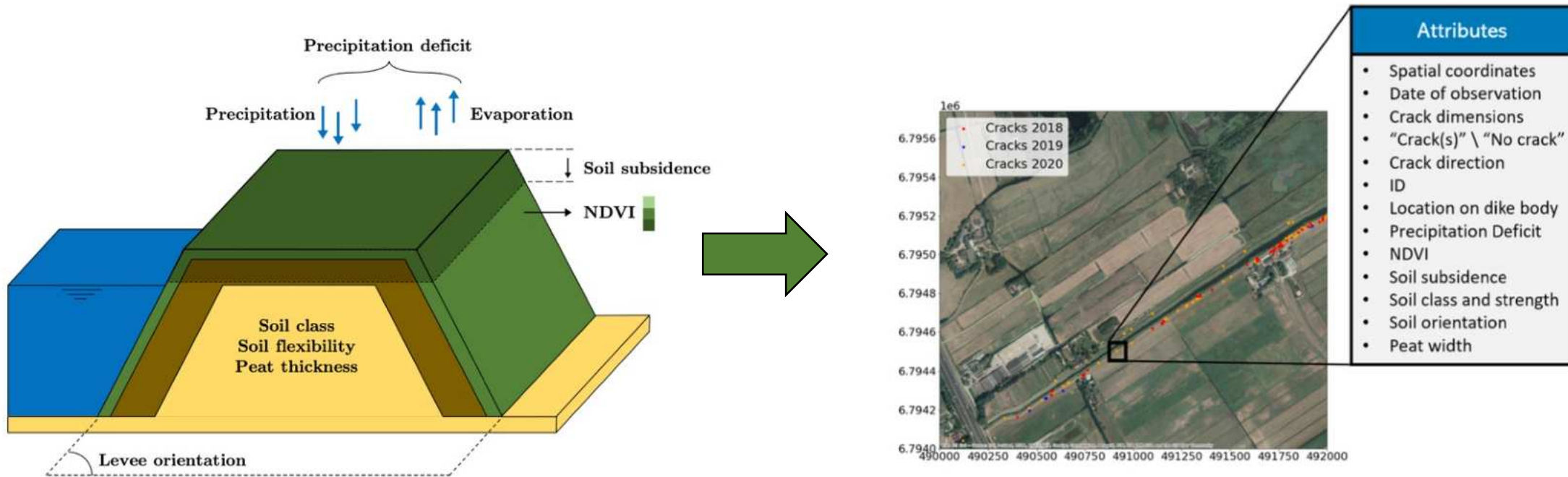


2018	Observed Cracks	555
	Observed non-cracks	43
	Not inspected	4
	Kilometers inspected	255
2019	Observed Cracks	61
	Observed non-cracks	15
	Not inspected	3
	Kilometers inspected	42
2020	Observed Cracks	368
	Observed non-cracks	116
	Not inspected	67
	Kilometers inspected	173

All data is intrinsic to the crack and not to the drought process.

How can we predict them ?

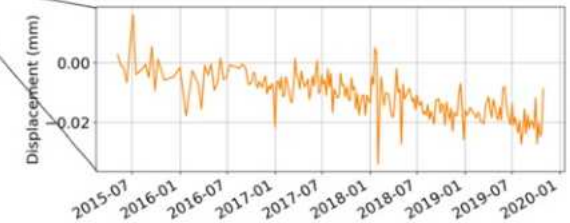
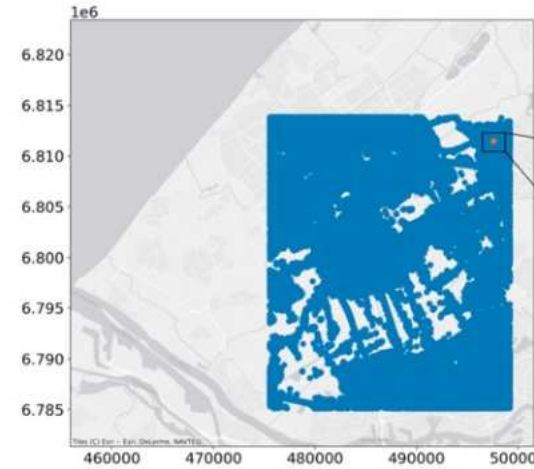
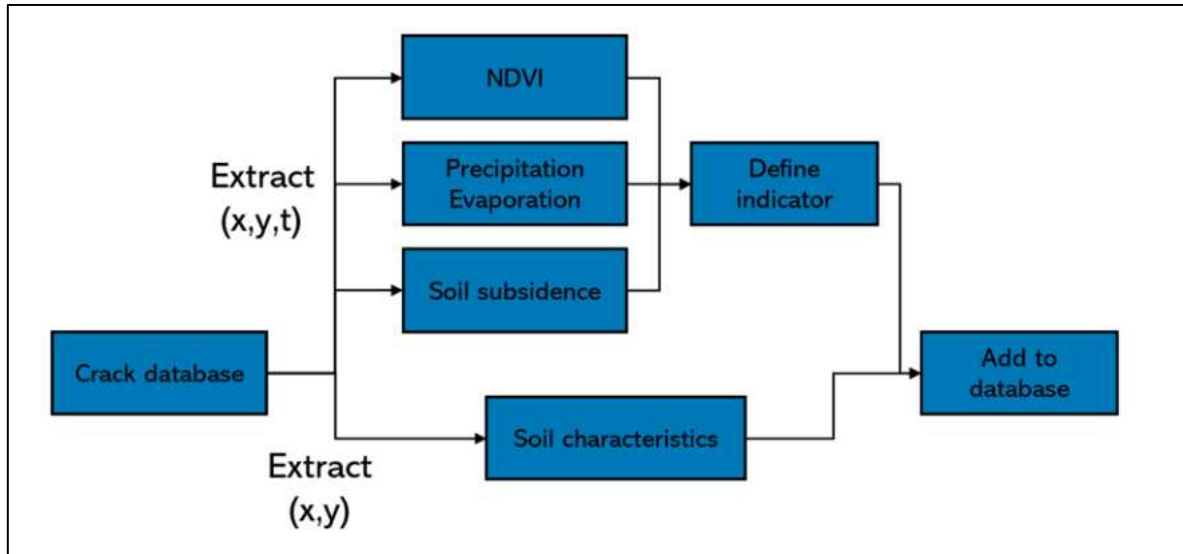
We need to do data "augmentation" !!!



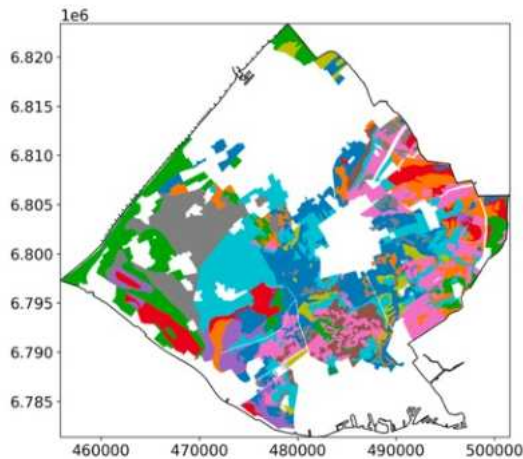
In a GIS environment, we located all cracks. For the same locations, we extracted timeseries of soil subsidence, Precipitation, evaporation, soil subsidence and NDVI "green-ness". In addition, local soil characteristics where also included.



