OECD Food, Agriculture and Fisheries Papers

Anticipating and monitoring water risks for agriculture

No. 226

OECD Food, Agriculture and Fisheries Papers

Anticipating and monitoring water risks for Agriculture

Disclaimer

This work was approved and declassified by the Joint Working Party on Agriculture and the Environment on 16 March 2026.

This document, as well as any data and map included herein, are without prejudice to the status of or sovereignty over any territory, to the delimitation of international frontiers and boundaries and to the name of any territory, city or area.

Photo credits: Cover © John Carnemolla/Shutterstock.

Abstract

This paper examines water risks for agriculture and outlines a typology of tools to support public authorities in anticipating, monitoring and assessing these risks. Agriculture faces multiple water risks including shortage, excess and poor water quality, alongside systemic risks from degraded freshwater systems and a destabilised water cycle. Monitoring and anticipating these risks is critical to sustaining agricultural production and protecting freshwater resources. Given the diverse water risks and decision contexts, the sector requires a suite of tools tailored to different risks and temporal and spatial scales. The relevance of specific tools depends on decisions being taken, with the highest value achieved when tools inform choices with high or irreversible costs. While technological progress is driving rapid tool development, gaps and challenges remain. Public authorities have a central role in promoting a robust data environment, while taking a long-term, holistic perspective to build systemic resilience.

Keywords: Floods, Drought, Climate, Extreme weather, Food systems, Risk assessment tools

JEL codes: Q25, Q15, Q54, D81, Q58

Acknowledgements

This paper was prepared by Martha Baxter, Agnes Szuda and Berte Gebreyohanes from the OECD Trade and Agriculture Directorate. The authors thank (OECD unless specified otherwise) Delia Sánchez Trancón, Enxhi Tresa, Annelies Deuss, Ada Ignaciuk, Guillaume Gruère and Julia Nielson for insightful comments and suggestions. The paper drew on the discussions in a Technical Workshop on "Anticipating and monitoring water risks for agriculture", which took place at the OECD on 5 November 2025. The authors are grateful to all the speakers: Inbal Becker-Reshef, NASA Harvest and Microsoft AI for Good Lab; Nick Brozovic, Water for Food Institute, University of Nebraska–Lincoln; Marie-Charlotte Buisson, International Water Management Institute; Elena De Petrillo, WaterToFood Lab, Politecnico di Torino; Anna Dupont, International Water Management Institute; Mikaël Maes, OECD Environment Directorate; Catarina Madaleno, Association of Beneficiaries of the Lezíria Grande of Vila Franca de Xira; Kayla Moore, Agriculture and Agri-Food Canada; Marie-Anne Paulin, Danone; Frank Rijsberman, The Nature Conservancy; Oriana Romano, OECD Centre for Entrepreneurship, SMEs, Regions and Cities; Maher Salman, FAO; Bengu Ozge Serifoglu, European Environment Agency; Sofie te Wierik, Potsdam Institute for Climate Impact Research (PIK); Marta Tuninetti, WaterToFood Lab, Politecnico di Torino; Lucy Watkinson, OECD Environment Directorate and Raffaella Zucaro, Consorzio Canale Emiliano-Romagnolo. Thanks to Hilary Gaboriau and Martina Abderrahmane for support with the publication.

This work has been made possible thanks to a voluntary contribution from the Government of Colombia.

Table of contents

Tables

Figures

Boxes

Key messages

- Agriculture is intrinsically dependent on water and increasingly exposed to growing water-related risks. These include water shortages, excess water and inadequate water quality, alongside systemic risks of degraded freshwater ecosystems and a destabilised water cycle.
- Trade can be a channel for impacts from agricultural water risks but also a mechanism to alleviate water risks. Countries may be exposed to water risks beyond their borders via their imports of agri-food products. At the same time, the ability to access goods on international markets reduces vulnerability to food insecurity and can relieve pressure on local water demand.
- Effective policy responses require a holistic understanding of water risks that accounts for both blue water resources, such as rivers, lakes and aquifers, and green water resources, including soil moisture and land-sourced rainfall, while understanding the role of cross-border linkages.
- Given the diverse water risks and decision contexts, the agricultural sector requires a suite of tools tailored to different risks, spatial scales and timeframes. From remote sensing to machine learning, the tools to assess agricultural water risks are advancing rapidly, yet gaps and challenges remain:
  - Moving from hazard monitoring to meaningful assessments of impacts on agriculture remains difficult, as this requires the integration of hydrological, agronomic and socio-economic data which are not always available or compatible.
  - Several critical dimensions of water risk – such as freshwater ecosystem health, groundwater depletion and land-atmosphere interactions – remain difficult to measure and monitor and are, therefore, insufficiently covered by existing tools.
  - There can be a mismatch between the scale of available data and the scale at which decisions are made (field level, basin level etc.).
  - Water risks frequently compound and cascade over time, yet most assessment tools analyse hazards in isolation.
- For water risk intelligence to deliver value, assessment tools must be effectively embedded in decision making. Tools are most useful when applied at critical decision points where the costs of poor or irreversible choices are high. At the same time, tools can be costly to develop and operate. Decision makers need to ensure that investments in water risk assessment deliver a proportionate return and are matched to the decision context.
- There is no single acceptable level of water risk, and context-specific approaches that consider different risk thresholds are needed. Public authorities can provide a long-term and holistic perspective on water risks. As a framework-setter, governments can encourage the uptake of water risk intelligence by promoting a more mature data environment, setting clear governance and co-ordination structures, and encouraging knowledge and technology transfer to the agricultural sector.

Executive summary

Agriculture is intrinsically dependent on water and increasingly exposed to growing water-related risks. These include water shortages, excess water and inadequate water quality, alongside systemic risks of degraded freshwater ecosystems and a destabilised water cycle. Trade can be a channel for impacts from water risks but also a mechanism to alleviate water risks. Countries may be exposed to water risks originating beyond their borders via their imports of agricultural and food commodities. At the same time, the ability to access goods on international markets reduces vulnerability to food insecurity and can relieve pressure on local water demand. Effective policy responses require a holistic understanding of water risks that accounts for both blue water resources, such as rivers, lakes and aquifers, and green water resources, including soil moisture and land-sourced rainfall that underpin crop production, while understanding the role of cross-border linkages.

Countries' ability to anticipate and monitor water risks is a critical component of agricultural resilience and food security. Water risk management contributes to the capacity of agricultural systems to plan and prepare for adverse events, absorb shocks, recover from disruptions and adapt over time. While evidence points to an intensification of water risks for agriculture, many countries lack the tools and methods needed to assess these risks comprehensively across time horizons, spatial scales and risk types. Existing approaches often focus on individual hazards rather than systemic risks and their impacts on agricultural outcomes.

Drawing on recent literature and an expert workshop, the paper examines water risks for agriculture; outlines a typology of tools to support public authorities in anticipating monitoring and assessing these risks; and discusses when and how to integrate risk assessment tools into decision-making processes.

Given diverse water risks and decision contexts, the agricultural sector requires a suite of tools tailored to different risks, spatial scales and across short-, medium- and long-term timeframes. The relevance of specific tools depends on the nature of decisions being taken, with the highest value achieved when tools inform choices with high costs.

Advances in technology are also expanding the possibilities for improved anticipation and monitoring. Satellite-based remote sensing, in situ sensors, the Internet-of-Things, modelling approaches, and the application of Artificial Intelligence and machine learning are increasingly underpinning tools that are used to inform water-related risk assessment. For example, a digital twin of a river basin can combine data streams from smart sensors and satellites with models to monitor water status in near real-time, explore scenarios and test interventions to see the simulated consequences.

Despite this progress, important gaps and challenges persist:

- **Moving from hazard monitoring to meaningful assessments of impacts** on agriculture remains difficult. While data on hydrological hazards are increasingly available, translating this into risk intelligence requires integration with agronomic and socio-economic data, such as crop types, planted areas, yields and exposure of farmers and communities. These datasets are often fragmented, outdated, insufficiently granular or incompatible across systems. Nevertheless, there are promising examples of tools that move towards outcome-based approaches, such as agricultural drought indicators that consider impact on crop yields, pasture growth and farm business profits.

- There is a **mismatch between the scale of available data and the scale at which decisions are made.** Farmers often require field-level and seasonal information; public authorities typically need risk assessment information at basin, regional or national levels. Temporally, seasonal data is often key yet missing in water risk assessment for agriculture. For example, tools may rely on outdated crop maps that fail to reflect actual planting patterns, limiting their usefulness for seasonal decision making. Moreover, water risks frequently compound and cascade over time, yet most assessment tools analyse hazards in isolation rather than capturing interacting and cumulative effects.
- **Several critical dimensions of water risk remain difficult to measure and monitor** and are, therefore, insufficiently covered by existing tools. Risks linked to freshwater ecosystem health, water quality, groundwater depletion and the recycling of moisture through terrestrial ecosystems are not yet fully integrated into commonly used assessment frameworks.

For water risk intelligence to deliver value, assessment tools must be effectively embedded in decision-making processes. Tools are most useful when applied at critical decision points where the costs of poor choices are high, such as prior to major infrastructure investments or policy reforms. At the same time, tools can be costly to develop and operate. Decision makers therefore need to ensure that investments in water risk assessment deliver a proportionate return and are matched to the decision context. In some cases, simple approaches may be sufficient; in others, data limitations and uncertainty mean that complex tools risk providing misleading signals unless uncertainty is clearly communicated. Attention is often placed on improving tools rather than understanding how decisions are made. A more effective approach may be to start from decision-making needs and work backwards to the information required. Furthermore, water risk information is only one input into decision making. While assessment tools can generate relevant evidence, policy choices are also influenced by the legal and institutional context as well as the cultural and social values attached to water. Consequently, policymakers may have valid reasons not to fully defer to the outputs of risk assessment tools.

There is no single acceptable level of water risk, highlighting the need for flexible, context-specific approaches that consider different risk thresholds rather than one-size-fits-all solutions. Governments play a central role in creating the enabling conditions for effective water risk management. This includes maintaining authoritative hydrological, meteorological and agronomic datasets, establishing clear governance and co-ordination structures, and encouraging knowledge and technology transfer. In doing so, governments can engage farmers as key partners in risk monitoring, as they are often the first to observe the impacts of water risks. Innovation ecosystems and market openness in terms of trade, private capital and competition can also be drivers of technology deployment. Finally, public authorities are also well-positioned to provide a long-term and holistic perspective on water risks. This helps counterbalance short-term incentives and support decisions that build systemic agricultural resilience rather than reactive responses to immediate water-related shocks.

Anticipating and monitoring water risks is a building block of agricultural resilience

Agricultural production is highly dependent on water and increasingly subject to water risks, such as floods, droughts and poor water quality. Mounting evidence suggests that supplies of freshwater are becoming less reliable and sustainable (GCEW, 2024[1]). As water risks can have significant economic and social effects (production, markets, trade, food security, shortages, loss of income) on the sector, countries' ability to anticipate and monitor these risks for agriculture is paramount.

Drawing on a review of recent literature and an expert workshop,[1] this policy paper documents the different facets of water risks facing agriculture and showcases the tools available to policymakers to anticipate and monitor these risks. Water risk management is an important component of building overall agricultural resilience, defined as the ability to plan and prepare for, absorb, recover from, and adapt to adverse events (OECD, 2020[2]). The ability to anticipate and monitor water risks forms part of the "prepare and plan" phase. While the evidence points to a confluence of water risks for agriculture, not all countries are equipped with tools and methods to assess these risks comprehensively.

This paper focuses primarily on physical water risks related to the quantity and quality of available water (as opposed to water-related financial, regulatory or reputational risks)[2] and the tools available to anticipate, monitor and assess them. An analysis of mitigation and adaptation measures in response to water risks is beyond the scope of this paper. Finally, this paper explores tools best suited to support decision making and water risk assessment by public authorities. While some of the tools used by public authorities may be the same or similar to those used by farmers to inform plot-level decision making, public authorities require a range of tools that cover several spatial scales, including watershed/basin, regional, national and potentially transboundary levels.

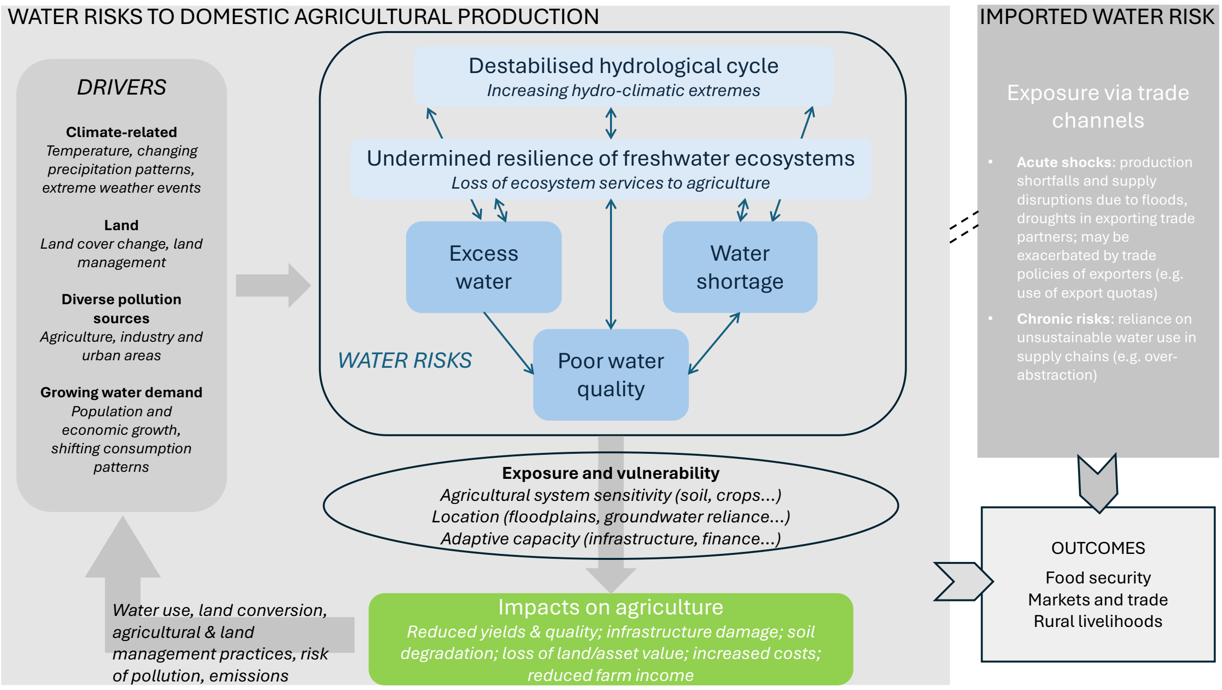
The paper starts by describing the different water-related risks that agriculture faces and their drivers. The next section showcases examples of tools to anticipate and monitor water risks for agriculture organised according to a typology. The final section sets out the public policy levers to facilitate better anticipation and monitoring of water risks.

The landscape of water risks for agriculture

"Too much", "too little" or "too polluted" water are often seen as the trifecta of water risks facing human systems, including agriculture. A more comprehensive view also considers systemic water risks in addition to these three quantifiable water-related pressures (Figure 1). The *OECD Recommendation on Water* (OECD, 2016[3]) recognises the "risk of undermining the resilience of water-related ecosystems" as a water-related risk, defined as exceeding the coping capacity of the surface and groundwater bodies and their interactions, possibly crossing tipping points, and causing irreversible damage to the system's hydraulic and biological functions (OECD, 2013[4]). The disruption to freshwater ecosystems may be triggered by various water risks (e.g. water pollution) and, in turn, amplify them. Recent findings by the Global Commission on the Economics of Water call attention to an additional systemic risk: pressures from human actions are driving the global hydrological cycle out of balance, rendering supplies of freshwater less reliable (GCEW, 2024[1]).

This section defines water risks and summarises the latest evidence on water risks facing agricultural production, including the often-overlooked role of "green water" in water security. It also considers the issue of "imported water risk", outlining how a country may be exposed to water risks beyond its borders via trade of agricultural commodities.

Figure 1. Water-related risks for agriculture



"Too much": The risk of excess water for agricultural production

Water excess hazards include sudden-onset events such as floods or intense rainfall episodes, as well as less extreme phenomena that can nevertheless affect agricultural production, such as wetter average conditions and waterlogging. Longer-term shifts in rainfall patterns may lead to wetter average conditions that are sub-optimal for crops currently under cultivation. Excess rainfall can result in waterlogged soils that affect crop growth. Globally, flooding affects over 17 million km^2 of land surface annually, with around 10% of agricultural land affected by waterlogging or severe soil drainage constraints (Kaur et al., 2020[5]).

Considerable attention is paid to the impacts of water shortages for agriculture, yet too much water can pose as great a risk (OECD, 2016[6]). Zampeiri et al. (2017[7]) found that wheat production is more sensitive to water excess than to drought in several countries, while Li et al. (2019[8]) found that excessive rainfall in conjunction with poorly drained soils leads to maize yield loss of a comparable magnitude to extreme drought in the United States, especially in cooler areas. Even rice, a semi-aquatic crop that benefits from controlled inundation, can be vulnerable to flood events. Li et al. (2025[9]) assessed the causal impact of rice crop submergence on yield losses from 1980 to 2015 and found that globally, these floods reduced annual rice yield by 4.3% while the East Coast of the People's Republic of China (hereafter "China") experienced losses of 14%. In the livestock sector, flooding can result in injury or death of animals, nutritional restriction and disease spread, with specific impacts varying by type of livestock (Crist, Mori and Lee Smith, 2020[10]).

The impact of excess water hazards on agriculture depends on several factors including timing, place and crop type, as well as water management infrastructure and practices (e.g. tile drainage, flow management) that have been incorporated into the production system. Crops are more vulnerable to excess water during certain growth stages (Schmitt et al., 2022[11]; Li et al., 2019[8]). Climate, soil type and topography as well as water management infrastructure can mediate the impacts of excess water. For example, Li et al (2019[8]) found that excessive rainfall can either decrease or increase maize yields depending on whether the crop was grown in warmer or cooler climes and whether soils have poor drainage.

"Too little": Water shortages

Water scarcity occurs when demand exceeds available supply, a relative and dynamic concept that varies based on local conditions and across time (OECD, 2025[12]), (FAO, 2012[13]). Definitions can encompass both physical factors (i.e. the physical availability of water in sufficient quantity and quality to meet demand), as well as broader socio-economic considerations (e.g. when human, institutional, infrastructural or financial capital limit access to water, even when it would be available to meet needs) (IPCC, 2022[14]). For example, high energy prices can make the cost of groundwater pumping prohibitive, even if water is physically available. Finally, water scarcity may be seasonal (e.g. in monsoon areas) or chronic (e.g. in arid regions) and can also be driven by pollution if water quality is too poor for use in agriculture.

Droughts can be an important underlying cause of water scarcity in agriculture, affecting the supply-side. They refer to periods of significant hydrological imbalance affecting various components of the water cycle, characterised by abnormal water deficit on different timescales. Dependent on their exogenous drivers, droughts can be classified as i) meteorological (a prolonged period of low precipitation), ii) agricultural or ecological (conditions when soil moisture levels fail to meet crop and vegetation needs) and iii) hydrological (prolonged periods with surface or groundwater water levels dropping below average) (OECD, 2025[12]). In addition, anthropogenic drought can be defined as drought events caused or intensified by human activities, considering the interactions of anthropogenic actions with natural systems (AghaKouchak et al., 2021[15]). Different types of droughts are often interlinked and can persist simultaneously (Liu et al., 2016[16]). Around 11% of rainfed croplands and 14% of pasturelands face frequent droughts and over 60% of irrigated cropland faces high water stress (FAO, 2020[17]).

The impacts of drought on agriculture are substantial. Agriculture bears the largest share of drought-caused economic costs across all sectors (Tikoudis, Gabriel and Oueslati, 2025[18]) and drought is the most impactful natural disaster for agriculture (OECD/FAO, 2021[19]). A metanalysis by Zhang et al (2018[20]) found that even mild drought stress intensity reduced average wheat and rice yields by 21% and 17% respectively. In 2021, drought conditions in California caused economic costs of USD 1.1 billion for the agricultural sector (Escriva-Bou et al., 2022[21]). FAO research shows that drought causes more harm to agricultural production than any other natural disaster in least developed and lower middle-income countries (FAO, 2021[22]).[3]

"Too polluted": Inadequate water quality

Poor water quality limits agricultural productivity, compromises food security and undermines rural livelihoods. Poor-quality water, whether due to salinity, nitrate pollution, toxic elements, chemical imbalances or microbial contamination, can reduce crop yields, degrade soils, harm livestock and pose risks to human health. For example, Pica et al (2017[23]) found that switchgrass and rapeseed suffered biomass losses of 25-90% when irrigated with water containing high levels of dissolved solids and organic carbon. Intensive horticulture faces additional stresses from contaminant mixtures. Closed irrigation loops in high-density nurseries accumulate nutrients, pesticides, microplastics and pathogens; extreme rainfall can flush these pollutants beyond facility boundaries, suppressing seedling growth and driving up treatment costs (Gomes et al., 2025[24]). Clean, reliable stock water is also critical to animal health and performance, but high nitrate concentrations pose significant risks to livestock health (FAO & IWMI, 2023[25]).

At broader scales, water quality constraints intensify water scarcity. Globally, adding water quality constraints to classic scarcity metrics reveals that river basins classified as water scarce could triple by 2050, threatening irrigation across 40 million km² and exposing an extra three billion people (Wang, 2024[26]).

Damaged resilience of freshwater ecosystems: Loss of ecosystem services

Freshwater ecosystems[4] are vital natural assets for agriculture. They provide the water that sustains crops and livestock, regulate flows and recharge groundwater, filter pollutants to maintain water quality, and protect farmland from floods and droughts. Wetlands, rivers and lakes also deliver nutrient-rich sediments, support pollinators and pest predators, and maintain the biodiversity that underpins agricultural productivity.

Degraded freshwater ecosystems undermine the ecological foundations of agriculture. The risk of undermining the resilience of freshwater systems includes exceeding the coping capacity of the surface and groundwater bodies and their interactions, possibly crossing tipping points, and causing irreversible damage to the system's hydraulic and biological functions (OECD, 2013[4]). Fluet-Chouindard et al (2023[27]) estimate that 3.4 million km² of inland wetlands have been lost since 1700, a net loss of 21%. They find that wetland loss has been concentrated in Europe, the United States and China and rapidly expanded during the mid-twentieth century. Freshwater biodiversity gains achieved since the 1970s have plateaued since 2010, with recovery weakest downstream of cropland, dams and urban areas (Haase et al., 2023[28]). Without decisive mitigation, the combined pressures of nutrient enrichment, higher temperatures and ongoing habitat conversion will further degrade freshwater ecosystems, threaten water security and undermine the resilience of agricultural production systems.

A destabilised hydrological cycle: Increasing hydro-climatic extremes

Rainfall is becoming more variable and extreme. Rising global temperatures combined with land-use changes are destabilising and accelerating the hydrological cycle, shifting precipitation patterns and undermining assumptions of a stable year-to-year supply of freshwater (GCEW, 2024[1]). The Global Commission on the Economics of Water call attention to this systemic risk, echoing similar warnings from the World Meteorological Organization that the hydrological cycle is becoming more erratic and unpredictable (WMO, 2023[29]; WMO, 2024[30]). The IPCC confirmed this trend of increasing hydro-climatic extremes (IPCC, 2022[14]).

A destabilised hydrological cycle may manifest locally as water excess or water shortages – two of the water risks identified above – yet the risk is qualitatively distinct. The risk concerns pushing year-to-year supplies of freshwater outside of the bounds of natural variability known for the last 12 000 years and under which existing agricultural and water management systems have developed. Part of the challenge for agriculture is coping with the increased variability of water availability and increased intensity of water-related hazards. Increased hydrologic variability can overwhelm human systems that were designed to manage a certain frequency or intensity of hazard event but may struggle as those events become more frequent or intense. The increased uncertainty means that farmers cannot necessarily depend on past patterns to plan planting or irrigation. It also raises questions about the reliability of risk assessment tools that draw solely on historical data.

Globally, average annual precipitation in the last two decades exceeded the average recorded between 1950-2000. That said, several regions, such as the Mediterranean, most of Africa, the Middle East, eastern Australia and the western parts of North America and parts of South America experienced up to a 20% reduction in average annual precipitation over the same reference periods (OECD, 2025[12]). Interannual precipitation patterns have also changed, with regional seasonal increases and decreases affecting the seasonal availability of water critical for agriculture. Summer precipitation decreased by over 20% with each degree of observed global warming in parts of southeastern and western Australia, southeastern South America and parts of eastern Africa, while it increased by around 20% in northern Europe (IPCC, 2022[14]).

Water risks are dynamic and interlinked

Water risks to agriculture result from dynamic interactions between water-related *hazards* and the *exposure* and *vulnerability* of agricultural systems to those hazards. This framing is in line with the IPCC concept of risk (Reisinger et al., 2020[31]),[5] defined as the "potential for adverse consequences to human or ecological systems" and where risks result from the dynamic interactions between hazards, exposure and vulnerability. Consequently, this paper considers water risks as the potential for adverse consequences for agriculture, also noting the vital importance of ecological systems for productive and sustainable agricultural systems, given the myriad ecosystem services they provide.

Agriculture faces water risks across different timescales and a range of tools to anticipate and monitor risks adapted to these different temporal scales are therefore needed. Rapid-onset hazards include flooding or intense rainfall episodes, where accurate weather forecasting and early warning systems play an important role in risk mitigation. Other hazards such as droughts can develop more slowly, affecting water availability over one or many growing seasons. Over a longer time horizon, agriculture may face water-related risks driven by a more variable climate or other megatrends such as population growth and urbanisation. Water risks to agriculture also vary across space. Regionally specific risks and variability across landscapes with different geographies, climates and production systems necessitate the need for locally adapted risk assessment and responses.

