



Improvements in Risk Assessment Tools

22/02/2022

The FORESEE EU Project – Final conference

Erlinda Biescas –Telespazio UK– & David García Sanchez –Fundación Tecnalia
Research & Innovation–

Improvements in Risk Assessment Tools

- ▶ FORESEE's developments that aims to improve the Risk Assessment Tools:
 - ▶ Risk mapping tool
 - ▶ Virtual Modelling platform and asset failure prediction
 - ▶ SHM BIM based alerting SAS platform
 - ▶ Flooding Methodology
 - ▶ Command and Control
- ▶ Key words: Satellite monitoring | Flooding and risk mapping | Structural health monitoring: satellite and ground data based | Shake maps | Data fusion / Common and Control Centre

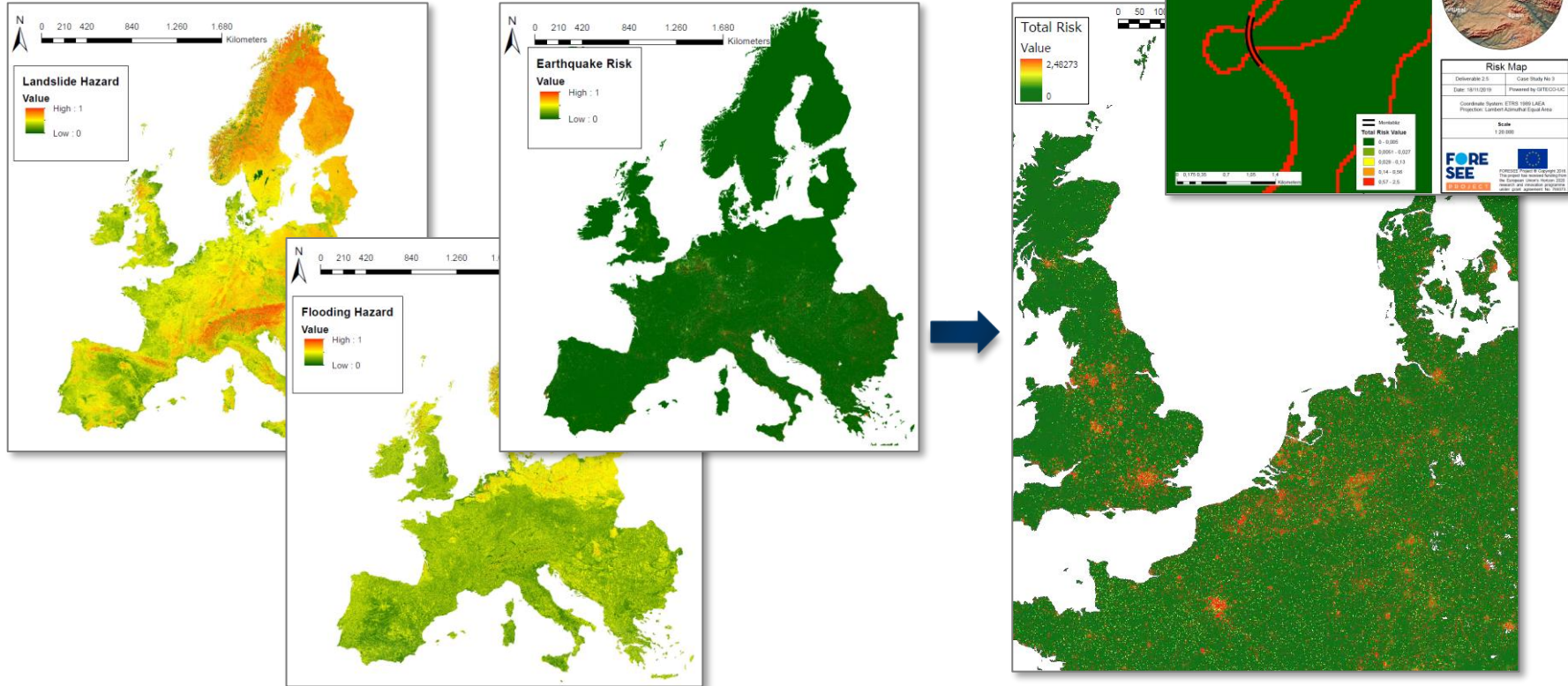


Risk Mapping Tool

- ▶ Objective: Early identification of large-scale risks to extreme natural disasters affecting road and railway infrastructures.
- ▶ Estimation of potential risks to be used in the early phases of project design.
- ▶ Definition of hazard and risk maps at European level.