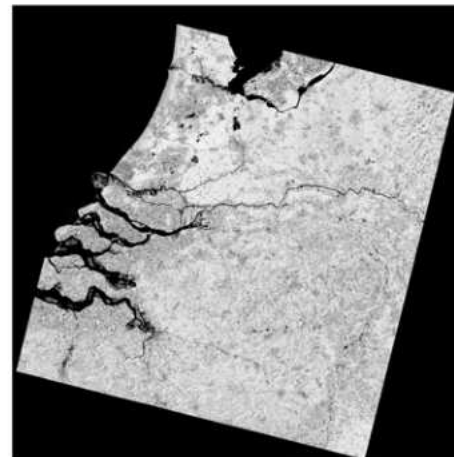
All variables come from different sensors at different spatial and temporal resolution..



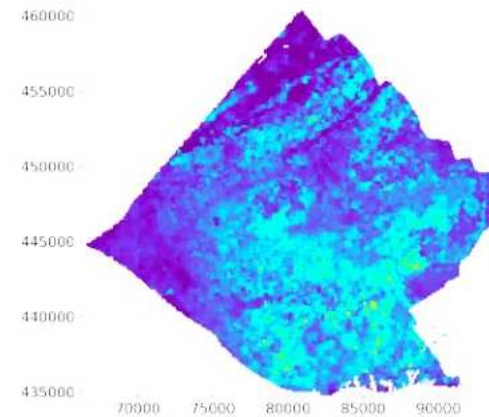
**Subsidence - InSar 300x300 m2
6 days -BODEMDALINGSKAART
(1.4 days average)**



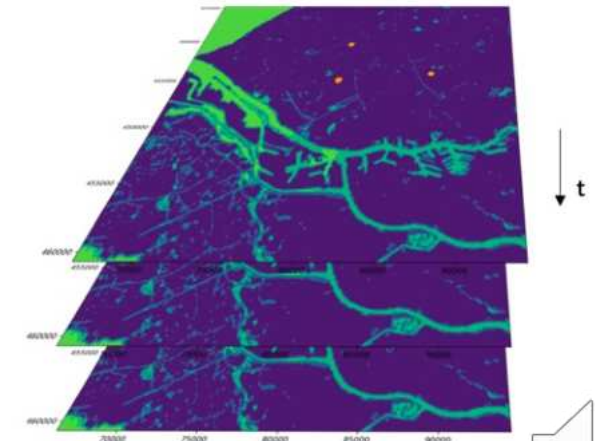
**Soil Map (Peat)
(Constant 1x1 Km)**



**NDVI - Landsat bands 4 and 5
- 30X30 mts - 16 days**



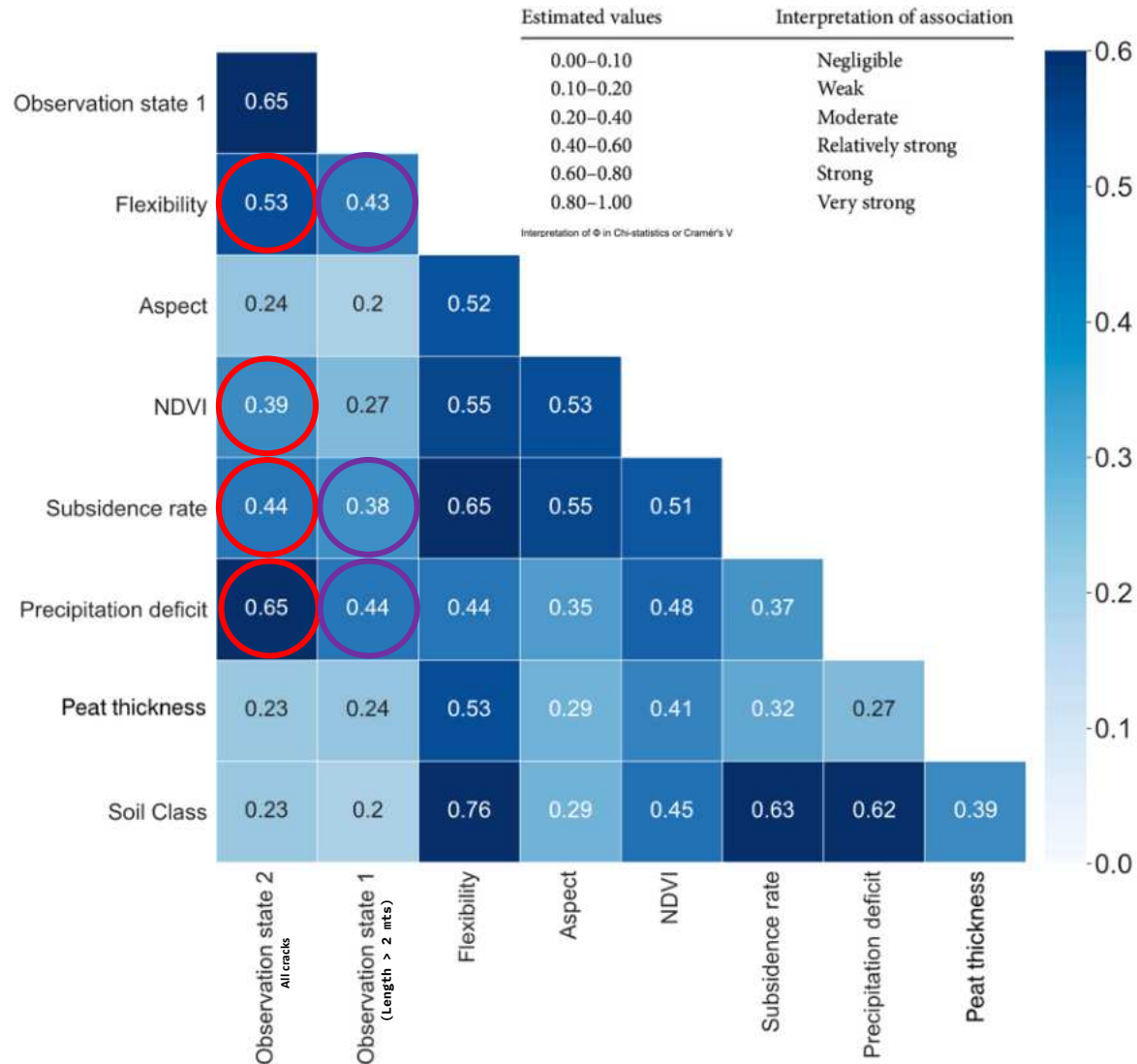
**Soil Flexibility
(Estimated Deformation)
100x100 mts**



**Evaporation and Precipitation
(Kriging Raster from
Points every 10 minutes)**



Association analysis (Cramer's V)

