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Focus Group on Artificial Intelligence for Natural Disaster Management
(FG-AI4NDM)

FG-AI4NDM WG-Modeling

Transformative AI Models for Natural Disaster Management

Working Group: Modeling

Acknowledgement

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Summary

This technical report provides an overview of some key principles and considerations when building an AI model for natural disaster management.

Keywords

Disaster management, disaster detection, AI algorithms, data processing

Note

This is an informative ITU-T publication. Mandatory provisions, such as those found in ITU-T Recommendations, are outside the scope of this publication. This publication should only be referenced bibliographically in ITU-T Recommendations.

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Transformative AI Models for Natural Disaster Management

Executive Summary

This technical report provides an overview of some key principles and considerations when building an AI model. It discusses best practices and critical aspects that should be accounted for when designing, implementing, and validating an AI model. By reviewing and analyzing all those aspects, it tries to focus on a specific field of application: natural disaster management. Although many of the points discussed here can be applied beyond this specific field of application, there are some peculiarities in natural disaster management that should be considered when developing and applying tailored AI models. While discussing all the key elements, from data preparation to model validation, this report acknowledges and highlights that a universal AI model does not exist and that the type of available data and the tasks to be performed are key elements that dictate the optimal approach.

The report stresses the importance of AI in natural disaster management as a tool to reduce risk, enhance preparedness, and support critical actions when a disaster occurs. AI models can help limit human and economic losses in a world that has been, and will be, experiencing an increasing frequency and intensity of natural disasters. While pointing to the role of AI, this report also discusses limitations and uncertainties that should always be considered when applying AI models in natural disaster management. All the steps in the AI life cycle are analyzed together with some elements related to responsibility and ethics. The report also emphasizes how AI models for natural disaster management must be designed in collaboration with field experts as well as policy and decision makers to take advantage of their knowledge and to enhance trust. Key guiding principles, such as transparency and interoperability, are discussed together with trust.

Concrete elements to select an AI approach are provided and analyzed together with available algorithms. Details on supervised, unsupervised, transfer, and reinforcement learning are also given in relation to the entire AI life cycle, from objectives definition to maintenance. Similarly, the evaluation of an AI model is analyzed in detail with respect to the need to ensure robustness, reliability, data protection, and transparency.

As stressed several times in the reports, there are limitations to be considered when developing and applying AI models as well as challenges and gaps that require further attention. Issues related to the validation of online AI systems and associated with non-stationary data are discussed and analyzed.

Finally, the report includes results to a questionnaire that was circulated among the use cases contained in eleven topic groups. These results helped tremendously to shape the content of this report.

It is important to mention that this report is only a basis for further activities and it is to be expected that its content will continue to evolve.

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The Focus Group on AI for Natural Disaster Management (FG-AI4NDM) was established by the International Telecommunication Union (ITU) in December 2020 in partnership with the World Meteorological Organization (WMO) and UN Environment Programme (UNEP). FG-AI4NDM's objective is to improve the following:

1. The understanding of natural disasters.
2. The ability to detect events in real time.
3. The capacity to forecast events.
4. The effectiveness of communication during ongoing disasters.

The Working Group on AI for Modeling (WG-Modeling) is one of three main sub-groups established under FG-AI4NDM. Figure 1 provides an overview of the different working groups of the focus group, their respective topics, and their interactions.

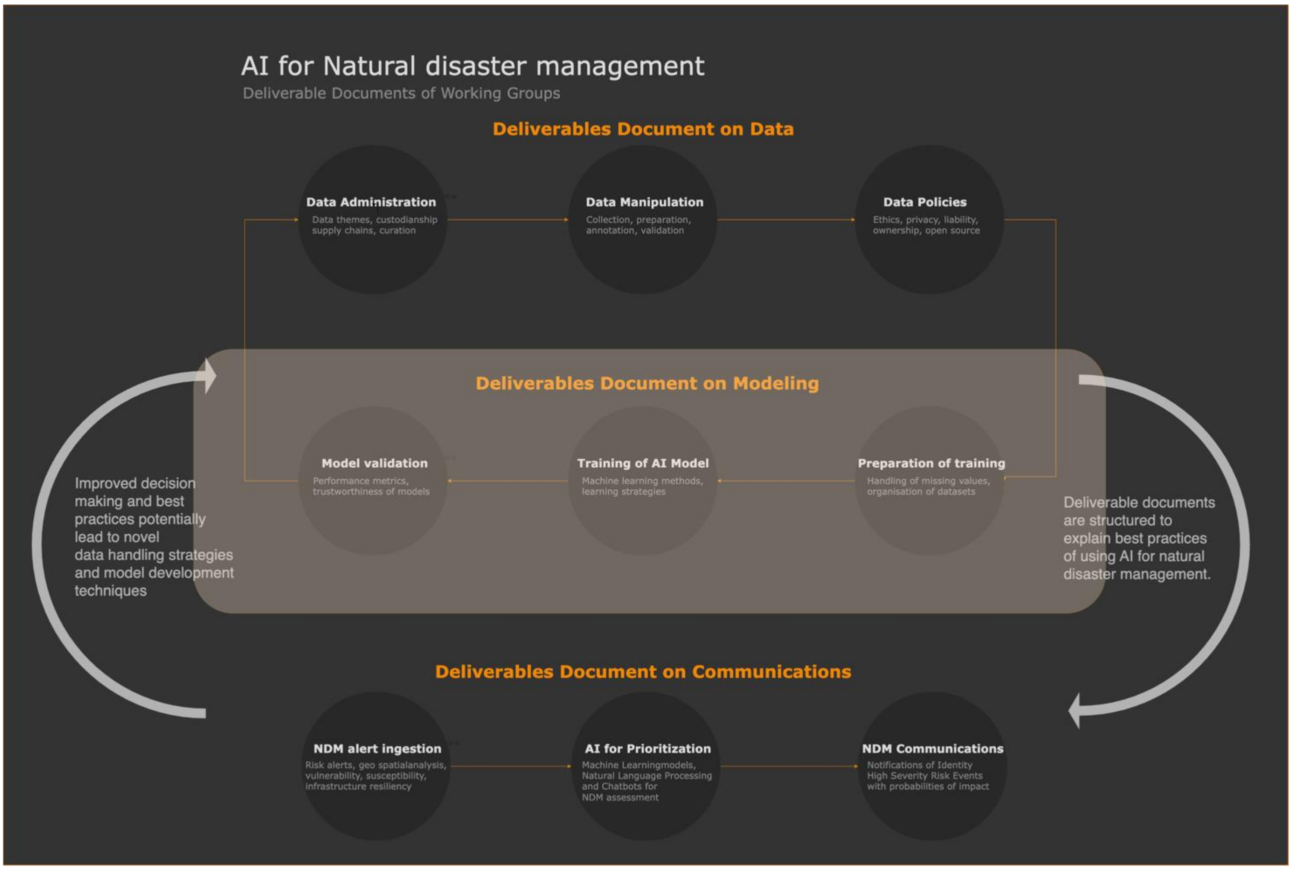

Figure 1: Overview of the Focus Group on AI for Natural Disaster Management

WG-Modeling is focused on best practices of AI development relevant for different applications in natural disaster management. This includes data preparation, AI training, and AI validation. It is important to mention that this report cannot cover all data specific components that are relevant for model development. The interested reader is referred to the deliverables document of the Working Group on Data for AI (WG-Data).

This report is only a basis for further activities and it is to be expected that its content will continue to evolve.

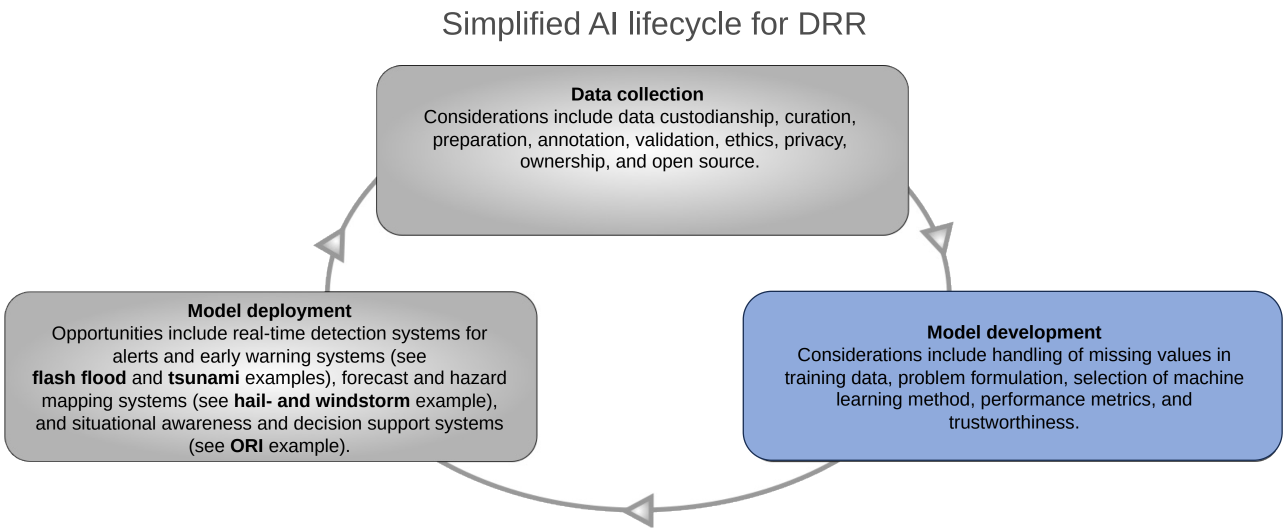

Figure 2: Simplified AI lifecycle for DRR [b-Kuglitsch]

2 Abbreviations

AI	Artificial Intelligence
AUROC	Area under the ROC
DAG	Directed Acyclic Graph
DEM	Digital Elevation Model
DRM	Disaster Risk Management
EU	European Union
GDPR	General Data Protection Regulation
GRIB	General Regularly-distributed Information in Binary form
Grad-CAM	Gradient-weighted Class Activation Mapping

IoU	Intersection over Union
IEC	International Electronical Commission
IEEE	Institute of Electrical and Electronics Engineers
ISO	International Standard Organisation
JRC	Joint Research Center
JTC	Joint Technical Committee
LRP	Layer Relevance Propagation
MAE	Mean Absolute Error
MSE	Mean Squared Error
ML	Machine Learning
MLOps	Machine Learning Operations
NDM	Natural Disaster Management
NetCDF	Network Common Data Form
PSNR	Peak Signal-To-Noise Ratio
ROC	Receiving Operating Characteristic
SSIM	Structural Similarity
UNESCO	United Nations Educational, Scientific and Cultural Organisation
XAI	eXplainable AI

3 Introduction

Characterizing, understanding, and predicting natural hazards as well as their impacts implies dealing with extremely complex systems involving different spatio-temporal scales. The interplay of several different processes (often non-linear and non-stationary), the large amount of data from different sources and formats, and an intrinsic uncertainty make dealing with natural hazards challenging. However, an improved understanding of natural disasters as well as an enhanced ability to detect, monitor, and predict them can save lives and reduce the impacts and losses on socio-economic sectors and ecosystems.

Traditional methods used to analyze natural hazards (including climate extremes) include statistical approaches developed in the framework of extreme value theory [b-Haan] and dynamical systems [b-Lucarini]. Numerical process-based models have also been used extensively to characterize and predict natural hazards and their impacts, such as floods [b-Hirpa] or impacts of heatwaves and drought on crops [b-Boote]. Computational aspects need to account for local physical processes and non-physical factors (e.g., associated with the human–environment interaction), which have inspired the increasing development, integration, and use of artificial intelligence (AI). AI has had great success in many disciplines, tied to the increasing power of computation and advancements in sub-fields such as deep learning [b-LeCun]. AI has been recently applied, for instance, to explore future climate suitability of cropland under the effects of more frequent and intense climate extremes [b-Ceglar], predict wildfire risk [b-Kondylatos], to predict floods [b-Mosavi], to predict rainfall–runoff [b-Kratzert], and beyond.

The particular choice of an AI model is affected by many different factors. In particular, the model choice strongly depends on the type of data and the task to be solved. Data can be of various types and have varying representations such as text, time series signals, images, videos, etc. Similarly, the task could require different models. AI models have been used to tackle tasks such as forecasting, reconstruction, segmentation, and classification, as demonstrated by the use cases in this report. These tasks influence the model choice as well as the evaluation methods. Evaluation can be in terms of technical metrics and, depending on the task, use measures of accuracy, area under the curve, intersection of union, etc. Evaluation can also involve trustworthiness of the AI model, transparency of the data and/or modeling approach, robustness, and explainability.

This document aims to present best practices—derived from literature, presentations, on-hand expertise and experience, and from use cases (Figure 3)—that highlight commonalities and differences of AI modeling for natural disaster management and foster standardization and education.

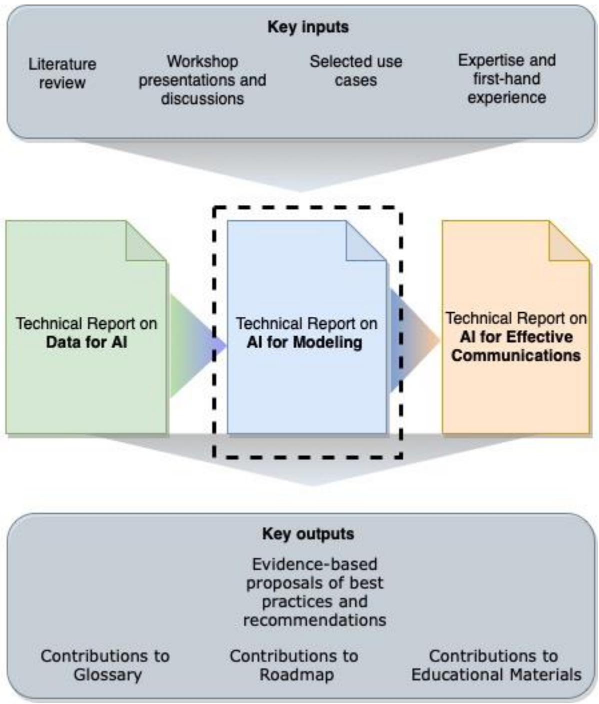

Figure 3: Overview of Working Group on Modeling for AI within the FG-AI4NDM

Following this introduction, the document will present a series of abbreviations and acronyms of relevance for the topic. Then, it will introduce key concepts related to digital transformation when using AI technology: from problem statements and guiding principles, to outcomes. This section will be followed by an overview of the elements of AI development for supporting modeling. The elements include data preparation for training, AI model training, AI model evaluation, and AI model deployment. Throughout the aforementioned sections, best practices will be presented. The penultimate section presents some further related standardization activities, as well as legal and ethical considerations. The final section gives an overview of the use cases, which were analyzed for the underlying report.

4 Digital transformation using AI technology

4.1 Problem statements

Each year millions of humans are dramatically affected by natural disasters (e.g., storms, floods, droughts, wildfires, and many others), thus highlighting the need for effective humanitarian support systems. Furthermore, natural disasters can concurrently affect multiple areas, with impacts on factories, infrastructure, and key sectors such as agriculture, and lead to cascading effects (e.g., on food supply chains). In addition, there can be direct effects on human health. Therefore, multiple stakeholders, including researchers, regulators, humanitarian aid organizations, etc., need to explore ways to prevent, prepare, and assess natural disasters to help their own community as well as others. In this regard, digital technologies are key to support emergency managers, first responders, citizens, and others, before, during, and after a natural disaster.

In recent years, there has been more and more work developed around the use of artificial intelligence (AI) to monitor, forecast, and predict natural disasters as more data is becoming available and computational resources are increasing. The use of AI tools in addressing issues related to natural disaster management have the potential to reduce human and economic loss globally. However, while developing an effective AI system is promising, throughout the AI life cycle, cf. Figure 2, several limitations could pose significant challenges. Limitations may range, for instance, from sudden cloud cover in optical imagery to false information on social media. Addressing them by exploiting multiple strategies (e.g., through the combination of satellite imagery, drone footage, time series data, etc.) and using appropriate AI algorithms can improve the accuracy and effectiveness of the system. Such a system would be able to provide real-time situational awareness and aid decision-making.

- *Monitoring: Real-time or near real-time detection of natural hazards, for example drought detection and tracking of its spatio-temporal evolution.*
- *Forecasting: Predictions of short-term hazards, such as flood occurrence and its spatial extent.*
- *Projecting: Long-term possible future evolution of extremes such as heatwaves and their impacts.*

Most AI methods used for natural disaster management require access to data such as satellite images, weather observations from ground stations, sensor signals, social media content, etc., to generate relevant information and contribution to communications tools [see accompanying technical report from the Working Group on AI for Communications (WG-Comms)].

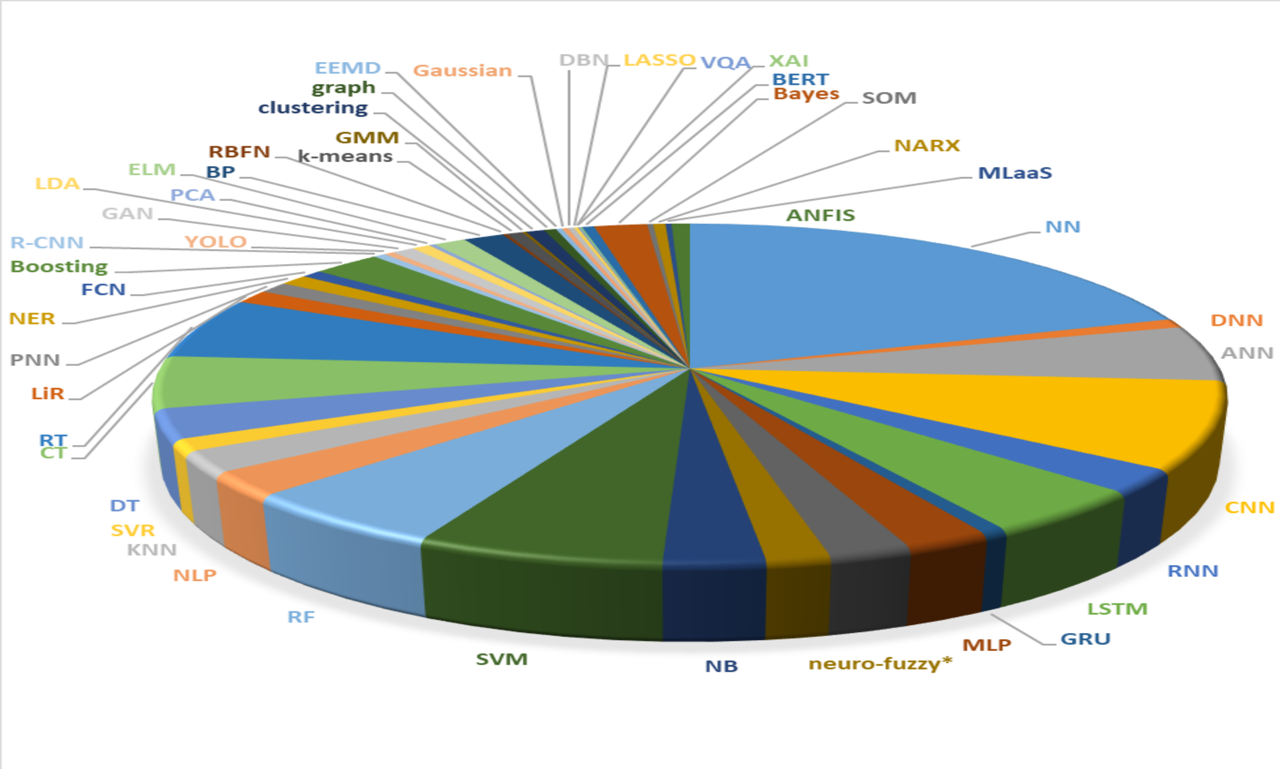

Figure 4: Statistics on algorithms used for natural hazard forecasting, prediction, detection, and monitoring [b-Pelivan]

Depending on the data type and the problem statement, different algorithms may be applicable. The AI literature is quickly growing and new algorithms are proposed to overcome previous limits and obtain new levels in terms of performance or efficiency. Therefore, the formalization of the problem statement is immensely important for the development of AI models.

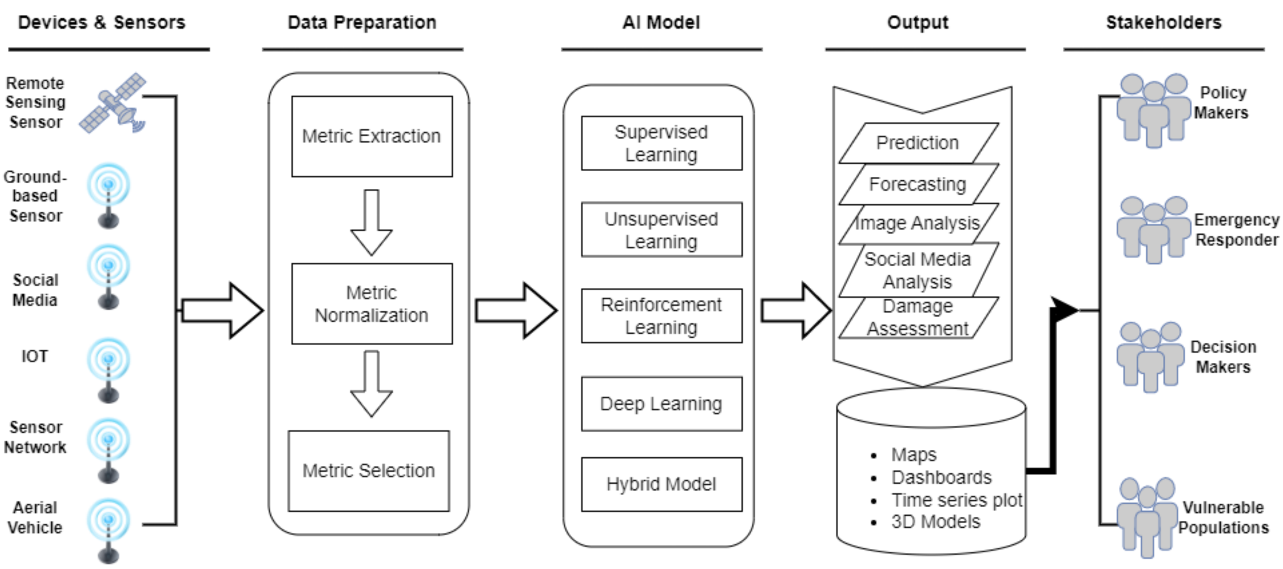

Figure 5: Framework of AI development for natural disaster management

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.

Topic group use cases:
Data quality can be a significant issue in AI modeling. Furthermore, it is important that data contain enough information about the actual events. For instance, ***Using ML to Reconstruct Flooded Area under Clouds in Optical Satellite Images*** *highlights that a major challenge is the availability of high-quality data in flood mapping applications because persistent cloud cover during floods seriously limits the use of optical imagery. A reference to consulting literature was made in* ***Geographical Data Science Applied to Landslide and Debris Flow Hazard in the Colombian Andes****. Here, the authors referred to the existing number of AI algorithms that are used in landslide studies to establish a good relationship between independent variable (predictors) and dependent variable (landslide inventory).*

4.2 Guiding principles

As natural disasters occur everywhere in the world, there is a great global interest in digital solutions, because they can potentially increase the efficiency and accuracy of information needed to prepare for disasters and to respond to them. Developing digital solutions to prepare for natural disasters and to deal with such disasters is an advanced multi-sectoral challenge.

The development of machine learning methods for natural disaster management requires not only multiple data sources but also input from experts from various research areas, as well as policy makers and regulators from different countries. It is crucial to align concepts and principles that guide the development of such technologies to maximize the efforts and outcomes. These principles are intended to ensure that AI is developed and used in a responsible and ethical manner. It is also important to prioritize stakeholder engagement, data access, and transparency in order to effectively utilize high-quality data and develop accurate models for disaster prediction, response, and recovery. This includes formalizing agreements with stakeholders and data sources, and providing end users with access to data and tools.

Additionally, it is important to consider the specific characteristics and features of the region of interest, and to use data that are as relevant and representative as possible, while also ensuring trust and transparency in the results of machine learning models to build confidence in the ability to effectively respond to natural disasters and protect people and communities. Additionally, providing access to data, tools, and models can enable stakeholders to develop new solutions and techniques to improve the decision-making and response process during natural disasters.

Best practices:
Using diverse and high-quality data is certainly essential. However, data itself are often not enough. Stakeholders and other experts should be involved during the entire life cycle; in particular, during data acquisition, model development, and decision-making. This ensures that the use of (multi-modal) data and AI models to make predictions and guide response efforts is accurate and relevant. Additionally, protocols for data access, storage, integration, retrieval, and sharing must be put in place to ensure transparency, interoperability, and trust in the results of machine learning models. This could increase effective decision-making and impact management of natural disasters. It is also important to be mindful of the limitations of the data and AI models, for instance, caused by the assumptions made when analyzing natural disasters.