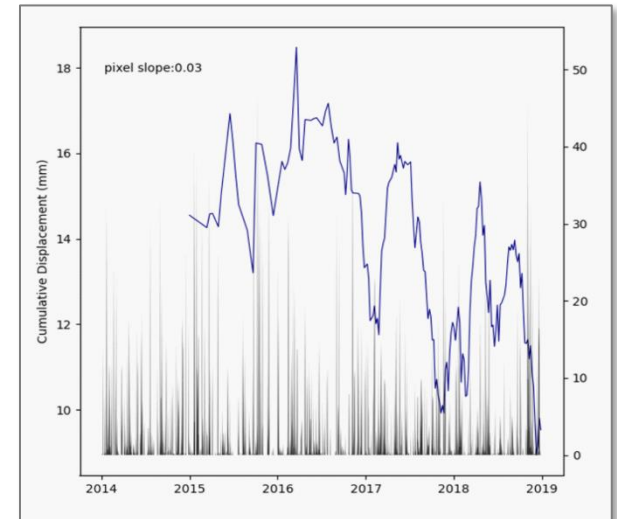


Risk Mapping Tool

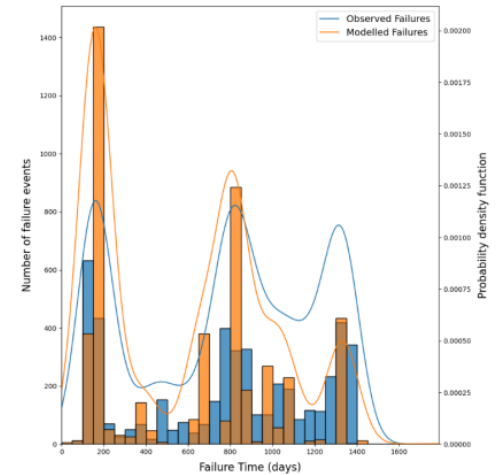
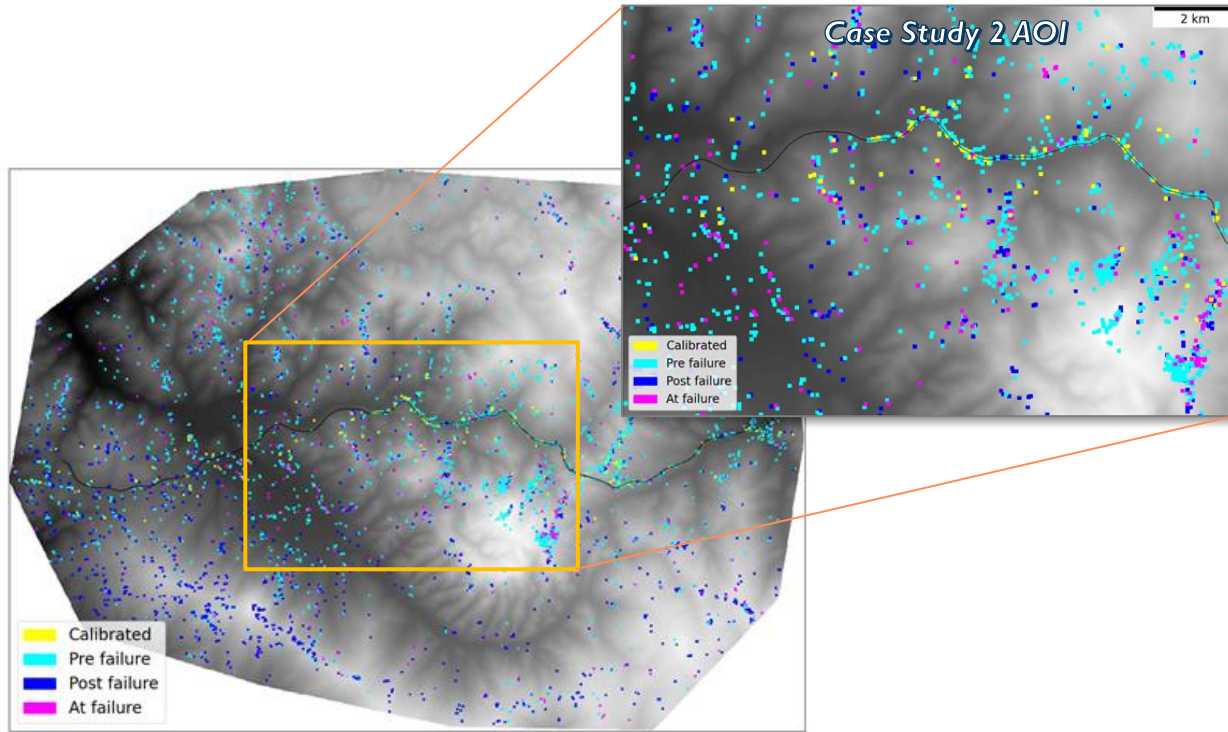


Virtual Modelling Platform and Asset Failure Prediction

- ▶ Objective: To predict timing of slope instability that may disrupt transport networks.
- ▶ The tool is based on a numerical model of slope failure where the stability of the slope depends on the pore pressure of water.
- ▶ The model innovative feature is its parametrization based on InSAR satellite data which provide ground motion time series.
- ▶ InSAR time series show precursor motion correlated with rainfall.