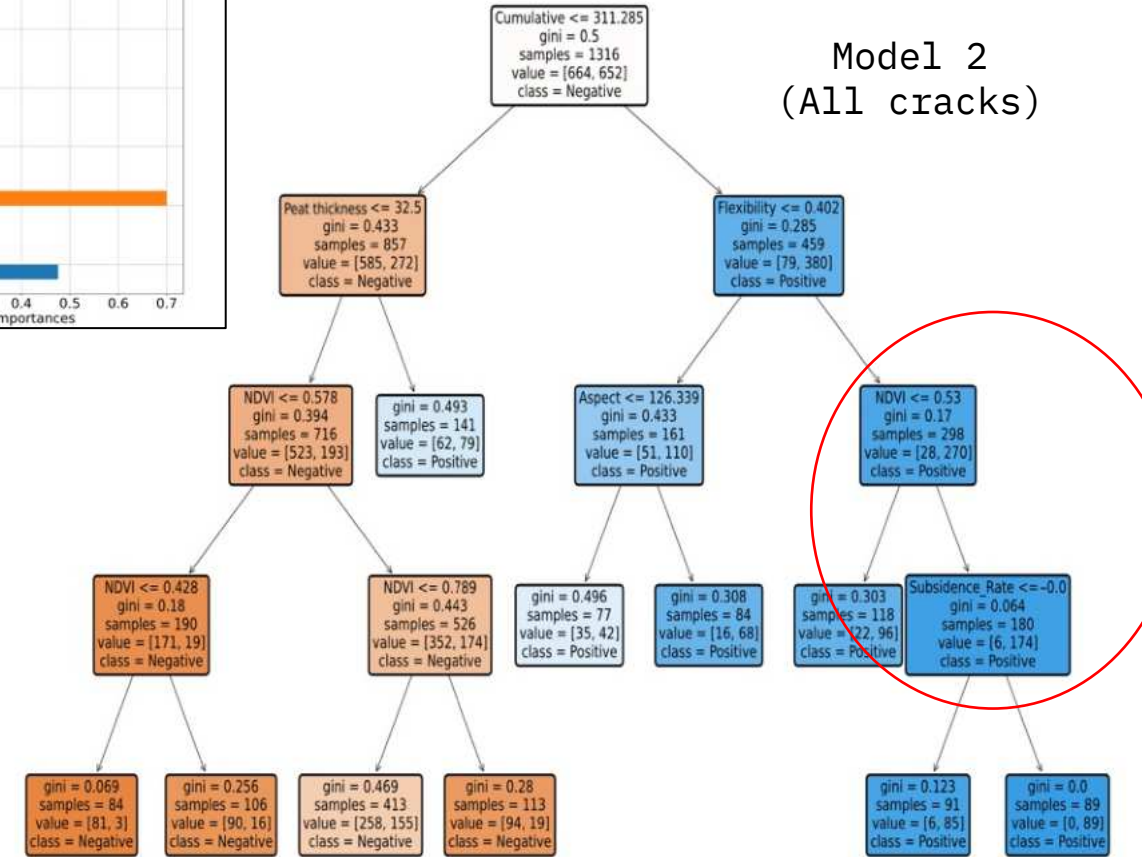
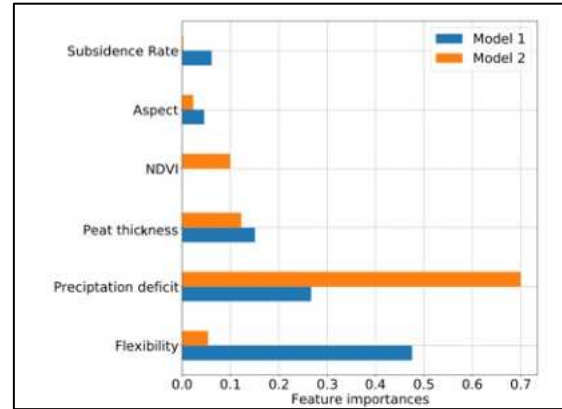
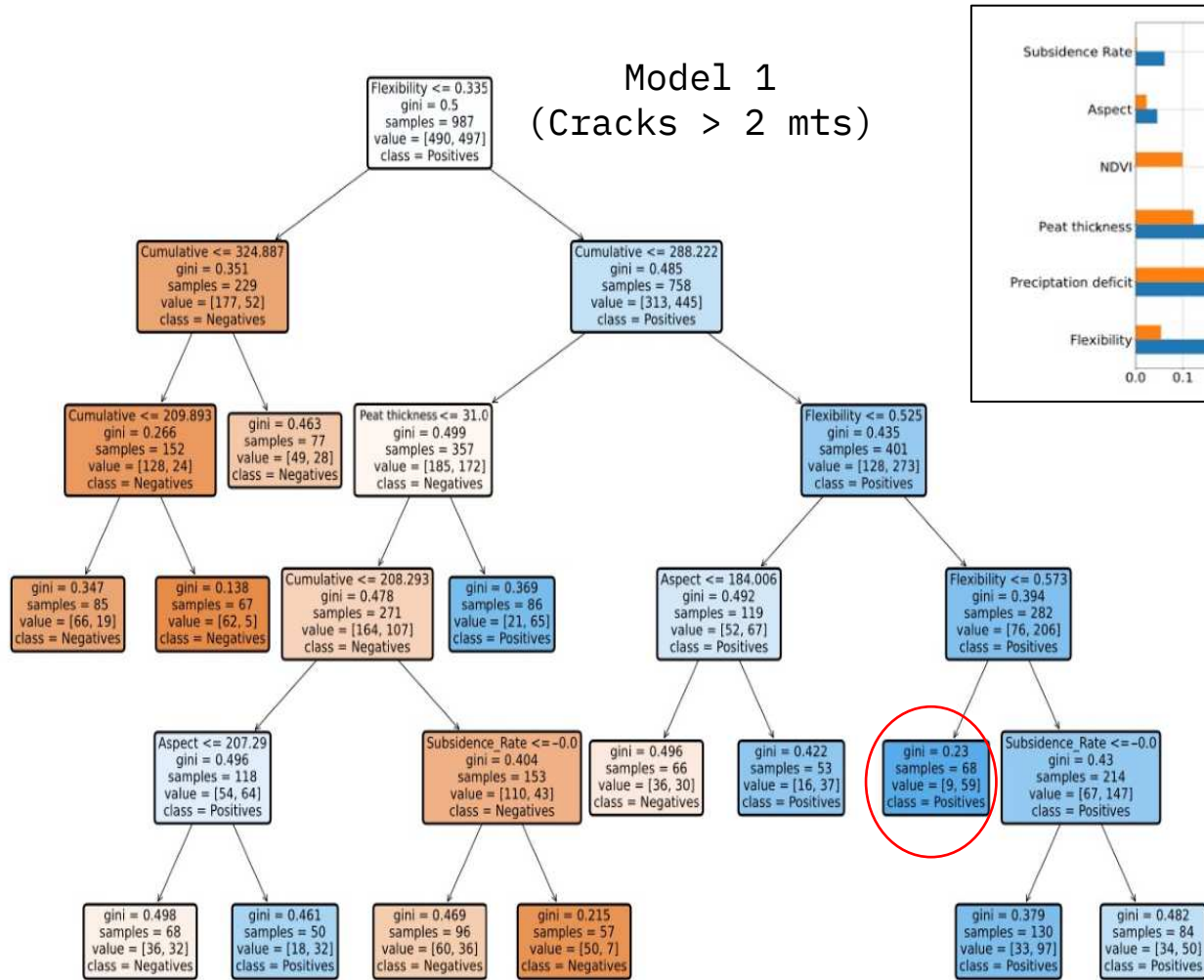


Observation state 1: Yes/No cracks (Length > 2 mts). Inspectors might not easily identify them .

Observation state 2: Yes/No cracks. Negatives were just random sampled from locations where crack were not observed.

So, we decided to build two models...

We implemented an ML Method: Principal Component Analysis (PCA)



From this models, we learn for example that cracks (2 mts) are not observed on soils characterized by a low flexibility.

From this models, we learn for example that cracks only occur with both drought and subsidence.

