
# 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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## Imprint

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Figure 0.1: Participants of the Workshop on AI and Climate.

## SATW promotes projects in the field of artificial intelligence and access to data

As part of activities associated with its Artificial Intelligence and Energy and Environment focus topics, SATW promotes projects in the field of artificial intelligence and identifies technologies that are important for climate neutrality and security of supply. This white paper and the accompanying fact sheet are the result of collaboration with IBM Research Europe - Zurich, Switzerland.

The project was launched with a kick-off workshop on 15 June 2023 attended by a broad community that included representatives of research, industry and government[1]. During the workshop, the 50 or so participants (Figure 0.1) identified important factors that require consideration in the context of the timely uptake of responsible and trustworthy AI for the purpose of creating a more sustainable and resilient future for everyone. In the following weeks and months, working groups of workshop participants and additional contributors discussed these topics in more depth and described them in greater detail. An editorial board (authors and editorial board above) coordinated the whole content creation process and more.

[1] https://www.satw.ch/de/news/ki-freund-und-helfer-in-zeiten-des-klimawandels

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# 1 Pre-amble: By Alessandro Curioni

Climate change has been on the world's radar for years and its effects are getting ever more significant. Switzerland has long been attuned to the urgence of sustainability, and the Swiss policymakers, companies, academia and the public have already been paying significant attention to help the environment thrive and slow down the effects of the changing climate. This is commendable, but we can and should do more. While regulatory measures and strategies remain of critical importance, so does cutting-edge technology. It can help us address the enormous challenges our society is facing because of the changing climate. And this is where artificial intelligence (AI) can be of great assistance, to streamline sustainability reporting, monitor climate impacts and greenhouse gas emissions from satellites and to forecast and alert about weather scenarios and extremes, to result in a more sustainable and resilient society.

To truly reap the benefits of AI though, several elements have to come together. We need to make sure that proper infrastructure is in place as well as the needed skills and talents. Collaboration is relevant, considering the interdisciplinary challenge with methods in place to share and build on observations and code. That is exactly what this whitepaper of the Swiss Academy of Engineering Sciences outlines – and that's what the authors hope will help us all to make a difference and to turn the challenges into opportunities.

During this study, experts from industry, government and academia came together to discuss technology trends in AI, Earth observation and Earth models with the potential to substantially benefit climate and sustainability in Switzerland, along with their corresponding applications. The team identified challenges for those technologies to unfold their full potential and proposed recommendations and actions for decision makers and practitioners to overcome those constraints.

I encourage any reader of this important document to put the suggestions made here into action. I know that the authors of the white paper will continue working on developing cutting-edge tech and deploying it in a variety of ways to reduce global warming and improve the resilience of the society. We all need to work together in a collaborative environment that fosters open innovation and promotes the dissemination and deployment of climate-related solutions. It is our responsibility to ensure that future generations still have a chance to live in a sustainable world.

Alessandro Curioni
IBM Fellow, Vice President Europe and Africa and Director IBM Research Europe – Zurich

## 2 Executive summary

Switzerland faces significant challenges from climate change, including direct impacts like infrastructure damage and indirect effects through economic transitions. With this whitepaper, the Swiss Academy of Engineering Sciences (SATW) lays out on how to unfold the full potential of recent technological and methodological breakthroughs like artificial intelligence (AI), Earth observation data, open-science principles, and AI workflow integration to increase the resilience of the society against climate risks, to accelerate the net-zero transition, and to benefit from sustainability related opportunities.

The study provides recommendations for researchers, data scientists and engineers and is a call for action for decision makers in the Federal Government, funding organisations, universities, private entities, and the Swiss society. The statements made in this study have been crafted by around 50 domain experts from more than 30 Swiss academic, government, and industrial institutions.

The main recommendations and action points for decision makers are:

1. ***Build capacity for Swiss actors in the field of AI for climate and sustainability:*** Reinforce national competence centers and research bodies in their capacity to support AI for climate and sustainability.
2. ***Ensure access to and involvement in international programmes:*** Negotiate participation in European and international initiatives supporting AI for climate and sustainability.
3. ***Implement the principles of open science:*** Reinforce open data and open-source principles (e.g., EMBAG), including data parsimony.
4. ***Promote scalable and reusable code and machine learning model base:*** Provide resources to enable collaborations between environmental scientists and software engineers.
5. ***Accelerate the translation of research results into market impact:*** Strengthen and establish inter- and transdisciplinary collaborations as well as Public-Private Partnerships (PPP).
6. ***Implement responsible AI applications:*** Conduct Technology Impact Assessments based on the UN SDG Agenda.
7. ***Foster a quantitative understanding of the implications of climate change:*** Conduct data-driven studies on climate-related impacts on all Swiss stakeholders.

The whitepaper starts with the authors vision, followed by a description of the expected climate impact on Swiss society, economy and ecosystem. Subsequently, technological and methodological enablers which can accelerate the transition towards a more sustainable society are depicted. The focus of the whitepaper is the discussion around gaps, hurdles, and opportunities to unlock the full potential of these enablers. As a result, we list recommendations and action points for decision makers and practitioners. Further, six case studies showcase AI applications which make a difference in climate impact and transition risk assessments. Finally, a reference architecture for reusable AI workflows, relevant to researchers who want to run their code at scale is provided.

With this manuscript, the authors hope to have a positive impact on the assessment of physical climate risk and more generally Switzerland's sustainability strategy, while enabling the industry to benefit from new opportunities.

A condensed form of the statements made in this whitepaper are available as a factsheet with the same title.[2]

[2] https://www.satw.ch/en/publications/ai-to-reduce-the-impact-of-climate-change-on-switzerland

## 3 Vision statement

Swiss stakeholders are more sustainable through quantitative climate impact and transition-risk assessments. State-of-the-art Artificial Intelligence (AI) and Earth System Models are key enablers to perform such assessments based on Earth observation data. They also raise general awareness about climate change and improve the current approaches focused on achieving climate resilience.

Swiss competence centers and innovation hubs focused on climate and sustainability include academics, government entities, the private sector, as well as citizens and are empowered to embrace, co-design and share climate-focused AI technologies. This collaborative environment fosters open innovation and facilitates the dissemination of digital climate applications, accelerates progress, and enables Swiss stakeholders to benefit from opportunities within the rapidly evolving climate sector.

These competence centers also provide computational infrastructure, facilitate access to open-data and methods to re-use research code and further develop existing AI models and explore novel innovative solutions. Funding organizations support interdisciplinary teams of researchers and software engineers, to fully embrace and implement best-practices in software development for operational climate and sustainability applications at scale.

Responsible and trustworthy AI principles are adopted from the very beginning of the application development cycle – they convey trust in data-driven decision making. Access to climate insights is provided to anybody in the society to raise awareness and result in equal opportunities.

By making the best use of these key enabling technologies in the described manner, the wider public, the government, the industry, and the public sector can better anticipate climate-related risks and thus implement required actions to collaboratively move towards a more sustainable and resilient future for everybody.

# 4 Impact of climate change on Swiss society, economy and ecosystem

In a climate change context, several climate extreme events are expected to become more frequent and intense. It is essential to assess climate physical risk properly in order to be able to design appropriate adaptation strategies. On the other hand, climate change mitigation through limitation of greenhouse gas emissions is crucial.

This chapter reviews the main impacts due to climate change in Switzerland, describes the affected stakeholders and the key actors in the development of climate services, and discusses the issues of adaptation and mitigation towards a net-zero economy.

## 4.1 Climate-change impacts in Switzerland

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### 4.1.1 Observed changes in meteorological and hydrological variables

Climate change is in full swing worldwide, as shown by Figure 4.1. On 17 November 2023, the global mean surface temperature anomaly with respect to the 1850–1900 period exceeded for the first time in history the 2°C threshold (+ 2.07°C). The effects of climate change are also clearly visible in Switzerland, where the mean temperature over the 2014–2023 decade has been 2.7°C above the 1871–1900 average as displayed in Figure 4.2, and the eight warmest years since 1864 were all recorded after 2010[3]. Related to this, the height of the zero-degree line has been substantially increasing, especially since 1990 (MeteoSchweiz 2023, Fig. 5.15, p.76), which has resulted in a thinner and shorter snow cover (FOEN 2021). Since in the winter months more precipitation falls as rain than snow due to rising temperatures, runoff increased in most catchments. In contrast, a decrease in average runoff was generally observed in summer - except in highly glaciated catchments (FOEN 2021, p.33). Hundreds of streams, rivers and lakes are subject to fundamental changes in the water cycle (Höge et al., 2023).

[3] https://www.meteoswiss.admin.ch/climate/climate-change.html

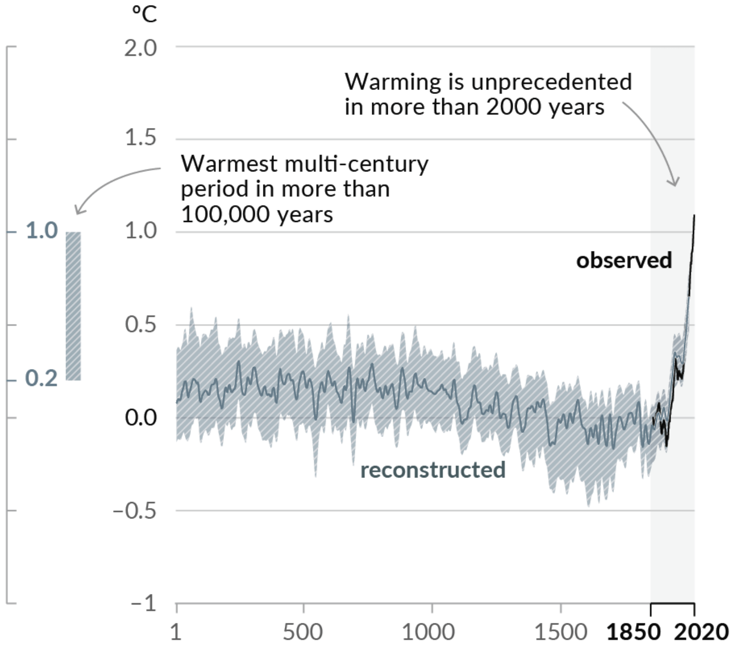


Figure 4.1: Changes in global surface temperature relative to 1850–1900 as reconstructed (1–2000) and observed (1850–2020). Source: IPCC (2021, Fig. SPM.1(a)).

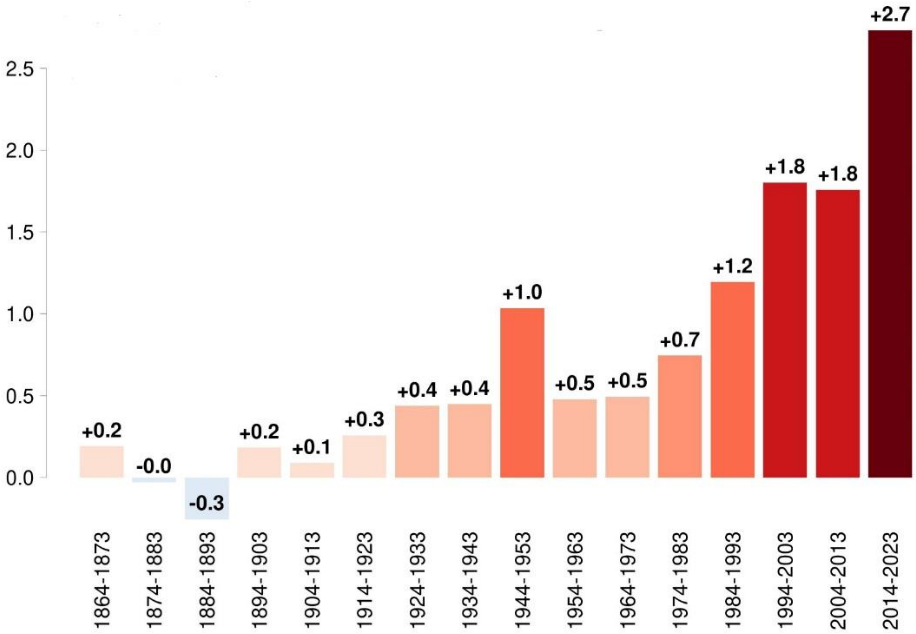


Figure 4.2: Deviation (in °C) of nationwide mean temperature relative to 1871–1900 for the 16 decades since records began. Source: MeteoSwiss website[3].

Observations further show that not only is the mean temperature changing, but also that extreme weather events are becoming more frequent. Days with extremely high temperatures have increased (MeteoSchweiz 2023), as have the frequency and intensity of extreme precipitation events in the past decades (Scherrer et al., 2016); see Meteoschweiz[4] for trends in further climate indicators. Drought conditions in recent summers have led to very low river discharge with enormous consequences for

[4] https://www.meteoschweiz.admin.ch/service-und-publikationen/applikationen/ext/climate-indicators-public.html

aquatic life, record melting of glaciers, and long-lasting high wildfire danger conditions; see, e.g., BAFU[5]. Figure 4.3 summarizes the main observed changes.

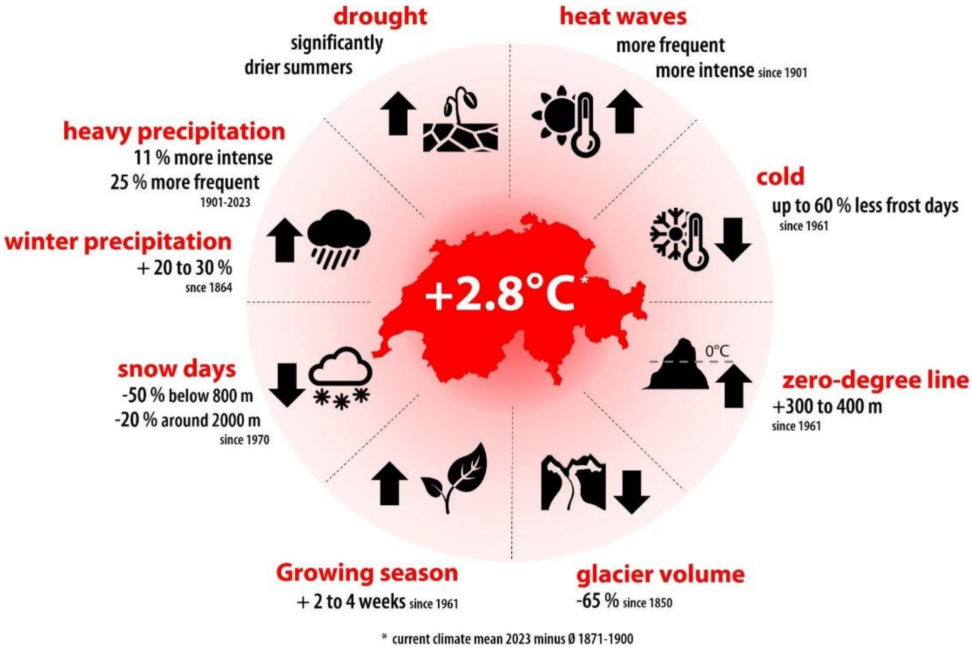


Figure 4.3: Key changes observed in Switzerland. Source: MeteoSwiss website[3].

### 4.1.2 Projected changes in meteorological variables

The magnitude of future climate change depends on the cumulative (past, present, future) worldwide emissions of greenhouse gases (IPCC, 2021). The magnitude of future climate change is therefore ultimately linked to future emissions. Socio-economic scenarios for these emissions cover a range of cases, going from strong to little or no mitigation actions. The severity of climate-related changes in Switzerland across all variables is substantially reduced in the strong mitigation scenario compared to the scenario with little to no mitigation (CH2018, 2018). Thus, rapid and effective mitigation is imperative; see BAFU[6] about the Swiss mitigation strategy.

Under the umbrella of the Swiss National Centre for Climate Services (NCCS), the Federal Office of Meteorology and Climatology MeteoSwiss together with ETH Zurich provide detailed information about projected changes of the physical climate until the end of the 21st century on their data and information portal[7]. The current information on future climatic changes stems from the CH2018 climate scenarios (CH2018, 2018; Fischer et al., 2022). Key expected changes are a continued increase in mean and extreme high temperatures, a decrease in summer mean precipitation, a rise in the duration of the longest precipitation-free period in summer, an increase of the frequency and intensity of heavy precipitation events, and a reduction of the snow falling period and cover in winter (CH2018). New Swiss climate scenarios are currently being elaborated by MeteoSwiss, ETH Zurich and partners, and will be released in 2025 (CH2025 Swiss Climate Scenarios; see Meteoswiss[8]). In addition to climate scenarios, a report by the Swiss Academies of sciences summarizes the relevant findings of

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[5] https://www.bafu.admin.ch/bafu/de/home/themen/wasser/dossiers/hitzewelle-und-trockenheit.html#-329505868
[6] https://www.bafu.admin.ch/bafu/de/home/themen/klima/fachinformationen/emissionsverminderung/verminderungsziele/ziel-2050/klimastrategie-2050.html
[7] https://www.nccs.admin.ch/nccs/de/home/klimawandel-und-auswirkungen/schweizer-klimaszenarien.html
[8] https://www.meteoswiss.admin.ch/about-us/research-and-cooperation/projects/2023/climate-ch2025.html

IPCC's AR5 for Switzerland covering the physical climate, but also climate impacts, adaptation and mitigation issues (Akademien der Wissenschaften Schweiz 2016). Based upon the CH2018 climate scenarios and under the umbrella of the NCCS, a report (FOEN 2021) by the Federal Office for the Environment (FOEN) provides updates on how climate change affects river discharge, groundwater, water temperatures, snow, and glaciers.

AI tools are well suited to complement and extend the existing systems and methodologies as further discussed, e.g., in Section 5.2 in the case of numerical weather prediction and climate model simulations.

### 4.1.3 Impacts

Climatic changes in Switzerland are expected to have broad and important impact and to affect all sectors. Some of the main risks are increasing heat stress (with detrimental effects for human health and leading to a decline in productivity at work); increasing levels of drought (with related agricultural yield reduction, water shortages, and decrease in summer hydroelectric production); more flooding and slope instabilities (causing injury and property damage); degradation of water, soil and air quality (inducing human health impairment and negatively affecting ecosystem services); spread of pests, diseases and exotic species (detrimental to human health, reducing agricultural yield, and damaging forest products and services). For a detailed overview, see the risk analysis performed by the FOEN in Köllner et al. (2017) and NCCS[9],as well as Akademien der Wissenschaften Schweiz (2016). For additional information about the impacts of climate change, see the links provided by Agroscope[10] and the Federal Office for Agriculture (FOAG)[11] for agricultural production including food supply, the FOEN[12] for forests, theSwiss Financial Market Supervisory Authority (FINMA)[13] for the financial sector, the NCCS[14] for cities, and the NCCS[15] for health. Moreover, the study by Köllner et al. (2017) is currently being updated and re-evaluated, and associated results are expected in 2024 on the NCCS-website[16]. Several new insights regarding the impact of climate change in Switzerland are also expected from the currently running NCCS-Impacts programme[17] that analyzes cross-sectoral impacts and tries to elaborate actionable climate services. Further insights are expected from dedicated research centers such as the Centre for Climate Systems Modeling (C2SM), the ETH AI center, the Weather and Climate Risks Group at ETH Zurich, the Mobiliar Lab for Natural Risks, and the Expertise Center for Climate Extremes (ECCE) at the University of Lausanne.

### 4.1.4 Adaptation

The diverse climatic impacts require adaptation by the Swiss society that will include behavioral, structural, regulatory, legal, and technical measures. In Switzerland, the adaptation strategy adopted by the Federal Council sets out a framework for a coordinated approach on the federal level (see

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9 https://www.nccs.admin.ch/nccs/en/home/climate-change-and-impacts/analyse-der-klimabedingten-risiken-und-chancen.html
10 https://www.agroscope.admin.ch/agroscope/en/home/topics/environment-resources/climate-air-quality/agriculture-under-climate-change.html
11 https://www.blw.admin.ch/blw/de/home/nachhaltige-produktion/umwelt/klima0.html
12 https://www.bafu.admin.ch/bafu/de/home/themen/wald/fachinformationen/belastungen-im-schweizer-wald/auswirkungen-des-klimawandels-auf-den-wald.html
13 https://www.finma.ch/en/documentation/dossier/dossier-sustainable-finance/risiken-aus-dem-klimawandel/
14 https://www.nccs.admin.ch/nccs/en/home/regions/cities-and-municipalities/climate-change-in-cities.html
15 https://www.nccs.admin.ch/nccs/en/home/the-nccs/priority-themes/human-health.html
16 https://www.nccs.ch/
17 http://www.nccs.admin.ch/impacts-en

FOEN[18]). With their pilot programme "Adaptation to Climate Change" (see NCCS[19]), where the second phase ended in May 2023, the Federal Council exemplified good practices in various sectors.

Key to successful adaptation in terms of planning and implementation are high-quality information on future hazards, in-depth knowledge of the current and future vulnerability and resilience of human and natural systems, and details on future exposure. We also need to better appraise how their interactions evolve over time (Simpson et al. 2021). AI provides potentially important tools to address associated gaps (in particular the information gaps in vulnerability and exposure) through effective use of Earth observation data (e.g., Kuglitsch et al. 2023). Challenges in that respect are the spatial and temporal inhomogeneity of data on vulnerability, the exponential increase in data volumes, and ensuring open public access data. For additional insight about the potential use of AI for impact assessment, see Section 5.3.However, waiting for the best possible knowledge to become available is sometimes not an option owing to some adaptation measures having long lead times and due to the shifting landscape of climate risks and their drivers (Garschagen et al. 2021, Simpson et al. 2023). There is also often little agreement amongst planners and decision makers on the objectives of specific adaptation responses, or such objectives are not constant over time (Marchau et al. 2019).

Approaches of decision making under the circumstances of deep uncertainties such as robust decision making (RDM), dynamic adaptive policy pathways (DAPP) and exploratory modeling have gained traction in the past 10 years in Europe and beyond (Kwakkel and Pruyt 2013, Marchau et al. 2019). These approaches foster flexibility, resilience, and the ability to learn and adapt over time. They provide a practical framework for dealing with the complex and unpredictable nature of future challenges, ensuring that adaptation strategies are better suited to navigate uncertainties and changing conditions (Haasnoot et al. 2020, Cradock-Henry et al. 2023).

Currently, key challenges remain for supporting adaptation and decision making under deep uncertainty. For example, the thresholds to which adaptation measures maintain their effectiveness relies on knowledge about which adaptation works and under which conditions, i.e., changes in exposure and vulnerability and their interaction over time. This information is seldomly available and often relies on plausible scenarios of future development and modeling of adaptation (Magnan et al. 2021).

Furthermore, Large Language Models (LLMs) can digest substantial amounts of information for various downstream tasks including climate information retrieval (Koldunov & Jung, 2024). With proper prompt engineering, LLMs can be deployed to improve the assessment of effectiveness and feasibility of specific adaptation responses. This, in turn, guides decision-makers in selecting the most suitable adaptation options and their combinations (Vaghefi et al., 2023).

Finally, in the shorter term, risk management is dependent on effective early warning systems and rapid information provision during and after events (see e.g., Swisstopo[20]). Ideally, warning systems should not only warn of hazards but should also provide an estimate of the expected impacts. With its OWARNA2[21] and Weather4UN[22] programs, MeteoSwiss will continue introducing impact-based warnings and further improve the direct relevance of warnings within existing and well-established communication channels.

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[18] https://www.bafu.admin.ch/bafu/en/home/topics/climate/info-specialists/adaptation/strategy.html
[19] https://www.nccs.admin.ch/nccs/en/home/measures/pak.html
[20] https://www.swisstopo.admin.ch/en/services/rapidmapping.html
[21] https://www.meteoschweiz.admin.ch/ueber-uns/forschung-und-zusammenarbeit/projekte/2020/owarna2-mch.html
[22] https://www.meteoswiss.admin.ch/about-us/research-and-cooperation/projects/2021/weather4un.html

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## 4.2 Managing transition risks – towards a lower-carbon economy

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[8] IBM Research – Europe, Switzerland

For stakeholders to move towards a low-carbon economy, bears administrative, legal, and other economic risks, beyond the obvious physical climate disaster risks, as depicted in Figure 4.4 These transition risks related to climate change are critical for organizations that need to manage the transition from a carbon-intensive economy to a more sustainable, lower-carbon economy. Transition risks are multi-faceted and arise from the need to adapt to evolving climate change mitigation policies, technological advances and changing consumer preferences. They pose significant challenges, including potential fluctuations in the value of assets, the emergence of stranded assets due to unforeseen or premature depreciation and shifts in operating costs. These changes are inseparably linked to a company's carbon emissions, as efforts to reduce these emissions often require significant changes in business operations and strategies.

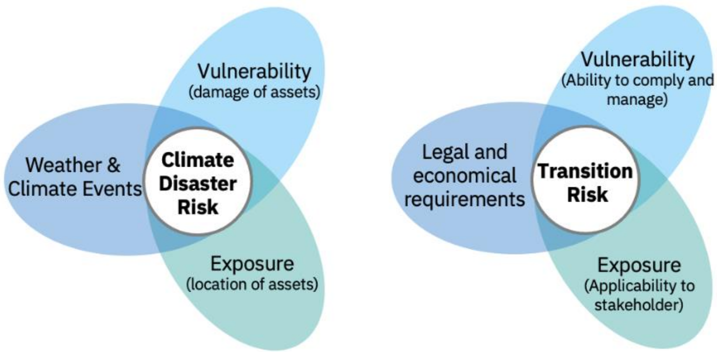


Figure 4.4: “Definition” of Climate Disaster Risk vs. Transition Risk

In this chapter we aim at providing guidance on how to identify exposures of stakeholders and how to deal with them, based on the examples of “Assessing Carbon Emissions” and linked “Required Reporting”. As to what extent an organization is vulnerable, i.e., has the ability to deal with imposed requirements, is beyond the scope of this introduction.

### 4.2.1 Assessing carbon emissions

As the global community intensifies efforts to combat climate change, a critical step for organizations is the comprehensive assessment of their carbon emissions across all scopes, including those directly produced (Scope 1), indirectly from purchased energy (Scope 2), and other indirect emissions related to the organization's activities (Scope 3). This provides a clear understanding of an organization's environmental impact and lays the foundation for targeted reduction strategies and sustainable business practices.

These assessments are of central importance for understanding and steering effective climate actions by organizations. Research has outlined a large need for investment shifts towards net-zero pathways (Klaassen et al., 2023). Recognizing these needs, organizations are increasing their efforts to define and pursue ambitious net-zero targets. While these efforts theoretically support an effective transition (Höhne et al, 2021), unstructured strategies about net-zero targets alone will very likely not contribute to the needed drastic emission reductions (see also Bingler at al., 2022). For instance, the failure to define clear projections for residual emissions represents a major obstacle to achieving net-zero emissions (Buck et al., 2023).