Topic group use cases:
The use of high-quality data with less noise is generally helpful for training algorithms that have a better performance, as seen in the use case ***Flash Flooding Monitoring System in Mexico****. Besides high-quality data, the use of multi-modal data can be very effective in detecting, monitoring, and predicting natural hazards, as demonstrated in the use case* ***Multimodal Databases and Artificial Intelligence for Airborne Wildfire Detection and Monitoring****. Notably, according to the use cases* ***Artificial Intelligence Modeling Tools for Monitoring Desert Locust (AI-Locust)*** *and* ***Multi-hazard Use Case for Operations Risk Insights and Day One Relief for Natural Disaster Response****, respectively, establishing comprehensive data agreements/integrity by enhancing data access rights ownership, integration, storage, retrieval, and sharing, and establishing formal agreements with stakeholders and data sources, can contribute in fostering trust and transparency in all stages of the ML processes and results.*

4.3 Outcomes

The potential of AI and the number of possible applications of AI tools to improve existing common practices is enormous. Certainly, these systems should be developed under common best practices and standards to allow for a secure and successful deployment. Once AI models are developed, they can be used in a variety of ways to improve existing practices. In the context of natural disaster management, AI tools can be used to better inform citizens; to support discussions, decisions, and actions at different levels; and to improve technological advancement. These tools have the potential to greatly enhance disaster management by providing valuable insights into hazard-likelihood, exposure, vulnerability, and impacts. These tools can be represented in maps to identify high-risk areas for natural disasters and to improve the accuracy and timeliness of disaster detection and warning systems. The maps can be used by policymakers, emergency responders, and other decision-makers to develop strategies for prevention and control, and to help save lives and minimize damage. Additionally, to ensure the safety and well-being of affected populations, it is essential to have systems in place that can accurately identify potential disasters while minimizing the number of false alarms. Machine learning models can be used to optimize the trade-off between false alarms and missed detections, and as more data becomes available, these models can be retrained to improve their accuracy.

The following areas show an immense potential for AI:

- *Decision-making: Informed decisions and actions*
- *Analysis: Objective evaluation of large volumes of data coming from multiple sources*
- *Management: Targeted outcomes and predictions for specific communities, regions, and sectors*
- *Adaptation: Design of effective and sustainable adaptation strategies*

AI models can also be used to analyze and decode data to extract relevant patterns and understand how they are changing over time and space. This information can be used to prioritize and organize emergency response efforts in affected areas, and to identify high and medium severity risks that need to be mitigated. Lastly, designing tools for decision support systems can assist in improving communication and information management by selecting the most appropriate communication channels, developing clear and concise messages, providing filtered and relevant information to disaster managers, and using feedback to continuously improve the system.

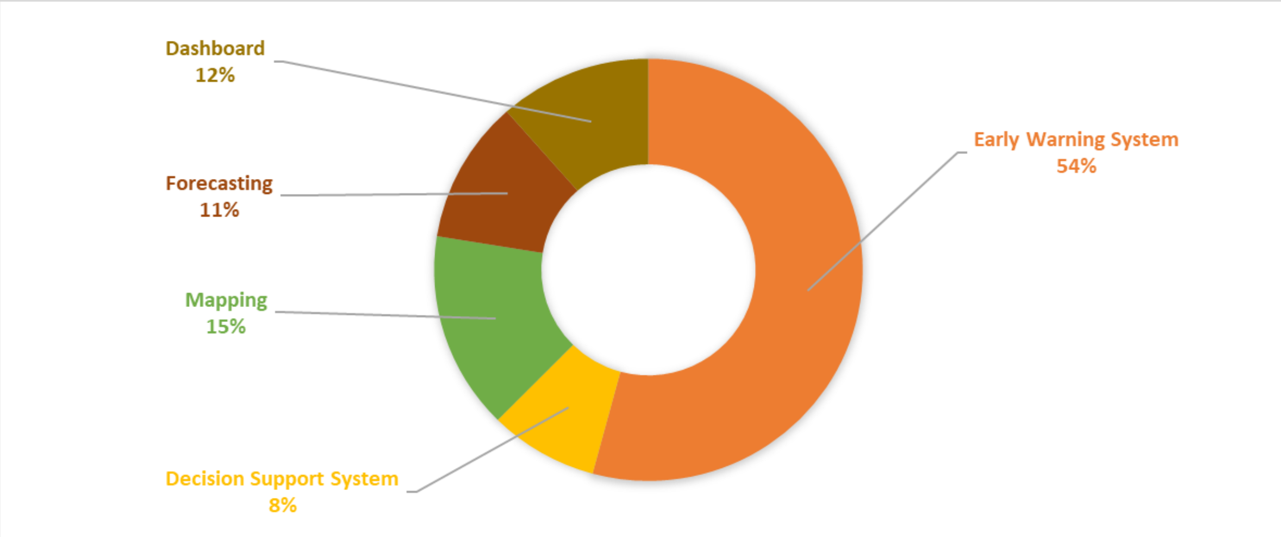

Figure 6: AI communication tools used to aid in decision-making [b-Pelivan]

Best practices:
AI models are developed using multiple insights and methods such as laboratory data, numerical simulations, and transfer learning to assist with natural disaster response and recovery. There are models with the aim of effectively analyzing satellite images, predicting disasters, or analyzing social media data to provide valuable information. However, it is important to keep in mind that these models may produce inaccurate or biased results, which is another reason why such models should be well evaluated before implementation. On the other hand, dashboards can be used to present the results in a clear and easy-to-understand format; for example, maps can be used to visualize and mitigate the impact of natural disasters, and decision support systems can be designed for effective communication and information management during a disaster. These tools help in making informed decisions and communicating effectively during a crisis.

Topic group use cases:
*These practices were applied in numerous use cases, including **Probing Seismogenesis for Fault Slip and Earthquake Hazards**. This use case highlights how transfer learning can be applied to various types of data (e.g., laboratory data, numerical simulations) to monitor faults. The outcome of applying AI models also proved efficient in **An Intelligent Big Data Analysis System for Wildfire Management**. Here, various data types were used with AI to identify forest species and predict forest growth. It is of immense importance that AI model results are effectively communicated to all stakeholders so that they can make informed decisions for early warning and better preparedness. In the use cases **Proposal of an AI Chatbot Use Case as a Multi Hazard Communication Technologies** and **Situational Awareness System for Disaster Response Using Space-based AI (SARA)**, model outputs were visualized on a map and dashboard.*

5 Elements of AI development for supporting modeling

The development of AI solutions for detecting, monitoring, forecasting, or projecting natural disasters is a complex task and requires considerations of the entire life cycle. WG-Modeling, therefore, only addresses the main elements relevant for the development of AI algorithms, even though a clear separation is often not desired and could simplify the overall picture. We refer the interested reader to the other working groups of the FG-AI4NDM: WG-Data and WG-Comms, respectively, cf. Figure 1, and continue with the presentation of modeling-specific aspects.

5.1 Overview structure

One forward pass of the development and deployment life cycle of an AI method can be divided into several steps. Starting with the (physical) sensors that acquire data on the environment, this process can be expensive and the outcome can be very different across different regions. When these data are (pre-)processed for further (model) development purposes, the potential differences in data and data quality can be a considerable hurdle for AI models that are trained and developed in one specific area, but intended for use in another area. Similarly, the outputs produced by an AI-based model may rest on different principles and requirements that are caused by the same effect.

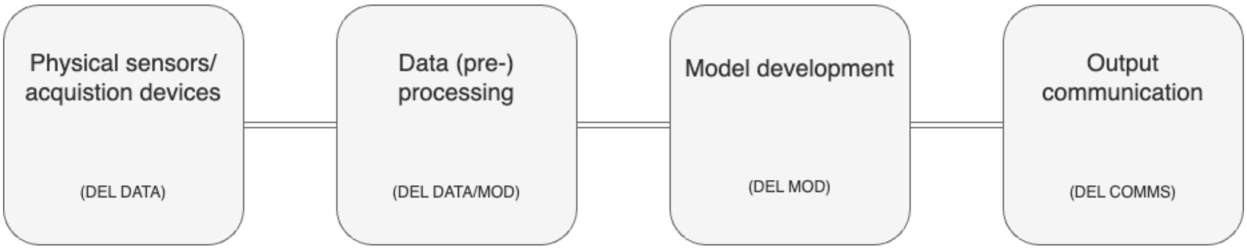

Figure 7: Different steps that are part of the model pipeline for AI systems with references to the other working groups

5.2 Data preparation for training

Data preparation is a fundamental process that needs to be completed before a successful training of any statistical or machine learning method can be conducted. The preparation techniques vary in complexity and scope, but in general terms, involve the manipulation of data so they can be used to train statistical and/or machine learning methods. Examples include: changes of the type of data (e.g., numeric, date, character, etc.); changes to the number of decimal positions for numeric inputs (e.g., integer or floating point); and data quality controls to detect and perform an action on outlier data, missing values, flagged values, and or changes involving the units of the data (e.g., Km, m, mm) or the unit system (e.g., Imperial vs Metric). Other common activities include normalizing and standardizing the data; changing file systems used by the native data (e.g., Geotiff, NetCDF, GRIB, .xls, etc.); and activities such as denoising, labeling, and handling missing records (completion, interpolation, and deletion). Additionally, depending on the characteristics of the dataset and the goals of the analysis, it may be beneficial to conduct exploratory data analysis [incl. statistical checks and compression/dimensionality reduction techniques such as a Principal Component Analysis (PCA)] before using the data for further analysis. By applying all the preparation steps exhaustively, the data can be transformed into a more manageable and informative form, which can help improve the performance of any machine learning models that are trained on the data.

In the case of preparing data for optimal use in geospatial applications, it has been noted that geospatial data and information are often not well integrated across governments, sectors, nor in formats that are easily used for analysis. This creates an impediment to the comprehensive use of data for geospatially informed decision-making. Geospatial information has historically been managed in silos, making data integration and exchange problematic. Often, data are neither discoverable nor interoperable, which makes innovative data exchange and integration in new applications problematic. Different map projections, roto-translated grids, regular and irregular grids, and different data formats contribute to make the integration of multiple-source geospatial data more difficult. Neural networks, specifically recurrent or dynamic networks, can be used to project data in places where there are no measurements and fill in missing information. Additionally, the use of Geospatial Augmented Data Fusion (GADF) may be useful in transforming data into a format that can be used in deep learning models, by combining information from different sources and resolving issues such as spatial misalignment, missing data, and data format differences.

Disaster risk reduction is inherently a multidisciplinary effort, and thereby requires a high level of coordination across governments, organizations, and other entities. Cross-sector coordination, multidisciplinary collaboration, and standards are needed to overcome impediments associated with data integration and overly complicated supply chains. This is particularly problematic when organizing, planning, acquiring, curating, cataloging, analyzing, integrating, publishing, and archiving geospatial information and data.

Figure 8: Activities that are performed in data pre-processing

Best practices:
Data preparation is a very important step in training AI models. It involves cleaning and preprocessing the dataset to ensure consistency, accuracy, and suitability for analysis. This can include handling missing values, scaling or normalizing data, and removing outliers. Additionally, a very good practice is to remove noise from images and use GADF techniques to transform data from multiple sources. Data labeling consistency and data augmentation are also important considerations. The preparation process includes standard data cleaning procedures such as data conversion, cleaning, data enrichment through feature engineering, data labeling and fusion, selection and training of AI classification models, and testing and prediction. AI can also be used to filter and categorize information from social media and other feeds.

Topic group use cases:
The use case ***Flash Flooding Monitoring System in Mexico*** *highlights the importance of data preprocessing through removing noise on optical images before feeding data into an AI model. The use case* ***Unified Methodology for Windstorm and Hail Storm Hazard Modeling and Mapping*** *underscores the essentiality of data preparation in the AI development process. This process includes data conversion and cleaning, data enrichment, data labeling and fusion, AI model selection, testing, and predictions.* ***The Intelligent Big Data Analysis System for Wildfire Management*** *employs a two-step model-building preparation. First, forest fire experts and botanists manually label fire plant images to ensure data labeling consistency. Then, data augmentation is applied to address the issue of unbalanced data, ultimately enhancing the model's performance. The conversion of data into image format using GADFs enables the application of deep learning models to predict natural hazards. For instance, the use case* ***Enabling Natural Hazards Risk Information Sharing Using Derived Products of Export-Restricted Real-Time GNSS Data for Detection of Ionospheric Total Electron Disturbances*** *adopts this particular approach.*

5.3 AI training

Methods of artificial intelligence are inspired by the human analytical approach and behavior of thinking and decision making. Many of these methods have trainable components that are trained to make predictions using observed data, for example, methods from machine learning or, in particular, deep learning.

The goal of training a machine learning model is to optimize the model's parameters so that it can accurately predict the output for new inputs. This is typically done using a combination of supervised and unsupervised learning techniques and may involve the use of various optimization algorithms and techniques such as backpropagation, gradient descent, and deep learning. The process of training an AI model can be computationally intensive and requires significant resources, including large amounts of data and computing power. Similar as for humans, albeit significantly less complex, there exist different learning strategies to train an AI model to make correct predictions. The choice of which learning strategy is used depends on many different aspects. For instance, it depends on the properties of the data that are used (e.g., availability of annotations, time series vs images, etc.) and the type of problem to be solved (e.g., detection of anomalies vs forecasting).

In general, the configuration of classification parameters and the sampling of training and testing data are important factors that can impact the performance of an AI model. However, there are additional factors that also play a role in the model’s accuracy such as the quality and characteristics of the training data. These aspects cannot be addressed in general and depend very strongly on the data and type of problem to be solved. For natural disaster management, in particular, this is often very challenging due to the vast spectrum of potentially important data (e.g., static demographic data, time series data, images from satellites, text data from social media posts, etc.) and corresponding machine learning models (e.g., decision trees, recurrent neural networks, language models, etc.). For more details about data-related considerations, the reader is encouraged to consult the accompanying report from WG-Data.

5.3.1 Considerations when selecting an AI algorithm

There are different considerations and aspects that are relevant for the choice of which AI algorithms are to be used.

<u>Categorize the problem</u>: The problem or task that is anticipated to be tackled using an AI algorithm must be carefully framed. Regression problems, classification problems, clustering problems, a

recommendation engine, an anomaly detection, etc. can each post different challenges which effect the choice of algorithms. In a first step, individual problems can be categorized as a supervised learning problem, an unsupervised learning problem, or a reinforcement learning problem. Each of these require learning strategies that use different input data (and labels) and the success of the trained models depend on the environment in which these are intended to be used. Similarly, the anticipated output and goal of these methods determine the problem that is to be solved; that is, a regression problem, a classification problem, a clustering problem, a recommendation engine, or an anomaly detection, etc.

Analyze the data: The process of analyzing the data plays a key role in the choice of algorithm for the problem at hand. For instance, some algorithms can work with smaller sample sets but are possibly limited in generalization abilities, while others require enormous samples and are more robust. Also, certain algorithms work with categorical data while others have shown to work better with numerical, non-categorical data input. Another data characteristic that should be analyzed in advanced is the data (im-)balance. Resulting data sampling and data augmentation methods may affect the choice of algorithm. The sequence of analysis, processing, and transforming data leads to the search of the available algorithms.

Identify the applicable algorithms: After categorizing the problem and analyzing the data, the next step is to identify the suitable algorithms that are applicable and practical to be implemented. For this, a comparison to the literature is highly valuable, as many problems share the same properties and can be tackled similarly. Some of these elements affecting the choice of a model are:

- Accuracy,
- Interpretability,
- Complexity,
- Scalability,
- Effectiveness.

AI algorithms are usually associated to the different types of learning problems:

- **Supervised learning**: A labeled dataset is provided to the computer in the form of inputs and outputs, from which the algorithm will recognize the association between them and be able to make predictions based on the fed examples. This type of algorithm has been used, for instance, to estimate flood damages [b-Wagenaar] or identify areas that will become climate unsuitable for specific crop production [b–Ceglar]. Typically, supervised learning problems can be differentiated into two types of problems:
    - *Classification*: The output variable is defined in classes.
    - *Regression*: The output variables are continues.

- **Unsupervised learning**: The machine acts without the guidance of labeled data, finding patterns on its own. This can be used as a tool for feature learning, or as the final goal of the algorithm. In natural disaster management, an example is the reconnaissance ground model for landslides in [b-Whiteley]. Unsupervised learning is also divided in two categories:
    - Association: As the name indicates, the general rule consists of associating the relation and/or dependency between variables and mapping it.
    - Clustering: Objects are gathered into a group (cluster) according to their similarities.

- **Transfer learning:** This starts from a model trained in another domain, even far away from the target application, but where abundant and reliable labeled data are available, followed by refinement and adaptation of such a model to the target domain [b-Pan]. The use of a pre-trained model sometimes allows reaching good results even with very few labeled examples available in the target domain.

- **Reinforcement learning**: A computer program is enrolled in an interactive environment, in which it is provided constant feedback, in order to achieve a goal. When the feedback is rewarded, the reinforcement is **positive**. When the feedback is punished, it is **negative**. The mapping method used by the machine, or agent, is called policy. To maximize the policy, the machine must decide whether it delves into new processes (exploration) or keeps getting rewards with the ongoing process it is following (exploitation trade-off). Some examples of this type of machine learning technique are disaster rescue operations [b-Tsai], scheduling the rapid deployment of volunteers to rescue victims [b-Nguyen], or the real-time assessment process of relief demand and network conditions [b-Nadi].

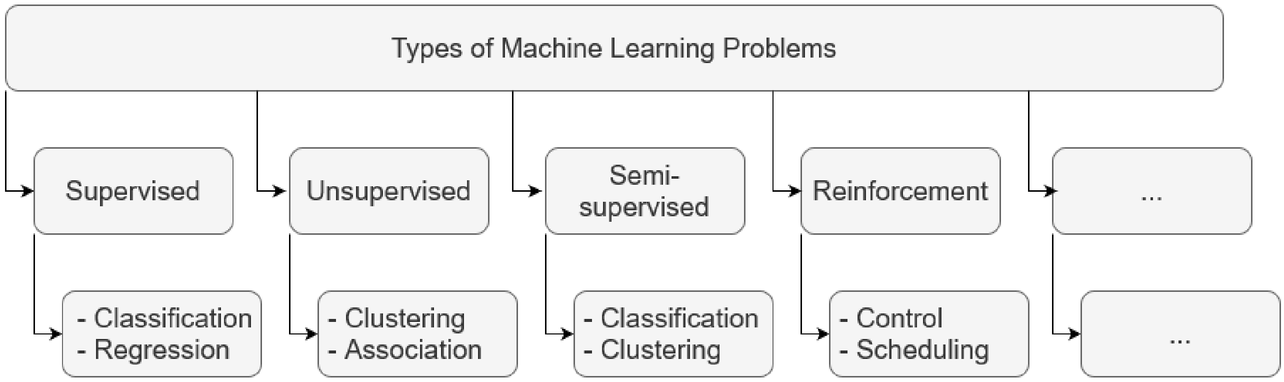

Figure 9: Algorithm learning styles

— Optimize hyperparameters: Hyperparameter optimization is a crucial step and is often performed in practiced, e.g. through grid search, random search, coarse to fine, Bayesian optimization, etc.

— Ensemble learning: Ensembles combine several machine learning models, each finding different patterns within the data to provide a more accurate solution. These techniques can improve performance, as they capture more trends. They can also reduce overfitting, as the final prediction is a consensus from many models. Among the most solid are bagging (or bootstrap aggregations), boosting, and stacking.

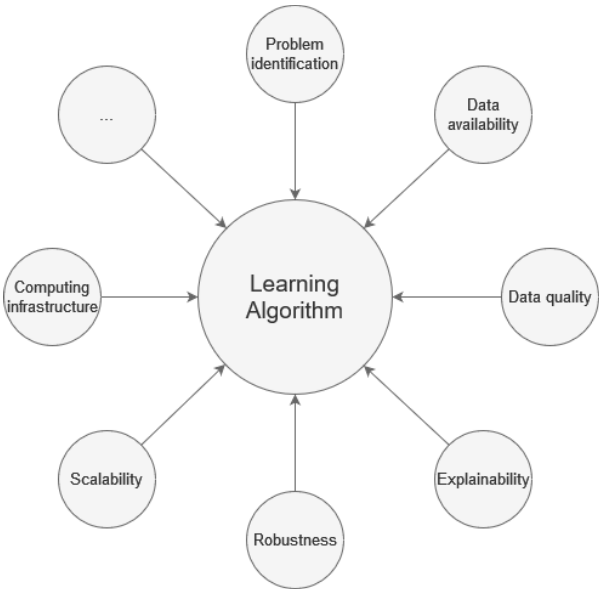

Figure 10: Considerations when choosing an AI algorithm

The Learning Life Cycle. A series of cyclical steps that data science projects follow to take advantage of AI/ML. These steps are:

1. **Define project objectives**: This essential first step is devoted to achieving a clear definition of the problem and what is expected to be obtained as a result. This includes identifying opportunities for improvement and possible obstacles.

2. **Data acquisition and preparation**: Choose enough relevant data to feed a model and arrange it to obtain a suitable format for the other steps.

3. **Model data**: Once the target variable is defined, the iterative process with the data will proceed with building, training, evaluating, deploying, and monitoring steps. This workflow is open to be modified until an optimal performance is reached.

4. **Interpret and communicate**: The ultimate goal here is to create an interpretable and transparent model, with an emphasis on making it understandable to non-scientific communities, such as stakeholders, industries, and regulatory bodies.

5. **Implement, document, and maintain**: This final step includes updating and improving the model.

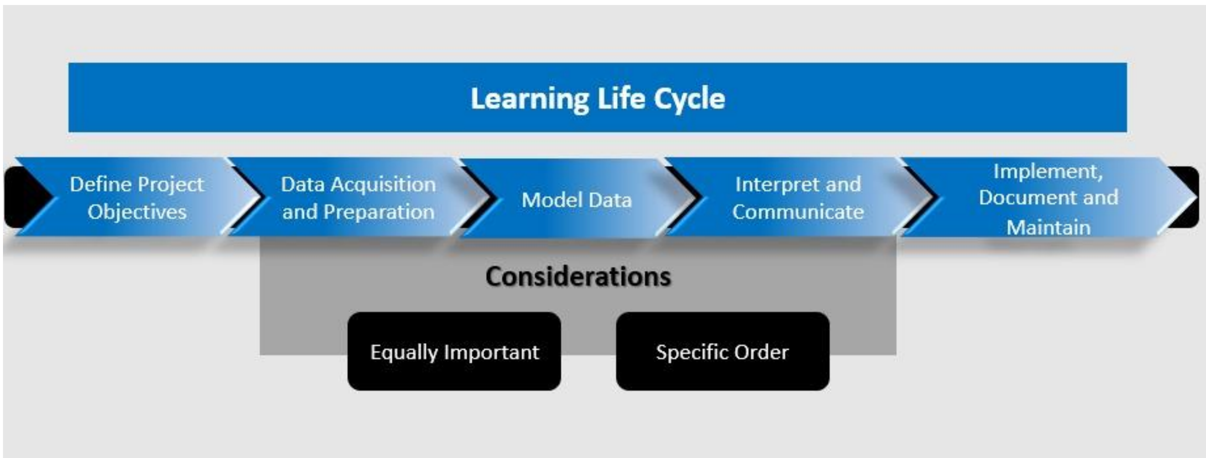

Figure 11: The cyclical steps in the AI/ML algorithm learning life

Distributed Algorithms is Distributed Learning. There are two subfields that can have value for natural disaster management applications: active learning and federated learning. Despite having been designed for other applications, they can be adapted and successfully used.

The **active learning paradigm** is sustained in the idea that an ML algorithm can optimize its performance with less labeled training data when authorized to cast the data that it will use for learning. The improvement throughout this process is constant and it is accompanied by an oracle, either a person or model acting as the information source, who/which may be consulted for the labels.

Federated learning is an innovative ML paradigm that holds the idea of decentralizing devices and instructing an algorithm across them, allowing several agents to build an ML model, having each server hold their own local data, which does not need to be shared. This approach helps with controversies such as data privacy, security, and access rights. It also considers the hosts' budget and resources. The main disadvantage is presented by the central server, which must be constantly consulted, since it does not provide the tools for the clients to estimate their performance. It has proven to be very effective and reliable for earthquake prediction [b-Tehseen].

5.3.2 Model training or learning process

AI models are often perceived as black box models because of their complex structure of coupled functions and unclear working mechanisms, which is a challenge for researchers and practitioners [b-Fekete, b-Shixia, b-Mühlbacher]. It is very much desired to develop more transparent and explainable systems for better understanding and analysis of such models, especially their inner working mechanisms. In this sense, interactive visualization techniques are capable of translating models into understandable and useful explanations for an expert through understanding the behavior between models, diagnosing the training process (measuring convergence), and guiding improvements to the performance and robustness of topologies.

Understanding. Visualization approaches to better understand the working mechanism of neural networks and other machine learning models can be classified into two categories [b-Paiva, b-Turner, b-Tzeng, b-Zahayy, b-LeCun]: point and network based. Point-based techniques [b-Zahayy, b-Rauber] reveal the relationships between neural network components, such as neurons or learned representations, by using scatterplots. Each learned representation is a high-dimensional vector whose entries are the output values of neurons in one hidden layer. Each component is represented by a point and components with similar roles are placed adjacent to each other by using dimension reduction techniques such as PCA [b-Wold] and *t*-SNE [b-Maaten]. Network-based techniques [b-Harley, b-Streeter, b-Craven] solve the disadvantage of point-based methods that fail to provide a comprehensive understanding of the roles of different neurons in different layers. These techniques usually represent a neural network as a directed acyclic graph (DAG) and encode important information from the network by the size, color, and glyphs of the nodes or edges in the DAG.

Diagnosis. Objective diagnostic techniques help experts understand why a training process did not achieve a desirable performance. Current techniques utilize the prediction score distributions of the model (i.e., sample-class probability) to evaluate the error severity and to study how the score distributions correlate with misclassification and selected features [b-Shixia, b-Zahayy]. By revealing multiple facets of the neurons (interactions between neurons and relative weight changes between layers), the training process can be studied and possibly corrected (to converge, to achieve an acceptable performance, or to prevent the process from being stuck). Using *t*-SNE, relationships between learned representations are disclosed and completed with saliency maps so that the modelers can analyze influential features.