Drivers of water risk

Water risks in agriculture are driven by several factors. Agriculture is not only highly vulnerable to water-related risks but also has the potential to be a major contributor to them, as it places significant pressure on freshwater resources, i.e. part of the risk agriculture faces is endogenous. Furthermore, drivers range from the local level to regional and global scales. For risk managers, this implies being aware of sources of water risk that may be beyond the basin or catchment level – such as land cover change in distant places upwind – and having the right tools to monitor and assess that risk.

Climate-related drivers of water risks

At a global level, rising temperatures alter the hydrological cycle. Higher temperatures drive more evaporation and increase the atmosphere's capacity to hold water: each 1°C rise in global temperatures increases water vapour in the atmosphere by 7% (NASA, 2022[32]). The increased energy in the system leads to more frequent and severe extreme weather events, including intense rainfall, floods and drought. Furthermore, increasing temperatures lead to glacier melt, affecting freshwater supplies and increasing flood risk in the short-term (The GlaMBIE Team, 2025[33]). More broadly, increasing rainfall variability year-to-year is altering the distribution and amount of water available and our ability to rebalance this disturbance via storage.

Looking forward, projections undertaken in the context of climate change analysis indicate increasing magnitude and frequency of water-related hazards, with regional variations (IPCC, 2022[14]). Under these projections, many regions are expected to experience increasingly volatile precipitation regimes characterised by "both longer dry spells and heavier events when precipitation does occur". Extreme agricultural droughts are also projected to become 150-200% more likely in western China, the Mediterranean and the northern parts of South America, North America and Eurasia under 2°C of warming. The magnitude and frequency of floods are projected to increase in Asia, central Africa, western Europe, Central and South America and eastern North America, and decrease in northern North America, southern South America, the Mediterranean and eastern Europe. The picture for annual mean precipitation is less clear. At 1.5°C warming, climate models consistently project increased precipitation in the central and eastern Sahel, south-central Asia, parts of Greenland and Antarctica, and the far northern regions of North America and Asia, but projections for other regions vary substantially.

Rising air and water temperatures, altered precipitation regimes and changing sea levels directly modify the dilution, transport and transformation of pollutants, affecting ***water quality***.

Land cover, land management and landscape level changes

Land cover changes and land management practices can disrupt the hydrological cycle by altering how water is stored, evaporated and transpired, giving rise to diverse water risks for agriculture. A farm's water security can be shaped by large-scale land cover changes occurring far beyond its immediate surroundings, as well as by on-farm land management practices that farmers directly control.

The feedback between land cover and rainfall has been under appreciated. The loss of natural ecosystems – particularly deforestation and loss of wetlands – disrupts the moisture that transfers from the land to the atmosphere[6] (i.e. green water flows) that then falls as rain downwind, a process referred to as "terrestrial moisture recycling". Given that 40-70% of terrestrial rainfall originates from land, land cover change in one place can influence water security in another place, sometimes thousands of kilometres away (GCEW, 2024[1]). *Precipitationsheds* (the area supplying evaporation to a downwind region's rainfall) and *evaporationsheds* (the downwind region where evaporation from upwind areas falls as rain) can be mapped to show the connections between upwind and downwind locations through these atmospheric rivers. Smith, Baker and Spracklen (2023[34]) found that even a 1% loss in tropical forest area can reduce precipitation by up to 0.25 mm per month in a 200 km radius of the deforested area, in addition to negatively affecting water balances locally. Several sectors are responsible for land cover change, but agriculture has altered the Earth's land area more than any other anthropogenic activity (UNCDD, 2022[35]).

As well as the impact on rainfall, land cover change can exacerbate other water risks. Looking at the case of Northeast China, Ma et al (2024[36]) show that conversion of forests and peatlands to agricultural area reduced the water retention capacity of the landscape, leading to greater flood risk. The loss of freshwater ecosystems such as wetlands also deprives agriculture of the ecosystem services they provide.

Agricultural land management practices can impact water risks. Heavy machinery and deep ploughing can compact soils, inhibiting infiltration and water retention, and thereby reducing groundwater and soil moisture availability for crops (Timár, Jakab and Székely, 2024[37]). Monocropping can reduce the soil water-holding capacity, while bare or fallow fields or overgrazing can also lead to soil moisture loss. Soil compaction can also have a major effect on flood peaks after high intensity, short duration storms in small catchments (Alaoui et al., 2018[38]). Erosion and soil degradation can lead to sediment deposits that impact the ecological functioning of freshwater ecosystems (Ramsar, 2021[39]).

Certain agricultural and land management practices, on the other hand, may reduce some water-related risks. In Japan's Suse region, paddy field dams (rice paddy fields combined with runoff control devices) were found to have reduced peak discharge by up to 48% during typhoon events (Kobayashi et al., 2021[40]).

Finally, landscape-level changes such as river regulation influence water risks. While river regulation may reduce flood risk and free up land for agriculture and other uses, it may also cause water shortages. As documented in Hungary, meander cut offs reduce water storage in the landscape and shorter rivers limit the time for water infiltration and groundwater recharge (Timár, Jakab and Székely, 2024[37]). Land drainage and diverting rivers for agriculture also impact wetland functioning.

On the other hand, certain landscape management, such as wetland restoration or gully woodland and riparian buffer zone planting can reduce flood risk (OECD, 2016[6]). Several countries are exploring the effects of rewilding of agricultural lands. As found in the Trollberget Experimental Area in Sweden, the rewetting of peatlands previously drained for agriculture and forestry can enhance hydrological balance by reducing peak flows and elevating low flows (Karimi et al., 2024[41]; Karimi et al., 2025[42]). The impact of peatland rewetting on reducing flood and drought risk, however, remains highly context-dependent (Elenius et al., 2025[43]).

Growing water demand and over-abstraction

The risk of water shortages for agricultural production may in part be driven by rising water demand and competition with other sectors. Population growth, economic development and changing consumption patterns have contributed to rising water abstraction, with water demand increasing by around 1-1.8% annually over the past century (Boretti and Rosa, 2019[44]). Water demand worldwide is projected to grow by 20-30% by 2050, compared to 2010. Domestic and industrial demand are projected to increase faster than agricultural demand, with water needs in the manufacturing sector projected to rise by 400% by mid-century. In addition to the water demands from conventional economic sectors, emerging sectors such as hydrogen production and data centres may create new challenges for water resource management.

Nevertheless, agriculture is projected to remain the major water user. Agriculture is the primary driver of water abstraction, responsible for around 70% of freshwater withdrawals worldwide. Globally, irrigated areas expanded by 11% between 2000-15, with more than half of this expansion occurring in already water-stressed areas (Mehta et al., 2024[45]). In certain cases, irrigation expansion exceeded water recharge rates. For example, the High Plains region of the United States experienced severe decreases in groundwater levels, with groundwater irrigation exceeding aquifer recharge rates up to 10 times (Scanlon et al., 2023[46]). The water intensity of chosen crops shape agriculture's demand on green water resources too. For example, in northern China, the expansion of agricultural area, fertiliser application and disproportionate increase in the cultivation of water intensive maize contributed to reduce soil moisture by about 29% per decade between 1983-2012 (Liu et al., 2015[47]).

Excessive water consumption reduces the amount of water available for nature and negatively affects freshwater ecosystems. Around 30% of irrigated crop production is estimated to affect environmental flow requirements and biodiversity (Jägermeyr, 2017[48]).

Some countries have turned to non-conventional water sources for irrigation such as desalinisation and wastewater reuse as a strategy to reduce pressure on freshwater sources. This can be a way to improve the environmental sustainability of irrigation, increase water supply to agriculture and address drought. For example, Israel and Spain have invested significantly in modernising irrigation systems and increasing the use of non-conventional water sources for agriculture.

Salinisation, nitrate and other diverse pollution sources

Drivers of poor water quality and freshwater ecosystem degradation include salinisation and pollution from industry, urbanisation and agriculture.

Globally, secondary salinisation[7] already affects over 1 billion ha across more than 100 countries, reducing yields of major food crops by up to 50 % (Singh, 2022[49]). At the basin scale, salinity export from irrigated lands is now the dominant water-quality stressor. A global assessment of 458 river basins showed that 57 % exhibit significant upward salinity trends, with irrigation-related salt fluxes explaining over 80 % of the observed increases; basin aridity index and irrigation intensity emerged as the best predictors of trend magnitude (Thorslund et al., 2021[50]). Likewise, projections for coastal aquifers indicate 10-25% increases in salinity by 2050 as sea-level rise and groundwater over-extraction promote seawater intrusion (Khondoker et al., 2023[51]).

Nitrate pollution significantly degrades water quality in both groundwater and surface water systems. Groundwater is particularly vulnerable due to the high mobility of nitrate in soils, resulting in contamination of aquifers and drinking-water supplies. Prolonged exposure can adversely affect human health (Ward et al., 2018[52]). In some localities, elevated nitrate inputs from agriculture, municipal and industrial discharge promote eutrophication in rivers, lakes and marine waters, driving excessive algal growth, oxygen depletion, the proliferation of invasive species and declines in aquatic biodiversity (Bijay-Singh and Craswell, 2021[53]; Akinnawo, 2023[54]). Eutrophication is now widely recognised as a persistent, system level problem rather than an occasional episode, especially in shallow, low volume lakes that receive heavy external nitrogen and phosphorus loads from cropland and settlements (Zhou et al., 2022[55]).

Intensive agricultural use of synthetic pesticides poses some of the most serious diffuse threats to fresh- and coastal-water quality. At regional and national scales, the chemical footprint of pesticide use is growing faster than that of nutrients (Yi, Gerbens-Leenes and Aldaya, 2024[56]). Certain synthetic pesticides are persistent, bio-accumulative and toxic to humans and wildlife (Kaur et al., 2024[57]). Past agricultural pesticide use included several substances now classified as Persistent Organic Pollutants (POPs), such as aldrin, chlordane, dieldrin, and heptachlor. Ecological consequences are also increasingly well quantified. Even in remote, non-agricultural headwater streams, atmospheric deposition of insecticides is sufficient to alter ecosystem community structure (Schweiger et al., 2025[58]).

Additional threats to water quality include other legacy POPs, such as PCBs and dioxins, heavy metals as well as ultra-persistent emerging contaminants that are spreading rapidly. While the effect on agricultural production is not yet clear, they bring with them public health risks. Agricultural soils also hold 23 times more micro- and nanoplastics than the oceans. These particles can be taken up by crops like lettuce, wheat and carrots, and have been shown to reduce the water-holding capacity of sandy loam soils by up to 12%, worsening drought stress (Boctor et al., 2025[59]).

Imported water risk: Exposure via international trade

As well as water risks affecting domestic agricultural production, countries may be exposed to agriculture-related water risks originating beyond their borders via their imports of agricultural commodities. The interconnected nature of global markets means that water risks in one locality can have impacts through trade channels, with potential consequences for food security. This can be through a short-term shock, such as a flood or drought, or longer-term phenomena. Different tools are needed to anticipate and assess water risks operating on these different timescales.

Awareness and assessment of this “imported water risk” can have implications for countries’ trade strategies (i.e. ensuring sufficiently diverse sources of supply) and decisions around domestic production capacities (i.e. ensuring domestic production of goods no longer accessible on international markets), although this needs to take account of the water risks posed by domestic production. Indeed, trade can be a mechanism to alleviate water risks, as the ability to access agricultural goods on international markets reduces vulnerability to food insecurity and can relieve pressure on local water demand (OECD, 2017[60]).

Acute shocks

Production shocks can lead to food shortages, price increases and increasing food insecurity in producer and importing countries alike. Following the 2023 drought in Brazil, global coffee prices were 55% higher in August 2024 compared to the previous year. Similarly, a prolonged drought combined with a heatwave affecting cocoa production in Ghana and Ivory Coast tripled year-on-year global cocoa prices in April 2024 (Kotz et al., 2025[61]). Market responses to agriculture production shocks depend on multiple market variables and prices do not always respond to changes in yields (OECD, 2017[60]). Nevertheless, in the case of large production shocks in a larger market for a product with relative inelastic demand and no immediate substitute, relative prices will rise (OECD, 2017[60]).

Chronic water risk exposure

As well as short-term shocks with immediate disruptions to supply chains, slower developing phenomena may over time increase the exposure of importing countries to water risks. For example, countries may become increasingly exposed to water risks if they rely on agricultural commodities from localities with unsustainable water use, such as the over-abstraction of groundwater for irrigated agriculture, or from agricultural regions projected to become more drought prone. Ercin, Chico and Chapagain (2019[62]) estimate that more than 44% of the EU agricultural imports from the global market under current trade patterns will become highly vulnerable to drought in the future. To understand their vulnerability and exposure to disruptions in agricultural production, including water related risks, the EU has assessed the impacts of climate change on the supply of agricultural commodities to Europe (EEA, 2021[63]).

The concepts of *virtual water trade* and *water footprint* (Box 1) have been applied to assess imported water risk. While many early studies using this approach calculated simply the volume of water embedded in a good, more recent research refines the concept to consider the sustainability of water resources. Hoekstra and Mekonnen (2016[64]) quantify and map the United Kingdom’s direct and indirect water needs to assess the “imported water risk” by evaluating the sustainability of the water consumption in the source regions. They find that 49% of the United Kingdom’s global blue water footprint – the direct and indirect consumption of ground and surface water resources behind all commodities consumed in the United Kingdom – is in places where the blue water footprint exceeds the maximum sustainable level.

That said, countries’ own domestic management of water risks will impact the extent to which they could pose water-related risks to others as exporters. This is particularly the case given that most countries are not simply exporters or importers in global agriculture and food markets, but play both roles (being exporters of some products and importers of others).

Trade can be a mechanism to alleviate water risks

At the same time, international trade can be a key mechanism to alleviate water risks. As noted by Muller and Bellmann (2016[65]), empirical studies have shown that "trade has helped maintain food security in countries where water availability limits domestic production and plays an important role in buffering the impact […] of floods or droughts". Similarly, Allan (2001[66]) argues that imports of water-intensive goods contributed to solving water shortages in the Middle East.

International trade is a mechanism by which countries can ensure the supply of goods that cannot be produced domestically (as, for example, can be the case for products that only grow in certain climatic conditions, such as tropical products) or where the quality, price or environmental trade-offs of domestic production are too high. Trade also allows countries to adjust to domestic supply shocks and maintain food security. Although there may be an initial shortage after a water-related event such as a flood, importing countries (and the affected producer country) can source goods from other producer countries. The degree of trade openness and purchasing power are two important factors that determine the extent to which countries can turn to trade to buffer the impacts of domestic supply shocks. Well-functioning food markets play a key role in diluting price effects and ensuring that when a problem arises it does not have a ripple effect (OECD, 2017[60]). Furthermore, to address risks to food security, including water-related risks, several countries such as Singapore and the United Kingdom set out to strategically diversify their import sources, alongside ramping up domestic production (Teng, 2020[67]); (Defra, 2025[68]). Open trade and diversified sourcing can be elements of country strategies to enhance resilience, lower prices and support food security.

Box 1. Virtual water trade

The relationship between water and trade has been explored through the concepts of *virtual water trade (VWT)* and the *water footprint*. Allan (1997[69]) introduced the concept of virtual water as the volume of water needed to produce a certain good (or "water footprint"), and VWT as the flows of virtual water resulting from the trade in these goods. The term virtual is used to indicate that the water is not physically present in the traded commodity but is embedded in its production (D'Odorico et al., 2019[70]). Agricultural, food and textile products account for about 66% of total global virtual water trade. Between 1986 and 2022, the global volume of VWT related to agricultural products almost tripled (Mekonnen et al., 2024[71]).

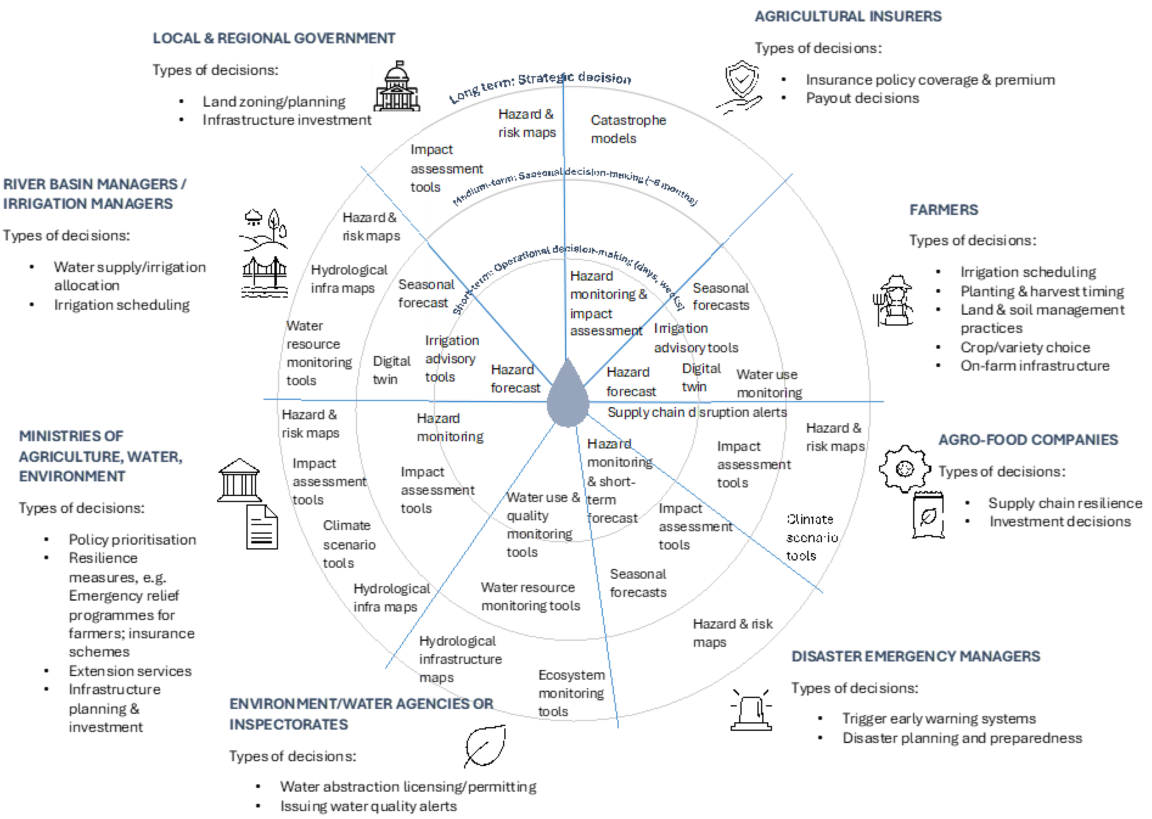
The usefulness of these concepts for policy purposes has been questioned, however. In particular, the lack of information on the economic implications of water use – notably the opportunity cost or the scarcity value of the input – limits the use as a guide for water resource strategy (Wichelns, 2015[72]). Furthermore, two products can have the same water footprint but very different environmental impacts depending on the local context, i.e. a litre of water use in a water abundant country does not have the same environmental implications as a litre of water use in an arid country (Berger et al., 2021[73]).

Nevertheless, the concepts have been used to observe the interplay between trade and water resources. Empirical studies have shown that the distribution of the water content of consumption across countries was not improved via trade (Afkhami et al., 2020[74]). At the same time, Carleton, Crews and Nath (2024[75]) note that differences in relative agricultural productivity and relative arable land endowments "can cause virtual water to flow from [water] scarce regions to abundant ones."

Tools to anticipate and monitor water risks in agriculture

A wide range of actors seek to understand the water risks facing agriculture in order to make informed decisions on planning, investment and operations, and a large and growing set of tools supports such assessments. The right tool will depend on the type of user and the nature of the decision (Figure 2). Public authorities need to be equipped with a suite of tools to support decision making and water risk management for agriculture across different timescales and for different purposes. Such purposes include early warning systems to bolster farmers' preparedness to floods and droughts; water allocation and permitting regimes to ensure sustainable water use across different uses and users; extension and advisory services for farmers for climate-resilient agriculture; or spatial planning decisions to guide the location of agricultural production, among others. In the private sector, farmers looking to optimise yields can use tools to guide on-farm water management decisions; agro-food corporations carry out water risk assessments to understand supply chain resilience and threats to business continuity; and agricultural insurers use sophisticated modelling tools to determine insurance policy coverage and premiums.

Figure 2. Different users require a variety of tools to inform risk assessment



From satellites to sensors, advances in technology are opening up new opportunities to improve the anticipation and monitoring of water risks. Many of the tools being used and developed today are underpinned by increasingly sophisticated data collection, processing and analysis techniques, including remote sensing, Internet-of-Things (IoT) enabled smart devices, modelling approaches, artificial intelligence (AI), machine learning and more.

At the same time, data collected with *in situ* measurement methods continue to feed into several tools and play an important role in the validation of results. With data at the core of water risk assessment, data quality is critical. Credible and usable tools are those built on or validated with accurate real-world data.

Nevertheless, accurate assessment of water risks is challenging given the inherent complexity of natural systems and human-nature interactions as well as varying degrees of uncertainty surrounding risk drivers. Water risks are interrelated and can impact each other given the nature of water as a hydrologically interconnected resource (OECD, 2013[4]). For example, the occurrence of drought increases the risk of flash floods in case of heavy rains, as drought-affected soils cannot absorb and retain water as much as healthy soils. Risks of shortage, inadequate quality and excess may all increase the risk of undermining the resilience of freshwater systems. These aspects of compounding or cascading risks introduce complexity that is difficult to capture in models and risk assessment tools.

Users should recognise the inherent limitations of tools. Transparency about uncertainties in data, assumptions and models is essential to prevent overconfidence and to support appropriate decision making, particularly as uncertainty increases over longer time horizons.

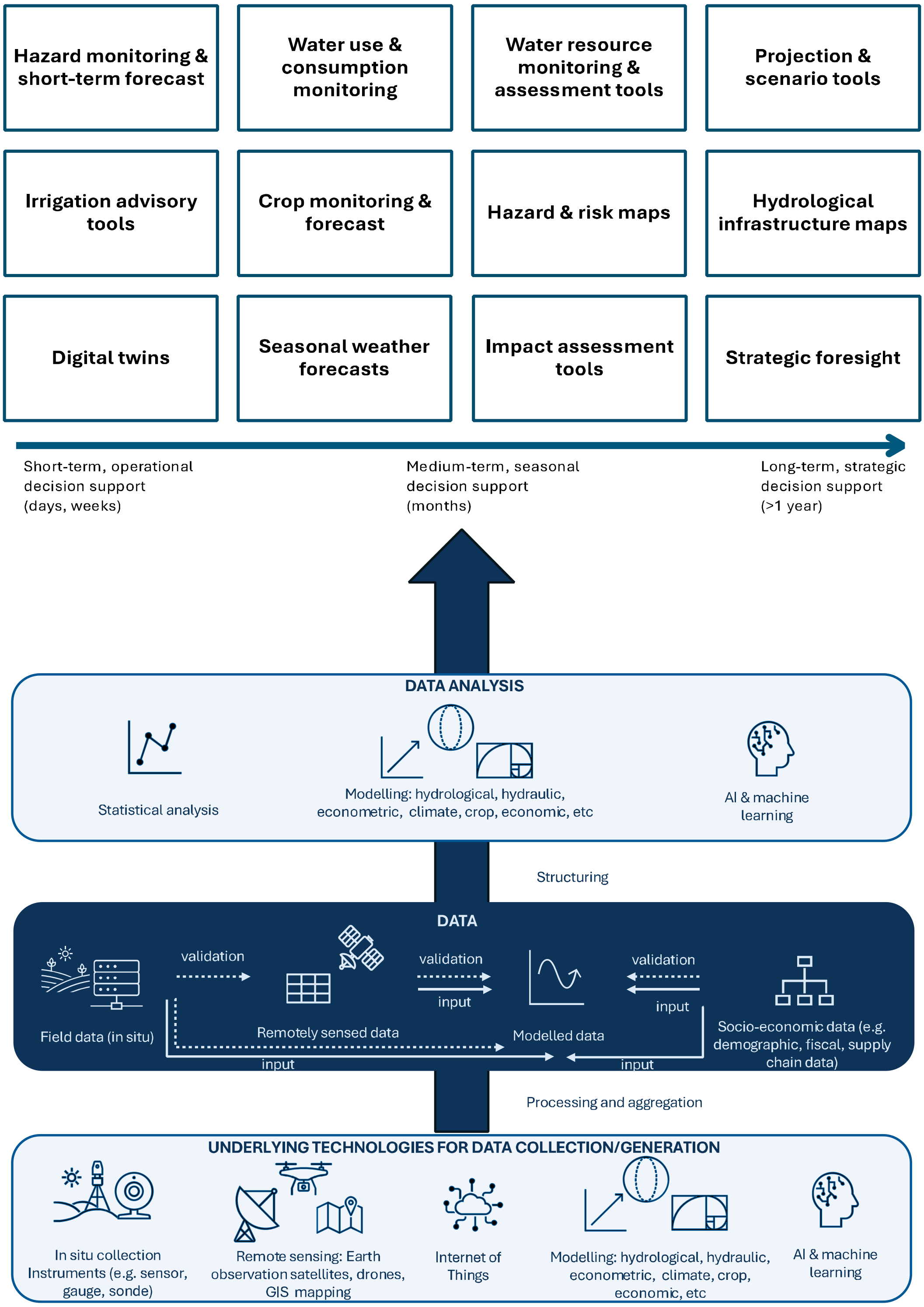
A typology of tools

This section showcases examples of tools that can support the anticipation and monitoring of water risks for agriculture organised according to a typology (Figure 3). It includes tools that give information on water resource status and trends as a component or input to risk assessment (e.g. water use monitoring) as well as those that are more explicitly focused on risk assessment (i.e. assessing probabilities and impacts of water-related hazards). Emphasis is placed on physical water risks as opposed to water-related financial, regulatory or reputational risks, although some of the tools reviewed assess these aspects in addition to physical risk. Many are well-established tools that have a proven track record of use by water risk managers. Others are more experimental in nature, often in initial or pilot phases and being developed in academic settings. More detailed descriptions of individual tools can be found in the Annex.