### 4.2.2 Required reporting (e.g., ESG, TCFD, TNFD)

While the immediate risk might not be apparent, the evolving legal requirements for detailed corporate reporting on environmental, social, and governance (ESG) matters are introducing significant organizational and operational challenges, which could lead to substantial economic transition risks (see Figure 4.4). In today's era, where transparency and sustainability are increasingly at the forefront of corporate responsibility, the demand for accurate and comprehensive ESG reporting frameworks has intensified. Entities are now expected to disclose their ESG performance, align reporting standards such as with the recommendations of the Taskforce on Climate-related Financial Disclosures (TCFD), or increasingly, adopt the principles outlined by the Taskforce on Nature-related Financial Disclosures (TNFD). This section provides insights into the significance of these reporting standards, their implementation, and the advantages they bring to organizations, stakeholders, and the environment.

While the reporting standards serve as guidelines or soft boundaries for reporting on sustainability matters, governments are increasingly tightening enforcing their application. Amongst the forerunners is the European Union. With the verification of the European Sustainability Reporting Standards, the EU is advancing towards mandatory disclosure from 2025 on (EU, 2023). Thus, more rigorous and strict reporting can be expected in the near future.

From a theoretical asset pricing perspective, disclosures mitigate investors' uncertainty, driven, for instance, by climate regulations. This results in the benefits of emissions disclosure manifesting as higher liquidity of a company's securities, consequently reducing the firm's cost of capital. The empirical evidence related to the impact of carbon disclosure on the cost of capital is growing fast (He et al., 2013; Kleimeier, 2016; Bolton and Kacperczyk, 2021).

### 4.2.3 How to guide companies on their net-zero strategy

Embarking on the journey towards achieving net-zero emissions is an ambitious but essential goal for companies aspiring to align with global climate objectives. This outlines key steps, from conducting a baseline emissions assessment to setting interim targets and selecting appropriate mitigation measures. By providing a roadmap tailored to an organization's specific context and industry, this guide empowers companies to navigate the complexities of their net-zero transition, fostering a sustainable and resilient future.

There is currently great interest from companies to reduce emissions associated with their products. This is due to the growing demand for more sustainable products and legislation to reduce emissions in productive sectors, including industry, transport, agriculture, and construction. Current efforts by companies to reduce emissions are aligned with the Special Report on Global Warming produced by the IPCC (SR15), indicating the limit of 1.5°C above pre-industrial and 2050 as target year for net-zero $CO_2$ emission levels (IPCC, 2018). It is also important to consider that the European Green Deal was established in line with SR15, by defining several policy initiatives with the goal of making Europe the first climate-neutral continent by 2050 (Fetting, 2020). Following the new rules and legislation in the scope of the European Green Deal is vital for companies whose consumer market includes EU countries.

***Baseline emission assessment:*** A first major challenge for companies to establish net-zero targets is defining reliable frameworks for reducing emissions. In this sense, initiatives such as Science Based Targets (SBTi) have emerged guidance protocols for companies towards net-zero emissions (Watson, 2021). Fundamentally, this type of initiative is focused on standardized strategies, known as 'net-zero standards', for guiding companies to reduce their emissions by 50% by 2030 and achieve net-zero emissions by 2050 using reliable procedures based on climate science. To reach SBTi-based net-zero standards, companies must reduce emissions in the scope 1, 2 and 3 to zero or to a residual level that must be neutralized by removing atmospheric $CO_2$ and adopt measures to sustain C sinks over time. The comprehension of potential trade-offs should be also taken into consideration by companies when defining the mitigation strategies (Sharifi, 2021). These strategies towards net-zero emissions have to follow mitigation pathways, which gives the basis for definition of mitigation targets (Bataille, 2020; Bergero et al., 2023). The net-zero guidance is usually set up in several parts, including (i) preparation of mitigation actions, (ii) measurements of emissions, (iii) definition of mitigation targets, such as base year, target year and interim target, (iv) neutralization of residual emissions, (v) reporting of the mitigation progress, and (vi) assessment of impacts (McGivern et al., 2022).

All these stages require intense processing of unstructured data, for which new AI-based tools can provide very robust support. Combining this intuition with a vast amount of existing transition plan frameworks, Bingler et al. (2023) provide a first conceptual basis for an automated AI tool that can assist the decision-making process. Assessing the common ground among 28 transition plan frameworks, the authors create a holistic set of 88 indicators to investigate inconsistencies and potential greenwashing behavior of companies. Highlighting the importance of this analysis, it is crucial for companies developing their own net-zero strategies to be aware of these indicators. This awareness not only helps in ensuring their strategies are genuinely effective and transparent but also aids in distinguishing their authentic efforts from superficial or misleading claims of sustainability.

### 4.2.4 Beyond emissions

While the global threat of climate change to economies is widely recognized, along with the feedback loop between climate change and economic factors, there is considerably less understanding of the economic impact posed by other nature-related challenges. These impacts include water stress and pollution, deforestation, biodiversity loss, invasive species, and soil degradation. Each poses significant risks that are yet to be fully quantified in economic terms, suggesting a gap in our current understanding of environmental challenges. Similarly, the influence of economic activities extends beyond the scope of increasing greenhouse gas emissions and their contribution to climate change. Economic actions have broader implications for nature loss, affecting diverse aspects of our environment. The development of policies effectively mitigating the negative impacts of economic activities on nature, and vice versa, remains an area only partially explored.

Nature underpins many economic activities, and its degradation poses real and financial risks to the economy. However, the quantification of such risks is challenging for several reasons. First, nature involves several dimensions and cannot be reduced to a single measure. Second, the direct consequences of nature loss tend to be local and context specific. Hence, looking at indirect effects of nature loss – for instance, by analyzing the propagation of nature-related shocks through supply chains – is crucial to understand the actual risks of nature loss for the economy and the financial system. Third, nature loss is deeply interconnected with climate change. For instance, deforestation is not only harmful for biodiversity, but also increases climate risks as less carbon emissions are absorbed from the atmosphere going forward. A more accurate quantification is the first of many steps that we need to take to appropriately deal with these risks and achieve a more sustainable allocation of resources.

Measuring the economic and financial risks associated with natural hazards is a major challenge given the diverse and complex interactions in nature. However, valuable insights can be obtained from the data in company disclosures and reports that provide information on the risks and impacts associated with nature. By using Natural Language Processing (NLP) technologies, we can gain deeper insights into the behavior of companies. However, for these tools to be fully effective, more comprehensive and standardized environmental reporting by companies is needed. Such improved reporting would provide the necessary breadth and quality of data to feed into analytical tools, enabling more accurate risk assessments and informed decisions. This synergy of technological advances and data practices is crucial for investors and policymakers to protect both economic stability and environmental health.

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## 4.3 Affected and involved stakeholders

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### 4.3.1 Physical climate risks

As mentioned in Section 4.1, an extended report (Köllner et al., 2017) by the Federal Office for the Environment (FOEN) analyzed and classified physical climate risks (and opportunities) for Switzerland. It defined priority risks that make up the "risk landscape" and must be considered in adapting to climate change. The results from eight regional case studies conducted with the participation of numerous experts from science, industry and administration have been merged into a Switzerland-wide synthesis. They identified the following main risks:

- Greater heat stress (impairment of human health, lower work performance, more cooling energy);
- Increasing levels of drought (harvest losses, water shortage, danger of forest fire, hydro energy loss);
- Rising snowline (yield losses in winter tourism);
- Greater risk of flooding (personal injuries, property damage);
- Decreasing slope stability / more frequent mass wasting (personal injuries, property damage);
- Impaired water, soil, and air quality;
- Change in habitats, species composition and landscapes (degradation of biodiversity);
- Spread of harmful organisms, disease and alien species (impairment of human health and health of farm animals and pets, harvest losses in agriculture, deterioration of forest products and services);
- "Wild card" risks (risks that are difficult to assess, unexpected risks);
- Climate-related impacts abroad with impact on Switzerland (indirect risks; see below).

This comprehensive analysis of climate-related risks for Switzerland is currently being re-evaluated and updated, and the new results are expected in 2024. For more details on the projections of meteorological and hydrological variables, see Section 4.1.

### 4.3.2 Main sectors impacted by climate change and regulations

Almost all sectors are impacted by climate change, be it directly or indirectly. Consequently, there is a strong need for adaptation in all sectors and a stringent necessity for mitigation in combination with rules, regulations, normative pressure, etc.

Some key impacts on the main sectors related to the physical climate risks listed above are provided in Table 4.1.

Table 4.1: Affected stakeholders for various physical climate risks.

| Sector | Affected Stakeholders | Affection by Impacts |
| --- | --- | --- |
| Health | Vulnerable persons, health services, hospitals | Stronger heat waves, extreme events, spread of diseases, negative effects on air quality, psychological stresses |
| Energy | Energy companies | Extreme events (on facilities), meteorological changes (on production), seasonal water supply |
| Agriculture and Forestry | Forest owners, wood industry, farmers, retailers | Extreme events, drought, spread of pests/diseases/alien species, change of growth conditions, need to change crops and forest species |
| Tourism | Tourism regions/ communities, organizers, tourists | Landscape changes (glaciers, snow cover), extreme events / natural hazards (on infrastructure), shift from winter to summer tourism |
| Mobility | Travelers, people responsible for infrastructures | Extreme events (heat, precipitation, soil movement etc.) on infrastructure |
| Services | Companies, employers, employees | Working conditions (heat), reduced labor productivity |
| Building and Infrastructures | Owners | Extreme events, heating/cooling demand |
| Industry | Firms, owners | Changes in demand of products (national and international), damage to infrastructures, supply chain interruption, working conditions, increase in cooling demand, reduced labor productivity |
| Finance and Insurance | Banks, Insurance companies, individuals | Extreme events, changes of insurability, changes of risks of (stranded) investments |
| Landscape, Biodiversity | | Glacier/permafrost melting, drought, changes in vegetation, invasive species and biodiversity loss |
| Water | Water users | Change of water supply, shortage in summer, seasonal shifts of precipitation, more intense events, extreme events (drought, heat, precipitation) on water bodies |

Almost all sectors are also affected by emission reduction regulations (transition climate risk) and some by technical regulations (energy, mobility); for more details on these aspects, see Section 4.2. In the energy sector, there are requirements for the extension of renewable production which may also impact landscape. Furthermore, there might be use restrictions or regulations in the water sector as well as investment regulations and risk assessment/reporting obligations in the financial sector.

### 4.3.3 Indirect risks from climate change abroad

Switzerland has well-developed international connections. It is linked to a very wide variety of world nations and their players, whether through trade relations, direct investments, tourism, foreign policy, migration, or development cooperation. As a result of this integration, Switzerland is also indirectly affected by developments and events abroad, such as climate-related disruptions of supply chains and other climatic events. Based on Kohli et al. (2018), the following areas of influence and interrelationships between climate change and the individual sectors have been identified as central for Switzerland:

- Financial services (e.g., impacts on global financial sector could damage Swiss investments abroad);
- Food sector (e.g., agricultural goods/upstream products come from areas vulnerable to climate change);
- Energy supply (some of the imported energy sources come from countries vulnerable to climate change);
- Security (fragility of states in which Switzerland is engaged (business/political) has increased due to climate change);
- Development cooperation (climate change has major impacts on the livelihoods of development cooperation target groups);
- Economic performance (impairment of production conditions or demand structure abroad by climate change);
- Migration (migration from vulnerable countries or of people facing decreasing economic prospects).

Since 2023, the analysis of the indirect impacts of global climate change on Switzerland is being deepened through a dedicated project within the NCCS-Impacts programme[23]. Associated results are expected at the end of 2025.

#### 4.3.4 Key players in providing services to assess climate risks, report ESGs and support companies on net-zero strategy

There are different kinds of players providing services to assess climate risks:

1. Under the umbrella of the National Center for Climate Services (NCCS), its members and partners develop user-centered climate services in a variety of priority themes[24] related to climate change, e.g., country-wide climate scenarios, hydrological changes, crop pests, forest impacts or human and animal health. The NCCS is organized in the form of a virtual center and brings together administrative federal bodies. It coordinates the collaborative development and provision of climate services and promotes dialogue among all actors involved. Currently, a major program is running to elaborate actionable climate services that support climate adaptation and climate mitigation in a cross-sectoral perspective.
2. Federal Offices of the Swiss government such as MeteoSwiss[25], the FOEN[26], and the Swiss Federal Office of Energy (SFOE)[27] are providing services on climate change, climate impacts, and are also recipients of climate services. MeteoSwiss, the Federal Office of Meteorology and Climatology, provides a substantial amount of climate data, services, and information. It operates the national surface and radar measurement network and collects, manages, and analyses weather and climate data. It also operates the numerical ICON weather and climate forecasting model over

[23] https://www.nccs.admin.ch/nccs/en/home/climate-change-and-impacts/nccs-impacts.html
[24] https://www.nccs.admin.ch/nccs/en/home/the-nccs/priority-themes.html
[25] https://www.meteoswiss.admin.ch/
[26] https://www.bafu.admin.ch/bafu/en/home.html
[27] https://www.bfe.admin.ch/bfe/en/home.html

Switzerland and produces forecasts, issues information, warnings, and advice. It also directly provides meteorological or climatological data for relevant sectors like renewable energy production (e.g., solar, wind) and is mandated to regularly update climate scenarios for Switzerland. MeteoSwiss is also engaged in applied research and development. The Swiss GAW/GCOS Office at MeteoSwiss coordinates atmospheric and climate observations in Switzerland in support of national partner institutions. The FOEN publishes reports[28] on environmental issues, national statistics on greenhouse gas emissions and collects a wide range of data that is available to the public, but also commissions universities, consulting companies and engineering firms to (scientifically) answer specific questions related to climate change, mitigation, and adaptation. It implements compensation projects reducing emissions abroad which can be acquired by actors mandated to offset some of their $CO_2$ emissions (like fuel importers).

3. ProClim[29], the climate forum of the Swiss Academy of Sciences, acts as platform linking science and the public (policy, media, economy, etc.) and provides assessments of current scientific knowledge on different climate-related questions. It coordinates the participation of Swiss scientists in international assessments (like IPCC, IPBES) and maintains a broad network of scientists of all disciplines working on climate-related topics. This allows ProClim to consult and provide experts on a wide range of issues in response to climate-related inquiries.
4. Universities, universities of applied sciences and research centers and their experts provide key basic research outcomes as a fundament to develop services out of it and are also taking on mandates to analyze specific climate impacts and develop specific climate services. Some examples are the Mobiliar Lab for Natural Risks, the Expertise Center for Climate Extremes (ECCE) at the University of Lausanne, the Center for Climate System Modelling (C2SM) and the Weather and Climate Risk Group, both at ETH Zurich.
5. Consultant companies provide different (paid) services on demand and mainly perform studies on a broad range of environmental issues, based on available knowledge. They often develop and use models of their own to be able to answer requests, based on scientific knowledge if available.
6. Sectoral organizations and associations act as multiplicators of key climate information within their sectors. They make the information sector-specific considering the user-specific needs (e.g., SIA[30] with recommended norms in the building sector).
7. Cantonal and communal administrations are important to translate data, services and information for their area considering the local conditions.

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[28] https://www.bafu.admin.ch/bafu/en/home/state/data.html
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# 5 Technological disruptions – high-resolution geospatial data & AI at scale

Geospatial data from Earth Observation (EO) provides key inputs into understanding land and ocean processes, their dynamics and "taking the pulse of our planet." Today, a huge number of EO sensors exist, ranging in resolutions (spatially, temporally, spectrally), data acquisitions (optical, thermal, Synthetic Aperture Radar (SAR), LiDAR), platforms (satellite, drones, High altitude platform systems) and coverage (local to global scales). However, a critical challenge remains in transforming petabytes of EO data into "actionable intelligence" for decision makers and stakeholders to take concrete action on climate change (Tuia et al 2023). The ability to extract valuable information from EO data is essential for monitoring and documenting the current state of climate, predicting or issuing warnings (for example of extreme events or natural disasters) or future projections based on climate models. Recent technological advances in EO, Artificial Intelligence (AI), next generation earth system models and scalable, robust and continuous deployment models have demonstrated the capability to have a major impact on the adoption of EO data in climate change research. Daily acquisition of large amounts of high-quality and high-resolution satellite (HRS) and aerial images are empowering AI to solve different environmental issues such as water and food scarcity, biodiversity loss or greenhouse gas emissions at local to global scales is allowing us to move slowly toward a more sustainable exploitation of our planet.

## 5.1 Roadmap of high-resolution geospatial data

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### 5.1.1 Earth observation data roadmap: Modalities relevant to climate change

Geospatial data has been recognized by the IPCC in its recent sixth assessment report[31] as critical information sources for 1) monitoring historical and current status of the Earth's climate and associated changes, 2) inputs into weather and climate modelling for status, understanding and projections, 3) monitoring and providing information on resilience to slow-onset climate events, 4) monitoring of extreme events caused by climate change (natural and man-made) and 5) providing indicators for climate change risk assessments (Caribou Space 2020). EO satellites have been acquiring data on the state and dynamics of Earth system processes for more than 40 years. In Europe, EUMETSAT coordinates weather observation satellites and Satellite Application Facilities (SAFs) whose role is to operationally produce widely used climatological and near-real-time datasets. Agencies such as European Space Agency (ESA) and NASA are now placing climate change at the forefront of upcoming satellite mission design, where the new suite of Copernicus Expansion Missions and NASA's Designated Observables aim to address challenges such as urbanization, food security, rising sea levels, diminishing polar ice, natural disasters and climate change through producing global and freely available data.

Alongside these challenges, from a commercial standpoint there is a need for reporting climate-related, nature, biodiversity and supply-chain risks. Easier access to space, increased miniaturization, and reducing costs in satellite design/launch has caused a paradigm shift in the commercial EO sector.

[31] https://www.ipcc.ch/assessment-report/ar6/

New *space-as-a-service* business models allow new actors to invest in space, through building and/or launching EO satellites. These new business models target emerging applications not covered or possible by traditional space missions, such as carbon monitoring (e.g., Planet constellation), fast disaster response (e.g., IceEye) parametric insurance or source emissions monitoring (e.g., GHGSat). Alongside data acquisition, there is a rapidly evolving commercial sector targeting the adoption of EO data by users, either through making data accessible (*platforms-as-a-service*) or actionable (through ready-made analytics and *insights-as-a-service*). Such *insights-as-a-service* can benefit the insurance industry (i.e., the risk of climate on assets), governments and national stakeholders (i.e., identify the largest sources of methane emissions or wildfire threats) or companies involved in carbon offset monitoring (i.e., verification of reported tree carbon storage in offset projects that plant or protect forests).

Currently a wealth of EO data exists, with the possibility to extract many downstream products related to climate change. Focus should be placed on prioritizing specific products that are relevant to Earth's climate (e.g., Essential Climate Variables; ECVs) and models. These products may require fusing multiple data sources and scales to generate them, moving away from current methods that generally focus on single-sensor products and/or single scales. Uncertainty quantification is currently under-valued in EO-derived products (however upcoming sensors begin to place requirements on providing uncertainties as well as products), yet they are critical for users and stakeholders to decide if EO data is *fit-for-purpose*. Similarly, ground-observations for Calibration and Validation need to keep up with rapidly evolving technologies at new spatiotemporal resolutions, and currently lack national or global coordination to provide standardized long-term validation data. EO data is already being integrated into climate and weather modelling, but these models represent such intricate and multi-faceted processes that improvements on the *fit-for-purpose* of satellite data (in terms of new resolutions, products and accuracies) can have significant advancements in our fundamental understanding of Earth system processes.

### 5.1.2 Weather and climate models: spatiotemporal resolution, scenarios

Predictions of weather and climate are incredibly complex, and Earth system components are connected non-linearly; we cannot represent, nor well-understand all important processes. Substantial investments have been made to build and launch sensors designed to observe products that are assimilated into numerical weather and climate prediction models, such as surface temperature, cloud properties, wind fields, radiation balance components and gas concentrations and distribution. Geostationary (GEO) and low-earth orbiting (LEO) satellite systems provide these products in different spatial and temporal resolutions. GEO missions focus primarily on meteorological nowcasting and long-term climate observations, using multi-spectral narrow/broadband imagers and atmospheric sounding to retrieve vertical profiles, to provide high temporal resolution (15 to 30 minutes) data (e.g., EUMETSAT's Meteosat satellites, NASA-GOES). Improvements of GEO missions aim to increase spatial resolution for local nowcasting and subpixel phenomena, improve spectral/radiometric accuracy to allow for new products and increase temporal resolution to observe rapid atmospheric phenomena. Future missions will target improvements in sounding capabilities, and move from narrowband to hyperspectral sensors to improve product accuracy and vertical profile resolutions. LEO missions complement GEO missions in the global weather satellite system, and often prototype experimental systems before operational use (e.g., ESA's Sentinel-5P and Sentinel-6, NASA's MODIS and the NOAA JPSS satellites). As well as improvements in spatial, spectral and radiometric resolution, testing new technologies and operational products are and will form the future of LEO missions. Major aims of upcoming experimental LEO missions are on novel technologies to retrieve rainfall and cloud properties (e.g., JAXA's GCOM-C satellites, the Global Precipitation Measurement mission), finer vertical distribution (e.g., ESA's Aeolous-2 mission) and improve atmospheric sounding of temperature and humidity (e.g., European Meteorological Operational (MetOp) program).

While these traditional space missions have generally adopted a high-capability but no-risk tolerance with regards to weather and climate satellites, new SmallSat or CubeSat constellations have and will open doors to explore new data types and products. New technologies without long-development times can be prototyped, such as the COSMIC-2 constellation that uses novel GNSS radio techniques to measure temperature, pressure and water vapor content and contributed to a 6-8% error reduction in NOAA's forecast[32]. Agile Small- or Cube-Sat constellations can provide data at higher temporal resolution or lower latency in data poor areas, such as SPIRE's LEMUR constellation that uses 150+ CubeSats in different orbits to provide global temperature, pressure and humidity profiles at 1-hour intervals, allowing tracking of fast-moving extreme weather events[33].

AI combined with new weather and climate satellites launched by traditional- or new-space can allow us to learn behaviors of complex linear systems, from data acquisition/observations to data assimilation and product dissemination. The European Commission recently started to place huge emphasis on combining EO data and AI research for weather and climate modelling through the Destination Earth (DestinE) project[34], which explores the concept of high-precision digital models (or "Digital Twins") of the Earth, with AI and EO data at its center. New space companies are implementing AI at the core of its technologies, to autonomously manage complex constellations (e.g., GomSpace), perform in-flight procedures (e.g., OP-SAT), analyze huge amounts of data on-board (e.g., COSINE's HyperScout) or on ground (e.g., SPIRE's Juno Neural Network for weather predictions). The weather and climate communities are only at the beginning of exploring the full potential of AI. In Switzerland, some unique challenges remain to fully adopt EO data combined with AI into weather and climate modelling. Complex topography not only makes EO data availability and accuracy a challenge (cloudiness, geometric accuracy) but also predictions of phenomena such as convective storms highly uncertain. Further work on optimal input and training data (short time-steps, high resolution, labelled) and hyper-parameter selection is needed. Given the close connection of climate to Swiss society and economy, reproducibility, responsibility and traceability of both EO data and AI models is critical.

### 5.1.3 Context data: OSM for assets, DEMs and others

The interpretation and processing of geospatial data requires context or ancillary data (i.e., data not acquired by the sensor itself), which aids analysis, classification, metadata generation or provides training data for AI models. During data processing, context data on terrain, land cover, geometry, atmospheric conditions (and more) at the same spatiotemporal resolution as input EO data is needed. In Switzerland specifically, accurate high spatial resolution Digital Elevation Models (DEMs) of terrain and geometric correction, as well as instantaneous atmospheric conditions are critical to retrieve accurate EO products in complex topography. Improvements in DEMs (e.g., SwissAlti3d), geometric correction databases (e.g., ESA's Global Reference Image; GRI) and additional context data from, e.g., Swisstopo have greatly increased EO product accuracy, but require specific processing schemes for Switzerland only (e.g., SwissDataCube).

Labelled datasets for assets, classification and training data are critical in the interpretation of EO data and development of AI models. However, gathering sufficient number of clean and quality-controlled

32 https://www.nesdis.noaa.gov/current-satellite-missions/currently-flying/cosmic-2
33 https://ir.spire.com/
34 https://digital-strategy.ec.europa.eu/en/policies/destination-earth

labelled datasets requires huge investment, and remains one of the main barriers to the wide-scale adoption of EO for AI applications. OpenStreetMap (OSM)[35] is a free, open source, constantly growing, collaborative online mapping platform, including roads, buildings, points of interest, waterways, public transport etc. OSM is one of the largest repositories of geographical information which can be used in a variety of use case, but can also serve as training data for AI models (roads mapping[36], population densities maps[37], etc.) due to its large number of labeled features and its regional diversity. Other examples of publicly available labelled datasets include the Google Buildings[38] or the Land-Use-Land-Cover maps (e.g., CORINE land cover). However, such examples rely on substantial investment (in both time and money), that thus far have relied on community efforts (OSM), large companies (Google Buildings) or institutions (CORINE from the European Commission). New research fields that use active learning or self-supervised training data to reduce efforts in labelled data are more promising options for large-scale EO and AI applications, with examples such as SpaceNet going in this direction.

### 5.1.4 Open government data and secondary-use right regulations

Availability and accessibility of data are considerable barriers for use of EO data, where interoperable data that is accessible for everyone in a seamless manner is critical (Tuia et al 2023). However, the heterogeneous nature of datasets, processing tools and algorithms renders accessibility a remaining challenge, alongside accessibility of sensitive data, interoperability of datasets/tools and scalable data processing. Initiatives such as Google Earth Engine (GEE), Open Data Cube and the Copernicus DIAS' are moving towards addressing these challenges. In Switzerland, the Swiss Data Cube (Giuliani et al., 2017) is developed, implemented, and operated by GRID-Geneva, with the main purpose to support Swiss environmental monitoring and to facilitate knowledge generation out of EO data, by providing rapid access to large spatiotemporal Analysis Ready Data (ARD). However, as introduced in Section 5.1.3, the availability of good quality labelled datasets alongside ARD (preferably at the same spatio-temporal resolutions) is critical in AI applications; emphasis should be placed on pursuing new research directions that utilize active learning, self-supervised training or domain adaption (i.e., transfer learning) alongside visual interpreted human labelled datasets.

The use of EO data for AI applications in climate change requires a coordinated approach between data providers, decision enablers and stakeholders that require insights on weather and climate. Thus far, the use of EO data and AI has focused primarily on one-off pilot projects that place data and methods in the foreground. A shift of focus toward product-oriented and repeatable models (i.e., recurring monitoring projects) is needed to provide useful insights, and help solve problems for stakeholders and customers. To achieve this, open standards in data (including geospatial, ancillary and meta-data), data sharing, and platforms and technologies that promote data interoperability is required.

To be beneficial to society, stakeholders and customers, operational AI tools should be reproducible, scalable, maintainable, transferable, and explainable (Bonavita et al 2022). Due to the massive amounts of complex, spread, heterogeneous EO (and context) data, actionable insight and supporting users in its uptake is still a major challenge. The notion that more data leads to better insights, and that EO data combined directly with AI can lead to actionable insights is not necessarily true[39].

[35] https://www.openstreetmap.org/
[36] https://ai.meta.com/blog/mapping-roads-through-deep-learning-and-weakly-supervised-training/
[37] https://ai.meta.com/blog/mapping-the-world-to-help-aid-workers-with-weakly-semi-supervised-learning/
[38] https://sites.research.google/open-buildings/
[39] https://newsletter.terrawatchspace.com/p/earth-observation-for-climate

Additional steps of fusion with other data sources and models, as well as algorithm development are fundamental steps in providing actionable insight. Improving awareness, capabilities, and adoption of EO data combined with AI methodologies is fundamental if we want to fully profit on its potential.