Virtual Modelling Platform and Asset Failure Prediction



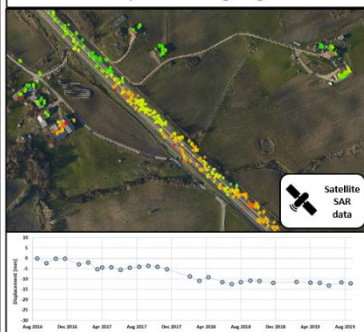
SHM BIM based alerting SAS platform

- ▶ Objective: To provide structural health monitoring assessment by using satellite data.
- ▶ How S-SHM can improve the infrastructure management towards resilience:
 - ▶ Integration of different data sources;
 - ▶ BIM model of the infrastructure and components to be kept under control;
 - ▶ Increased reliability of identifying warning thresholds;
 - ▶ Used to program and design interventions;
 - ▶ Timely warning of potential events with a positive impact on mobility and safety.

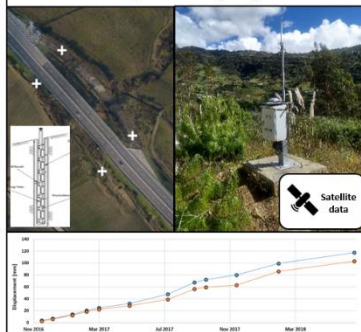
SHM BIM based alerting SAS platform

Dynamic site data

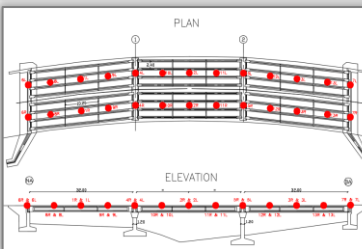
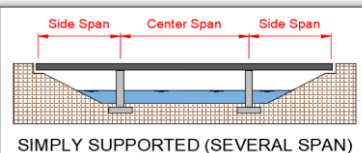
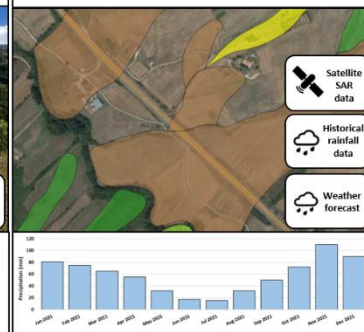
PSI data:
Observed past and ongoing motion



In-situ sensors data:
Observed past and ongoing motion



Landslide Failure Prediction Model:
Predicted terrain motion



Static site data

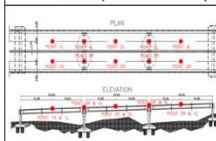
BIM



Motion Thresholds

Description	Typical velocity	Response
Extremely rapid	5 m/s	Nil
Very rapid	3 m/min	Nil
Rapid	1.8 m/h	Evacuation
Moderate	13 m/month	Evacuation
Slow	1.6 m/year	Maintenance
Very slow	16 mm/year	Maintenance
Extremely slow		Nil