The selected tools have been chosen with the needs of public authorities in mind, such as ministries of agriculture, public irrigation managers, water agencies, spatial planning offices etc. This paper does not review the full range of tools and technologies designed to support farm-level water management decisions, although it notes the potential benefits of data sharing between farmers and public authorities.

Tools to monitor and assess water-related risks in agriculture vary by decision-making horizon, spanning real-time operational use to medium-term risk management and long-term planning and preparedness. For tools designed to support short-term, often operational decision making (days, weeks), advances in remote sensing, IoT and machine learning are transforming the ability to monitor water resources and water-related hazards in real or near real time. Other tools lend themselves to monitoring and assessing medium-term risks (seasonal, months) or to supporting decisions for longer-term planning and preparedness (years, decades). Some types of tools can be applied for several time horizons. For example, impact assessment tools may be used for short-term decision making, e.g. assessing damage for insurance claims post-disaster, or for longer-term planning and preparedness purposes, e.g. estimating the potential impacts of different drought scenarios to design agricultural support packages.

Figure 3. Typology of tools to support water-related risk assessment for agriculture



Hazard monitoring and short-term forecast tools

Real-time monitoring and short-term forecasts provide vital information for several uses, including early warning systems to minimise damage and loss in the occurrence of hazards.

Flood monitoring systems are typically based on real or near real-time meteorological information and remote sensing data, combined with hydrological models to provide short-term forecasts. The choice of the most suitable flood forecasting model may depend on the type of watershed and climatic characteristics of the area (Jam-Jalloh et al., 2024[76]). The GloFAS Global Flood Monitoring, for example, integrates real-time precipitation information from multiple satellites into a quasi-global hydrological runoff and routing model to provide near-real time monitoring of global flood risk (Annex A). Forecast rating curves are an alternative tool that can provide early warning of downstream flood events and their probable severity (see Annex C).

National meteorological services have traditionally provided **near-term forecasts for extreme weather events,** and some have developed apps to deliver information on severe weather directly to users. For example, the NOAA Hi-Def Radar Pro app developed by the US National Weather Service provides alerts of tornadoes, storms, and flood watches and warnings. Numerous commercial weather services offer high-resolution forecasts tailored for farmers at resolutions as low as 1km Many of these commercial services rely on data, infrastructure and technologies developed and maintained by public institutions. For example, one commercial provider employs NASA's digital terrain model to downscale weather information to provide hyperlocal forecasts globally.

Drought monitoring systems map drought conditions based on drought indices (Annex C) calculated from observed meteorological and hydrological data from weather stations and Earth observation data. Drought monitoring systems are often complemented with a forecasting and early warning function that predict the probability of a drought occurring in a region based on historical weather patterns, real-time meteorological monitoring, weather forecasts and modelling (e.g. European Drought Observatory, US Drought Monitor, and the Canadian Drought Monitor; Annex A). An interesting recent development in the field of drought indicators is a shift from meteorological to impact-based indicators, as shown by the Australian Agricultural Drought Indicators (see Impact assessment tools section below and Annex A for more details).

Recent advances are pushing inland **water quality monitoring** from isolated case studies often requiring the physical presence of technical personnel toward real-time and spatially resolved monitoring. Remote sensing can provide insights into salinity, algal blooms and nutrient fluxes. Machine-learning models can process satellite imagery and sensor data to forecast eutrophication, detect harmful algal blooms and predict tipping points in agricultural systems. However, remote sensing cannot currently capture all aspects of water quality; including total suspended matter and nitrates (Arias-Rodriguez et al., 2023[77]).

Bridging that gap requires fine-scale, in-situ sensing (Annex C). When high-frequency data from in situ sensors are combined with Earth observation and meteorological inputs, hybrid machine learning can outperform traditional empirical indices for irrigation water quality (El Bilali and Taleb, 2024[78]). Combining data from multi-parameter and other in situ measurement techniques with machine learning approaches, the Digital Water City prototype system was developed in Peschiera Borromeo, Italy to forecast potential contamination from the reuse of wastewater for agricultural purposes (DigitalWater.City, 2022[79]). Other innovative monitoring solutions include ‘fish tracking’, a method that monitors fish behaviour to detect changes in water quality over time (see the example of FISHTRAC integrated into the digital twin developed by IWMI/CGIAR Annex A).

Irrigation advisory tools

Remote sensing has become a cornerstone of precision irrigation and soil moisture monitoring. High-resolution soil moisture maps derived from remote sensing can provide actionable data for farmers and authorities, supporting targeted irrigation scheduling and the identification of water-stressed areas (Parra-López et al., 2025[80]; Dari et al., 2021[81]) (Annex C). Italy’s IRRINET is a prime example of remote sensing technologies applied to optimise irrigation scheduling (Annex A). This online irrigation advisory service provides free daily irrigation scheduling via web, SMS or mobile apps. In Spain, the Agroclimatic

Information System for Irrigation (*Sistema de Información Agroclimática para el Regadío,* SiAR), provides daily information on crop irrigation needs through its website, mobile application and web GIS viewer (Annex A).

At the farm level, smart irrigation frameworks that combine remote-sensing, IoT-enabled soil moisture sensors, and AI-based forecasting of weather and water demand are being deployed to optimise water productivity and crop yields (Al Mashhadany et al., 2024[82]). These digital systems blur the line between monitoring and decision support. AI-based predictive models are increasingly embedded in the systems to link monitoring with automated responses. By linking forecasting directly to control such as pump activation and valve adjustment, these systems can autonomously trigger irrigation events or alert managers to pollution risks, thereby supporting a shift from passive monitoring to proactive water management. Drone-mounted multispectral and thermal sensors further enhance this capability. For instance, thermal imagery used in the Crop Water Stress Index (CWSI) enables within-field detection of plant water deficits, allowing highly localised irrigation interventions (Cheng et al., 2023[83]). Drone imagery combined with machine learning has been applied to optimise irrigation across diverse crops, from kiwifruit orchards (Zhu et al., 2023[84]) to vineyards (Romero et al., 2018[85]).

Irrigation advisory tools help optimise production by ensuring crops receive the right amount of water – minimising crop water stress or avoiding overwatering. However, such tools do not assess whether water use is sustainable at the catchment level in terms of staying within renewable resource limits or ensuring enough water is left within the system for environmental flows. Public authorities mandated with promoting environmental sustainability will require different tools to assess these water risks, including accurate estimates of agricultural water use.

Water use and consumption monitoring

Accurate information on actual and projected water use and consumption can help gauge the risk of water shortages for agriculture, yet water resource management is often hindered by a lack of reliable data.

While often estimated at the country level, more granular estimates of total water withdrawn from surface or groundwater sources for irrigation usually requires on-the-ground measurement systems. To overcome *in situ* monitoring gaps, remote sensing-based modelling approaches combine satellite observations and agro-hydrological models[8] (see, for example, Zaussinger (2019[86])), although such methods are subject to uncertainty when validated with in situ irrigation data at field and regional scales given discrepancies observed (Ji et al., 2025[87]). In situ monitoring requires on-farm water flow meters or water level sensors (for measuring groundwater levels), which are commercialised for farm-level decision making and regulatory reporting.

Tools exist to estimate crop water consumption, although their coverage tends to be regional rather than global. A few recently created platforms provide real-time or near real-time data on how much water crops consume, mainly through satellite-based estimates of evapotranspiration (ET). A leading example is FAO's WaPOR, which offers near real-time data on ET and biomass production across Africa and the Near East (Annex A). This enables estimates of water productivity (how much crop is produced per unit of water consumed) and to identify areas where water is being overused or where efficiency gains are possible. Similarly, the OpenET platform makes satellite-based estimates of ET at field to basin scales in the western United States, while the EEFlux app produces field-scale maps of water consumption using satellite imagery allowing users to check water-use maps in near real-time on any mobile device. Nevertheless, these tools may be subject to degrees of error. For example, one study found that the EEFlux tool led to large ET overpredictions and error of up to 181% (Kadam et al., 2021[88]).

Digital twins

A digital twin is a virtual representation of a physical system, such as a river basin or a farm system. Acting as a platform, it combines real-time data streams (from sensors, satellites, IoT) with multiple models (process-based and/or machine-learning models). Users can explore “what-if” scenarios, test interventions and see the simulated consequences in near real time. Furthermore, digital twins can evolve as the physical system changes. Whereas models like SWAT or WEAP are simulation tools that are usually run periodically, a digital twin is live and continuously updating. IWMI has developed a digital twin of the Limpopo River Basin that allows monitoring of reservoir levels, environmental flows and water quality among many other features (Annex A).

Crop monitoring and forecasting tools

Several tools monitor crop conditions globally, providing early warning on crop failures and supply chain disruptions. Timely and reliable information on crop yields supports decision making around food security planning and market access. Crop yield estimates were traditionally generated through field surveys or farmer interviews. Increasingly, countries have developed crop monitoring and yield forecasting systems that combine satellite, meteorological and ground-sourced data (Annex A). For example, the Canadian Crop Metrics application produces reports and data that provide market information and analysis on the situation and outlook for Canadian principal field crops, including grains, oilseeds and some pulse and special crops. NASA Harvest provides a suite of tools including the GEOGLAM Crop Monitor that produces monthly updates about crop supply in major crop producer countries to the Agricultural Market Information System. The FAO Global Information and Early Warning System on Food and Agriculture (GIEWS) monitors the condition of major food crops across the globe to assess production prospects and provides alerts on emerging food shortages. It integrates the Agricultural Stress Index System, based on earth observation data on water stress. CropWatch, developed by the Chinese Academy of Sciences, provides an outlook to the global production situation of major grains (CropWatch, 2025[89]).

Seasonal weather forecasts

Seasonal weather forecasts provide information about the likely average weather conditions over a period of several months, typically three to six months, rather than specific daily weather events. They estimate how variables such as temperature and precipitation for an upcoming season are expected to compare with long-term historical averages, often expressed in terms of probabilities: for example, the likelihood of a warmer-than-normal or drier-than-normal season. Seasonal forecasts help anticipate the influence of climate patterns such as El Niño, La Niña or the North Atlantic Oscillation. Seasonal forecasts do not aim to predict exact weather on particular days but instead provide probabilistic guidance on general trends that can inform planning and risk management. For example, the EU’s Copernicus Climate Change Service (C3S) provides forecasts in the form of charts and other graphical products for the three coming months, updated monthly.

Hazard and risk maps

Hazard maps allow decision makers to spatially visualise hazard levels. Complemented with information on exposure and vulnerability, hazard maps can be expanded into risk maps, with risk often calculated through observed or expected impact, e.g. losses due to exposure and vulnerability to the hazard. For example, the European Drought Risk Atlas provides drought risk for five agricultural crops at subnational level in the EU, quantifying average annual losses to a 1-in-50-year drought under current climate conditions (JRC, 2023[90]).

Drought hazard maps have become increasingly advanced, moving beyond historical data to integrate machine learning and climate modelling that offer forward-looking insights for decision making. Early drought hazard maps typically estimated hazard levels by extrapolating observed or historical data. Today, methods such as machine learning allow for the quantification of hazards via indices calculated from hydrometeorological data (Annex C), while climate models can project future hazard levels under different warming scenarios. For example, the European Drought Risk Atlas combines conceptual models of drought risk with data-driven assessment of sectoral drought risk based on machine learning, and provides maps showing projected changes in drought hazard across the EU under different climate scenarios (JRC, 2023[90]) (see Annex A for more details). Given increasing climate variability, such tools may be more reliable than those that rely solely on historical data.

Flood hazard and risk maps are underpinned by different types of flood modelling (empirical, hydrodynamic and simple conceptual models), each with their own advantages and limitations (Annex C, Table C.2.). Advances in remote sensing are improving empirical approaches (see IWMI flood risk mapping for South Asia, Southeast Asia and Nigeria in Annex A). Remote sensing is also essential to calibrate and validate hydrodynamic models. The data and computational demands for hydrodynamic modelling can be significant and simply unavailable in many places. Simple conceptual models overcome some of these challenges. For example, Natural Resources Canada developed a simplified flood model covering the entire country, which only requires topographic data of a watershed and the shape and depth of the river network (see HAND model, Annex C). Ultimately the most suitable model will depend on the purpose, data availability and computational demands, with multi-model, multi-discipline approaches representing a promising area of research (Teng et al., 2017[91]).

In recent years, modelling approaches have complemented observed data to develop indicators that can proxy **water quality** and the **resilience of freshwater ecosystems** (e.g. modelling of salinity levels and biological oxygen demand based dynamical surface water quality model**s**). The WWF Water Risk Filters provide hazard maps of several indicators on water quality and freshwater ecosystem resilience (Annex A).

Hydrological infrastructure maps

Irrigation and drainage maps provide information that helps to assess agriculture's vulnerability to water-related hazards as well as agriculture's potential impact on water risks. High-resolution satellite data and large-scale machine learning are replacing agricultural survey or census data as a way to produce **irrigation maps**. Irrigation maps can help identify over-abstraction of water resources and identify illegal irrigation, supporting regulatory enforcement of water allocation regimes. Brazil's national water agency, ANA, produces an Irrigation Atlas using satellite data and machine learning techniques to identify irrigated areas. The agency uses the information to estimate water use and update water balances (ANA, 2024[92]).

Drainage water from agricultural areas can often contain heavy nitrate, pesticide and other contaminant loads. **Drainage mapping** is therefore an important tool for assessing water quality risks. Drainage maps can also be used for flood risk assessment, as water travelling through artificial drainage systems may impact flood events. In Latvia, the country's drainage maps have been digitalised, providing open access to information on drainage systems for agricultural land.[9] In France, the Agricultural Drainage Database ("BD Drainage") is being built as an interactive mapping tool to provide information on the path taken by water from agricultural plots that have been drained, through to its discharge into the natural environment, watercourses or groundwater (Annex A).

Impact assessment tools

Advance knowledge of how water-related hazards might impact farming can guide policymakers in planning measures that strengthen resilience and adaptation. While hazard mapping tools often show the extent of hazard-affected agricultural areas (exposure), relatively fewer tools provide quantitative estimates of losses in terms of yields or income. One such tool is the FAO **Drought Impact Assessment** Platform (d-iap). This web-based platform integrates advanced crop modelling with economic, climate and soil datasets to estimate drought impacts on yields and income under both present and future climate scenarios. In Australia, the ABARES farmpredict model helps anticipate production and financial outcomes for Australian farms using a machine-learning micro-simulation incorporating weather and climatic conditions, commodity prices and farm-level survey data, with a particular aim to foresee potential drought impacts (Annex A). Australia is also focusing on drought impacts through its recently developed Australian Agricultural Drought Indicators. Unlike most drought indicators (see section above), these indicators aim to anticipate and monitor agricultural and economic impacts of drought for non-irrigated extensive agriculture (Hughes et al., 2025[93]).

Flood modelling or mapping, as described above, can be combined with flood damage models to predict or evaluate **flood impacts on agriculture**. Examples of tools include the Agricultural Flood Damage Analysis Model, the floodam-agri, developed in France to estimate flood damage at the plot level, and AGRIDE-c, a conceptual model for the estimation of flood damage to crops designed to be applicable to different territories (Annex C). Flood damage can be modelled in many ways, varying by model type, categories of damage assessed; and flood parameters (water height, flooding duration etc.) (Modjeska and Brémond, 2022[94]). Nevertheless, a lack of observed data on flood damage to agriculture limits the development of empirical models or the validation of synthetic ones (Molinari et al., 2019[95]).

At a broader scale, macroeconomic models can be used to assess economy-wide and agriculture-sector economic impacts of water-related phenomena. The World Bank has developed a model that estimates the macroeconomic implications of climate change impacts and adaptation options, many of which are water-related, highlighting the sources and magnitude of countries' vulnerability (World Bank, 2025[96]).

Water resource monitoring and assessment tools

In addition to hazard risk assessment, policymakers need information on freshwater availability to assess agricultural water resource security. Many tools in this category rely on modelled estimates rather than observed data. In many instances, the risk assessment information derived from these tools will need to be communicated effectively to farmers to support better on-farm water management decisions.

A starting point can be integrated water availability assessments, which examine the spatial and temporal distribution of water quantity and quality in surface water and groundwater in a defined geographical area. Such assessments typically examine water supply (through climatic inputs), water quality, and water use, and may analyse water availability under different climate scenarios. The United States Geographical Survey (USGS) has developed a National Water Availability Assessment Data Companion to provide regularly updated, model-based estimates of water availability and use, derived from USGS scientific models that underlie the US National Water Availability Assessment.

Water supply monitoring and projection tools allow the agricultural sector to respond more flexibly to water shortages. Monitoring and forecasting of available water supplies is often used by administrators to make decisions about how much water to release and to whom (e.g. across senior and junior water rights holders), as well as by irrigation organisations to determine whether and how to implement water restrictions if current or projected water supplies are insufficient to meet demand. The California Water Watch monitors current water availability and provides short-term forecasts using daily updated weather data, groundwater, reservoir and snowpack levels, streamflow, as well as soil moisture and vegetation conditions (Annex A).

Model-based tools have been developed to better plan water resources. The Soil and Water Assessment Tool (SWAT) is one of the most widely used tools to simulate the quality and quantity of surface and groundwater at the watershed scale (Annex A). Another commonly used model is Water Evaluation and Planning (WEAP) that integrates water supply and demand (including agriculture), allocation rules and scenarios to help optimise allocation and can be used to test how policy changes, drought or new demands affect water availability for irrigated agriculture (Annex C). Hydrologic models such as HydroGeoSphere can simulate the movement of water between surface, soil, and groundwater systems and can be used to evaluate the impact and risk associated with climate for water resources. Canada1Water is a continental-scale model of Canada's complete hydrologic system based on the HydroGeoSphere platform (Annex A).

At the macro scale, global water models are widely used to understand changes in water resources over time, but differences between them mean their results should be interpreted with caution. Numerous models have been developed over the last 30 years with more recent versions improved by incorporating the interactions of human activities with the water cycle (e.g. irrigation, reservoir construction). Nevertheless, disagreements between simulated variables make model-based inferences uncertain (Gnann, Reinecke and Stein, 2023[97]).

Satellite technology is improving empirical data on freshwater resources and provides complementary techniques to assessing water resources and calibrating water models. For example, the Soil Moisture Active Passive (SMAP) and the Soil Moisture and Ocean Salinity (SMOS) missions have demonstrated an ability to quantify moisture extremes impacting agricultural production. The GRACE satellite missions provide information on changes in "terrestrial water storage" – the total amount of freshwater stored on land that includes surface water, soil moisture and water in underground aquifers. This technology is being applied to fields such as groundwater monitoring, which has typically been hampered by a lack of data (NASA, 2022[98]). Remaining constraints include the relatively coarse spatial and temporal resolution of satellite data as well as the need to improve techniques to fuse data from multiple sources (Ibrahim et al., 2024[99]).

Many water scarcity or water stress metrics have been developed. Octavianti and Staddon (2021[100]) identify 67 distinct assessment tools that use resource-based metrics. Some are designed specifically for agriculture. Calculation of indices rest on estimates of processes of hydrology, crops and human activities which can introduce uncertainties. The spatial resolution can be relatively large meaning that results can be inaccurate at local level.

Water footprint and virtual water trade analysis

Information on the water footprint of agriculture can inform assessments of water resource sustainability. Hoekstra and Chapagain (2008[101]) were among the first to apply the concept of water footprint to agriculture, aiming to provide a comprehensive measurement standard to define the amount of water required to produce a specific crop (Wang et al., 2023[102]). While early studies of water footprint only considered the volume of blue water consumed, more recent studies tend to incorporate the green water footprint, sometimes grey water footprint (the volume of freshwater required to dilute pollutants to meet water quality standards), [10] and increasingly the sustainability of water footprints (Annex C).

Water footprint analysis can be combined with trade flow data to enable virtual water trade analysis. This can inform assessments of imported water risks by looking at the proportion of trade flows that depend on unsustainable water use.

Projection and scenario tools for long-term trends

Projection and scenario tools can help identify potential long-term trends and emerging risks. These can be useful inputs into broader cost-benefit, risk-based and options-based planning approaches that incorporate uncertainty, local data and economic feasibility to guide governments and producers in their choice of interventions.

Climate scenarios

Informed by climate models, climate scenario-based tools have been developed to support the anticipation of long-term water-related risks for agriculture. CANARI-Europe shows projections based on moderate and high-emissions scenarios for 2020-2050 and 2050-2100 for agro-climatic indicators and risk for specific agricultural sectors (e.g. water deficit for winter cereals) (Solagro and Makina Corpus, 2025[103]). Similarly, the AgriAdapt Webtool for Adaptation (Annex A) provides simulations of the next 30 years that can be compared with the past three decades to show agro-climatic trends, with information tailored for specific agricultural production areas (Agri-Adapt, n.d.[104]). The AquaPlan App enables users to identify how different climate scenarios will change exposure of farms to drought and water scarcity, and what adaptation measures can be taken to mitigate these risks (Annex A).

In Australia, the My Climate View platform helps farmers plan for long-term climatic shifts, providing an on overview of how seasonal climatic variables will change for over twenty-two agricultural commodities at specific farms. The interactive user interface allows farmers to compare projections for 2030s, 2050s and 2070s under medium and high-emissions scenarios to past climatic data. In addition, the tool also provides seasonal (1-3 months) forecasts (MyClimateView, n.d.[105]).

Climate modelling is also used to assess long-term trends in water quality, covering nutrients, salinity and climate–agriculture interactions by combining hydrological and water-quality models with climate and socio-economic scenarios.

Water demand forecasts

Water demand forecasts are used to anticipate potential water shortages for agriculture, especially in the context of rising demand from competing needs in other sectors. Perez et al (2024[106]) estimate a 17% increase in irrigation water demand between 2020 and 2050, while WRI estimate that global water demand is projected to increase by 20-25% by 2050 (World Resources Institute, 2023[107]). Nevertheless, forecasting future water demand is highly challenging. The factors that affect demand are numerous and interconnected and include population, socio-economic development, increasing climatic variability, industrial structure, technological innovation, water prices, consumer behaviour, regulations, etc. In addition, water demand is highly variable from season to season. Water demand forecasting has been notoriously inaccurate as methods have struggled to cope with this complexity. Traditional methods rely on mathematical and statistical techniques that at their simplest involve multiplying current per capita water consumption by expected future population, which tends to overestimate future demand (Fang et al., 2024[108]). Statistical methods struggle with nonlinear and irregular changes in water demand data, and simply extrapolating past trends is unlikely to accurately reflect a changing future (Maußner, Oberascher and Autengr, 2025[109]). Artificial intelligence is being applied with promising results (Fang et al., 2024[108]).

Strategic foresight

Strategic foresight is a structured and systematic approach of exploring plausible futures to anticipate and better prepare for change. Rather than making predictions based on linear extrapolation of past and current trends, foresight cultivates the capacity to anticipate alternative futures and an ability to imagine multiple and non-linear pathways. Strategic foresight helps policymakers improve the effectiveness of governments by identifying opportunities, challenges, risks and disruptions that may arise over the coming years. It draws on multiple methodologies including horizon scanning, megatrends analysis, scenario planning and visioning and back-casting (OECD, 2025[110]). The European Parliament carried out a foresight study on future of water availability and use in the EU that included a literature review, qualitative and quantitative data analysis, scenario development and stakeholder consultation, to develop policy options (Duin, Van Lanen and Zehnder, 2025[111]). In France, the Centre for Studies and Strategic Foresight (CEP) is the internal think-tank of the French Ministry of Agriculture created in 2008 to provide the ministry with strategic monitoring, strategic foresight work and policy evaluation. CEP has examined how the agricultural sector has been taken into account in foresight studies (see (CEP, 2014[112]).

Avenues for future tool development: Gaps and challenges

Monitoring and assessment tools still provide limited coverage of some critical water-related risks, particularly those linked to resilience of freshwater ecosystems, water quality, groundwater monitoring and terrestrial moisture recycling (green water) (Table 1). The risks related to loss of freshwater ecosystem services to agriculture are difficult to capture as many ecosystem services are hard to quantify or value. When this risk is integrated into assessment tools, the focus is often narrow, for example, calculating environmental flow requirements. While useful, this focus overlooks key dimensions such as water quality and broader ecosystem health, including nutrient loads and pollutants. Many current indicators also rely on simplistic proxies – for example, measuring kilometres of unobstructed rivers – which do not adequately reflect ecological condition or function. More comprehensive approaches are needed to assess the quality, health and resilience of freshwater ecosystems and the risks their degradation poses to agriculture.

Few established tools have so far been developed and deployed for monitoring and assessing water quality risks for agriculture, compared to other risks such as water shortage and excess. Nevertheless, several databases that track water quality are available. Annex B provides examples of the databases that can facilitate monitoring water quality related risks.

Groundwater monitoring also remains a persistent challenge. While satellite data on groundwater storage and ground motion has advanced, its relatively coarse spatial and temporal resolution still limits practical application. This is particularly concerning because aquifer depletion is often non-linear: water levels may appear stable even as underlying conditions deteriorate until a tipping point is reached and depletion accelerates rapidly.