We trained and used a **Random forest** model for hazard mapping

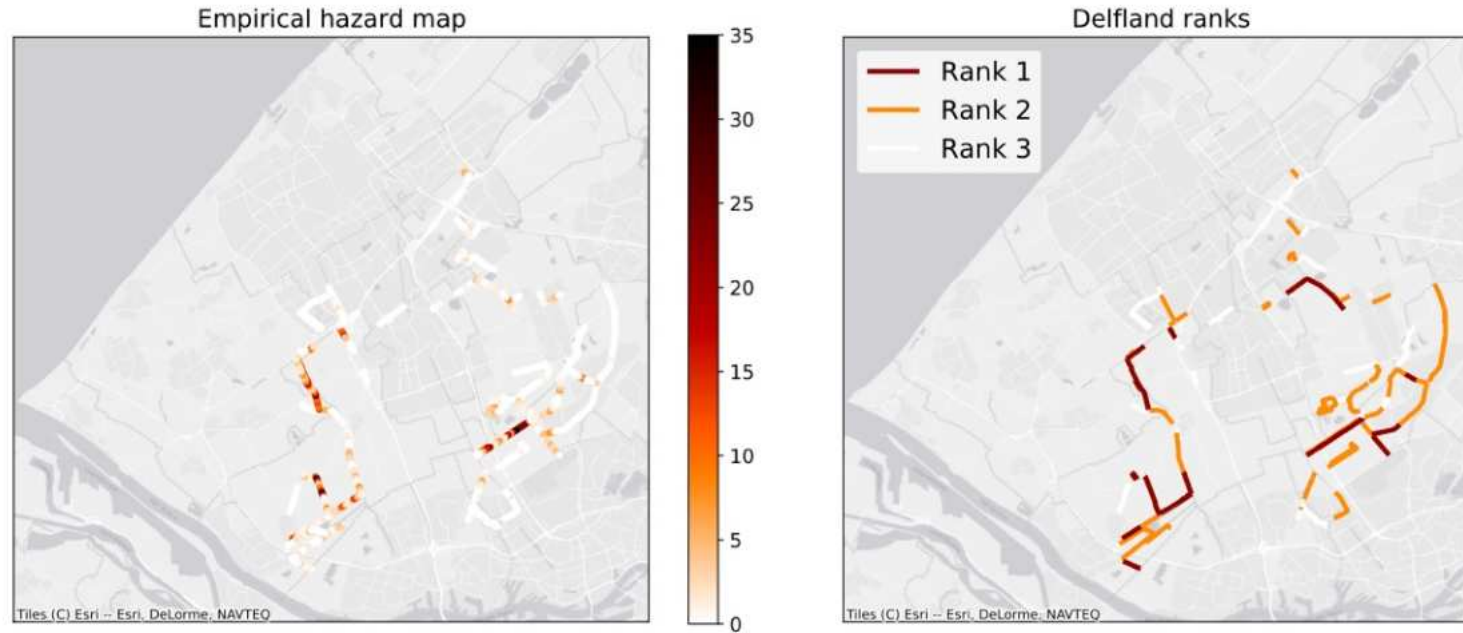


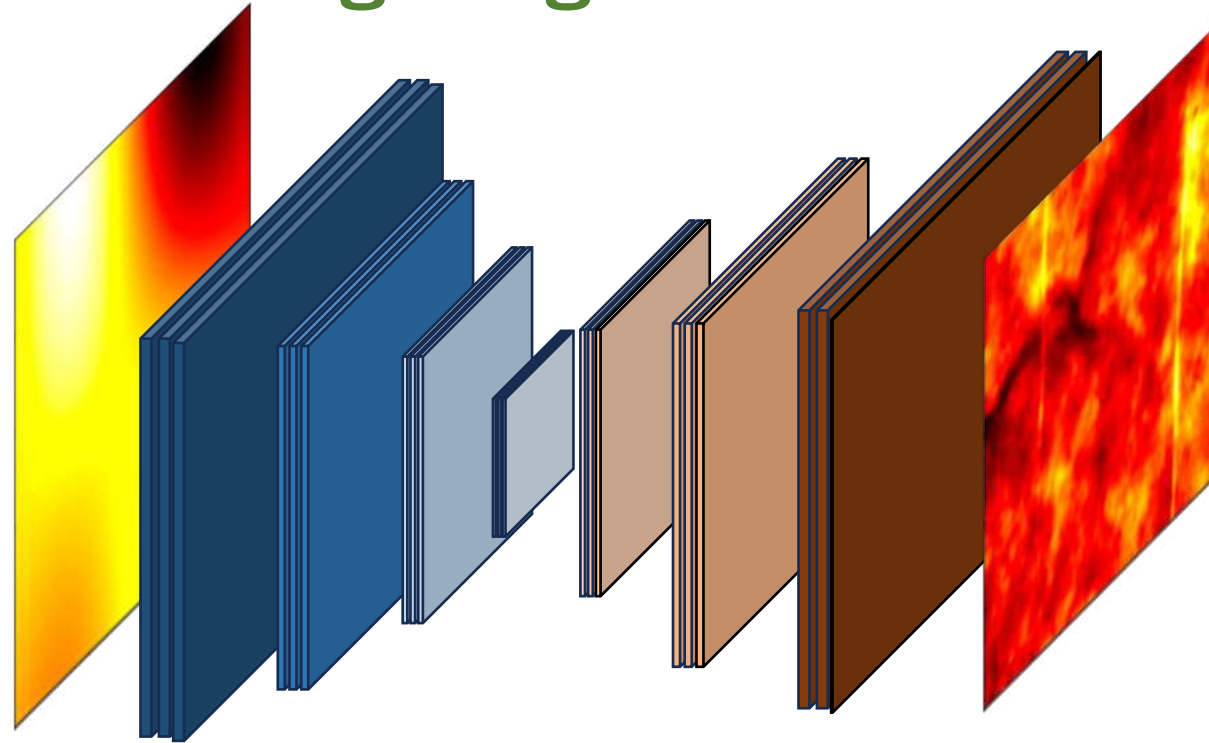
Figure 17. The (left) image shows the constructed empirical hazard map. The (right) image shows the Delfland ranks for comparison with the other maps.

Decision trees showed us that:

- Long cracks are not observed on levees for flexibility was smaller than 0.355 m/kPa .
- Long cracks (longer than 2mts) are more often found on levees of which the slope is oriented towards the southern side.
- Both model trees state that a peat thickness of the upper layer of at least 31 cm indicates that levees are susceptible to the formation of cracks.
- Levees composed of soils which have peat layers thinner than 31 cm do not seem to crack for precipitation deficit values lower than 311 mm.



Case c: How to detect desiccation cracks in dikes with fiber optic sensors and deep learning algorithms?



Leonardo Duarte
TUDELFT -GeoSciences



Simone de Roos
Witteveen+Bos

"Crack detection for dikes using distributed temperature sensing" MSc Thesis Simone de Roos (2022) – TU Delft