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## 5.2 Next-Generation Earth System Models: Towards Reliable Hybrid Models for Weather and Climate Applications

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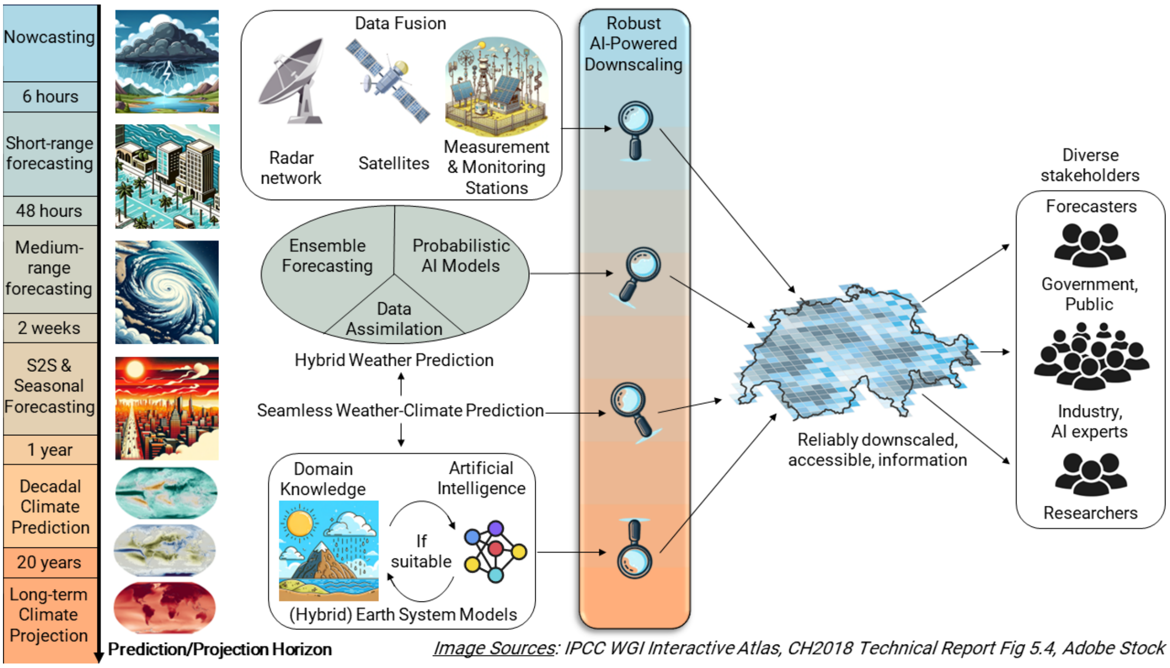


Figure 5.1: Advancements in data collection, data access, hybrid AI-physical Earth system modeling, and downscaling empower stakeholders with increased accessibility to local predictions and projections, encouraging collaborative efforts across disciplines to improve climate change preparedness.

Here, we review how machine learning has transformed our ability to model the Earth system, and how we expect recent breakthroughs to benefit end-users in Switzerland in the near future.

### 5.2.1 Limitations of traditional Earth system models

Earth system models (ESMs), which encode our knowledge of the Earth system into equations that can be integrated forward in time, serve the double purpose of understanding and prediction (Prinn 2013, Held 2005). Weather forecasting predicts the atmospheric state at short timescales, typically less than two weeks. At longer timescales, chaos makes the exact atmospheric state unpredictable, and ESMs are used to predict or project climate statistics. Except for seamless weather-climate prediction setups (Hoskins, 2013), the ESMs used for numerical weather prediction (NWP) and climate projections are different and face their own sets of challenges.

While significant progress has been achieved in data assimilation (Courtier et al., 1994; de Rosnay et al., 2022), physical process representation (Bauer et al., 2015), and ensemble forecasting including extreme events (BenBouallègue et al., 2019), the computational cost of NWP remains a major bottleneck, forcing a delicate balance between ensemble size and model resolution. Progress on leveraging the capabilities of current and emerging supercomputer architectures for ESMs and NWP is slower than expected (Schulthess et al., 2018). High-fidelity, high-resolution ESMs, will thus require very substantial investments in high-performance supercomputers (Bauer et al., 2021) and re-engineering the model codes (Tal Ben-Nun et al., 2022).

On long timescales, ESMs used for climate projections face several challenges in faithfully representing Earth system processes in the atmosphere, ocean, and land, even if they accurately simulate the rise in global mean temperatures linked to anthropogenic forcing (Eyring et al., 2021). In the atmosphere, uncertainties in climate projections primarily arise from convection and cloud-aerosol interactions (Rosenfeld et al., 2014). These lead to structural biases in warming patterns (Andrews et al., 2022) and precipitation (Palmer and Stevens, 2019). Global storm-resolving models can mitigate some of these biases by explicitly simulating deep convection (Stevens et al., 2020), but cannot be easily calibrated and used for century-long projections because of their high computational cost; these models also still rely on low-level clouds, aerosols, and microphysics parameterizations (Schneider et al., 2017). In the ocean, uncertainties persist due to unresolved mesoscale eddies and turbulent processes (Couldrey et al., 2021). Predicting the land carbon sink remains a challenge (Friedlingstein et al., 2022), progressively addressed through observationally-driven reductions in model uncertainties (Dagon et al., 2020), notably those related to extremes (Reichstein et al., 2013), and land water and carbon cycles (Gentine et al., 2019).

Therefore, the ESMs' role in understanding the climate system remains paramount in part because they allow us to explore counterfactuals that are relatively unconstrained by observations, such as a variety of forcings and the long-term climate response to forcings (Balaji et al., 2022). However, current roadblocks of traditional ESMs, such as providing consistent bounds on equilibrium climate sensitivity (Forster et al., 2021), appear inconsistent with our quickly increasing computational and observational capabilities.

### 5.2.2 Can we use unconstrained AI for weather and climate prediction?

"Pure", or "hard" AI (Chantry et al., 2021), unconstrained by the structure of dynamical equations, can leverage the "deluge" of Earth system data, from remote sensing to in-situ measurements via citizen observations (Reichstein et al., 2019).

This progress has already revolutionized NWP (BenBouallègue et al., 2023). In nowcasting, where forecasts are made for the next (0–3) hours, deep generative models used for video prediction (Ravuri et al., 2021) are particularly suitable for combining different observational sources and making fast inferences. Medium-range (up to a couple of weeks) forecasting has recently witnessed high-performance, high-resolution, purely data-driven forecasts, notably GraphCast (Lam et al., 2022), Pangu-Weather (Bi et al., 2023), and FourCastNet (Pathak et al., 2022; Bonev et al., 2023). Their deterministic error is on par with and in some cases even lower than that of our best NWP models (Rasp et al., 2023), despite making inferences using one GPU instead of thousands of CPUs. As generative modeling allows the creation of "infinite ensembles", we expect rapid progress in "pure AI" probabilistic forecasts following successful prototypes for, e.g., atmospheric river prediction (Chapman et al., 2022) and medium-range forecasting (Garg et al., 2022; Price et al., 2023).

In climate change research, flexible machine learning (ML) approaches have advanced our understanding of connected, nonlinear, or non-Gaussian Earth system processes (Huntingford et al., 2019).

ML can offer multiple benefits, including accelerated computing, enhanced data fidelity, and added value to climate simulation outputs.

For acceleration, ML models are trained to closely mimic Earth process models, leveraging the inherent speed of ML algorithms, including neural networks, which typically involve fewer floating-point operations and benefit from GPU computing. This approach has a history of improving the temporal resolutions of radiative transfer models in weather (Chevallier et al., 1998) and climate (Pal et al., 2019) simulations. It can also expedite the execution of computationally expensive parameterizations (modules) in ESMs, such as convection (O'Gorman and Dwyer, 2018) and complex bin microphysical schemes (Gettelman et al., 2021).

In terms of data fidelity, ML enhances our Earth system representation by learning from high-fidelity data, such as observations, reanalyses, or high-resolution model runs, such as "digital twins" (Bauer et al., 2021). These "digital twins" are too costly for extended simulations but offer millions of samples for developing ML parameterizations. Recent applications include enhancing subgrid-scale parameterization in climate models by learning from storm-resolving simulations, which improves various critical climate model statistics, from extreme precipitation distributions to tropical wave spectra (Rasp et al., 2018). Deep learning and symbolic regression have also been employed for subgrid parameterization (Ross et al., 2023) and vertical mixing (Sane et al., 2023) in the ocean.

ML has also demonstrated its value in augmenting observational datasets, as shown by its use in estimating spatiotemporal land-water fluxes through random forests (Jung et al., 2011) and ocean carbon fluxes via neural networks (Landschützer et al., 2013). Recent applications, like "ClimateNet", showcase its role in automating climate analysis by segmenting extreme weather events in climate model output (Prabhat et al., 2021). Generative models such as Gaussian processes (Camps-Valls et al., 2016) can also add value by inherently estimating uncertainty, with applications to, e.g., constraining sensitivities from climate model ensembles (Watson-Parris et al., 2020). Finally, foundation models (Bommasani et al., 2021), have emerged as promising tools for weather and climate applications, as exemplified by ClimaX (Nguyen et al., 2023). These large neural networks, originally pre-trained on diverse data, can be fine-tuned with minimal samples for specific tasks like forecasting and downscaling.

The limitations of "pure AI" are most visible with sparse or difficult-to-process data, such as ground-based observations (Schultz et al., 2021). Standardized benchmark datasets are being developed for weather and climate applications to address this issue (Dueben et al., 2023). Even in cases where data are plentiful, purely data-driven weather forecasts often rely on meteorological reanalysis data for success, indirectly tying their quality to traditional ESMs and data assimilation systems. Challenges in climate modeling and projection include poor out-of-climate generalization (O'Gorman and Dwyer., 2018), instabilities from AI components-ESM interactions (Brenowitz et al., 2018), disparities in offline and online skill (Brenowitz et al., 2020), and physical inconsistencies, such as the violation of conservation laws (Beucler et al., 2019).

Many of the aforementioned challenges can be resolved by combining data-driven models for accurate in-sample prediction and knowledge-based models for induction. This is broadly referred to as knowledge-guided ML (Karpatne et al., 2022), which includes physics-guided ML (Willard et al., 2020) and spans methods ranging from physics-informed neural networks (Raissi et al., 2019) to Gaussian processes-based calibration of physical model parameters (Cleary et al., 2021).

### 5.2.3 Hybrid Climate-AI Modeling: Towards the best of both worlds

Finding the optimal balance between knowledge-based and data-driven components is delicate; Chantry et al. (2021) argue that the longer the prediction timescale, the softer the AI should be. This seems broadly consistent with the recent breakthroughs in deep learning applications for NWP, starting with nowcasting (Sonderby et al., 2020; Leinonen et al., 2023) and progressively permeating medium-range forecasting.

Irrgang et al. (2021) coined the term "neural ESMs" to describe hybrid models that can reproduce and predict out-of-distribution samples and extreme events, perform constrained simulations that obey physical conservation laws, include measures to self-validate and self-correct, and allow replicability and interpretability.

Practical progress towards this framework has been made in recent years, such as architecture-based constraints to ensure conservation laws (Beucler et al., 2021), incorporation of symmetry to enhance generalization (Wang et al., 2022), coupled online learning to mitigate instabilities and biases (Lopez-Gomez et al., 2022), input restrictions to improve stability (Bretherton et al., 2022), causal model evaluation (Nowack et al., 2020) and causal deep learning (Iglesias-Suarez et al., 2023) to respect underlying physical processes, data-driven equation discovery (Grundner et al., 2023), and the use of transfer learning and climate-invariant inputs to enhance generalization (Chattopadhyay et al., 2020; Beucler et al., 2021). Recently, NeuralGCM has emerged as the first fully differentiable hybrid general circulation model, coupling a dynamical core that spectrally solves the primitive equations with neural networks trained to accurately represent physical processes for optimal short-term weather prediction (Kochkov et al., 2023).

Regional and global climate, pure AI or hybrid climate-AI models frequently exhibit grid spacings exceeding 10 kilometers, making them of limited usefulness for risk assessment. Impact models indeed typically require climate inputs at a local scale of, at most a few kilometers. This gap can be filled to some extent by downscaling algorithms.

### 5.2.4 From climate data to actionable information: AI-assisted downscaling

AI, and in particular super-resolution (Wang et al., 2020), has already proven its potential to revolutionize statistical downscaling, which predicts societally relevant variables at the local scale from coarser-scale ESM output. We briefly survey some of the recent developments in this field.

Convolutional neural networks (CNNs) have been successfully used to super-resolve precipitation projections from ESMs (Vandal et al., 2019; Rampal et al., 2022), satellite images (Pouliot et al., 2018), radar reflectivity scans (Geiss and Hardin, 2020), winds over complex terrain (Dujardin and Lehning, 2022), and idealized turbulent flows (Fukami et al., 2019) with high pixel-wise accuracy.

Despite outperforming conventional techniques such as bicubic interpolation (as shown in Baño-Medina et al, 2020) and offering the possibility of increasing temporal resolution by using multiple channels (Serifi et al, 2021) or a recurrent structure (Harilal et al, 2021), CNNs trained with standard loss functions typically underestimate extremes (Sachindra et al, 2018) as they tend to predict the average of all possible solutions to minimize the error at each pixel.

While Ghosh et al. (2008) and Sachindra et al. (2018) demonstrated that relevance vector machines (a Bayesian approach to learning probabilistic sparse generalized linear models, Tipping et al., 1999) enhance the downscaling of river streamflow and precipitation extremes, recent investigations have shifted towards generative modeling, specifically focusing on conditional Generative Adversarial Networks (cGANs). For example, Stengel et al. (2020) used a sequence of two cGANs to super-resolve wind velocity and solar irradiance on the 2km scale using 100 km-scale climate model output. They showed that the resulting spatial variability (as quantified by the turbulent kinetic energy spectra and solar irradiance semivariograms) was more consistent with that of high-resolution climate model outputs than the one generated by interpolation and simple CNNs, consistent with studies using GANs to downscale precipitation (Watson et al., 2020). Groenke et al. (2020) adapted recent work in normalizing flows (Rezende et al., 2015) for variational inference (Grover et al., 2020) to develop an unsupervised neural network approach that generates the joint distribution of high- and low-resolution climate maps. Leinonen et al. (2020) used the stochastic nature of GANs to generate ensembles of time-evolving, super-resolved radar-measured precipitation over Switzerland, and satellite-derived cloud optical thickness fields.

Miralles et al., (2022) used a similar Wasserstein recurrent GAN architecture (Gulrajani et al., 2017) to downscale meteorological reanalysis winds to storm-resolution over Switzerland. In 2023, diffusion models witnessed their first atmospheric applications (Leinonen et al., 2023), including solar irradiance (Hatanaka et al., 2023) and precipitation (Addison et al., 2022) downscaling. Notably, Mardani et al., (2023) simultaneously downscaled winds, temperature, and radar reflectivity using a two-step approach akin to that from Price et al. (2022).

For downscaled (or bias-adjusted, or more broadly post-processed) outputs to be actionable, they must ideally meet several key requirements, including:

- several features (e.g., change signal for the mean and extremes) should be conserved;
- inter-variable dependencies should be well preserved;
- extremes should be reliably represented at a very local scale;
- misrepresented relations in the original model output should be corrected;
- spatial consistency of the fields should be ensured;
- the temporal resolution should be sub-daily.

To our knowledge, there exists no universal post-processing/downscaling approach fulfilling all these requirements at the same time. The available methods typically satisfy some of them only and, in practice, the employed technique is chosen depending on the specific application. Further research is therefore needed to fill these gaps.

### 5.2.5 Recommendations with a focus on Switzerland

There is high confidence that climate change in Switzerland will inter alia increase temperatures and extreme summer rainfall, change the seasonality of river discharge, and affect groundwater, water temperatures, snow, and glaciers (see also Section 4.1.1). Adapting to these changes requires accessible information at the local scale. The intricate topography of Switzerland, like the Jura Mountains and the Alps, poses a tremendous challenge in generating climate projections at fine scales. In pursuit of this goal, the Swiss climate modeling community has made notable strides in recent years, advancing the precision of climate-time scale simulations to encompass the Alpine region and Europe at model resolutions of mere kilometers (Ban et al., 2014; Ban et al., 2020; Ban et al., 2021; Leutwyler et al., 2017; Schär et al. 2020). These achievements will enable kilometer-resolution regional climate projections and bulk assessment of changes for an entire region, like the Swiss Plateau (Langhans et al., 2012).

However, the effective modeling and evaluation of climate impacts on these diverse terrains necessitates even more granular, higher resolution, and bias-free data of multiple meteorological variables. For example, creating a dynamic model of a glacier requires incredibly detailed boundary conditions that include data on precipitation, temperature, and the surface radiation balance, potentially down to hectometer or even decameter resolutions. Achieving such fine granularity in the foreseeable future will likely depend on downscaling techniques that can bridge the gap between kilometer-scale simulations and the microclimates of these landscapes.

In the CH2018 Swiss climate change scenarios (Fischer et al., 2022), the quantile mapping (QM) applied for downscaling and bias adjustment has been performed at the univariate level (variable by variable; Feigenwinter et al. 2018), which implies that inter-variable dependence might have been violated, especially for extremes (Michel et al., 2021). Moreover, biases in the inter-variable dependencies inherent to the raw outputs from GCMs and RCMs cannot be corrected by univariate QM. Reliably representing the extremal inter-variable dependence is essential to forecast/project compound events and for impact models (e.g., consistent 2m temperature, precipitation, and surface radiation balance for glacier models). In the upcoming CH2025 climate change scenarios, inter-variable dependence should be partially preserved owing to multivariate bias-correction methods (e.g., Ortner et al., 2023; Cannon et al., 2018), but new techniques will be needed to ensure spatial consistency of the fields, as this is essential for impact assessment of short and heavy rainfall.

Efforts to find out the best synergies between physical modeling, AI methods, and statistical models grounded in probability theory for forecasting/projecting extremes (i.e., to develop “physically and statistically-informed ML”), such as those carried out by the recently created Expertise Center for Climate Extremes (ECCE) at the University of Lausanne, are essential to moving a step forward on these methodological aspects. Extreme-value theory (EVT), a field that has sustained a long tradition in Switzerland, for example in insurance (Embrechts et al. 1997) or environmental applications (Davison et al. 2012), provides such an example of an elegant and mathematically justified framework to estimate the probabilities of rare events by extrapolating beyond the range of the data. Its combination with machine learning tools is recent, and studies have mainly focused on adapting the loss functions used in ML algorithms to focus predominantly on extremes and to incorporate the modulation of these events with relevant predictors. This has been done to predict conditional tail distributions using gradient boosting (Koh, 2023), random forest (Gnecco et al., 2023), and neural network architectures (Richards et al., 2022, Pasche and Engelke, 2023). The paucity of data in the distributional tail makes it challenging to fit well and verify these models, highlighting the need for further research. Another central task then consists of elaborating detailed information and scenarios about extremes at a very local scale, combining them with vulnerability models and exposure data to provide risk assessments, and informing the cantons, the confederation, and other stakeholders (such as insurance companies).

Finally, data-driven modeling has a longstanding history in Swiss NWP applications, notably for mesocyclone and severe thunderstorm tracking based on radar observations (Hering et al., 2004) and satellite images. With the advent of deep learning, the use of AI has accelerated. Neural networks now play a pivotal role in diverse tasks, such as post-processing cloud cover ensemble forecasts (Dai and Hemri, 2021) and real-time nowcasting of hail and lightning events (Leinonen et al., 2022). As NWP practitioners acclimate to AI tools, a prevailing consensus emerges, favoring their supplementary role alongside existing methodologies rather than outright replacement (Boukarba et al., 2020). This consensus emphasizes the enduring importance of domain knowledge, fostering the development of hybrid models wherein human expertise is seamlessly integrated into AI frameworks for weather applications (e.g., Zanetta et al., 2023) and beyond, a trend we anticipate will persist in the foreseeable future.

**Recommendation 1:** Develop Hybrid AI-Physical Models: Emphasize the integration of AI and physical modeling for improved reliability, especially for longer prediction horizons, acknowledging the delicate balance between knowledge-based and data-driven components required for optimal performance.

**Recommendation 2:** Emphasize Robustness in AI Downscaling Approaches, favoring techniques that respect physical laws, preserve inter-variable dependencies and spatial structures, and accurately represent extremes at the local scale.

**Recommendation 3:** Promote Inclusive Model Development: Ensure Earth System Model development is open and accessible to diverse stakeholders, enabling forecasters, the public, and AI/statistics experts to use, develop, and engage with the model and its predictions/projections.

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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.

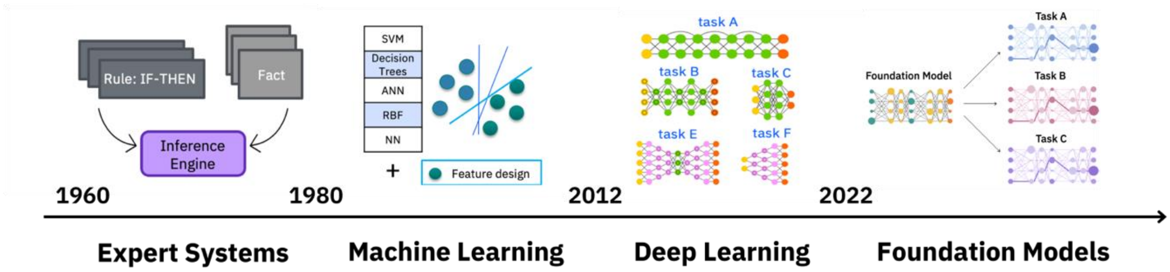


Figure 5.2: Historic view on AI algorithm paradigms: from hand-crafted and specific, to fully data driven and general models.

### 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

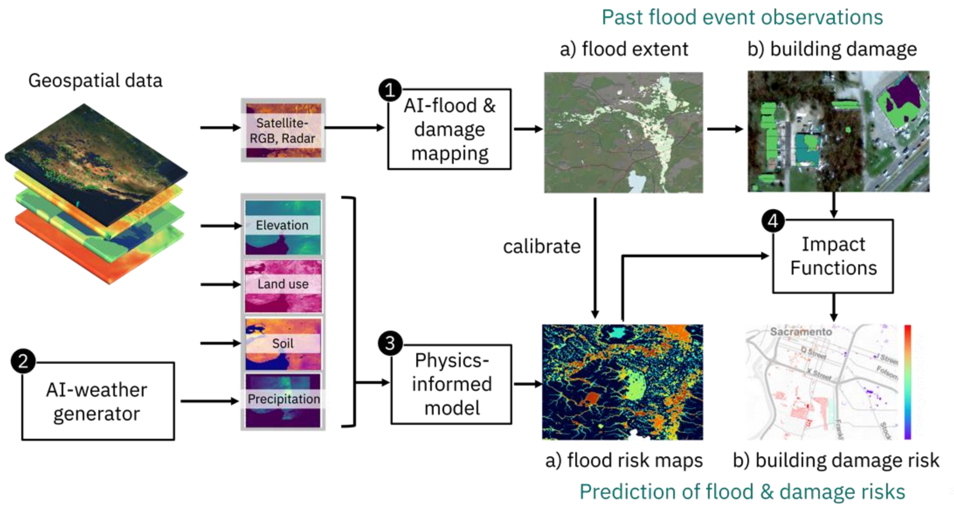


Figure 5.3: Example workflow of AI methods applied for flood event impact assessments.

***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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## 5.4 Re-usable, scalable and interoperable scientific work through the use of CI/CD & ML-Ops

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In (big) data driven science, which is a foundation of our modern economy, reproducibility and reusability are key challenges. Data scientists and researchers are skilled in the process from idea to publication. Although some publication channels require source code and data to be made publicly accessible, rerunning and verifying experiments is usually hard to impossible due to a lack of standards. Therefore, we suggest for scientists to adopt the otherwise successfully implemented methodologies in three stages, for turning scientific data processing code from state-of-the-art research into reusable, valuable assets for a larger community and society:

- ***Stage One: Experiment tracking and asset versioning***
  State-of-the-art software development, using versioning tools like Git, is often poorly adopted in science. E.g., by using Git for all assets (including source code, references to data, configuration files and experiment results) with version control on individual experiments, it will always be transparent who ran what experiment using which data, code and external library versions and what the results where.
- ***Stage Two: Containerization***
  Even if versioning and proper documentation is in place, setting up an environment for reproducing or reusing published results can become tedious and error prone. By providing a container image additionally to the versioned repository including its instructions code can be run anywhere.
- ***Stage Three: CI/CD (Continuous Integration and Deployment)***
  With stage one and two in place, with CI/CD, the system automates the pipeline from code to production so that only code needs to be saved (pushed) to the code repository, all subsequent steps are automated.

We consider Stage One to be absolutely essential, but we recommend to also exercise Stages two and three, which are all discussed in more detail in the following sections.

**Repeatable and reusable science:** In this section we introduce a framework for CI/CD & ML-Ops for scalable and interoperable data science applications with a reference architecture that supports all three stages of maturity as was introduced above.

### 5.4.1 Code Revisioning and Tracking (Stage One)

Using Git, or similar versioning tools for science projects increases reproducibility and reusability by facilitating to track changes of code and data over time. Furthermore, to collaborate with others on projects, and easily revert to previous versions of the work if needed is much simplified, which in turn helps to ensure the integrity and reproducibility of the results. Finally, Git allows multiple scientists to work on a project simultaneously and control changes through *forks*, *pull requests* and *branches*.

While tools like Git keep track of versions of various types of assets, files in general, it is not recommended to version raw data files using Git due to file size. For this, either a third-party data versioning tool should be used, or additional metadata should be collected to detect changes more easily in raw data sources. Subsequent runs of experiments can then compare versioned and current derived metadata and inform a user if it matches or not.

### 5.4.2 Containerization (Stage Two)

Writing software can quickly become a very complex endeavor. Whole disciplines of software engineering research focus on mitigating complexity (e.g., Object Oriented Programming (OOP), Functional Programming (FP), …). The gist of those is to (1) Separate concerns (modularization) and (2) Create clear interfaces between modules (encapsulation).

As OOP and FP concepts are complex, we use modularization at a code-file level instead. As a rule of thumb, one module should not span more than 100 lines of code, and each module needs to expose a clear typed interface. Tools like the CLAIMED framework[43], Repo2Docker[44] or Source2Image[45] address exactly this problem. The scientist writes short and concise modules which automatically get compiled into runtime specific operators which can run on top of docker[46], slurm[47] or kubernetes[48].

Using (docker) containers addresses modularization and encapsulation. Code, dependencies (e.g., 3rd party libraries) and even runtime specific data like environment variables are self-contained in a container and can't interfere with a host machine. Additionally, such a container will be able to run within seconds on any computer in a repeatable fashion.