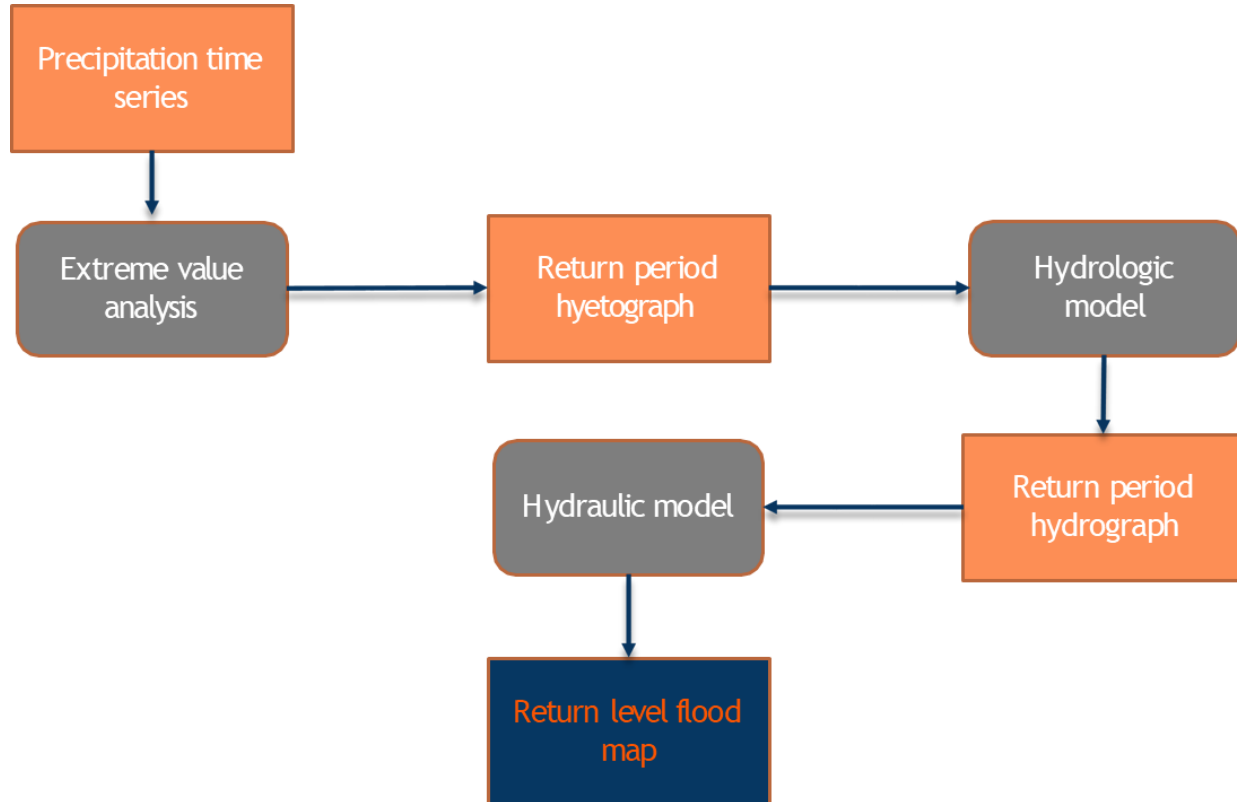
BRIDGE (SIMPLY SUPPORTED)



POINT	LENGTH/ HEIGHT [m]	LIMIT VALUE (mm)	
		COMFORT	TRAFFIC SAFETY
Point SR	32,00 m	12,80 mm	22,38 mm
Point SL	32,00 m	12,80 mm	22,38 mm
Point SR	32,00 m	5,14 mm	16,00 mm
Point SL	32,00 m	5,14 mm	16,00 mm
Point SR	32,00 m	12,80 mm	22,38 mm
Point SL	32,00 m	12,80 mm	22,38 mm
Point SR	8,50 m	17,80 mm	29,67 mm
Point SL	8,50 m	17,80 mm	29,67 mm
Point SR	8,55 m	17,10 mm	28,50 mm
Point SL	8,55 m	17,10 mm	28,50 mm