Techniques to assess the dependence of agriculture on moisture recycled through terrestrial ecosystems are still at an early stage of development. Although tracking of moisture recycling networks is improving, significant uncertainties remain. Atmospheric water-tracking models are constrained by limited validation data, and complex meso-climatic interactions make regional vulnerability difficult to predict. Emerging academic work is advancing the field – for example, mapping atmospheric water connectivity in agricultural supply chains to show how green water evaporation from Brazilian soy contributes to rainfall in Argentina, Bolivia and Paraguay (Cigna et al., forthcoming[113]) – but operational tools for decision makers are still lacking. More robust, validated approaches are needed to reliably integrate concepts such as precipitationsheds and evaporationsheds into risk assessment. Future research avenues could explore the sensitivity of rainfall distribution to vegetation management, and how shifts in land use and land cover may propagate hydrological impacts across scales (Dupont et al., 2025[114]).

More broadly, while hazard monitoring is relatively well developed, translating this information into meaningful risk assessments for agriculture remains challenging. Risk analysis requires integrating hazard data with agricultural data, such as planted areas, crop types and yields, as well as socio-economic data. These datasets are often fragmented, outdated or incompatible, limiting the ability to assess vulnerability and potential impacts. More integrated data systems are needed to support comprehensive risk assessments.

Finally, a persistent challenge is the mismatch between the scale of available data and the scale at which decisions are made. Spatially, farmers often require field-level information, whereas public authorities typically require basin or regional level tools. Temporally, seasonal data is often key yet missing in water risk assessment for agriculture. For example, some tools rely on static or outdated crop layers that do not reflect actual planting patterns, underscoring the need for timely seasonal crop masks and yield estimates. In addition, risks often compound and cascade over time, yet most tools still assess hazards in isolation. Bridging these spatial and temporal gaps is essential for effective risk management.

Table 1. Anticipation, monitoring and assessment tools by water risk

Water risks to domestic agricultural production					Imported water risk
Water excess	Water shortage	Poor water quality	Freshwater ecosystem degradation	Destabilised hydrological cycle	Disruption to agricultural imports
▪ Flood monitoring and forecasting ▪ Adverse weather forecasts ▪ Digital twins ▪ Seasonal weather forecast ▪ Drainage maps ▪ Flood risk maps ▪ Flood impact assessment ▪ Agro-climatic indicators based on climate scenarios ▪ Strategic foresight	▪ Drought monitoring and forecasting ▪ Digital twins ▪ Irrigation advisory tools ▪ Water use monitors ▪ Satellite estimates of ET ▪ Seasonal forecasts ▪ Irrigation maps ▪ Drought risk maps ▪ Drought impact assessment ▪ Water resource assessment tools: WEAP, SWAT… ▪ Water footprint analysis ▪ Water demand projection ▪ Agro-climatic indicators based on climate scenarios ▪ Strategic foresight	▪ In-situ water quality monitoring in agricultural water source areas/on-farm ▪ Remote sensing augmented with machine learning ▪ Drainage maps ▪ Climate-water quality models ▪ Strategic foresight	By nature, a longer-term, systemic risk. Leading indicators could be used to anticipate risk in the near to medium term, e.g. water quality, species diversity, biodiversity loss. Tools for longer term risk anticipation and assessment include: ▪ Environmental flow assessment ▪ Strategic foresight	A destabilised hydrological cycle is expressed in the near term as extreme weather events (storms, floods, droughts) – see columns on water excess and water shortage. Tools for longer term risk assessment include: ▪ Agro-climatic indicators based on climate scenarios ▪ Strategic foresight	▪ Crop monitoring and yield forecasting tools ▪ Early warning systems for supply chain disruptions ▪ Virtual water trade analysis ▪ Climate models: analysis of exposure of imports to climatic extremes ▪ Strategic foresight

Public policy levers

Better anticipation, monitoring and assessment of water risks for agriculture can support sound decision making around what can be done to reduce risk exposure and vulnerability and increase preparedness, as well as prioritise investments that build resilience capacities both on-farm and for the sector as a whole. These decisions will not only concern water resource management directly, but also a wide range of areas that influence water risks for agriculture, from land use zoning and economic development strategies to infrastructure planning, environmental protection and more.

This section discusses the public policy levers that can promote the use of water risk information for decision making, highlighting the circumstances where risk assessment tools provide the greatest benefit, and where their application may offer limited added value. It also delineates the role of the public sector vis a vis farmers and agro-food businesses and the private sector more broadly in innovation and technology deployment for water risk monitoring and assessment for agriculture.

When to use water risk assessment tools… and when not

Water risk information is just one potential input into decision making. While water-related tools for risk management provide important evidence, decisions are rarely based on risk information alone. Additional factors include the cultural and social value of water, as well as legal and institutional contexts, including water rights regimes that vary significantly within and across countries. As a result, there may be valid reasons why policymakers do not fully defer to the outputs of risk assessment tools, particularly when these tools do not align with broader policy objectives, legal constraints or social priorities. Moreover, different users will have different levels of risk tolerance. As such, there is no single “acceptable” level of risk, underscoring the need for flexible, context-specific approaches rather than one-size-fits-all solutions.

Developing and maintaining water risk assessment tools can be costly, making it essential for decision makers to ensure that their use delivers a clear and proportionate return on investment. The value of such tools is highest when they are applied at decision points where the costs of poor choices are large or irreversible. For public authorities, this includes use prior to major infrastructure or policy investments, where risk assessments can help avoid sunk costs; in public budget allocation and policy prioritisation, to target limited public funds more effectively; and in situations involving competing water users or sectors, where transparent, evidence-based trade-offs can help build trust and prevent disputes. For producers and agri-food companies, higher returns on investment are most likely in contexts of increasing climate variability or more frequent droughts, where tools can help prevent production and supply-chain losses, and where rising regulatory, compliance or environmental risks create exposure to fines and reputational damage. Across all actors, the potential impact of risk assessment tools is greatest in mature data environments, which support reliable analysis and enable the sustained, long-term use of tools rather than one-off applications.

There are several valid reasons why decision makers may choose not to use water risk assessment tools. In some contexts, the decision at hand does not warrant complex analysis, for example where risks are low, operations are routine, and regulatory frameworks are stable. In other cases, high levels of data or model uncertainty can make tool outputs misleading, particularly when data quality is poor, models are poorly matched to the decision context, or results convey a false sense of precision; transparency about uncertainty is therefore essential. Institutional and timing constraints can also limit uptake, including short decision cycles, limited technical capacity or fragmented authority across agencies. Practical cost-benefit considerations matter as well, as high set-up and maintenance costs, complex user requirements, or limited incremental value can outweigh potential benefits. Finally, governance and political factors play a critical role: lack of trust in tools or their developers, limited stakeholder participation, and the need for discretion and flexibility in policy decisions can all reduce reliance on risk tools. Very often, attention is placed on improving tools rather than on understanding how decisions are made. A more effective approach may be to start from decision-making needs and work backwards to the information required.

The role of the public sector

There is a strong case for government involvement in providing public goods and implementing "no regrets" policies to strengthen agricultural resilience. Encouraging the production and use of high-quality water risk information is one such example of a public good. As stated in the OECD report *Strengthening Agricultural Resilience in the Face of Multiple Risks* (OECD, 2020[2]), "even in cases where the relevant actor is the farm or the private sector, there is a "behind-the-scenes" role for government in providing information, supporting knowledge systems, and engendering an overall enabling environment to support informed on farm decision making." The public sector can address many of the barriers to the use of water risk information mentioned above and create the enabling conditions that encourage uptake where there is a clear case for high return on investment.

Governments can also create the enabling conditions for private-sector innovation. Innovation ecosystems and market openness in terms of trade, private capital and competition can be drivers of technology deployment such as sensors, AI, precision irrigation and water-quality monitoring. Market-based tools, such as voluntary standards or performance-based incentives, as well as private data sharing can further accelerate the adoption of technologies that bolster agricultural resilience.

Framework setting

As framework-setters, public authorities play a central role in encouraging water risk assessment that takes a holistic view of water risks for agriculture, beyond the common focus on floods and droughts to also consider water quality, freshwater ecosystem resilience and encourage a "whole of water cycle" approach.

Governments are also well positioned to ensure a long-term perspective on water risks. By producing and disseminating forward-looking risk information over longer time horizons, public authorities can help counterbalance the short-term imperatives that often shape decisions by farmers and businesses. This long-term focus is essential to encourage actions that build systemic resilience, rather than reactive responses to immediate water-related shocks. At the same time, governments should engage farmers as key partners in risk monitoring, given that they are often the first to directly observe the impacts of water-related risks.

The public sector has an important role at larger spatial scales, such as river basins, watersheds and national systems. While farm-level decision-support tools can guide water risk management at the field or plot level, risk assessment and management at basin or watershed level requires different tools, shared data and multi-stakeholder governance and co-ordination arrangements. Public authorities are critical to convene actors, align incentives and manage risks that transcend individual farms or users.

Finally, governments can deploy water risk assessment tools to support decisions that balance multiple policy objectives. Tools designed to optimise agricultural production, such as precision irrigation systems, may at times conflict with other public goals, including sustainable aquifer management or ecosystem protection. The public sector is therefore responsible for balancing competing objectives and safeguarding the public interest in the face of systemic and cross-sectoral water risks. In this context, governments play a central role in tracking water abstraction across agriculture and other uses, assessing whether abstraction levels are sustainable, and establishing priorities where competing demands arise under conditions of water scarcity. In such situations, deliberative water planning tools can be valuable to build community confidence (Tan, Bowmer and Mackenzie, 2012[115]).

Data environment

The public sector is well positioned to promote a mature data environment that enables the sustained, long-term use of water risk assessment tools. While agricultural producers and agri-food companies increasingly generate granular, operational data, governments generally retain primary responsibility for providing continuous, high quality, coherent, and authoritative datasets, including the climate, hydrological and water-quality baselines.

Public intervention is critical across the full data value chain. This includes investment in data collection infrastructure such as satellite and remote sensing systems, as well as the operation of meteorological, hydrological and water-quality monitoring networks. Governments also play a key role in data validation and quality assurance. In Canada, for example, the Real-Time In-Situ Soil Monitoring for Agriculture (RISMA) network provides ground-sourced data that is vital for the calibration and validation of remotely sensed data and various modelling application. Setting standards or guidance for how uncertainty in models and tools is measured and communicated is another way governments can further strengthen the usability and trustworthiness of risk information.

Transparency and integration are equally important. Public authorities can provide open access to core water risk information, ensuring a level playing field for market participants and stakeholders. Moving from fragmented, siloed datasets toward harmonised and interoperable systems – enabling tool developers to, where needed, better link meteorological, hydrological, agricultural, land-use, and socio-economic data, often held by different local and national bodies – can significantly enhance risk assessment.

The public sector can also shape data governance arrangements that encourage responsible data sharing. This includes promoting standards that enable voluntary sharing of private-sector data while protecting commercial confidentiality and encouraging agri-food companies to disclose methodologies used in supply-chain water risk assessments. As well as meeting potential compliance obligations, companies that transparently measure and report risk information are viewed more favourably by their capital market signatories, helping secure access to capital (CDP, 2026[116]).

Finally, as a knowledge producer, the public sector plays a critical role in generating actionable water risk intelligence for agriculture. This includes the provision of early-warning systems for droughts, floods and other water-related hazards, as well as the production of national water risk assessments that integrate climate variability and longer-term change in ways tailored to agricultural decision making. In increasingly interconnected food systems, governments also have a responsibility to assess imported water risks, systematically analysing exposure embedded in food and feed imports as part of broader national food security assessments.

Governance and co-ordination

Clear governance and co-ordination mechanisms are essential to ensure that risk information informs action rather than remaining purely diagnostic. Experience shows that governance structures are most effective when they are established well before a crisis occurs. When roles, responsibilities and lines of authority are clearly defined and understood by all stakeholders prior to a drought or flood event, the likelihood that early-warning information and risk assessments are acted upon in a timely manner is significantly higher.

The public sector has a critical convening role in bringing together a broad range of stakeholders and breaking down institutional and knowledge silos. This includes coordinating across ministries with potentially competing objectives (such as agriculture, energy, environment or regional development) as well as facilitating dialogue among competing water users and sectors. Spain's National Irrigation Board provides an example of multi-level co-ordination. This national coordination and advisory body attached to the Ministry of Agriculture brings together central and regional administrations and stakeholders to improve the governance of irrigated agriculture. Strengthening collaboration between meteorological services, water agencies and agricultural institutions would help integrate agronomic, hydrological and meteorological knowledge. Government leadership is also indispensable for addressing transboundary water risks, where no single actor has the mandate to act alone.

Governance challenges are also becoming more complex. Rising interdependence between water and other policy domains (i.e. the water-energy-food- nature nexus), greater uncertainty linked to climate variability and socio-economic change, as well as diversity in actors and governance levels demand innovative governance approaches. For example, in contexts where an increasing share of irrigation investment is private sector-led, additional efforts will be required to promote the public goods of sustainable water use and long-term food security, especially for groundwater, where monitoring and enforcement are more difficult. In this context, effective agricultural water governance will increasingly need to rely on convening all relevant stakeholders to build trust and understanding of the context specificities and stakeholder needs and incentives. Solutions are likely to be as much social and economic as they are technical. For example, the concept of a "social licence to irrigate" may become increasingly important as water use by agriculture and the impacts of agriculture on water quality raise concerns around resource sustainability and public health (Shepheard and Martin, 2008[117]).

Knowledge and technology transfer

Knowledge transfer is a critical link between risk assessment and application, particularly in agriculture, where decisions are made under uncertainty and where many farmers, especially small producers, lack access to sophisticated analytical tools. Farmers need to be able to access relevant risk information, interpret it and apply it to day-to-day farm management decisions. Designing user-friendly, accessible tool interfaces is an important first step in translating complex analysis into real-world decision making.

Public authorities play a key role in communicating water risk information in usable and actionable formats. Advisory and extension systems are central to this effort. In Spain, irrigator advisory offices, the vast majority of which are linked to SiAR, disseminate and use data on crop water requirements and irrigation scheduling in all autonomous communities. Similarly, Italy's IRRINET platform provides farmers with tailored irrigation advice through a publicly supported digital service. Knowledge transfer strategies must also take behavioural and social factors into account. Cultural values linked to land and water use, resistance to change and limited awareness of water risks or available adaptation options can all constrain acting on risk information. In this context, improving awareness of water risks and the benefits of innovative practices is as important as improving the technical quality and usability of tools themselves.

Intermediary institutions are essential to this process. Basin organisations, irrigation districts and extension services are often well placed to interpret water risk information and tailor it to local conditions, while also building trust with farmers. In some contexts, universities and research institutes can act as credible knowledge brokers, supporting dialogue between scientists, policymakers and practitioners.

Governments can encourage farmers and other risk managers to adopt tools. Well-designed financial incentives, behavioural nudges and tailored accompaniment can be necessary to overcome adoption barriers. For example, Ouvrard et al (2023[118]) tested different policy instruments designed to foster farmers' voluntary adoption of smart water meters that automatically transmit real-time water usage to authorities, finding that a conditional subsidy combined with a nudge encouraged their adoption. Furthermore, the use of certain tools depends on adequate infrastructure. For instance, precision irrigation requires modern irrigation systems. In Spain, investment in irrigation infrastructure since 2000 has supported the adoption of tools to better anticipate and monitor water scarcity risks. Finally, farmers and local actors may benefit from capacity building to use risk assessment tools effectively and integrate them into routine management practices.

References

ABARES (2025), *ABARES farmpredict model*, https://www.agriculture.gov.au/abares/research-topics/climate/drought/farmpredict (accessed on 8 December 2025). [159]

ABARES (2024), *The Australian Agricultural Drought Indicators: Progress report*. [157]

Afkhami, M. et al. (2020), "Virtual Water Trade: The Implications of Capital Scarcity", *SSRN*, https://doi.org/10.2139/ssrn.3166874. [74]

AghaKouchak, A. et al. (2021), "Anthropogenic Drought: Definition, Challenges, and Opportunities", *Reviews of Geophysics*, Vol. 59/2, https://doi.org/10.1029/2019RG000683. [15]

Agri-Adapt (n.d.), *AWA - AgriAdapt Webtool for Adaptation*, https://awa.agriadapt.eu/en/ (accessed on 21 July 2025). [104]

Akinnawo, S. (2023), "Eutrophication: Causes, consequences, physical, chemical and biological techniques for mitigation strategies", *Environmental Challenges*, Vol. 12, https://doi.org/10.1016/j.envc.2023.100733. [54]

Al Mashhadany, Y. et al. (2024), "Irrigation intelligence—Enabling a cloud-based Internet of Things approach for enhanced water management in agriculture", *Environmental Monitoring and Assessment*, Vol. 196/5, p. 438, https://doi.org/10.1007/s10661-024-12606-1. [82]

Alaoui, A. et al. (2018), "Does soil compaction increase floods? A review", *Journal of Hydrology*, Vol. 557, https://doi.org/10.1016/j.jhydrol.2017.12.052. [38]

Allan, J. (2001), *The Middle East water question: Hydropolitics and the global economy.*, I.B. Tauris, London. [66]

Allan, J. (1997), "Virtual water: A long term solution for water short Middle Eastern economies?", *Paper presented at the 1997 British Association Festival of Science, University of Leeds, 9 September 1997*. [69]

Allen, R. et al. (2019), "EEFlux: A Landsat-based Evapotranspiration mapping tool on the Google Earth Engine", *Written for presentation at the Emerging Technologies for Sustainable Irrigation A joint ASABE / IA Irrigation Symposium.*, https://www.researchgate.net/publication/338051596_EEFlux_A_Landsat-based_Evapotranspiration_mapping_tool_on_the_Google_Earth_Engine_Written_for_presentation_at_the_Emerging_Technologies_for_Sustainable_Irrigation_A_joint_ASABE_IA_Irrigation_Symposium. [139]

ANA (2024), *Irrigation Atlas*, Agência Nacional de Águas, Brazil, https://www.ana.gov.br/atlasirrigacao/. [92]

AquaPlan (n.d.), *Home*, https://aquacropos-aquaplan-aquacropgui01--home-5c7mm0.streamlit.app/ (accessed on 27 November 2025). [167]

Arias-Rodriguez, L. et al. (2023), "Global Water Quality of Inland Waters with Harmonized Landsat-8 and Sentinel-2 Using Cloud-Computed Machine Learning", *Remote Sensing*, Vol. 15/5, p. 1390, https://doi.org/10.3390/rs15051390. [77]

Berger, M. et al. (2021), "Advancing the Water Footprint into an Instrument to Support Achieving the SDGs – Recommendations from the "Water as a Global Resources" Research Initiative (GRoW)", *Water Resources Management*, Vol. 35, pp. 1291–1298. [73]

Bieger, K. et al. (2016), "Introduction to SWAT+, A Completely Restructured Version of the Soil and Water Assessment Tool", *Journal of the American Water Resources Association*, https://doi.org/10.1111/1752-1688.12482. [186]

Bijay-Singh and E. Craswell (2021), "Fertilizers and nitrate pollution of surface and ground water: an increasingly pervasive global problem", *SN Applied Sciences*, Vol. 3/4, https://doi.org/10.1007/s42452-021-04521-8. [53]

Boctor, J. et al. (2025), "Microplastics and nanoplastics: Fate, transport, and governance from agricultural soil to food webs and humans", *Environmental Sciences Europe*, Vol. 37/1, p. 68, https://doi.org/10.1186/s12302-025-01104-x. [59]

Boretti, A. and L. Rosa (2019), "Reassessing the projections of the World Water Development Report", *npj Clean Water*, Vol. 2/1, p. 15, https://doi.org/10.1038/s41545-019-0039-9. [44]

BRGM (2019), *"BD Drainage", a database of agricultural drainage data*, https://www.brgm.fr/en/reference-completed-project/bd-drainage-database-agricultural-drainage-data#:~:text=BD%20Drainage%3A%20drained%20agricultural%20plots%2C%20where%20does%20the%20rainwater%20go%3F&text=The%20BD%20Drainage%20collaborative%20database,na. [156]

Brookfield, A. et al. (2024), "Estimating Groundwater Pumping for Irrigation: A Method Comparison", *Groundwater*, Vol. 62/1, pp. 15-33, https://doi.org/10.1111/gwat.13336. [191]

California Water Watch (n.d.), *California Water Watch*, https://web.archive.org/web/20250820050843/https://cww.water.ca.gov/ (accessed on 12 December 2025). [161]

Cammalleri, C. et al. (2021), "A revision of the Combined Drought Indicator (CDI) used in the European Drought Observatory (EDO)", *Natural Hazards and Earth System Sciences*, Vol. 21/2, pp. 481-495, https://doi.org/10.5194/nhess-21-481-2021. [124]

Canada1Water (n.d.), *Canada1Water*, https://portal.canada1water.ca/ (accessed on 17 December 2025). [162]

Carleton, T., L. Crews and I. Nath (2024), "Is the World Running Out of Fresh Water?", *AEA Papers and Proceedings*, Vol. 114, pp. 31–35, https://doi.org/10.1257/pandp.20241008. [75]

CDP (2026), *Why disclose environmental data*, https://www.cdp.net/en/disclose/why-disclose. [116]

CEP (2014), "The future of water resource availability in France: how is the agricultural sector taken into account in foresight studies?", *CEP Analyses*, Vol. 68, https://agriculture.gouv.fr/analysis-ndeg68-april-2014-future-water-resource-availability-france-how-agricultural-sector-taken. [112]

CGIAR/IWMI (2024), *Digital twin for water management handed over for trial in the Limpopo River Basin*, https://www.cgiar.org/news-events/news/digital-twin-handover-limpopo/. [140]

Cheng, M. et al. (2023), "Evaluation of UAV-based drought indices for crop water conditions monitoring: A case study of summer maize", *Agricultural Water Management*, Vol. 287, p. 108442, https://doi.org/10.1016/j.agwat.2023.108442. [83]

Chipanshi, A. et al. (2015), "Evaluation of the Integrated Canadian Crop Yield Forecaster (ICCYF) model for in-season prediction of crop yield across the Canadian agricultural landscape", *Agricultural and Forest Meteorology*, Vol. 206, pp. 137-150, https://doi.org/10.1016/j.agrformet.2015.03.007. [142]

Cigna, G. et al. (forthcoming), "Evapotranspiration shed of key agricultural crops: combining agro-hydrological estimates with atmospheric moisture dynamics, in prep.". [113]

Climate-ADAPT (2025), *CANARI-Europe – Climate ANalysis for Agriculture Recommendations and Impacts*, https://climate-adapt.eea.europa.eu/en/mission/solutions/tools/036_canari-europe-climate-analysis-for-agriculture (accessed on 21 July 2025). [164]

Copernicus (n.d.), "European Drought Observatory", https://www.copernicus.eu/en/european-drought-observatory (accessed on 21 November 2025). [125]

Copernicus Emergency Management Service (n.d.), *GloFAS Global Flood Monitoring (GFM)*, https://global-flood.emergency.copernicus.eu/technical-information/glofas-gfm/ (accessed on 20 August 2025). [119]

Crist, S., J. Mori and R. Lee Smith (2020), "Flooding on Beef and Swine Farms: A Scoping Review of Effects in the Midwestern United States", *Preventive Veterinary Medicine*, Vol. 184, https://doi.org/10.1016/j.prevetmed.2020.105158. [10]

Crop Monitor (2026), *GEOGLAM Crop Monitor*, https://www.cropmonitor.org/. [146]

CropWatch (2025), *CropWatch*, http://cloud.cropwatch.com.cn/ (accessed on 7 August 2025). [89]

D'Odorico, P. et al. (2019), "Global virtual water trade and the hydrological cycle: patterns, drivers, and socio-environmental impacts", *Environ. Res. Lett. 14 053001*. [70]

Dari, J. et al. (2021), "Detecting and mapping irrigated areas in a Mediterranean environment by using remote sensing soil moisture and a land surface model", *Journal of Hydrology*, Vol. 596, p. 126129, https://doi.org/10.1016/j.jhydrol.2021.126129. [81]

Defra (2025), "A UK government food strategy for England, considering the wider UK food system. Annex A: Outcome summaries". [68]

DigitalWater.City (2022), *Early Warning System for safe reuse of treated wastewater for agricultural irrigation*, https://www.digital-water.city/solution/early-warning-system-for-safe-reuse-of-treated-wastewater-for-agricultural-irrigation/. [79]

Duin, P., H. Van Lanen and A. Zehnder (2025), *The future of water availability and use in the EU - A foresight study and policy options to address water scarcity*, Brussels, European Union, https://doi.org/10.2861/6213761. [111]

Dupont, A. et al. (2025), *Brief: Integrating Green Water Risks in Agricultural Commodities Supply Chains*, International Water Management Institute., https://doi.org/10.5337/2026.203. [114]

EEA (2025), *Waterbase - Water Quality ICM*. [172]

EEA (2021), "Briefing: Global climate change impacts and the supply of agricultural commodities to Europe", https://www.eea.europa.eu/publications/global-climate-change-impacts-and/global-climate-change-impacts-and (accessed on 26 August 2025). [63]

EEA (n.d.), *European Drought Observatory*, https://www.eea.europa.eu/policy-documents/european-drought-observatory-edo#:~:text=The%20European%20drought%20observatory%20(EDO,%2C%20modelled%20soil%20moisture%20content). (accessed on 21 November 2025). [126]

El Bilali, A. and A. Taleb (2024), "State-of-the art-on irrigation water quality management using data-driven methods: Practical application, limitations, and prospective directions", *Physics and Chemistry of the Earth, Parts A/B/C*, Vol. 136, p. 103794, https://doi.org/10.1016/j.pce.2024.103794. [78]

