How to use the power of AI to reduce the impact of climate change on Switzerland

Recommendations for the Swiss society and economy to become more resilient against the impact from a radically changing climate

Make key technologies broadly available and overcome challenges through key methodologies in climate- and AI-related fields.

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5.3 Artificial intelligence for climate impact assessments

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5.3.1 Climate impact assessments

Climate impact assessments can be based on earth observation data from historical natural disasters. Climate models allow the forecasting of the damage probability of assets considering specific greenhouse gas emission scenarios (Section 4.1). Such assessments are most often performed qualitatively or on a regional level only, due to limited data and automation. However, with the availability of frequent earth observation data, global climate projections, and machine-learning (ML) methods (a subcategory of artificial intelligence) near real-time, quantitative assessments at global scale have become feasible (Yuan et al., 2020 and Jain et al., 2023).

5.3.2 The history of AI

It can be explained in four phases (Figure 5.2): i) Until the 80's, *Expert Systems* with manually-crafted symbolic representations and rules dominated the domain. These systems turned out to be very limited and brittle. ii) With the advent of the internet, data driven *Machine Learning* approaches with handcrafted features started to dominate. Many of them are still in use, especially in business applications. iii) In 2012, *Deep Learning* started to disrupt domains like computer vision and natural language with fully data driven models, resulting in ever-improving object detection and language translation models. However, large amounts of annotated data sets are required to train these models. iv) Most recently (2022), *Foundation Models* (Sun et al., 2023) emerged (e.g., GPT used for ChatGPT), with unprecedented performance. They are fully data-driven and trained by self-supervision, meaning that they learn the underlying characteristics of the data themselves and only need limited labels to be fine-tuned to various down-stream tasks.

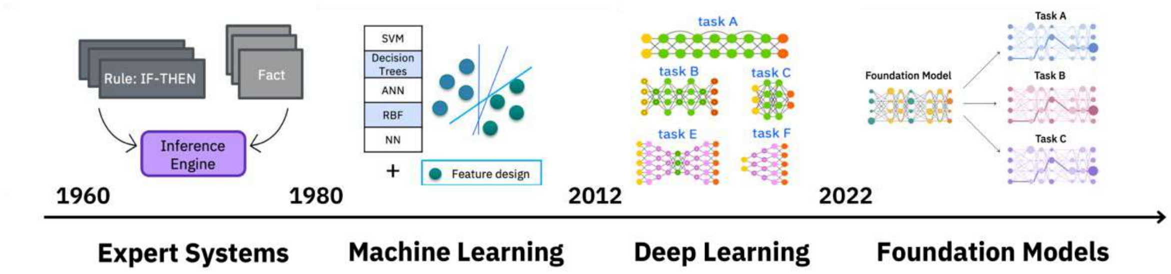

Figure 5.2: Historic view on AI algorithm paradigms: from hand-crafted and specific, to fully data driven and general models.

5.3.3 Application of AI models for climate impact assessments

In this section, we try to provide an example workflow describing AI models to assess flood risks by i) the observation of past flood events and ii) by predicting future flood and damage risks (Figure 5.3). This workflow, with some differences, is also applicable for other natural hazard impact assessments, such as wildfires or droughts. The main steps of the flood impact workflow are:

1. To assess a past flood event, Sentinel-1 (radar signal) and Sentinel-2 (RGB and NIR signal) imagery can be used in combination with ***semantic segmentation models*** to detect the flood extent (Muszynski et al., 2022). Such models assign to each pixel of an image a class like water or land-mass, respectively. In combination with digital elevation maps, the flood depth can be determined. Historic flood risk maps can be computed from the flood extent observations. Further, ***semantic change detection*** using Siamese deep-neural-networks with pre- and post-imagery of the event enables the classification of the damage state of critical infrastructure (e.g., buildings and streets) (Nitsche, et al. 2023).
2. To predict future flood events, extreme precipitation patterns need to be generated. This can be obtained by AI Weather Generators which are trained on observed local weathers and are conditioned on climate change estimated by global climate models. Traditional ***Markov chain sampling*** (Steinschneider et al., 2013) or deep learning models like ***variational autoencoders*** (Oliveira et al., 2022) have been demonstrated to result in synthetic weather, analogous to widely discussed deep-fakes used to generate faces of non-existing persons. However, the aim in this case is to provide precipitation time-series, as expected to observer with a one-in 1'000- or 10'000-year return period, as input to flood models.
3. Currently, physics-based numerical models solving partial differential equations (e.g., shallow wave equation for floods) are used to calculate a future flood event (e.g., flood depth and velocity) based on various topographic and hydrological modalities (e.g., elevation maps, land use, and soil class) in combination with the synthetic precipitation from the weather generator. High resolution assessments are computationally demanding and thus, are performed infrequently. Recently, AI models, such as flood ***susceptibility models*** (Meuriot et al., 2021) or ***physics-informed neural networks*** (Karniadakis et al., 2021) have demonstrated similar performance, however at orders of magnitude reduced computational cost. The susceptibility model is a regression model (e.g., k-nearest neighbors, support vector machine or random forest) and performs a point-wise assessment of the flood depth based on model training on historic events and topographic and hydrological modalities. A physics-informed neural network combines a data-driven learning process with constraints from the governing physical laws of the process to model. Effectively, a regularization term is added to the loss-function of the neural network, describing the physical law by partial differential equation. For all these models, some calibration might be required. Thus, flood mappings of past events from step 1 (of the Workflow listed here) can be applied to improve the prediction accuracy.
4. ***Impact functions*** (Aznar-Siguan et al., 2019) can be used to estimate the damage of future flood events. These relations can be derived from observed hazard variables and damages of specific infrastructure (step 1) (e.g., flood depth and building damage probability). The predicted flood depth and velocity from step 3 can then be used to sketch out the damage risk of the infrastructure in a given region, based on assets indicated on Open Street Map[40] (free and open geographic database)