Flooding Methodology – Usual Methodology

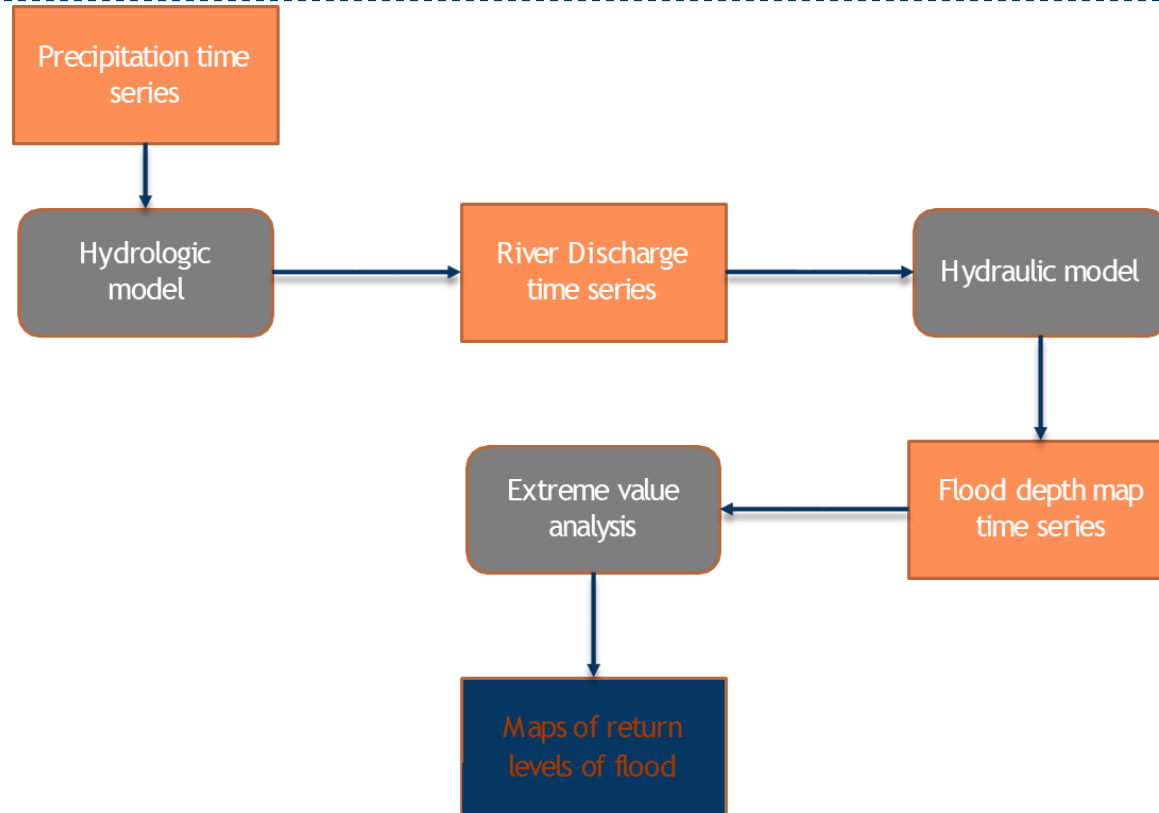


Flooding Methodology

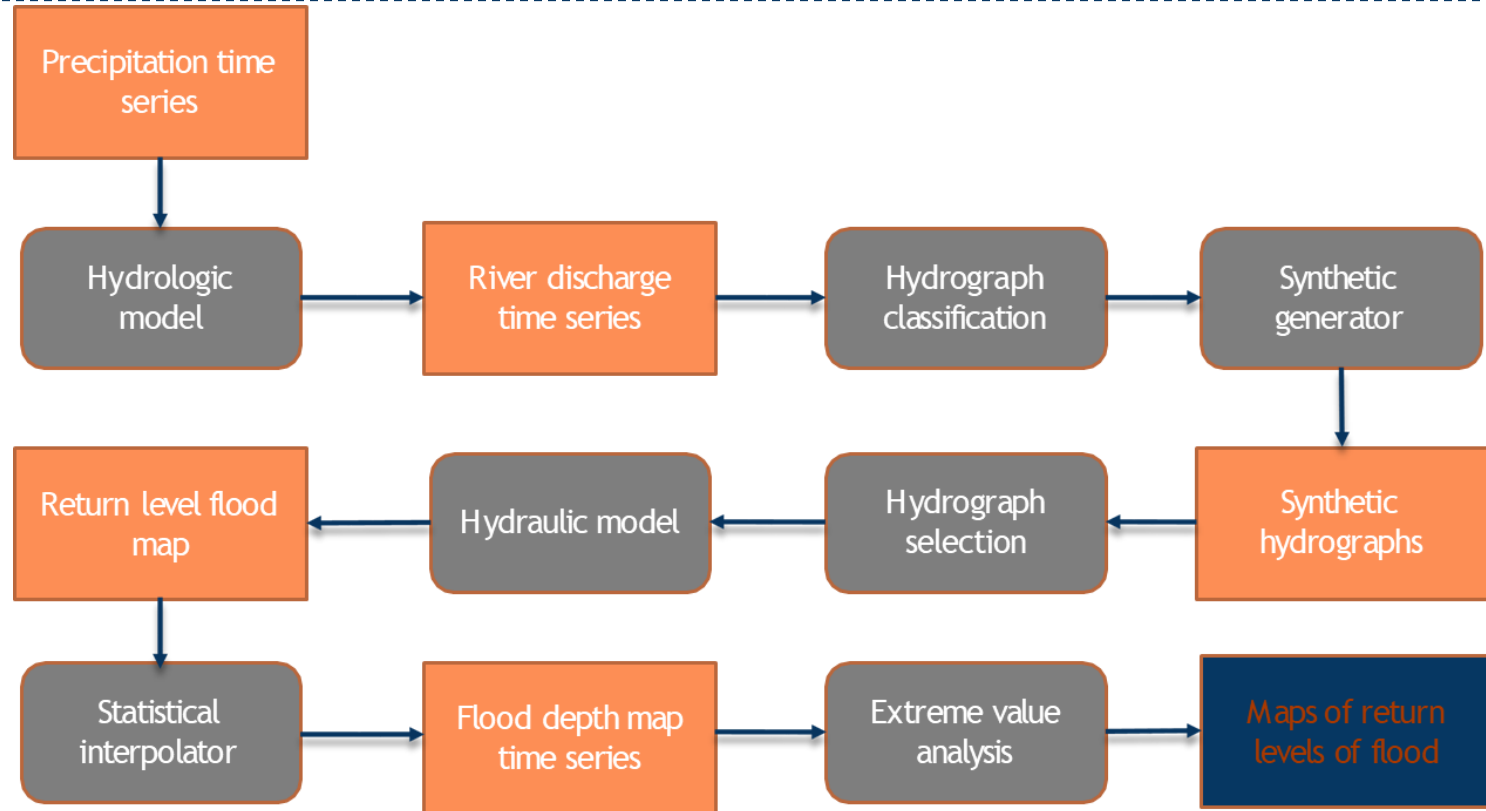
Question:

Is the flood generated by the event of a given return period a good estimator of the return level of the flood for the same return period?

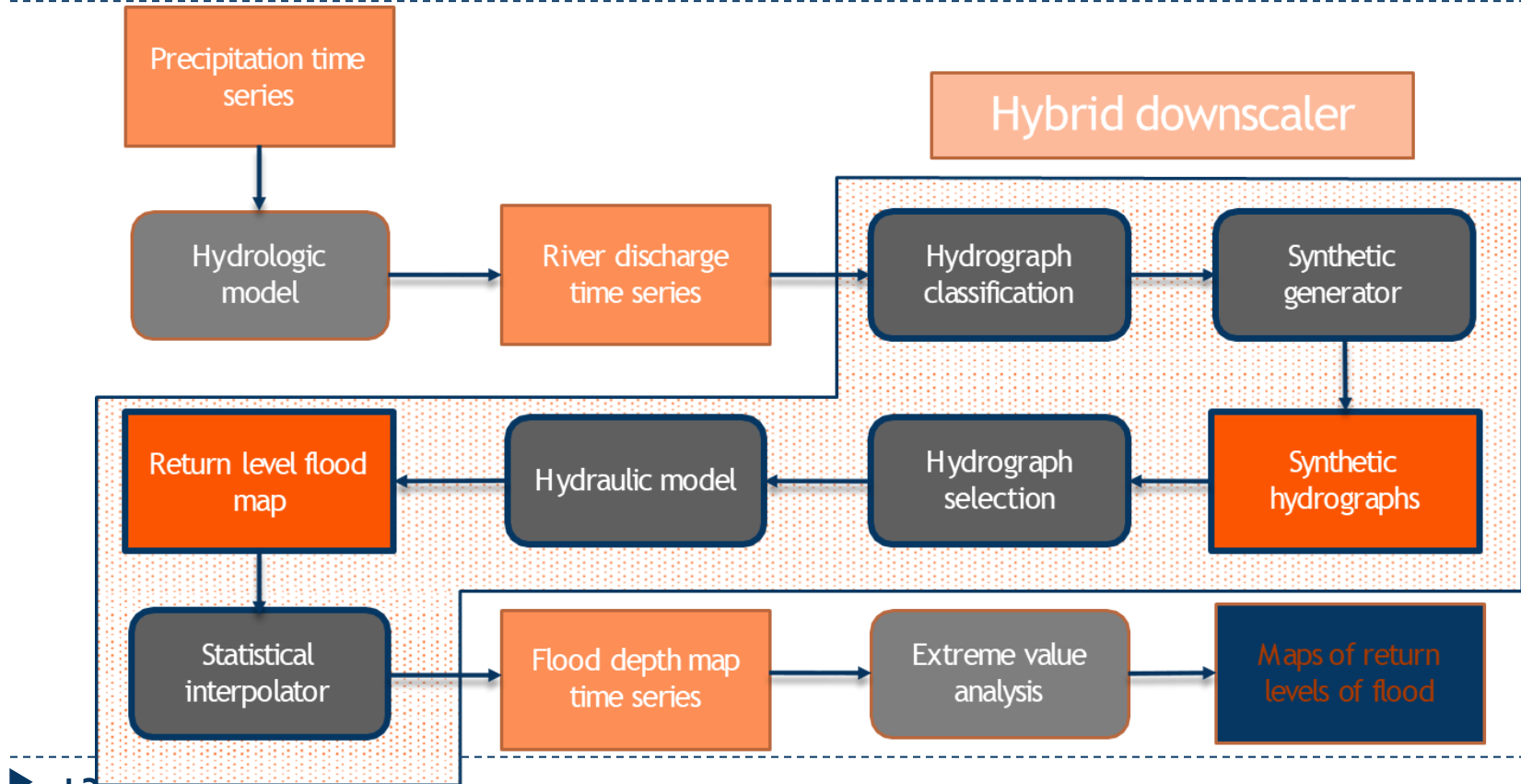
Flooding Methodology - Desired methodology



Flooding Methodology - Proposed methodology



Flooding Methodology - Proposed methodology



Flooding Methodology – Flood Maps



10 year return period flood



10 year return period flood

Flooding Methodology – Flood Maps



500 year return period flood

Not using a stochastic methodology can leave us very much on the side of insecurity!