Elenius, M. et al. (2025), "Where can rewetting of forested peatland reduce extreme flows? Model experiment on the hydrology of Sweden", *Hydrology and Earth System Sciences*, Vol. 29/17, pp. 4307-4325, https://doi.org/10.5194/hess-29-4307-2025. [43]

EPA (2025), *Water Quality Data Download*, https://www.epa.gov/waterdata/water-quality-data-download (accessed on 17 December 2025). [173]

Ercin, E., D. Chico and A. Chapagain (2019), "Vulnerabilities of the European Union's Economy to Hydrological Extremes Outside its Borders", *Atmosphere*, Vol. 10/10, https://doi.org/10.3390/atmos10100593. [62]

Escriva-Bou, A. et al. (2022), *Drought and California's Agriculture*, https://www.ppic.org/publication/policy-brief-drought-and-californias-agriculture/. [21]

Fang et al. (2024), "Review of the Mechanism and Methodology of Water Demand Forecasting in the Socio-Economic System", *Water*, Vol. 16/11, https://doi.org/10.3390/w16111631. [108]

FAO (2026), *AQUASTAT - FAO's Global Information System on Water and Agriculture: The WaPOR database*, https://www.fao.org/aquastat/en/geospatial-information/wapor. [138]

FAO (2026), *Drought Impacts Assessment Platform*, https://diap.ias.csic.es/. [158]

FAO (2025), "ASIS Datasets on ArcGIS Online", https://asis.apps.fao.org/ (accessed on 21 November 2025). [144]

FAO (2025), *Earth Observation*, https://www.fao.org/giews/earthobservation/asis/index_1.jsp?lang=en (accessed on 22 August 2025). [143]

FAO (2021), *The Impact of Disasters and Crises on Agriculture and Food Security*, http://www.fao.org/3/cb3673en/cb3673en.pdf. [22]

FAO (2020), *The State of Food and Agriculture 2020. Overcoming water challenges in agriculture.*, https://doi.org/10.4060/cb1447en. [17]

FAO (2012), “Coping with water scarcity: An action framework for agriculture and food security”, *FAO Water Reports*, https://www.fao.org/4/i3015e/i3015e.pdf (accessed on 17 June 2025). [13]

FAO & IWMI (2023), *Water quality in agriculture: Risks and risk mitigation. (n.d.)*, https://openknowledge.fao.org/items/efc4aeb7-9b7d-44c4-b158-9a41527b8586. [25]

FAO, SEI, CI & TNC (2025), *Climate and ecosystem service benefits of forests and trees for agriculture.*, https://doi.org/10.4060/cd7599en. [192]

Fluet-Chouinard, E. (2023), “Extensive global wetland loss over the past three centuries”, *Nature*, Vol. 614, pp. 281–286, https://doi.org/10.1038/s41586-022-05572-6. [27]

Foster. T., T. et al. (2022), “AquaPlan: A new interactive tool for agricultural water management and climate risk assessment”, https://medium.com/@agwater/aquaplan-a-new-interactive-tool-for-agricultural-water-management-and-climate-risk-assessment-82c50cb10144 (accessed on 27 November 2025). [169]

Freire, P. et al. (2021), “Flood and drought risk assessment for agricultural areas (Tagus Estuary, Portugal)”, *Nat. Hazards Earth Syst. Sci.*, Vol. 21, pp. 2503–2521, https://doi.org/10.5194/nhess-21-2503-2021. [185]

Frey, S., H. Russell and A. Kirkwood (2024), *Canada1Water research and development phase 1 report*, https://doi.org/10.4095/p5mq5bduv7. [163]

GCEW (2024), *The Economics of Water: Valuing the Hydrological Cycle as Global Common Good*, Global Commission on the Economics of Water, https://economicsofwater.watercommission.org/. [1]

GEMSTAT (n.d.), *GEMSTAT*, https://gemstat.org/ (accessed on 17 December 2025). [170]

GEO Aqua Watch (2024), *Global Water Quality Maps*, https://www.geoaquawatch.org/global-water-quality-maps/#dineof (accessed on 22 August 2025). [133]

Gnann, Reinecke and Stein (2023), “Functional relationships reveal differences in the water cycle representation of global water models”, *Nature Water*, Vol. 1, pp. 1079–1090, https://doi.org/10.1038/s44221-023-00160-y. [97]

Gomes et al. (2025), “Waterborne contaminants in high intensity agriculture and plant production: A review of on-site and downstream impacts.”, *Science of The Total Environment*, Vol. 958, https://doi.org/10.1016/j.scitotenv.2024.178084. [24]

Government of Canada (2025), *Canadian Crop Metrics*, https://agriculture.canada.ca/en/agricultural-production/weather/canadian-crop-metrics (accessed on 17 December 2025). [141]

Government of Canada (n.d.), “Canadian Drought Monitor”, https://agriculture.canada.ca/en/agricultural-production/weather/canadian-drought-monitor (accessed on 4 December 2025). [131]

Haase, P. et al. (2023), “The recovery of European freshwater biodiversity has come to a halt.”, *Nature*, Vol. 620, pp. 582–588, https://doi.org/10.1038/s41586-023-06400-1. [28]

Hanadé Houmma, I. et al. (2022), "Modelling agricultural drought: a review of latest advances in big data technologies", *Geomatics, Natural Hazards and Risk*, Vol. 13/1, pp. 2737-2776, https://doi.org/10.1080/19475705.2022.2131471. [177]

Hoekstra, A. and A. Chapagain (2008), *Globalization of water: Sharing the planet's fresh-water resources*, Blackwell. [101]

Hoekstra, A. and M. Mekonnen (2016), "Imported water risk: the case of the UK", *Environmental Research Letters* 11 055002. [64]

Hughes, N. et al. (2025), "Monitoring agricultural and economic drought: the Australian Agricultural Drought Indicators (AADI)", *Natural Hazards and Earth System Sciences*, Vol. 25/9, pp. 3461-3482, https://doi.org/10.5194/nhess-25-3461-2025. [93]

Hughes, N. et al. (2022), "Improving the performance of micro-simulation models with machine learning: The case of Australian farms", *Economic Modelling*, Vol. 115, p. 105957, https://doi.org/10.1016/j.econmod.2022.105957. [160]

Ibrahim, A. et al. (2024), "Remote Sensing Technologies for Unlocking New Groundwater Insights: A Comprehensive Review", *Journal of Hydrology*, https://doi.org/10.1016/j.hydroa.2024.100175. [99]

Institute of Industrial Science (n.d.), *Satellite-based drought monitoring and warning system*, https://wtlab.iis.u-tokyo.ac.jp/DMEWS/ (accessed on 9 July 2025). [127]

IPCC (2022), *Climate Change 2022 – Impacts, Adaptation and Vulnerability*, Cambridge University Press, https://doi.org/10.1017/9781009325844. [14]

IRRIFRAME (n.d.), *IRRIFRAME*, https://www.irriframe.it/Irriframe (accessed on 17 December 2025). [134]

ITC (n.d.), *Geospatial World Excellence Award 2016*, https://www.itc.nl/alumni/70-years-of-itc/timeline-stories/Geospatial-World-Excellence-Award-2016/ (accessed on 21 November 2025). [145]

IWMI (2025), "Flood Risk Mapping", https://www.iwmi.org/news/flood-risk-mapping/ (accessed on 26 November 2025). [147]

IWMI (2025), "Flood Risk Mapping: South Asia", https://waterdata.iwmi.org/Applications/Catastrophic_Flood_Risk_Mapping/ (accessed on 26 November 2025). [148]

Jägermeyr, J. (2017), "Reconciling irrigated food production with environmental flows for Sustainable Development Goals implementation", *Nature Communications, Vol. 8/1,*. [48]

Jam-Jalloh, S. et al. (2024), "Coupling WRF with HEC-HMS and WRF-Hydro for flood forecasting in typical mountainous catchments of northern China", *Nat. Hazards Earth Syst. Sci., 24, 3155–3172*, https://doi.org/10.5194/nhess-24-3155-2024. [76]

Ji, L. et al. (2025), "Estimating agricultural irrigation water consumption for the High Plains aquifer region with integrated energy- and water-balance evapotranspiration modeling approaches", *Agricultural Water Management*, Vol. 309, https://doi.org/10.1016/j.agwat.2025.109308. [87]

JRC (2023), *European drought risk atlas*, https://op.europa.eu/en/publication-detail/-/publication/21a1984a-7478-11ee-99ba-01aa75ed71a1/ (accessed on 7 July 2025). [90]

JRC (n.d.), *European and Global Drought Observatories*, https://joint-research-centre.ec.europa.eu/european-and-global-drought-observatories_en (accessed on 9 July 2025). [121]

JRC and UNCDD (2024), *World Drought Atlas*, Publications Office of the European Union, Luxembourg, https://data.europa.eu/doi/10.2760/3842670 (accessed on 19 June 2025). [150]

Kadam, S. et al. (2021), "Suitability of Earth Engine Evaporation Flux (EEFlux) Estimation of Evapotranspiration in Rainfed Crops", *Remote Sensing*, Vol. 13/19, https://doi.org/10.3390/rs13193884. [88]

Karimi, S. et al. (2024), "Rewetting impact on the hydrological function of a drained peatland in the boreal landscape", *Journal of Hydrology*, Vol. 641, p. 131729, https://doi.org/10.1016/j.jhydrol.2024.131729. [41]

Karimi, S. et al. (2025), "Does peatland rewetting mitigate flooding from extreme rainfall events?", *Hydrology and Earth System Sciences*, Vol. 29/12, pp. 2599-2614, https://doi.org/10.5194/hess-29-2599-2025. [42]

Kaur, G. et al. (2020), "Impacts and management strategies for crop production in waterlogged or flooded soils: A review", *Agronomy Journal*, Vol. 112/3, pp. 1475-1501. [5]

Kaur, R. et al. (2024), "Pesticides: An alarming detrimental to health and environment", *Science of The Total Environment*, Vol. 915, p. 170113, https://doi.org/10.1016/j.scitotenv.2024.170113. [57]

Khondoker, M. et al. (2023), "Freshwater Shortage, Salinity Increase, and Global Food Production: A Need for Sustainable Irrigation Water Desalination—A Scoping", *Earth*, Vol. 4/2, pp. 223-240, https://doi.org/10.3390/earth4020012. [51]

Kobayashi, K. et al. (2021), "Estimation of paddy field dam effect on flood mitigation focusing on Suse region of Hyogo, Japan", *Hydrological Research Letters*, Vol. 15/3, pp. 64-70, https://doi.org/10.3178/hrl.15.64. [40]

Kotz, M. et al. (2025), "Climate extremes, food price spikes, and their wider societal risks", *Environmental Research Letters*, Vol. 20/8, p. 081001, https://doi.org/10.1088/1748-9326/ade45f. [61]

Krklješ, D. and E. al. (2024), "Multiparameter Water Quality Monitoring System for Continuous Monitoring of Fresh Waters", *IEEE Sensors Journal*, Vol. 24/7, pp. 11246-11260, https://doi.org/10.1109/JSEN.2024.3368560. [179]

Liu, X. et al. (2016), "Agricultural drought monitoring: Progress, challenges, and prospects", *Journal of Geographical Sciences*, Vol. 26/6, pp. 750-767, https://doi.org/10.1007/s11442-016-1297-9. [16]

Liu, Y. et al. (2015), "Agriculture intensifies soil moisture decline in Northern China", *Scientific Reports*, Vol. 5/1, p. 11261, https://doi.org/10.1038/srep11261. [47]

Li, Y. et al. (2019), "Excessive rainfall leads to maize yield loss of a comparable magnitude to extreme drought in the United States", *Global Change Biology*, Vol. 25/7, https://doi.org/10.1111/gcb.14628. [8]

Li, Z., L. Rosa and S. Gorelick (2025), "Severe floods significantly reduce global rice yields", *Science Advances*, Vol. 11/46, https://doi.org/10.1126/sciadv.adx7799. [9]

Luo, L. et al. (2022), "A Novel Early Warning System (EWS) for Water Quality, Integrating a High-Frequency Monitoring Database with Efficient Data Quality Control Technology at a Large and Deep Lake (Lake Qiandao), China", *Water*, Vol. 14/4, p. 602, https://doi.org/10.3390/w14040602. [182]

MAPA (n.d.), *Sistema de Información Agroclimática del Regadío*, https://www.mapa.gob.es/es/desarrollo-rural/temas/gestion-sostenible-regadios/sistema-informacion-agroclimatica-regadio/presentacion (accessed on 17 December 2025). [135]

Ma, S. et al. (2024), "Land use/land cover change and soil property variation increased flood risk in the black soil region, China, in the last 40 years", *Environmental Impact Assessment Review*, Vol. 104, https://doi.org/10.1016/j.eiar.2023.107314. [36]

Maußner, Oberascher and Autengr (2025), "Explainable artificial intelligence for reliable water demand forecasting to increase trust in predictions", *Water Research*, Vol. 28, https://doi.org/10.1016/j.watres.2024.122779. [109]

Mehta, P. et al. (2024), "Half of twenty-first century global irrigation expansion has been in water-stressed regions", *Nature Water*, Vol. 2/3, pp. 254-261, https://doi.org/10.1038/s44221-024-00206-9. [45]

Mekonnen , M. et al. (2024), "Trends and environmental impacts of virtual water trade.", *Nature reviews earth & environment*, Vol. 5, pp. 890–905, https://doi.org/10.1038/s43017-024-00605-2. [71]

Meng, H. et al. (2024), "Classification of inland lake water quality levels based on Sentinel-2 images using convolutional neural networks and spatiotemporal variation and driving factors of algal bloom.", *Ecological Informatics, 80, 102549.*, https://doi.org/10.1016/j.ecoinf.2024.102549. [180]

Modjeska, M. and P. Brémond (2022), "Contribution to improve modelling and observation of flood impacts on agricultural assets: Scientific report", https://hal.inrae.fr/hal-03911224/file/rapport_moom-agri-final.pdf. [94]

Molinari, D. et al. (2019), "AGRIDE-c, a conceptual model for the estimation of flood damage to crops: development and implementation", *Natural Hazards Earth Systems Sciences*, Vol. 19, pp. 2565–2582, https://doi.org/10.5194/nhess-19-2565-2019. [95]

Mullapudi, A. et al. (2023), "A review of agricultural drought assessment with remote sensing data: methods, issues, challenges and opportunities", *Applied Geomatics*, Vol. 15/1, pp. 1-13, https://doi.org/10.1007/s12518-022-00484-6. [178]

Muller, M. and C. Bellmann (2016), *Trade and Water: How Might Trade Policy Contribute to Sustainable Water Management?*, Geneva: International Centre for Trade and Sustainable Development (ICTSD). [65]

MyClimateView (n.d.), *About My Climate View*, https://myclimateview.com.au/about (accessed on 9 December 2025). [105]

NASA (2022), *News: NASA finds new way to monitor underground water loss (April 5)*, https://gracefo.jpl.nasa.gov/news/154/nasa-finds-new-way-to-monitor-underground-water-loss/. [98]

NASA (2022), *Steamy Relationships: How Atmospheric Water Vapor Amplifies Earth's Greenhouse Effect*, https://science.nasa.gov/earth/climate-change/steamy-relationships-how-atmospheric-water-vapor-amplifies-earths-greenhouse-effect/#:~:text=For%20every%20degree%20Celsius%20that,driver%20of%20Earth's%20current%20warming. [32]

NASA (2021), *OpenET: A Satellite-Based Water Data Resource*, https://www.nasa.gov/image-article/openet-satellite-based-water-data-resource/. [136]

National Drought Mitigation Center (2025), *Drought Risk Atlas*, https://droughtatlas.unl.edu/ (accessed on 7 July 2025). [151]

National Drought Mitigation Center (2025), *US Drought Monitor*, https://droughtmonitor.unl.edu/About/WhatistheUSDM.aspx (accessed on 4 December 2025). [132]

Natural Resources Canada (n.d.), *Science behind flood mapping*, https://natural-resources.canada.ca/science-data/science-research/natural-hazards/flood-mapping/science-behind-flood-mapping#Height (accessed on August 2025). [183]

NOAA (n.d.), *North American Drought Monitor (NADM) Overview*, https://www.ncei.noaa.gov/access/monitoring/nadm/ (accessed on 4 December 2025). [130]

Núñez Cobo, J. and K. Verbist (2018), *Atlas de Sequía de América Latina y el Caribe*, UNESCO and CAZALAC. [153]

Núñez J. and K. Verbist (n.d.), *Latin American and Caribbean Drought Atlas*, https://www.cazalac.org/mwar_lac/fileadmin/imagenes2/Brochures/Drought_Atlas_for_Latin_America_and_the_Caribbean_brochure_eng_final_light.pdf (accessed on 7 July 2025). [154]

Octavianti and Staddon (2021), "A review of 80 assessment tools measuring water security", *WIREs Water*, Vol. 8/3, https://doi.org/10.1002/wat2.1516. [100]

OECD (2025), *Embedding Water-related Risks in Financial Stability Frameworks*, OECD Studies on Water, OECD Publishing, Paris, https://doi.org/10.1787/ee1757f9-en. [190]

OECD (2025), *Global Drought Outlook: Trends, Impacts and Policies to Adapt to a Drier World*, OECD Publishing, Paris, https://doi.org/10.1787/d492583a-en. [12]

OECD (2025), *Strategic Foresight Toolkit for Resilient Public Policy: A Comprehensive Foresight Methodology to Support Sustainable and Future-Ready Public Policy*, OECD Publishing, Paris, https://doi.org/10.1787/bcdd9304-en. [110]

OECD (2020), *Strengthening Agricultural Resilience in the Face of Multiple Risks*, OECD Publishing, Paris, https://doi.org/10.1787/2250453e-en. [2]

OECD (2017), *Water Risk Hotspots for Agriculture*, OECD Studies on Water, OECD Publishing, Paris, https://doi.org/10.1787/9789264279551-en. [60]

OECD (2016), *Mitigating Droughts and Floods in Agriculture: Policy Lessons and Approaches*, OECD Studies on Water, OECD Publishing, Paris, https://doi.org/10.1787/9789264246744-en. [6]

OECD (2016), *OECD Council Recommendation on Water*, OECD, Paris. [3]

OECD (2013), *Water Security for Better Lives*, OECD Studies on Water, OECD Publishing, Paris, https://doi.org/10.1787/9789264202405-en. [4]

OECD/FAO (2021), *Building Agricultural Resilience to Natural Hazard-induced Disasters: Insights from Country Case Studies*, OECD Publishing, Paris, https://doi.org/10.1787/49eefdd7-en. [19]

OpenET (2026), *OpenET: Filling the biggest data gap in water management*, https://etdata.org/. [137]

Ouvrard, B. et al. (2023), “Nudging and subsidising farmers to foster smart water meter adoption”, *European Review of Agricultural Economics*, Vol. 50/3, pp. 1178–1226, https://doi.org/10.1093/erae/jbad013. [118]

Parra-López, C. et al. (2025), “Digital technologies for water use and management in agriculture: Recent applications and future outlook”, *Agricultural Water Management*, Vol. 309, p. 109347, https://doi.org/10.1016/j.agwat.2025.109347. [80]

Perez, N. et al. (2024), “Ending groundwater overdraft without affecting food security”, *Nature Sustainability*, Vol. 7, pp. 1007–1017, https://doi.org/10.1038/s41893-024-01376-w. [106]

Pica, N. et al. (2017), “Produced water reuse for irrigation of non-food biofuel crops: Effects on switchgrass and rapeseed germination, physiology and biomass yield”, *Industrial Crops and Products,* 100, pp. 65–76, https://doi.org/10.1016/j.indcrop.2017.02.011. [23]

Ramsar (2021), *Wetlands and agriculture: impacts of farming practices and pathways to sustainability*, The Secretariat of the Convention on Wetlands, https://elearning.fao.org/pluginfile.php/1102395/mod_scorm/content/1/story_content/external_files/bn13_agriculture_e.pdf. [39]

Reisinger, A. et al. (2020), *The Concept of Risk in the IPCC Sixth Assessment Report: A Summary of Cross-Working Group Discussions. Intergovernmental Panel on Climate Change, Geneva, Switzerland. pp15*, https://www.ipcc.ch/site/assets/uploads/2021/02/Risk-guidance-FINAL_15Feb2021.pdf. [31]

Romero, M. et al. (2018), “Vineyard water status estimation using multispectral imagery from an UAV platform and machine learning algorithms for irrigation scheduling management”, *Computers and Electronics in Agriculture*, Vol. 147, pp. 109–117, https://doi.org/10.1016/j.compag.2018.02.013. [85]

Rotteveel, L., F. Heubach and S. Sterling (2022), “The Surface Water Chemistry (SWatCh) database: a standardized global database of water chemistry to facilitate large-sample hydrological research”, *Earth System Science Data*, Vol. 14/10, pp. 4667-4680, https://doi.org/10.5194/essd-14-4667-2022. [176]

Saha, T. et al. (2021), “A drought monitoring tool for South Asia”, *Environmental Research Letters*, Vol. 16/5, p. 054014, https://doi.org/10.1088/1748-9326/abf525. [129]

Salls, W. et al. (2024), "Expanding the Application of Sentinel-2 Chlorophyll Monitoring across United States Lakes. Remo", *Remote Sensing*, Vol. 16/11, https://doi.org/10.3390/rs16111977. [181]

Scanlon, B. et al. (2023), "Global water resources and the role of groundwater in a resilient water future", *Nature Reviews Earth & Environment*, Vol. 4/2, pp. 87-101, https://doi.org/10.1038/s43017-022-00378-6. [46]

Schmitt, J. et al. (2022), "Extreme weather events cause significant crop yield losses at the farm level in German agriculture", *Food Policy*, Vol. 112. [11]

Schweiger, L. et al. (2025), "Pesticide contamination is associated with invertebrate community change in non-agricultural streams", *Water Research*, Vol. 282, p. 123903, https://doi.org/10.1016/j.watres.2025.123903. [58]

Shepheard, M. and P. Martin (2008), "Social Licence to Irrigate: The Boundary Problem", *Social Alternatives*, Vol. 27/3, pp. 32-39., https://www.proquest.com/openview/67eec01a229aab2dfd3348e0c7fe4e53/1?cbl=31438&pq-origsite=gscholar. [117]

Singh, A. (2022), "Soil salinity: A global threat to sustainable development", *Soil Use and Management*, Vol. 38/1, pp. 39–67, https://doi.org/10.1111/sum.12772. [49]

Smith, C., J. Baker and D. Spracklen (2023), "Tropical deforestation causes large reductions in observed precipitation", *Nature*, Vol. 615/7951, pp. 270-275, https://doi.org/10.1038/s41586-022-05690-1. [34]

Solagro and Makina Corpus (2025), *CANARI*, https://canari-europe.com/ (accessed on 21 July 2025). [103]

Solagro and Makina Corpus (2025), *Data and pairs of simulations*. [165]

Solagro and Météo-France (2025), *Climadiag Agriculture: À propos*, https://climadiag-agriculture.fr/a-propos (accessed on 21 July 2025). [166]

Svoboda, M. et al. (2015), "The drought risk atlas: Enhancing decision support for drought risk management in the United States", *Journal of Hydrology*, Vol. 526, pp. 274-286, https://doi.org/10.1016/j.jhydrol.2015.01.006. [152]

Takeuchi, W. et al. (2015), *Near-real time meteorological drought monitoring and early warning system for croplands in Asia*. [128]

Tan, P., K. Bowmer and J. Mackenzie (2012), "Deliberative tools for meeting the challenges of water planning in Australia", *Journal of Hydrology*, Vol. 474, pp. 2-10, https://doi.org/10.1016/j.jhydrol.2012.02.032. [115]

Teng, J. et al. (2017), "Flood inundation modelling: A review of methods, recent advances and uncertainty analysis", *Environmental Modelling & Software*, Vol. 90. [91]

Teng, P. (2020), "Assuring food security in Singapore, a small island state facing COVID-19", *Food Security*, Vol. 12/4, pp. 801-804, https://doi.org/10.1007/s12571-020-01077-0. [67]

The GlaMBIE Team (2025), "Community estimate of global glacier mass changes from 2000 to 2023", *Nature*, Vol. 639, pp. 382–388, https://doi.org/10.1038/s41586-024-08545-z. [33]

Thorslund, J. et al. (2021), “Common irrigation drivers of freshwater salinisation in river basins worldwide”, *Nature Communications*, Vol. 12/1, pp. 1-13, https://doi.org/10.1038/s41467-021-24281-8. [50]

Tikoudis, I., M. Gabriel and W. Oueslati (2025), “The toll of droughts: Environmental impacts, economic costs, and international consequences”, *OECD Environment Working Paper 260.*. [18]

Timár, G., G. Jakab and B. Székely (2024), “A Step from Vulnerability to Resilience: Restoring the Landscape Water-Storage Capacity of the Great Hungarian Plain—An Assessment and a Proposal”, *Land*, Vol. 13/2, p. 146, https://doi.org/10.3390/land13020146. [37]

Tuninetti, M., S. Tamea and C. Dalin (2019), “Water Debt Indicator Reveals Where Agricultural Water Use Exceeds Sustainable Levels”, *Water Resources Research*, Vol. 55/3, https://doi.org/10.1029/2018WR023146. [189]

UNCDD (2022), “Global Land Outlook. Second Edition. Land Restoration for Recovery and Resilience”, https://www.unccd.int/sites/default/files/2022-04/UNCCD_GLO2_low-res_2.pdf (accessed on 18 June 2025). [35]

United Nations (n.d.), *Global Drought Observatory (JRC)*, https://www.un-spider.org/links-and-resources/data-sources/global-drought-observatory-jrc#:~:text=The%20Global%20Drought%20Observatory%20provides,%2C%20modeled%20soil%20moisture%20content). (accessed on 21 November 2025). [122]