Refinement. Integration of the deductions from the two previous stages is known as refinement. For supervised [b-Paiva] or unsupervised models [b-Wang, b-Liu], the most notorious processes mainly focus on multi-class classifiers [b-Alsallakh]. These techniques permit controlling factors (training samples, features, types of classifiers, and hyperparameters) to significantly affect results. Some techniques allow users to interactively select training samples, modify their labels, incrementally update the model, and rebuild the model by using new classes [b-Tzeng-1, b-Choo, b-Liu, b-Paiva].

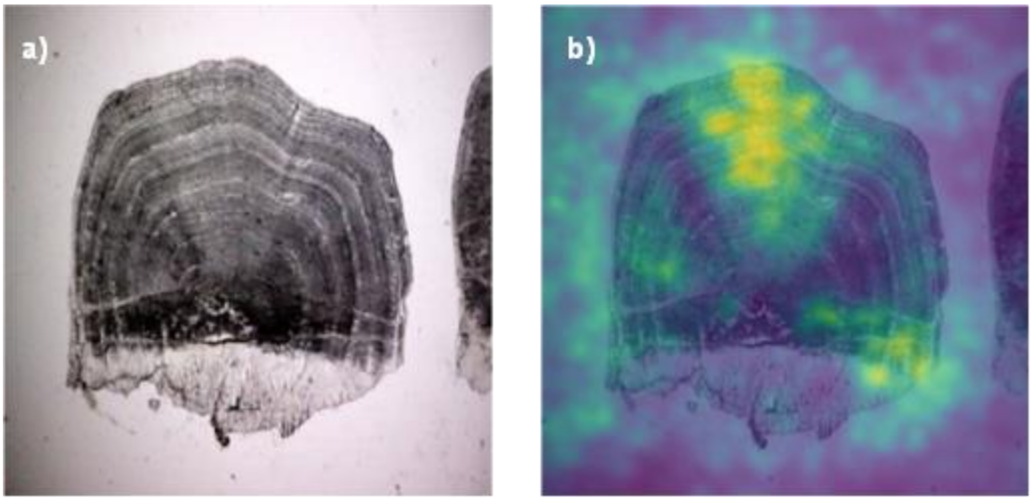

Figure 12: Neural network predictions with saliency maps: a) original input image of a fish scale, b) saliency map overlaid on the original image. The resulting plot shows the pixels that had the greatest influence on predicted class in yellow.

There are many more considerations and practical obstacles that might affect the training of AI models, such as storage (data and/or model), time (for training), availability (of models), and many more. To make decisions on how to train the AI model ultimately depends on the available resources (expertise and computational power).

Best practices:
In order to emulate good AI training practice with regards to natural disaster management, classification parameters should be carefully configured while selecting appropriate training samples and sample tests. Factors such as training data, features selection, type of classifier, and hyper-parameters should be controlled and optimized to improve the model's performance. Meanwhile, techniques such as interactive sample selection, label modification, and retraining with new classes can also be used to refine the model. Furthermore, the accuracy of a machine learning model is largely dependent on the quality and diversity of the training data.

Topic group use cases:
*The effective implementation of AI systems greatly depends on the quality of training data and constant model refinement. For instance, in the use case entitled **Landslides of Masses of Soil and Rock: Intelligent Risk Management in Areas Highly Threatened by Climate Change**, threat identification is improved by refining neural models through controlling factors such as training samples, classifier type, and hyperparameters. Similarly, the use case **Soft Computing Paradigm for Landslide Monitoring and Disaster Management** emphasizes that the accuracy of the model depends on the quality of training data, predominantly sourced from satellite images. The enhancement of the high-resolution satellite imagery can significantly improve model accuracy. For the use case **AI for Snow Avalanche Monitoring and Detection**, minimizing false alarms while maintaining high detection probability is paramount, and this can be achieved by regularly retraining models with increasing amounts of newly collected data. Therefore, all these attributes are pivotal for achieving a high-performance AI model training in disaster management.*

5.4 AI evaluation

Evaluating an AI model is a highly non-trivial task and should be *application specific or task oriented* [b-Hernández]. Further, it poses a multi-dimensional problem where performance is only one aspect and even this one is dependent on the task and model. Evaluating a classification model is generally different to a regression model or a segmentation model. If possible, including human discrimination (performance measured and compared against or by humans) is favorable. Problem benchmarks (performed against a repository or generator of problems), and peer confrontation (1-vs-1 or multi-system 'matches') are further possibilities. To measure a system's performance on a specific task, one or more metrics are derived based on the task definition. Depending on the complexity of the system to be evaluated, it is obtained through algorithm analysis ('white-box' evaluation) or exclusively from its behavior in an empirical way ('black-box' evaluation). As the set of input observations used for evaluation is finite, the expected value of each performance metric is typically computed. The results of all tasks are aggregated, and the worst-case, best-case, and/or average-case performances are usually reported.

A wide range of metrics are reported in the literature [b-Bishop, b-Goodfellow], which have to be properly chosen depending on the task to evaluate (e.g., detection, forecasting, prediction, etc.) and the application domain. Metrics and tools for classification tasks include but are not limited to confusion matrix [b-Stehman], from which well-known terminology and derivations can be analyzed, such as accuracy, precision, recall, and F1-score; and the Receiving Operating Characteristic (ROC) curve, which can be summarized by means of the Area Under the ROC (AUROC) curve [b-Fawcett]. In contrast, when evaluating the performance of a regression task, metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), or the inlier ratio can be considered. Lastly, statistical metrics like Pearson Correlation Coefficient [b-Pearson] or the Coefficient of Determination [b-Wright] can also be used, along with metrics tailored to Computer Vision applications like Peak Signal-To-Noise Ratio (PSNR), structural similarity (SSIM), or Intersection over Union (IoU).

Other factors that are to be considered while assessing an AI system for deployment in a real-life scenario are discussed in the JRC Technical Report "Robustness and Explainability of Artificial Intelligence" [b-Hamon]. These include:

1) The *robustness* of the system, which is its ability to perform in the presence of invalid inputs or stressful environmental conditions. Two important aspects to consider are: a) the minimization of the amount of false alarms and misdetections by using collected validation data and b) the use of standardized methodologies to assess AI robustness, establishing the field of action given the data used during the training stage, the type of mathematical model, or the context of use.

2) The *reliability* of the system, which determines its capacity to avoid failures or malfunctions due to edge cases or malicious intentions. The main vulnerabilities of AI systems must be identified, in order to develop technical solutions to ensure that they will not fail or be manipulated by an adversary.

3) The main indicator that a machine learning model is not reliable is poor *performance*. This is observed when a model cannot perform well in a task under normal conditions for humans. It should be highlighted that, despite the good performance achieved by many recent AI systems, most of them are not yet considered reliable enough to be fully autonomous (without human supervision) in complex environments.

    a. Models can perform well but have vulnerabilities, which may lead to the appearance of malfunctions in specific conditions, either naturally (during the execution of the program) or intentionally provoked by an adversary with malicious intentions. Typical vulnerabilities include data poisoning, which consists of deliberately introducing false data at the training stage of the system, silently opening backdoors exploitable by adversaries; crafting of adversarial examples or input data to the trained model, which are designed to be misclassified; and model flows, which allow to take advantage of the inherent weaknesses of the mathematical procedures involved in the learning process of the model.

b. When assessing the reliability of systems, it is of paramount importance 1) to choose the right procedure of evaluation and metrics; 2) to have an external evaluation (independent from the training phase) to avoid overfitting, which goes beyond the well-known testing phase by collecting data at different spatial and temporal situations; and 3) to evaluate the risk of spectrum bias, which corresponds to the presence of examples in the dataset that are obvious and do not reflect the diversity and the complexity of real and more ambiguous situations.

c. A promising approach to increase the reliability of AI systems is to follow the security-by-design principle. For that purpose, several methodologies can be tackled in order to take the security of the models into account from the beginning of the design process:

    i. Before training the model, it is advised to 1) define handcrafted rules, 2) use a second AI system as a filter, or 3) perform human interventions for training data sanitization or cleaning to prevent data poisoning.

    ii. Carry out robust learning or explicit training against known adversarial examples. To this end, the mathematical foundation of the algorithms can be redesigned by employing techniques from statistics (e.g., regularization, robust inference), and distillation can be conducted to reduce the sensitivity of the outputs of the model to adversarial examples.

    iii. Extensive testing is necessary and should not be limited to a singular database. Augmented datasets can be utilized to evaluate the systems' robustness against various modifications, including noise and weather conditions, among others.

    iv. Follow a formal verification protocol, in order to demonstrate the correctness of a system with respect to particular properties, using mathematical proofs. With this aim, two main properties are usually investigated: 1) (un)satisfiability (i.e., the feasibility of a certain output given an input) and 2) robustness, by checking if adding noise to a given input changes its corresponding output.

4) The *protection and security of sensitive data* in AI systems must be guaranteed by means of organizational and technical controls. Any machine learning system that relies on sensitive data must ensure that all actors involved in the pipeline - from data collection and processing, to model training, maintenance, and use - are trustworthy and capable of handling the data. Due to the capacity of memorization of machine learning models, sensitive data could be directly accessible by an untrustworthy actor, due to malicious intent or vulnerabilities in the data structure. To overcome this problem, the following steps may be considered:

    a. Differential privacy can be applied by adding noise to the training data, to reduce the influence of each individual sample on the output. This method also prevents overfitting but may significantly reduce the performance of a system if the level of privacy is too high.

    b. Consider distributed and federated learning, both of which constitute situations where the learning of the model is not performed by a single actor, but by a multitude of different parties that may or may not be connected with each other. While in distributed learning all parties are learning the same model and sharing information about the gradients, only parameters of the model are exchanged between actors in federated learning, where each actor only has access to its part of the dataset, in order to reduce the disclosure of sensitive data.

c. The use of encrypted data for training is, albeit a possible increase in complexity, another interesting consideration that is becoming more relevant in certain research questions.

5) The *transparency* of the system, which allows for a complete view or analysis of the system, together with the documentation of the AI processing chain, which includes but is not limited to the technical definition of the model, the description of the data used for its conception, and the elements to provide a good understanding or interpretability of the model [e.g., eXplainable AI (XAI) methods such as Integrated Gradients, Grad-CAM, Layerwise Relevance Propagation (LRP), etc.]. An explainable-by-design principle must be followed for AI systems, highlighting potential negative impacts on fundamental rights of users. There are different aspects of transparency that can become relevant for an AI systems such as:

   a. Implementation: AI systems can be implemented differently and technical principles of the model (e.g., sequence of operations, structure of layers, set of conditions, etc.) and its associated parameters (coefficients, weights, thresholds, etc.) can be used for transparent descriptions of the models. Depending on its intended use an open-source model may be preferred over models with unknown designs.
   b. Specifications and information on its intended use that led to the implementation, such as: tasks, objectives, context, training dataset, training procedure (hyper-parameters, loss function, etc.), evaluation metrics and performances, etc., are relevant for the traceability and can help to reproduce the implementation from scratch.
   c. Interpretability: The interpretability of AI systems requires the user to understand the reasoning or decision making of the AI system. This is very often of utmost importance in practical applications, but it is also a highly complex and active field of research and linked to other concepts such as fairness. In general, this level of transparency cannot be taken for granted for current AI systems. More complex models are often preferred in order to achieve higher predictive performance or to solve more complex tasks. On the other hand, such models can be more difficult to explain. However, the question of how much the outputs of an algorithm are still understandable for a human is crucial for a reliable assessment of its security.

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.

In practice:
Regarding AI evaluation, the recommended approach is context specific, focusing on the particular application or task [b-Hernandez]. It employs a range of different performance metrics [b-Stehman, b-Fawcett, b-Pearson, b-Wright], ensuring accurate and comprehensive performance measurement, which guides towards robust AI solutions.

5.5 Validation of online AI systems

The usage of online AI systems has been increasing in different fields, and the natural disaster management sector is not an exception. These continuously allow for the training of machine learning models within larger dynamic systems that generate data, which can make the validation process challenging. To address these challenges, several approaches can be taken while ensuring the effective implementation of online AI systems. This includes pre-training the AI system on representative data to reduce initial fluctuations and implementing regularization techniques and tailored loss functions. Constructing validation sets that reflect the expected distribution of data can also assist to augment the dynamically generated dataset, and continuously fine tuning the model with a growing database can also be relevant to improve transferability.

Online AI systems can provide valuable insights and real-time information in specific application areas such as flood response, tsunami monitoring, and snow avalanche monitoring. For example, in the case of flood response, the FloodSENS system (see section 8 for details) is an algorithm proposed by the RSS-Hydro team to efficiently reconstruct flooded areas under partial cloud cover in optical satellite images. The goal is to continuously fine tune the model on a growing database of cases to improve its accuracy over time. Similarly, for tsunami monitoring, real-time buoy data can be collected and used to produce an inundation forecast. The performance of the model in predicting maximum inundation maps can be evaluated, and sensitivity tests can be conducted to determine the optimal number and placement of buoys. In avalanche activities, models can also provide real-time information, with accuracy increasing as more data are collected. The validation process would involve testing the accuracy and reliability of the models in detecting avalanche signals in real-time and reducing false alarms. Obtaining reliable ground truth data is also crucial to train the models effectively.

To ensure effective deployment of online AI systems, it is important to have a good understanding of both the application and the machine learning development, to use appropriate constraints to prevent misbehavior of the learning algorithms. Pre-processing of data, training of the model architecture, and testing for generalization are also crucial steps in the development of an effective online AI system. In the training phase, static data such as the Copernicus digital elevation model (DEM) and continuous data such as *Sentinel-2* imagery can be used to provide specific properties concerning the flood mapping. There are often alternatives to this type of implementation that should be preferred. When necessary for the implementation, it takes the skillful implementation of constraints of the system.

6.6 Additional data consideration for model validation

In addition to considerations that need to be made based on the type of data, there are general considerations that can impact the validity of a model. These are often based on how the data were acquired. Moreover, especially systems in production can experience drift, which will deteriorate the model performance over time, due to the ground truth shifting from the training dataset.

Data leakage / snooping

Data leakage or snooping is a difficult topic, as it needs deep insight into the data at hand.

Figure 13: Watermark on horse image in Pascal VOC [b-Lapuschkin]

There are several terms for this concept, but they all boil down to the model gaining illegitimate insight from the data that improves the performance. A machine learning model will often exploit this type of leakage to gain high accuracy values, without learning meaningful connections within the data. It is very difficult to write about this topic in the abstract, hence various examples are provided to illustrate a few different ways that data can leak target information.

There is a famous example, where object identification models trained on the Pascal VOC dataset would perform very well on the training data, however abysmally on real-world data. The horse images were downloaded from a digital archive that watermarked the images in the bottom left corner. This was not caught, because the train–test split still splits data from the same source.

Other examples can include calculating aggregate statistics for normalization or other purposes and including the test set. Especially, when it comes to temporal data, including a potential mean shift of the test data into the normalization can aggravate the impact of concept drift in a production model.

It is possible for variables to leak information, depending on how they were collected. Precipitation values are a good example. Historically, rainfall is measured in a cylinder over time and dumped out in regular amounts. The same is true for radiation measures with a Geiger counter and census data counting commuters on bridges. These data accumulate over time. This means a model can learn an implicit understanding of time from this variable, undoing any type of time series processing that was applied to the data.

Finally, it is possible to overlook a directly predictive variable in the data. This could be from a pre-processing step, but it can also be very hidden. A good example here is the Statoil Iceberg competition on Kaggle [b-Howard]. The challenge was to predict whether an image contained an iceberg or a ship. Unfortunately, the satellite images were taken at specific angles that are contained in the metadata of the training files. Competitors noticed this flaw in the data preparation and were able to exploit this oversight, winning the competition with a mostly meaningless model.

Systematic model drift

Training data and, therefore, the train–validation–test split of the data used for model development is often assumed to be static. Data are acquired, pre-processed, and supposed to not change (distributionally speaking) anymore. Unfortunately, many natural systems are non-stationary. This means that the distribution of the data does not remain the same over time. This can be periodic, but there can also be a trend in the data. An example of this is the global mean temperature that is currently experiencing an increase as time progresses due to climate change. This means that future data that will be collected will be different, and the model performance will deteriorate. In machine learning, this phenomenon is often referred to as data drift or feature drift. Additionally, there is concept drift, where the inherent relationship between input and output data changes. Since machine learning systems aim to learn statistical relationships between input and output, ideally causal relationships, a change in the real world mapping from input to output data renders a trained machine learning system entirely unable to predict the outcome.

6 Further standardization, legal, and ethical aspects

6.1 Standardization activities for AI modeling and beyond

It is important to note that the field of AI is rapidly evolving and standardization efforts are ongoing and may not yet be fully developed. There are several organizations and initiatives that work on standardizing various aspects of AI. There are also standardization activities aiming at establishing common guidelines, best practices, and protocols for the development and use of AI systems, with the goal of ensuring consistency, interoperability, and trustworthiness of AI systems. Some of these activities include:

- Development of standards, guidelines, and best practices by organizations such as the IEEE Standards Association, ISO/IEC JTC 1/SC 42, Partnership on AI, OpenAI, and AI Ethics Lab.
- Establishment of testing and certification programs by organizations such as ISO/IEC JTC 1/SC 42, Partnership on AI, and industry groups and consortia.
- Organization of workshops and conferences by organizations such as IEEE Standards Association, ISO/IEC JTC 1/SC 42, and industry groups and consortia, to discuss and share the latest developments and best practices in AI [b-Cihon].

Some standards developed by ISO/IEC JTC 1/SC 42 include ISO/IEC 23026-1:2019 “Artificial Intelligence – Vocabulary,” ISO/IEC 23026-2:2019 “Artificial Intelligence – Requirements for trustworthiness,” ISO/IEC 23026-3:2019 “Artificial Intelligence – Ethical guidelines,” ISO/IEC 23026-4:2020 “Artificial Intelligence – Governance,” ISO/IEC 23026-5:2022 “Artificial Intelligence – Interoperability,” and ISO/IEC 23026-6:2022 “Artificial Intelligence – Explainability.”[1]

In the context of natural disaster management, standardization activities play a crucial role in ensuring compatibility and effective communication among the various technologies and systems used for disaster response. This can help to improve the overall coordination and effectiveness of disaster response efforts. There are several organizations and initiatives that focus specifically on standardizing various aspects of natural disaster management. Organizations such as the International Organization for Standardization (ISO) and the International Telecommunication Union (ITU) are developing standards related to AI and disaster management to ensure compatibility and effective communication among technologies and systems used for disaster response. An example is the Focus Group on AI for Natural Disaster Management, which is based at the ITU but in collaboration with the World Meteorological Organization (WMO) and the United Nations Environment Programme (UNEP). The focus group aims to address the increasing prevalence and severity of natural disasters using AI. The group is actively working on analyzing relevant use cases of AI and developing roadmap for international action based on the emerging best practices [b-Kuglitsch]. In addition, other organizations such as Global Standards Collaboration (GSC) and United Nations Office for Disaster Risk Reduction (UNDRR) also focus on standardization and best practices for disaster management, respectively.

Disasters, whether they are natural or manmade, have a devastating impact on human lives, communities, and the environment. According to the Centre for Research on the Epidemiology of Disasters, natural hazards such as hurricanes, floods, and earthquakes result in more than 50,000 fatalities every year [b-CRED]. With the increasing focus on manmade risks, disaster risk management (DRM) has become a critical aspect of modern society [b-OECD/G20]. In response, many countries have implemented "all-hazards" and "whole-of-society" approaches to DRM [b-

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[1] https://www.iso.org/obp/ui/#home

OECD], which promote a more holistic risk management perspective. Similarly, the COSO framework is also an important standard that provides a structured approach to identifying, assessing, and managing environmental risks.

According to the ISO standard on disaster risk management[2], a disaster risk management system needs to identify risks, analyze them, make decisions on risk-reducing measures, and implement and monitor these decisions in order to reduce the occurrence or consequences of harmful events. Natural disaster management is a collective effort that requires the participation of various actors, including governments, organizations, communities, and individuals. An increased level of standardization can help these actors collectively identify risks, analyze them, and implement measures to reduce their impact. For example, standardizing how risks are identified, analyzed, described, evaluated, and decisions are made can help ensure a consistent approach to effective natural disaster management.

On the other hand, the role of policy and law is also essential in establishing and maintaining effective and standardized natural disaster management practices. They play a vital role in ensuring that disaster response and recovery efforts are effective, efficient, and well coordinated. National disaster management acts outline the responsibilities of various government agencies, private organizations, and individuals in the event of a disaster. These acts provide the legal framework for disaster response and recovery operations, including the allocation of resources, the coordination of efforts, and the management of relief and recovery programs.

International conventions and agreements such as the Hyogo Framework for Action and the Sendai Framework for Disaster Risk Reduction provide a basis for cooperation and coordination among nations in the event of a disaster. These agreements also provide a framework for standardization and best practices in disaster management.

Technical standards such as building codes and safety standards help to ensure the safety and resilience of critical infrastructure in the event of a disaster. These standards are often established by government agencies or industry organizations and are designed to minimize the damage and disruption caused by disasters. Guidelines and procedures developed by organizations and agencies involved in disaster management support standardization and best practices in disaster response and recovery. These guidelines and procedures cover a range of activities; from the initial assessment of a disaster to the allocation of resources and to the coordination of relief efforts.

6.2 Open-source activities

Data that are freely available and accessible to the public are open-source data. These data are open and in machine readable formats, allowing individuals, scientists, and organizations to easily find, access, and use them for a variety of purposes, such as research analysis and decision-making. In most cases, these data are clearly documented and described in dedicated guides/manuals on how to access and use the data. Data may also be stored in different formats and locations, making it difficult to find and use them (refer to the WG-Data report, chapter 11, for more in-depth information about this topic).

In the context of natural disasters, accessibility of data is important for organizations such as governmental agencies, non-profits, and humanitarian organizations, who need to quickly and effectively respond to the disaster. For example, weather forecasts can be used to predict the path of a hurricane and satellite imagery can be used to assess damages after a storm. Topographical maps and demographic data can be used to understand the population and infrastructure at risk. Social media data can provide real-time information about the disaster that can be used for emergency response. Organizations such as the National Oceanic and Atmospheric Administration (NOAA), the European Commission Joint Research Centre, European Commission Global Disaster Alert and Coordination System (GDACS), European Commission Copernicus Emergency Management Service (CEMS), the European Centre for Medium-Range Weather Forecasts (ECMWF), NASA

[2] ISO 31000 Risk Management. online: https://www.iso.org/iso-31000-risk-management.html

Earth Exchange (NEX), Open Data for Resilience Initiative (OpenDRI), United Nations Office for Disaster Risk Reduction (UNDRR), and many others can provide data and information that are used in analysis and decision-making in disaster management.

Alongside open-source data, AI developers can benefit from varieties of open-source frameworks and libraries available in Python and R studio that can assist with the major aspects of AI deployment, including data gathering, model development, and model deployment. Popular packages in Python are Tensorflow, Keras, pytorch, Scikit-learn, Numpy, Seaborn, Pyproj, and OpenCV; while packages such as Caret, Deepnet, dplyr, e1071, and others are used for machine learning, deep learning, image and video processing, topic modeling, text classification, text similarity analysis, cartographic transformations, and data manipulation. During the AI deployment phase, it is highly recommended to use version control systems such as github, gitlab, and bitbucket. This allows multiple people to work simultaneously on the same codebase, to track changes, and to identify who made what change and when. It provides a historical record of all changes made to the code, allowing users to easily revert to a previous version if necessary, while keeping track of the changes made to the codebase.

Finally, it is also worth mentioning cloud-based platforms, such as Google Earth Engine (GEE), which provide powerful and flexible frameworks for machine learning and model deployment particularly for geospatial analysis. These allow users, scientists, and organizations to access and analyze large datasets in real-time, to train and evaluate models, and to deploy them as web services for other stakeholders to use for further analysis and decision-making in disaster management.

6.3 Legal and ethics

As part of the cycle of creating an effective model for natural disasters, special consideration should be given to the ethical and legal implications of modeling decisions. The modeling process needs to be conducted with responsible AI tools and follow policies and recommendations to ensure that policy, ethics, and legal concerns are well addressed.

There are a number of resources on legal and ethics, see [b-Kuglitsch2023] with a particular focus on natural disaster management. Further, there are numerous documents that lay out recommendations and guidelines, that have formed legal requirements.

The EU has a proposed law for artificial intelligence named the Artificial Intelligence Act, which categorizes applications and systems into the categories of unacceptable risk, high-risk applications, and those not falling into these categories that are left largely unregulated.[3] Further proposed regulations and guidelines are the General Data Protection Regulation (GPDR) published in 2018 and and the Ethical Guidelines for Trustworthy AI in 2019.

In 2021, China released the Code of Ethics for a New Generation of Artificial Intelligence, which also aims to provide ethical guidelines in artificial intelligence-related activities, addressing privacy, prejudice, discrimination, fairness, ethical norms, and organization and implementation.[5]

UNESCO has put out guidance on ethical AI called the Recommendation on the Ethics of Artificial Intelligence. This includes social considerations such as development, the environment, gender, culture, education, communication, the economy and labor, and health.[6] It also lists a number of values and principles that should be considered. Although this document does not have the legal implications of the documents put out by the Chinese and European governments, it gives best

[3] "The AI Act," The Artificial Intelligence Act, September 7, 2021, https://artificialintelligenceact.eu/.
[5] "The Code of Ethics for a New Generation of Artificial Intelligence Was Released - Ministry of Science and Technology of the People's Republic of China," accessed August 10, 2022, https://www.most.gov.cn/kjbgz/202109/t20210926_177063.html.
[6] UNESCO, "Recommendation on the Ethics of Artificial Intelligence" (Paris, November 23, 2021), https://unesdoc.unesco.org/ark:/48223/pf0000381137.

practices with good context for understanding why the recommendations are important to be followed.

