

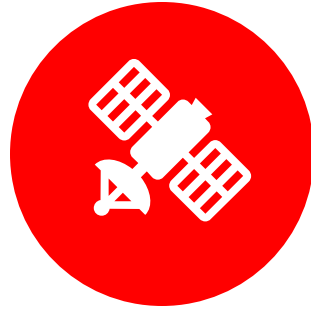
International AI Standards for Disaster Risk Management

Elena Xoplaki, CMCC Foundation
Euro-Mediterranean Center on Climate Change

Activities thus far:



COMPONENTS
OF AI PIPELINE



GUESS THE
FEATURE

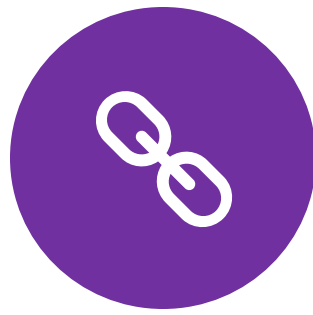


MODEL
TRAINING



OPERATIONAL
DEPLOYMENT

Next step: addressing challenges with standards

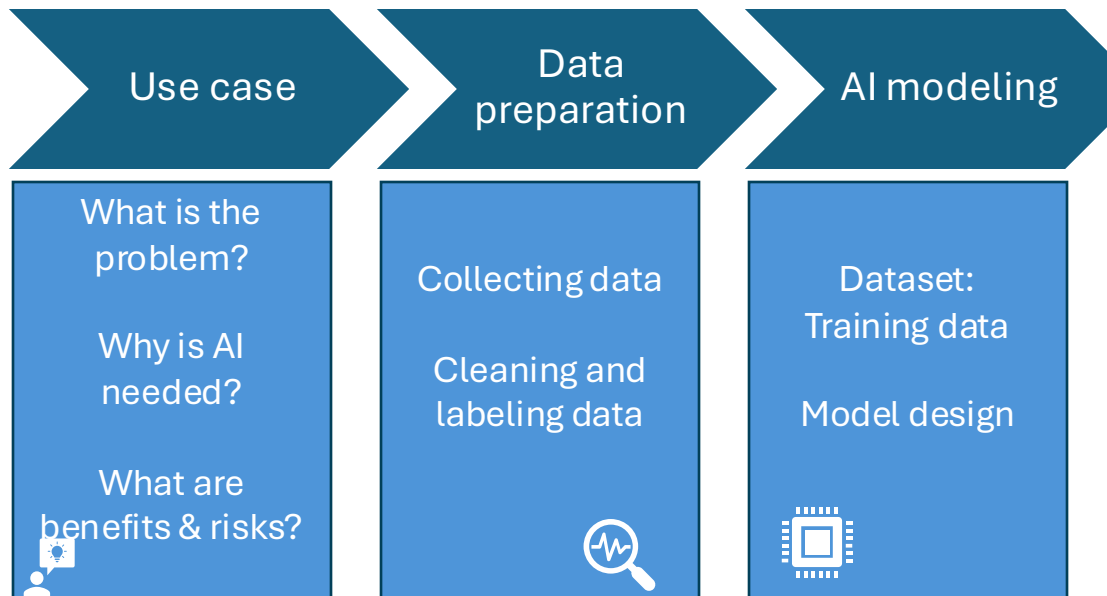


COMPONENTS OF AN AI PIPELINE

Some challenges

- It is important to understand each step and to put them in the correct sequence.
- Since each problem statement (and dataset) can have different requirements, additional (sub)steps can emerge.

(adapted from Vincenzi et al., 2024)



6.4 AI-system life cycle

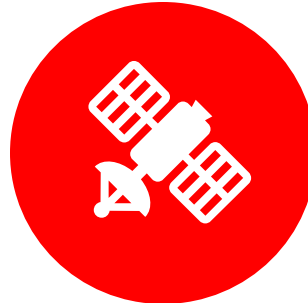
An AI system life cycle encompasses the comprehensive series of stages involved in the creation, deployment, and maintenance of an AI-based system. This life cycle helps in structuring the development process to ensure effective, reliable, and ethical AI-based solutions. The life cycle typically includes several phases, each critical to the success of the AI-based system.