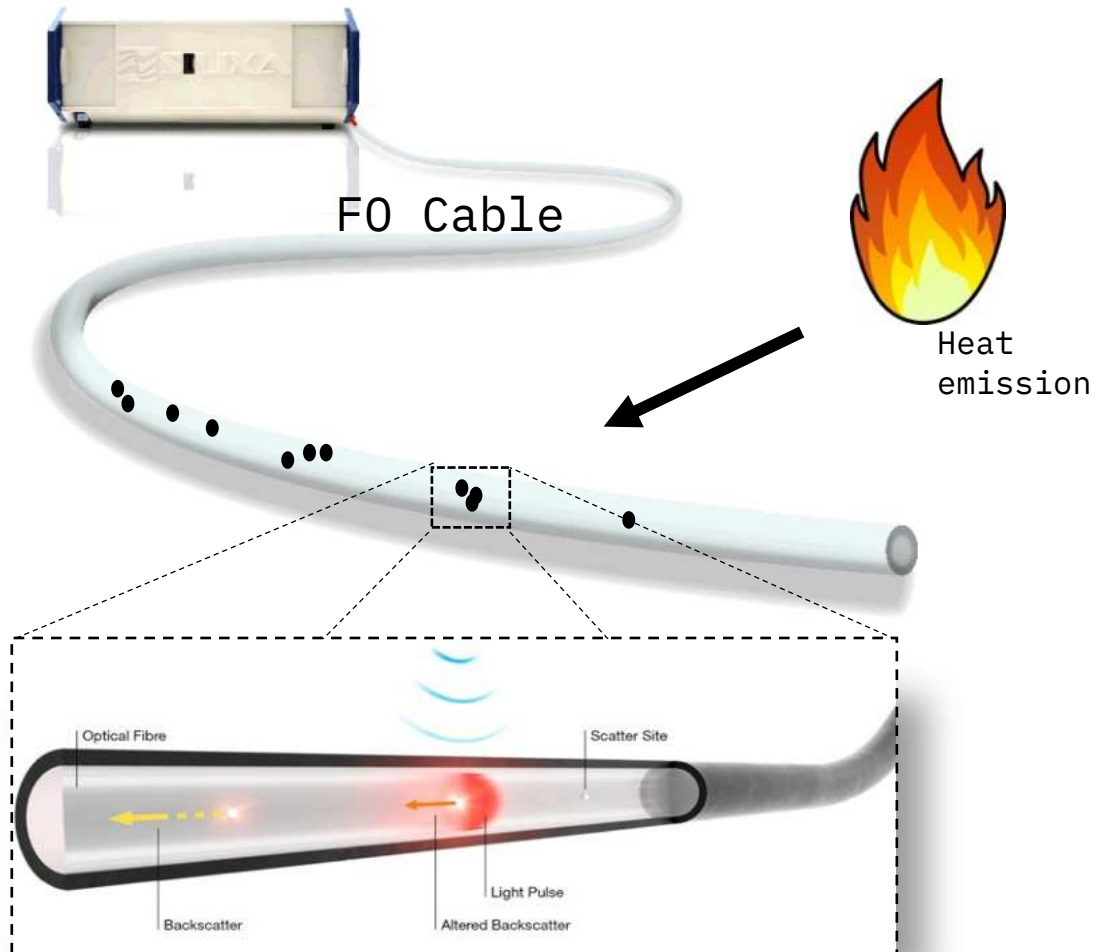
De Roos, Simone, et al. **"Understanding the thermal response of an unburied fiber-optic sensor for dike cracks detection."** submitted to – Sensors Journal 2022.

Grant No. NWA.1228.192.258 Idea Generator (50k€) **"Crack detection with FOS and DL"**

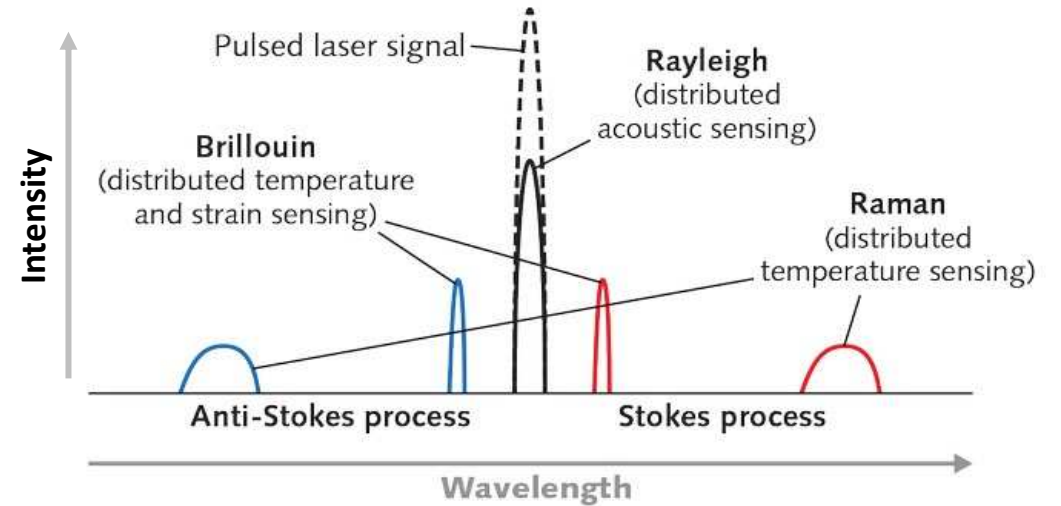


Thermal Distributed Fiber Optic Sensing (DTS)

DAS Interrogator



Backscatter Spectrum

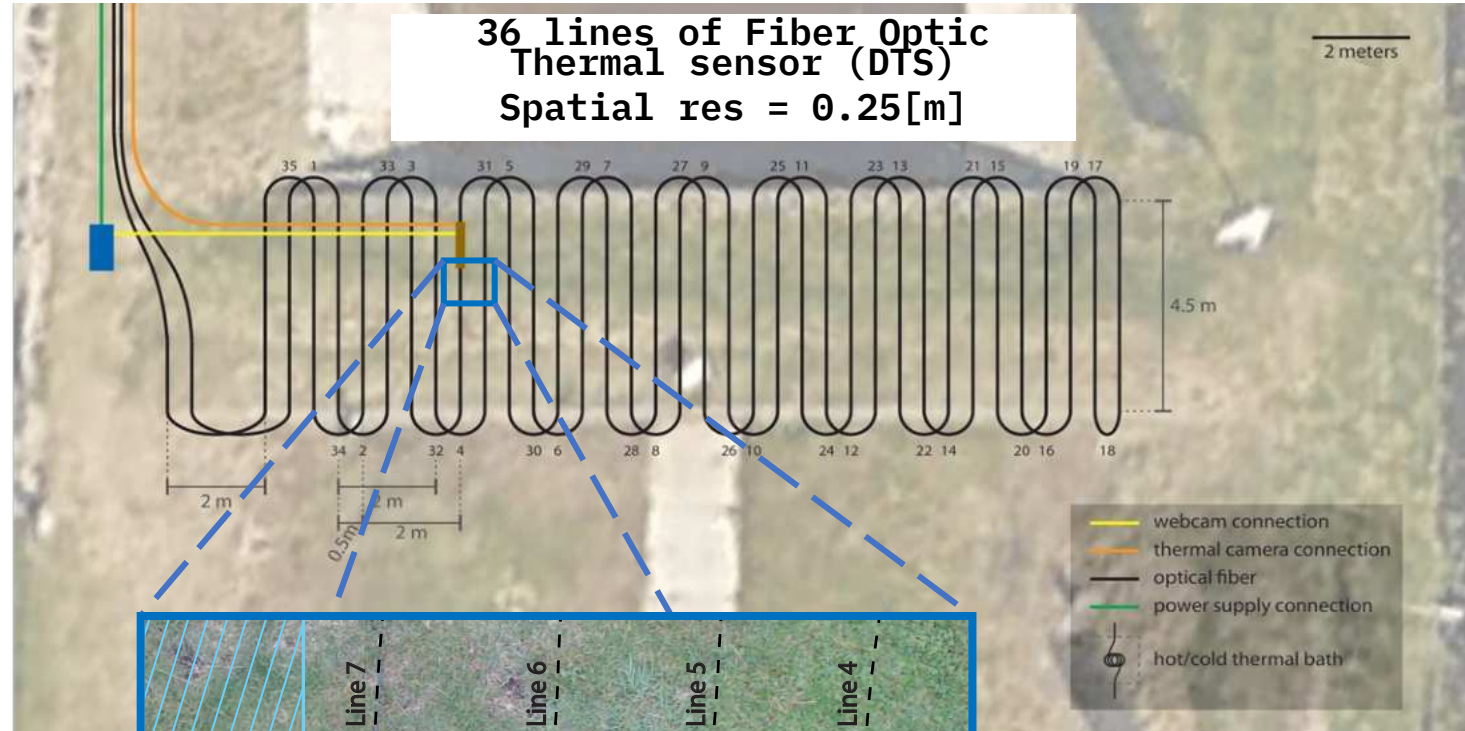


Atomic structure and impurities of glass fiber re-organize due to local heat and strain changing its photoacoustic intrinsic properties in time and space influencing light propagation properties such as intensity, phase, polarization and wave-length.