These are just a few examples of sources containing practices that make AI more legally and ethically sound. More general documents with implications to AI, such as the Universal Declaration on Human Rights, should also be considered and followed when developing an AI model.

While the creation of a model in the AI process creates its own legal and ethical problems, any problems that were created during the data gathering step of the process will necessarily be carried through as the AI is making decisions based on the data.

Considering many sources and literature, below are a few frequently cited considerations in modeling:

- Harm Avoidance
  Mitigate foreseeable misuse including the adherence to practices that may result in unintended harmful consequences, such as controls or mechanisms or restrictions in model distribution.
- Autonomy
  Ensure that interested parties can challenge or contest the outcomes derived from models that can impact their autonomy through the use of assessments or collaborative inputs regarding the model.
- Transparency
  The assessment of models in terms of their relevance to intended outcomes ought to be documented in a manner that is understandable to key stakeholders including the logic, limitations, and consequences of decision-making.
- Representativeness
  The outcomes of trained models can intentionally or unintentionally disadvantage vulnerable groups who have protected characteristics through under/overrepresentation in data. These outcomes can be reduced through corrective efforts toward representational errors by domain experts.
- Stakeholder Inclusion
  Impacted stakeholders ought to be provided with a rationale behind the decision-making process of the model. Explanations that do not overly rely upon technical or formal detail would be more accessible to stakeholders who are not specialists within the domain. This use of 'every-day' language may also increase the ability for the model outcomes to be translated more easily into socioeconomic implications.
- Legal Implications of Model Outcomes
  When algorithmic models are applied to personal data, inferred information may be generated. If the generated data are considered to be new personal data, then they will be subject to the same legal protections under GDPR, including the ways in which the underlying data are accessed, handled, and made accessible to individuals.
- Personal Data and Model Training
  In complex datasets, a single record of data is not likely to overly impact model outcomes. However, without an adequate anonymization process or safe handling, there is a risk for misuse, especially if the model or data is acquired by third-parties.
- Scalability
  A model should be created in a way that it can be expanded (in the case where a very powerful model is needed) or shrunk (in the case where resources are limited) to fit the problem that the model is attempting to solve.
- Peer Reviewed

The model should go through a number of checks from people with diverse backgrounds to ensure that the model is functioning properly and that there are no oversights due to factors such as unconscious biases.

7 Conclusion

This report provides an overview of different aspects of AI development with a focus on its applications in the field of natural disaster management. In fact, the presented aspects and concepts were derived from best practices that were collected throughout the work of this focus group. However, as the research field of Artificial Intelligence is rapidly evolving, and, with this, new applications of well-developed AI models arise to support end-users, this report cannot be viewed as complete or final in the sense that it covers all aspects of AI development, and its content will remain unchanged. However, it is fair to assume that the key principles and concepts will remain relevant for future developments.

AI models are often developed for a specific application/task. Therefore, the many aspects that are discussed in this report, such as model training, model evaluation, development of quality assessment tools, data collection, visualization of predictions (the latter two are further discussed in the reports of WG-Data and WG-Communications, respectively), should always be considered with respect to the problem statement that arises from the application or task, as these will shape and influence the life cycle of such models.

The development of AI requires a collective effort from, but not limited to, research organizations, regulators, governments, and ultimately the industrial sector. Thus, the WG-Modeling looks forward to future collaborations that work toward the goal of achieving more safe and more effective technologies for natural disaster management.

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Annex A

Topic group (TG) use cases

As shown in Figure 3, a key source of information used to derive best practices is the topic group use cases. These use cases were acquired through an open call for proposals that was put on the focus group website in advance of meetings A (16-17 March 2021), B (24-25 June 2021), C (31 August - 2 September 2021), D (20 October 2021), E (26-28 January 2022), and F (7-9 June 2022). To facilitate the systematic analysis of the use case proposals (for relevance, maturity, etc.), proponents were provided a template. Specifically, the proponents were requested to provide a project summary (a half page that describes the project and aspect being considered—data for AI, AI for modeling, or AI for communications—for a given natural disaster type), a two-page project plan, a one-page outline of milestones, and a one-page description of impacts. For the project summary, information about the research question and context, the method, the data, and the evaluation were requested. These use case proposals were presented by the proponents at the respective focus group meeting. Following a discussion, the focus group decided whether to adopt the use case for inclusion in its activities. In total, 31 use cases were adopted. In a next step, the proponents of these 31 use cases were requested to complete a detailed questionnaire containing questions pertinent to the three working group technical reports (on "Data for AI," on "AI for Modeling," and on "AI for Effective

Communications”). Out of the 31 use cases, 27 provided responses to these detailed questionnaires. An excerpt of these original responses can be found below.

8.1 TG-AI for Earthquake Monitoring, Detection and Forecasting

“Earthquake Disaster Mitigation through AI on Smart Seismic Networks”

proposed by Marius Kriegerowski (1)

(1) QuakeSaver GmbH, Germany

High-Level Questions	Responses
1. General information about the use case	
a. Please provide the name of the associated topic group (e.g., TG-AI for Flood Monitoring and Detection).	TG-AI for Earthquake Monitoring, Detection, and Forecasting
b. Please provide the name of the use case from the proposal (e.g., Flash Flooding Monitoring System in Mexico).	Earthquake Disaster Mitigation Through AI on Smart Seismic Networks
c. Please provide a short description of the use case.	A lot of details can be retrieved from the MSc. Thesis “A hybrid deep-learning approach for reliable real-time assessment of high magnitude earthquakes“ by Viola Hauffe (University Magdeburg, Germany). This project tackles earthquake preparedness by developing artificial neural networks to be deployed on affordable smart seismic household sensors. The purpose of these is to (1) quickly identify if a signal is a seismic event or a different source of noise (2) analyze the vulnerability of a building within which the sensor was installed and (3) analyze a potential structural damage while and after a significant earthquake occurred.
d. Please provide a short description of the datasets.	Continuous time series recorded by publicly available seismic stations (hosted at https://geofon.gfz-potsdam.de) and seismic data acquired by QuakeSaver GmbH. The data sets are continuously recording 100 samples per second of accelerometer data.

e. Please provide a short description of the model/method.	Deep convolutional neural networks trained on aforementioned continuous data to detect events, locate clustered events and pick first onsets of events recorded by the stations.
f. Please provide a short description of communications technologies that benefit or result from this use case.	The described technology allows to improve earthquake early warning in terms of speed and robustness against network failure due to the distributed computation (no single point of failure). Also in case of an event only relevant information from a large number of stations can be transmitted (time of first onset, maximum shaking intensity, damage reports) in a highly compressed data format.
2. Modeling-related questions	
a. Please provide the problem statement including a description of the intended use.	AI and ML have proven helpful in detecting earthquakes and picking events. However their application is mostly limited to data centers and post disaster mitigation. The application on the edge in an IoT environment is ground breaking. We intend to train neural networks and implement these trained neural networks on seismic sensors to enhance earthquake early warning and structural health monitoring. These analyses on the sensors will allow a much greater scalability of large sensor networks. This is mostly due to reduced information latency and a much lower requirement for large bandwidth for data transmission.
b. Please elaborate on the guiding principles and assumptions (as relevant).	The general assumption is that a neural network is capable of detecting an earthquake on a single station waveform stream within the first seconds after an onset arrives at a seismic station. As a second step we assume that basic information on seismic source location and magnitude can be roughly estimated based on a single station event onset. In the MSc work of Viola Hauffe (see above) a method to combine a neural network with seismological information has been tested which explored this second step.

c. Please provide information about the outcomes (e.g., how the outcomes will be used, what their expected impact is, what the weaknesses/strengths of the outcomes are, and how the system will be monitored and improved).	The detection of earthquake onsets has been proven successful. Informing the neural network with geometrical details of the recording setup has slightly improved event magnitude estimation but has left room for optimisation.
d. Please provide information about the elements of AI modeling including where AI is used and information about preprocessing. For the latter, please explain if the data are ready to use or if additional manipulations are needed. Also, please describe the readiness and quality of the data (e.g., if formatting or indexing is required for efficiency or if bias/label noise impacts quality).	AI is used to detect earthquake onsets. This is intended to be used in a single station fashion rolled out to seismic sensors.
Based on your use case and your understanding of the other use cases in your topic group, what are the challenges when using AI for this application and what recommendations can you offer to someone who intends to apply AI?	The main problem in seismological applications of AI with respect to early warning is the bias of magnitude and frequency. Large mega thrust events are very rare as data but are the most interesting aspect.

"Probing Seismogenesis for Fault Slip and Earthquake Hazards"

proposed by Christopher W. Johnson (1) and Paul A. Johnson (1)
(1) Los Alamos National Laboratory, U.S.A.

High-Level Questions	Responses
1. General information about the use case	
a. Please provide the name of the associated topic group (e.g., TG-AI	TG-AI for Earthquake Monitoring, Detection, and Forecasting

for Flood Monitoring and Detection).	
b. Please provide the name of the use case from the proposal (e.g., Flash Flooding Monitoring System in Mexico).	Probing Seismogenesis for Fault Slip and Earthquake Hazards
c. Please provide a short description of the use case.	For active seismic fault systems, particularly when located near dense urban environments, predicting instantaneous and future characteristics of fault slip has long been a fundamental goal of geoscientists from an earthquake hazards perspective, but also to improve the basic understanding of fault mechanics. However, on natural faults the repeat cycles for all but the smallest earthquakes can span timescales on the order of decades to hundreds of years. Thus, *in-situ* geophysical measurements as input for data-driven ML models are generally not available or sufficiently complete for more than a portion of a single earthquake cycle. Transfer learning for AI models is the focus of this use case and may provide a tractable means of bringing the success of data-driven machine-learning approaches for predicting fault-slip characteristics in the laboratory to natural fault systems in the Earth.
d. Please provide a short description of the datasets.	Laboratory experiment data is routinely collected and a viable source of information to train models for application to nature fault systems. Numerical simulation data is available that matches the laboratory results and more simulations are needed to broaden the variance in the numerical results. With future application to faults in seismically active regions, obtaining sufficient training data is a challenge. In Earth systems data generally only exists for a portion of an interseismic slip cycle on a fault. Many data exist for continuous recording, but repeating seismic cycles at a single location, i.e., multiple large magnitude events within a decade, is not generally available. Transfer learning applications and cross-training techniques with the laboratory and numerical data are the solution to produce deep learning models of the necessary data to learn the seismic cycle. The trained model is applied to regional network seismic data.

e. Please provide a short description of the model/method.	The model combines data recorded in a laboratory setting to simulate earthquake rupture and numerical models to describe earthquake rupture. These data are combined in a convolutional encoder-decoder modeling framework to train the deep learning model with the numerical simulation data and then apply transfer learning with the laboratory data to fine tune the model. The final model is applied to new laboratory data to test if the evolving material properties are described directly from the input waveforms.
f. Please provide a short description of communications technologies that benefit or result from this use case.	NA
1. Modeling-related questions	
a. Please provide the problem statement including a description of the intended use.	Earthquake forecasting is still an elusive goal; however, by analyzing continuous geophysical data streams applying ML models, remarkable progress is being made toward forecasting and characterizing fault physics. Models developed to extract and identify hidden signals in seismic noise will provide new insight to the fault physics that control the accumulation and release of stress in the crust.
b. Please elaborate on the guiding principles and assumptions (as relevant).	The primary assumption is that faults emit a signal that manifests as changes in the seismic noise during the loading cycle on active fault systems. This is based on laboratory data analysis using machine learning to characterize the state of the lab-fault from the acoustic noise.
c. Please provide information about the outcomes (e.g., how the outcomes will be used, what their expected impact is, what the weaknesses/strengths of the outcomes are, and how the system will be monitored and improved).	Models are being developed with laboratory data and numerical simulations using transfer learning. As more advancements are made the transfer learning will be applied to Earth data to monitor faults.

d. Please provide information about the elements of AI modeling including where AI is used and information about preprocessing. For the latter, please explain if the data are ready to use or if additional manipulations are needed. Also, please describe the readiness and quality of the data (e.g., if formatting or indexing is required for efficiency or if bias/label noise impacts quality).	AI is used to analyze the continuous waveform data. Model types include convolution encoder-decoder designs with transfer learning applied to the latent space when training for specific applications. Data preprocessing includes inputting as continuous waveforms and represented in the time-frequency domain.
Based on your use case and your understanding of the other use cases in your topic group, what are the challenges when using AI for this application and what recommendations can you offer to someone who intends to apply AI?	The main challenge is designing a data set and model that generalizes to all applications, which is not necessarily the primary goal if a location specific model is applicable.

8.2 TG-AI for Flood Monitoring and Detection

"Flash Flooding Monitoring System in Mexico"

proposed by Raúl Aquino (1) and Noel Garcia Diaz (2)
(1) Universidad de Colima, Mexico
(2) Instituto Tecnológico de Colima, Mexico

High-Level Questions	Responses
1. General information about the use case	
a. Please provide the name of the associated topic group (e.g., TG-AI for Flood Monitoring and Detection).	TG-AI for Flood Monitoring and Detection
b. Please provide the name of the use case from the proposal (e.g., Flash Flooding Monitoring System in Mexico).	Sentinel Satellite images and machine learning for mapping flood

c. Please provide a short description of the use case.	In Mexico, different regions suffer from floods every year, affecting economic activities, human health, agriculture, and livestock, among others. This makes it important to monitor water bodies and areas affected by floods to help reduce risks and make decisions in response to these disasters. Consequently, obtaining data that is very useful for mapping risk areas is very useful for agriculture, fishing, population settlement and different human activities. There are satellites that generate large amounts of data on the Earth and tools for processing large volumes of images and that are very useful for monitoring floods, detecting forest areas, crop areas and bodies of water, classification of land use, among others. Machine learning, particularly deep learning, has been used for the analysis of satellite images with satisfactory results, which has allowed the development of methods for land cover classification, flood detection, etc. In this research proposal, the mapping of the flooded areas and bodies of water is proposed, in the Los Ríos region of the state of Tabasco, made up of the municipalities of Balancán, Emiliano Zapata and Tenosique, in the period 2018-2022, through images. Sentinel-1 and Sentinel-2 satellites and deep learning algorithms. This, in order to collaborate in reducing the damage caused by floods and considerably reduce direct and indirect economic losses in municipalities vulnerable to this phenomenon.
d. Please provide a short description of the datasets.	SAR Sentinel-1 and Multispectral Sentinel-2 images will be used in this study. Images will be collected from the study area, from the municipalities of Balancán, Tenosique and Emiliano Zapata for the years 2018, 2019, 2020, 2021 and part of 202q. The Google Earth Engine platform will be used for this purpose.
e. Please provide a short description of the model/method.	The methodology proposed mapping flood using SAR and multispectral satellite images and deep learning consists of 5 stages: 1) input data, obtain datasets of images from the sentinel satellite, 2)Sentinel images selection: It is proposed to combine of Sentinel-1 and Sentinel-2 images, 3) Images preprocessing: in order to obtain a collection of cleaner and sharper images, 4) Deep learning model, use convolutional neural networks (CNN) to analyze images, 5) Evaluate interpretability, interpret the data obtained with CNN and 6) finally classify the images to mapping flood areas
f. Please provide a short description of communications	Satellite technologies: Sentinel-1 and Sentinel 2 images. Machine learning algorithms (deep learning). Hardware for

technologies that benefit or result from this use case.	data processing and algorithm training, graphics processing unit, GPU, and TensorFlow
2. Modeling-related questions	
a. Please provide the problem statement including a description of the intended use.	Floods are considered among the most destructive natural phenomena, causing serious human damage and economic losses in the world. In Mexico, different regions suffer from this phenomenon every year, affecting economic activities, human health, agriculture, livestock, among others. This makes it important to monitor water bodies and areas affected by floods to help reduce risks and make decisions in response to these disasters. Likewise, obtain data that is very useful for mapping risk areas that are useful for agriculture, fishing, population settlement and different human activities. On the other hand, there are satellites that generate large amounts of data on the Earth and tools for processing large volumes of images and that are very useful for monitoring floods, detecting forest areas, crop areas and water bodies, classification of land use, among others.
b. Please elaborate on the guiding principles and assumptions (as relevant).	Obtaining satellite images with less noise (clouds) for a better training of the algorithms and obtaining better results. The development of a new Deep Learning strategy and the correct training and validation of the algorithm.
c. Please provide information about the outcomes (e.g., how the outcomes will be used, what their expected impact is, what the weaknesses/strengths of the outcomes are, and how the system will be monitored and improved).	The development of an application of maps of flood risk areas, flood zones and the analysis of changes in water bodies, becomes important tools for predicting them and improving the development of strategies for prevention and control. Access to this application by municipal, state and federal government will make it possible to: • Establish better policies for population settlements. • Structure better forecasting processes and strategies in cases of contingencies due to floods, reducing the economic losses caused by floods. • Establish disclosure mechanisms with the information resulting from this project, through the corresponding government agencies to prevent the different affected sectors from the presence of floods. • Develop government forecasting strategies that reduce the impact of floods in marginalized areas.

	• Creation of an open data set that can be used for further research and serve as a reference for future work related to floods. • Collaborate in reducing the number of people affected by floods.
d. Please provide information about the elements of AI modeling including where AI is used and information about preprocessing. For the latter, please explain if the data are ready to use or if additional manipulations are needed. Also, please describe the readiness and quality of the data (e.g., if formatting or indexing is required for efficiency or if bias/label noise impacts quality).	The images obtained from the years of study require preprocessing for noise removal. This is necessary since it is impossible to obtain optical images without noise (clouds, since floods, rains, precipitation are being analyzed). Likewise, spectral bands and calculation of spectral indices and the creation of mosaics and clips in the images are selected. Until now, AI classification algorithms are being used to later use CNN. The configuration of classification parameters, the training sample and sample tests have been made to later train the classifiers. In relation to CNN, a model will be created that obtains better results than the classic ML algorithms.
Based on your use case and your understanding of the other use cases in your topic group, what are the challenges when using AI for this application and what recommendations can you offer to someone who intends to apply AI?	Pending

"Satellite Images and Machine Learning for Mapping Flood"

proposed by Fernando Pech-May (1) and Joger Magaña Govea (1)
(1) Instituto Tecnológico Superior de los Ríos, Mexico

High-Level Questions	Responses
1. General information about the use case	
a. Please provide the name of the associated topic group (e.g., TG-AI for Flood Monitoring and Detection).	TG-AI for Flood Monitoring and Detection
b. Please provide the name of the	Sentinel Satellite images and machine learning for mapping

use case from the proposal (e.g., Flash Flooding Monitoring System in Mexico).	flood
c. Please provide a short description of the use case.	In Mexico, different regions suffer from floods every year, affecting economic activities, human health, agriculture, and livestock, among others. This makes it important to monitor water bodies and areas affected by floods to help reduce risks and make decisions in response to these disasters. Consequently, obtaining data that is very useful for mapping risk areas is very useful for agriculture, fishing, population settlement and different human activities. There are satellites that generate large amounts of data on the Earth and tools for processing large volumes of images and that are very useful for monitoring floods, detecting forest areas, crop areas and bodies of water, classification of land use, among others. Machine learning, particularly deep learning, has been used for the analysis of satellite images with satisfactory results, which has allowed the development of methods for land cover classification, flood detection, etc. In this research proposal, the mapping of the flooded areas and bodies of water is proposed, in the Los Ríos region of the state of Tabasco, made up of the municipalities of Balancán, Emiliano Zapata and Tenosique, in the period 2018-2022, through images. Sentinel-1 and Sentinel-2 satellites and deep learning algorithms. This, in order to collaborate in reducing the damage caused by floods and considerably reduce direct and indirect economic losses in municipalities vulnerable to this phenomenon.
d. Please provide a short description of the datasets.	SAR Sentinel-1 and Multispectral Sentinel-2 images will be used in this study. Images will be collected from the study area, from the municipalities of Balancán, Tenosique and Emiliano Zapata for the years 2018, 2019, 2020, 2021 and part of 202q. The Google Earth Engine platform will be used for this purpose.
e. Please provide a short description of the model/method.	The methodology proposed mapping flood using SAR and multispectral satellite images and deep learning consists of 5 stages: 1) input data, obtain datasets of images from the sentinel satellite, 2)Sentinel images selection: It is proposed to combine of Sentinel-1 and Sentinel-2 images, 3) Images preprocessing: in order to obtain a collection of cleaner and sharper images, 4) Deep learning model, use convolutional neural networks (CNN) to analyze images, 5) Evaluate interpretability, interpret the data obtained with CNN and 6) finally classify the images to mapping

	flood areas
f. Please provide a short description of communications technologies that benefit or result from this use case.	Satellite technologies: Sentinel-1 and Sentinel 2 images. Machine learning algorithms (deep learning). Hardware for data processing and algorithm training, graphics processing unit, GPU, and TensorFlow
2. Modeling-related questions	
a. Please provide the problem statement including a description of the intended use.	Floods are considered among the most destructive natural phenomena, causing serious human damage and economic losses in the world. In Mexico, different regions suffer from this phenomenon every year, affecting economic activities, human health, agriculture, livestock, among others. This makes it important to monitor water bodies and areas affected by floods to help reduce risks and make decisions in response to these disasters. Likewise, obtain data that is very useful for mapping risk areas that are useful for agriculture, fishing, population settlement and different human activities. On the other hand, there are satellites that generate large amounts of data on the Earth and tools for processing large volumes of images and that are very useful for monitoring floods, detecting forest areas, crop areas and water bodies, classification of land use, among others.
b. Please elaborate on the guiding principles and assumptions (as relevant).	Obtaining satellite images with less noise (clouds) for a better training of the algorithms and obtaining better results. The development of a new Deep Learning strategy and the correct training and validation of the algorithm.
c. Please provide information about the outcomes (e.g., how the outcomes will be used, what their expected impact is, what the weaknesses/strengths of the outcomes are, and how the system will be monitored and improved).	The development of an application of maps of flood risk areas, flood zones and the analysis of changes in water bodies, becomes important tools for predicting them and improving the development of strategies for prevention and control. Access to this application by municipal, state and federal government will make it possible to: • Establish better policies for population settlements. • Structure better forecasting processes and strategies in cases of contingencies due to floods, reducing the economic losses caused by floods. • Establish disclosure mechanisms with the information resulting from this project, through the corresponding government agencies to prevent the different affected

	sectors from the presence of floods. • Develop government forecasting strategies that reduce the impact of floods in marginalized areas. • Creation of an open data set that can be used for further research and serve as a reference for future work related to floods. • Collaborate in reducing the number of people affected by floods.
d. Please provide information about the elements of AI modeling including where AI is used and information about preprocessing. For the latter, please explain if the data are ready to use or if additional manipulations are needed. Also, please describe the readiness and quality of the data (e.g., if formatting or indexing is required for efficiency or if bias/label noise impacts quality).	The images obtained from the years of study require preprocessing for noise removal. This is necessary since it is impossible to obtain optical images without noise (clouds, since floods, rains, precipitation are being analyzed). Likewise, spectral bands and calculation of spectral indices and the creation of mosaics and clips in the images are selected. Until now, AI classification algorithms are being used to later use CNN. The configuration of classification parameters, the training sample and sample tests have been made to later train the classifiers. In relation to CNN, a model will be created that obtains better results than the classic ML algorithms.
Based on your use case and your understanding of the other use cases in your topic group, what are the challenges when using AI for this application and what recommendations can you offer to someone who intends to apply AI?	Pending

"Using ML to Reconstruct Flooded Area under Clouds in Optical Satellite Images: The Mozambique Use Case"

proposed by Guy Schumann (1)

(1) RSS-Hydro, Luxembourg

High-Level Questions	Responses
1. General information about the use case	

a. Please provide the name of the associated topic group (e.g., TG-AI for Flood Monitoring and Detection).	TG-AI for Flood Monitoring and Detection
b. Please provide the name of the use case from the proposal (e.g., Flash Flooding Monitoring System in Mexico).	Using ML to reconstruct flooded area under clouds in optical satellite images: the Mozambique use case
c. Please provide a short description of the use case.	The Machine Learning algorithm developed by the RSS-Hydro team requires as inputs a cloud-covered low-resolution optical (e.g. Sentinel-2) satellite flood image and auxiliary data, both during the training and the inference phase. During training, the model additionally requires a ground-truth flood map. Auxiliary data like, for example, digital elevation model and derived datasets such as slope and topographic wetness, help the FloodSENS algorithm learn the correlation between flooded areas and their surrounding topography.
d. Please provide a short description of the datasets.	Within this study we categorize feature data into two different types: • Static data, such as the Copernicus DEM, has been acquired or generated for a particular point in time, generally before a given flood event. • Continuous data, such as Sentinel-2 images, generally exist in the form of time series, and have a cycle that covers pre- and post-event dynamics. Technically these data sources come with specific properties concerning the flood mapping. Considering as an example the properties of a static DEM for the mapping of a dynamic event, which are not reflected in the dataset, this DEM still offers indirectly fluvial forms that can serve as proxy, even if acquired totally independently of such event. On the other hand, a Sentinel-2 time series might suffer from impenetrable cloud cover after flood events, rendering the data obsolete even if available. Two types of input data are required for training and deployment; optical data and static auxiliary data.