ETSI TR 104 119 V1.1.1 (2025-09)

Best practices:

Researchers and developers of artificial intelligence systems intended to be used for natural disaster management should carefully define the AI task and check the availability and quality of data that is planned to be used. Additionally, a vast amount of literature on different types of AI developments exists, and comparing similar studies can be helpful to obtain further knowledge. Finally, multi-effects of natural disasters should not be neglected but kept in mind.

WG-Modeling Technical Report

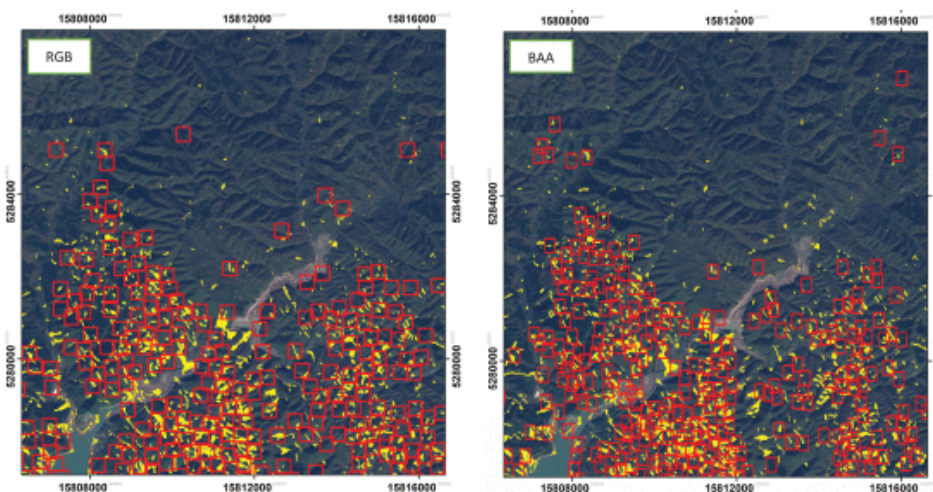


GUESS THE FEATURE

Some challenges

- Units and unit systems impact interoperability. Data preparation is an important step in any AI pipeline.
- Subjectivity (“cultural bias”) impacts the identification and labelling of features.

Landslide detection (Nava et al., 2021)



“Data preparation is a fundamental process (...) examples include (...) units of the data (e.g., Km, m, mm) or the unit system (e.g., Imperial vs Metric).”

WG-Modeling Technical Report

Best practices:

- Attempt to minimize the subjectivity in the class label definitions, by including a diverse group of experts that help reduce cultural biases.
- Provide different examples for the annotation task, given the annotators might have a different background of culture, social context, etc.
- Critically analyse assumptions on annotations. For instance, labelled data might not always be applicable as ground-truth as the meaning of class labels might change in the future.
- Decide the level of expertise required and accordingly, consider the background of annotators suitable for the task; consider test annotation exercises.

WG-Data Technical Report



MODEL TRAINING

Some challenges

- The problem statement should guide the selection of an appropriate model architecture and training method.
- Model evaluation should be task specific and include performance metrics, benchmarks, and human discrimination.

Best practices:

The evaluation of AI systems is application specific or task oriented and includes human discrimination, problem benchmarks, and peer confrontation. There is a wide range of metrics and methods reported in the literature such as confusion matrices, ROC curves, MSE, MAE, inlier ratio, Pearson Correlation Coefficient, PSNR, SSIM, and IoU. Additional quality aspects such as robustness, reliability, and explainability should be considered when assessing an AI system for deployment, in particular, for high-risk scenarios. Additionally, poor performance and vulnerabilities such as data poisoning should be considered when evaluating the reliability of a machine learning model. It is also a good practice to involve domain experts such as meteorologists, emergency responders, and other relevant stakeholders in the testing and evaluation of natural disaster management models to ensure they align with the needs of those who will be using the models in real-world situations and provide valuable insights that can inform response and recovery efforts. This can help to ensure that the models are accurate, reliable, and useful in real-world applications.