Animation borrowed from: <https://silixa.com/resources/what-is-distributed-sensing/>

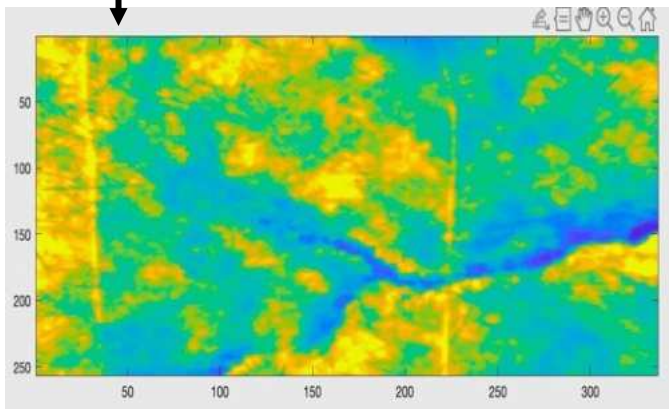
We monitored a dike and its crack for 3 months

Thermal camera
(320x256)

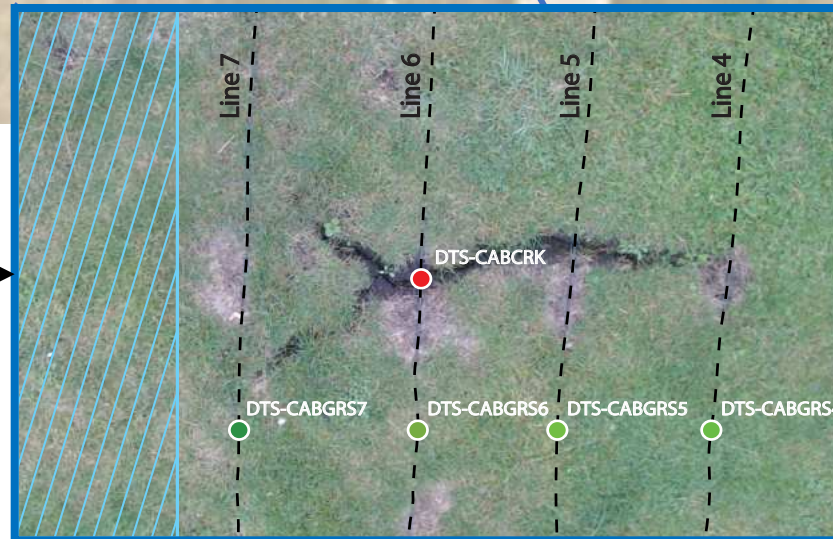


36 lines of Fiber Optic
Thermal sensor (DTS)
Spatial res = 0.25[m]

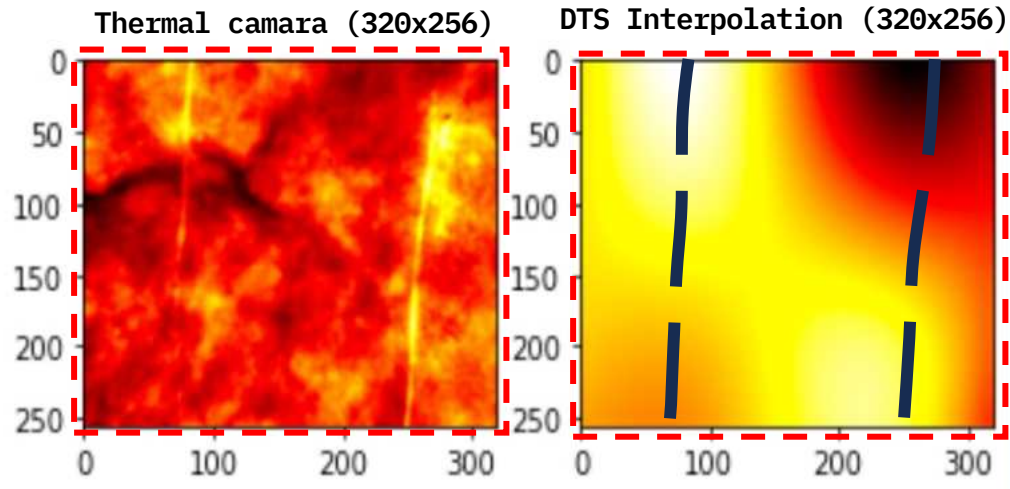
- webcam connection
- thermal camera connection
- optical fiber
- power supply connection
- hot/cold thermal bath