### 5.4.3 CI/CD automation (Stage Three)

As Figure 5.4 shows, to further liberate the scientist or researcher from creating and testing reusable, container-based operators, a CI/CD pipeline can handle this transparently. Once an artifact (e.g., python script) is pushed to Git, a CI/CD pipeline handles the build, test and deployment lifecycle which might include:

1. Validate that the artifact complies with the underlying specification (e.g., contains a name, description and interface in the case of CLAIMED);
2. Trigger unit tests;
3. Install library dependencies into the container image;
4. Add source code to the container image;
5. Push container image to the container registry;
6. Create execution engine specific deployment artifacts (e.g., kubeflow, kubernetes or slum configuration files);
7. Push artifacts to code repository;
8. Push artifacts to operator or workflow catalogs;
9. Trigger integration tests;
10. Install artifacts on staging environments;
11. Trigger end to end tests;
12. Register a new version of the operator or workflow for auditability.

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[43] https://github.com/claimed-framework
[44] https://repo2docker.readthedocs.io/en/latest/
[45] https://github.com/openshift/source-to-image
[46] https://www.docker.com/
[47] https://slurm.schedmd.com/overview.html
[48] https://kubernetes.io/

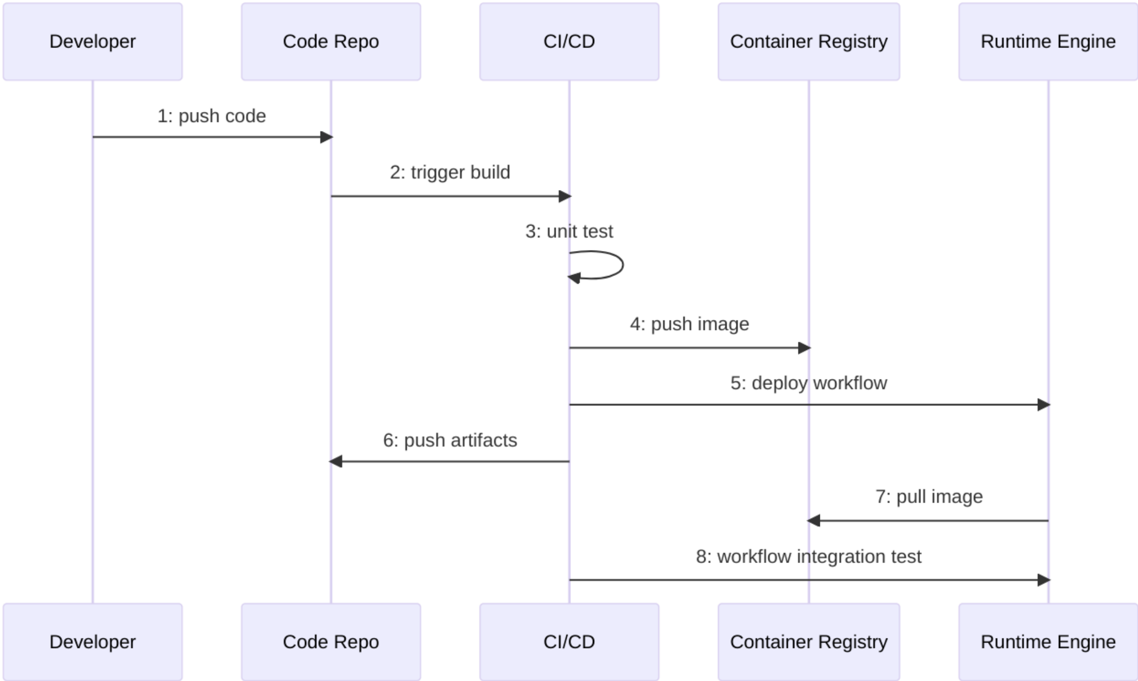


Figure 5.4: A common example of an MLOps CI/CD pipeline creating reusable, deployable artifacts from source code

**Workflows** are composed of modules which are often called operators, tasks, components, stages or similar. They act as a reusable unit to be shared across different workflows and different teams and are usually concentrating on implementing coarse-grained tasks like reading, writing or transforming data, or train models. If researchers start to think and work in modules (instead of overly long code scripts) reusability increases. There exists a variety of workflow execution engines and standards like Common Workflow Language (CWL)[49], Snakemake[50], Airflow[51] or Kubeflow[52]. CLAIMED (as of December 2023) automatically creates tasks for CWL and Kubeflow.

**Data Catalogs:** Once a set of versioned workflows and tasks is in place, each data item can be tracked to the workflow and task versions involved in creating it using a data catalog. In the geospatial world for example, Spatio-Temporal Asset Catalog (STAC)[53] emerged as de facto standard. This way, in case of data issues, one can always identify the responsible code and developer involved in creation of a specific data item because through proper use of Git, code, task definitions and workflow specifications are versioned as well. Finally, such a catalog can also be used to keep a record on the source datasets. For each data item in the catalog its source is known – it is either a raw data item coming from an external source, or a derived data item created by a workflow which has a version. Also, all tasks involved in the workflow and the associated 3rd party libraries referenced by the tasks are known by their origin. This concept is referred to as data lineage.

**Model Catalogs:** Once, data lineage is in place, auditability for experiment results needs to be supported too, e.g., for machine learning models. In this paragraph we focus on models. Thus, a model needs to reference a data set version it has been trained on as well as a hyper-parameter set it has

49 https://www.commonwl.org/
50 https://snakemake.readthedocs.io/en/stable/
51 https://airflow.apache.org/
52 https://www.kubeflow.org/
53 https://stacspec.org/en

been parameterized with. Ideally, the same workflow system used for data-integration is also used for orchestrating model training, e.g., triggering model training after a (lazy) data ingestion pipeline has been triggered. Often, hyper parameter tuning is performed to generate the best performing model. This data can be stored in the model catalog as well for further (automated) analysis, e.g., how do changes in data and hyper parameters influence model performance.

Model Quality Assessment: A static view on model performance is already accessible from the model catalog. On continuous data ingestion, model performance drifts. Therefore, continuous reassessment and retraining of models on new data can become a necessity. Especially if those models are used for continuous inference in embedded business processes. E.g., geospatial risk maps of severe weather events used in insurance risk calculations.

### 5.4.4 Summary

By bringing state-of-the-art software engineering principles to MLOps, automation of data engineering and model training can be achieved. Changes of code artifacts result in automatic versioning, testing, deployment of code and potentially automated re-triggering of (sub) workflows, liberating users from complex understanding of underlying infrastructure. By using open source and open standards as foundation, data, code and models are interchangeable and reusable. Even more value can be created by agreeing between involved stakeholders on additional best-practice to further simplify component-reuse. This helps to accelerate science, and deployment of results to operational systems in support of societies and ecosystems most pressing needs.

# 6 Vision, Gaps, Opportunities, and Actions to Enable AI to Reduce Climate-Change Impact

Technical disruptions like geospatial data and AI at scale to effectively reduce climate-change impact can only unfold their potential with infrastructure, methodologies, and policies in place. However, if done right, the opportunity for the Swiss society is vast. Thus, in this chapter, we discuss the vision, gaps, opportunities, and actions along six key enabling dimensions: i) data discovery and accessibility, as the foundation of AI applications, ii) robust machine learning at scale, discussing the need to successfully transition AI models from research to production, iii) Swiss communities and activities, supporting the uptake and guidance of AI model exploration, iv) Swiss geo & climate ICT infrastructure, needed to provide such services at scale, v) recommendations for sustainability transition applications, to result profitable business models and finally, vi) responsible and inclusive AI, to proliferate climate recommendations relevant for any stakeholder in Switzerland.

## 6.1 Data Discovery and Accessibility

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### 6.1.1 Vision

Earth Observations (EO) are increasingly produced by many environmental monitoring systems at all scales (from local to global). These systems are generating huge data volumes on a daily and weekly basis making their management and processing a major challenge. EO data can significantly contribute to establishing the baseline for determining trends, defining present conditions, and informing future evolution of the earth and its climate. EO data have the potential to drive progress against key national and international development agendas providing new insights and support better policy making across diverse issues of environmental sustainability. However, the vision of EO data-driven decision making has not been fully addressed, challenges remain, and therefore the full information potential of EO data has not been yet realized. Consequently, efforts have to be made to facilitate the discoverability, accessibility and use of EO data for a more sustainable future. Actions should promote open, coordinated, and sustained data sharing and infrastructure to strengthen research, policy making, decisions and action across different disciplines.

### 6.1.2 Current state

There is an increasing need for translating the massive amount of climate data and information that already exists into customized tools, products, and services to monitor the range of climate change impacts and their evolution. It is crucial to pre-process the recorded raw data to be readily available for the various analysis tasks of different stakeholders, to unfold the maximal utility.

There is an unprecedented array of new satellite technologies with capabilities for advancing our understanding of environmental processes and the assess changes at scales from local plots to the entire planet. Currently, almost 50 instruments and more than 10 satellites with multiple instruments that are of broad interest to the environmental sciences that either collected data in the 2000s, were recently launched, or are planned for launch in this decade (Figure 6.1). If we look only at Landsat (NASA) and Sentinels (ESA) they generate 30'000 images per day. In 2021, the total Sentinel data volume available for retrieval from the Copernicus Data Access System was 41.86 Petabyte, with a total download volume of 80.5 Petabyte[54].

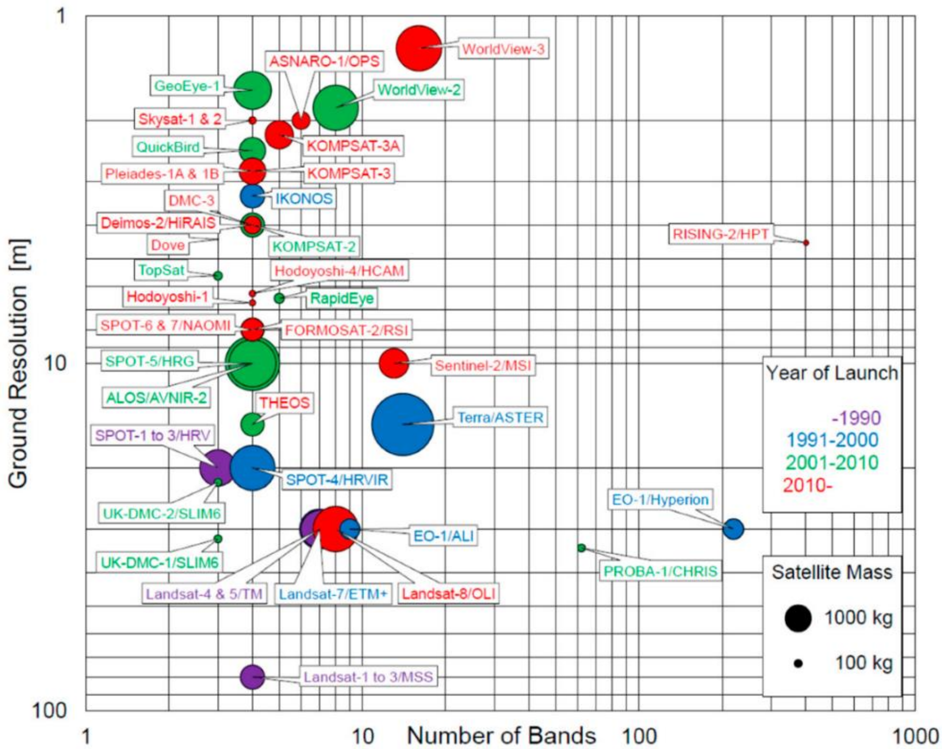


Figure 6.1: Overview chart depicting spatial and spectra (number of bands) resolution of Earth observation satellites (Kurihara et al., 2018).

However, most of these systems are designed for a specific purpose and therefore are operating in silos contributing to the fragmentation of the EO landscape and ultimately making hard to discover and access these invaluable resources. This in particular is true for commercial satellites fleets with high spatio-temporal resolution.

Further, EO data is clearly posing challenges related to Big Data handling, especially Volume (amount of data); Variety (diversity of data types & source); Velocity (speed of data generation); Value (extraction of meaningful information) and Veracity (accuracy of data). Addressing Big Data challenges

[54] https://scihub.copernicus.eu/twiki/pub/SciHubWebPortal/AnnualReport2021/COPE-SERCO-RP-22-1312_-_Sentinel_Data_Access_Annual_Report_Y2021_merged_v1.0.pdf

requires a paradigm change away from traditional local data processing approaches towards data-centric processing, to lower the barriers caused by data size.

To tackle the mentioned issues emerging global trends of (1) free and open data access policies for Landsat and Sentinel data; (2) the increasing provision of Analysis Ready Data (ARD) from EO satellites and (3) the distribution of open source software for managing and exploiting EO data, enables monitoring environmental changes at various spatial and temporal scales while complementing traditional data sources such as national statistics, administrative data or census information. Significant work has recently been done to lower barriers and facilitate the access of end-users to harness the full potential of EO data, and to address mandates, national processes, or reporting obligations. Earth Observation Data Cubes (EODCs such as Digital Earth Australia, Digital Earth Africa, or the Swiss Data Cube) and cloud-based processing platforms (such as the Copernicus DIASes, Earth on Amazon, Google Earth Engine, MS Planetary Computer) have emerged as technology enablers to manage, access, and analyse Big EO Data, thereby strengthening connections between data providers, applications, and end-users**.**

In addition, the advancement of data management and sharing principles such as FAIR (Findable-Accessible-Interoperable-Reusable) together with new cloud-optimized data formats (Cloud-Optimized Geotiff, Zarr) and Application Programming Interfaces like the Spatio-Temporal Asser Catalog (STAC) are paving the way to efficient and effective discovery and access to large volumes of EO data while facilitating spatio-temporal analysis over a given region anywhere in the world.

Ultimately, having access to open data will provide many opportunities/benefits[55], such as (1) supporting broad bconomic benefits and growth, (2) enhancing social welfare, (3) growing research and innovation opportunities, (4) facilitating the education of new generations and (5) benefits for effective governance and policy making.

### 6.1.3 Gaps, limitations, and concerns

Data interoperability ensures a seamless exchange of data between systems, applications, and services. It enables data discovery and transfer across diverse sources, facilitating analytics, data integration, and sharing. There are two key types of interoperability, which are:

1. ***Data-level interoperability:*** Enables data sharing across applications and platforms.
2. ***Semantic-level interoperability:*** Ensures data is correctly interpreted by various systems.

These interoperability levels can be achieved following a three steps procedure:

1. Data-level interoperability is achieved through infrastructures or platforms. They collect data from diverse sources, store it in a dedicated repository, and provide access in various formats. This ensures common data formats (e.g., COG, Zarr) and protocols (OGC APIs & webservices) for analytics and machine learning.
2. Semantic-level interoperability is attained by adding metadata and linking data to a standardized vocabulary. Data standards ensure data are correctly interpreted by different AI systems, leading to uniform, consistent datasets.

[55] https://www.earthobservations.org/documents/open_eo_data/GEO-XII_09_The%20Value%20of%20Open%20Data%20Sharing.pdf

3. Establishing a data vocabulary linked to an ontology can be done through two methods: data mapping (unifying data elements) and data federation (sharing data as if from a single source). These standards facilitate data sharing across businesses without relying on other information systems.

Other data exchange concerns and solutions are:

- ***Common APIs and Protocols***: Standardized APIs and protocols like REST are vital for data discovery and accessibility and supporting machine learning tool interoperability. REST, using HTTP and JSON, is widely adopted for exposing services as web APIs, allowing seamless communication for model training, inference, and data sharing. This is the case for openEO[56] or PANGEO[57], as well as the emerging OGC APIs[58].
  By embracing such interoperability standards, data providers and ML practitioners create interoperable services, promoting ease-of-consumption by other systems. These APIs establish a common communication language and facilitate the integration of multiple frameworks and tools into a unified system.
- ***Metadata and Standards:*** Interoperability goes beyond models and APIs, encompassing data exchange and metadata. Standardized metadata and data formats are crucial for sharing, understanding, and using data across various machine learning frameworks. Initiatives like Data Catalog Vocabulary (DCAT), Data Package, ISO 19115/19139 series and Open Geospatial Consortium (OGC) establish common metadata standards, enhancing data-level interoperability. In particular the Spatio-Temporal Asset Catalog (STAC) is becoming the de facto standard for meta data of spatio-temporal data[59].
  Metadata standards like DCAT[60] offer a common vocabulary for describing datasets, simplifying discovery, and understanding. Data Package focuses on packaging data and metadata for easier sharing. OGC CSW and OGC Records API allows implementing catalogs and search interfaces for metadata while ISO standards provide the necessary elements to produce standardized data descriptions also known as metadata. Adopting these standards ensures seamless integration of datasets into different frameworks and tools, improving data discovery, interoperability, and collaboration. Adopting these standards ensures seamless dataset integration across frameworks, improves data discovery, enhances interoperability, and fosters efficient data-driven collaborations.

### 6.1.4 Opportunities for Swiss stakeholders

Improving the discoverability, interoperability, and accessibility to quality-controlled data using web-based technologies could optimize the regular update of inventories of current and planned climate data records. This could reduce the time invested in finding datasets and could allow linking data records with relevant documentation and user feedback. Furthermore, this could facilitate the browsing, filtering, retrieval, and ingestion of these records into automated data processing pipelines, in order to help the generation of community-driven tools, libraries (e.g., Python client libraries) and added value applications across catalogues.

[56] https://openeo.org/
[57] https://pangeo.io/
[58] https://ogcapi.ogc.org/
[59] https://stacspec.org/
[60] https://www.w3.org/TR/vocab-dcat-3/

#### 6.1.5 Recommendations and actions

***Best Practice:*** To tackle the challenges of data and machine learning interoperability, consider these approaches:

- ***Community Collaboration:*** Promote cooperation among developers, researchers, and practitioners through industry-wide consortiums, open-source initiatives, and forums. This fosters consensus, standardization, and knowledge sharing, providing a platform for collective problem-solving.
- ***Standards and Best Practices:*** Encourage adopting established standards for interoperable data discovery and access (e.g. OGC) as well as for model interchange. Develop and document best practices for data storage, management, discovery, access and model integration and deployment, emphasizing performance optimization and compatibility. Comprehensive guides and documentation can aid practitioners.
- **Tooling and Integration Libraries:** Create tools and libraries to simplify model conversion and framework communication. These should automate common interoperability tasks, easing the workload for developers. Integration libraries can abstract framework complexities, allowing developers to focus on their applications.
- **Research and Innovation:** Invest in ongoing research for improved interoperability. Explore techniques for model adaptation, cross-framework optimization, and efficient serialization to minimize performance trade-offs. Collaboration between academia and industry can drive innovative approaches and address emerging challenges.
- **Interconnection of infrastructures:** different models such as data federation[61], system of systems (GEOSS[62]) or data spaces[63] can help enabling interoperability between systems, infrastructures, and platforms.

##### 6.1.5.1 Recommendations for decision makers

- Ensure that open government data principles are implemented by agencies.
- Facilitate the discovery and access to data made available by governmental agencies (e.g. MeteoSwiss, swisstopo, BAFU, FSO).
- Bring interoperability along the entire data value chain. It will facilitate storing, visualizing, accessing, processing, analyzing, and integrating climate data and information and enables users to add create value-added products and services.
- Delivering climate services using interoperable web services can lower the barriers for both data providers and data users. In particular, it can enhance the reusability of data and components in various applications, and get increased return on investment.
- Interoperable climate services together with corresponding technical and scientific capacities can play a crucial role in ensuring quality, integrity and availability of datasets and consequently promoting, contributing and supporting research activities and a trusted open science.
- Governance, policies, and institution: Open Data policies and Data Sharing and Management Principles are spreading in various communities and this will strongly influence climate community as well as institutions that are providing data and delivering climate services.

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[61] https://earthserver.xyz/
[62] https://www.earthobservations.org/geoss.php
[63] https://dataspaces.info/

- Development of capacities at human, institutional, and infrastructure levels: Building capacities will help to reach large adoption, acceptance and commitment on data sharing principles. It will also strengthen the capacity of scientists to provide usable and understandable information to decision makers and convince data holders to make available their data to a wide audience facilitating data discovery, access, and processing.

#### 6.1.5.2 Recommendations for stakeholders

- Make as much data available under FAIR principles and keep as little as possible proprietary.
- Publish data on trusted public digital repositories (like Zenodo), ideally that provide interoperability arrangements.
- Develop capacities in Data Science at the human, institutional, and infrastructure levels.
- Adhere to Open Data policies and Data Sharing and Management Principles.
- Contribute to relevant governance bodies.

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## 6.2 Robust Machine Learning at Scale

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### 6.2.1 Vision

In addressing climate change challenges, scalable ML will reshape the scientific landscape by enabling researchers to decipher complicated and previously inscrutable phenomena. It will also play a central role for policymakers when it comes to driving the development and adoption of solutions to reduce climate change and to adapt to its ineluctable consequences. It will contribute to climate change mitigation in several ways: from optimizing energy consumption and reducing greenhouse gas emissions across industries to real-time environmental monitoring and enhancing climate modelling with improved accuracy and granularity of predictions while significantly decreasing simulation times. To make this vision a reality, research models need to be hardened and generalized to meet requirements for production models as scale and need to be accessible for decision makers around the globe.

### 6.2.2 Current state

ML has advanced remarkably in recent years, transforming industries and offering substantial opportunities for science and policy. Current developments include the widespread adoption of discriminative and generative predictive models, but also the extensive collection of annotated data, and the availability of specialized hardware for efficient computation - both crucial for the success of more and more data-hungry ML approaches.

In climate science, statistical and data-driven models have been used for a long time, but the recent developments in ML make it possible to robustly encode a lot more complex, non-linear, spatio-temporal relationships and will accelerate climate science. As it becomes more complex to solve more challenging problems with larger and larger data sets, scalable methods and software are needed to enable training of these models. Consequently, scalability becomes a central problem and solutions are being worked out in this regard, including vertical scaling (i.e., improving an existing machine) and horizontal scaling methods (i.e., distributing processes across several machines). In this context, significant developments are currently taking place towards the creation of deep learning models that are able to handle the complexity of climate data and their patterns and relations in space and time.

A lot of research effort is put into designing large-scale methods based on ***Transformer Architectures*** (e.g., spherical transformer models like Microsoft's ClimaX (Nguyen et al., 2023), NVIDIA's FourCastNet (Pathak et al., 2022), or ClimFormer (Cachay et al., 2022)), as fast emulators for climate and weather models. This goes hand in hand with more general developments, aiming for instance at more efficiency (e.g., scaling models like EfficientNet (Tan et al., 2019)), ***Reinforcement Learning*** (e.g., HPC simulations with SmartSim (Partee et al., 2021)), privacy preservation through ***Federated Learning*** (enabling ML on decentralized data while protecting individual privacy), ***AutoML*** (automating model selection, hyperparameter tuning, and deployment (Tu et al., 2022)), and ***Large Language***

***Models*** (LLMs coupled with vision blocks like Meta's SegmentAnythingModel (Wang et al., 2023), allowing to analyze images via text prompts).

Beyond those general trends, and especially in the field of climate modelling, development is increasingly moving in the direction of ***adaptive modelling***, ***automated scenario testing***, and ***real-time monitoring and reporting***. From a technical point of view, new pipelines for configuring and deploying ML via cloud computing leading to a convergence of software development and deployment. This has the potential to enable more efficient development and deployment, using c***ontinuous integration, deployment and delivery pipelines*** (CI/CD) (Alam et al., 2023; see also section 5.4).

### 6.2.3 Gaps, limitations and concerns

Despite the spectacular progress, several limitations and concerns persist. Next to the more general challenges of ML methods, such as the need for large training datasets, overfitting issues, and a bottleneck between model prototyping and production, the following aspects are becoming more and more important:

- ***Model life-cycle:*** At Swiss universities, researchers develop cutting-edge AI models to investigate regional climate change aspects. Many of these codes are not re-usable, due to limited modularity, testing and documentation and thus, never reach production level quality. To overcome this loss of intellectual property, environmental scientists should collaborate with software engineers, to apply computer science methodologies to result in scalable and maintainable software code (see Appendix 9.1).
- ***Generalization:*** The robust and reliable generalization beyond the training data remains challenging, particularly in dynamic and non-stationary environments. This point is particularly important, as ML models are mainly designed for interpolating, but less suitable for extrapolating outside of their training domain. The climate being a highly dynamical and changing system, there is a risk that present models are limited in their ability to adapt to deviations from the regimes and trends observed in the past ca. 50 years of data (Reichstein et al., 2019).
- ***Interpretability:*** Providing workflows that are reproducible and auditable, so as to comply with accountability requirements.
- ***Computational Resources:*** Training large-scale ML models need substantial computational resources, raising not only environmental concerns but also creating accessibility challenges for SMEs and research organizations.
- ***Regulatory and Ethical Framework*s:** Ensuring the responsible use of ML given the potential societal impact, as models may unintentionally inherit biases present in the data used to train them and could then fail to meet ethical and/or legal standards (see Section 6.6).

### 6.2.4 Opportunities for Swiss stakeholders

ML has already started to fundamentally transform the way science and industry use data to assist problem understanding and solving. In the last decade, ML has been responsible for turning data into a key asset for many organizations, and has penetrated almost all domains of science, leading to an exponential growth in research investment and output. The demand for customized software solutions, corresponding infrastructure setups and consulting services around ML systems will further increase - not only in the economy, but also in academic and governmental sectors. Furthermore, ML provides actionable insights from remote sensing data, supporting governmental and non-governmental organizations with fact-based decision-support during scenario planning activities and thus, will be key for a resilient Switzerland.

### 6.2.5 Recommendations and actions

#### 6.2.5.1 Recommendations for decision makers

- The federal government should promote building an appropriately open community and support initiatives for sustainable, responsible and value-generating use of ML, as it will play a pivotal role in using ML for the benefit of society in the context of climate change mitigation and adaptation.
- Funding organizations should support the development of advanced platform technologies and adherence to Open Science principles to best leverage the potential of ML. They should also provide resources to enable environmental scientists to collaborate with software engineers, to ensure a scalable and maintainable code basis.

#### 6.2.5.2 Recommendations for stakeholders

- Academia and industry need to work hand in hand, and the respective expertise needs to be present in-house to ensure that ML applications and outputs are as trustworthy and reliable as possible.
- Development should focus on scalable ML systems, not only in terms of infrastructure and flexible algorithms, but also in terms of scalable and reusable computer codes, and of services for their flexible deployment and application.
- ML predictions as well as the underlying models themselves should be accessible to everyone. Furthermore, transparency about the data used to train and the pipeline should become a matter of course (an area where current ML solutions, especially in the private sector, fall short).

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### 6.3 Swiss communities, activities, and collaborations

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#### 6.3.1 Vision

Climate change and the related impact is not only about our environment or about potential financial losses, but also about human suffering. While a global challenge, climate change initiatives at the local level across various domains such as policy, economic incentives, research, and community science will be the driving forces behind a climate resilient development in a changing climate. "Think Globally, Act Locally" became a popular environmental movement slogan during the 1970s - and is back in the spotlight. Through the exchange between the various stakeholders and an open science and open innovation approach, sustainable value generation for society in Switzerland can be achieved and the negative effects of climate change can be counteracted more efficiently.