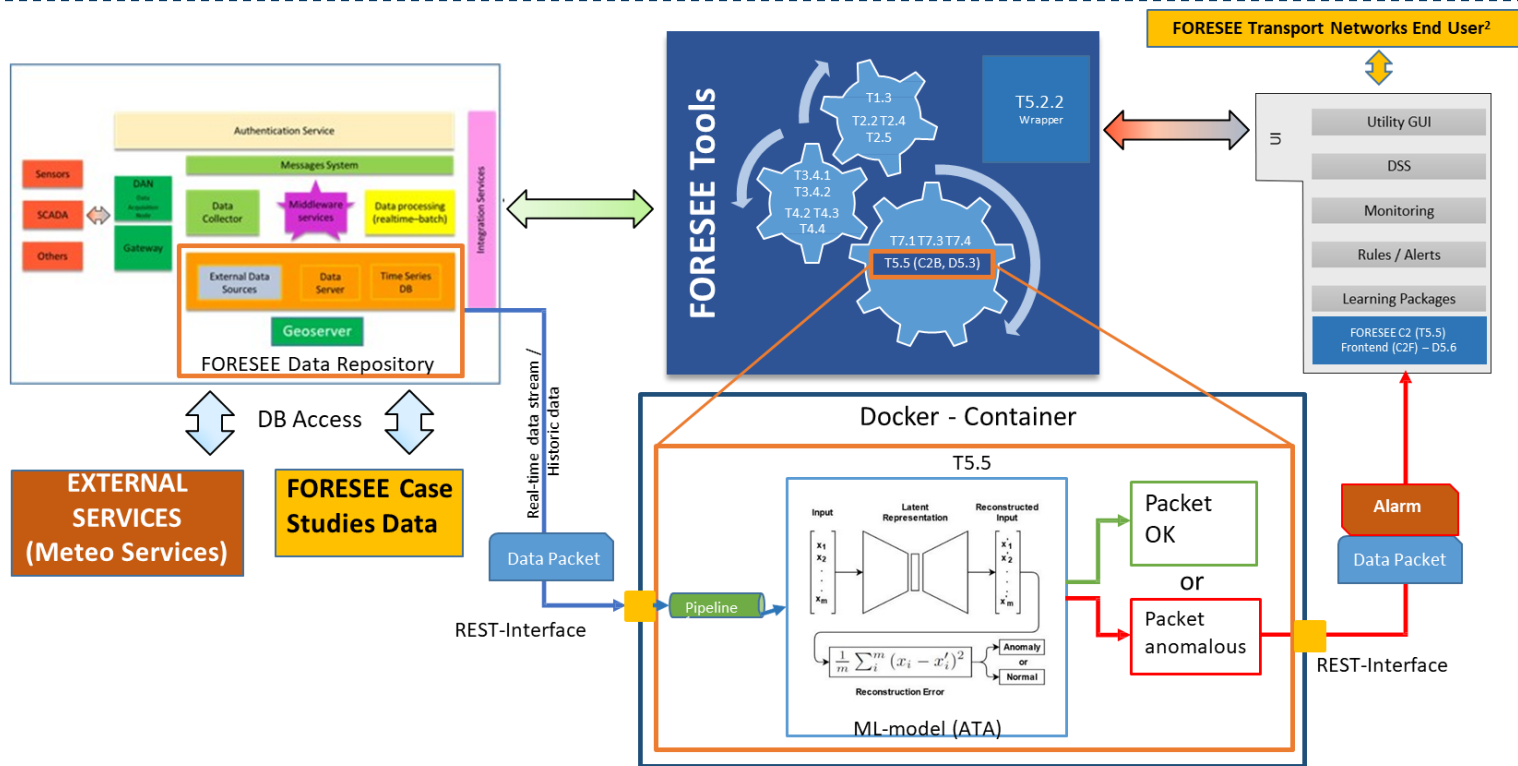


10 year return period flood

Command and Control Centre (C2)

- ▶ Objective: The C2 serves for training purposes to increase (situation) awareness of the users in the FORESEE Toolkit
- ▶ It provides interactive real-time visualization and natural Human Computer Interaction
- ▶ Big data analytics and machine learning