e. Please provide a short description of the model/method.	It is important to note that at this stage in the project, all the pre-processing part as well as the data for the training and references is completed. We are now at the stage where we train the model architecture on different use cases and test it for generalization. The ML algorithm will go through two separate phases namely training and inference. Training an effective algorithm is the main challenge and the next three sub chapters are focusing on training related aspects of the project. In a first instance a static trained algorithm will be deployed on WASDI, meaning once deployed the weights are frozen and will not be changing. A major source of information lies in the propagation auxiliary data. Tiling them could be enough for good results since the auxiliary dataset of the flow accumulation numbers is in itself a propagation of information from other tiles (in the same hydrological basin). Our goal is to grow our model. This means, we have a live model, that is continuously fine-tuned on a growing database of cases and study sites, and which will improve iteratively its transferability,
f. Please provide a short description of communications technologies that benefit or result from this use case.	NA
2. Modeling-related questions	

a. Please provide the problem statement including a description of the intended use.	EO still has some serious limitations when used in flood mapping applications, such as assisting flood disaster response efforts or (re-)insurance operations. RSS-Hydro's engagement with these two major customer segments over many years has revealed that there are three major challenges that need to be addressed to further increase the value and, consequently, the uptake of EO in end-user operation protocols: (1) persistent cloud cover during floods seriously limit the use of optical imagery; (2) SAR has much shorter historic archives than optical imagery, is difficult to interpret and has its own limitations, particularly in urban areas; (3) often slow processing and long latency from image acquisition to flood map delivery.
b. Please elaborate on the guiding principles and assumptions (as relevant).	Not using satellite data efficiently or discarding entire sensor types because of limitations will without a doubt be detrimental to effective disaster response assistance at global level.
c. Please provide information about the outcomes (e.g., how the outcomes will be used, what their expected impact is, what the weaknesses/strengths of the outcomes are, and how the system will be monitored and improved).	In response to popular demand of drones, AI/ML and EO data within the disaster response community, RSS-Hydro is proposing an innovative ML-based application software solution, called FloodSENS, that can efficiently reconstruct flooded area under partial cloud cover in optical satellite images and scale between satellite imagery and drone data, thereby overcoming the aforementioned EO (optical) limitations to offer a better flood disaster response.

d. Please provide information about the elements of AI modeling including where AI is used and information about preprocessing. For the latter, please explain if the data are ready to use or if additional manipulations are needed. Also, please describe the readiness and quality of the data (e.g., if formatting or indexing is required for efficiency or if bias/label noise impacts quality).	It is important to note that at this stage in the project, all the pre-processing part as well as the data for the training and references is completed. We are now at the stage where we train the model architecture on different use cases and test it for generalization. The ML algorithm will go through two separate phases namely training and inference. Training an effective algorithm is the main challenge and the next three sub chapters are focusing on training related aspects of the project. In a first instance a static trained algorithm will be deployed on WASDI, meaning once deployed the weights are frozen and will not be changing. A major source of information lies in the propagation auxiliary data. Tiling them could be enough for good results since the auxiliary dataset of the flow accumulation numbers is in itself a propagation of information from other tiles (in the same hydrological basin). The objective is to expand the model. This entails having a live model, that is continuously fine-tuned on a growing database of cases and study sites, and which will iteratively improve its transferability.
Based on your use case and your understanding of the other use cases in your topic group, what are the challenges when using AI for this application and what recommendations can you offer to someone who intends to apply AI?	Pending

“Exploring Deep Learning Capabilities for Surge Predictions in Coastal Areas”

proposed by Anaïs Couasnon (1)
(1) Vrije Universiteit Amsterdam, the Netherlands

High-Level Questions	Responses
1. General information about the use case	

a. Please provide the name of the associated topic group (e.g., TG-AI for Flood Monitoring and Detection).	TG-AI for Flood Monitoring and Detection
b. Please provide the name of the use case from the proposal (e.g., Flash Flooding Monitoring System in Mexico).	Exploring Deep Learning Capabilities for Surge Predictions in Coastal Areas
c. Please provide a short description of the use case.	This use case applies tide station data (from GESLA-2) and atmospheric conditions (from ERA-5) to train four types of deep learning models (artificial neural networks, convolutional neural networks, long short-term memory layer, and a combination of the latter two) to predict hourly storm surge ensembles at a global scale. The models are assessed using minimum absolute error as the selected loss function as well as Continuous Ranked Probability Score for the ensemble of models.
d. Please provide a short description of the datasets.	For the predictand variable, we used observed sea levels from the Global Extreme Sea-Level Analysis Version 2 database (GESLA-2). We selected stations with a high temporal frequency (15 min to one hour) which resulted in 736 stations spread globally. This dataset is already controlled for potential errors and has been used in many coastal studies. We extracted the storm surge from the total sea levels by detrending sea levels and subsequently applying a harmonic analysis. For the predictor variables, we extracted the selected atmospheric variables (mean sea level pressure, meridional, zonal wind at 10 m) from the most recent ECMWF high resolution climate reanalysis dataset, ERA-517. This global dataset has a spatial resolution of 0.25° and an hourly temporal resolution. While it is documented to have some biases, its increased temporal and spatial resolution resulted in considerable improvements in performance over its predecessor ERA-Interim.

e. Please provide a short description of the model/method.	In our study, we compared four neural network (NN) models. The input layer is connected to the following hidden layer: • ANN A fully connected layer with an l2 kernel regularizer. • LSTM a stateless LSTM layer with a hard sigmoid recurrent activation function. • CNN a 2D convolution layer. Each filter has a kernel size of 3 × 3 with the same padding and the convolution step is followed by a max-pooling layer with a kernel size of 2 × 2. • ConvLSTM a 2D convolution layer following a stateless LSTM layer with a hard sigmoid recurrent activation function. Each filter has a kernel size of 3 × 3 with the same padding and the convolution step is followed by a max-pooling layer with a kernel size of 2 × 2. All of the NN models are activated using the ReLu activation function as is common in NNs. In the cases of the LSTM and ConvLSTM, a hard sigmoid function is used for the recurrent activation. The last hidden layer is a fully connected layer with an l2 weight regularizer and a dropout is added. We select the Adam optimizer algorithm for the learning rate optimization algorithm and train the NN model to minimise the mean absolute error, the selected loss function, between observed and predicted surge. The output layer, with one node only, represents the predicted surge levels.
f. Please provide a short description of communications technologies that benefit or result from this use case.	Forecasting systems, critical infrastructure
2. Modeling-related questions	

a. Please provide the problem statement including a description of the intended use.	To improve coastal adaptation and management, it is critical to better understand and predict the characteristics of sea levels. At the global scale, studies have used hydrodynamic modeling or data-driven approaches to reconstruct surge time series. The advantage of hydrodynamic models is that with adequate model resolution and meteorological forcing, they can resolve physical coastal processes and their interactions. However, these models are computationally demanding and take a long time to set up. In this project, we explored the capabilities of four deep learning methods to predict the surge component of sea level variability based on local atmospheric conditions. Our results show that the deep learning models developed are able to capture the temporal evolution of storm surges. We provide the deep learning models and predicted time series at 736 tide stations globally
b. Please elaborate on the guiding principles and assumptions (as relevant).	Please see the Technical section. Standard data curation methods have been applied as well as deep learning architectures. (see also question e in the General information of the use case)
c. Please provide information about the outcomes (e.g., how the outcomes will be used, what their expected impact is, what the weaknesses/strengths of the outcomes are, and how the system will be monitored and improved).	We foresee many applications of the deep learning methods tested in our study. Our study provides an initial application of the use of deep learning for coastal predictions. It also helps in understanding the capabilities of four deep learning model types (CNN, ANN, LSTM and ConvLSTM) to probabilistically predict storm surges, a first for coastal studies. Produced storm surge time series and models are available at https://doi.org/10.5281/zenodo.5216849 The models fitted in our study can be used to probabilistically nowcast storm surge levels. As the predicted time series have an hourly resolution, they can be used for example as input to a hydrodynamic model to simulate predicted sea levels. While the models have been trained on data from 1979 onwards, the ECMWF has now released the ERA-5 dataset from 1950 until now. Using this additional predictor data could provide a much longer time series of storm surge than performed in our study. In turn, these predicted time series can be used to better understand long term decadal fluctuations or improve the quantification of extreme storm surges.

d. Please provide information about the elements of AI modeling including where AI is used and information about preprocessing. For the latter, please explain if the data are ready to use or if additional manipulations are needed. Also, please describe the readiness and quality of the data (e.g., if formatting or indexing is required for efficiency or if bias/label noise impacts quality).	Four deep learning models (ANN, CNN, LSTM, ConvLSTM) have been used to predict storm surge based on climate variables. Data and models are ready to use and openly available at https://doi.org/10.5281/zenodo.5216849
Based on your use case and your understanding of the other use cases in your topic group, what are the challenges when using AI for this application and what recommendations can you offer to someone who intends to apply AI?	The main challenge is not to "misuse" the model and apply it for purposes outside of its original design/ application. While some models can be modified for other applications, it is often difficult to do so from unforeseen logistical applications (for example, data is not updated frequently enough etc).

8.3 TG-AI for Geodetic Enhancements to Tsunami Monitoring and Detection

"Deep Learning Detection of Elasto-Gravity Signals for Earthquake and Tsunami Early Warning"

proposed by Bertrand Rouet-Leduc (1) and Quentin Bletery (2)
(1) Kyoto University, Japan
(2) Geoazur, France

For this use case, no completed questionnaire was received by the submission deadline. Therefore, the details of this use case have been omitted during the derivation of best practices in this technical report.

"Enabling Natural Hazards Risk Information Sharing Using Derived Products of Export-Restricted Real-Time GNSS Data for Detection of Ionospheric Total Electron Disturbances"

proposed by Allison Craddock (1), Attila Komjathy (1), and Valentino Constantinou (1)
(1) NASA Jet Propulsion Laboratory/California Institute of Technology, U.S.A.

High-Level Questions	Responses
1. General information about the use case	
a. Please provide the name of the associated topic group (e.g., TG-AI for Flood Monitoring and Detection).	TG-AI for Geodetic Enhancements to Tsunami Monitoring and Detection

b. Please provide the name of the use case from the proposal (e.g., Flash Flooding Monitoring System in Mexico).	Enabling Natural Hazards Risk Information Sharing Using Derived Products of Export- Restricted Real-Time GNSS Data for Detection of Ionospheric Total Electron Disturbances
c. Please provide a short description of the use case.	Tsunamis can trigger internal gravity waves (IGWs) that propagate to the ionosphere, causing a perturbation in the natural Total Electron Content (TEC). These perturbations are often referred to as Traveling Ionospheric Disturbances (TIDs) and are detectable through the Global Navigation Satellite System (GNSS) signals. In this interdisciplinary work, we describe a framework for leveraging slant total electron content (sTEC) produced by the VARION (Variometric Approach for Real-Time Ionosphere Observation) algorithm and Convolutional Neural Networks (CNNs) in a process which trains a generalized model for TID detection, applicable across various atmospheric conditions and geographic areas.
d. Please provide a short description of the datasets.	Slant total electron content (sTEC) timeseries data produced by the VARION (Variometric Approach for Real-Time Ionosphere Observation) algorithm was used for initial trails. Future versions of this work will leverage data from the GUARDIAN system.
e. Please provide a short description of the model/method.	Timeseries sTEC data is transformed into images using an approach called Gramian Angular Difference Fields (GADFs). These images are subsequently used to train a Convolutional Neural Network (CNN), a type of deep learning network that leverages computer vision techniques. This combined methodology of using GADFs together with a CNN results in an approach that’s robust to missing data.
f. Please provide a short description of communications technologies that benefit or result from this use case.	N/A
2. Modeling-related questions	
a. Please provide the problem statement including a description of the intended use.	The use of technologies for the real-time detection of tsunami waves can enhance existing tsunami detection systems and

	improve the accuracy of such systems.
b. Please elaborate on the guiding principles and assumptions (as relevant).	N/A
c. Please provide information about the outcomes (e.g., how the outcomes will be used, what their expected impact is, what the weaknesses/strengths of the outcomes are, and how the system will be monitored and improved).	The products produced by this system (predictions of whether a TID is generated by a tsunami wave) can be used to improve existing tsunami warning systems and provide open-ocean detection capability, a new capability over the existing buoy-based systems. These systems have the potential to significantly improve our tracking of tsunami waves and the ability to direct coastal communities to safety.
d. Please provide information about the elements of AI modeling including where AI is used and information about preprocessing. For the latter, please explain if the data are ready to use or if additional manipulations are needed. Also, please describe the readiness and quality of the data (e.g., if formatting or indexing is required for efficiency or if bias/label noise impacts quality).	As explained, data is altered into an image using GADFs prior to being used in the deep learning model. Data is good quality and ready for use in AI applications, but is not "machine learning ready" in the sense that significant improvements must be made to the number of labeled events in the data and the integration of a HIL process to update the dataset with new observations of interest.
Based on your use case and your understanding of the other use cases in your topic group, what are the challenges when using AI for this application and what recommendations can you offer to someone who intends to apply AI?	Continued data curation and educating scientists on the importance of providing funding, support and continued labeling of data to ensure the effective use of AI systems.

"Building a Coupled Earthquake-Tsunami-TEC Simulator in a Parallel HPC Environment"

proposed by John Rundle (1) and David Grzan (1)
(1) University of California, Davis, U.S.A.

High-Level Questions	Responses
1. General information about	

the use case	
a. Please provide the name of the associated topic group (e.g., TG-AI for Flood Monitoring and Detection).	TG-AI for Geodetic Enhancements to Tsunami Monitoring and Detection
b. Please provide the name of the use case from the proposal (e.g., Flash Flooding Monitoring System in Mexico).	Building a Coupled Earthquake-Tsunami-TEC Simulator in a Parallel HPC Environment
c. Please provide a short description of the use case.	The project here represents advancements made towards the creation of a neural network-based tsunami warning system which can produce fast inundation forecasts with high accuracy. This was done by first improving the waveform resolution and accuracy ofTsunami Squares, an efficient cellular automata approach to wave simulation. It was then used to create a database of precomputed tsunamis in the event of a magnitude 9+ rupture of the Cascadia Subduction Zone. Our approach utilized a convolutional neural network which took wave height data from buoys as input and proved successful as maps of maximum inundation could be predicted for the town of Seaside, OR with a median error of ~0.5 m. Other hypothetical configurations of buoys were tested and compared to determine the lowest number of buoys necessary in order to make such a prediction.
d. Please provide a short description of the datasets.	For this project, three datasets were created via simulation. These include a dataset of 3000 earthquakes, 3000 tsunamis, and 3000 inundation maps. The earthquakes range in magnitude from 8.9 to 9.4. The tsunami simulations were used to generate time series wave height data from buoys and acted as the input for the neural network. The inundation maps acted as the output for the neural network.
e. Please provide a short description of the model/method.	A convolutional neural network was utilized to predict inundation maps by analyzing off-shore wave height data collected by buoys. Datasets for training and testing data were simulated. In addition to existing buoys, various hypothetical configurations of buoys were tested to determine the most optimal amount and placement of said buoys. This was done using a sensitivity test to determine which buoys were prioritized more by the neural network.
f. Please provide a short description of communications technologies that benefit or	N/A

result from this use case.	
2. Modeling-related questions	
a. Please provide the problem statement including a description of the intended use.	Utilizing open ocean buoys and convolutional neural networks to give timely and accurate warnings of an approaching tsunami to at risk locations.
b. Please elaborate on the guiding principles and assumptions (as relevant).	N/A
c. Please provide information about the outcomes (e.g., how the outcomes will be used, what their expected impact is, what the weaknesses/strengths of the outcomes are, and how the system will be monitored and improved).	This project will provide added insight and advancements towards machine learning methods which provide accurate tsunami inundation forecasting to vulnerable areas. The system would involve collecting real-time buoy data and inputting it into a convolutional network in order to produce an inundation forecast.
d. Please provide information about the elements of AI modeling including where AI is used and information about preprocessing. For the latter, please explain if the data are ready to use or if additional manipulations are needed. Also, please describe the readiness and quality of the data (e.g., if formatting or indexing is required for efficiency or if bias/label noise impacts quality).	Wave height time series data is used as input for the convolutional neural network. As already done in this project, it can be easily simulated for any number of buoys in any location. Real-time buoy data is in a similar form (wave height vs time) and does not require any significant processing. The convolutional neural network design allows for an arbitrarily large or small number of time series used as input. Meaning if there are two buoys, then two separate time series are used as the input for the network.
Based on your use case and your understanding of the other use cases in your topic group, what are the challenges when using AI for this application and what recommendations can you offer to someone who intends to apply AI?	The most important part of any project involving AI is having a sound database to train your model with.

8.4 TG-AI for Insect Plague Monitoring and Detection

"Identification and Classification of Pest Infested Coniferous Forest Using AI"

proposed by Ha Trang Nguyen (1), Tobias Leidemer (2), Gonrou Dobou Orou Berme Herve (1), Larry Lopez (1), and Yago Diez (1)
(1) Yamagata University, Japan
(2) Leibniz Universität Hannover, Germany

High-Level Questions	Responses
1. General information about the use case	
a. Please provide the name of the associated topic group (e.g., TG-AI for Flood Monitoring and Detection).	TG-AI for Insect Plague Monitoring and Detection
b. Please provide the name of the use case from the proposal (e.g., Flash Flooding Monitoring System in Mexico).	Identification and Classification of Pest Infested Coniferous Forest Using AI
c. Please provide a short description of the use case.	In this use case, we aim at developing a system that uses Deep Learning and UAV-acquired forest images that can identify individual tree health conditions (defoliation rate) in areas of hundreds or thousands of hectares to comprehensively evaluate the health of diverse forest ecosystems.
d. Please provide a short description of the datasets.	The data of the tree health were divided into training and testing datasets for DL classification
e. Please provide a short description of the model/method.	The use case used Deep Neural Network to automatically identify different categories of tree healths including 1. healthy, no defoliation; 2. Very low. < 10 % defoliation; 3. Low, 10–25 % defoliation; 4. Medium, 26–50 % defoliation 5. High, 51–75 % defoliation and 6. Very High (Dead), > 75 % defoliation.
f. Please provide a short description of communications technologies that benefit or result from this use case.	This project presents the development of an automatic tree health classification method based on UAV-acquired very high-resolution images for training of a deep learning model that is unprecedented in terms of practical application and generalization potential.

2. Modeling-related questions	
a. Please provide the problem statement including a description of the intended use.	There were no problems
b. Please elaborate on the guiding principles and assumptions (as relevant).	Not Applicable
c. Please provide information about the outcomes (e.g., how the outcomes will be used, what their expected impact is, what the weaknesses/strengths of the outcomes are, and how the system will be monitored and improved).	The outcome will be used for forest management purposes. The forest staff and manager would use it to identify the trees that are infested by bark beetles and monitor the stages of the infestation. The strength of the outcome is that it provides an entire automation process with high accuracy. The weakness is that it uses UAV data which requires the pilots to fly frequently to cover a large area.
d. Please provide information about the elements of AI modeling including where AI is used and information about preprocessing. For the latter, please explain if the data are ready to use or if additional manipulations are needed. Also, please describe the readiness and quality of the data (e.g., if formatting or indexing is required for efficiency or if bias/label noise impacts quality).	Information about the AI elements is not possible. AI is used in Automatic Image Recognition. The images to be recognized must conform to defined standards. For example, height, width and number of color bands.
Based on your use case and your understanding of the other use cases in your topic group, what are the challenges when using AI for this application and what recommendations can you offer to someone who intends to apply AI?	Require numerous data for each degree of infestation which is not easy to get in the case of natural hazard.

“Artificial Intelligence Modeling Tools for Monitoring Desert Locust (AI-Locust): Breeding Grounds, Hatching Time, Population and Spatio-temporal Distribution”

proposed by Elfatih Mohamed Abdel-Rahman (1), Emily Kimathi (1), and Henri E. Z. Tonnang (1)
(1) International Centre of Insect Physiology and Ecology, Kenya

High-Level Questions	Responses
1. General information about the use case	
a. Please provide the name of the associated topic group (e.g., TG-AI for Flood Monitoring and Detection).	TG-AI for Monitoring Desert Locust
b. Please provide the name of the use case from the proposal (e.g., Flash Flooding Monitoring System in Mexico).	**A**rtificial **I**ntelligence Modeling tools for Monitoring Desert **Locust** (AI- Locust): breeding grounds, hatching time, population dynamics and spatio-temporal distribution
c. Please provide a short description of the use case.	The use case aims to develop an early warning and decision support system for monitoring desert locusts for sustainably managing its impact in Eastern Africa and Sahel-Maghreb regions. The use case will build an innovative platform essentially based on the use of cross-cutting artificial intelligence (AI) tools and algorithms (e.g., Artificial neuro Fuzzy) and means of near-real-time and long-term (> 30 years) Earth observation tools viz., satellite-based systems. We will use readily available climate, soil, and vegetation datasets, and AI-analytics to forecast desert locust outbreaks. The use case will utilize long-term desert locust observations that are readily available from the DLIS-FAO hub and other sources. Specifically, the use case will predict locust breeding grounds, hatching time, spatial distribution, and forecast its outbreaks. We will roll out the AI-model outputs to assess the site-specific risk of locust breeding and predict future migratory patterns and intensity of desert locusts; improve the locust monitoring system; determine the economic, food security, health, and environmental burden of the locust invasion. We will also study the impact of climate change on locust resurgence.

d. Please provide a short description of the datasets.	The use case will combine datasets from various sources for AI-analytics. Specifically, we will use long-term (> 30 years) satellite-based monthly rainfall, temperature, wind speed, and vegetation variables; and edaphic factors to predict and forecast desert locust breeding sites and outbreaks. The rainfall and temperature datasets are freely available from Envidat (https://www.envidat.ch/#/metadata/chelsa_cmip5_ts). The Envidat provides mean monthly maximum and minimum temperatures, as well as monthly precipitation at ~5 km spatial resolution globally for the years 1850-2100. While the wind speed will be obtained from the worldclim database (https://www.worldclim.org/data/worldclim21.html) and the edaphic factors include soil moisture (1985 – 2021) and sand content at 0 – 20 cm depth at 4 km spatial resolution from Terraclimate (https://climate.northwestknowledge.net/TERRACLIMATE/index_directDownloads.php). All these variables will be pre-processed and harmonized at 5 x 5 km resolution. The desert locust observations (adult and nymph occurrence data) are available from the DLIS-FAO data hub (https://locust-hub-hqfao.hub.arcgis.com/). This dataset compiles ground survey observations spanning 36 years, from 1985 to 2021, covering ~ 29 million km^2. We will use records for both desert locust nymphs and adult occurrence for 36 years (1985 and 2021). The desert locust data will be explored using open data science approaches and procedures. A grid of different sizes (5 x 5, 10 x 10, 50 x 50 km) will be applied to the entire study area which covers the desert locust occurrence observation points. Data sets within the grid that provide the most spatio-temporal desert locust observations over the 36 years will be used for calibrating the AI-modeling experiment. Socio-economic and other variables will be sources from individual countries' databases.

e. Please provide a short description of the model/method.	The proposed use case will employ different machine learning (ML) and AI analytics to predict desert locust breeding grounds and forecast its outbreak. Specifically, we will use the maximum entropy (MaxEnt) approach to assess the suitable habitats for desert locust breeding grounds. The MaxEnt model is a machine learning model that uses the entropy approach to predict species distribution. The MaxEnt model outputs (desert locust suitability maps) together with the climate, soil, and vegetation variables to be utilized to develop the AI-based model (AI-Locust). We will use the artificial neuro-fuzzy algorithm for developing the AI-model. Among multiple hybrid modeling approach, the evolutionary adaptive-Network-based Fuzzy Inference System (GA-ANFIS) that integrates the benefit of Fuzzy logic, Neural network (NN) and Genetic algorithm (GA) appears to be the most promising due to its high degree of diagnostic accuracy, which is justified by its application in various fields. This technique will be widely used in our use case.
f. Please provide a short description of communications technologies that benefit or result from this use case.	Our main communication tools will be scientific, publications, policies briefs, reports, interviews etc. We further plan to use mobile and digital technology to disseminate our findings.
2. Modeling-related questions	

a. Please provide the problem statement including a description of the intended use.	Desert locusts (*Schistocerca gregaria*) are considered the world's most destructive migratory pest. The pest can transverse across oceans and vast land traveling approximately 145 km in a day. A swarm covering a one-kilometer grid can eat cropland equivalent to feeding a human population of 35,000 people in a day. The current management strategy for desert locust swarms is aerial and ground spraying with large quantities of chemical pesticides, which has a high negative impact on humans, livestock, and the environment in addition to its economic burden to the governments. Many digital systems are developed to identify and predict desert locust suitable habitats and outbreaks, thus providing useful information to aid decision-making and timing of integrated pest management strategies. However, the current desert locust early warning systems have proven to be invaluable in helping communities stay ahead of desert locust breeding, hatching time, outbreaks, and upsurge. Therefore, there is a need to strengthen desert locust decision support and early warning tools, particularly in Eastern Africa and the Sahel-Maghreb regions by taking advantage of the enormous data already available on locust occurrence and density. A very good practice is developing. We propose to develop an AI-Locust platform that builds and expands on the successes achieved by 'big' long-term satellite data assets and desert locust data and AI algorithms. The main goal of the proposed AI-Locust is to develop an early warning system for monitoring desert locusts in Eastern Africa and the Sahel-Maghreb regions for improved application of management strategies. To achieve this goal the use case will leverage AI-based approaches and readily available desert locust as well as predictor variables to establish a user-friendly digital platform to predict desert locust breeding grounds, hatching time, spatial distribution, and frequency of outbreaks.