#### 6.3.2 Current state

In Switzerland, various stakeholders and communities are active in the field of climate change, ranging from governmental organizations (e.g. MeteoSwiss, FOEN, SFOe) and research institutions (e.g. EPFL, ETHZ, PSI, WSL, EAWAG, EMPA, Agroscope) to local environmental groups, energy cooperations, or community-led initiatives (see section 4.3.4). They make an important contribution to national and international research, working on enhancing climate resilience and climate change mitigation strategies or run companies that offer services and products in this area. One way of grouping these stakeholders is to organize them into the categories of public authorities, the economic sphere and civil society.

Stakeholders in the category **civil society** include networks like the Swiss Academy of Science (e.g. with the platform ProClim), the universities (e.g. ETHZ, EPFL, UZH, UNIBE, UNIL) and universities of applied sciences (e.g. FHNW, ZHAW, BFH, HES-SO), associated research institutions (e.g. PSI, WSL, EMPA, EAWAG), competence centers and networks (e.g. Center for Climate Systems Modeling (C2SM)[64], CLIMACT[65], DS3Lab[66]), as well as a wide range of foundations (e.g. Klik[67], Swiss Climate Foundation[68]), associations and communities (e.g. Klima-Allianz Schweiz[69], AI for Good[70], Climate-

[64] https://c2sm.ethz.ch/
[65] CLIMACT - Center for Climate Impact and Action: Home https://climact.ch/
[66] DS3Lab Climate+AI Initiative https://climateai.org/
[67] KliK | KliK Foundation https://www.klik.ch/en/foundation/
[68] Home - Swiss Climate Foundation (klimastiftung.ch) https://www.klimastiftung.ch/en/
[69] Romandie • Klima-Allianz https://www.klima-allianz.ch/arbeitsgruppen/romandie/
[70] AI for Good - All Year Always Online (itu.int) https://aiforgood.itu.int/

KIC[71], Klima-Bündnis Schweiz[72], Geneva Association[73]). On the side of **public authorities**, the federal network NCCS (National Center of Climate Services) acts as national coordination and innovation body for all climate services provided by the federal administration. Such federal offices, like MeteoSwiss, FOEN (Federal Office for the Environment), BAFU (Federal Office for the Environment) or SFOE (Swiss Federal Office of Energy) all provide information, initialize projects and offer data and services related to climate-change impacts. In the **economic sector**, consultant companies provide services and partly perform smaller studies based on existing scientific knowledge (e.g. myclimate[74]).

At the **European level**, it is primarily the programs of the European Union (EU) and the European Commission (EC) that deal with aspects of climate change at various levels (e.g. Climate Action[75], European Green Deal[76], Copernicus Climate Change Services[77]). With Horizon Europe[78] (for example with the pillars 1 and 2) or the Destination Earth[79] (DestinE) program, the EU drives the digital modelling capabilities of the Earth to enhance the EU's ability to monitor and model environmental changes, predict extreme events, and adapt EU actions and policies to climate-related challenges. Next to it, the European Environment Agency[80] delivers knowledge and data to support Europe's environment and climate goals.

In addition, the European Space Agency (ESA) has many programs running - some in close cooperation with the EC - to improve access to actionable information as fundamental component to fight climate change, to support knowledge-based policies and initiatives and their implementation, and to ensure that this is balanced with sustainable economic development and societal benefits (e.g. CCI[81], EO4SD[82], FutureEO[83], EO4Society[84]).

Beyond the European framework, networks like GEO[85] (often with a European branch, like EuroGEO[86]) are important community drivers, connecting governmental organisations, research institutions, and businesses to create innovative solutions to global challenges at a time of exponential data growth, human development and climate change that transcend national and disciplinary boundaries. Further, UN organisations like the WMO (World Metrological Organizations) with their initiative named "Early Warnings for All"[87] try to ensure that everyone on Earth is protected from future hazardous weather, water, or climate events through a worldwide early warning systems by the end of 2027.

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71 Climate-KIC | The EU's main climate innovation initiative https://www.climate-kic.org/
72 Der Zweck > Klima- und Energie-Charta | Klima-Bündnis Schweiz (klimabuendnis.ch) https://klimabuendnis.ch/de/info/klima-und-energie-charta/der-zweck
73 Climate Change & Environment | The Geneva Association https://www.genevaassociation.org/research-topics/climate-change-and-environment
74 myclimate – your partner for effective climate protection https://www.myclimate.org/en/
75 Climate Action (europa.eu) https://commission.europa.eu/about-european-commission/departments-and-executive-agencies/climate-action_en
76 https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/european-green-deal_en
77 https://climate.copernicus.eu/
78 https://research-and-innovation.ec.europa.eu/funding/funding-opportunities/funding-programmes-and-open-calls/horizon-europe_en
79 https://ec.europa.eu/newsroom/dae/redirection/document/85565
80 Delivers knowledge and data to support Europe's environment and climate goals.
81 https://climate.esa.int/en/esa-climate/esa-cci/
82 https://eo4sd.esa.int/
83 https://www.esa.int/Applications/Observing_the_Earth/FutureEO
84 https://eo4society.esa.int/
85 https://earthobservations.org/geo_community.php
86 https://research-and-innovation.ec.europa.eu/knowledge-publications-tools-and-data/knowledge-centres-and-data-portals/eurogeo/about-eurogeo_en
87 https://wmo.int/activities/early-warnings-all

### 6.3.3 Gaps, limitations and concerns

Switzerland has committed to the Paris Agreement's goal of achieving net-zero emissions by 2050, however, it encountered difficulties meeting its climate targets. While the discussion on climate change in Swiss politics is generally quite advanced with a broad consensus on the need for action, there is some disagreement on the best way to achieve this goal, with some parties and economic stakeholders advocating more ambitious targets and others calling for a more gradual approach.

One of the primary challenges confronting Swiss climate policy is the country's federal system of government. Additionally, the robust influence of the business lobby in Swiss politics presents another challenge, with certain businesses opposing climate policies arguing that they would be excessively expensive and detrimental to the economy. The present-day discourse on global climate change reflects the significance of the topic. While a considerable amount of research exists on global environmental concerns and policy efforts, understanding how the general public comprehends global climate change and the related impact for Switzerland remains insufficient.

### 6.3.4 Recommendations and actions

- Strengthening of national competence centers, to bring together various stakeholders in an open-community approach and support coordinated and structured research, to generate added value for Switzerland, particularly with regard to transdisciplinary and solution-oriented research. In addition, involving the wider public could lead to a better awareness and understanding of climate-related issues.
- In order to benefit optimally from the knowledge, data and resources available at European level as well as from the European financial support programs, Swiss stakeholders must be given access to and participation in European initiatives at all levels (e.g. Horizon Europe, Copernicus Program, Destination Earth). This requires an appropriate political agenda and representation.
- The latest research results, findings and the underlying data for Switzerland should be harmonized and publicly accessible. The establishment and financing of a knowledge and data platform in this regard would be a suitable approach to linking the relevant stakeholders and initiating new research and innovative approaches in the economy.

## 6.4 Swiss Geo & Climate ICT Infrastructure and Policy

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### 6.4.1 Vision

While there is a large potential for the economy and society to benefit from AI-based applications relying on geospatial and climate data, some technical challenges often make it too difficult for companies and start-ups to invest in such technologies. Examples from abroad and from Swiss research institutions show that solutions exist that can remove such barriers and accelerate the growth of next-generation AI-compatible business models. The overarching objective is to provide an ICT infrastructure that centralizes access to big data, computational resources, and AI programming environments within a single access point.

### 6.4.2 Current state

The main producers of geospatial, meteorological and climate data in Switzerland have traditionally been governmental institutions (Table 6.1) as well as research and academic institutions. As these institutions have non-profit and secured funding (e.g., >5 years), they can assume the relatively high costs of developing and maintaining long-term and comprehensive data products, which can today be used to develop and deploy artificial intelligence applications. Over recent years, governmental institutions have published an increasing amount of such data in an open-access format. This is the result of various political initiatives, like the Open Government Data strategy[88], which are aimed at supporting government transparency, public participation, and innovation in all sectors.

However, in Switzerland, innovation and the private sector also heavily rely on additional data sets, provided by non-Swiss institutions at the European or global scale. This includes for instance weather forecasts and climatological reanalyses from the European Centre for Medium-Range Weather Forecast (ECMWF) and a large amount of satellite data archives (Sentinel, Landsat), many of which are easily accessible through (international) publicly funded centralized platforms like the Climate Data Store (e.g. see these Copernicus pages[89],[90]) or private cloud-based solutions such as Google Earth Engine. AI applications typically require large amounts of diverse data, however, while these data sets nowadays exist, accessing and processing them is still very challenging. For multinational companies or start-ups, the advantage of using globally available data is that it becomes technically easier to scale up a successful product and provide it to customers at any location in the world.

[88] https://www.bfs.admin.ch/bfs/en/home/services/ogd/strategy.html
[89] https://cds.climate.copernicus.eu/
[90] https://dataspace.copernicus.eu/

Table 6.1: Examples of some of the main Swiss institutional providers of geospatial and climate data.

| Swiss governmental big data providers:<br>– *Area of activities is thematically prescribed by a legal mandate*<br>– *Usually, the primary data provider and the data owner*<br>– *Non-uniform array of formats and solutions*<br>– *Does not yet offer computational services* | |
|---|---|
| Federal Office of Meteorology and Climatology (MeteoSwiss) | Provides meteorological and climate data and forecasts (data available on a website and on demand) |
| Swiss Federal Office of Topography (swisstopo) | Provides topographic data, geospatial information (most data visualized and/or available for download) |
| Federal Office of the Environment (FOEN) | Hydrological, environmental and geospatial data for research and policy-making (data available on a website) |

### 6.4.3 Gaps, limitations and concerns

Because many different actors are distributing data through different platforms, each using non-uniform formats and conventions, a major technical difficulty in any AI-based application today is to ensure that these different data streams are homogenized and ingested within a productive computing system without interruptions. Because this problem is redundant for most business models concerned with geo & climate AI services, many recent initiatives (Table 6.2) have aimed to provide centralized facilities where analysis-ready datasets and sometimes computing resources are provided as a service. In Switzerland, only few examples, all oriented towards research applications, can offer a combination of data streams, computing resources, and AI algorithmic workflows within a single environment (see for instance renkulab.io[91], a solution from the Swiss Data Science Center). This situation is a major issue because Swiss economic and innovation actors currently lack access to such centralized services. They must instead rely on solutions provided by foreign companies like Google, Microsoft or Amazon which only provide coarse and global-scale datasets. As a result, they miss access to the national and regional data most relevant to Swiss customers, which publicly funded Swiss governmental institutions intend to freely provide with the aim of fostering economic growth and innovation.

[91] https://renkulab.io/

Table 6.2: Examples of centralized data and computing environments suitable for AI applications in Switzerland.

| Swiss data gatherers and AI enablers<br>✓ Provides analysis-ready (homogenized) datasets<br>✓ A computing solution that includes AI algorithms or workflows<br>× Mainly research-oriented and not suitable for commercial use | |
|---|---|
| Swiss Data Science Center (SDSC) | Offers frameworks, data analytics, machine learning, and cloud computing resources for climate and geographical data research (partly public) |
| Swiss National Supercomputing Centre (CSCS) | Provides high-performance computing for climate and weather modeling, data analysis, etc. (research and governmental) |
| Swiss Data Cube | A project that processes satellite data for environmental monitoring, including climate change (UniGe-initiative, not operational) |

### 6.4.4 Opportunities for Swiss stakeholders

Successful research-oriented platforms (e.g. renkulabs.io) have demonstrated that it is possible to resolve the challenge of bringing together heterogeneous data sources, computational resources, and AI algorithms in a single environment (Figure 6.2). Swiss stakeholders and policymakers must facilitate the transfer of such technology as a service in the private sector. This could occur in the form of encouragement programs or public-private partnerships. On the topic of climate and weather data, the most successful global-scale AI services (e.g., PanguWeather, FourCastNet) developed in the private sector have been developed based on climatological reanalyses (e.g. ERA5) which integrate all available observations and climate data within a single database. The production of a regional climatological reanalysis specific to Switzerland or the alpine domain would also foster the development of accurate AI-based climate services at a local scale.

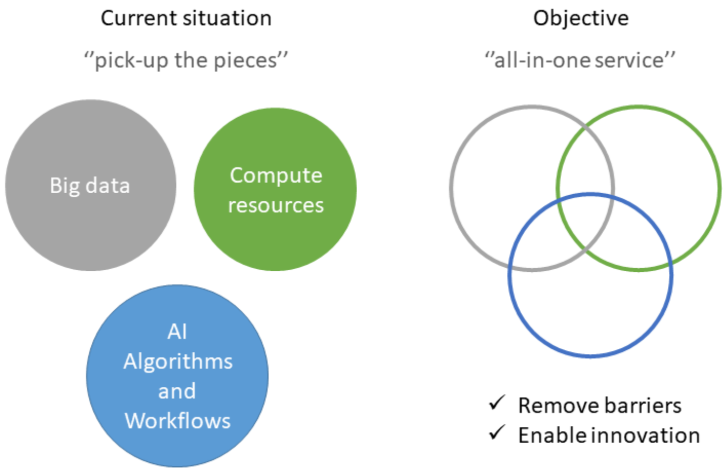


Figure 6.2: The Swiss geo and climate ICT infrastructure seen from the perspective of Swiss economic and innovation actors. The current situation creates many barriers that could be removed if the objective could be reached.

### 6.4.5 Recommendations and actions

#### 6.4.5.1 Recommendations for decision makers

| Desired state | Action | To execute by stakeholder |
|---|---|---|
| Governmental actors support AI deployment and innovation in a coordinated manner | Define a national strategy to support the integration of AI services into the Swiss economy and an internal coherent AI infrastructure. | Federal government |
| Swiss economic agents can rely on state-of-the-art tools and ICT infrastructure at a competitive price (or for free) | Accelerate innovation by supporting open solutions to problems that are common to most actors (e.g. big data acquisition and transfer, access to computational resources, automated deployment of AI algorithms and solutions).<br>Invest into educational or knowledge transfer programs to integrate technological advances into existing economic sectors. | Swiss National Science Foundation, Innosuisse, Academies of science |
| Duplicate efforts are avoided and resources are optimally invested | Prioritize solutions that bring together *all* components of the AI development chain (Figure 6.2).<br>Allocate more resources to facilitate centralized access to publicly available governmental data. | Swiss 'institutional' big data providers (Table 6.1) |

## 6.5 Establishing business models that foster the sustainability transition

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### 6.5.1 Vision

Swiss universities today continuously translate cutting-edge climate research into actionable tools for the market. Private enterprises, from startups to major corporations, will refine these tools, driven by both sustainability and profitability. The government acts as an enabler, offering incentives, setting clear regulations, and championing international collaborations.

Our vision for a Swiss ecosystem of viable climate-services involves the private sector in the same manner as the academic sector and the government. By 2030, Switzerland will provide an ecosystem for sustainability-related business models that forms a global role model of successfully realizing the economic transition towards climate neutrality and resilience.

Open data serves as the foundation, spurring widespread innovation, while proprietary analytics drives business value. Collaborative hubs across Switzerland, for instance the Green Fintech Network[92] foster mentorship and knowledge exchange (Figure 6.3). As a result, Switzerland boasts resilient infrastructures, businesses with profound climate insights, and innovations that benefit the global fight against climate change. Through this harmonious integration of science, business, and policy, Switzerland exemplifies a prosperous pathway to a climate-resilient future.

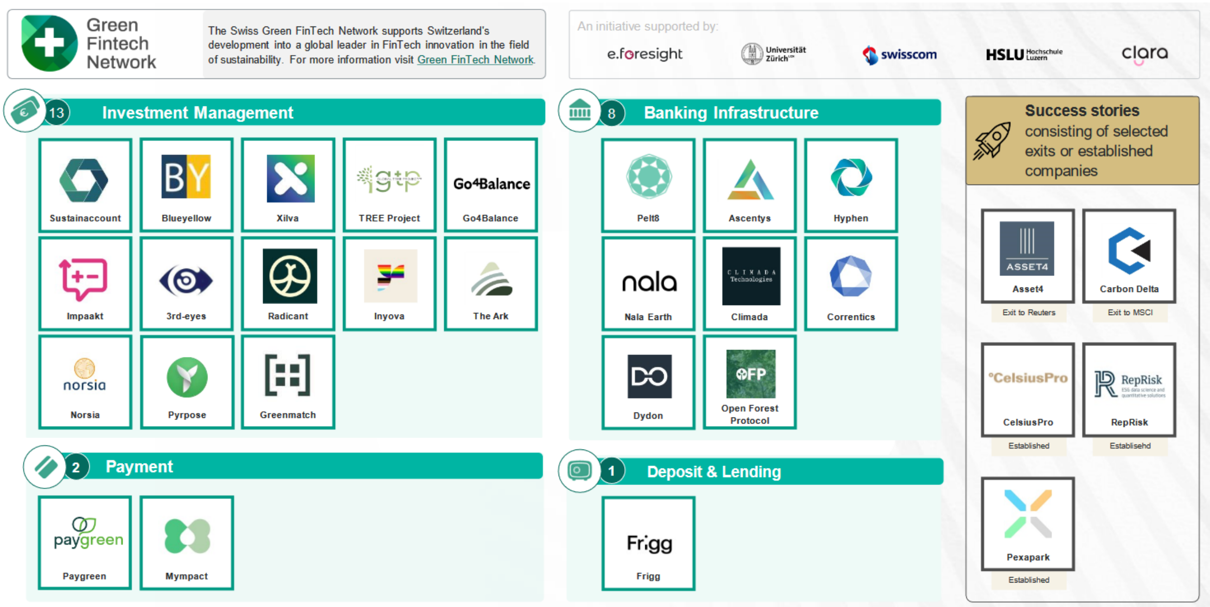


Figure 6.3: Swiss Green Fintech map as of July 2023. (Source: Fintechmap[93])

### 6.5.2 Current state

Climate-service based business models are becoming increasingly prominent as climate change continues to impact various sectors of the economy. These models leverage climate-related data,

[92] https://www.greenfintechnetwork.org/
[93] https://fintechmap.ch/

insights, and predictions to provide value-added services to businesses, governments, and individuals. Major drivers for these business models are:

- **Increasing Climatic Events**: With the rising number of extreme weather events, such as hurricanes, floods, droughts, and heatwaves, there is a growing demand for services that can predict, mitigate, or adapt to these events.
- **Risk Management**: Companies, especially those with considerable assets or operations exposed to climate-related risks, require accurate information and predictions to manage and reduce risks.
- **Regulatory & Policy Shifts**: Governments around the world are imposing stricter regulations and standards related to climate change. These create a demand for services that can help companies comply.

**Focus on regulatory action regarding climate impact and climate risk disclosure:** In Switzerland and across Europe, regulatory pressure concerning climate disclosure has intensified significantly. European entities, particularly the European Union (EU), have been proactive in establishing frameworks like the Sustainable Finance Disclosure Regulation (SFDR)[94] and the EU Taxonomy Regulation[95], which mandate entities to disclose their environmental, social, and governance (ESG) activities, with a strong focus on both, climate-related impacts (aka greenhouse-gas emissions) and climate-related risks. Switzerland, while not an EU member, is aligning its regulatory standards with these European initiatives, aiming to foster transparency in financial markets and ensuring that companies are more accountable for their climate-related risks and opportunities. Concretely, the Swiss Federal Council brings ordinance on mandatory climate disclosures for large companies into force as of 1 January 2024[96]. This regulatory push has invariably catalyzed the growth of climate-service based business models. As companies navigate the complexities of compliance, they are increasingly turning to climate-service providers for data, insights, and tools that can help them measure, report, and reduce their climate footprint. These services not only aid in regulatory adherence but also offer a competitive advantage in a market that is progressively valuing sustainability and climate resilience.

### 6.5.3 Gaps, limitations and concerns

As with any novel market offering, creating viable business models for climate risk applications poses unique challenges. Some of the main blockers include:

- **Data Quality and Availability**: Reliable climate data is crucial for building robust applications. In some regions or sectors, consistent, high-resolution data may be unavailable or expensive, affecting the application's accuracy and reliability.
- **Complexity of Climate Modeling**: Predicting future climate scenarios involves a lot of complexities and uncertainties. Translating these complex models into actionable insights for businesses can be challenging.
- **Regulatory Uncertainties**: As governments around the world grapple with the realities of climate change, regulations can change rapidly. This shifting landscape can make it hard for businesses to commit to long-term solutions.

Besides these major, domain-specific challenges, other hurdles exist similarly to other innovative technology solutions.

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94 https://finance.ec.europa.eu/sustainable-finance/disclosures/sustainability-related-disclosure-financial-services-sector_en
95 https://finance.ec.europa.eu/sustainable-finance/tools-and-standards/eu-taxonomy-sustainable-activities_en
96 https://www.admin.ch/gov/en/start/documentation/media-releases.msg-id-91859.html

From the market viewpoint, not all businesses are aware of or understand the potential impact of climate risks on their operations. Educating the market and convincing potential clients of the applications' value can be time-consuming and costly, irrespective whether education is provided by consultants, or through onboarding into software solutions. These lengthy sales processes, especially when dealing with larger corporations or governmental entities, affect cash flow and growth for startups.

On the one hand the market for climate risk applications is diverse, catering to various industries with different needs. Typical climate risk solutions take the geolocation of assets of business processes under investigation into account. Analyses can be performed for real estate or infrastructure assets, for supply chains, or for companies as a whole. The analyses include on one side an assessment of the risk of climate-impacted natural hazards onto said entities, on the other side a translation of these impacts into economic outcomes. Due to these various niches in which climate risk analysis plays a role, developing a one-size-fits-all solution can be challenging.

On the other hand, as the importance of understanding climate risk grows, the market may become saturated with solutions, making it harder for new entrants to stand out.

Finally, many businesses already have established systems and processes. Integrating a new climate risk application with these systems can pose technical and organizational challenges. And as our understanding of climate science evolves, applications need to be updated regularly to incorporate the latest findings. This demands continuous investment in research and development.

For a climate risk application to be successful, it is crucial to understand and address these blockers, ensuring that the solution remains relevant, reliable, and valuable to its target audience.

#### 6.5.4 Opportunities for stakeholders: revenue models for viable climate-service businesses

Another important aspect is the revenue model applied for a climate-service application. For a climate-tech business, the choice for selling climate-related data can significantly influence its revenue stream, scalability, and customer relationships.

One of the most often used business models in software- or data-as-a-service applications is ***time-based subscriptions***. Customers subscribe to the service within a revolving contract and thus, this model provides a predictable and recurring revenue stream for the climate-service business, enabling better financial forecasting. It can also foster ongoing customer relationships and facilitate regular feedback, leading to product improvements. Continuous access can also enhance customer loyalty and dependency on the service. On the downside, pricing can be a challenge, as the climate-services need to demonstrate consistent value over time to justify subscription costs. There is also a risk of subscription fatigue among customers, especially if they subscribe to multiple services.

Another model, less frequently used, is ***pay-per-use***. This model allows customers to pay only for what they consume, which can be attractive for those who do not need consistent access. This model can also capture a wider range of clients, including those hesitant to commit to a subscription. It might also result in higher revenue per transaction compared to subscription models. On the downside, revenue can be unpredictable, making it harder for the climate-service business to forecast finances and scale operations. It also might not encourage long-term customer engagement or loyalty, leading to sporadic and infrequent interactions.

The third approach is the ***one-off*** business model, which is typically used in consulting but may also apply to a data technology business. It is often seen when data is provided or consumed in a governmental context. The upside here is the potentially large one-time payments, especially from governmental bodies, that provide a substantial influx of capital. Such contracts can also enhance the climate-service's reputation and credibility, opening doors for further collaborations or partnerships. On the downside, it is a non-recurring revenue model, leading to potential financial instability if not supplemented with other revenue streams. Serving government contracts can also be complex and slow, with lengthy procurement processes and strict compliance requirements. Additionally, customizing data for one-off clients can divert resources from improving core offerings.

To create a viable climate-service business, aligning the chosen commercial model with its strategic goals, target customer segments, and operational capabilities is crucial for long-term sustainability and growth.

#### 6.5.5 Recommendation: bringing climate-services from universities to the market

Often, climate services are developed at universities and such, with a time-limited budget. The translation of climate services developed in academic settings to commercialized products is indeed a significant challenge, but also an opportunity (cf. 6.2.3). For Swiss stakeholders, several avenues can be explored to bridge this gap and create viable business offerings.

Swiss universities and governmental bodies can form collaborations with private entities in ***Public-Private Partnerships (PPP)*** to co-develop, commercialize, and market climate services (e.g., the NCCS facilitates climate services and is a key player in linking between universities, federal level and the market). Universities can license their technology or findings to existing companies or startups specializing in climate services. This comes with the advantage of combining academic rigor with business acumen, ensuring that the product is both scientifically robust and commercially viable. This also involves existing innovation hubs & incubators, such as Innosuisse on the government side, and various private climate-tech organizations. These entities can provide resources, mentorship, and funding to budding entrepreneurs from academic settings. They create an ecosystem for innovation, ensuring that promising ideas don't wither away due to lack of business support.

A distinction between ***Open Data and Private Data*** is helpful. Open Data today, such as basic climate models, historical datasets, and foundational research are or can be made open source. This access to cutting-edge data typically fosters innovation as businesses and climate-service businesses can build upon this base layer. Advanced analytics, proprietary algorithms, high-resolution forecasts, and specialized tools developed from such base data can be kept private and monetized. This ensures that there is a value proposition for businesses and a revenue stream for service providers.

Business, the academic sector and the government can also collaborate in ***educational & awareness campaigns***. This may involve organizing seminars, webinars, and workshops targeting businesses to educate them about the importance and utility of climate services, resulting in increased market demand as businesses become more aware of the benefits of integrating climate services into their operations. Similarly, standardization & quality assurance can be driven in such constellations.

***Standards for climate services*** to ensure consistency, reliability, and quality are valuable to generate trust in the service providers and can be achieved in collaboration with Swiss accreditation bodies.

Switzerland, with its strong academic institutions, innovative business environment, and supportive government policies is well-poised to harness these opportunities and become a global leader in commercialized climate services.

#### 6.5.5.1 Recommendations for decision makers

| Desired state | Action | To execute by stake-holder |
|---|---|---|
| Governmental actors support the transition to a decarbonized and climate resilient Swiss economy | Accelerate the efforts to incentivize the transition of the Swiss economy, focusing on instruments such as holistic price for carbon emissions. | Federal government |
| In-depth understanding of the implications of climate change on human well-being and economic prosperity in Switzerland | Conducting studies on climate-related impacts on all Swiss stakeholders, using scenario analysis and considering Switzerland as a player which is highly integrated in the European and Global economy, ecosystems, and social relations | Federal government, academic and private partners, Swiss public society |

### 6.6 Responsible and inclusive AI for climate recommendations

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*The authors would like to thank Lina Stein (Uni Potsdam) and Tamar Eilam (IBM Research) for their helpful comments.*

#### 6.6.1 Vision

The current AI revolution holds immense societal potential, but responsible usage is paramount for a positive impact. Thus, nations are realizing the need for regulatory frameworks (e.g., the EU AI Act). As discussed earlier, AI can play a crucial role in providing data-driven insights and recommendations concerning climate change resilience and adaptation (Miailhe et al., 2021). To unleash AI's positive potential to tackle the global warming crisis, we must adhere to responsible principles, respecting the needs of diverse stakeholders and provide access to such services to all regions of the globe, enabling climate justice[97]. Additionally, we need to ensure sustainable AI operations, reducing energy requirements and associated greenhouse gas emissions. Only through these measures can AI become a global force for good (Figure 6.4).