Command and Control Centre (C2)



¹Pipeline for preprocessing incoming data packets for ML

²Infrastructure owners and operators, passengers, drivers, logistic operators etc. (WP 7)

Command and Control Centre (C2)

▶ Working hypothesis:

- ▶ Efficient anomaly detection -> machine learning techniques: neural networks
- ▶ Alarms raised using anomaly detection -> enhance the situational understanding of the infrastructure operators
 - ▶ Faster detection time when problems occur (compared to a manual observation of the sensor data)
- ▶ Neural networks achieve efficient anomaly detection by learning the **normal 'behaviour'** of an infrastructure
- ▶ Allowing them to detect when new data points lay **outside of this normal 'behaviour'** and issue meaningful alerts.

Command and Control Centre (C2)

▶ Machine Learning Architecture Research

- ▶ First approaches with unsupervised Generative Adversarial Network (GAN) and Autoencoder
 - GAN: Adversarially Learned Anomaly Detection (ALAD)
 - Autoencoder: Deep Autoencoding Gaussian Mixture Model (DAGMM)
- ▶ Discussions with experts:
 - Instead of an unsupervised learning approach with ALAD or DAGMM, a supervised learning approach might be more appropriate
 - A framework developed by Fraunhofer IAIS: Adversarially Trained Autoencoders (ATA)

▶ Data

- ▶ Pre-processing of sensor data
 - PostgreSQL, HDF5
 - Data preparation, data harmonization, data cleaning, data scaling

▶ Training of neural networks

- ▶ Due to the different nature of the data of the case studies -> One neural network per Case Study necessary

▶ Deployment

- ▶ Containerization of the trained network with Docker
- ▶ Deploy on a Fraunhofer server and provide it via Internet
- ▶ Building REST API (FastAPI) and providing endpoints
- ▶ Frontend development / integration into toolkit lead by RINA-C

Command and Control Centre (C2)

▶ Machine Learning:

▶ Model building

- ▶ Historical data randomly split into **trainset** and **testset** (e.g., 80% and 20%)
- ▶ Model trained and build on **trainset** of historical data
- ▶ Trained and fixed model tested and validated on **testset** of historical data

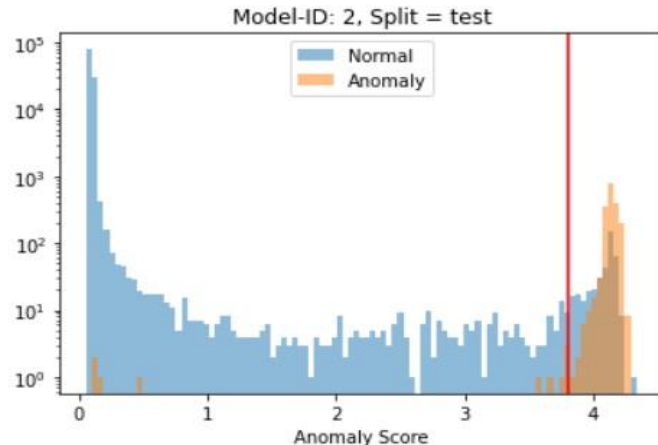
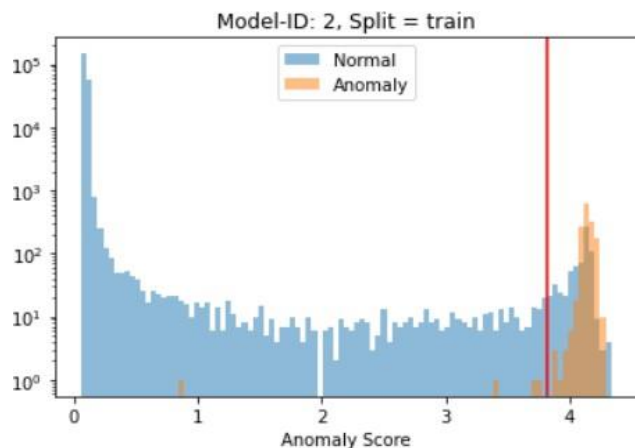
▶ Model application

- ▶ Trained and fixed model applied on **new data** (“live data” / “real time”)
- ▶ Output:
 - Prediction for new data based on the model
 - Anomaly score as an indicator for normal or anormal event / hazard

Command and Control Centre (C2)

► Anomaly score:

- Indicator on “how” abnormal an event is
- Threshold as an output of the trained and fixed model
 - Anomaly score > threshold → abnormal event / hazard → alarm
 - Anomaly score < threshold → normal event → no alarm





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