Universität Hamburg (2019), *GLORICH - Global River Chemistry Database*. [171]

University of Manchester (2024), *AquaPlan: award-winning app revolutionising agricultural water management*, https://www.socialresponsibility.manchester.ac.uk/all-news/aquaplan-wins-a-making-a-difference-award/. [168]

University of Maryland (n.d.), “Global Flood Monitoring System (GFMS)”, http://flood.umd.edu/ (accessed on 20 August 2025). [120]

Virro, H. et al. (2025), “Data catalog of Global River Water Quality Archive (GRQA) v1.4”, https://zenodo.org/records/15335450 (accessed on 18 December 2025). [175]

Virro, H. et al. (2021), “GRQA: Global River Water Quality Archive”, *Earth System Science Data*, Vol. 13/12, pp. 5483-5507, https://doi.org/10.5194/essd-13-5483-2021. [174]

Vogt, J. (2019), *Global Drought Information System (GDIS) and Global Drought Observatory (GDO)*, https://www.droughtmanagement.info/documents/presentations/2019/4_5_GDIS_GDO.pdf (accessed on 21 November 2025). [123]

Wang, M. (2024), “A triple increase in global river basins with water scarcity due to future pollution”, *Nature Communications*, Vol. 15/1, p. 880, https://doi.org/10.1038/s41467-024-44947-3. [26]

Wang, Q. et al. (2023), “Factors affecting crop production water footprint: A review and meta-analysis.”, *Sustainable Production and Consumption*, Vol. 36, pp. 207-216, https://doi.org/10.1016/j.spc.2023.01.008. [102]

Ward, M. et al. (2018), "Drinking Water Nitrate and Human Health: An Updated Review", *International Journal of Environmental Research and Public Health*, Vol. 15/7, p. 1557, https://doi.org/10.3390/ijerph15071557. [52]

WEAP (2025), *WEAP: Water Evaluation and Adaptation Planning*, https://www.weap21.org/. [187]

Wichelns (2015), "Virtual water and water footprints: Overreaching into the discourse on sustainability, efficiency, and equity.", *Water Alternatives*, Vol. 8/3, pp. 396-414. [72]

WMO (2024), *State of Global Water Resources report 2023*, World Meteorological Organization, https://library.wmo.int/records/item/69033-state-of-global-water-resources-report-2023. [30]

WMO (2023), *State of Global Water Resources 2022 report*, World Meteorological Organization. [29]

World Bank (2025), *The Macroeconomic Implications of Climate Change Impacts and Adaptation Options: A Modeling Approach*, https://documents1.worldbank.org/curated/en/099722205282528064/pdf/IDU-dbd893e5-502b-457d-b2a9-54ccc5e6cf4c.pdf. [96]

World Meteorological Organization (2025), *Dynamic Water Resources Assessment Tool (DWAT)*, https://wmo.int/activities/dynamic-water-resources-assessment-tool-dwat. [188]

World Resources Institute (2023), *25 Countries, Housing One-Quarter of the Population, Face Extremely High Water Stress*, https://www.wri.org/insights/highest-water-stressed-countries. [107]

WRI (2021), "Aqueduct Food", https://www.wri.org/data/aqueduct-food (accessed on 21 November 2025). [149]

WWF (2025), *WWF Risk Filter Suite*, https://riskfilter.org/ (accessed on 23 January 2026). [155]

Yi, J., P. Gerbens-Leenes and M. Aldaya (2024), "Crop grey water footprints in China: The impact of pesticides on water pollution", *Science of The Total Environment*, Vol. 935, p. 173464, https://doi.org/10.1016/j.scitotenv.2024.173464. [56]

Yildirim, E. and I. Demir (2022), "Agricultural flood vulnerability assessment and risk quantification in Iowa", *Science of The Total Environment*, Vol. 826, https://doi.org/10.1016/j.scitotenv.2022.154165. [184]

Zampeiri, M. et al. (2017), "Wheat yield loss attributable to heat waves, drought and water excess at the global, national and subnational scales", *Environmental Research Letters*, Vol. 12/6, https://doi.org/10.1088/1748-9326/aa723b. [7]

Zaussinger, F. (2019), "Estimating irrigation water use over the contiguous United States by combining satellite and reanalysis soil moisture data,", *Hydrology Earth Systems Sciences*, Vol. 23, pp. 897–923, https://doi.org/10.5194/hess-23-897-2019. [86]

Zhang, J. et al. (2018), "Effect of Drought on Agronomic Traits of Rice and Wheat: A Meta-Analysis", *International Journal of Environmental Research and Public Health*, Vol. 15/5, p. 839, https://doi.org/10.3390/ijerph15050839. [20]

Zhou, J. et al. (2022), "Anthropogenic eutrophication of shallow lakes: Is it occasional?", *Water Research*, Vol. 221, p. 118728, https://doi.org/10.1016/j.watres.2022.118728. [55]

Zhu, S. et al. (2023), “Digital Mapping of Root-Zone Soil Moisture Using UAV-Based Multispectral Data in a Kiwifruit Orchard of Northwest China”, *Remote Sensing*, Vol. 15/3, p. 646, https://doi.org/10.3390/rs15030646. [84]

Notes

[1] The workshop convened delegates of the OECD Joint Working Party on Agriculture and the Environment and experts from academia, government, NGOs, multilateral organisations, agro-food corporations and irrigation associations.

[2] *Embedding water-related risks in financial stability frameworks* (OECD, 2025[190]) provides a thorough exploration of water-related financial risks.

[3] The seven types of natural disasters that adversely impacted agricultural production systems were drought, followed by floods, storms, earthquakes/landslides/mass movements, plant and animal pests/diseases, extreme temperatures and wildfires.

[4] Freshwater ecosystems encompass wetlands, river, lake and groundwater systems as well as forests. Water-related ecosystem services from trees and forests to agriculture include freshwater supply, regulation of water flows, local climates and temperatures, supporting an intact and reliable hydrological cycle, water damage mitigation and water purification (FAO, SEI, CI & TNC, 2025[192]).

[5] Developed to guide climate risk assessment, the IPCC framing is well adapted to considering water-related risks given that many climate hazards are water hazards, such as floods and drought.

[6] Water is transferred from the land to the atmosphere via evaporation from the soil and other surfaces and transpiration by plants, together known as evapotranspiration.

[7] Secondary salinisation is salinity that results from human activities (e.g. farming, irrigation) as opposed to naturally occurring salinity.

[8] Hydrological-based, crop demand-based and integrated methods (Brookfield et al., 2024[191]).

[9] The drainage map is available here: https://www.melioracija.lv/?lang=EN&loc=503959;271613;4.

[10] In other contexts, the term “grey water” can refer to the wastewater generated from household activities such as bathing, washing hands and laundry.

Annex A. Tools fiches

This annex contains examples of tools that aggregate analysed data to support decisions by monitoring and anticipating water risks. Tools marked with an asterisk (*) are still in experimental phase and may not yet be fully deployed. Other tools are operational and established tools, already in use.

Real-time hazard monitoring and short-term forecast tools

Water excess

Table A A.1. GloFAS Global Flood Monitoring

Developed by	Copernicus Emergency Management Service
Type(s) of physical water risk covered	Water excess (flood) Blue water
Dimensions of risk included	Hazard
Purpose	Near real-time global flood monitoring
Intended user	Disaster emergency managers, river basin managers, environment/water agencies, ministries of agriculture/water/environment, international development/aid agencies.
Format	GloFAS map viewer online platform
Data source	Immediate processing of information from the SENTINEL-1 satellite through water and flood mapping algorithms to provide flood and water extent maps in a fully automated system.
Methodology/technology	Modelling using algorithms, remote sensing: Integrated real-time precipitation information from multiple satellites into a quasi-global hydrological runoff and routing model
Temporal scale	Near-real tine
Update frequency	N/A
Spatial resolution	10 m
Geographical coverage	Global
Limitations and caveats	The tool indicates where the quality of flood mapping may be reduced due to environmental conditions (e.g. dry soil influencing flood dynamics) or degraded data input quality.

Source: (Copernicus Emergency Management Service, n.d.[119]).

Table A A.2. Global Flood Monitoring System*

Developed by	University of Maryland (funded by NASA)
Type(s) of physical water risk covered	Water excess (flood) Blue water
Dimensions of risk included	Hazard – flood detection and intensity (flood levels) mapped
Purpose	Anticipation: short-term (4-5 day) flood forecasting Real-time monitoring
Intended user	Disaster emergency managers, river basin managers, environment/water agencies, ministries of agriculture/water/environment, insurers, international development/aid agencies
Format	Web-based map
Data source	Integrated real-time precipitation information from multiple satellites into a quasi-global hydrological runoff and

	routing model, international organisations
Methodology/technology	Modelling using algorithms and remote sensing
Temporal scale	Short-term (4-5 days)
Update frequency	Real time
Spatial resolution	Inundation, streamflow and surface water storage are calculated with a 1km resolution
Geographical coverage	Quasi-global (50°N - 50°S)
Limitations and caveats	The tool is in experimental phase.

Source: (University of Maryland, n.d.[120]).

Water shortage

Table A A.3. Global Drought Observatory (GDO)

Developed by	Copernicus Emergency Management System/ Joint Research Centre
Type(s) of physical water risk covered	Water shortage (drought) Blue and Green water
Dimensions of risk included	Forecast and monitor drought hazard Risk of impact assessed by sector, based on hazard, exposure and vulnerability.
Purpose	Anticipation (forecasting) and monitoring
Intended user	Disaster emergency managers, river basin/irrigation managers, environment/water agencies, ministries of agriculture/water/environment, international development/aid agencies, insurers, extension officers…
Format	Interactive, publicly available, web-based map and analytical reports
Data source	Precipitation measurements, satellite measurements, modelled soil moisture content
Methodology/technology	The Combined Drought Indicator (CDI) for agricultural/ecosystem drought is calculated based on three indicators: Precipitation Anomalies (SPI), Soil Moisture Anomalies and Fraction of Absorbed Photosynthetically Active Radiation (fAPAR) A Risk of Drought Impact for Agriculture (RDrI-Agri) index is calculated, showing the probability of having drought impacts, particularly for vegetation, combining hazard (combination of precipitation anomaly (SPI), anomaly of photosynthetic activity (fAPAR) and soil moisture anomalies) exposure (of population, livelihoods and assets) and vulnerability.
Temporal scale	Monitoring: near real time Forecasting: one, three and six months
Update frequency	Every 10 days
Spatial resolution	1 km
Geographical coverage	Global
Limitations and caveats	N/A

Source: (JRC, n.d.[121]), (United Nations, n.d.[122]), (Vogt, 2019[123]).

Table A A.4. European Drought Observatory (EDO)

Developed by	Copernicus Emergency Management System/ Joint Research Centre
Type(s) of physical water risk covered	Water shortage (drought) Blue (e.g. reservoir levels) and green water (e.g. soil moisture)
Dimensions of risk included	Short-term forecasting and monitoring of drought hazard Risk of impact assessed by sector, based on hazard, exposure and vulnerability.
Purpose	Near-real time monitoring and early warning of drought Forecasting of unusually dry (and wet) conditions
Intended user	Disaster emergency managers, river basin/irrigation managers, environment/water agencies, ministries of agriculture/water/environment, insurers, extension officers
Format	Interactive, publicly available, web-based map and analytical reports
Data source	Precipitation measurements, satellite measurements, modelled soil moisture content
Methodology/technology	The EDO provides the following indicators: Standardized Precipitation Index (SPI), Standardized Snowpack Index (SSPI), Soil Moisture Anomaly (SMA), Anomaly of Vegetation Condition (FAPAR

	Anomaly), Low-Flow Index (LFI), Heat and Cold Wave Index (HCWI), Combined Drought Indicator (CDI). The Combined Drought Indicator is calculated integrating precipitation (standardized precipitation index, SPI), soil moisture (soil moisture anomaly, SMA), vegetation health (fraction of the absorbed photosynthetically active radiation, FAPAR) The CDI interprets drought as a cascade process: a precipitation shortage (WATCH stage) may develop into a soil water deficit (WARNING stage), leading to stress for vegetation (ALERT stage).
Temporal scale	Monitoring: near real time Forecasting: one, three and six months
Update frequency	Every 10 days
Spatial resolution	5 km
Geographical coverage	Europe and part of North Africa
Limitations and caveats	N/A

Source: (Cammalleri et al., 2021[124]), (Copernicus, n.d.[125]) (EEA, n.d.[126]) (JRC, n.d.[121]).

Table A A.5. Near-real Time Meteorological Drought Monitoring and Early Warning System for Croplands in Asia

Developed by	The University of Tokyo's Institute of Industrial Science
Type(s) of physical water risk covered	Water shortage (drought) Blue and green water (evapotranspiration)
Dimensions of risk included	Drought hazard and impact on croplands
Purpose	Near-real time monitoring and early warning of drought Forecasting of unusually dry (and wet) conditions
Intended user	Agriculture Ministries in the Asia Pacific Region Ministries of Environment/Water, disaster emergency managers, river basin/irrigation managers, environment/water agencies, extension officers, insurers, international development and aid agencies
Format	Interactive web-based map and drought warning provided to public authorities
Data source	Remote sensing: satellite-based measurement of temperature, rainfall and vegetation
Methodology/technology	The Keeth–Byram Drought Index calculated from satellite-based rainfall, temperature and vegetation phenology data
Temporal scale	Near real time monitoring and short-term early warning
Update frequency	Daily
Spatial resolution	N/A
Geographical coverage	Asia Pacific
Limitations and caveats	N/A

Source: (Institute of Industrial Science, n.d.[127]), (Takeuchi et al., 2015[128]).

Table A A.6. South Asia Drought Monitoring System

Developed by	IWMI
Type(s) of physical water risk covered	Water shortage (drought) Includes blue and green water (soil moisture)
Dimensions of risk included	Hazard – drought severity is monitored, including for agricultural drought.
Purpose	Monitoring and anticipation, through early warning
Intended user	Public authorities
Format	Interactive web-based tool, with map
Data source	Integrates remote sensing (moderate resolution imaging spectroradiometer (MODIS) and tropical rainfall measuring mission (TRMM), ESA Soil Moisture (ASCAT) Products) and ground truth data (vegetation indices, rainfall data, soil information, hydrological data)
Methodology/technology	Modelling and remote sensing Drought severity is calculated based on the soil moisture index (SMI), which is derived from a hydrological model considering observed meteorological data, morphological variables and ecological processes. The SMI is classified into five drought severity levels adopted from the US Drought Monitor scaling.

Temporal scale	Short term (near real time monitoring)
Update frequency	Daily (latency of five days)
Spatial resolution	High (0.25°), regional and local levels
Geographical coverage	Afghanistan, Bangladesh, Bhutan, India, Nepal, Pakistan and Sri Lanka
Limitations and caveats	N/A
Additional notes	IWMI received the Geospatial World Excellence Award for its innovative work using remote sensing technology to help nations monitor and mitigate the impacts of drought.

Source: (Saha et al., 2021[129]).

Table A A.7. US Drought Monitor

Developed by	National Drought Mitigation Center at the University of Nebraska-Lincoln, the National Oceanic and Atmospheric Administration and the U.S. Department of Agriculture
Type(s) of physical water risk covered	Water shortage (drought) Blue and green water (e.g. soil moisture)
Dimensions of risk included	Drought hazard and impact
Purpose	Monitoring
Intended user	Ministry of Agriculture: The United States Department of Agriculture and its agencies use it to trigger drought warning, disaster declarations and determine farmers' eligibility to low interest loans and other support programmes. Local decision makers for drought response measures, river basin and irrigation managers, farmers, extension officers, insurers
Format	Interactive web-based format with maps
Data source	Observed meteorological and hydrological data, satellite data and expert judgement
Methodology/technology	Drought indices are calculated (e.g. Palmer Drought Index, Standardized Precipitation Index) and combined with expert judgement, a map indicating drought impacted areas is drawn. Drought-impacted areas are classified in a five-category system (from "abnormally dry", i.e. 1-to-3-year drought events, to exceptionally dry, i.e. 1 to 50 year drought events), defining the severity, spatial extent and impacts of the drought.
Temporal scale	One week
Update frequency	Weekly
Spatial resolution	N/A
Geographical coverage	United States
Limitations and caveats	N/A
Additional notes	Together with the Canadian Drought Monitor and the Mexico Drought Monitor, it forms the North American Drought Monitor (NADM). The NADM is a co-operative effort between drought experts of the three countries. Maps from the North American continent are published monthly, using the same five category classification system.

Source: (NOAA, n.d.[130]), (Government of Canada, n.d.[131]), (National Drought Mitigation Center, 2025[132]).

Table A A.8. Canadian Drought Monitor

Developed by	Agriculture and Agri-Food Canada
Type(s) of physical water risk covered	Water shortage (drought) Blue and green water (e.g. soil moisture)
Dimensions of risk included	Drought hazard and impact
Purpose	Monitoring
Intended user	Ministry of Agriculture, Water, Environment (The Government of Canada, including Agriculture and Agri-Food Canada uses this tool to monitor drought), environment/ water agencies, river basin/irrigation managers, disaster emergency managers, farmers, extension officers, insurers
Format	Interactive web-based format with maps and animations
Data source	Observed meteorological and hydrological data, satellite data and expert judgement
Methodology/technology	Drought indices are calculated and combined with expert judgement, a map indicating drought impacted areas is drawn. Drought-impacted areas are classified in a five-category system, defining the severity, spatial extent and impacts of the drought.
Temporal scale	Current drought conditions
Update frequency	Monthly

Spatial resolution	N/A
Geographical coverage	Canada
Limitations and caveats	N/A
Additional notes	Together with the US Drought Monitor (see above) and the Mexico Drought Monitor, it forms the North American Drought Monitor (NADM). The NADM is a co-operative effort between drought experts of the three countries. Maps from the North American continent are published monthly, using the same five category classification system. The CDM also underpins the Canadian Drought Outlook, a monthly national-scale forecasts of drought conditions.

Source: (NOAA, n.d.[130]), (Government of Canada, n.d.[131]).

Water quality

Table A A.9. GEO AquaWatch

Developed by	Group on Earth Observations (GEO) initiative.
Type(s) of physical water risk covered	Water quality (chlorophyll, algal blooms, coloured dissolved organic matter turbidity, etc.) Blue water
Dimensions of risk included	Hazard
Purpose	Satellite-derived water quality maps.
Intended user	Water resource and environmental managers, policymakers, private sector, international organisations, researchers
Format	Suite of services and resources: Satellite maps, timeseries, algorithm repositories
Data source	NASA, NOAA, Copernicus Global Land Service
Methodology/technology	Remote sensing and in-situ measurements
Temporal scale	Seasonal to monthly
Update frequency	N/A
Spatial resolution	From coarse to high resolution regional products.
Geographical coverage	Global
Limitations and caveats	Cloud cover interference
Additional notes	Integrates multiple satellites products, a coordination and service initiative

Source: (GEO Aqua Watch, 2024[133]).

Table A A.10. Digital-WATER.city ALERT system *

Developed by	Digital-WATER.city Project (EU Horizon 2020 consortium).
Type(s) of physical water risk covered	Water quality: Microbial contamination (E. coli) Blue water
Dimensions of risk included	Hazard
Purpose	Provide early warning and real-time risk assessment for wastewater reuse in agriculture.
Intended user	Municipalities, wastewater utilities, public health and environmental regulators.
Format	Integrated early warning systems: In-situ sensors & machine learning dashboard.
Data source	Microbial sensors at Milan Peschiera Borromeo Wastewater Treatment Plant
Methodology/technology	Combination of in-situ sensors and machine learning algorithms predicting E. coli concentration in real time.
Temporal scale	High frequency / real-time.
Update frequency	Continuous.
Spatial resolution	Plant level monitoring (point location at WWPT outflow).
Geographical coverage	Peschiera Borromeo WWTP, Milan, Italy.
Limitations and caveats	Pilot stage, scalability and cost considerations.
Additional notes	Supports water reuse risk management and reduces monitoring delays of culture-based E. coli tests.

Source: (DigitalWater.City, 2022[79]).

Irrigation advisory tools

Table A A.11. IRRINET / IRRIFRAME

Developed by	Emilia Romagna Regional Authorities
Type(s) of physical water risk covered	Water shortage
Dimensions of risk included	Hazard, vulnerability and exposure
Purpose	Irrigation scheduling based on crop water needs Optimise irrigation to reduce water use and energy consumption
Intended user	Farmers (12 000+ registered farms)
Format	Web platform, SMS, mobile app
Data source	Regional Weather Service, Geological Service, CER
Methodology/technology	Mathematical model integrating meteorological, soil, groundwater, and crop data to calculate water balance for individual crops that allows to refine water demand.
Temporal scale	Daily
Update frequency	Daily
Spatial resolution	Plot-level (integrated with Google Maps)
Geographical coverage	Emilia Romagna, Italy.
Limitations and caveats	Requires local calibration; limited by meteorological and soil map availability.
Additional notes	Saves approximately 90 million m^3 of water annually; 20% water demand reduction; funded by public/EU funds.

Source: (IRRIFRAME, n.d.[134]), https://www.irriframe.it/Irriframe.

Table A A.12. Agroclimatic Information System for Irrigation (*Sistema de Información Agroclimática para el Regadío*, SiAR)

Developed by	Ministry of Agriculture, Fisheries and Food, Spain
Type(s) of physical water risk covered	Water quantity (rainfall, soil moisture)
Dimensions of risk included	Hazard, exposure and vulnerability
Purpose	Provides daily information on crop irrigation needs.
Potential users	Farmers, Water Authority
Format	Website (www.siar.es), mobile application and web GIS viewer (www.espaciosiar.es)
Data source	Meteorological data from > 500 weather stations; remote sensing data from Sentinel and Landsat-8 satellites.
Methodology/technology	Calculates reference evapotranspiration and effective precipitation based on data collected by more than 500 weather stations located in irrigated agricultural areas, along with information on crop type, irrigation method and soil characteristics. Furthermore, it enables monitoring and tracking of crop development using remote sensing. The Espacio SiAR tool combines data from field weather stations with satellite imagery to map irrigated areas and estimate their annual and monthly water requirements based on a daily water balance across the entire country. The result is the generation of 10 x 10 m raster layers related to water use in irrigated crops, which can be accessed through its GIS web portal (www.espaciosiar.es).
Temporal scale	Short term
Update frequency	Real time. The stations record temperature and humidity values every 10 minutes and radiation, precipitation, and wind speed and direction every 10 seconds, generating average hourly and daily records. Data is provided to users in the form of daily, weekly and monthly logs; average hourly logs are also provided.
Spatial resolution	10 x 10m
Geographical coverage	Spain
Limitations and caveats	N/A
Additional notes	Irrigator Advisory Offices have been set up in each autonomous community, managed by the respective regional administrations, which contribute to the dissemination of data – including data from the SiAR – providing the public with information on crop water requirements, irrigation programmes and other data of agronomic interest.

Source: (MAPA, n.d.[135]).

Water use and consumption monitoring

Table A A.13. OpenET

Developed by	Public-private collaboration led by NASA, Environmental Defense Fund, Desert Research Institute, Google Earth Engine, HabitatSeven and several universities, with input from more than 100 stakeholders.
Type(s) of physical water risk covered	Water shortage (green water – evapotranspiration)
Dimensions of risk included	Exposure, vulnerability.
Purpose	Monitor crop water consumption by providing satellite-based information on evapotranspiration (ET).
Intended user	Farmers, water managers
Format	Online data explorer with maps of ET and the FARMS tool (Farm and Ranch Management Support), a user-friendly interface that can generate customisable reports.
Data source	Relies on publicly available satellite, meteorological, land use and soil data as inputs to the ET models: Landsat is the primary satellite dataset; also uses weather station measurements to produce spatially distributed or gridded weather datasets; ancillary datasets come from the U.S. Department of Agriculture (USDA) (e.g. crop type, soils), the U.S. Geological Survey (USGS) and state agencies.
Methodology/technology	Uses open-source models and Google Earth Engine: OpenET uses a multi-model ensemble approach, combining results from several ET models, using inputs with satellite imagery, weather data and land surface information.
Temporal scale	Short-term
Update frequency	Daily, monthly and yearly intervals
Spatial resolution	Finest resolution can be a quarter of an acre
Geographical coverage	Western United States
Limitations and caveats	Varying accuracy across different models, regions and land cover types, e.g. OpenET models are systematically biased high in evergreen and mixed forests and have lower accuracy in shrublands and grasslands. Results are also affected by quality and availability of satellite data, e.g. small regions of missing satellite data. The OpenET website discloses the tool's limitations under "Accuracy & Known Issues".

Source: (NASA, 2021[136]); (OpenET, 2026[137]).

Table A A.14. WaPOR

Developed by	FAO
Type(s) of physical water risk covered	Water shortage; green water (evapotranspiration)
Dimensions of risk included	Hazard, exposure, vulnerability
Purpose	Monitoring of agricultural water productivity at different scales; other applications include monitoring crop water consumption, stressor impact on agriculture (e.g. drought); water accounting, monitoring irrigation performance…
Intended user	Extension services, policymakers, water and irrigation managers,
Format	Publicly accessible near real-time database using satellite data
Data source	Data derived from open-access remote-sensing data and open-source algorithms. CHIRPS Precipitation, Copernicus DEM, (Ag)ERA5 Meteorological Data, GEOS-5 Meteorological Data, IMERG Precipitation, Landsat satellites, MODIS sensors, MSG satellites, Sentinel-2 satellites, VIIRS sensors and WorldCover Land Cover.
Methodology/technology	Satellite/remote sensing data.
Temporal scale	Near real time information with a temporal coverage from 2009 to the present.
Update frequency	WaPOR data is made available at different frequencies, depending on the data layer and the resolution in question: annual, seasonal, monthly, every 10 days, daily. For example, Actual Evapotranspiration and Interception is made available annually, monthly and every 10 days at all resolutions; Land Cover Classification is made available every 10 days at 20m resolution and annually at 100m and 200m. Gross Biomass Water Productivity is made available seasonally.
Spatial resolution	3 different levels corresponding to different resolutions at which different applications for the data are possible: Level 1 (global) = 300m resolution; Level 2 (continental and national) = 100m; Level 3 (irrigation scheme and sub-basin) = 20m
Geographical coverage	The global level (300m resolution) covers the entire globe; the continental and national / river basin level (100 m ground resolution) covers Northern and sub-Saharan Africa and the Near East (roughly a square of -30W, -40S,

	65E, 40N); the irrigation scheme and sub-basin (20 m ground resolution) is available in 36 areas as of July 2024 (latest information available on website).
Limitations and caveats	Known limitations of remotely sensed data including coarse spatial resolution for some variables; cloud interference; land cover noise; inaccurate estimation of transpiration (T) and evaporation (E) depending on land use classes.