Comment

<https://doi.org/10.1038/s41561-025-01639-x>

Explainability can foster trust in artificial intelligence in geoscience

Jesper Søren Dramsch, Monique M. Kuglitsch, Miguel-Ángel Fernández-Torres, Andrea Toreti, Rustem Arif Albayrak, Lorenzo Nava, Saman Ghaffarian, Ximeng Cheng, Jackie Ma, Wojciech Samek, Rudy Venguswamy, Anirudh Koul, Raghavan Muthuregunathan & Arthur Hrst Essenfelder

Check for updates

Uptake of explainable artificial intelligence (XAI) methods in geoscience is currently limited. We argue that such methods that reveal the decision processes of AI models can foster trust in their results and facilitate the broader adoption of AI.

determine the importance of climatic variables such as precipitation for meteorological drought prediction¹⁴. In the latter example, the results aligned with physical model interpretations, emphasizing the need to include specific climatic variables as predictors in the model. Figure 1 demonstrates the possible benefits of XAI across different dimensions, using natural hazards as an example domain.

Uptake of XAI in geoscience

Given these benefits, we were curious to see how the geoscience community is applying XAI. To acquire an overview, we extracted

OPERATIONAL DEPLOYMENT

Some challenges

- Trust in AI-based systems depends on many factors; these can include the “stakes,” the performance, and the interpretability.
- To ensure that an AI-based systems meets end-user needs, diverse and interdisciplinary teams are encouraged.

Best practice(s): For those using AI in communication systems for NDM, it is also suggested to: **Cultivate diverse, interdisciplinary and local teams.** AI-based algorithms are often developed by geoscience or ML experts in an academic setting, where development is not always tied to the inclusion of end user needs. Also, data scientists and machine learning practitioners may not have the necessary background or expertise to fully evaluate potential risks, while DRR practitioners are not necessarily experts on AI / ML.

WG-Comms Technical Report



AI & domain experts



Possible end users



COMMENT

<https://doi.org/10.1038/s41467-022-29285-6>

OPEN

Facilitating adoption of AI in natural disaster management through collaboration

Monique M. Kuglitsch¹, Ivanka Pelivan¹, Serena Ceola², Mythili Menon³ & Elena Xoplaki⁴



Standards for responsible,
interoperable AI

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COMMENT | 01 October 2024

AI to the rescue: how to enhance disaster early warnings with tech tools

Artificial intelligence can help to reduce the impacts of natural hazards, but robust international standards are needed to ensure best practice.

“AI tools created in the absence of international standards could have a variety of problems, including (...) not being compatible or interoperable with each other. Because disasters can move across borders, this is a lost opportunity for continuous early-warning coverage.”