4 Webcams



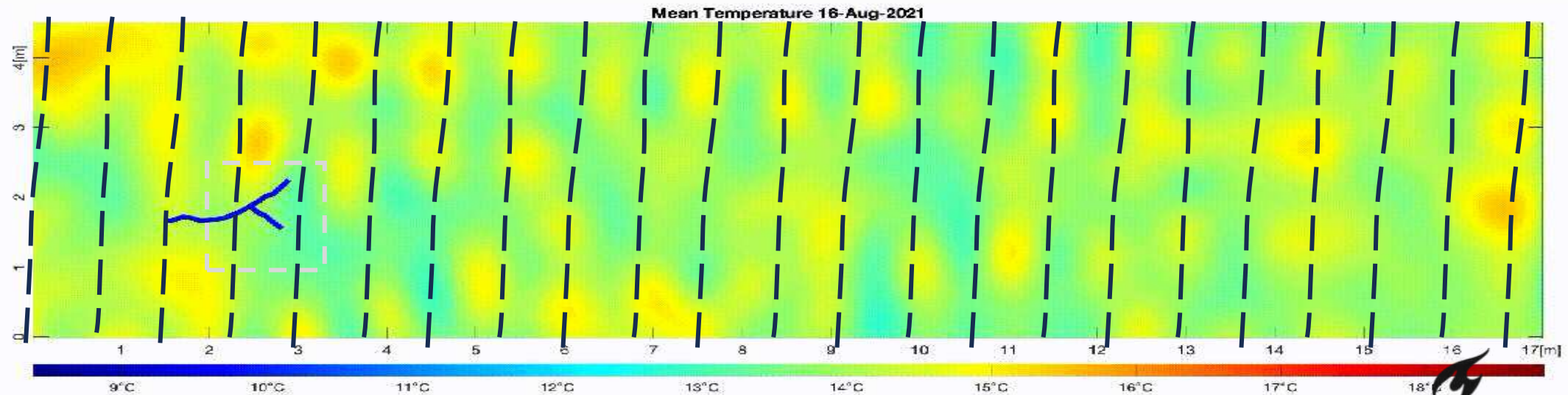
Heat distribution maps along the dike



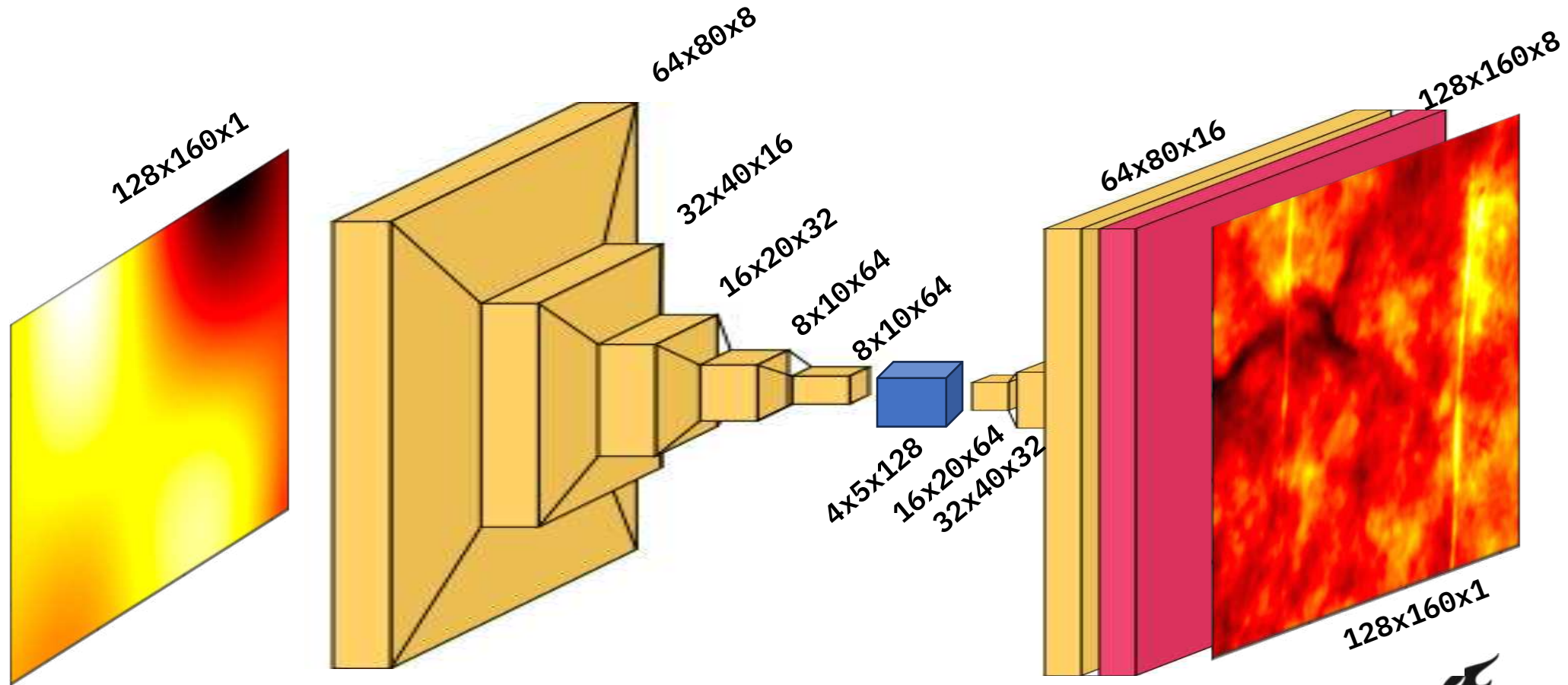
We have temperature points measured every 30 mins on a spatial Resolution of 0.25m. Cables are spaced every 0.5m.

With this information we generated heat distribution maps based on a Kriging interpolation.

We extracted 16x20 from interpolation and resized to 256x320 so that Thermal camera and DTS are aligned.

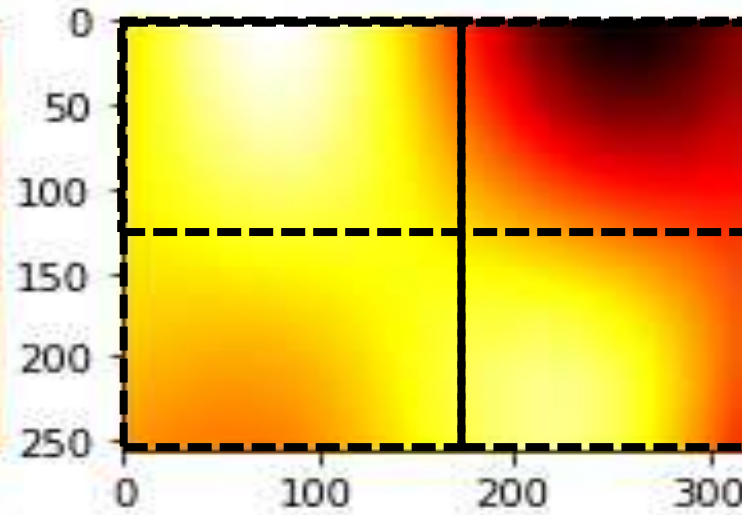
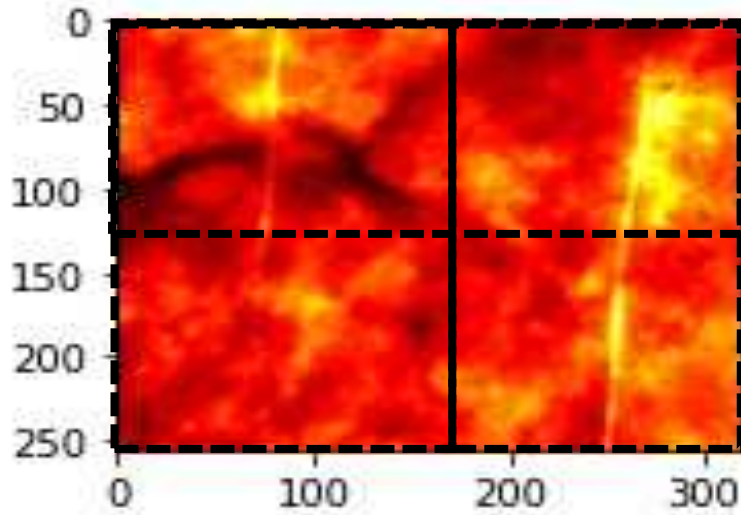


We built and trained a convolutional high-resolution image to image encoder-decoder



Total trainable parameters = 245,697

Data augmentation (DTS+TRC)



We Started with:

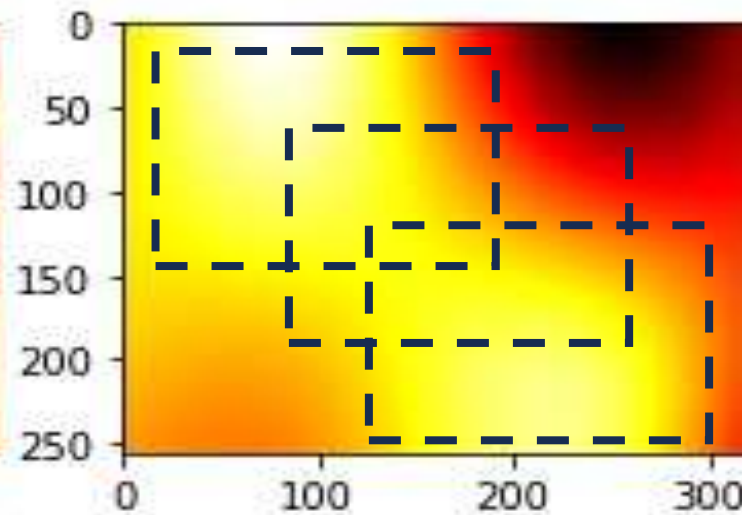
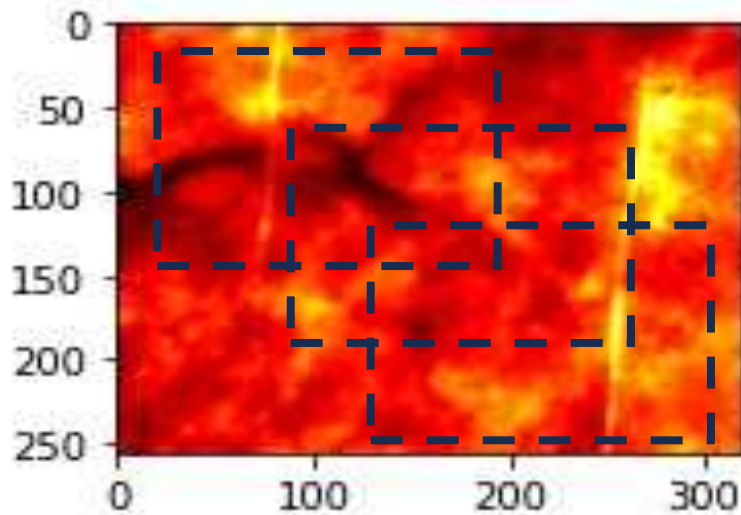
Dataset: 992 images of 256x320

We crop them by half.