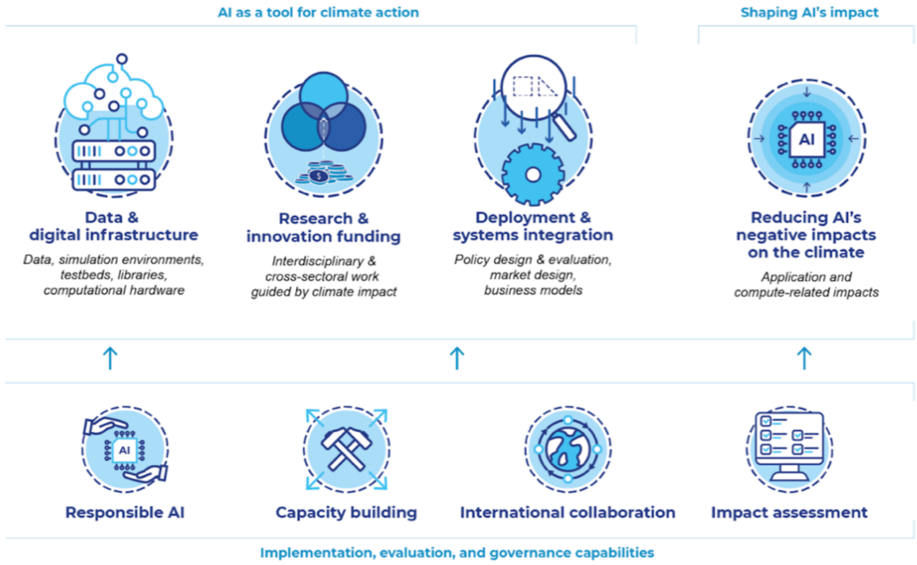


Figure 6.4: Areas of action for governments in supporting the responsible use of AI in the context of climate change.

For the further analysis of the topic, we will distinguish between i) Climate responsible AI and ii) Sustainable AI Operations (van Wynsberghe et al., 2021).

#### 6.6.2 Roadmap towards Climate responsible AI

For discussing the concerns for climate AI, it is helpful to differentiate between the challenges that apply to AI in general and those specific to climate AI.

[97] https://leap.unep.org/en/knowledge/glossary/climate-justice

**General AI challenges include** (Bengio et al., 2021)**:**

- data quality and lack of trust in data, data provenance and data diversity in models,
- model quality: representation of uncertainty, accuracy,
- context of use and integration of AI in decision-making processes,
- privacy concerns,
- impact assessment: establishment of metrics to understand the accuracy of AI enabled decisions in the long-term and processes to adapt models and contexts of use,
- model and data biases,
- lack of safety guardrails (Bengio et al., 2023),
- model lacking explainability, interpretability, transparency (black box), causality,
- labour market issues with automation,
- Issues with synthetic and fake generative AI data (Knott et al., 2023)

**Specific challenges for Climate AI are:**

- representation of climate uncertainty in models (climate is a complex system that is very difficult to model accurately and hence to infer from for predictions),
- interdisciplinarity: using AI for climate simulations requires domain experts, affected communities and policymakers to collaborate for the quality of algorithms as well as their use. This is logistically and culturally challenging,
- equitable distribution of benefits: the use of AI for climate can have significant benefits, however it is challenging to ensure that those are distributed for the benefit of the most affected communities,
- lack of regulation for the use of AI in climate can lead to irresponsible uses (e. g. using for weather prediction with false trust in the reliability of the model and in turn thereby create mistrust when predictions are not accurate),
- agility and responsiveness to changes in climate scenarios and new scientific discoveries.

To ensure the implementation of the above challenges in Climate AI applications, we propose a roadmap with four key pillars, to result in technological solutions which are proactively responsible in nature. This ***Responsible Climate AI Roadmap*** entails the following four key pillars:

1. ***Inclusivity:*** AI should be developed using participatory methods to ensure that applications are relevant for communities most affected by climate change. While technological solutions tend to be developed in the global North, the solutions are required mostly in the global South. Those communities have to be involved in the development process from the start. Positive and negative examples are:

    - participatory development methods have been tested and are available by the OECD[98],
    - the Copernicus program[99] provides global Earth observation data for free,
    - however, African countries often lack high-resolution digital evaluation maps, required to perform flood risk assessments,
    - in addition, research on flood, drought and landslide risks is underrepresented in low-income countries (Stein et al., 2024).

[98] https://www.oecd.org/governance/innovative-citizen-participation/icp-evaluation.pdf
[99] https://www.copernicus.eu/en

2. ***Interpretability & Accountability:*** When AI applications are used to 'predict' climate-related risks or environmental behaviour, there must be mechanisms that allow users to understand the recommendation[100]. Levels of interpretability must be adjusted according to the technical ability of users. Further, individual users or user groups must be able to question recommendations and raise concerns where recommendations seem to be misleading or wrong. Within the developing, as well as the deploying organisation, clear processes of accountability have to be documented. If required, the respective accountable person has to address the concerns raised.
3. ***Accessibility:*** To proliferate AI for climate technologies accessibility is key. This entails open-source access to algorithms, education on how to use and train algorithms as well as (ideally community-driven) technical support. The principle of accessibility also holds for datasets used to train AI models. Unless otherwise governed (e. g. personal sensitive information), where environmental data is gathered, it should be made accessible to all. The open-source platforms chosen should respect the principle of Inclusivity. They should enable co-development and the benefit of the resulting models should be shared between platform users and data providers.
4. ***Responsible Communication:*** While the potential of emergent AI technologies used for climate applications is significant, it is important not to overstate its capabilities. Clear and transparent communication of both the capabilities *and the limitations* of any given AI system is critical. This involves i) where large-scale environmental data is collected for the purpose of AI for climate, ii) where AI is used in the public decision-making processes and iii) the role of AI therein. Statistics and sources should be thoroughly checked to ensure scientific standards such as peer review and scientific objectivity are maintained. In areas where the use of such technology is new and met with skepticism, open public discourses held engaging with the publics concerns and hopes.

### 6.6.3 Roadmap towards Sustainable AI Applications

For a responsible use of Climate AI Applications, we need to consider their impact on the climate itself. This entails the mitigation, tracking, and reporting of their carbon footprint. The following three key aspects need to be addressed:

- ***AI Model Efficiency:*** The training process for large-scale AI models demands significant computational power and energy resources[101]. As these models grow in complexity and size, their energy consumption during operations becomes critical as well. Researchers are increasingly focusing on developing more energy-efficient algorithms, exploring techniques like model pruning, quantization, and alternative model architectures to reduce the energy consumption associated with training and deploying AI models (Behnke et al., 2021).
- ***Mitigating Greenhouse Gas Emissions from Datacenters:*** One strategy to reduce data center emissions is to improve the efficiency of the computation and cooling infrastructure. Researchers are working on AI specific processing units (Iyer, 2023), with orders of magnitude lower power consumption and are proposing the re-use of the power dissipated from the data center in district heating systems (Brunschwiler et al., 2010). Additionally, cloud providers are investing in renewable energy sources to reduce the carbon-footprint.
- ***Reporting of Carbon Footprint:*** Many tech companies are increasingly disclosing their carbon footprint, detailing the emissions associated with data centers that support AI operations. Further, they are establishing applications to predict and report on the carbon emissions of a specific

[100] https://gdpr.eu
[101] https://towardsdatascience.com/the-carbon-footprint-of-gpt-4-d6c676eb21ae

workload of a customer during operations (e.g., IBM Cloud Carbon Calculator[102]). With the availability of such tools, stakeholders can make informed decisions, to reduce the environmental impact of AI technologies.

### 6.6.4 Recommendations and actions

#### 6.6.4.1 Recommendations for decision makers

- Establish unified and transparent benchmarks and standards for the energy usage of AI applications, including their development. This should include environmental impact assessments.
- Data governance and clear policies for data quality, accessibility, and sharing, along with standardized formats, to ensure reliable and comprehensive data for AI models in climate applications. Ensure responsible data collection and usage.
- Enforce guidelines for responsible and ethical AI in climate applications. Develop policies for requiring transparency in AI models, ensuring clear communication of uncertainties and potential biases. Establish mechanisms for accountability in case of errors or unintended consequences. This should be connected to strong incentivization for developers and users to follow ethical and responsible AI principles.
- Avoid funding distribution biases to avoid techno-solutionism, i.e., the assumption or over-reliance on technology being the solution to systemic problems. Whilst programs that use technology to address systemic climate issues should be funded, a situation where technology-heavy approaches are prioritised should be avoided.
- Require participatory design mechanism in publicly funded development and interdisciplinary research.
- Require diverse stakeholders in decision-making processes within the respective institutions (politics & administration, academia or industry). In any decision regarding funding (administration), product development (industry) or new research (academia), representatives from different disciplines but also different parts of society should be involved. Ideally, in all cases representatives from affected communities should be present.
- Develop programs aimed at educating the public and policy makers about the possibilities and challenges in using AI to fight the climate crisis.

#### 6.6.4.2 Recommendations for stakeholders

**General (including users)**

- Conduct Technology Impact Assessments with diverse sets of stakeholders before starting to implement a given technological solutions. This should include environmental impact assessments. Use AI systems with care and energy usage in mind.
- Educate constituencies about areas of use.
- Responsible communication about the capabilities and limitations of models. Ensure highlighting potential biases, hallucination (for generative models) and transparently communicate reliability scores.

**Opportunities for Swiss stakeholders**

- Thought-leadership in establishing unified and transparent benchmarks for the energy usage of AI applications.

[102] https://www.ibm.com/downloads/cas/DKBQEB9M

- Using the SDG Agenda 2030[103], SDGlab[104] and other mechanisms to further AI for Climate.
- Ensure participation of affected communities and realize use case applications according to their priorities.

### Developers

- Follow principles of ethical and responsible AI in development.
- Follow unified and transparent benchmarks and standards for the energy usage of AI applications, including their development.
- Check for potential biases repeatedly.
- Perform Data Quality assessments (data validation, cleaning, provenance verification, ethical data labeling practices, etc.).
- Develop algorithms according to trustworthy AI frameworks (e.g., IBM AI Fairness 360[105])
- Contribute to communities focused on responsible AI practices (sharing insights and learnings from your experiences) and to the development and implementation of ethical standards in AI development for climate applications.
- Track and minimize emissions from AI and data transfer (see tinyML[106]).
- Clearly and accurately state the capabilities and limitations of a model and the data used.
- Follow principles of interdisciplinarity and closely work together with affected communities and climate experts.
- Continuously assess the energy usage of your models and minimize it.
- Develop human-centered AI by e. g. following practices of constitutional AI[107].

### 6.6.4.3 Recommendations Summary

| # | Recommendations | Target Group |
|---|---|---|
| 1 | Conduct Technology Impact Assessments with diverse sets of stakeholders before starting to implement a given technological solutions. This should include all the aforementioned principles, and, in particular, an environmental impact assessment. | Users, Decision-makers, Innovators proposing to use AI solutions |
| 2 | Follow unified and transparent benchmarks and standards for the energy usage of AI applications, including their development. Continuously assess the energy usage of your models and optimise it. | Developers |
| 3 | Use the SDG Agenda 2030, SDGlab and other mechanisms to further AI for Climate use cases. Make sure to choose applications most relevant to affected communities and ensure that mutual benefit is obtained. | Opportunity for Swiss stakeholders |

[103] https://sdgs.un.org/2030agenda
[104] https://www.sdglab.ch/
[105] https://github.com/Trusted-AI/AIF360
[106] https://www.tinyml.org/
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T. Brunschwiler et al., "Direct Waste Heat Utilization From Liquid-Cooled Supercomputers." International Heat Transfer Conference. Washington, DC, USA. 2010.

# 7 Main recommendations and actions

The study team concludes on the following main recommendations and action points for decision makers and stakeholders to enable AI to reduce and adapt to climate-change impact on Swiss society and support the Swiss economy to leverage current opportunities of sustainable applications and business-models, to make a lasting difference.

## 7.1 Main recommendations for decision makers

| Desired state | Action | Targeted decision maker |
|---|---|---|
| Swiss stakeholders with strong transdisciplinary and solution-oriented competence in AI for climate and sustainability | ***Reinforce national competence centers and research bodies in their capacity to support AI for climate and sustainability***, to co-create transdisciplinary and solution-oriented research and innovation in an open-community approach. | Swiss science and innovation bodies |
| Access and exposure of Swiss stakeholders to international programs related to climate and sustainability research and innovation | ***Negotiate participation in European and international initiatives supporting AI for climate and sustainability*** like Horizon Europe, Copernicus Program, Digital Europe (such as Destination Earth), EuroHPC, ELISE,etc. | Federal government |
| Open-Science principles implemented for government agencies and funded research projects | ***Reinforce open-data and open-source principles*** (like EMBAG[108]) for government agencies (e.g., MeteoSwiss, swisstopo, BAFU, FSO) and research projects accelerating data-driven climate and sustainability applications. Apply principles of data parsimony (reduce redundant data collection, leverage existing crowdsourced data). | Federal government, funding bodies |
| Scalable and re-usable code and ML model base | ***Provide resources to enable environmental scientists to collaborate with software engineers***, to ensure a scalable and maintainable code basis and ML models. | Funding organisations |
| Rapid transition of research results to market impact | Universities and governmental bodies to ***strengthen and establish inter- and transdisciplinary collaborations and Public-Private Partnerships (PPP)*** with private entities to co-develop, commercialize, and market climate services through existing incubators, such as NCCS, Innosuisse and private climate-tech organizations. | Universities, governmental bodies and private entities |

[108] https://www.fedlex.admin.ch/eli/fga/2023/787/de

| | | |
|---|---|---|
| Responsible climate and sustainability AI applications | ***Conduct Technology Impact Assessments*** with diverse sets of stakeholders before starting to implement a given technological solutions, based on the UN SDG Agenda. | Product managers |
| Quantitative understanding of the implications of climate change on human well-being and economic prosperity in Switzerland | Conducting ***data-driven studies on climate-related impacts on all Swiss stakeholders***, using scenario analysis, considering Switzerland being highly integrated in the Global economy and social ecosystems. | Funding bodies, academic and private partners, Swiss public society |

## 7.2 Main recommendations for researchers, data scientists and engineers

| Desired state | Action | Targeted stake holder |
|---|---|---|
| FAIR (find, access, interoperate, and reuse data) data principles implemented | ***Adopt open standards*** for data discovery and access (e.g., OGC) as well as for model interchange (e.g., ONNX). ***Publish research data*** on trusted public digital repositories (like Zenodo). ***Provide documentation*** for data schema, management, discovery, access and model integration. | Researchers, data scientist, data engineer |
| Sustainable applications by federation principles | ***Implement data and model federation[1] principles*** to minimize data transfer related emissions and latencies. | Researchers, data scientist, data engineer |
| Re-usable and scalable code base | Apply data, code, and model ***versioning*** principles. Include *tests and validation* into your pipeline. Use state-of-the-art software architecture like **Cloud-native** and development concepts, such as **DevOps, CI/CD and MLOps.** | Researchers, data scientist, data engineer |
| Responsible ML models | ***Be transparent about the data used to train ML models***, including licenses, lineage and generalization of the data set and consider social fairness, i.e., potential negative impacts on vulnerable groups in the society (based on communication, classification, value assignment, etc.) | Researchers, data scientist |
| Sustainable AI | ***Reduce and benchmark the energy usage and carbon emissions of your AI applications*** by model optimization and deployment strategies. | Data engineer |

# 8 AI powered case-studies

## 8.1 Case-studies introduction

In this section, we provide six case-studies to depict the potential of AI and satellite imagery in climate and sustainability related applications. They can be categorized in reporting, climate mitigation and adaptation services with different level of maturity, from research-level to early services available (Table 8.1)

Table 8.1: List of case-studies presented in this chapter, including category and maturity.

| # | Case-study | Category | Maturity |
|---|---|---|---|
| 1 | *Product Carbon Footprint Reporting* | Reporting | Service available |
| 2 | *Greenhouse Gas Emission Monitoring* | Mitigation | Research |
| 3 | *Above Ground Biomass Monitoring* | Mitigation | Research |
| 4 | *Urban Heat Island Prediction* | Adaptation | Service available |
| 5 | *Climate Risk and Resilience Assessments in the Agri-Food Sector* | Adaptation | Research to early services |
| 6 | *Vegetation Health Forecasting* | Adaptation | Research to early services |

## 8.2 Case-Study #1: Product Carbon Footprint Reporting

**Authors:** Remo M. Frey[1], Stefan Frei[1]

[1] myclimate, Switzerland

### 8.2.1 Motivation and Challenges for Product Carbon Footprint Reporting

The motivation to report a Product Carbon Footprint (PCF) lies in the desire to understand and reduce the environmental impact of a product or service. This allows businesses to set clear and measurable goals for reducing their carbon footprint, enhancing their brand image, and staying competitive in a market increasingly driven by eco-conscious consumers.

However, there are significant challenges in creating a PCF. It involves collecting extensive data across a product's lifecycle, including raw material sourcing, production, transportation, usage and recycling while accounting for various influencing factors and uncertainties. Accurately calculating greenhouse gas emissions can be complex, as it depends on numerous variable factors, often necessitating collaboration throughout the supply chain and access to specialized tools and expertise.

### 8.2.2 Methodology of Product Carbon Footprint Application

Creating a PCF using AI has the potential to significantly streamline data collection and analysis, improving the accuracy and efficiency of emissions calculations. AI can enable predictive analytics, allowing companies to identify emissions reduction opportunities and optimize their supply chains for sustainability. Additionally, AI-powered PCF can enhance transparency and consumer engagement by providing real-time information about a product's environmental impact.

As a case study, the non-profit organization myclimate is offering an AI-system which predicts PCF’s by leveraging data from existing product assessments. Their machine learning algorithm (Figure 8.1) identifies patterns and similarities among products, allowing an efficient estimation, especially for new or less-documented items. This approach can save time and resources, making sustainability assessments more accessible for a wider range of products and businesses.

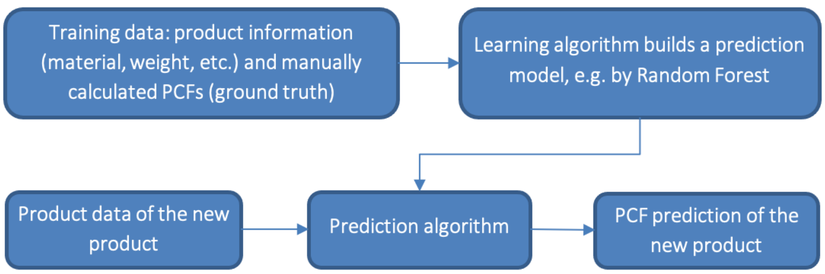


Figure 8.1: Machine learning workflow to predict the PCF of a new product.

### 8.2.3 Performance and Roadmap

Solutions like the one described can be seamlessly integrated into online retail stores, functioning as a decision-support system catering to eco-conscious consumers. The AI-generated PCFs are presented to consumers as supplementary product information, empowering them to make environmentally responsible choices. Given the vast and dynamic nature of product catalogs in large online stores, a fully automated, AI-driven approach proves to be the most viable and practical solution.

With these results, the footprint across the entire product portfolio can be estimated with acceptable accuracy and thus helps to complete the company carbon footprint. In an internal study utilizing the presented machine learning model, the prediction of the total Scope 3 emissions (indirect greenhouse-gas emission from up- and downstream activities) for a product portfolio exhibited an accuracy with less than a 20% deviation from the ground truth.

### 8.2.4 Available Services and Recommendations

There is an increasing number of footprint solutions on the market that offer AI-generated insights. If readers wish to implement their own solution, we make the following recommendations:

First, ensure high-quality and comprehensive data sources covering the entire product lifecycle and supply chain. Invest in data management and integration tools to streamline data collection and preparation for AI analysis. Train AI models with accurate historical data from PCF assessments and engage domain experts to validate model outputs.

Second, integrate AI-driven PCF estimations into your sustainability strategy. Use the insights to set ambitious reduction targets, inform product design decisions, and engage with stakeholders transparently about your environmental efforts. Make AI an integral part of your sustainability journey to maximize its impact on carbon footprint reduction.

## 8.3 Case-Study #2: Greenhouse Gas Emission Monitoring

**Authors:** Gerrit Kuhlmann[1], Márcio dos Reis Martins[2]

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[2] Agroscope, Switzerland

### 8.3.1 Motivation and Methodologies of Greenhouse Gas Emission Monitoring

The signatory parties of the Paris Agreement on Climate Change are required to report their greenhouse gas (GHG) emissions as part of the enhanced transparency framework. The collective progress towards achieving the purpose of the agreement is then assessed every five years in global stocktakes that evaluate the world's progress towards net-zero emissions and, if necessary, prompts the implementation of more ambitious actions (UNFCCC, 2015). Currently, countries mainly report their emissions through emission inventories that are compiled from socioeconomic and environmental statistics following the IPCC Guidelines for National Greenhouse Gas Inventories [IPCC 2019]. However, the compilation and processing of the required data for producing GHG inventories is resource-intensive, time-consuming, and associated with high uncertainty, and thus insufficient for assessing the impact of policies in near real-time (Pinty et al., 2018). To better support the mitigation actions of the parties, measurement-based monitoring systems are in development that provide global information on GHG emissions in a consistent, reliable, and timely manner. Measurement-based monitoring systems determine emissions of countries, regions, and hot spots (i.e., cities, power plants and industrial facilities) using coupled data assimilation systems that combine in situ and satellite measurements of atmospheric GHGs with atmospheric transport simulations (see Figure 8.2) (Janssens-Maenhout et al., 2020). They will improve current inventories and provide data where currently no inventories are available.

AI plays an important role for such monitoring systems making it possible to process a large amount of data accurately in a timely manner. AI-driven algorithms will be used for retrieving GHGs from remote sensing measurements, for detecting and quantifying emission hot spots in the remote sensing images, for advancing atmospheric modelling systems (e.g., very fast radiative transfer and chemistry schemes), for mapping model fields to observations, and for downscaling global products for stakeholder uptake such as product carbon footprints (see Case Study #1, Section 8.2).

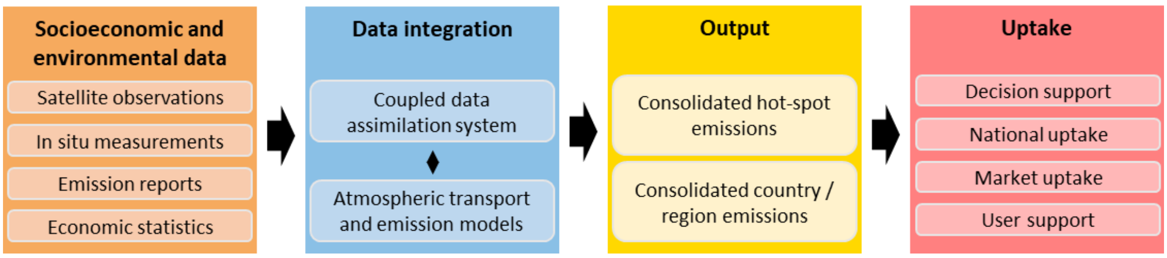


Figure 8.2: The dataflow of a GHG monitoring system based on the Copernicus $CO_2$ Monitoring System (Janssens-Maenhout et al., 2020)

### 8.3.2 Applications and Beneficiaries of Greenhouse Gas Emission Monitoring

GHG monitoring systems will benefit the parties of the Paris Agreement by providing global maps of GHG emissions (carbon dioxide ($CO_2$), methane ($CH_4$) and nitrous oxide ($N_2O$)) at high spatial resolution that will provide support in the validation of emission inventories. Consistent, global GHG emission datasets are an important input for modelling consumption based GHG emissions that adjust national emissions for trade.

$CO_2$ is emitted primarily by fossil-fuel combustion from electricity and heat production, industry and transportation. $CO_2$ emission monitoring of hot spots will support cities and industry in monitoring their reduction measures. $N_2O$ is mainly emitted by the agriculture sector, primarily associated with fertilization, animal excreta in grazing livestock systems, and crop residues (Velthof and Rietra, 2018; Hergoualc'h et al., 2019). Countries with complex agricultural systems, like Switzerland, with diversified crop rotations and grassland categories, can benefit from a reliable and efficient $N_2O$ monitoring. $CH_4$ is another major GHG emitted by the oil and gas sector, livestock farming, landfills and waste, and coal mining. $CH_4$ emission reductions constitute an attractive target for climate change mitigation because it can be captured and used, for example, for energy production. $CH_4$ emissions, for example, from leakages have high uncertainty and measurement-based emission monitoring can guide cost and time effective mitigation strategies.

### 8.3.3 Roadmap and Available Services of Greenhouse Gas Emission Monitoring

The development of an emission monitoring system requires the development of the in situ and satellite measurement infrastructure and the data integration system processing the observations to obtain consolidated country, region, and hot spot emissions. Finally, it will be necessary to develop products and services to provide the required support to the different stakeholders. The first two components are currently in active development and planned to be available for the second global stocktake in 2028.

**Environmental measurements:** GHG emission monitoring requires observations with (1) high accuracy to identify the signals from individual sources, (2) imaging capabilities to resolve emission plumes, and (3) global coverage to support the Paris Agreement (Janssens-Maenhout et al., 2020).

$CH_4$ observations from space are available from area mappers that provide ***global coverage*** with spatial resolution of a few kilometers that can detect methane anomalies (e.g., GOSAT and TROPOMI) and imagers that are able to resolve strong ***point sources*** at about 100 m resolution (e.g., Landsat, Sentinel-2, GHGSat and PRISMA) (Jacob et al., 2022). In addition, airborne imagers have been used to determine $CH_4$ emissions from weaker sources at 1–10 m resolution.

The feasibility for quantifying anthropogenic $CO_2$ emissions with satellite measurements has been demonstrated with the OCO-2 and OCO-3 satellite at 2 km resolution (Nassar et al., 2017; 2022; Weir et al., 2021). However, there are currently no $CO_2$ satellites that fulfill the requirements for a global monitoring system. To fill this gap, Europe is building the Copernicus $CO_2$ Monitoring Mission (CO2M), which will be a constellation of two or more satellites that provide $CO_2$ and $CH_4$ satellite images at 2 km resolution with weekly global coverage (see Figure 8.3). The first CO2M satellites will be launched in 2026. Likewise, Japan is developing the GOSAT-GW mission that is planned for launch in 2024. Point source imagers with high spatial resolution are also available or in preparation (GHGSat, TANGO and CO2Image). The $CO_2$ satellites are supplemented by tropospheric monitoring instruments measuring co-emitted carbon monoxide (CO) and nitrogen dioxide ($NO_2$) (Sentinel-5P, GEMS, TEMPO, Sentinel-4 and Sentinel-5).

$N_2O$ monitoring missions for area sources have been suggested for ESA's Earth Explorer 11 (i.e., MIN2OS (Ricaud et al., 2021)). Since the mission was not successful, there is currently no imminent mission that can monitor $N_2O$ emissions on the regional scale.