From regional to international scale



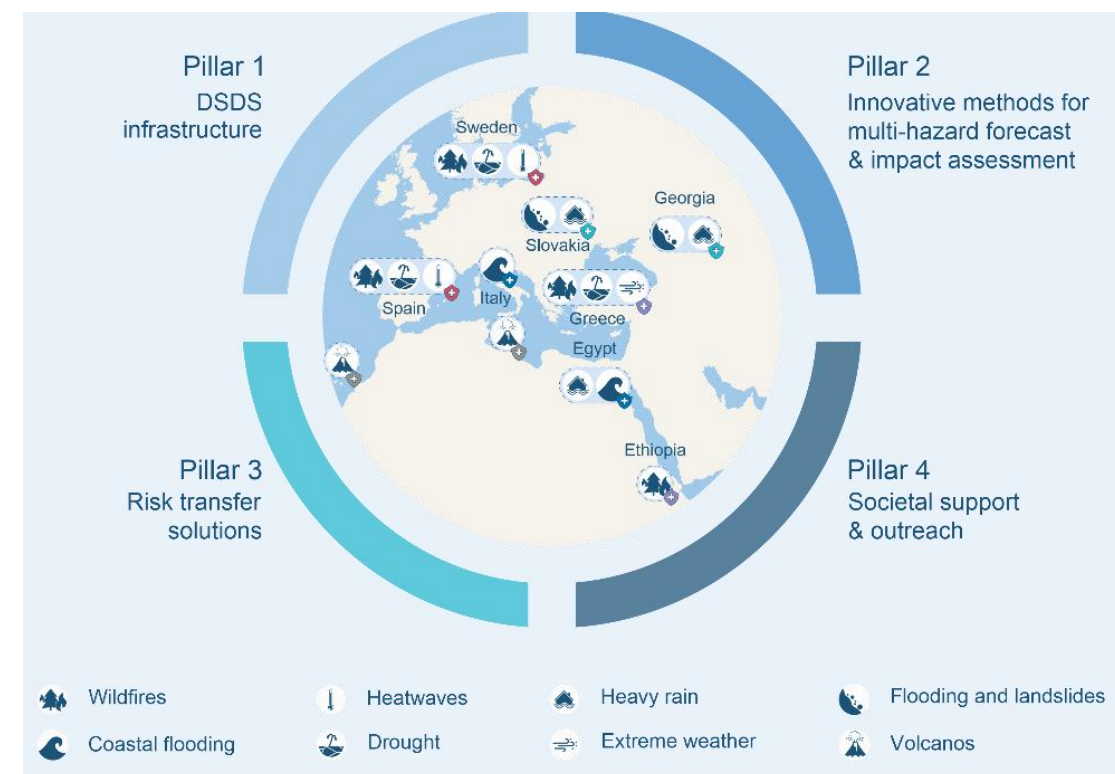
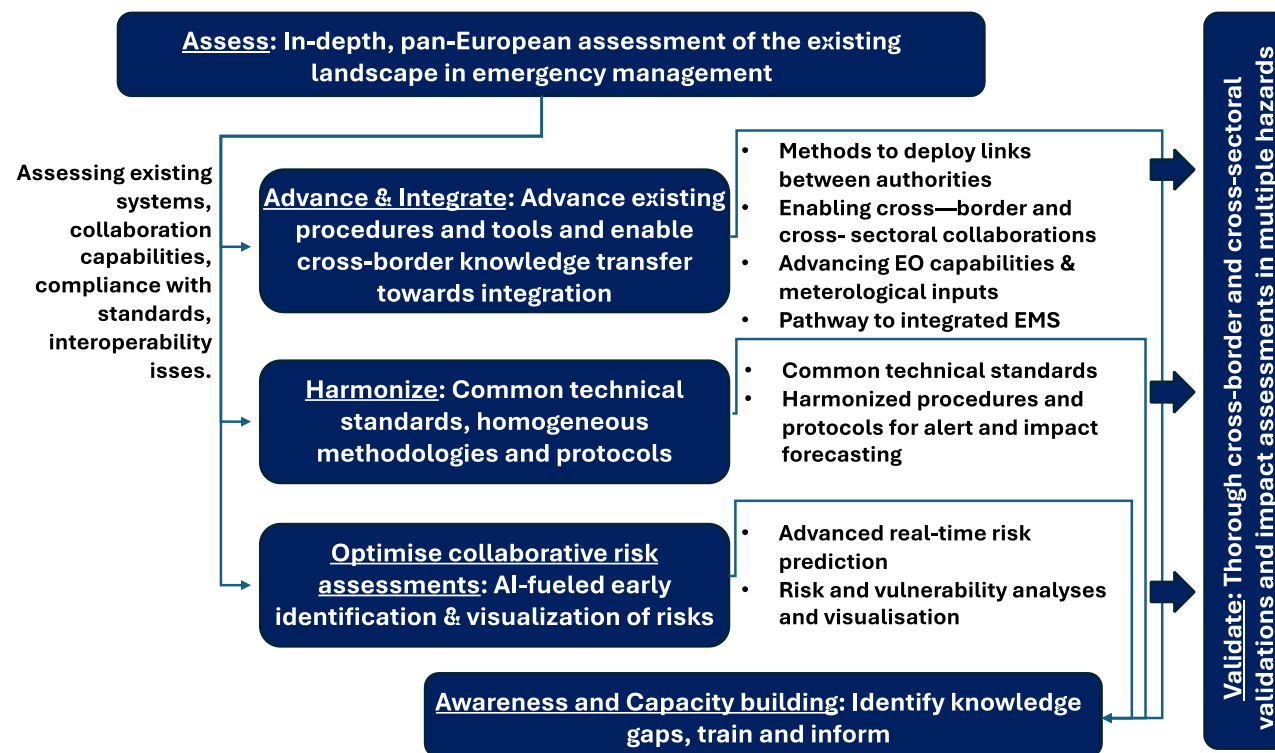
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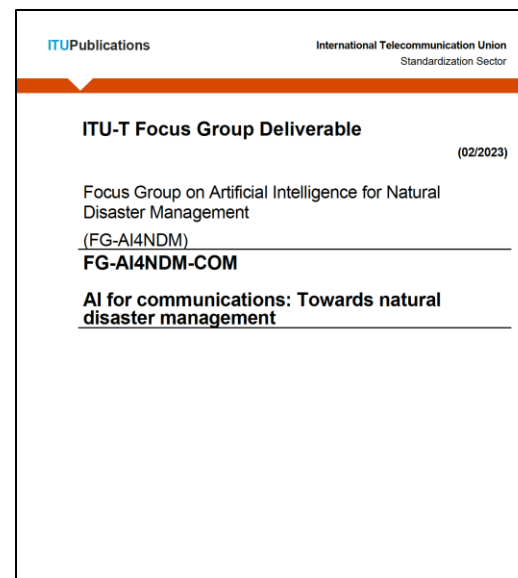