Dataset: 3968 images of 128x160

We crop 3 more blocks in locations with and with cable and crack.

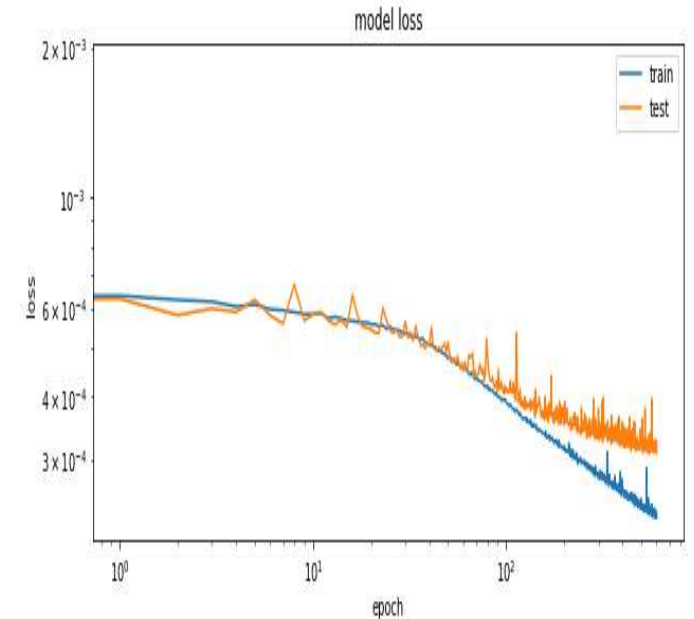
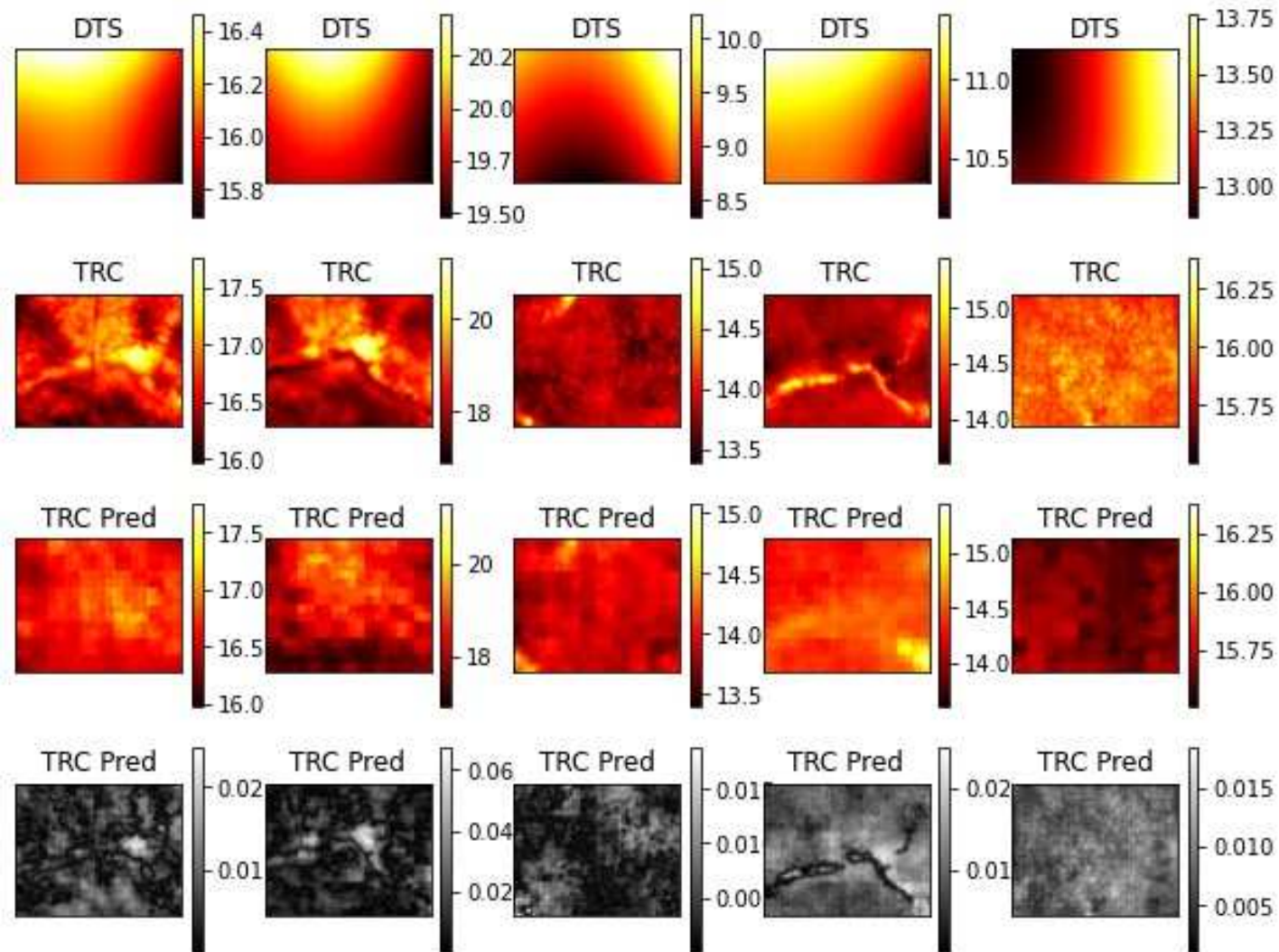
Dataset: 3968 + 2976 images of 128x160



We flip them and mirror them.

Final Dataset: 31,744 of 128x160

The results are promising but more training and architecture testing is needed.



We set for 1000 epochs and finished early in 602 epochs with a mean loss on val of 4.64×10^{-4} . Around 1.4 degrees Celsius

Conclusions

- Machine learning can be used to design a sensor system based on dimensionality reduction capacity.
- AI requires sensors before being operational (ML) and after becoming operational,
- Sensor combination can pose a challenge in AI and ML performance due to its variability in frequency and spatial resolution.
- AI, ML and DL are tools for knowledge augmentation. However, their capacity is completely determined by the sensor with highest spatial resolution and frequency.



Thanks



A transient backward erosion piping model based on laminar flow transport equations. Wewer, M., Aguilar-López, J. P., Kok, M., & Bogaard, T. (2021). *Computers and Geotechnics*, 132, 103992

"A data-driven method for identifying drought-induced crack-prone levees based on decision trees."
Chotkan, Shaniel, et al. - *Sustainability* 14.11 (2022): 6820.

"Understanding the thermal response of an unburied fiber-optic sensor for dike cracks detection." De Roos, Simone, et al. - submitted to - *Sensors Journal* 2022.

"Development of an optimal sensing strategy for dike monitoring of backward erosion piping with fibre optic cable based sensors"
MSc Thesis Manuel Wewer (2019) - TU Delft/TU Dresden

" Predicting drought-induced cracks in dikes with artificial intelligence " MSc Thesis Shaniel Chotkan (2021) - TU Delft

"Crack detection for dikes using distributed temperature sensing" MSc Thesis Simone de Roos (2022) - TU Delft