b. Please elaborate on the guiding principles and assumptions (as relevant).	The success of this use case is built on the following assumptions: ● If full commitment of partners and successful advocacy campaigns are conducted, this will create an enabling environment for the large data to be obtained across countries affected by the pest. ● If the capacity on data access right ownership, integration, storage, retrieval and sharing is strengthened through formal agreements with stakeholders and data sources, we will be able to conduct several modeling experiments and scenarios analysis. ● If end users have access and use the data, tools and models, this will stimulate discoveries and product developments such as automated early systems for surveillance of locusts that cause serious crop losses.
c. Please provide information about the outcomes (e.g., how the outcomes will be used, what their expected impact is, what the weaknesses/strengths of the outcomes are, and how the system will be monitored and improved).	The short- and long-term outcomes of the proposed use case will be utilized by different stakeholders to manage the impact of the desert locust sustainably and effectively. This use case will improve farmers' and government capacity and skills to better prepare for crop losses due to desert locust damage; enhance food and nutritional security for better health; and will enhance the use and applications of digital tools for decision-making in agriculture. Some of the project countries' development objectives are to reduce poverty and food insecurity and increase farmers' income by enhancing agriculture productivity; as well as providing technological options to help increase resilience and adaptation to the effects of natural disasters like desert locust invasion. The use case will provide a desert locust monitoring tool that enables the application of site-specific management options, hence reducing the negative impact of excessive use of chemical pesticides on human and environmental health (e.g., non-target insect species). Moreover, the developed tool will precisely identify sites of desert locust outbreaks, where stakeholders could establish projects for catching desert locust for animal feed and human food. The outcomes can provide the knowledge necessary to quantify crop yield reduction due to desert locust under a changing climate. It will also provide an understanding of the impact of climate change on desert locust invasion and outbreaks. In general, the use case will contribute to creating a cross-cutting research and science modeling

	protocol in relation to agriculture and food systems. The developed AI-based models on desert locust monitoring will act as a forewarning tool that can guide informed decisions regarding food gaps. However, monitoring desert locust could be quite uncertain due to some geo-political issues that could suddenly lead to desert locust outbreaks and upsurge. Like conflicts in desert locust frontline countries, which could hinder the application of desert locust management options, therefore lead to locust invasion and outbreaks.

d. Please provide information about the elements of AI modeling including where AI is used and information about preprocessing. For the latter, please explain if the data are ready to use or if additional manipulations are needed. Also, please describe the readiness and quality of the data (e.g., if formatting or indexing is required for efficiency or if bias/label noise impacts quality).	Among various subdivisions of AI, machine learning (ML) and deep learning (DL) are key approaches. ML denotes the ability to discover and mine consequential patterns from data by experience. These algorithms build a mathematical expression based on sample data called "training data" which allows forecasting and making decisions. DL is inspired from the human brain processing memory mechanism denoted as "artificial neural network". This algorithm is employed in supervised, semi-supervised or unsupervised. For this use case, we will be selecting a combination of AI; Cellular Automata (CA), fuzzy logic (FL) coupled with Individual-based modeling (IBM) modeling approach. CA is a spatially and temporally discrete system characterized by local interactions and synchronous dynamical evolution. It consists of five main elements: (i) a grid of cells, (ii) cell states, (iii) neighborhood, (iv) transition rules that determine how a cell changes from one state to another, and (v) time step. During simulations, each cell representing the locust position at time *t* will be considered as a given state. The subsequent state of the cell will be obtained from the current state, the state of the neighborhood cells and with predefined rules derived from the state of the organism within the designated population. Temporal increments and state variables of the system will be assumed discrete. FL will be applied denote the degree of accuracy of the CA rules in comparison to collected data using the following steps (i) identification of the input and output variables of the locust invasion (ii) construction of an appropriate membership function to represent these mechanisms (iii) formulation of appropriate linguistic rules linking the output and the input variables. The application of IBM approach to study complex pest spreading will provide means to include physical contact patterns that result from movements of individuals between locations Open-source platforms such as NetLog will be used to implement IBM. We will complement this analysis with R codes and if needed MATLAB multi-link platform can be used. Appropriate formatting and normalization of the data are required. Because of a long time of familiarity with the case, most the of weather and locust occurrence data will be formatted and labeled accordingly and noise will also be removed.

Based on your use case and your understanding of the other use cases in your topic group, what are the challenges when using AI for this application and what recommendations can you offer to someone who intends to apply AI?	The main challenge is having access to good quality data. Today, many AI tools and algorithms exist and are very powerful to extract knowledge from data and produce raisable outputs which can help in decision making and then transform the society. It is advisable to establish and build nature solid teamwork, disseminate best practices in data management which are aligned with the FAIR and open data principles and promote policies that are favorable to the use and application of advanced analytics for knowledge discovery.

8.5 TG-AI for Landslide Monitoring and Detection

"Landslides of Masses of Soil and Rock: Intelligent Risk Management in Areas Highly Threatened by Climate Change"

proposed by Silvia García (1)

(1) National Autonomous University of Mexico, Mexico

High-Level Questions	Responses
1. General information about the use case	
a. Please provide the name of the associated topic group (e.g., TG-AI for Flood Monitoring and Detection).	TG-AI for Landslide Monitoring and Detection
b. Please provide the name of the use case from the proposal (e.g., Flash Flooding Monitoring System in Mexico).	Landslides of masses of soil and rock: intelligent risk management in areas highly threatened by climate change

c. Please provide a short description of the use case.	To handle the complex dynamics of the factors involved -with temporal and spatial dependence- Data Science (factorial analysis, fuzzy clustering, and CART) and Artificial Intelligence (Neural Networks) are used to study landslides events (as cause-effects) from geology, geomorphology, geotechnics, and climate data (the threat is rainfall -extreme-). The neural model shows remarkable capacities to spatially quantify the impact of geomorphological, anthropic, and hydric variables on mass removal processes. Mud and debris flows, as well as other destructive processes in mountainous areas are associated with the existence of rural developments and civil infrastructure to define integral risk scenarios and to measure the impact of deforestation (and other harmful human activities) on natural environment stability. Based on the results, vulnerability and exposure maps are constructed (at useful scales) for the poorest southern states of Mexico, but the methodology is general and can be extrapolated to other world regions.
d. Please provide a short description of the datasets.	According to the universe of descriptors, this research is based on information from government offices, academic/research institutions and civil organizations linked to the NDM. The main source of data is the CENAPRED (National Center for Disaster Prevention), institution that compiles information from the army, navy, civil protection offices and the national university (UNAM) in questionnaires that describe the process in an organized way (footprint, approximate volume slide, materials on the foot, date, etc.). The CENAPRED is also in charge of reviewing and publishing geological, geotechnical and relief maps, among others. To categorize the threat (rain) we have agreements with the Mexican government to open the information from the hydrometeorological stations in the studied areas.

e. Please provide a short description of the model/method.	Once the area (poorest southern regions in Mexico) and the events (hurricane and cyclone season in the Mexican pacific) are descriptive, the information is analyzed with Data Science to define the best representation of the variables. At this stage a CART for getting the most efficient training set for the intelligent models, for example, examples of geographical situations that slide compared with the number of situations that do not, force the modeler to define the best proportion of the YES/NO occurrence (slide) for the NN. Also, the CART is used for integrating boundaries or limits of application. Then a neural network (multilayer feed-forward, quick propagation, supervised learning) is trained to predict i) if a “patch”, or a group of them, slides (a patch is the best spatial unit to characterize the environment and to measure the effects of the hydrometeorological phenomenon), ii) to characterize the inputs effects and iii) to define the dependence between the rainfall and the event. These patches are conceptualized as 3D (voxels) and are communicated in 2D (pixels, maps) where each unit is filled with information of the exposition and susceptibility.
f. Please provide a short description of communications technologies that benefit or result from this use case.	The first communication is through high-resolution static hazard maps (that could be migrated to dynamic ones). The alert system of the Mexican government is benefited with the model outputs because it informs when the rainfall is approaching high levels, so the risk of sliding in susceptible areas will also be high and the specialized team must be mobilized. The disaster manager receives alarm messages to different recipients, and it should use different communication mediums. The model gradually qualifies the warning messages, being the most important ones sent directly to the targeted populations. Because the studied areas are poor regions, the communication follows the restrictions of infrastructure and security.
2. Modeling-related questions	

a. Please provide the problem statement including a description of the intended use.	Landslides are one of the most frequent causes of human and economic losses around the world. Among all the landslide triggers, it is imperative to predict the threat of rain-induced landslides since the largest percentage of the total mass removals in the world is due to rainfall. In this project the evaluation of the vulnerable zones and the prediction of the movements is recognized as a very complex task where factors involved (with temporal and spatial dependencies) make necessary the intervention of analysis tools robust enough to work in the high dimension and flexible to adapt to monitoring gaps -at various scales, local and regional- and contaminated/incomplete data. In this sense, Data Science and Artificial Intelligence are used to study events (cause-effects) in geologically, geomorphologically, geotechnically and structurally characterized regions and where climate data (rain) is sufficient. Distinguishing exactly where a landslide will occur is a difficult operation because the characteristics of the susceptible areas are often too difficult to read and when the process happens it is also complex to determine geometry and velocity. But this does not mean that the signs are not there, it just means that we have not learnt the best way to read them yet. And this is where the data plays a crucial role. In this project to characterize, predict, and monitor landslides, several data sources are included. These data sources, from underground and overground, are integrated for better interpretation of the characteristics that increment the susceptibility and how they affect the mass removal potential and the geometry of the displacement. Products of this research are the static (that could migrate to dynamic) maps of the components of the risk of landslides. Contrary to the common idea of publishing regional maps that are not normally applicable to low-scale geographic situations, the resulting maps are micro-mapping related to the small-scale patches. The micro regionalization permits people and governments to modify their behaviors facing the disaster with alarm systems (rescue strategies and calls to specific emergency teams) and/or moving towns away from streams, adjusting the route of roads, containing the growth of human settlements, stopping deforestation, restoring vegetation, for example. The proper use of the neural network also facilitates the simulation of alternative scenarios in virtual reality, an effective manner to integrate teams into discussions on this complex problem.

b. Please elaborate on the guiding principles and assumptions (as relevant).	A landslide is a process where masses of rock, earth (soils) or debris move down on a slope. The ultimate state of the processes is the downward and outward movement of slope-forming materials. The materials may move by falling, toppling, sliding, spreading, or flowing. Although landslides are primarily associated with mountainous regions, they can also occur in areas of generally low relief (cut-and-fill failures -roadway and building excavations-, river bluff failures, lateral spreading landslides, collapse of mine-waste piles and quarries and open-pit mines). The detonating factor (in this project) is intense rainfall. The studio is run as a system with inputs and outputs. The system is the natural environment. The input is the rainfall and the output is the mass removal process. For the complete cycle to be generated, it is necessary that certain conditions happen in a patch (or group of them) in the studied time (during the intense rain) and these conditions can be very different between regions and materials, for example, although some landslides require lengthy rain and saturated slopes, a debris flow can start on a dry slope after only a few minutes of intense rain. The models are efficient because they can predict complex aspects such as the instantaneous spatial-temporal change of critical, secondary, and aggravating variables.

c. Please provide information about the outcomes (e.g., how the outcomes will be used, what their expected impact is, what the weaknesses/strengths of the outcomes are, and how the system will be monitored and improved).	The task in this project is, with AI and Data Science DS, to characterize i) the threaten (rainfall that activates processes), ii) the exposition (the geomorphological conditionings) and the susceptibility (topographical, subsoil - geotechnical conditions) through micro-mapping of specific regions in the southern of Mexico. Describing these conditions will permit us to predict where a landslide is likely to occur enough time before it happens. Warning signs are always there in the lead up to an event, these warnings can be very subtle and identifying them requires a deep knowledge of failure dynamics. The intelligent model proposed here, analyses and decodes the data on the registered movements to extract relevant patterns on motion and how they are changing with space and time. The potential of this analytics technology extends beyond the prediction of landslides. The idea is to anticipate the more vulnerable conditions adapting this regionalization as the threat changes, modifying conditions that make them vulnerable to the soils and rocks. About its applicability, this is a methodology that can be transferred to any region of the world, threatened by the same agent. It is recognized that its effectiveness can be increased if the number and quality of variables that describe the medium increase as well. Including parameters of monitoring in real time would allow this network to migrate directly to an alarm/alert system that informs to the most threatened communities and the government agents that a disaster potentially could happen instants (minutes) after. The research aims at strengthening disaster preparedness and response activities, improving the early warning system, building capacities of disaster management practitioners at all levels and that of communities as well as strengthening structural and non-structural resilience of infrastructure. To achieve this task, the proposal has holistic targets: 1) develop an spatial and temporal neural representation of landslide hazard (intrinsic parameters, geo), 2) evaluate micro-regional threat for local emergency management services (rainfall level in which the removal process is activated and the lapses-accumulated ratio), 3) establish a simple method for meteorological and hydrologic services to understand-interpret- and respond according the characteristics of raining seasons, 4) offer tools for identifying the opportunities (i.e. urban planning, education, warning systems) to reduce the impact of landslide events.

d. Please provide information about the elements of AI modeling including where AI is used and information about preprocessing. For the latter, please explain if the data are ready to use or if additional manipulations are needed. Also, please describe the readiness and quality of the data (e.g., if formatting or indexing is required for efficiency or if bias/label noise impacts quality).	The variety of input parameters (numerical data -continuous or discrete-, categorical data -numerical values, class labels-, time-series data (sequence of numbers collected at regular intervals over some period, in this case over some depth), and text -words-) and the description of landslides cases (biased, with missed/contaminated values, etc.), besides the uncertainty attached to interpretation and measurement of manifestations can efficiently be modeled using neural networks. 1. In the instances preprocessing, the Data Science tools are applied to recognize trends, relationships, biases, and factors (univariate / multivariable analysis, factor analysis, CART -regression and classification tree-, matrix graphs, among others) and to clean them from outliers and missed values. 2. For projection of data (spatial variation of geo-parameters) in places where there are no measurements (in situ or results of laboratory tests on samples) a neural system is applied (recurrent/dynamic network - patented) to grow the data population and “fill” the patches that need it with information. 3. For the prediction of landslides on relationships of the type IF certain geoconditions THEN the patch (or group of them) slides, multilayer feed forward, quick/back prop NNs are used. In this stage, a double register is made through a micro-local CART that predicts the occurrence of mass removal under a smaller scale definition; this allows inserting entries on the interactions between soil particles or rock blocks. The aim of this CART is to evaluate the efficiency of the NN but, above all, to check that the sensitivity of the NN inputs is as close as possible to the dynamics of the process. Applying this technique gives a clear and direct diagnosis about the desirable performance. 4. For the construction of the maps of the risk components, simulations developed with the NN of point 3 are used to reproduce the results for the dynamic ranges of the parameters that are identified as those that express the threat, exposure, and susceptibility. This NN is modified from the patented system to introduce geographical inputs (coordinates) and a control parameter. 5. All the neural models are refined by controlling factors (training samples, features, types of classifiers, and hyperparameters) that significantly affect results. Some techniques are applied to interactively select training samples, modify their labels, or/and rebuild the model by using new classes.

	6. To prepare the alarm/alert response guides, a (very simple) fuzzy system is proposed. It uses the rainfall measurement at the meteorological station and the susceptibility + exposition ranking (by group of patches) as inputs, and a response action (gradual) that goes from a message, turning on sounds, announcements in mass media, among others. The resulting intelligent predictor shows notable abilities to spatially quantify the impact of geo, anthropic and hydrological variables on the mass removal processes. This flexibility and robustness, as the principal characteristic of this cognitive proposal, is the basis for constructing reliable risk maps. Because of the concept “patch” the maps are useful for the marginated microregions with an acceptable level of confidence.

Based on your use case and your understanding of the other use cases in your topic group, what are the challenges when using AI for this application and what recommendations can you offer to someone who intends to apply AI?	One of the greatest challenges to study landslides is the survey of the events. The supervised training of neural networks with "real" cases allows us to discover relationships between very important parameters that conventional models (those that calculate the susceptibility to landslide based on topography, relief, and surface geo-materials) cannot handle. Constructing risk maps based on few or wide-ranging parameters means that the information is not useful for micro-regions or small communities that are strongly threatened. For this, it is necessary to summon sufficient and competent authorities to go to the field and fill out the questionnaires that the disaster prevention centers have built to study this phenomenon. Unfortunately, this is not always possible, either because of the difficulty in reaching the affected sites or because of the economic limitations to bring observation crews. Then the data has biases from various sources that the modeler must understand and deal with appropriate tools. Another important consideration is that the meteorological stations selected to manage the diffuse system (alerts) must be maintained and operated in optimal conditions, so it must be protected from vandalism, supplied with energy, and financed so that it works and communicates without loss of information. On the modeling side, the inputs and outputs constitute a challenge by themselves since they have different natures. Some are vectors relative to depth, for some their meaning is in the plane, in others the categorization is too general (regional maps) and when it is lowered to small areas it loses resolution or relevance and must be discarded. Some of the parameters change on time and this must be introduced in the model. On the other hand, when the displaced volume is measured, sufficiently precise tools are not always available, and the data may cause inconsistencies in the model. Also, and very important is that this project is based on information cause-effect from an historical perspective, i.e., using simple and easy to get information from past events. In order to increase the predictive capabilities of the model, it is necessary to instrument specific geo-situations where movements are expected and from which closer symptoms could be obtained (displacement monitors, humidity, for example), behaviors more related to the dynamics could be observed and survey of more comprehensive scenarios could be developed. Through the histories thus recorded, the understanding of the susceptibility and the beginning of the movement because of intense rains could be improved.

“Geographical Data Science Applied to Landslide and Debris Flow Hazard in the Colombian Andes”

proposed by Edier Aristizábal (1) and Juan Pablo Ospina (1)

(1) Universidad Nacional de Colombia, Colombia

High-Level Questions	Responses
1. General information about the use case	
a. Please provide the name of the associated topic group (e.g., TG-AI for Flood Monitoring and Detection).	TG-AI for Landslide Monitoring and Detection
b. Please provide the name of the use case from the proposal (e.g., Flash Flooding Monitoring System in Mexico).	Application of Artificial Intelligence and machine learning techniques for landslide susceptibility assessment
c. Please provide a short description of the use case.	Landslides are one of the most naturally occurring phenomena with the highest human and economic losses around the world, reason for the susceptibility and hazard assessment is a fundamental tool for land use planning. There is a wide range of Artificial Intelligence algorithms in the recent literature with completely different approaches to establish the relationship between the independent variable (predictors) and the dependent variable (landslide inventory). In the present study, a wide range of algorithms were used for the La Miel creek basin, in the Colombian Andes, and the methodology implemented for this type of data-based modeling is presented in detail and step by step. The results obtained show that the assembled boosting models present the best values in terms of performance and predictability. Contrasting with the linear parametric models, pointing dataset was derived from two sources: (**see below**)

d. Please provide a short description of the datasets.	1. 5 m x 5 m digital elevation model from which from ArcGis the variables of slope, aspect, roughness, profile curvature, plane curvature, standard curvature, elevation, Stream Power Index (SPI), Topographic Wetness Index (TWI) and flow accumulation were obtained. 2. The landslide inventory was obtained from the photo-interpretation of aerial images of the area at a scale of 1:10000 and the historical events reported by the Colombian Geological Service through SIMMA (Information System of Mass Movements) in the basin area.
e. Please provide a short description of the model/method.	The models used to predict the susceptibility maps were: stochastic gradient boosting, random forest, support vector machines, xgboost, decision tree, adaboosting, linear discriminant analysis, artificial neural network, logistic regression, K nearest neighbors.
f. Please provide a short description of communications technologies that benefit or result from this use case.	The main result of the project is the mass movement susceptibility map, with the best model built with the available data. This map can be used by decision makers as an input for a more complete risk analysis involving temporal and economic factors, and eventually in land-use planning.
2. Modeling-related questions	
a. Please provide the problem statement including a description of the intended use.	Landslides are one of the most naturally occurring phenomena with the highest human and economic losses around the world, reason for the susceptibility and hazard assessment is a fundamental tool for land use planning. There is a wide range of Artificial Intelligence algorithms in the recent literature with completely different approaches to establish the relationship between the independent variable (predictors) and the dependent variable (landslide inventory). In the present study, a wide range of algorithms were used for the La Miel creek basin, in the Colombian Andes, and the methodology implemented for this type of data-based modeling is presented in detail and step by step.

b. Please elaborate on the guiding principles and assumptions (as relevant).	In this project, landslides are considered as movements of material (soil, rock, or debris) downslope, based on that definition we make assumptions regarding the variables that cause such movement since there is the possibility that they are not good predictor variables, however, to avoid this, an exploratory data analysis is carried out.
c. Please provide information about the outcomes (e.g., how the outcomes will be used, what their expected impact is, what the weaknesses/strengths of the outcomes are, and how the system will be monitored and improved).	The main outcome of the project is the landslide susceptibility map, which serves as a fundamental input for the planning and ordering of the territory and in this way occupy the land in a more adequate way. This map functions as a starting point for a landslide risk assessment, however, it is limited to the spatial occurrence of the event and does not incorporate temporal variables, volume, area, propagation, etc., which are fundamental if a more detailed study is required. This project does not contemplate a warning system, since the main product is the landslide susceptibility map.
d. Please provide information about the elements of AI modeling including where AI is used and information about preprocessing. For the latter, please explain if the data are ready to use or if additional manipulations are needed. Also, please describe the readiness and quality of the data (e.g., if formatting or indexing is required for efficiency or if bias/label noise impacts quality).	AI is used when we supply data to the model to make predictions based on historical information. For the supply of this information, a preprocessing was made which consisted of extracting the characteristics or variables of the 5 m x 5 m digital elevation model and the landslide inventory from orthophotographs at a scale of 1:10,000 and the historical events reported by the "Sistema de Información de Movimientos en Masa" (http://simma.sgc.gov.co/). Once this dataset was formed, an exploratory data analysis and dimensionality reduction was performed through principal component analysis (PCA), in order to provide only relevant information to the model and thus also reduce the computational cost.

Based on your use case and your understanding of the other use cases in your topic group, what are the challenges when using AI for this application and what recommendation can you offer to someone who intends to apply AI?	The most important thing to keep in mind when applying AI to this type of problem is that the database must be robust and effectively represent the reality of the target variable. In our case, we consider it fundamental to perform a proper photointerpretation and to be sure of the incorporation of the historical databases that have events. If there is not a good landslide inventory, there simply will not be good results, since in machine learning it is well known that "thrash in, thrash out", so if we do not have a solid base we will only receive bad results. Regarding the implementation of the algorithms it is important to keep in mind that when using geospatial data we are working with big data, due to the high amount of pixels that raster images have, so it is vital to oversample or undersample, since it is an unbalanced problem (the pixels of mass movements are much smaller than those that are not), this affects the learning of the model because if the dataset is not balanced with some technique it will predict only the cells that are not landslides, which would not have any relevance. On the other hand, performing these subsampling techniques has a huge impact on the computational cost of the algorithms, so they are highly advised to be performed.

"Improving Landslide Prediction by Machine Learning and Deep Learning"

proposed by Christian Mejia-Escobar(1)
(1) Universidad Central del Ecuador, Ecuador

For this use case, no completed questionnaire was received by the submission deadline. Therefore, the details of this use case have been omitted during the derivation of best practices in this technical report.

"Soft Computing Paradigm for Landslide Monitoring and Disaster Management"

proposed by Shweta Vincent (1), Tanweer Ali (1), Sameena Pathan (1), and Om Prakash Kumar (1)
(1) Manipal Institute of Technology, Manipal Academy of Higher Education, India

High-Level Questions	Responses

1. General information about the use case	
a. Please provide the name of the associated topic group (e.g., TG-AI for Flood Monitoring and Detection).	TG-AI for Landslide Monitoring and Detection
b. Please provide the name of the use case from the proposal (e.g., Flash Flooding Monitoring System in Mexico).	Soft Computing Paradigm for Landslide monitoring and Disaster Management
c. Please provide a short description of the use case.	The Remote Sensing of disasters such as landslides is one of the most important forms of gathering information prior to the occurrence of a catastrophe. The use case is the usage of the space-borne technique for creation of landslide susceptibility maps (LSM) for the region of Nainital, India using machine learning algorithms.
d. Please provide a short description of the datasets.	In our study of the region of Nainital, the Landslide Inventory Map (LIM) has been downloaded for the region from the Bhukosh portal provided by the Geological Survey of India at a scale of 1:100000. Geological data of various regions in India can be downloaded from this portal.
e. Please provide a short description of the model/method.	The machine learning algorithms of Maximum Likelihood, ISO and Random Forest are used for creation of the landslide susceptibility map of Nainital.
f. Please provide a short description of communications technologies that benefit or result from this use case.	--Not Applicable--
2. Modeling-related questions	

a. Please provide the problem statement including a description of the intended use.	Landslide susceptibility maps(LSM) provide information of landslide prone areas. In this use case, we generate LSM for Nainithal region, which is one of the Himalayan region of India experiencing landslides frequently.
b. Please elaborate on the guiding principles and assumptions (as relevant).	The creation of LSM involves usage of historical landslides. By studying the characteristics of these landslides and the relationship between the landslide points and triggering factors, LSM is generated. So, the model makes an assumption that the future landslides will also have a similar relationship with triggering factors.
c. Please provide information about the outcomes (e.g., how the outcomes will be used, what their expected impact is, what the weaknesses/strengths of the outcomes are, and how the system will be monitored and improved).	Generated LSM can be used by the local administration to take necessary steps before the landslides occur. By predicting the landslide prone areas while planning any development activities would avoid the damages that might occur because of the disaster.
d. Please provide information about the elements of AI modeling including where AI is used and information about preprocessing. For the latter, please explain if the data are ready to use or if additional manipulations are needed. Also, please describe the readiness and quality of the data (e.g., if formatting or indexing is required for efficiency or if bias/label noise impacts quality).	By using AI based Machine learning models, the relationship between the historical landslide points in the inventory and conditioning factors is established. Through this relationship, the models predict the future landslides in the given study area. The accuracy of the model depends on the data provided while training the dataset. The data used in this use case is from the publicly available dataset. The dataset from the satellite images with better resolution would improve the accuracy of the result.
Based on your use case and your understanding of the other use cases in your topic group, what are the challenges when using AI for this application and what recommendations can you offer to someone who intends to apply AI?	Using the AI based machine learning models to build LSM requires accurate and sufficient data for training. The amount of data used in training also matters while assessing the efficiency of the model. Too many or too few landslide points might lead to overfitting and underfitting problems respectively. There are different sources from which the dataset of landslide inventory and DEM can be downloaded. Verification of these data sources for correctness is important before using it in our implementation.

