

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 Al-related fields.

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

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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).

Al 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.

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

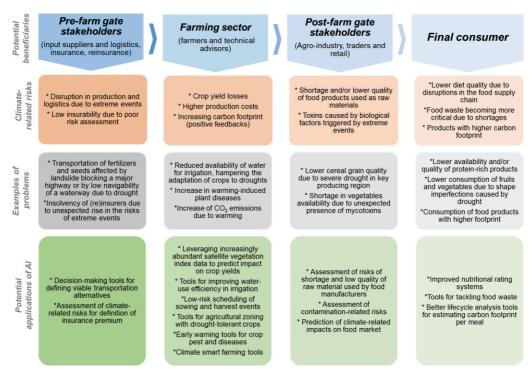


Figure 8.7: Use of AI to tackle negative impacts of climate change in the agri-food sector.

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. 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. 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. 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:

- *Al-Enhanced Crop Models:* Al 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 Al:** Al 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).
- Al for Climate Resilient Markets and Supply Chains: Al 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: Al-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 Al for warning of crop pests and diseases developed (Grünig et al., 2021). This type of Al 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 Al models.

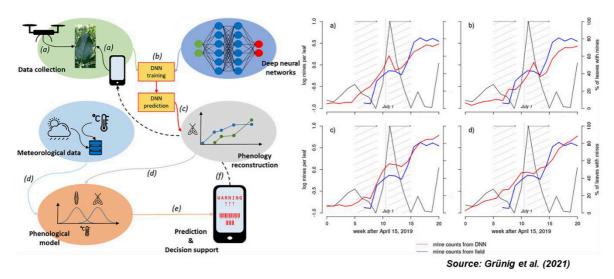


Figure 8.8: Example of AI-based tools for warning of crop pests and diseases, which are expected to cause increasing damage to agriculture under climate change (Grünig et al., 2021).

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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