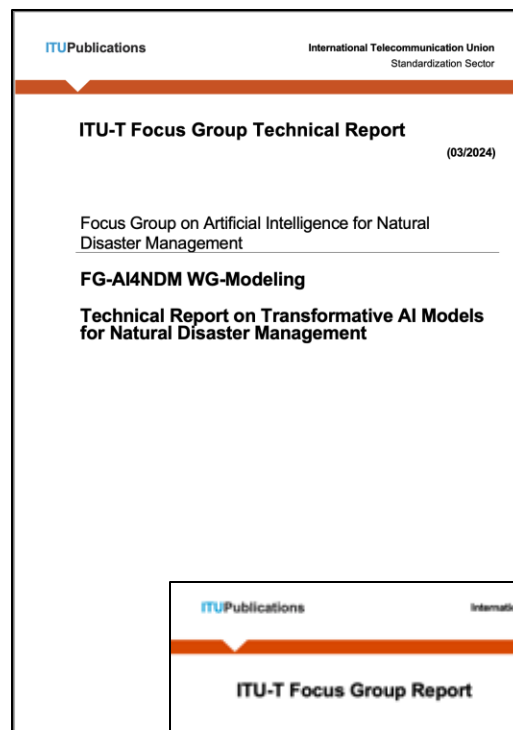
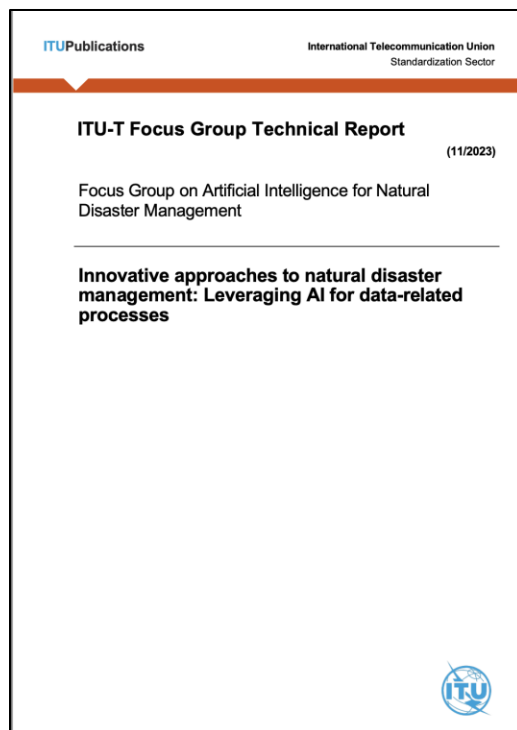


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AlERT and impact-forecast standards
for Emergency Management



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