In addition to satellite observations, ground-based and airborne measurement are critical for the validation of the global system. International networks such as ICOS[109], ACTRIS[110] and AGAGE[111] are critical to produce standardized, high-precision and long-term measurements. Airborne measurement campaigns will be possible, for example, with the Swiss Airborne Research Facility for the Earth System (ARES[112]) that will be able to monitor $CH_4$ leakages at facility level.

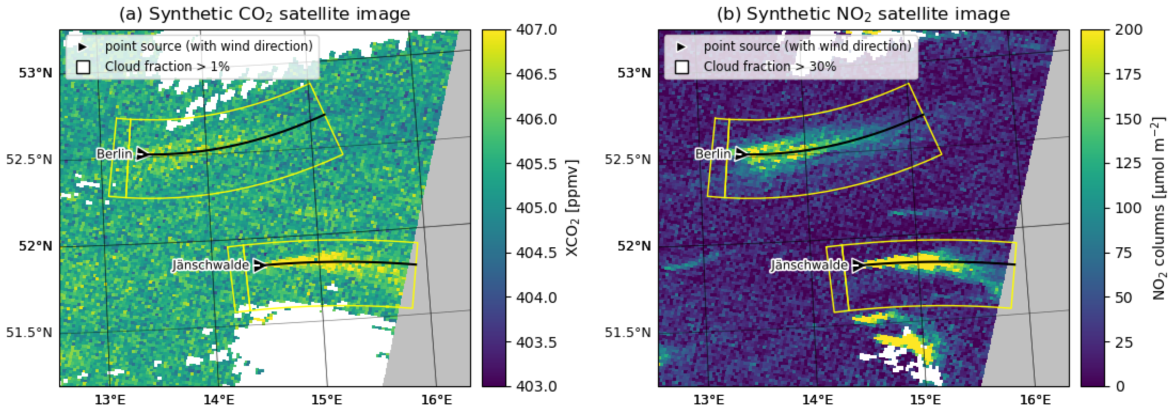


Figure 8.3: Model simulation showing expected $CO_2$ and $NO_2$ satellite images (2km resolution) of the upcoming CO2M satellite constellation. The images show the emission plumes of the city of Berlin and a power plant near Jänschwalde, from which $CO_2$ emissions can be determined using machine-learning models (Kuhlmann et al., 2019).

**GHG monitoring systems:** Many operational monitoring systems are currently being developed, including NASA's Carbon Monitoring System (CMS), the European Monitoring and Verification Support (MVS) capacity, and many national activities around the globe. The global efforts are coordinated by the WMO Global Greenhouse Gas Watch (G3W) program established in 2023. Methane activities are coordinated by the UNEP's International Methane Emissions Observatory (IMEO). The European GHG monitoring system will be implemented as part of the Copernicus Atmospheric Monitoring Service (CAMS) in ECMWF's Integrated Forecasting System (IFS). The prototype system is being developed in the Horizon 2020 CoCO2 project[113] and other Horizon Europe projects (e.g., CORSO[114]). In the IFS model, ***machine-learning models*** are developed to map model fields to satellite observations and to develop faster algorithms, for example, for atmospheric chemistry and radiative transfer. For hot spots, the large number of images provided by satellites requires fast algorithms for which machine-learning models have been identified as the most promising candidates. The main challenge is the lack of training data, because information on true emissions at satellite overpass is generally not available or only known with large uncertainties. Machine-learning models were therefore trained with synthetic satellite observations generated from highly realistic atmospheric transport simulations, which requires access to high performance computers (Jongaramrungruang et al., 2022; Joyce et al., 2023; Dumont Le Brazidec et al., 2023).

**Uptake:** Output from the GHG monitoring system will be taken up by the scientific community, companies, and NGOs to develop products and services that provide information about GHG emissions. A

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109 https://www.icos-cp.eu/
110 https://www.actris.eu/
111 http://agage.mit.edu/
112 https://ares-observatory.ch/
113 https://www.coco2-project.eu/
114 https://corso-project.eu/

first example is the Global Carbon Project, which provides an atlas of global GHG emissions[115] based on currently available data. To maximize the value of the global maps of GHG emissions need to be combined with additional socioeconomic and environmental data. For example, machine-learning models can be used for downscaling satellite images as demonstrated for example for air pollution maps (de Hoogh et al., 2019; Kim et al., 2021). Likewise, machine-learning models can be developed to obtain information about consumption-based emissions and product carbon footprints (see Case Study #1, Section 8.2).

### 8.3.4 Recommendations to Enable Accurate Greenhouse Gas Emission Monitoring

The global GHG monitoring system will be an important tool for monitoring the progress towards a net-zero society. The development of such models requires access to socioeconomic and environmental datasets as well as access to high performance computers.

The European Copernicus program is currently leading the development of GHG monitoring systems with the upcoming CO2M satellite constellation and the GHG monitoring system implemented in CAMS. Access to Copernicus services will be essential if Switzerland is to continue to participate in developments in this area.

The development of the GHG monitoring systems is strongly driven by the research community through international project (e.g., Horizon Europe) and the implementation is funded international organizations such as ESA, EUMETSAT and ECMWF through the European Commission and thus is limited to Copernicus member states. Since Switzerland is currently not a member, Swiss researchers and companies cannot compete in calls for tenders.

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### 8.4 Case-Study #3: Above Ground Biomass Monitoring

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#### 8.4.1 Motivation and Methodologies of Above Ground Biomass Monitoring

The conservation of the Earth's forests has become a global priority[116] because the society depends on a multitude of terrestrial ecosystem services. Plant-based carbon storage is one way to limit and reduce $CO_2$ content in the atmosphere. The United Nations have formulated global forest goals that include maintaining and enhancing global carbon stocks and increasing forest cover by 3% between 2017 and 2030. Earth observation is key in this context because it provides data to monitor forests on a large scale because of its increased availability, reduced costs, and growing global coverage over the last decades. Optical imagery collected by satellites, such as Landsat, MODIS and Sentinel-2 has been involved in area estimates of deforestation and land cover, for example, but also to densely regress vegetation parameters like above ground biomass monitoring. To measure progress in terms of carbon and biodiversity conservation, as well as the negative impact of global demand for commodities that is driving deforestation (Hoang and Kanemoto, 2021), we need novel, accurate, and largely automated methods that can analyze the ever-growing data deluge from spaceborne sensors consistently, at global scale. Novel deep learning methods in combination with space missions like NASA GEDI (Dubayah et al., 2020), custom-designed to measure forest structure, offer new pathways to compute dense, accurate, trustworthy above-ground biomass (AGB) maps globally with high refresh rates (Figure 8.4).

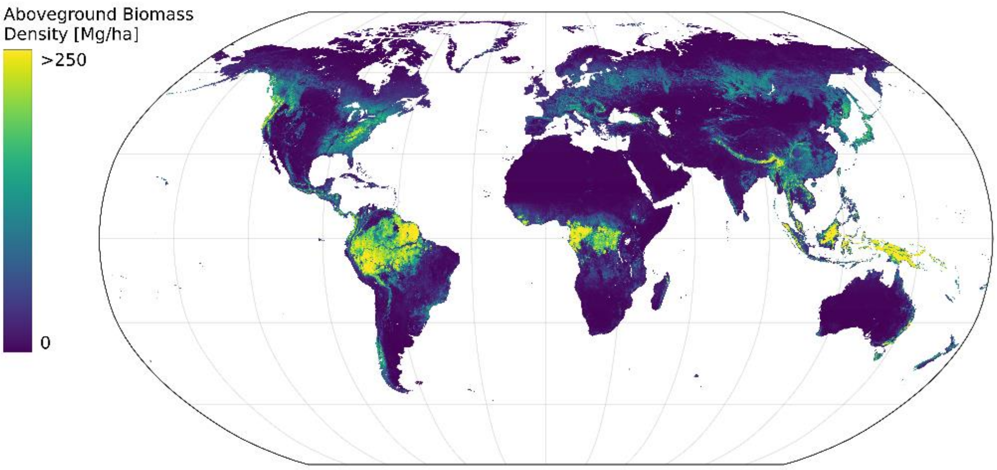


Figure 8.4: Global maps of aboveground biomass density for the year 2020 with 50-meter grid spacing (Lanfranchi, 2022).

#### 8.4.2 Applications and Beneficiaries of Above Ground Biomass Monitoring

Global, up-to-date, wall-to-wall maps will benefit the understanding of ecosystem processes, biological diversity, and climate change mitigation (Skidmore et al., 2021). Worldwide mapping of vegetation properties is crucial to understand the global carbon cycle and the impact of human activities on carbon emissions (Friedlingstein, et al. 2021). Novel, dense, globally consistent AGB maps will play an

[116] United Nations strategic plan for forests 2017–2030. https://www.un.org/esa/forests/documents/un-strategic-plan-for-forests-2030/index.html

important role for conservation efforts, for example, by analyzing how much forest with high AGB is located within protected areas and to alert in case of illegal logging (Reiche et al., 2021). Beyond pure observation, trustworthy AGB maps will allow for decision making under uncertainty and can thus serve ongoing efforts in forest conservation in support of the Sustainable Development Goals (Persello et al., 2022). It may also foster advances in climate modelling (Jucker et al., 2018), carbon stock estimation (for ESG reporting; Duncanson, et al., 2022), biodiversity modelling (Tuanmu and Jetz, 2015), and possibly the monitoring of carbon offsetting projects.

### 8.4.3 Performance and Roadmap of Above Ground Biomass Monitoring

Estimating forest change by area, canopy height or AGB from spaceborne sensors is challenging. Area estimates of deforestation using signal processing and machine learning applied to optical or synthetic aperture radar (SAR) data exist (Reiche et al., 2021; Karaman et al., 2023) with accuracies of up to 70.7%. Much research relies on time-series of freely available NASA/USGS Landsat imagery to map forest structure (Potapov et al., 2021). Another promising source of freely available satellite imagery is the ESA Copernicus program with its Sentinel-1 and Sentinel-2 missions, offering 10-meter ground sampling distance and three to five days revisit time. In the last years, Sentinel imagery and deep learning methods became a valuable source for predicting forest biophysical variables like AGB or canopy height (Puliti et al., 2021; Lang et al., 2023) and carbon stocks (Lang et al., 2021). Associated predictive AGB density uncertainties are depicted in Figure 8.5. A global mean absolute error of 26.44 Mg/ha results compared to the GEDI reference footprints (Lanfranchi, 2022). The negative residuals indicate that model estimates are lower than the reference data. It should also be noted that the error increases relative to the biomass, i.e., high biomass is significantly underestimated. To improve the AGB estimation, future work should assimilate data from other spaceborne missions like ICESat-2, NASA TanDEM-X, NASA-ISRO NISAR and ESA BIOMASS.

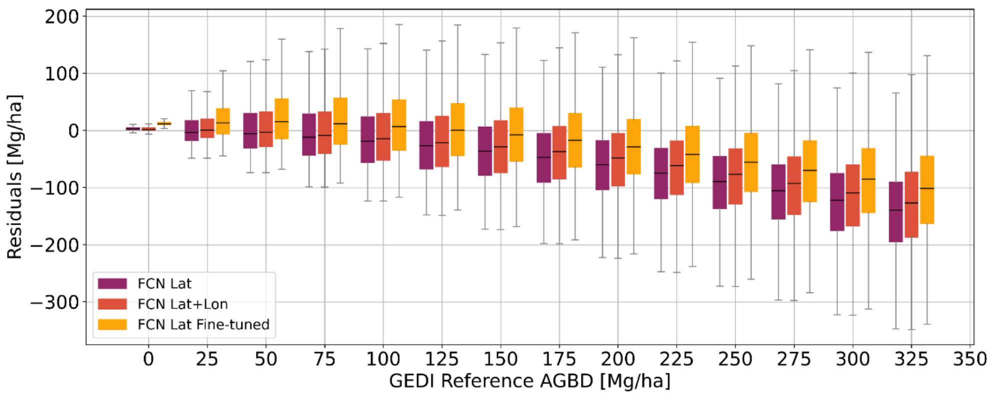


Figure 8.5: Aboveground biomass (AGB) density residuals w.r.t. reference AGB density intervals of the global AGB density map of 2020 shown in Figure 8.4. Different colors indicate three different deep learning approaches (Lanfranchi, 2022).

### 8.4.4 Available Services and Recommendation for Accurate Above Ground Biomass Monitoring

To leverage the full potential of global AGB maps for practical use, well-calibrated uncertainties should be computed at the same spatial resolution along with each AGB prediction to quantify the trustworthiness of each individual estimate. Although some web-based platforms like global forest watch[117], Google dynamic world[118], ESRI ArcGIS Living Atlas of the World[119] or the Microsoft Planetary Computer[120] provide land cover maps globally that also include some forest properties, a consistent, dense mapping of AGB with at least annual updating rate seems missing. Moreover, most of the products come at high financial costs, e.g., costs for downloading data, training a deep ensemble approach on a high-performance GPU cluster, and dense AGB prediction at global scale with 50-meter grid spacing for the map shown in Figure 8.4 amounts to approximately 50'000 CHF (without considering any labor or development costs and under the assumption that all input and reference data is publicly available at no charge). Outside public research institutions, AGB products are often not publicly accessible, and the applied methods are often not published and transparently validated with good scientific standards, ultimately limiting their use for society. Quantitative evaluation metrics and benchmark datasets should become an integral part of the development process of Earth observation systems producing AGB maps.

To reduce overall costs and accessibility, reference data, source code, and trained models should be open-sourced and benchmarked against one another. Switzerland should invest in cooperations with global space agencies like ESA and NASA but also private companies like Maxar, Planet etc. to provide access to high-quality, high-resolution remote sensing data more easily. Due to the large data volume that must be handled as well as the very high GPU capacity needed to train and apply models at global scale, more resources should be invested into Swiss cloud solutions accessible to public institutions and companies to allow for a unified approach across sectors.

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## 8.5 Case-Study #4: Urban Heat Island Prediction

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### 8.5.1 Motivation and Methodologies for Urban Heat Island Prediction

Understanding high-resolution intra-urban temperature variability is important for urban planning, climate impact assessments, and climate adaptation evaluation. Data-driven modeling can be successfully applied in this domain and provides valuable insights and predictions. Generally, there are two rationales why data-driven modeling is applied: efficiency and epistemic rationale (Knüsel et al., 2019). In any case, a common constraint of these methods is their reliance on a substantial volume of training data. This limitation can be overcome by making use of novel kinds of data, e.g., data that is collected as a consequence of human behavior such as temperature measurements from citizen weather stations (CWS). While the underlying physical principles causing spatial urban temperature variability are well-understood (Oke, 1982; Oke et al., 2017), physically-based modeling is computationally expensive and the results are often not thoroughly validated (Toparlar et al., 2017), data-driven modeling can overcome those limitations. In a study (Zumwald et al., 2021), we used a combination of open government data (e.g., 3D building data), freely available satellite data, and CWS data, to predict temperature in high spatiotemporal resolution (10x10m) in cities (Figure 8.6).

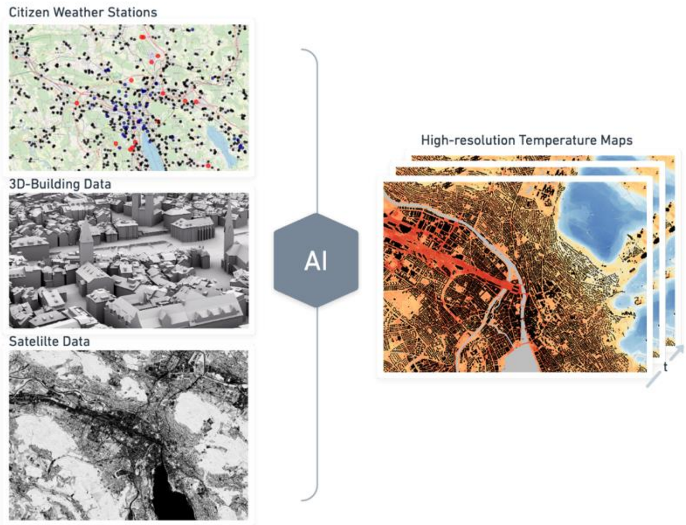


Figure 8.6: By utilizing various temperature sensor data, 3D building data, satellite data, and other openly available data sources, in combination with data processing techniques and machine learning, it is possible to derive accurate high-resolution temperature maps for the city of Zürich (Zumwald et al., 2021).

### 8.5.2 Applications and Beneficiaries for Urban Heat Island Prediction

High resolution heat maps and derivative products can potentially overcome problems stakeholders are facing in the realm of urban heat islands. The primary beneficiaries span from city authorities to urban planners, architects, and city inhabitants. City authorities can potentially leverage AI tools for strategic planning and emergency response. Urban planners and architects use AI-assisted design and simulation models to create heat-resilient infrastructure, balancing urban development with environmental sustainability. Meanwhile, city inhabitants benefit directly from AI applications that provide personalized heat risk alerts and community heat maps, helping them navigate and cope with extreme heat conditions.

While there are certainly technological and methodological advancements needed, the presented approach already provided some of the needed innovations. First, the presented approach is highly efficient. Predicting temperature distribution using computational fluid dynamics models would require vast computational resources from supercomputers, whereas the presented approach using AI can run on a standard personal computer. Second, the approach can be validated using measurements from reliable measurement stations. Third, the approach supports nowcasting or short-term forecasting of temperatures. Fourth, the applied algorithms and developed methods allow assessing the uncertainties in the predictions in a spatially explicit manner. All these advantages are beneficial for urban planning and design. This is because temperature patterns and hotspots within urban regions are idiosyncratic and influenced by various factors, such as urban form, weather patterns, and topography (Table 8.2).

Table 8.2: Stackeholders benefiting from urban heat island prediction.

| | City Authorities | Urban Planners & Architects | City Inhabitants |
|---|---|---|---|
| Problems | Managing heat-related health emergencies.<br>Ensuring efficient allocation of resources for heat mitigation.<br>Limited (real-time) data on heat distribution and impact.<br>Budget constraints for implementing large-scale solutions. | Designing heat-resilient infrastructure and public spaces.<br>Integrating green spaces effectively to reduce urban heat.<br>Balancing urban development with environmental concerns.<br>Adapting existing structures to new heat mitigation designs.<br>Balance densification and urban heat trade-off. | Exposure to extreme heat.<br>Awareness and education about heat-related health risks.<br>Unequal distribution of heat mitigation resources. |
| AI applications | Heat maps to identify high-risk areas.<br>Predictive analytics for resource allocation and emergency response planning. | AI-assisted design tools for heat-resilient urban planning.<br>Simulation models to predict the impact of architectural changes on urban heat. | Now-casting maps.<br>Heat risk alerts using.<br>Identifying cool areas. |

### 8.5.3 Roadmap of Urban Heat Island Prediction

Looking to the future of applying machine learning and novel data sources in the context of predicting (extreme) heat, several key points stand out. High-resolution heat maps have the potential to enhance vulnerability and risk assessments. Current spatial approaches, which rely on climate model outputs, tend to underestimate temperatures in urban areas (Stalhandske et al., 2022). Machine learning can offer deeper insights into how urban form features, such as road networks, topography, urban green spaces, and buildings, relate to intra-city temperature variations (Zekaret al., 2023). The achievable spatial resolution is limited by the available data of the incorporated predictors. In principle, resolutions of 1x1 meter are possible[121]. However, freely available satellite data (i.e., Sentinel-2[122]) is limited to a 10x10m spatial resolution, being the current limit for scalable solutions. At this resolution, the signal of single street, trees or green roofs cannot be captured[123]. Hence, an increase in spatial resolution is a pre-requisite to develop methods that allow to understand the effect of small-scale adaptation measures, such as planting trees. This could for instance be achieved by either statistical downscaling methods and/or including higher-resolution commercial satellite data. By integrating measurements or outputs from numerical weather predictions, it is possible to make short-term forecasts with high resolution. This capability can support real-time decision-making and facilitate the deployment of impact-based warnings, for example for Winter Storms (Röösli et al., 2021).

### 8.5.4 Available Services and Recommendations of Urban Heat Island Prediction

Currently, no service offers consistent high-resolution temperature maps that cover a wide variety of regions and geographies and are constantly updated. While the case study presented here focuses on the city of Zurich, the methodology can, in principle, be applied to other cities worldwide. A major obstacle to this expansion is data availability. Fortunately, there is a growing trend of publishing curated large-scale datasets containing relevant information, such as details about buildings (Milojevic-Dupont et al., 2023). Other pertinent data sources are available as services, including Sentinel-2 data, open street map data, and land cover data (Corine Land Cover). While CWS data is primarily available for purchase through APIs, such as Netatmo[124] and Wunderground[125], there are also open-source networks and infrastructure provided by organizations like the UK Metoffice (WOW)[126] and private initiatives like OpenSenseMap[127].

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## 8.6 Case-Study #5: Climate Risk and Resilience Assessments in the Agri-Food Sector

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[4] 2blades, Switzerland

### 8.6.1 Motivation and Methodologies for Climate Risk and Resilience Assessments

Sectors directly affected by climate change could benefit from AI for i) better assessment of the risks; and ii) decision-support for both mitigating deleterious effects and adapting to conditions. To illustrate the potential of AI for tackling climate change (Rolnick et al., 2022) on tangible examples, we selected the **agri-food sector as a case study** (Hasegawa et al., 2022; Rezaei et al., 2023; World Bank, 2015). This sector has significant climate change-related risks due to:

- the implied high-exposure agriculture to extreme events,
- the typical climate-related hazards potentially impacting different steps of the pre-farm gate to final consumer chain, such as crop growth (*e.g.*, droughts), animal welfare (*e.g.*, heatwaves) (Lacetera, 2019) and logistics (*e.g.*, flooding, landslides)[128] and
- the vulnerabilities of "business-as-usual" (*e.g.*, use of non-drought tolerant crops, unimodal transportation of agricultural goods).

AI methodologies offer crucial support in addressing these climate impact topics (Mourtzinis, 2021). Large language models enhance understanding and decision-making by analyzing vast climate-related data and generating insights (Rillig et al., 2023). Numerical and quantitative approaches including statistical learning, can help predict climate phenomena and bridge data gaps (Huntingford et al., 2019).

### 8.6.2 Applications and Beneficiaries of Climate Risk Assessments in the Agri-Food Sector

The illustration below (Figure 8.7) highlights potential beneficiaries, climate-related risks, examples of challenges and potential applications of AI spanning over the entire agri-food sector value chain, from pre-farm gate to final consumers.

[128] https://e360.yale.edu/features/how-climate-change-is-disrupting-the-global-supply-chain

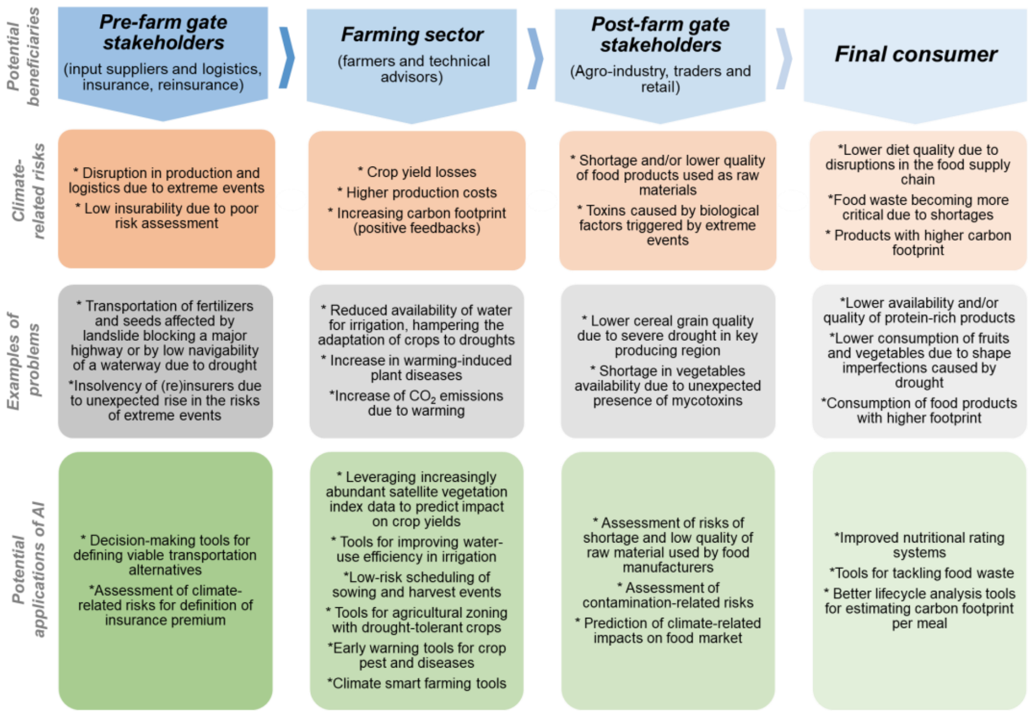


Figure 8.7: Use of AI to tackle negative impacts of climate change in the agri-food sector.

### 8.6.3 Performance and Roadmap of Climate Risk in the Agri-Food Sector

The following Tools for Climate Risk and Resilience Assessment are available in the ***Agri-Food Sector*** (see Table 8.3).

Table 8.3: Tools for Climate Risk and Resilience Assessment in the agri-food Sector (Liu et al., 2022).

| | |
|---|---|
| Crop Models | Performance: Crop models are used to simulate crop growth under various climate scenarios. They provide insights into yield changes and potential risks.<br>Limitations: Crop models rely on historical climate data and may not fully capture the effects of extreme weather events. |
| Weather Data and Remote Sensing | Performance: Weather data and remote sensing are used for monitoring weather conditions, pest outbreaks, and crop health.<br>Limitations: Data resolution and coverage can vary, impacting the accuracy of assessments. |
| Climate Services for Agriculture | Performance: Climate services provide agricultural stakeholders with climate information and forecasts for decision-making.<br>Limitations: Services may not always be tailored to specific local needs or include advanced predictive capabilities. |

A roadmap for potential performance improvement in future usage of AI-Based Tools includes:

- *AI-Enhanced Crop Models:* AI can improve crop models' accuracy by incorporating real-time weather data, satellite imagery, and machine learning algorithms, enabling better predictions of crop yields and risks (Liu et al., 2022).
- *Precision Agriculture and Pest Disease Detection with AI:* AI can optimize agricultural practices by analyzing vast amounts of data, including soil health, weather conditions, and crop health. The

health aspect includes AI-based image recognition and data analysis to enhance pest and disease detection. This leads to more efficient resource allocation and to risk reduction (Liu et al., 2021).

- *AI for Climate Resilient Markets and Supply Chains:* AI can enhance supply chain resilience by assessing climate-related vulnerabilities, improving predictions for extreme weather events and aiding market analysis for better risk assessment and decision-making in the agri-food sector (Singh et al., 2023).

Overall Potential in the Agri-Food Sector: AI-based tools hold significant potential for the agri-food sector in enhancing climate risk and resilience assessments. They can provide real-time data, precision agriculture solutions, and predictive analytics for better decision-making. These tools can help increasing crop yields, reducing losses, and improving the resilience of the agri-food supply chain against climate-related challenges. Figure 8.8 below shows an example of application of AI for warning of crop pests and diseases developed (Grünig et al., 2021). This type of AI tools can be a very useful to tackle warming-induced damages. However, successful broadscale implementation of this type of tool will require data infrastructure, collaboration, and sector-specific AI models.