Source: (FAO, 2026[138]).

Table A A.15. EEFLUX

Developed by	Consortium of researchers and Google Inc.
Type(s) of physical water risk covered	Water shortage
Dimensions of risk included	Exposure, vulnerability; green water (evapotranspiration)
Purpose	Produce field-scale maps of water consumption to track agricultural water use.
Intended user	Water managers
Format	Mobile app
Data source	Landsat satellite images; North American Land Data Assimilation System hourly gridded weather data collection for energy balance calibration and time integration of ET; Reference ET is calculated using the ASCE (2005) Penman-Monteith and GridMET weather data sets; Statsgo soil data base of the USDA provides soil type information.
Methodology/technology	Surface energy balance model “METRIC” (Mapping ET at high Resolution with Internalized Calibration) drawing on the Google Earth Engine which gives access to Landsat image collection and in conjunction with access to a suite of gridded weather system data.
Temporal scale	Short term. In addition, given that Landsat satellites have collected thermal data since 1984, water consumption under existing conservation practices can be compared with those occurring in the past 40 years.
Update frequency	Near real-time.
Spatial resolution	Field-scale / 30m.
Geographical coverage	Continental United States.
Limitations and caveats	Studies have found large ET overpredictions and errors of up to 181% (Kadam et al., 2021[88]).

Source: (Allen et al., 2019[139]).

Digital twins

Table A A.16. Digital Twin of the Limpopo River Basin

Developed by	CGIAR/IWMI
Type(s) of physical water risk covered	Water shortage, water excess, water quality
Dimensions of risk included	Hazard
Purpose	The digital twin houses several tools, including: a drought monitor; an irrigation mapping tool; river discharge & environmental determination tool; reservoir volume monitoring; reservoir forecasting; water quality monitoring.
Intended user	Limpopo Watercourse Commission (LIMCOM), established between the Republics of Botswana, Mozambique, South Africa and Zimbabwe to support transboundary water management.
Format	The Digital Twin Portal is the central hub for accessing and interacting with the digital twin model. An interactive tool for visualising datasets through graphics and maps enables exploration of spatial and temporal trends in water resources and an AI-virtual assistant allows users to interact with datasets through a natural language chat interface.
Data source	305 discharge stations provided by South Africa’s Department of Water and Sanitation. 303 rainfall stations based on CHIRPS data and incorporates three types of forecasts, supported by a 20-year historical database.
Methodology/technology	The foundation of the digital twin is a SWAT hydrological model running in near real time, including a three-month seasonal forecast. River discharge & environmental flow estimates underpinned by PROBFLO, an environmental flow

	determination tool, Machine learning is used in the irrigation mapping and reservoir monitoring and forecasting tools. Water quality monitoring uses FISHTRAC, where sensors are attached to fish to gather real-time data on river health and water quality that triggers water pollution alerts.
Temporal scale	Short and medium term.
Update frequency	Near real time for some variables.
Spatial resolution	Varies; as fine as 10m for irrigation mapping.
Geographical coverage	Limpopo River Basin, Republics of Botswana, Mozambique, South Africa and Zimbabwe. A total of 1 408 channels covering 400 000 km² are available for seasonal forecasting.
Limitations and caveats	

Source: (CGIAR/IWMI, 2024[140]).

Crop monitoring and forecasting tools

Table A A.17. Canadian Crop Metrics application

Developed by	Agriculture and Agri-Food Canada Forecasts are jointly produced by Agriculture and Agri-Food Canada and Statistics Canada
Type(s) of physical water risk covered	Water quantity (rainfall, soil moisture)
Dimensions of risk included	Impact (yields)
Purpose	Early warning information on crop yield and production. The application allows users to examine in-season weather, satellite-based and risk data impacting crop yields in Canada alongside historical and forecasted crop yields.
Potential users	Producers, grain traders, transporters and government policymakers for market access and food security planning
Format	Web application: Interactive website with maps. The Canadian Crop Metrics application allows users to look at specific regions and generate reports, graphs and tables to compare current conditions to historical conditions for 14 different crop types.
Data source	Historical yield data from climate and satellite data as inputs. The ICCYF integrates climate, remote sensing derived vegetation indices, soil and crop information through a physical process-based soil water budget model and statistical algorithms.
Methodology/technology	Forecasted yield comes from the Canadian Crop Yield Forecaster, a regional crop yield forecasting tool which models yields of major crops in Canada from a statistical model trained on historical yield from Statistics Canada. The model integrates climate, remote sensing derived vegetation indices, soil and crop information through a physical process-based soil water budget model and statistical algorithms. Production numbers are arrived at by weighting the modelled crop yield forecast against Statistics Canada's estimates of the harvest area from the June or July survey whenever it is available. For regions where model-based estimates were not available because of insufficient input data to build and train the model, mean values of the previous five years of farm survey data are used.
Temporal scale	Medium-term: Seasonal
Update frequency	Weather data is updated regularly and yield estimates are updated monthly from July to October. Forecasts are made at the beginning of the months of July, August and September for all crops and an additional forecast is made for corn and soybeans (late season crops) at the beginning of October.
Spatial resolution	Census agricultural region (CAR). CARs are used by the Census of Agriculture to disseminate agricultural statistics.
Geographical coverage	Canada (CAR, province and national levels).
Limitations and caveats	Model performance is better from regions with a good coverage of climate stations and a high percentage of cropped area. The CAR is a relatively coarse unit that may contain several soil and climate zones, limiting the predictive power of the model; forecasts at sub-CAR levels is limited by a lack of yield data at finer scales.
Additional notes	The information from Canadian Crop Metrics feeds into the GEOGLAM Crop Monitor global forecasting tool.

Source: (Government of Canada, 2025[141]) (Chipanshi et al., 2015[142]).

Table A A.18. Agricultural Stress Index System (ASIS)

Developed by	FAO, in collaboration with the Joint Research Centre of the European Commission (JRC), the Flemish Institute for Technological Research (VITO) and International Institute for Geo-Information Science and Earth Observation (ITC) of the University of Twente, Netherlands
Type(s) of physical water risk covered	Water shortage (drought) Blue and green water
Dimensions of risk included	Drought hazard, exposure and impact: Indicate agricultural areas (cropland and grassland) under water stress
Purpose	Drought monitoring
Intended user	International organisations, Ministries of Agriculture, Ministry of Trade, insurers, disaster emergency managers, agri-food companies, international development and aid agencies
Format	Openly accessible platform with map
Data source	Historical data on cropping cycles, remote sensing data of vegetation and land surface temperature
Methodology/technology	The index is calculated based on remote sensing data of vegetation health, combined with information on agricultural cropping cycles (historical data), taking into account the duration and intensity of drought.
Temporal scale	10 days
Update frequency	3 times per month
Spatial resolution	1 km
Geographical coverage	Global
Limitations and caveats	N/A
Additional notes	Won the 2016 Geospatial World Excellence Award. In April 2024, ASIS was recognised as a Digital Public Good (DPG) by Digital Public Goods Alliance.

Source: (FAO, 2025[143]), (FAO, 2025[144]), (ITC, n.d.[145]).

Table A A.19. GEOGLAM Crop Monitor

Developed by	NASA Harvest
Type(s) of physical water risk covered	Water shortage (droughts), excess (floods) Blue and green water (rainfall, soil moisture)
Dimensions of risk included	Hazard, exposure, vulnerability; impact on crop yields, food security.
Purpose	Agricultural monitoring: Open and timely information on crop conditions in support of market transparency and early warning of production shortfalls.
Intended user	International organisations, Ministries of Agriculture, Ministry of Trade, national agencies responsible for food security policy and response programmes/ disaster emergency managers, insurers, agri-food companies, international development and aid agencies
Format	Online crop monitor exploring tools (interactive maps), synthesis maps, agrometeorological indicators, accompanied by monthly crop monitor bulletins and supplemental reports.
Data source	Earth observation satellite data (NOAA, CHIRPS, NASA MODIS…)
Methodology/technology	Partner organisations submit crop condition information using the common crop condition classification system using the web-based interface based on their own data sources and decision support systems. The web-based interface provides up to date key EO data products for agricultural monitoring along with crop condition plots of EO data, and contextual information on crop spatial extent (Crop Masks) and crop growth stages (Crop Calendars) at the sub-national level.
Temporal scale	Medium term, seasonal
Update frequency	Monthly
Spatial resolution	National and sub-national (regional) level information
Geographical coverage	>97% of the world's croplands
Limitations and caveats	N/A
Additional notes	N/A

Source: (Crop Monitor, 2026[146])

Hazard and risk maps

Water excess

Table A A.20. IWMI Flood Risk Mapping

Developed by	IWMI
Type(s) of physical water risk covered	Water excess (flood) Blue Water
Dimensions of risk included	Hazard, Exposure (changes in population, land use and shifting climatic patterns), Vulnerability (e.g. where people are vulnerable to floods) and Impact (Where crop losses can occur)
Purpose	Anticipation: estimate the extent and dynamics of flood inundation
Intended user	Ministries of Agriculture/Environment/Water, local and regional governments, disaster emergency managers, river basin managers, environment/ water agencies, insurers, farmers
Format	Web-based mapping tool and dataset
Data source	Satellites and airborne instruments (MODIS satellite data and data from optical sensors)
Methodology/technology	Maximum flood inundation extent is estimated using an estimation algorithm.
Temporal scale	8-day, monthly maximum inundation extent, seasonal (duration of inundation cycles)
Update frequency	N/A
Spatial resolution	500 m
Geographical coverage	South Asia, Southeast Asia and Nigeria.
Limitations and caveats	N/A

Source: (IWMI, 2025[147]), (IWMI, 2025[148]).

Water shortage

Table A A.21. Aqueduct Food

Developed by	World Resources Institute (WRI)
Type(s) of physical water risk covered	Water shortage (water stress; water depletion; drought risk; interannual variability, groundwater table decline, etc.) Blue water
Dimensions of risk included	Hazard and exposure
Purpose	Anticipation. Identifies current and future water risks to agriculture and food security. Aqueduct Food combines global data on water risks and agriculture to illustrate water-related threats to and opportunities for food security, and how these dynamics may develop over time. The tool allows users to see how changes in climate and demand for water could affect their food-producing areas
Intended user	Ministries of water/environment and agriculture, agri-food companies, international development organisations (e.g. development banks, international aid agencies)
Format	Web-based mapping tool
Data source	Diverse, including modelled data
Methodology/technology	The tool combines water data from WRI Aqueduct (e.g. drought risk)) with food data from the International Food Policy Research Institute (IFPRI) (e.g. crop production, market and trade data, data on hunger). Modelling approaches help show water risks for crops.
Temporal scale	Baseline (present day and past, dependent on the dataset, 2030 and 2050.
Update frequency	Unknown
Spatial resolution	10km^2
Geographical coverage	Global
Limitations and caveats	The datasets combined (WRI Aqueduct and IFPRI) were generated with different inputs and modeling approaches; Limitations of the datasets used as inputs; Different years from which baseline data is derived from, limited data availability; There may be more variation in the risk scores in each region, compared to what aggregated results show in the tool; Modelling uncertainties; No data on pastureland and livestock; The vulnerability of crops to water risks is not modelled; Food availability is estimated based on food demand only. Other influencing factors, e.g. price, are not modelled.

Source: (WRI, 2021[149]).

Table A A.22. European Drought Risk Atlas

Developed by	CIMA Research Foundation, Vrije Universiteit Amsterdam, the European Commission's Joint Research Centre
Type(s) of physical water risk covered	Water shortage (drought) Blue and green water (e.g. soil moisture, groundwater)
Dimensions of risk included	A systematic overview of current and future drought risk (considering hazard, vulnerability and exposure) as well as impact.
Purpose	Anticipation Mapping and understanding current drought risk and forecasting future drought risk under different levels of global warming (+1.5°C, +2°C, +3°C).
Intended user	The tool covers several sectors, including agriculture. Ministries of Agriculture/Environment/Water, Agro-food companies, international development/aid agencies, local/regional governments, river basin managers, extension officers
Format	Static publication (published in 2023)
Data source	For agriculture, crop yield data, combined with modelled data from the Regional Climate Models of the EURO-CORDEX initiative under the RCP 4.5 and 8.5 scenarios.
Methodology/technology	Impact-based drought assessment characterising how drought hazard, exposure and vulnerability interact and affect different but interconnected systems/sectors. It uses i) impact chains (sector/system specific conceptual models of drought risk built based on a European literature review and expert consultations visualising risk drivers and their interactions determining impact) and ii) the quantitative data-driven assessment of sectoral drought risk based on machine learning models and the available data (both historical climate data and data from future-looking climate and hydrological models). Socio-economic evolution and technological development are not considered. Based on the information from impact chains, vulnerability factors and exposure are assessed at European level. Subsequently, European regions are clustered based on their vulnerability to drought risks. Machine learning models are then trained to learn the relationship between impact and drought hazard per vulnerability cluster, based on which risk is estimated (i.e. the likelihood of experiencing certain impacts) and summarised into the average annual loss risk metric (i.e. annual drought-induced impact). This metric is represented as relative production loss of region-specific production and combined with exposure data, estimated average annual and probable maximum production losses can be calculated.
Temporal scale	Current and future drought risk (time is not specified, only the level of farming)
Update frequency	N/A
Spatial resolution	NUTS-2 regions
Geographical coverage	European Union
Limitations and caveats	Socio-economic developments are not covered which can impact the reliability of future projections. Drought impact data can be sparse and limited, enhancing uncertainty.

Source: (JRC, 2023[90]).

Table A A.23. World Drought Atlas

Developed by	The European Commission's Joint Research Centre, UNCCD, CIMA Research Foundation, United Nations University and Vrije Universiteit Amsterdam
Type(s) of physical water risk covered	Water shortage (drought) Blue and green water (e.g. soil moisture)
Dimensions of risk included	A systematic overview of current and future drought risk (considering hazard, vulnerability and exposure) and impact. Cascading impacts and cross-sectoral risks are considered as well.
Purpose	Mapping and understanding current drought risk and forecasting future drought risk under different levels of global warming (+2°C, +3°C, +4°C) and scenarios of socio-economic development.
Intended user	Ministries of Agriculture/Environment/Water, Agro-food companies, international development/aid agencies, local/regional governments, river basin managers, extension officers The tool covers several sectors, including agriculture.
Format	Static publication (published in 2024), including maps and graphs to conceptualise drought risk
Data source	data on past droughts (e.g. Standardized Precipitation-Evapotranspiration Index during past droughts, modelled data (e.g. data from climate scenarios and socio-economic pathways, including population trends).
Methodology/technology	Impact-based drought risk assessment: impact chains, i.e. conceptual models outlining the main drought drivers for specific sectors and their impacts, highlighting interconnections and dependencies that need to be considered

	to reduce drought risk.
Temporal scale	Varies (current drought risk, past impact and long-term risks depicted)
Update frequency	N/A
Spatial resolution	N/A
Geographical coverage	Global
Limitations and caveats	N/A
Additional notes	The atlas aims to provide policymakers with an understanding of drought risk, including the ways in which it affects critical sectors, providing examples through case studies of past events and future-looking projections based on modelled socio-economic and climatic data. The atlas is not comprehensive but aims to provide policymakers with examples of actions to take to help reduce and manage drought risk proactively.

Source: (JRC and UNCDD, 2024[150]).

Table A A.24. United States Drought Risk Atlas

Developed by	National Drought Mitigation Center together with national agencies
Type(s) of physical water risk covered	Water shortage (drought) Blue water
Dimensions of risk included	Drought hazard (drought frequency, intensity, duration and magnitude)
Purpose	Anticipation/foresight (based on historical data). Explore historic trends in various drought indicators from thousands of weather stations.
Intended user	River basin and irrigation managers, environment/water agencies, local/regional government, ministries of agriculture/environment, insurers, extension officers
Format	Interactive web-based platform, with maps, graphs and tables. It provides pre-computed drought indices for more than 4 000 locations across the United States, including e-generated heat maps, time series, tabular analyses and weekly Standardized Precipitation Indices, Standardized Precipitation and Evapotranspiration Indices, Palmer Drought Severity Indices, self-calibrated Palmer Drought Severity Indices, Standardized Streamflow Indices.
Data source	Historical data from weather stations that have at least 40 years of record.
Methodology/technology	Regional frequency analysis conducted on historical data, using L-moments which allows to combine observation series from different stations determining a common distribution over a larger area, ensuring that outliers from the historical record do not distort final results.
Temporal scale	Historical data spanning at least 40 years
Update frequency	Varies, weekly for some indices
Spatial resolution	Data from specific weather stations
Geographical coverage	United States
Limitations and caveats	N/A
Additional notes	N/A

Source: (National Drought Mitigation Center, 2025[151]) (Svoboda et al., 2015[152]).

Table A A.25. Latin American and Caribbean Drought Atlas

Developed by	CAZALAC (Water Centre for Arid Zones), UNESCO, US Army Corps of Engineers and JRC
Type(s) of physical water risk covered	Water shortage (drought) Blue water
Dimensions of risk included	Drought hazard (frequency)
Purpose	Anticipation
Intended user	River basin and irrigation managers, environment/water agencies, local/regional government, ministries of agriculture/environment, insurers, extension officers
Format	Web-based platform, with maps, graphs and tables. Maps of drought frequency (with return periods associated to drought intensities), minimum expected rainfall amount associated to certain return periods, maximum expected rainfall associated to certain return periods.
Data source	Historical data based on weather stations
Methodology/technology	Regional frequency analysis using L-moments (see above for the United States Drought Risk Atlas) to determine the common distribution of observation series over larger areas

Temporal scale	N/A
Update frequency	N/A
Spatial resolution	Country-level maps, with data extrapolated from weather stations
Geographical coverage	Latin America and the Caribbean
Limitations and caveats	N/A
Additional notes	N/A

Source: (Núñez Cobo and Verbist, 2018[153]) (Núñez J. and Verbist, n.d.[154]).

Water quality and risk of undermined freshwater ecosystem resilience

Table A A.26. WWF Water Risk Filter

Developed by	WWF
Type(s) of physical water risk covered	Water quality, risk of undermined freshwater ecosystem resilience (Water excess and water shortage are mapped too, but this table focuses on water quality and the risk of undermined freshwater ecosystem resilience. Some of the filters the tool uses for measuring the former too are covered under tools above)
Dimensions of risk included	Hazard and exposure (population density and GDP) Hazards mapped: • Water quality: nitrate-nitrite concentration, periphyton growth potential, toxicity stress, mismanaged plastic waste, risk of pesticide pollution, total dissolved solids and surface water quality • Ecosystem service status: Catchment ecosystem services degradation level, violation of environmental flows, wetland degradation, invasive species, river extent change, fragmentation status of rivers
Purpose	Anticipation
Intended user	Ministries of agriculture/environment, environment/water agencies, local/regional government and the private sector
Format	Web-based maps
Data source	Historical observed data (within a range of mostly from the early 2000s to 2022) and modelled data
Methodology/technology	• Nitrate-nitrite concentration: Annual average nitrogen in rivers, based on observed monitoring data and a machine learning prediction model, predicting values between 2006-2010. • Periphyton Growth Potential: Global modelling of dissolved and total nitrogen (N) and phosphorus (P) concentrations and ratios that can limit periphyton proliferation during the growing season. • Toxicity stress: pressure of ecological impact using predicted (modelled) environmental concentrations of 1 785 chemicals • Mismanaged plastic waste; risk of pesticide pollution: modelled data • Total Dissolved Solids: Salinity between 2010-2019 based on the results of the dynamical surface water quality model • Surface Water Quality Index BOD: Shows biological oxygen demand (BOD) based on a dynamical surface water quality model of 2010-2019. • Surface Water Quality Index Electrical Conductivity: A proxy indicator for salinity based on the Electrical Conductivity (EC) parameter of the World Bank's Environmental Water Quality Index, mapped based on machine learning models using remote sensing and monitoring station data from 2000-2010. • Global Forest Change: Tress cover loss proxying catchment ecosystem services degradation, using Landsat data from 2000-2022. • Violation of Environmental Flows: modelling using discharge data and environmental flow envelopes • Wetland degradation: Maps of wetland loss between 1700-2020 based on drainage records, wetland conversion records, maps of land-use and land-use change, and simulated wetland extent. • Invasive species: Observed data from the Invasive Species Specialist Group's Global Invasive Species Database • River extent change: based on Landsat imagery • Fragmented status of rivers: An integrated connectivity status index (CSI) calculated using a geometric network of the global river system and its hypergeometric properties.

Temporal scale	N/A
Update frequency	N/A
Spatial resolution	N/A
Geographical coverage	Global
Limitations and caveats	N/A

Source: (WWF, 2025[155]).

Hydrological infrastructure maps

Table A A.27. Agricultural Drainage Database ("BD Drainage")

Developed by	L'Office français de la biodiversité (OFB), le Bureau de Recherche Géologique et Minière (BRGM), l'Association de recherche sur le Ruissellement, l'Érosion et l'Aménagement du Sol (AREAS). Original pilot involved Seine Normandy Water Agency, Eure and Seine-Maritime Departmental Councils.
Type(s) of physical water risk covered	Water excess; water quality.
Dimensions of risk included	Exposure, vulnerability.
Purpose	Provides information on the path taken by water from agricultural plots that have been drained, through to its discharge into the natural environment, watercourses and groundwater. The enrichment of the drainage database with related services makes it a useful decision-making tool for water and risk management and resource protection.
Intended user	Local authorities; engineering design firms.
Format	Interactive mapping tool
Data source	Survey of sub-national authorities and chambers of agriculture who hold data on local drainage infrastructure.
Methodology/technology	Publicly available database contains map layers, services showing upstream and downstream paths and more detailed technical data sheets.
Temporal scale	Long-term
Update frequency	n/a
Spatial resolution	Plot level
Geographical coverage	Initially applied in the Normandy region of France, the database is being extended nationally.
Limitations and caveats	
Additional notes	

Source: (BRGM, 2019[156]).

Impact assessment tools

Water shortage

Table A A.28. Australian Agricultural Drought Indicators *

Developed by	Australian Bureau of Agricultural and Resource Economics (ABARES) in partnership with the Commonwealth Scientific and Industrial Research Organisation (CSIRO), with input from the Queensland Department of Environment and Science (DES)
Type(s) of physical water risk covered	Water shortage (drought) Blue water
Dimensions of risk included	Hazard, vulnerability, exposure and impact.
Purpose	Drought anticipation and monitoring: estimate anticipated agricultural and economic impacts for Australian broadacre agriculture (non-irrigated extensive livestock and cropping)
Intended user	Staff of the Australian Government
Format	A user interface is in preparation.
Data source	Observed and forecasted weather data, as well as data and assumptions on the types of soil, pasture and

	agricultural activity, including farm survey data. For observed data, the model uses data from the past 33 years on a rolling basis.
Methodology/technology	Outcome/impact-based drought forecasting using biophysical and economic modelling. The bio-physical and economic modelling system translates climate observations and forecasts to outcome-based indicators of crop yields, pasture growth and farm business profits. The models include machine learning. The modelling system builds on and integrates input from other existing Australian models, including pasture growth via the AussieGRASS system and the GrassGro model, winter and summer crop yields via APSIM and farm business profits via the *farmpredict* model (see above).
Temporal scale	Annual (data is shown for the Australian financial year, running from July to June)
Update frequency	Monthly, using observed data from the past months and forecasted for the rest of the year
Spatial resolution	5 km Aggregates at national, state or local government areas can be produced as well, with weightings to consider the relative amount of agricultural activity.
Geographical coverage	Australia, for defined agricultural zones (areas with no agricultural activity, e.g. forestry, protected areas, are excluded)
Limitations and caveats	The tool is in an experimental/prototype phase.
Additional notes	N/A

Source: (ABARES, 2024[157]) (Hughes et al., 2025[93]).

Table A A.29. Drought Impact Assessment Platform (d-iap)

Developed by	FAO
Type(s) of physical water risk covered	Water shortage
Dimensions of risk included	Hazard, exposure, vulnerability
Purpose	Evaluate drought impacts on crop and water productivity as well as irrigation water requirements under present and future climate scenarios.
Intended user	Farmer advisory services, water authorities and managers, policymakers, insurers
Format	Web-based tool
Data source	Global Land Cover - SHARE (GLC-SHARE) database from FAO; climate data from European Centre for Medium-Range Weather Forecasts (ECMWF); projected climate data for the future scenarios from the database of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP); soil data from Harmonized World Soil Database version 2.0; among others.
Methodology/technology	Integrates diverse methodologies and tools, including the AquaCrop crop simulation models.
Temporal scale	Present: 1960-2022 (63 years); Future: 2040-2059 (Mid-century); 2080-2099 (End-century).
Update frequency	n/a
Spatial resolution	9km grid square (0.1°x 0.1°)
Geographical coverage	Global
Limitations and caveats	Does not yet take into account: sub-national cropping patterns; crop cycle or varieties; rooting depth; groundwater, soil and water salinity and other stressors affecting outcomes.
Additional notes	Covers 16 crops; rainfed and irrigated systems;

Source: (FAO, 2026[158]).