8.6 TG-AI for Snow Avalanche Monitoring and Detection

"AI for Snow Avalanche Monitoring and Detection"

proposed by Alec van Herwijnen (1) and Markus Eckerstorfer (2)

(1) SLF, Switzerland
(2) NORCE, Norway

High-Level Questions	**Responses**
1. General information about the use case	
a. Please provide the name of the associated topic group (e.g., TG-AI for Flood Monitoring and Detection).	TG-AI for snow avalanche monitoring, detection, and forecasting
b. Please provide the name of the use case from the proposal (e.g., Flash Flooding Monitoring System in Mexico).	AI for snow avalanche monitoring and detection.
c. Please provide a short description of the use case.	In this use case, we focus on the use of AI to improve avalanche detection methods to obtain more accurate and reliably avalanche data. Such AI methods are poised to drastically change operational avalanche forecasting.
d. Please provide a short description of the datasets.	We use data from ground-based detections systems (radar, infrasound and seismic) and avalanche observations from automatic camera systems and field surveys.
e. Please provide a short description of the model/method.	We intend to use machine learning models (e.g. random forest) to automatically detect avalanche signals.

f. Please provide a short description of communications technologies that benefit or result from this use case.	Results from our work will be used in operational avalanche forecasting, will be published in open access papers, and will be disseminated to avalanche professionals in courses.
2. Modeling-related questions	
a. Please provide the problem statement including a description of the intended use.	We investigate if we can automatically identify signals from snow avalanches in real-time in continuous streams of seismic and infrasound data. Such information would be useful to better understand avalanche formation processes and to improve avalanche forecasting.
b. Please elaborate on the guiding principles and assumptions (as relevant).	Signals from avalanches have distinct characteristics, and it should thus be possible to identify those automatically.
c. Please provide information about the outcomes (e.g., how the outcomes will be used, what their expected impact is, what the weaknesses/strengths of the outcomes are, and how the system will be monitored and improved).	The models should provide real-time information on avalanche activity in a specific area. The main challenge is to reduce the number of false alarms without reducing the probability of detection. As we collect more data, we can retrain the models to increase the accuracy.
d. Please provide information about the elements of AI modeling including where AI is used and information about preprocessing. For the latter, please explain if the data are ready to use or if additional manipulations are needed. Also, please describe the readiness and quality of the data (e.g., if formatting or indexing is required for efficiency or if bias/label noise impacts quality).	We extract features from the raw seismic and infrasound data to distinguish signals from avalanches from other sources. To distinguish signals originating from avalanches from other sources, features are extracted from raw seismic and infrasound data.An important component here is using signals from multiple sensors, as it improves the signal-to-noise-ratio, and allows us to add information about the location of the source.

Based on your use case and your understanding of the other use cases in your topic group, what are the challenges when using AI for this application and what recommendations can you offer to someone who intends to apply AI?	The main challenge in the our field is obtaining reliable ground truth data to train our models. Avalanches are relatively rare events, and mostly occur during periods of bad visibility.

"Limitations of Predicting Snow Avalanche Hazards in Large Data Sparse Regions"

proposed by Simon Horton (1)

(1) Avalanche Canada, Canada

High-Level Questions	**Responses**
1. General information about the use case	
a. Please provide the name of the associated topic group (e.g., TG-AI for Flood Monitoring and Detection).	TG-AI for Snow Avalanche Monitoring and Detection
b. Please provide the name of the use case from the proposal (e.g., Flash Flooding Monitoring System in Mexico).	Limitations of predicting snow avalanche hazards in large data sparse regions
c. Please provide a short description of the use case.	Our use case explores relationships in snow avalanche datasets including observation, model, and expert assessment data, with findings that highlight limitations of using AI methods to predict avalanches in large data-sparse regions.

d. Please provide a short description of the datasets.	Our data includes expert assessments of avalanche danger and character from western Canada as well as relevant snowpack and weather datasets (both from field observations and model generated datasets).
e. Please provide a short description of the model/method.	We explore relationships with classification trees (e.g., conditional inference trees).
f. Please provide a short description of communications technologies that benefit or result from this use case.	Our work has informed operational avalanche forecasters about inconsistencies in their assessments and supported the development of dashboards that illustrate uncertainties in their datasets.
2. Modeling-related questions	
a. Please provide the problem statement including a description of the intended use.	We intend to explore relationships in avalanche-related datasets to better understand and predict avalanche hazard.
b. Please elaborate on the guiding principles and assumptions (as relevant).	Avalanche forecasting follows a conceptual model that guides the synthesis of observation data into a standard set of factors that describe the nature of avalanche hazard. We assume AI methods should help relate the observations to these factors.
c. Please provide information about the outcomes (e.g., how the outcomes will be used, what their expected impact is, what the weaknesses/strengths of the outcomes are, and how the system will be monitored and improved).	Decision trees should explain and quantify the driving factors of avalanche hazard, and we compare the classification trees produced with our datasets to our understanding of these factors. With refinement, this could lead to decision support tools for avalanche forecasters.

d. Please provide information about the elements of AI modeling including where AI is used and information about preprocessing. For the latter, please explain if the data are ready to use or if additional manipulations are needed. Also, please describe the readiness and quality of the data (e.g., if formatting or indexing is required for efficiency or if bias/label noise impacts quality).	Our weather and snowpack data has many dimensions and inconsistencies, so we need to filter, interpolate, and reduce the data into sets of key factors that we assume are relevant to avalanche hazard. We then use conditional inference trees to explore and plot relationships in our datasets.
Based on your use case and your understanding of the other use cases in your topic group, what are the challenges when using AI for this application and what recommendations can you offer to someone who intends to apply AI?	Our challenge is obtaining ground truth data that describes the true likelihood of avalanches across space and time. We also deal with challenges of communicating the complex data and uncertainties to avalanche forecasters.

8.7 TG-AI for Wildfire Monitoring and Detection

"An Intelligent Big Data Analysis System for Wildfire Management"

proposed by Helen Li (1)

(1) CAICT, MITT, China

High-Level Questions	Responses
1. General information about the use case	
a. Please provide the name of the associated topic group (e.g., TG-AI for Flood Monitoring and Detection).	TG-AI for Wildfire Monitoring and Detection

b. Please provide the name of the use case from the proposal (e.g., Flash Flooding Monitoring System in Mexico).	An Intelligent Big Data Analysis System for Wildfire Management
c. Please provide a short description of the use case.	Our existing work is to build an intelligent big data analysis system for fire management, which uses IoT equipment and AI technology to monitor potential fire risks in real time and assess the risks in key areas. This system has been applied in China's provincial regions and is extending to forest fire management.
d. Please provide a short description of the datasets.	Training and testing data mainly come from public and private datasets, which include popular image datasets like ImageNet, COCO and data collected from remote sensing satellites, monitoring devices and social media. AI models pre-trained on top datasets like ImageNet, COCO and DOTA display high accuracy in wildfire detecting. Datasets of remote sensing forest images and monitoring pictures are important in risk assessment, which contain forest terrain, plant species, dryness, tree density and distribution, as well as plant growth and leaf oil composition. Now tremendous existing data sources like DOTA, RSSCN7, which include remote sensing data for forest and trees guarantee the accuracy of wildfire predicting models.
e. Please provide a short description of the model/method.	By applying computer vision (CV) and natural language processing (NLP) techniques, AI systems can help to reduce wildfire loss significantly. In detail, the wildfire AI system includes an object detection model, image classification model, image segmentation model etc. Additionally, AI systems can assess wildfire damage and generate restoration plans precisely after a disaster. For the purposes of this proposal, however, we are focusing on wildfire detection and risk mapping.

f. Please provide a short description of communications technologies that benefit or result from this use case.	There are several IoT equipment(remote sensing satellites, monitors, social media apps,etc.) for supporting the wildfire detection and risk assessment system.These communications technologies enable to reduce labor and business costs by predicting wildfire risk and marking high risk areas in advance, reporting wildfire immediately, predicting wildfire spread and guiding fight wildfire accurately, rescuing trapped people quickly and safely.
2. Modeling-related questions	
a. Please provide the problem statement including a description of the intended use.	· Thermal imaging + Red UV spectrum detection + video depth analysis detection The comprehensive coupling detection model establishes thermal imaging temperature detection by analyzing and comparing red ultraviolet spectrum detection. · Deep Learning Image Recognition Model + Red UV Detection Model The ultraviolet detection data model is able to predict the forest fire by recognizing the change of red and ultraviolet detection data.
b. Please elaborate on the guiding principles and assumptions (as relevant).	N/A
c. Please provide information about the outcomes (e.g., how the outcomes will be used, what their expected impact is, what the weaknesses/strengths of the outcomes are, and how the system will be monitored and improved).	The project helps the government to control and reduce the risk of potential forest fires. Based on remote sensing images and monitor pictures, training and deploying plant identification models, can identify forest species, density, distribution, dryness and predict forest growth. By knowing the species and growth of the plant, AI will identify plant oil composition, leaf density and leaf thickness. Combined with data of temperature, wind, and precipitation trends in several days, AI will generate forest fire risk maps and mark high risk areas and precautionary zones, which can help prevent fires earlier and efficiently.

d. Please provide information about the elements of AI modeling including where AI is used and information about preprocessing. For the latter, please explain if the data are ready to use or if additional manipulations are needed. Also, please describe the readiness and quality of the data (e.g., if formatting or indexing is required for efficiency or if bias/label noise impacts quality).	The model building preparation include data Labeling consistency and data augmentation. For the data labeling part, there are several fire forest experts and botanists label the fire plants image by hand. Secondly, we use data augmentation for solving the unbalanced data problem to improve the performance of the model.
Based on your use case and your understanding of the other use cases in your topic group, what are the challenges when using AI for this application and what recommendations can you offer to someone who intends to apply AI?	The application of artificial intelligence for natural disasters, especially for fire management, is still in the exploratory stage, the application is relatively scattered, the available data and standard AI model is lacking. Therefore, there are many challenges that we have to face. Based on the experience of AI systems for wildfire management, we hope to summarize a system architecture to provide reference for AI application and research in natural disaster in the future, including innovative core applications, data requirement, and standard AI method.

"Wildland Fire Detection and Strategic Intelligence from Camera and Satellite Data Analysed Using AI"

proposed by Tim Ball (1)
(1) Fireball Information Technologies, U.S.A.

For this use case, no completed questionnaire was received by the submission deadline. Therefore, the details of this use case have been omitted during the derivation of best practices in this technical report.

"Multimodal Databases and Artificial Intelligence for Airborne Wildfire Detection and Monitoring"

proposed by Maria João Sousa (1) , Alexandra Moutinho (1), and Miguel Almeida (2)
(1) IDMEC, Instituto Superior Técnico, Universidade de Lisboa, Portugal
(2) ADAI, University of Coimbra, Portugal

High-Level Questions	Responses
1. General information about the use case	

a. Please provide the name of the associated topic group (e.g., TG-AI for Flood Monitoring and Detection).	TG-AI for Wildfire Monitoring and Detection
b. Please provide the name of the use case from the proposal (e.g., Flash Flooding Monitoring System in Mexico).	Multimodal Databases and Artificial Intelligence for Airborne Wildfire Detection and Monitoring
c. Please provide a short description of the use case.	AI methods for wildfire detection and monitoring and data annotation pipelines
d. Please provide a short description of the datasets.	Multimodal datasets comprising thermal and visible range data for airborne
e. Please provide a short description of the model/method.	Deep neural networks using transfer learning and interpretable fuzzy modeling approaches
f. Please provide a short description of communications technologies that benefit or result from this use case.	NA
2. Modeling-related questions	
a. Please provide the problem statement including a description of the intended use.	- We aim to use multimodal data to detect and monitor wildfire using airborne vehicles (e.g., drones and high-altitude balloons) - We aim to use multimodal data to detect and monitor wildfire using airborne vehicles (e.g., drones and high-altitude balloons)
b. Please elaborate on the guiding principles and assumptions (as relevant).	We argue both approaches as necessary, complementary, and requiring concomitant efforts.

c. Please provide information about the outcomes (e.g., how the outcomes will be used, what their expected impact is, what the weaknesses/strengths of the outcomes are, and how the system will be monitored and improved).	Contributions on: - Wildfire detection and monitoring - Data annotation pipelines
d. Please provide information about the elements of AI modeling including where AI is used and information about preprocessing. For the latter, please explain if the data are ready to use or if additional manipulations are needed. Also, please describe the readiness and quality of the data (e.g., if formatting or indexing is required for efficiency or if bias/label noise impacts quality).	On the one hand, we investigate deployment-oriented models for wildfire detection and monitoring. On the other hand, we also research development-oriented solutions to empower the use of AI for wildfire detection and monitoring.
Based on your use case and your understanding of the other use cases in your topic group, what are the challenges when using AI for this application and what recommendations can you offer to someone who intends to apply AI?	NA

8.8 TG-AI for Vector borne Disease Forecasting

"AI and Vector-Borne Diseases"

proposed by Pantelis Georgiadis (1)
(1) The Cyprus Institute, Cyprus

High-Level Questions	Responses
1. General information about the use case	
a. Please provide the name of the associated topic group (e.g., TG-AI for Flood Monitoring and Detection).	TG-AI for Vector borne Disease Forecasting

b. Please provide the name of the use case from the proposal (e.g., Flash Flooding Monitoring System in Mexico).	Using machine learning for vector control and vector-borne disease risk mitigation
c. Please provide a short description of the use case.	In this use-case, field data from surveillance efforts for mosquitoes which are able to transmit diseases to humans (i.e. act as vectors of disease) are used to train machine learning models. The models are able to predict the spatio-temporal distribution and seasonality of certain mosquito species, which in turn can aid in vector control strategies. The ultimate aim is to mitigate the risk of vector-borne disease outbreaks.
d. Please provide a short description of the datasets.	Climate data (eg. CMIP6 or ERA5), land-use (LUH2) and population density data can be used to spatio-temporally characterize a grid for which field surveillance data are available, in order to train the models and perform predictions.
e. Please provide a short description of the model/method.	The field surveillance data are summarized into monthly presence/absence form for each grid cell/month, which are characterized by the climate, land-use and population density data. A binary classification machine learning model is then trained on this data, to predict whether a grid cell in a specific point in time has the appropriate conditions for the vector to survive (i.e. predict habitat suitability).
f. Please provide a short description of communications technologies that benefit or result from this use case.	The models create forecasts of vector habitat suitability with a monthly temporal resolution, which stakeholders can use for policy decision support.
2. Modeling-related questions	

a. Please provide the problem statement including a description of the intended use.	Climate change poses a difficult problem in the field of vector-borne diseases, as environmental and climate changes have the potential to significantly affect the spatial and seasonal distribution of suitable habitats for certain vectors. In this use case, we concentrated on the tiger mosquito (*Aedes albopictus)* which has spread to a large part of the world in the past decades. We aim to identify how climate change is going to affect the global suitable habitats of the tiger mosquito in order to advise future field surveillance and vector-control measures, especially in regions which were not suitable for the vector but will be in the future due to climate change.
b. Please elaborate on the guiding principles and assumptions (as relevant).	Due to limitations in the completeness of the training data (field surveillance data available from a limited range of regions in the world and gaps in the timelines), the assumption that no temporal dependence exists between months was made.
c. Please provide information about the outcomes (e.g., how the outcomes will be used, what their expected impact is, what the weaknesses/strengths of the outcomes are, and how the system will be monitored and improved).	The outcomes of the models can be used to assess the seasonal vector control strategies in regions where there are established populations of the tiger mosquito. In addition, it can prepare other regions where there is no established population to formulate effective surveillance strategies for risk mitigation of *Ae. albopictus* introduction.
d. Please provide information about the elements of AI modeling including where AI is used and information about preprocessing. For the latter, please explain if the data are ready to use or if additional manipulations are needed. Also, please describe the readiness and quality of the data (e.g., if formatting or indexing is required for efficiency or if bias/label noise impacts quality).	No AI pre-processing was performed. The input vector data is provided in regular grid format and manipulations were performed for the datasets to have a common 0.25^{o} grid cell size and monthly temporal resolution (through interpolation).

Based on your use case and your understanding of the other use cases in your topic group, what are the challenges when using AI for this application and what recommendations can you offer to someone who intends to apply AI?	Since vectors of diseases have a diverse biology and, especially the tiger mosquito, have been demonstrated to adapt to their local environment extremely effectively, the biological variability has to be taken into account and it's extremely difficult to obtain reliable data from several regions plagued by such problems, such as Africa, Asia and Latin America. A centralized repository for data gathering and management and established common protocols for surveillance and data reporting are crucial for researchers to be able to formulate effective AI models, which are tailor-made for specific regions and vector species.

8.9 TG-AI for Volcanic Eruption Forecasting

"Towards Forecasting Eruptions Using Machine Learning of Volcano Seismic Data"

proposed by Corentin Caudron (1) and Zack Spica (2)
(1) ISTerre, France
(2) University of Michigan, U.S.A.

High-Level Questions	Responses
1. General information about the use case	
a. Please provide the name of the associated topic group (e.g., TG-AI for Flood Monitoring and Detection).	TG-AI for Volcanic Eruption Forecasting
b. Please provide the name of the use case from the proposal (e.g., Flash Flooding Monitoring System in Mexico).	Towards Forecasting Eruptions using Machine Learning of Volcano Seismic Data
c. Please provide a short description of the use case.	We try to locate volcanic tremor associated with the 2018 Lower East Rift Zone Eruption in Hawai'i
d. Please provide a short description of the datasets.	We use earthquake catalogs and provide volcanic tremor locations

e. Please provide a short description of the model/method.	We train a regression model based on seismic amplitudes (features) and earthquake locations (target). We then locate the tremor associated with the 2018 Lower East Rift zone eruption using this model.
f. Please provide a short description of communications technologies that benefit or result from this use case.	N/A
2. Modeling-related questions	
a. Please provide the problem statement including a description of the intended use.	Volcanic tremor location is notoriously hard to locate
b. Please elaborate on the guiding principles and assumptions (as relevant).	We can use ML-based approaches of existing events to locate volcanic tremor focusing on amplitude of waveforms which decay as a function of distance. This allows us not to pick any wave arrival.
c. Please provide information about the outcomes (e.g., how the outcomes will be used, what their expected impact is, what the weaknesses/strengths of the outcomes are, and how the system will be monitored and improved).	The derived locations are similar to other existing ones (based on the papers published), but we also find differences compared to existing studies.
d. Please provide information about the elements of AI modeling including where AI is used and information about preprocessing. For the latter, please explain if the data are ready to use or if additional manipulations are needed. Also, please describe the readiness and quality of the data (e.g., if formatting or indexing is required for efficiency or if bias/label noise impacts quality).	The element of AI used is linear regression and multilayer perceptron. The seismic data is pre-processed and reduced to significant features. Those are basically amplitudes of the band-pass filtered waveforms and measured in the time domain.

Based on your use case and your understanding of the other use cases in your topic group, what are the challenges when using AI for this application and what recommendations can you offer to someone who intends to apply AI?	The results are promising but we would like to test how they would apply in areas monitored with less sensors.

"Real-time Volcano-Independent Seismic Recognition as Volcano Monitoring Tool"

proposed by Guillermo Cortés (1)

(1) University of Granada, Spain

High-Level Questions	Responses
1. General information about the use case	
a. Please provide the name of the associated topic group (e.g., TG-AI for Flood Monitoring and Detection).	TG-AI for Volcanic Eruption Forecasting
b. Please provide the name of the use case from the proposal (e.g., Flash Flooding Monitoring System in Mexico).	Real-time Volcano-Independent Seismic Recognition as Volcano Monitoring tool
c. Please provide a short description of the use case.	Proposal of a real-time seismic-based monitoring system for *any volcano* using statistical models built by other volcanoes with the ultimate aim of forecasting eruptions and detect dangerous volcano-seismic (VS) events (as collapses, floods, explosions…) for people living nearby.
d. Please provide a short description of the datasets.	Waveform data bases (DBs) labeled (a.k.a: manually classified in VS types) of ~ 10 volcanoes and open-access data from internet servers of seismic networks.

e. Please provide a short description of the model/method.	Statistical classification models, built by the labeled DBs, are used to classify continuous VS data remotely retrieved from a monitoring network of one given volcano. Automatic VS- catalogs are built by the classification output and are analyzed to detect eruption precursor's patterns and VS events involving population safety.
f. Please provide a short description of communications	Even if they're not scheduled in the project, a subsystem of SMS- cell phone warnings (in case of dangerous VS event detection) could be designed -as already exists in other monitoring systems.
2. Modeling-related questions	
a. Please provide the problem statement including a description of the intended use.	The VI.VSR system aims to build a 'volcano-independent' (portable) recognition model in order to detect and classify VS events on any volcano without the need of having any prior information (neither VSR models) of the volcano to be monitored.
b. Please elaborate on the guiding principles and assumptions (as relevant).	The main assumption regarding the VI.VSR system is that 'portable (Volcano-Independent) recognition models can be achieved using enough data from multiple types of volcanoes'. Besides the use of state-of-the-art technology: waveform standardization, feature selection and system architecture
c. Please provide information about the outcomes (e.g., how the outcomes will be used, what their expected impact is, what the weaknesses/strengths of the outcomes are, and how the system will be monitored and improved).	The direct outcome is the VS event cataloging, being extracted in real-time (*online monitoring*) or in an offline operation. VS catalogs allow: · *volcano monitoring* detecting and tracking the so-called precursor events

	· *offline studies* as 3D tomographies, source location, and identification of local precursors, of the monitored volcano The secondary outcome is the sequence of feature vectors: the tracking of changes in some of these features can be related to a precursory behavior or *precursory feature-patterns*. However: this identification is one of the objectives of the project which requires human elicitation and, eventually, the design of a working warning system.
d. Please provide information about the elements of AI modeling including where AI is used and information about preprocessing. For the latter, please explain if the data are ready to use or if additional manipulations are needed. Also, please describe the readiness and quality of the data (e.g., if formatting or indexing is required for efficiency or if bias/label noise impacts quality).	AI is used in the design and implementation of the VI. The VSR system, precisely in the building of statistical structured models (Probabilistic Graphical Models, as Hidden Markov Models – HMMs-) Data preprocessing process has been already detailed in question 2.e. *'The' main problem* regarding this VI.VSR system (and mainly all supervised VSR-based ones), is the data labeling reliability: manual labeling has to be reliable-enough to build the 'universal' labeled-DB as the first step to design the portable models. This encompasses a lot of hard working, human elicitation processes.
Based on your use case and your understanding of the other use cases in your topic group, what are the challenges when using AI for this application and what recommendations can you offer to someone who intends to apply AI?	Main challenge (in our proposal, and I assume in others similar) from the proposal is the availability of reliable, open access labeled data to be used to design the AI system. A QA on these DBs is crucial. This QA process may be controlled or taken into account under a standardized protocol. In spite of that, recommendations are clear: - Open data, open-access and open software. - Standardization of evaluation indexes for AI, recognition-based systems (as F1-score, accuracy or similar metrics). - Open-access resources and corpus to compare and evaluate diverse technologies performing the same tasks.

8.10 TG-AI for Hail and Windstorm Hazard Mapping

"Unified Methodology for Windstorm and Hailstorm Hazard Modeling and Mapping"

proposed by Alejandro Marti (1)

(1) Mitiga Solutions & National Supercomputing Center, Spain

High-Level Questions	Responses
1. General information about the use case	
a. Please provide the name of the associated topic group (e.g., TG-AI for Flood Monitoring and Detection).	TG-AI for Severe Convective Events Detection
b. Please provide the name of the use case from the proposal (e.g., Flash Flooding Monitoring System in Mexico).	Hailstorm and Windstorm hazard mapping in Georgia
c. Please provide a short description of the use case.	AI-based software tool that predicts the probability of observing a convective event for a specific day at a given location under certain atmospheric conditions.
d. Please provide a short description of the datasets.	Tabular dataset of more than 50 years of reported events in the US including location, time, intensity, etc. Reanalysis data providing historical hourly estimates of a large number of atmospheric, land and oceanic climate variables.
e. Please provide a short description of the model/method.	The models used are binary classifiers (yes or no) of different types. Each classifier is given a score depending on its performance, and an ensemble classifier is created using the outputs of the original ones weighted by their scores.
f. Please provide a short description of communications technologies	Effective communication of the risks derived from severe convective events to society and stakeholders in the shape of maps of probability of occurrence and return periods.

that benefit or result from this use case.	
2. Modeling-related questions	
a. Please provide the problem statement including a description of the intended use.	Estimation of the probability that under certain atmospheric conditions a thunderstorm can develop and become hazardous applying AI techniques on historical reanalysis data to build probabilistic hazard maps. The aim here is to overcome main deficiencies coming from sparse and sketchy observational datasets preventing the further spatial and temporal comprehensive hazard mapping.
b. Please elaborate on the guiding principles and assumptions (as relevant).	The guiding principle is that AI can pick up the signals and information contained in complex and large datasets that directly relate to weather related natural hazards, without any physical models or input from experts apart from initial variable selection. A secondary aim is to enrich local and sparse data with open, coherent, and long ranged data from public sources like Copernicus. The strongest assumption is that data from a far and different region of the world can be used to accurately train models that work in the region of interest with its own geographical peculiarities.
c. Please provide information about the outcomes (e.g., how the outcomes will be used, what their expected impact is, what the weaknesses/strengths of the outcomes are, and how the system will be monitored and improved).	There are two types of outcomes; one is data directly used to build coarse hazard maps, the other is used as input to a physical downscaling methodology where high probability extreme events are simulated, and the hazard intensity quantified of further hazard mapping actions.

d. Please provide information about the elements of AI modeling including where AI is used and information about preprocessing. For the latter, please explain if the data are ready to use or if additional manipulations are needed. Also, please describe the readiness and quality of the data (e.g., if formatting or indexing is required for efficiency or if bias/label noise impacts quality).	The data is processed according to standard data cleaning and preparation procedures as follows: · Data conversion and cleaning: the convective events annotations are processed and converted to the same internal format, so that they can be used indistinctly. · Data enrichment (feature engineering): the meteorological data are enriched with newly calculated features like maxs, mins, and additional compound parameters. · Data labeling & fusion: meteorological conditions and newly calculated features are associated with reported convective events. · AI model selection (classification models) and training · Test and prediction
Based on your use case and your understanding of the other use cases in your topic group, what are the challenges when using AI for this application and what recommendations can you offer to someone who intends to apply AI?	The main challenges are; first, to build the labeled data set for model training using sparse and sketchy observational datasets; second, to overcome the extreme data imbalance using resampling techniques.