[40] https://www.openstreetmap.org

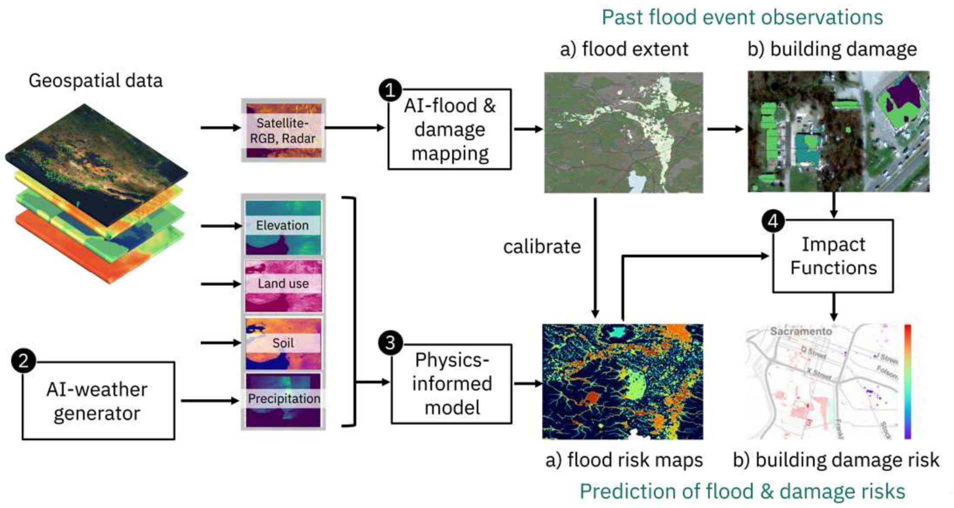

Figure 5.3: Example workflow of AI methods applied for flood event impact assessments.

Sustainable AI for Climate Impact: Several of the discussed models were borrowed from other disciplines, such as the computer vision domain and were adapted to the ideosyncratic nature of Earth Observation and climate data, which include many more modes (e.g., infrared bands), compared to the RGB channels of consumer grade cameras and thus, is called ***multi or hyper-spectral data***. Furthermore, the ***AI model efficiency*** is of high importance, to result in sustainable applications with minimal electric energy, as petabytes of data are required to be transferred and analyzed. Thus, approaches like recursive inference using low resolution data in areas of minimal variation, compared to high-resolution satellite images in areas of high class variation (e.g., in case of water detection: lakes and coastal areas, respectively) were proposed (Brunschwiler et al., 2023). Further shortcomings of AI models need to be considered as well, including potential biases, limited explainability, and poor ability to adapt to changing conditions (Yuan et al., 2020). However, the discussed speed-ups from AI workflows do not only result in ***near real-time and quantitative assessment of climate risk at scale***, but they also enable to run ensembles of workflows to perform model ***validation, calibration, and uncertainty estimations***, as well as ***counterfactual assessments*** (Jones, Anne, et al., 2023). Those responsible AI features can support decisionmakers and stakeholders to anticipate the impacts of climate change and plan effective mitigation and adaptation actions[41].

The ***Maturity of AI Models*** in the climate impact domain varies. Traditional machine learning models are already operational for a few years to perform natural disaster segmentation (e.g., the Global Flood Monitoring product of the Copernicus Emergency Management Service (Salamon et al., 2021). Deep-neural-networks and physics-informed neural networks are currently being tested to perform hazard assessments and forecasts at scale (e.g., FloodHub, the world-wide fluvial flood forecasting (Moshe et al., 2020). In comparison, earth observation (Jakubik et al., 2023) and weather foundation models (Nguyen et al., 2023) just emerged in 2023 and are still in the research state (Mukkavilli et al., 2023), but first models are being validated at scale and are expected to penetrate the market in 2024[42].

[41] https://gpai.ai/projects/responsible-ai/environment/
[42] https://www.ecmwf.int/en/about/media-centre/news/2023/how-ai-models-are-transforming-weather-forecasting-showcase-data

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