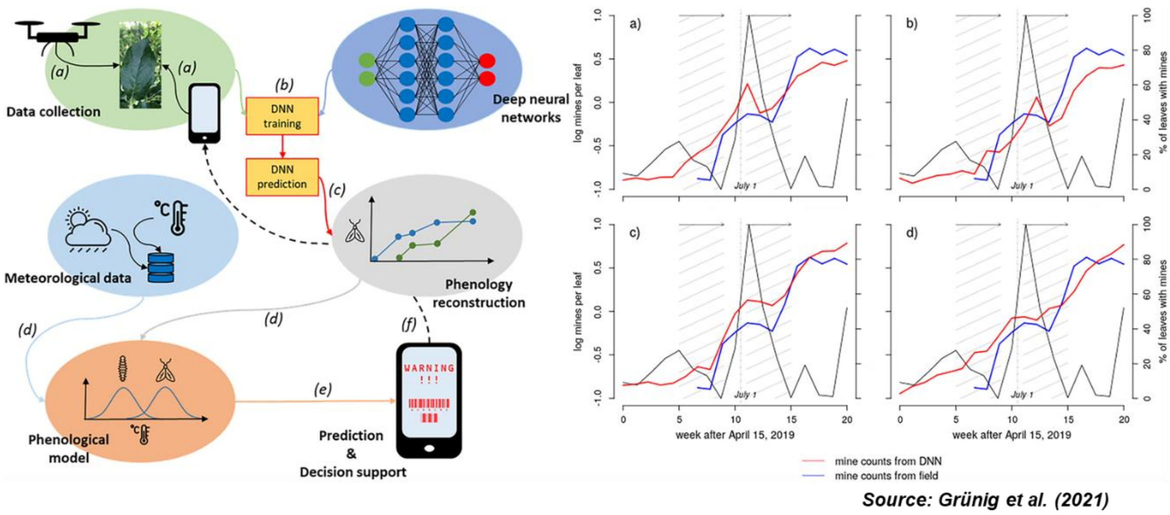


Figure 8.8: Example of AI-based tools for warning of crop pests and diseases, which are expected to cause increasing damage to agriculture under climate change (Grünig et al., 2021).

### 8.6.4 Available Services and Recommendations for the Agri-Food Sector

In recent decades, there has been significant progress in the development and accessibility of satellite and meteorological data for use in the Agri-Food sector.

Data Advancements in Satellite and meteorological data have enabled more comprehensive agricultural risk assessments (dissemination by NASA and ESA for example). Despite the availability of satellite data to the public, there is a growing need for governments and private stakeholders to extract actionable insights from this data, particularly in the context of food security. But the limited resources of governments with emerging economies and the parties that need access to the data and want to use it to ensure food availability are a problem.

To address this gap, private providers of agricultural data analytics have emerged, aiming to fulfill the unmet needs of agricultural stakeholders. While private companies have played a vital role, their data resources are often proprietary, posing accessibility challenges, especially for emerging economies.

To maximize the climate and societal benefits of future AI applications for agriculture, like those mentioned in this chapter, researchers and developers should focus on creating access to data silos and computational tools. As we have seen in the past, it is not enough to develop AI climate impact tools and acquire large sets of data without providing broad access.

With early investments, society can benefit from open-access and open-source inclusive AI models that not only improve yields for producers but also extend these benefits to farmers in less profitable sectors and thereby contributing to global food security.

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## 8.7 Case-Study #6: Vegetation Health Forecasting

**Authors:** Benjamin Stocker [1], Márcio dos Reis Martins [2]

[1] University of Bern, Switzerland

[2] Agroscope, Switzerland

### 8.7.1 Vegetation Health Forecasting Service Description

Ecosystem services and vegetation productivity are sensitive to climate and weather anomalies. Meteorological extreme events can drive large variability in agricultural yields, can impair forest health and services, and can trigger ecological disturbances, including wildfires. Adverse climate impacts on vegetation are expressed, for example, through reduced crop growth or wood production, tree mortality, reduced carbon uptake and storage. AI has spurred and will enable new developments in vegetation health monitoring and forecasting to inform management decisions in agriculture, forestry and ecosystem conservation and restoration. However, it remains challenging to connect information of what can be observed with predictions for what stakeholders seek to understand.

Developments in AI for vegetation health monitoring and forecasting are fundamentally driven by the increasing volume, accessibility, and diversity of Earth Observation (EO) data and near-range remote sensing techniques. A range of applications and long-standing challenges have seen new advances thanks to AI, including field-scale plant disease detection and vegetation health monitoring[129], drought stress detection and monitoring[130] [131], carbon cycle monitoring[132], or phenology, plant growth, and crop yield forecasts in agricultural settings and forests[133] [134] (Lees et al., 2020).

In Switzerland, climate anomalies and extreme events with impacts on ecosystems are mostly related to summer drought and heat, late frost, hail, floods, and windstorms. Impacts of hail, floods, and windstorms are primarily determined by the magnitude of the meteorological forcing. In contrast, impacts by heat, drought and frost are strongly determined by the predisposition of the ecosystem to the meteorological forcing and are subject to the ecosystem's evolution and meteorological conditions over past weeks to months (or even years). They are the focus of this sub-chapter.

***Vegetation monitoring*** **and** ***impact detection*** uses continuous ecosystem monitoring and EO data for “now-casting" (state estimation, quantification of anomaly levels from current or recent measurements). In contrast, near-term *forecasts* for weeks to months lead time and *projections* for decades lead time under novel climates rely on models of how the abiotic environment (climate, $CO_2$, soils, topography) drives ecosystem responses. AI has great potential for impact detection, now-casting, and near-term forecasting, but is limited for long-term projections because relevant model training data from current observations do not cover novel climates and $CO_2$.

Modelling ecosystems and climate impacts on forests and agricultural systems is challenging due to the nature and diversity of biotic processes that often vary between species or even individual plants, and due to landscape heterogeneity at small spatial scales, arising from topography, variations of soils and bedrock, and land use. These spatial variations underlie large variations in vegetation *exposure* to abiotic stress. Nevertheless, a rich history of dynamic vegetation and land surface modelling based on

[129] https://doi.org/10.1186/s13007-019-0479-8
[130] https://www.biorxiv.org/content/early/2022/08/17/2022.08.16.504173
[131] http://arxiv.org/abs/2303.16198
[132] https://www.nature.com/articles/s41597-019-0076-8
[133] https://www.sciencedirect.com/science/article/pii/S0168169923001096
[134] https://doi.org/10.1080/01431161.2017.1410296

mechanistic models has been established that climate impacts on vegetation are, to a certain extent, predictable[135]. AI bears promise in making best use of the recent surge in high-resolution EO data (10-500 m) and continuous ecosystem monitoring data for reliable, data-informed and stakeholder-relevant forecasts (e.g., yields, growth, carbon balance) beyond the coarse-resolution (50-100 km global) of land surface model simulations available today.

AI-guided impact detection, monitoring, and forecasts will be important for guiding management decisions in agriculture and forestry, revenue planning and insurances, and for early warning of impacts by climate extreme events guiding adaptation measures. The relevance of AI-tools for drought impact forecasting is depicted in (Figure 8.9). Solutions will have to be found for implementing regular updates of now-casting and forecasting outputs based on continuously ingested EO and ecosystem data. Projections, including trained models, will have to be made accessible through web applications and open-access APIs.

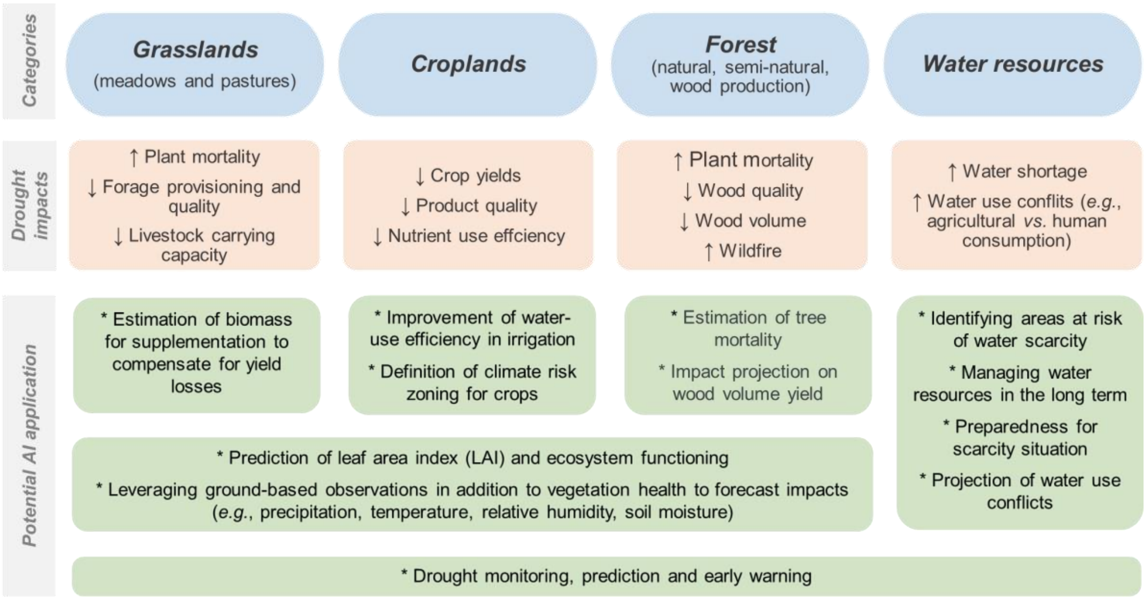

Figure 8.9: Use of AI tools associated to remotely sensed vegetation health for drought impact forecasting.

### 8.7.2 Methodology of Vegetation Health Forecasting: Data and AI Workflow Implementation

AI will be most successful if it can be effectively informed by the most abundant data sources. Satellite-based EO generates the most voluminous data and will continue to play a central role for vegetation monitoring, impact detection and forecasting. The most widely used EO data for vegetation is derived from multispectral satellite-remote sensing of surface reflectance in the optical, near-infrared, and thermal range, commonly sourced from the MODIS, Landsat, and Sentinel missions[136]. For certain modelling applications and target variables, information may be enhanced by LiDAR (Light Detection and Ranging), microwave, or near-range remote sensing using unmanned aerial vehicles (UAVs) or field phenotyping infrastructure in demonstration and research settings.

Vegetation monitoring and forecasting requires EO data from satellites with relatively frequent revisit times to capture the seasonal evolution and the response to weather anomalies that evolve over days to weeks. Frequent cloud cover limit data availability of satellite remote sensing data in the visible range. This further enhances the necessity for high temporal resolution. To generate stakeholder-

[135] https://royalsocietypublishing.org/doi/10.1098/rstb.2017.0304
[136] https://doi.org/10.1038/s41477-021-00952-8

relevant information, spatialized forecasts should be provided at scales of 100-500 m for forests and 10-50 m for agricultural settings. The freely available EO data from Sentinel-2 (min. 5-daily, 20 m) and MODIS/VIIRS (daily, 200 m) missions satisfy the spatial and temporal requirements for such applications. Higher resolution (10–100 cm) EO data will provide information at the level of individual trees and may enable stress impact and tree mortality detection and forecasts[137], potentially considering species information, in the future.

Vegetation impact forecasts informed by weather predictions may be provided with lead times of 1–10 days and may be driven by medium-range to extended-range weather forecasts (up to 1.5 months). Although affected by stochasticity in the weather, persistent atmospheric conditions may be forecasted with sufficient reliability. And although ecological quantities vary at multiple temporal scales and are highly heterogenous in space (soils, species, landscape), ecological systems are typically not stochastic *per se*, making ecological forecasting a highly relevant and achievable target[138].

With the available data, a machine learning model can be trained, needs to be evaluated, and will be deployed in case quality criteria like accuracy and generalization can be met (Figure 8.10).

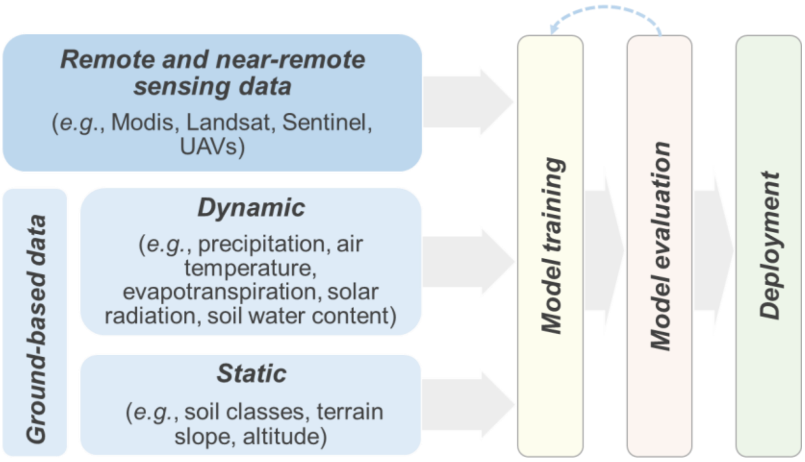


Figure 8.10: A basic workflow of machine learning application to forecast drought impacts on vegetation health based on remote sensing, near-remote sensing and ground-based data.

### 8.7.3 Current Limitations & Recommendation for Vegetation Health Forecasting Services

Stakeholder-relevant impact monitoring often requires data indirectly related to observable space-based quantities. For instance, obtaining labeled data for training ML-based crop yield predictions is laborious or subject to data use restrictions. Also, technical challenges have to be resolved for treating heterogenous data, combining the information of only indirectly related but abundant EO data with more directly related but sparse target data.

Alternatively, impact detection and forecasting can target EO-derived variables directly. For example, anomaly detection algorithms in surface reflectance data show promise for early intervention in vegetation health. However, challenges arise from varied tree species and topographical differences. Forecasting the Normalized Difference Vegetation Index (NDVI), using past evolution, weather, and predictors like topography and soil, enables operational drought forecasting. Such NDVI forecasting models may also serve as *foundational models* for related, more directly stakeholder-relevant

[137] https://doi.org/10.5194/egusphere-egu23-5917
[138] https://pnas.org/doi/full/10.1073/pnas.1710231115

variables. Challenges related to variable tree species compositions, topographical heterogeneity, and data quality will have to be addressed.

The data richness from EO poses challenges in data handling for effective analysis and model training and causes costs for data storage and ML training. Various data cube services are now available (Google Earth Engine, Microsoft Planetary Computer, IBM PAIRS, Swiss Data Cube), host Petabyte-scale EO and climate data, and freely provide (limited) compute resources. Combining their rich data resources with data-side computing environments for efficient ML training and inference will lower the bar of entry to AI for vegetation monitoring and forecasting at scale.

Many of the AI applications for ecosystem forecasting mentioned in this section are in a development stage. Applications of ecosystem now-casting and continuous monitoring are established (Zweifel et al. 2021; Thomas et al., 2023)[139] but are partial in geographic coverage or are not continuously updated.

An integration of multiple EO and ecosystem monitoring data streams for low-latency anomaly detection, early warning services for stakeholder-relevant variables, and spatialized forecasts of climate impacts is achievable and will be critically needed for climate-smart planning of ecosystem management. User-friendly tools for predicting drought impacts on crop yields or early warning systems for crop pests and diseases management would be examples of applications of AI leveraging increasingly abundant vegetation index data with finer temporal and spatial resolution.

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139 https://lwf.wsl.ch/de/

# 9 Appendix

## 9.1 Reference Architecture for Re-Usable AI Workflows

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### 9.1.1 Collaboration and Re-Usability of Code to Reproduce Scientific Studies

In scientific projects, researchers often work individually or in very small groups, using local machines or local compute clusters with a set of code scripts to get their work done. When collaboration between teams and organizations becomes more prevalent, reproducibility and reusability aspects become more relevant. One typical issue in re-using someone's research code are hard-coded file paths, specific to the originators machine, requiring tedious code changes by other users. This is, only one example of how lack of adaptability hinders collaboration and slows down scientific progress and reproducibility of scientific studies. To overcome this obstacles, software engineering tools and practices should be applied, like:

- ***Data versioning and lineage:*** Typically, datasets are named and versioned (e.g. public datasets on Kaggle or HuggingFace) or obtained using a metadata service (e.g. Spatio-Temporal Asset Catalog, STAC). The safest option to trace data lineage is to compute a hash on the source dataset and subsequent processing steps.
- ***Code versioning and release management:*** The de-facto standard in source code management is the use of versioning tools. Git is the most popular distributed version control system. Although, using Git is a prerequisite, for reproducibility it is necessary to use tags or branches adequately to freeze source code to different versions and map these versions to the models, results, and datasets.
- ***Proper versioning of 3rd party libraries:*** Different library versions include subtle changes, resulting in bugs or even differences in the output of a data analysis. Therefore, we recommend pinning libraries to specific (major) versions, being transparent in their usage and automating their installation into the execution environment.
- ***Model Lifecycle Management & Reproducible Results:*** To reproduce models or other results, code, data, and the environment needs to be exactly the same. Therefore, versioning needs to be introduced and stored for code, data, libraries, and the final results like models, such that others can reproduce the original experiments.

### 9.1.2 Run-Time Environment Compatibility through Containerized Workflows

AI code is often developed on local machines but finally needs to run on local clusters in the Cloud or on High-Performance Compute (HPC) systems. Thus, multiple runtime architectures need to be supported to yield re-usable AI workflows. To achieve this goal concepts and best practices from microservice architectures should be taken into account, like:

- ***Containerization[140]:*** Coarse grained operators of a data processing pipeline can be packaged into (docker) containers to encapsulate all versioned dependencies and code to become another versioned asset. Docker containers can be created and tested on local machines and scaled on the Cloud without changing the code.

[140] https://www.youtube.com/watch?v=lXZh03Vc648

- *Container orchestration*[141]*:* Container orchestrators like Kubernetes orchestrate containerized operators. Kubernetes provides a platform-independent way to manage and scale containerized applications transparently across huge compute clusters.
- *Workflow orchestration*[142]*:* Once individual, coarse-grained operators are derived and containerized, those can be orchestrated in form or a workflow or data processing pipeline. It is helpful to use a workflow engine which allows for local development, execution, and debugging and seamlessly scales to large HPC clusters.

### 9.1.3 Automation of Workflows to Reduce Implementation Complexity

To develop microservice workflows requires substantial knowledge in software engineering. To make such architectures also available to non-computer science researchers, automation tools are under development, to cope with the complexity. One of these frameworks is CLAIMED (available under open governance by the Linux Foundation) and has the following properties.

1. Coarse grained operators can be implemented in python or R using scripts and notebooks.
2. 3rd party library dependencies can be specified inline (in the script or notebook) or externally (e.g., using a requirement.txt file).
3. Each script (operator) runs within its own virtual environment, (e.g., python, venv, anaconda or docker) to prevent library incompatibilities.
4. Each operator expresses its interface by environment variables. Through type casting, data types can be inferred.

CLAIMED enables ease-of-use development and deployment of cloud native data processing applications on Kubernetes using operators and workflows. A central tool of CLAIMED is the Claimed Component Compiler (C3) which creates a docker image with all dependencies, pushes the container to a registry, and creates the necessary deployment descriptors for various runtime and workflow execution engines.

Although HPC and Cloud scale runtime and workflow execution engines are targeted, local development, debugging and testing is preferred. This can be achieved by the creation of Common Workflow Language (CWL) tasks and workflows which are supported by C3, enabling local debugging by accessing log files directly (Figure 9.1).

141 https://www.youtube.com/watch?v=2vMEQ5zs1ko&list=PLOspHqNVtKABAVX4azqPlu6UfsPzSu2YN
142 https://www.youtube.com/watch?v=Dbwj-NHnHfw

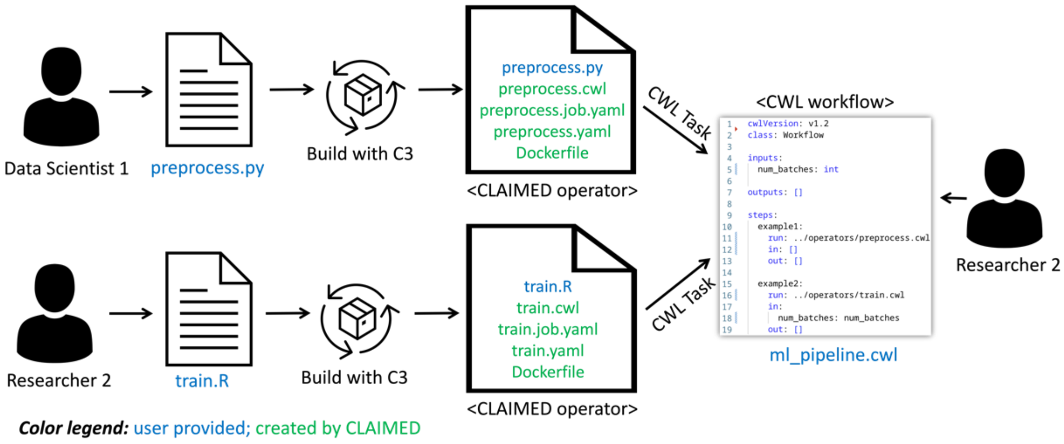


Figure 9.1: Local workflow development with CLAIMED and CWL (Common Workflow Language). Users provide only code in their preferred data science language and a CWL file orchestrating execution of that code. Logs are accessible and code is debugable as everything remains on a local development machine.

A boilerplate project[143] is provided on github to get started with the workflow described above. By forking the repository to the local machine, all necessary files and folders are readily available, especially an empty python script file, as well as a build and run file, enabling local development. Detailed instructions can be found in the readme file.

Once the locally developed and tested version of a workflow is ready, it can be scaled through cluster or cloud-based workflow execution engines like Airflow and Kubeflow. Tools like CLAIMED help to automate this deployment step by compiling the CWL workflow description into an execution engine specific format (Figure 9.2). Once a workflow has been deployed to an appropriate execution engine, it can be run at scale, is versioned, and can be used by a wider audience by instantiating runs using different parameters (Figure 9.3).

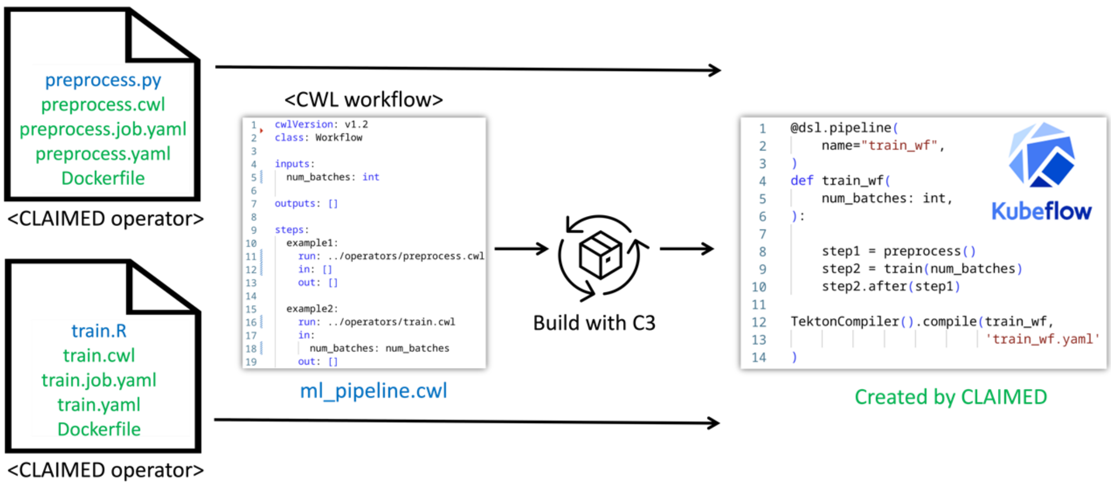


Figure 9.2: Workflows expressed in CWL can be automatically transformed into runtime specific workflow expression languages. Here, Kubeflow pipelines for example.

[143] https://github.com/claimed-framework/boilerplate/

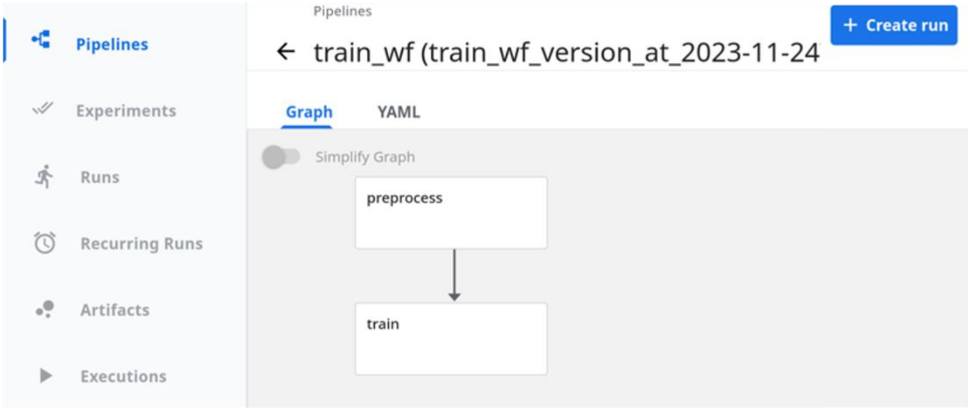


Figure 9.3: Once a workflow has been deployed to Kubeflow, a run can be executed by clicking on "Create run". Please note that in the title one can see the workflow version created on deployment.

With this boilerplate example, we hope to enable researchers to rapidly and efficiently pick-up methods to create reproducible and reusable code in their data science projects. Using an automation framework like CLAIMED reduces complexity and increases code quality.

## 9.2 Glossary

| Term | Explanation |
|---|---|
| CWS | Citizen Weather Stations |
| PCF | Product Carbon Footprint |
| IPCC | Intergovernmental Panel of Climate Change |
| $CO_2$ | Carbon Dioxide |
| $CH_4$ | Methane |
| GHG | Greenhouse Gas |
| $N_2O$ | Nitrous Oxide |
| CO | Carbon Monoxide |
| CMS | Carbon Monitoring System |
| G3W | Global Greenhouse Gas Watch |
| $NO_2$ | Nitrogen Dioxide |
| MVS | Monitoring and Verification Support |
| IMEO | International Methane Emissions Observatory |
| CAMS | Copernicus Atmospheric Monitoring Service |
| EO | Earth Observation |
| ESG | Environmental, Social, and Corporate Governance |
| AGB | Above Ground Biomass |
| ALS | Airborne Laser Scanning |
| NASA | National Aeronautics and Space Administration |
| ESA | European Space Agency |
| USGS | United States Geological Survey |
| LiDAR | Light Detection and Ranging |
| UAV | Unmanned Aerial Vehicle |
| NDVI | Normalized Difference Vegetation Index |
| IDE | Integrated Developer Environment |
| DAG | Directed Acyclic Graph |
| COS | Cloud Object Storage |
| NAS | Network Attached Storage |
| SAN | Storage Area Network |
| SBTi | Science Based Targets initiative |
| TCFD | Taskforce on Climate-related Financial Disclosures |
| TNFD | The Taskforce on Nature-related Financial Disclosures |