“Predicting Hail with XBoost in Switzerland”

proposed by Hélène Barras (1)
(1) Météosuisse, Switzerland

For this use case, the proponent withdrew the use case. Therefore, the details of this use case have been omitted during the derivation of best practices in this technical report.

8.11 TG-AI for Multihazard Communications Technologies

“Utilizing AI & Probabilistic Modeling for Strategic Resilience”

proposed by Ahmad Wani (1) and Joe Paluska (1)
(1) One Concern, U.S.A.

High-Level Questions	Responses
1. General information about the use case	

a. Please provide the name of the associated topic group (e.g., TG-AI for Flood Monitoring and Detection).	AI for multi-hazard communications technologies. Reference document: [FGAI4NDM-I-131]
b. Please provide the name of the use case from the proposal (e.g., Flash Flooding Monitoring System in Mexico).	Ready (emergency response system that incorporates AI/ML) in Kumamoto City
c. Please provide a short description of the use case.	One Concern combines AI/machine learning and probabilistic modeling with data from the natural and manmade environment to create a digital twin of target regions. The digital twin is used to predict damage to the built environment from natural disasters.
d. Please provide a short description of the datasets.	Data comes from 4 sources: Data vendors (e.g., Corelogic, Estated); Open source directly related (e.g., available from municipalities); Open source indirectly related (e.g, satellite images); Direct collection.
e. Please provide a short description of the model/method.	The model uses k-nearest neighbor and statistical imputation to fill in missing building features. It uses ML techniques (e.g., PCA and logistic regression) to predict damage probabilities given building features and hazard intensities. Random Forest is used to detect potential flood levee locations to construct synthetic levee data for locations with missed ground truth data.
f. Please provide a short description of communications technologies that benefit or result from this use case.	One Concern uses automated emails to communicate about predicted damage during and following a disaster. More broadly, telecommunications infrastructure could be included in the modeling of the digital twin, enabling the estimation of technological resilience.
2. Modeling-related questions	

a. Please provide the problem statement including a description of the intended use.	The One Concern problem statement is to predict flood inundation and building damage from flood and seismic shaking during and after natural disasters. The intended use is to enable rapid situational awareness for emergency responders and to facilitate efficient response.
b. Please elaborate on the guiding principles and assumptions (as relevant).	The key point is to highlight regions of higher risk to natural disasters by modeling hazard and exposure. The models are developed to be informative for a specific region, but general enough to provide actionable results when a new disaster occurs.
c. Please provide information about the outcomes (e.g., how the outcomes will be used, what their expected impact is, what the weaknesses/strengths of the outcomes are, and how the system will be monitored and improved).	The outcomes are used to organize and prioritize emergency response efforts during and after a natural disaster. The expected impact is that regions with higher levels of damage will receive mitigations and resources faster than less impacted areas. The strength of this model is that it accounts for building features and fragility, where many other catastrophe models only account for hazard intensity. This model also learns from past events and can be updated when new disaster related data is available. As the digital twin is expanded to include dependency risk (such as power, water, and telecommunications networks), the model will be improved to include impacts to these systems.
d. Please provide information about the elements of AI modeling including where AI is used and information about preprocessing. For the latter, please explain if the data are ready to use or if additional manipulations are needed. Also, please describe the readiness and quality of the data (e.g., if formatting or indexing is required for efficiency or if bias/label noise impacts quality).	ML approaches are used in several steps of this methodology: (1) synthesizing data in order to fill in material gaps in the digital twin, in particular, for building characteristics; (2) predicting the probability of damage to buildings from seismic shaking; and (3) creating synthetic levee data by using digital elevation data to integrate flood defense information to improve flood prediction. Data are preprocessed by imputing missing features, interpolating hazard information to the building level, and incorporating physics-based models with ML to constrain ML-based predictions.

Based on your use case and your understanding of the other use cases in your topic group, what are the challenges when using AI for this application and what recommendations can you offer to someone who intends to apply AI?	The primary challenge for our use cases arises from the fact we cannot directly validate all resilience analytics. ML can be used to synthesize data and generate simulations based on the hybrid physics-based/ML approach. Unsupervised AI/ML and even non-hybrid, supervised AI/ML do not work in this space given the fragmented and incomplete nature of the data. A mix of hybridized modelling and subject-matter expertise is essential to iterate (in a Bayesian manner) useful models to quantify resilience in a consistent, comparable, and benchmarkable manner.

"AI Enabled Citizen-centric Decision Support System for Disaster Managers"

proposed by Rajkumar Upadhyay (1), Pankaj Kumar Dalela (1), Saurabh Basu (1), Sandeep Sharma (1), and Anugandula Naveen Kumar (1)

(1) Centre for Development of Telematics, India

High-Level Questions	**Responses**
1. General information about the use case	
a. Please provide the name of the associated topic group (e.g., TG-AI for Flood Monitoring and Detection).	TG-AI for Multi-hazard Communications Technologies Reference document: FGAI4NDM-I-131
b. Please provide the name of the use case from the proposal (e.g., Flash Flooding Monitoring System in Mexico).	AI enabled Citizen-centric Decision Support System for Disaster Managers

c. Please provide a short description of the use case.	The use case explores how AI can assist disaster managers to use communication tools in an effective way. Using data from the C-DOT developed Integrated Alert System and other media types, the decision support system provides text classification, prediction, and transfer learning through neural network and supervised learning approaches to: (a) Filter information: the model categorizes received information into actionable classes for disaster managers from social networks and other agencies. (b) Predict alert scope: the model informs the disaster manager of the best way to target a message to different recipients and with different communication mediums (c) Message content analyser: the model to determine the effectiveness of warning messages to be sent to the targeted populations. Reference documents: FGAI4NDM-I-011R1
d. Please provide a short description of the datasets.	The system uses alert feeds from PAN India Integrated Alert System developed by C-DOT. The data is also prepared from social networking feeds for filtering information. For predicting alert scope, tele-density and other infrastructure data is taken from respective concerned organization's sources in India.
e. Please provide a short description of the model/method.	The system uses various supervised learning algorithms as well as Natural language processing based pre-trained models like BERT.
f. Please provide a short description of communications technologies that benefit or result from this use case.	The decision support system will benefit the disaster managers in effective utilization of communication media like SMS, Internet based notifications, Radio, TV, social media, etc. for alerting vulnerable populations.
2. Modeling-related questions	

a. Please provide the problem statement including a description of the intended use.	The problem system is to assist the disaster managers in decision making for efficient warning dissemination to the targeted vulnerable population through Integrated Alert System.
b. Please elaborate on the guiding principles and assumptions (as relevant).	Trust and inclusiveness
c. Please provide information about the outcomes (e.g., how the outcomes will be used, what their expected impact is, what the weaknesses/strengths of the outcomes are, and how the system will be monitored and improved).	The outcome is to identify best means like communication channels, message content, and provide filtered information to the disaster managers for decision making. The system will be improved based on feedback channel.
d. Please provide information about the elements of AI modeling including where AI is used and information about preprocessing. For the latter, please explain if the data are ready to use or if additional manipulations are needed. Also, please describe the readiness and quality of the data (e.g., if formatting or indexing is required for efficiency or if bias/label noise impacts quality).	AI use in filtering and categorizing information from social media and other feeds. The data received from social media need to be preprocessed. The alert source feeds from Integrated Alert System are CAP (Common Alerting Protocol) compliant.
Based on your use case and your understanding of the other use cases in your topic group, what are the challenges when using AI for this application and what recommendations can you offer to someone who intends to apply AI?	The main challenge is the data availability and correctness of available data with respect to the ground situation.

"Proposal of an AI Chatbot Use Case as a Multihazard Communication Technologies"

proposed by Kiyonori Ohtake (1), Toshiaki Kuri (1), Tsutomu Nagatsuma (1), Masugi Inoue (1), and Hideo Imanaka (1)
(1) NICT, Japan

High-Level Questions	**Responses**
1. General information about the use case	
a. Please provide the name of the associated topic group (e.g., TG-AI for Flood Monitoring and Detection).	TG-AI for multi-hazard communications technologies. Reference document: FGAI4NDM-I-131
b. Please provide the name of the use case from the proposal (e.g., Flash Flooding Monitoring System in Mexico).	NICT – Japan, consists of three AI-based tools that operate together to leverage social network service (SNS) messages and to assist with disaster communication.
c. Please provide a short description of the use case.	The NICT solution contains: · DISAANA: a disaster information analyser, which uses natural language processing (Question & Answering) to discover relevant information from Japanese SNS data (Twitter). · D-SUMM: an information summarizer, which uses the "BERT" natural language processing model to derive situational awareness for a specified area. · SOCDA: a chatbot system, which uses a rule-based method to distribute and collect disaster information about victims, damage areas, and evacuation places and communicates with first responders. Collected texts are analyzed by both DISAANA and D-SUMM, and a big-picture of a damaged area can be drawn with collected disaster-related information. DISAANA and D-SUMM are freely available at https://disaana.jp/ and they have proven to be useful for disaster response of local governments in actual disasters. SOCDA is also freely available at LINE ID:@socda and it is in the process of conducting a demonstration test. In addition, some local governments in Japan started to use commercial versions of SOCDA that are customized to each local government.

d. Please provide a short description of the datasets.	Japanese SNS (Twitter and LINE) messages and manually created texts that simulate SNS messages in disaster situations. We prepared a training dataset by annotating these messages to build a ML model.
e. Please provide a short description of the model/method.	Supervised machine learning methods, especially SVMs and BERT, are used. We have been using SVMs until now, but we are now developing it into deep learning such as BERT.
f. Please provide a short description of communications technologies that benefit or result from this use case.	By appealing as a fast-paced medium, SNS can benefit from this use case. Chatbot technology also results from this use case.
2. Modeling-related questions	
a. Please provide the problem statement including a description of the intended use.	During a large-scale natural disaster, SNS can be used for confirming safety, sharing a variety of information on damage, collecting relief information, and more. On the other hand, anyone can easily post information on SNS, so it is also recognized that false rumors and unverified information can easily confuse/mislead the real world and that it is not easy to obtain desired information from SNS, where an enormous amount of data is exchanged. AI models automatically extract not only disaster-related information but also its contradicting information. If both kinds of information are extracted, then one of them may be incorrect, so the system calls attention to this by presenting both possibilities along with the contradictory information.
b. Please elaborate on the guiding principles and assumptions (as relevant).	Massive amount of disaster-related information that is important to the rescue workers and the victims is transmitted into SNS, but it takes a lot of time to search for such information using a conventional search engine. Analyzing SNS with AI instead of humans and sharing the results in an easy-to-understand manner make disaster response more efficient and support evacuations of victims

c. Please provide information about the outcomes (e.g., how the outcomes will be used, what their expected impact is, what the weaknesses/strengths of the outcomes are, and how the system will be monitored and improved).	DISAANA is a question answering system focusing on “what” and “where” questions. D-SUMM is a system that automatically extracts disaster-related information from Japanese Twitter and summarizes disaster conditions in a compact and user-friendly form. DISAANA and D-SUMM analyze place names appropriately and they can visualize their outputs on a map and can compose their outputs in a list form, in which the output is semantically categorized. Although these outputs support first responders including local governments, and citizens as victims, we become aware of the limits of handling information that is voluntarily posted on Twitter. SOCDA can bi-directionally communicate with users: collecting comprehensive information from users and providing detailed information to those who need it.
d. Please provide information about the elements of AI modeling including where AI is used and information about preprocessing. For the latter, please explain if the data are ready to use or if additional manipulations are needed. Also, please describe the readiness and quality of the data (e.g., if formatting or indexing is required for efficiency or if bias/label noise impacts quality).	AI models for natural language processing are used to detect disaster-related information on SNSs posts. As the AI-engine, the latest version of D-SUMM uses a deep-learning technology called Bidirectional Encoder Representations from Transformers (BERT). To achieve such AI-engine, we must prepare learning data to detect disaster-related information.
Based on your use case and your understanding of the other use cases in your topic group, what are the challenges when using AI for this application and what recommendations can you offer to someone who intends to apply AI?	N/A

“AIDERS: Real-time Artificial Intelligence for DEcision Support via RPAS Data AnalyticS”

proposed by Constantinos Heracleous (1), Panayiotis Kolios (1), and Maria Michaelopoulou (1)
(1) KIOS CoE, Cyprus

High-Level Questions	**Responses**
1. General information about the use case	
a. Please provide the name of the associated topic group (e.g., TG-AI for Flood Monitoring and Detection).	Focus Group on AI for Natural Disaster Management (FG-AI4NDM-I-147)
b. Please provide the name of the use case from the proposal (e.g., Flash Flooding Monitoring System in Mexico).	AIDERS: Real-time Artificial Intelligence for DEcision support via RPAS data analyticS
c. Please provide a short description of the use case.	The AIDERS project aims at developing application-specific algorithms and a novel mapping platform that will harness the large volume of data that first responders are now able to collect through heterogeneous sensors (including visual, thermal, and multispectral cameras, LIDAR, CBRN sensors, etc.) on-board RPAS units, and converting that data into actionable decisions for improved emergency response.
d. Please provide a short description of the datasets.	The AIDERS project uses datasets for training and testing its AI solution acquired from multiple sensors attached as payloads to RPAS units. The datasets include RGB images, thermal images, multispectral images, elevation, structural data from lidar sensors, and multi-gas detection data from CBRNE sensors.
e. Please provide a short description of the model/method.	The AIDERS project utilizes machine learning models such as the Darknet Framework for training, and the tiny version of the YoloV4 Neural Network model for real-time object detection.

f. Please provide a short description of communications technologies that benefit or result from this use case.	Dashboards and Emergency Services Network (ESN) are benefited from the AIDERS use case.
2. Modeling-related questions	
a. Please provide the problem statement including a description of the intended use.	During emergency response, situational awareness is essential for first responders to devise effective mission plans and for safety. Remotely Piloted Aircraft Systems (RPAS) or drones are excellent tools that if used wisely can provide real-time view of the situation. However, how is this possible to achieve? The AIDERS project objective is to utilized RPAS units along with AI techniques to provide real-time situational awareness to first responders during emergency response. To achieve this objective AI techniques for object detection and identification capable of running on RPAS units as well as, algorithms for intelligent RPAS path planning and techniques for sensor data fusion and data analysis are designed.
b. Please elaborate on the guiding principles and assumptions (as relevant).	For effective situational awareness the some of the AI algorithms developed through the AIDERS project must run onboard RPAS units. These includes algorithms for object detection and area mapping. Moreover, the data streams from RPAS units must be transferred to the mission control center and to incident commanders.
c. Please provide information about the outcomes (e.g., how the outcomes will be used, what their expected impact is, what the weaknesses/strengths of the outcomes are, and how the system will be monitored and improved).	The AIDERS solution provides an AI toolkit that consist of application-specific algorithms and novel mapping platform utilizing AI techniques that will harness the large volume of data that first responders are now able to collect through heterogeneous sensors (including visual, thermal and multispectral cameras, LIDAR, CBRN sensors, etc.) on-board RPAS units, and converting that data into actionable decisions for improved emergency response. This saves valuable time during emergency response and provides an informed view of the situation in hand.

d. Please provide information about the elements of AI modeling including where AI is used and information about preprocessing. For the latter, please explain if the data are ready to use or if additional manipulations are needed. Also, please describe the readiness and quality of the data (e.g., if formatting or indexing is required for efficiency or if bias/label noise impacts quality).	Detects in real-time objects of interest (e.g., vehicles, people) and provides information about their location using the Global Positioning System. The detected objects are highlighted in each frame using bounding boxes and are also represented as 3D objects on the map. The detection models are pre-trained using Convolutional Neural Networks with aerial imagery obtained from both the AIDERS team and public datasets. Each frame from UAVs live video feed is also resized prior to being provided as an input to the network.
Based on your use case and your understanding of the other use cases in your topic group, what are the challenges when using AI for this application and what recommendations can you offer to someone who intends to apply AI?	The main challenge is the appropriate data acquisition by the RPAS units during emergencies that are then used by the AI solution to provide the necessary output.

"Situational Awareness System for Disaster Response Using Space-based AI (SARA)"

proposed by Reza Arghandeh (1), Eren Erman Ozguven (2), and Michele Gazzea (3)
(1) Western Norway University & StormGeo AS, Norway
(2) Florida State University, U.S.A.
(3) Western Norway University, Norway

High-Level Questions	**Responses**
1. General information about the use case	
a. Please provide the name of the associated topic group (e.g., TG-AI for Flood Monitoring and Detection).	TG-AI for Multi-hazard Communications Technologies
b. Please provide the name of the use case from the proposal (e.g., Flash Flooding Monitoring System in Mexico).	Situational Awareness System Response for Hurricanes in Florida (SARA)

c. Please provide a short description of the use case.	The use case explores the potential of satellite images, meteorological data and AI to increase the situational awareness against natural disasters. The output is a Geographical Information System (GIS) map showing the most vulnerable areas in a region (e.g., a city) before the event, which can be conveyed into dashboards for early warning and immediate response.
d. Please provide a short description of the datasets.	High-resolution satellite images are acquired for the study area. Typical images have from 4 to 8 spectral bands (ranging from blue to infrared) and a resolution between 0.5 and 3 meters/pixel. Meteorological dataset consists of hourly weather data (wind and precipitations) will be investigated in future Infrastructure datasets (building locations, roadways, emergency stations, etc.) are shapefiles with geographical coordinates and attributes.
e. Please provide a short description of the model/method.	The main model for satellite image analysis is a Unet-based deep learning model. The model characterizes tree structure and land use properties. In future, we will design a new strategy to make the training procedure less dependent on data via self-learning and consistent learning with unlabeled data, for example using cross-pseudo regression technique (CPR).
f. Please provide a short description of communications technologies that benefit or result from this use case.	Highly-vulnerable geographical locations are conveyed into a GIS dashboard for early warning and immediate response by emergency responders and municipality operators.
2. Modeling-related questions	
a. Please provide the problem statement including a description of the intended use.	The problem is how to enhance the situational awareness of our communities and infrastructures with respect to natural disasters, in particular hurricanes.

b. Please elaborate on the guiding principles and assumptions (as relevant).	The main principle is that remote sensing technologies, here in the form of satellite imagery, can provide up-to-date, cheap, fast and accurate observations of the study areas. This leads to a highly efficient way of monitoring, and consequently a more updated communications about criticalities among the parties.
c. Please provide information about the outcomes (e.g., how the outcomes will be used, what their expected impact is, what the weaknesses/strengths of the outcomes are, and how the system will be monitored and improved).	The main outcome is a GIS map showing the most vulnerable areas in a selected region to municipalities, emergency responders, and citizens. It can be easily conveyed into dashboards for early warning and better preparedness (e.g., resource allocation, preventive restoration). The strength is the efficient and fast analysis using earth observation compared to slow manual surveys. A possible weakness could be the lack of details and enough quality of the data for some areas to make accurate analysis. The system will be improved by adding weather data and weather forecast, for better risk predictions.
d. Please provide information about the elements of AI modeling including where AI is used and information about preprocessing. For the latter, please explain if the data are ready to use or if additional manipulations are needed. Also, please describe the readiness and quality of the data (e.g., if formatting or indexing is required for efficiency or if bias/label noise impacts quality).	AI models are used to analyze satellite images. Specifically, to estimate the trees' structure (density, height, type and canopy structure) and classify land use. Satellite images, especially if acquired from commercial operators, require little preprocessing as ortho-rectification and pan-sharpening processes are already done by the provider. Additional pre-processing steps consist of contrast enhancement and scaling, for example into the range (0,1) for better ML training.
Based on your use case and your understanding of the other use cases in your topic group, what are the challenges when using AI for this application and what recommendations can you offer to someone who intends to apply AI?	One of the challenges is the transferability: make sure that an approach built for a use case can still work (in case with little modifications) with another use case. Shortage of data to train models is often also a limitation.

“Multi-hazard Use Case for Operations Risk Insights and Day One Relief for Natural Disaster Response”

proposed by Jil Christensen (1), Tom Ward (2), Chet Karwatowski (2), and Rinku Kanwar (2)
(1) Day One Relief, U.S.A.
(2) IBM, U.S.A.

High-Level Questions	Responses
1. General information about the use case	
a. Please provide the name of the associated topic group (e.g., TG-AI for Flood Monitoring and Detection).	AI for multi-hazard communications technologies. Reference document: FGAI4NDM-I-131
b. Please provide the name of the use case from the proposal (e.g., Flash Flooding Monitoring System in Mexico).	Operations Risk Insights (ORI) with Watson from IBM in US and India
c. Please provide a short description of the use case.	ORI aggregates global, country, regional, or local risk alert data from many trusted sources. ORI applies natural language processing and machine learning to identify higher impact risks
d. Please provide a short description of the datasets.	ORI uses alert feeds from GDACS, USGS, TWC, NWS, Meteo and many other WMO based national alert services. Plus, ORI ingests and analyzes news feeds from 1000’s of trusted news sources.
e. Please provide a short description of the model/method.	ORI uses Natural Language Processing for finding and aligning new data to high and medium severity risk events. ORI uses a Support Vector Machine (SVM) – linear programming-based machine learning model for high model result transparency.

f. Please provide a short description of communications technologies that benefit or result from this use case.	ORI uses automated email and slack based user notifications. Aggregated alert, severity and geospatial location details can also be obtained via API.
2. Modeling-related questions	
a. Please provide the problem statement including a description of the intended use.	The ORI problem statement is to identify and mitigate multi-hazard NDM risk via monitoring and communications for early warning of high and medium severity natural disasters including earthquakes, floods, cyclones, wildfires, and pandemic tracking
b. Please elaborate on the guiding principles and assumptions (as relevant).	Trust and transparency of ML results is a guiding principle for ORI.
c. Please provide information about the outcomes (e.g., how the outcomes will be used, what their expected impact is, what the weaknesses/strengths of the outcomes are, and how the system will be monitored and improved).	The key outcome from ORI is to identify high and medium severity risks to be mitigated for key user points of interest. These risk alerts will be used to identify which events to mitigate and which to monitor. The strength of this solution is less false alarms and details to review for disaster relief, IT and business resiliency leaders.
d. Please provide information about the elements of AI modeling including where AI is used and information about preprocessing. For the latter, please explain if the data are ready to use or if additional manipulations are needed. Also, please describe the readiness and quality of the data (e.g., if formatting or indexing is required for efficiency or if bias/label noise impacts quality).	AI is used for both NLP (Natural Language Processing) to find and associate relevant news and social media notices to global risk events for more details. AI is also used for Machine Learning model refinements to assess risk severity. Some NLP preprocessing to filter less severe risk types from the ML model is completed. For the most part, the alert data feeds in compliance with CAP (Common Alerting Protocol) are of good quality. Those which are not CAP compliant typically have lower data quality.

Based on your use case and your understanding of the other use cases in your topic group, what are the challenges when using AI for this application and what recommendations can you offer to someone who intends to apply AI?	The main challenges to be overcome are the inconsistent reporting and granularity of data globally to develop and maintain an application like ORI. Specifically, a good county or district level of data granularity is available for the US, much of Europe and other developed countries. But, less developed countries typically only have details at a country level. So, deep insights and forecasts are much more challenging for parts of Africa, SE Asia, South America and other regions.

Appendix I

A.1 Model card

MODEL CARD	Category:	Number:
…		
MODEL INFORMATION – General description		
Name/Owner		
Model name		
Model date		
Model version		
..		
MODEL INFORMATION – Usage		
Intended Use		

Application area/region	
License	
Resource information	
Contact	
…	
MODEL INFORMATION – Functionality	
Task	
Assumptions	
Learning algorithm	
Input	
Output	
…	
MODEL INFORMATION – Performance	
(Train, test, validation data)	
Evaluation metrics/performance	
Benefits (of algorithm)	
Weaknesses/Limitations (of algorithm)	

Generalisability	
Quality Assessment	
…	
Added value	
Proposition	
Strengths	
Benefits (in terms of NDM)	
…	
Further considerations	
Weaknesses/Limitations (in terms of NDM)	
Side-effects	
Risks	
Legal considerations	
Recommendations	
Caveats	
…	