Table A A.30. ABARES farmpredict

Developed by	Australian Bureau of Agricultural and Resource Economics (ABARES)
Type(s) of physical water risk covered	Water shortage (drought) Blue and green water
Dimensions of risk included	Hazard, vulnerability and exposure to weather related risks, particularly drought
Purpose	Anticipate physical and financial outcomes for Australian farms based on weather and climatic conditions and commodity prices. Potential modelled outcomes include: farm financial performance (e.g. farm business profit, farm cash income, rate-of-return), production and revenue (of various crop and livestock types), input use and cost (e.g. fertiliser, fuel) and change in stock. The model is used for forecasting, drought monitoring and climate scenario modelling.

Intended user	ABARES
Format	Model (not publicly accessible)
Data source	Climate and weather data (rainfall, soil moisture, temperature, frost, heat extremes); Price data (input and output prices), and farm-specific information (e.g. location, size, livestock, grain stock, machinery, etc.) based on data from the Australian Agricultural and Grazing Industry Survey (AAGIS).
Methodology/technology	A non-parametric machine-learning micro-simulation model using a gradient boosted regression tree algorithm.
Temporal scale	N/A
Update frequency	N/A
Spatial resolution	Farm level
Geographical coverage	Australia (national coverage)
Limitations and caveats	N/A
Additional notes	N/A

Source: (ABARES, 2025[159]) (Hughes et al., 2022[160]).

Water resource assessment tools

Table A A.31. California Water Watch

Developed by	California Department of Water Resources
Type(s) of physical water risk covered	Water shortage Blue water
Dimensions of risk included	Hazard
Purpose	Water supply monitoring and forecasting Monitor precipitation, temperatures, groundwater, reservoir and snowpack levels, streamflow, soil moisture and vegetation conditions. Provide short-term forecasts on these variables for river basins to make real-time decisions on water rights allocations.
Intended user	Water management agencies
Format	Freely accessible online portal with an interactive interface, providing maps and graphs
Data source	Observed, forecasted and remotely sensed water and weather data, as well as modelled information (e.g. water supply forecasts for river basins)
Methodology/technology	Remote sensing and GIS mapping, hydrological modelling and weather forecasting
Temporal scale	Monitoring information: daily Forecasts: 6-10-day, 30-day and 90-day outlook
Update frequency	Most information is updated daily
Spatial resolution	N/A
Geographical coverage	The State of California, United States
Limitations and caveats	N/A

Source: (California Water Watch, n.d.[161]).

Table A A.32. Canada1Water

Developed by	Natural Resources Canada (Geological Survey of Canada) and Aquanty Inc. with additional contributions from Agriculture and Agri-Food Canada
Type(s) of physical water risk covered	Water quantity (blue and green water resources); Destabilised hydrological cycle
Dimensions of risk included	Hazard
Purpose	Provide historical and forward-looking projections to the middle and end of the 21st century for: Water resources (Groundwater and surface water levels, flows and trends); Land surface (Evapotranspiration and potential evapotranspiration, snow depth and density, soil moisture); Climate change (Regional simulations of climate patterns including large lake effects for maximum accuracy).
Intended user	
Format	An online decision support system platform will provide a window to the model results and provide information accessible to the nontechnical user at public, community, watershed management level, and higher governmental

	levels. The second phase of Canada1Water due to run to 2029 aims to: Develop national groundwater metrics Deliver total water storage metrics based on Gravity Research and Climate Experiment (GRACE) satellite data Partition those total water storage metrics to support more accurate groundwater estimates Provide complete water budgets — for both groundwater and surface water — by watershed across Canada
Data source	HGS is a physical-based model calibrated using more than 400 Environment Canada and U.S. Geological Survey stream-gauging locations and more than 3 000 groundwater monitoring wells. Model draws on 20 input datasets.
Methodology/technology	Canada1Water is a continental-scale model of Canada's complete hydrologic system based on the HydroGeoSphere platform. Canada1Water also models regional climate, using the Weather Research and Forecasting (WRF) model for climate and the Community Land Model (CLM) for near surface processes associated with the energy balance between the land surface and atmosphere. The outputs generated by WRF feed into CLM5, and the combined output of WRF and CLM5 feeds into HGS, which serves as the engine for the final, integrated groundwater– surface water simulation of Canada's water resources.
Temporal scale	Medium to long-term: The outputs provide insight into projected changes in groundwater storage, soil moisture levels, surface water flows, evaporation and plant transpiration in monthly increments between historic and future conditions.
Update frequency	n/a
Spatial resolution	The WRF and CLM models have respective grid resolutions of 12.5 km and 5 km, and outputs are integrated to monthly temporal increments. HGS groundwater-surface water modelling utilises unstructured model grids constructed to resolve Strahler Order 5 and 4 stream networks with length scales of < 1km to 5km.
Geographical coverage	Canada plus transboundary watersheds shared by Canada and the United States.
Limitations and caveats	N/A
Additional notes	N/A

Source: (Canada1Water, n.d.[162]) (Frey, Russell and Kirkwood, 2024[163]).

Projection tools for long-term trends

Table A A.33. CANARI-Europe

Developed by	French laboratory Institut Pierre Simon Laplace (climate modelling) and the JRC (adaptation in the agriculture sector) providing research, Makina Corpus providing the IT solutions for the platform and Solagro, the presentation of results towards end users
Type(s) of physical water risk covered	Water excess and shortage Blue water
Dimensions of risk included	Hazard and impact on different crops/livestock sectors
Purpose	Anticipation: calculate over 100 agroclimatic indicators considering local agroclimatic conditions The tool is developed specifically for the agriculture sector.
Intended user	Ministries of Agriculture, Water and Environment, Local and regional authorities, agro-food companies, farmers, extension officers, environment and water agencies, river basin managers, disaster preparedness and risk reduction, insurers
Format	free, openly accessible web-based decision-support platform: showing maps, charts, summary tables, summary reports and data exports
Data source	Modelled data from Regional Climate Models of the EURO-CORDEX initiative, using medium and high-emissions (RCP 4.5 and 8.5) scenarios, historic agroclimatic data
Methodology/technology	Statistical and dynamic downscaling of climate models, incorporating agricultural data (e.g. yields)
Temporal scale	1985 and 2100. Each agroclimatic indicator can be calculated and spatially mapped for the past, as well as the near (2020-2050) and far future (2050-2100) periods
Update frequency	Daily
Spatial resolution	12.5 km
Geographical coverage	Europe
Limitations and caveats	Advanced customisation requires external support. The tool requires intermediate technical knowledge for optimal use.
Additional notes	Besides water risks, the tool also covers agri-climatic indicators for non-water related risks. The tool is available in English, Spanish, Estonian, French.

	In France, CANARI Europe can be complemented by the Climadiag-Agriculture platform, integrating data from the French meteorological service (Météo-France) and phenological indicators that uses annually updated plant-growth models and 17 climate models. It can be integrated with several other tools, including the AWA AgriAdapt Webtool (see below), and the Climadiag-Agriculture France platform. It can also be combined with insurance and risk platforms for refining agricultural climate risk assessments and with National Meteorological Services for real time observations.

Source: (Climate-ADAPT, 2025[164]), (Solagro and Makina Corpus, 2025[103]), (Solagro and Makina Corpus, 2025[165]), (Solagro and Météo-France, 2025[166]).

Table A A.34. AgriAdapt Webtool for Adaptation

Developed by	Solagro, the Estonian University of Life Sciences, Fundacion Global Nature and Bodensee Stiftung
Type(s) of physical water risk covered	Water excess and shortage Blue water
Dimensions of risk included	Hazard and impact on different crops/livestock sectors
Purpose	Anticipation: assess the vulnerability of key European agricultural products to changing climatic patterns, including water related risks. Simulations show trends of several water related indicators (e.g. annual average rainfall, potential evapotranspiration) in the recent past and near future, as well as agroclimatic indicators for specific agricultural production sectors (e.g. hydric deficit for arable crops). The tool is developed specifically for the agriculture sector.
Intended user	Ministries of Agriculture, Water and Environment, Local and regional authorities, agro-food companies, farmers, extension officers, environment and water agencies, river basin managers, disaster preparedness and risk reduction, insurers
Format	Web-based tool including a map interface with overview on agronomic (yields) and climatic (observations and projections) data for different geographic locations
Data source	(past) yield data, as well as observed and projected (based on a moderate emissions scenario) climate data
Methodology/technology	Climate modelling simulations, modelling agri-climatic indicators for specific sectors
Temporal scale	recent past (past 30 years) and the near future (next 30 years)
Update frequency	N/A
Spatial resolution	N/A
Geographical coverage	Europe (specific farm locations across the continent)
Limitations and caveats	N/A
Additional notes	Besides water risks, the tool also covers agri-climatic indicators for non-water related risks. The tool is combined with a test to self-assess the vulnerability of farms to changing climatic patterns, including water-related risks, the tool allows farmers to understand climate-related risks. Complemented by a toolbox of potential measures, it provides a decision-support tool for agricultural stakeholders to plan climate change adaptation actions

Source: (Agri-Adapt, n.d.[104]).

Table A A.35. My Climate View

Developed by	Commonwealth Scientific and Industrial Research Organisation (CSIRO) and the Australian Bureau of Meteorology
Type(s) of physical water risk covered	Water excess and water shortage
Dimensions of risk included	Hazard and impact on agricultural sectors/commodities at specific locations
Purpose	Anticipate how climate change will impact farms, including for water related risk factors. A decision support tool providing information on past climate data, seasonal forecasts and future climate projections for specific locations for over 22 agricultural commodities
Intended user	Landholders, producers, agricultural advisers, Federal, state and territory governments
Format	Free, publicly accessible portal with a user interface, showing charts, summary tables, summary reports and data exports
Data source	Observed climate data, modelled climate data based on a moderate (RCP 4.5) and high emissions scenario (RCP

	8.5)
Methodology/technology	Climate modelling for specific agricultural commodities and locations
Temporal scale	Past data from 1965 to now, seasonal forecasts for the next 1-3 month and future projections for the 2030s, 2050s and 2070s
Update frequency	N/A
Spatial resolution	5km grid
Geographical coverage	Australia
Limitations and caveats	N/A
Additional notes	The tool covers a broad range of climate risk relevant to agricultural commodities such as key seasonal changes in rainfall patterns, temperature and evapotranspiration.

Source: (MyClimateView, n.d.[105]).

Table A A.36. AquaPlan

Developed by	University of Manchester and Development Seed
Type(s) of physical water risk covered	Water shortage and water excess Blue water
Dimensions of risk included	Hazard, vulnerability, exposure and impact (on crops)
Purpose	Forecasting crop yield predictions under different water management strategies, taking into account soil, crop type and weather conditions The tool helps understand irrigation requirements, make field-level irrigation decisions and forecast climate change impacts on water-related crop production risks.
Intended user	The tool is specifically designed for the agriculture sector. Farmers, Ministries of Agriculture, Water and Environment, Local and regional authorities, agro-food companies, farmers, extension officers, environment and water agencies, river basin managers, disaster preparedness and risk reduction, insurers
Format	Interactive web application
Data source	cloud-hosted weather (Daymet, NASA-POWER) and soil (SoilGrids) datasets that are integrated into the application, combined with data generated from SSP scenarios and modelled data from the AquaCrop model
Methodology/technology	The app uses the “AquaCrop-OSPy” crop-water model which simulates how management decisions and climate variability affect crops. The model provides yield predictions under a variety of water management strategies, soil, crop type, and weather conditions. This is the open-source python version of the AquaCrop model, initially developed by FAO. Automated data integration and cloud processing enables to run the application.
Temporal scale	varies
Update frequency	N/A
Spatial resolution	Field-level
Geographical coverage	Global
Limitations and caveats	N/A
Additional notes	The app is intuitive and easy to use, compared to other water resource planning models that may be challenging to operate due to the complexity of uploading and managing data.

Source: (AquaPlan, n.d.[167]), (University of Manchester, 2024[168]), (Foster. T. et al., 2022[169]).

Annex B. Databases facilitating water quality monitoring

While a fairly low number of complex tools (as showcased in Annex A) have so far been developed and deployed for water quality compared to other risks (such as water shortage and excess), several databases are available to track water quality. This annex provides examples of databases available that can facilitate monitoring water quality related risks.

Table A B.1. Global Freshwater Quality Database (GEMStat)

Developed by	UNEP GEMS/Water Programme.
Type(s) of physical water risk covered	Water quality - Chemical, physical, biological.
Dimensions of risk included	Hazard: 600+ parameters covered (inorganic, organic, nutrients).
Purpose	Global water quality monitoring. To provide a global repository of freshwater quality data for assessment, research, and international reporting.
Intended user	Researchers, policymakers.
Format	Online database.
Data source	National monitoring programmes and country submissions to the UNEP GEMS/Water network.
Methodology/technology	Data aggregation and classification (CUAHSI Hydrosphere Ontology)
Temporal scale	1906–
Update frequency	When countries submit new data.
Spatial resolution	Station level.
Geographical coverage	Global. Over 90 countries (strongest coverage in Latin America, Europe)
Limitations and caveats	Dependent on country submissions. Spatial imbalance in monitoring intensity.
Additional notes	Contains over 29 million entries from 21 000 stations. covers rivers, groundwater, and lakes, with rivers most represented.

Source: (GEMSTAT, n.d.[170]).

Table A B.2. GLORICH (GLObal RIver CHemistry Database)

Developed by	University of Hamburg, Institute for Geology
Type(s) of physical water risk covered	Water quality - Hydrochemical parameters.
Dimensions of risk included	Hazard: Major ions, nutrients, carbon, alkalinity, pH, DO, temperature.
Purpose	To provide a harmonised dataset of global river chemistry for biogeochemical, hydrological and Earth-system research.
Intended user	Researchers.
Format	Database
Data source	Global river chemistry datasets compiled historically from diverse monitoring programmes.
Methodology/technology	Standardisation and harmonisation of hydrochemical data; catchment delineation using global GIS datasets.
Temporal scale	Historic (one-time dataset)
Update frequency	None (not updated)
Spatial resolution	Catchment level
Geographical coverage	Global river systems.

Limitations and caveats	No updates. Static dataset.
Additional notes	Contains 1.27 million samples from 17 000 locations.

Source: (Universität Hamburg, 2019[171]).

Table A B.3. Waterbase – Water Quality ICM

Developed by	European Environment Agency (EEA)
Type(s) of physical water risk covered	Water quality and quantity
Dimensions of risk included	Hazard
Purpose	Monitor European water bodies status (Rivers, lakes, groundwater, coastal, transitional, coastal and marine waters)
Intended user	EU Member states, environmental agencies, policymakers.
Format	Online database
Data source	National monitoring programmes submitted through EEA reporting mechanisms.
Methodology/technology	Harmonisation under EU water directives; standardised indicators and QA/QC.
Temporal scale	1900-2024
Update frequency	Yearly.
Spatial resolution	Station level.
Geographical coverage	Europe (EU + co-operating countries).
Limitations and caveats	Variable national monitoring intensity. Historical data may lack consistency.
Additional notes	

Source: (EEA, 2025[172]).

Table A B.4. Water Quality Portal (WQP)

Developed by	U.S. Geological Survey (USGS) and U.S. Environmental Protection Agency (EPA).
Type(s) of physical water risk covered	Water quality (freshwater). Blue water
Dimensions of risk included	Hazard: Chemical, physical and biological water quality
Purpose	To provide a unified access point for publicly available U.S. water-quality data.
Intended user	Researchers, water managers, environmental agencies, utilities
Format	Online database
Data source	USGS National Water Information System (NWIS), EPA STORET/WQX, and other partner networks.
Methodology/technology	Harmonised data integration; standard U.S. federal water-quality reporting formats.
Temporal scale	Historic to present.
Update frequency	Daily or weekly depending on data source.
Spatial resolution	Station level
Geographical coverage	United States
Limitations and caveats	Large heterogeneity among sites; not all parameters measured everywhere; metadata coverage varies.
Additional notes	Over 1.5M monitoring sites

Source: (EPA, 2025[173]).

Table A B.5. Global River Water Quality Archive (GRQA)

Developed by	University of Tartu (Estonia) and Yale University (United States)
Type(s) of physical water risk covered	Water quality
Dimensions of risk included	42 parameters aggregated from multiple sources.
Purpose	Provide harmonised global water quality dataset.
Intended user	Researchers, policymakers.
Format	Open-access archive (Zenodo).

Data source	CESI, GEMStat, GLORICH, Waterbase, WQP
Methodology/technology	Data harmonisation, standardisation and aggregation.
Temporal scale	1898-2023.
Update frequency	Static (published dataset).
Spatial resolution	Station level.
Geographical coverage	Global.
Limitations and caveats	No ongoing updates. Variations in original source methods, uneven spatial and temporal coverage.
Additional notes	Over 17 million measurements. Enables global-scale trend analysis and consistent parameter comparison across continents.

Source: (Virro et al., 2021[174]) (Virro et al., 2025[175]).

Table A B.6. SWatCh (Surface Water Chemistry database)

Developed by	Dalhousie University.
Type(s) of physical water risk covered	Water quality (surface water chemistry). Blue Water
Dimensions of risk included	Hazard
Purpose	Provide standardised global surface-water chemistry dataset of 24 harmonised variables.
Intended user	Researchers.
Format	Harmonised global dataset with GIS shapefile of site locations.
Data source	Multiple global data providers compiled and harmonised by Dalhousie University.
Methodology/technology	Data cleaning, standardisation, harmonisation of sites, variables, methods, metadata and GIS integration.
Temporal scale	1960-2022.
Update frequency	Static (published dataset).
Spatial resolution	Station level.
Geographical coverage	Global.
Limitations and caveats	No updates.
Additional notes	33 722 sites across seven continents and over 5 million samples.

Source: (Rotteveel, Heubach and Sterling, 2022[176]), The Surface Water Chemistry (SWatCh) database (zenedo).

Annex C. Techniques, methods and models

Hazard monitoring and short-term forecasting

Water excess (flood)

Flood forecast rating curves (FRC) can be used to provide early flood warnings of up to several days. An FRC indicates the ratio of measured upstream water levels in comparison to estimated downstream discharge. This enables downstream water level forecasts by assessing upstream water levels. FRCs can be used to provide timely early warning of downstream flood events and their probable severity. Upstream flows and water levels can be measured in situ or via satellite remote sensing.

Water shortage (drought)

Drought indices are used to characterise the complex nature of droughts with an indicator. Monitoring and forecasting tools frequently rely on them to illustrate drought severity in a quantifiable way. Hundreds of indices have been developed to date, each of which is calculated based on different data available. While the first tools initially considered precipitation as a sole factor, later indices started to consider variables such as soil moisture, evapotranspiration, vegetation, etc. Initially, drought indices were mainly calculated based on meteorological (weather station) data; however, as satellite technology developed, this was later complemented with remote-sensing data. Drought indices may be based on a single variable or several variables (compound indices). Due to the complexity of droughts, compound indices are increasingly used. The relevance of drought indices varies based on space and time, as well as drought type (Table C.1.). As several drought indices were developed for geographically specific conditions, their reliability may differ if applied in a different region or ecosystem (Hanadé Houmma et al., 2022[177]) (Liu et al., 2016[16]) (Mullapudi et al., 2023[178]).

Table A C.1. Drought types and commonly used drought indices

Drought type	Commonly used drought indices
Meteorological drought	Palmer drought severity index (PDSI): monitors moisture deficiency Standardized Precipitation Index (SPI): compares precipitation deficit to the climatological record
Agricultural drought	Indices derived directly from soil moisture, such as the crop moisture index (CMI), standardised soil moisture index (SSMI), soil moisture percentile (SMP), normalised soil moisture (NSM).
Hydrological drought	Palmer hydrologic drought index (PHDI, measures hydrological drought impacts, e.g. reservoir and groundwater levels), runoff or streamflow percentile, and standardised runoff index (SRI)

Note: The table provides a non-exhaustive list of drought indices commonly used to detect various drought types.
Source: (Hanadé Houmma et al., 2022[177]) (Liu et al., 2016[16]) (Mullapudi et al., 2023[178]).

Water quality

Multiparameter, low-power buoys deliver near-real-time alerts of episodic pollution in freshwater at a fraction of the cost of conventional sondes. Such platforms point towards scalable, high-resolution monitoring networks. The prototype by Krklješ et al. (2024[179]) demonstrated stable operation, and an algorithm successfully mitigated interference from suspended solids in the coliform channel. The system provides early-warning capability downstream: by flagging spikes in turbidity, conductivity or thermotolerant coliforms within minutes, it lets water utilities or environmental agencies intervene before episodic pollution events propagate.

Combining remote sensing with machine learning, a **convolutional neural networks model** was employed to establish the relationship between satellite (Sentinel-2) images and in-situ water quality levels of Lake Dianchi (Meng et al., 2024[180]). This approach is useful for forecasting algal blooms and trophic status. It revealed month-to-month changes in water-quality grades, providing local authorities with seasonally explicit targets for phosphorus mitigation.

Salls et al (2024[181]) applied machine-learning calibration of spectral indices (Maximum Chlorophyll Index, Normalised Difference Chlorophyll Index) to over 100 lakes in the United States, predicting chlorophyll-a with high accuracy and classifying trophic states at 82%, making it useful for forecasting eutrophication risk.

Luo et al. (2022[182]) at Lake Qiandao, China, combined high-frequency in-situ monitoring with automated quality control and machine learning to detect anomalies and provide early warning of water-quality deterioration.

Irrigation advice

The DISPATCH method (DISaggregation based on Physical And Theoretical scale CHange) combines microwave and optical remotely sensed data to assess soil moisture levels. A study carried out in the Iberian Peninsula in Spain showed that using these high-resolution remote sensing data allows accurate estimation of irrigation water requirements, improving water use efficiency and optimising agricultural productivity (Dari et al., 2021[81]); (Parra-López et al., 2025[80]). Similarly, the SiAR tool in Spain combines data from field weather stations with satellite imagery to map irrigated areas and estimate their annual and monthly water requirements based on the daily water balance for the whole country (www.espaciosiar.es.).

Hazard and risk mapping

Water excess (floods)

Flood modelling approaches underpin flood hazard and risk mapping. Table C.2 summarises the strengths and weaknesses of different flood modelling approaches.

Table A C.2. The strengths and limitations of different flood modelling approaches

Method	Strength	Limitation	Suitability
Empirical methods	Relatively quick and easy to implement Based on observation Derived inundation estimate is independent Technology is rapidly improving	Non-predictive No/indirect linkage to hydrology (difficult to use in scenario modelling) Coarse spatial and temporal resolution (although improving) Engineering limitations (sensors, carriers, transmission devices) Environmental limitations (clouds, wind, damaging weather conditions, other natural constrains) Processing limitations (algorithm, artificial errors …)	Flood monitoring Flood damage assessment Serve as observations to support calibration, validation and data assimilation for other methods
Hydrodynamic models	Direct linkage to hydrology Detailed flood risk mapping Can account for hydraulic features/structures	High data requirements Computationally intensive Input errors can propagate in time	Flood risk assessment Flood damage assessment Real-time flood forecasting Flood related engineering

	Quantify timing and duration of inundation with high accuracy		Water resources planning Riverbank erosion Floodplain sediment transport Contaminant transport Floodplain ecology River system hydrology Catchment hydrology
Simplified conceptual models	Computationally efficient	No inertia terms (not suitable for rapid varying flow) No/little flow dynamics representation	Flood risk assessment Water resources planning Floodplain ecology River system hydrology Catchment hydrology Scenario modelling

Source: Reproduced from Teng et al (2017[91]).

Height Above Nearest Drainage and on-the-fly Flood Mapping: Traditional flood maps require large amounts of data to complete complex flow calculations. For many parts of Canada, these data are not available. Natural Resources Canada researchers developed a simplified flood model covering the entire country, which only requires topographic data of a watershed and the shape and depth of the river network. By calculating the height difference between the land grid and the river grid, the Height Above Nearest Drainage (HAND) model produced accurate results in only a fraction of the processing time. This paves the way to complete on-the-fly flood maps that can be used to assist first responders during a flood emergency in any region (Natural Resources Canada, n.d.[183]).

Water shortage (drought)

16. Agricultural drought modelling is used for monitoring and anticipating water shortage and encompasses the following approaches i) multivariate descriptive drought modelling of drought parameters (e.g. onset, intensity), ii) multivariate predictive modelling of drought risk, and iii) predictive modelling of expected drought impacts (Table C.3.) (Hanadé Houmma et al., 2022[177]).

Table A C.3. Three drought modelling approaches

Approach	Description	Recent advancements
Multivariate descriptive drought modelling of drought parameters	Combines variables and attempts to get qualitative and quantitative information on drought parameters for drought assessment and monitoring. Used to monitor ongoing drought conditions	Improved accuracy in drought parameter estimates thanks to the availability of multi-source data through the joint use of remote sensing and machine learning models (as opposed to previous methods using spatial interpolation of in-situ measurements or multivariate statistical modelling)
Multivariate predictive modelling of drought risk	Predictive mapping of expected drought risk, its intensity and spatial extent. Used for forecasting and can facilitate effective early responses to drought. Modelling the frequency of drought parameters can facilitate proactive management	Relatively new technique based on machine and deep learning.
Predictive modelling of expected drought impacts	Predictive modelling primarily based on the history of several biophysical and hydroclimatic variables. Contextual socio-economic vulnerabilities are rarely considered. Highly challenging field, as drought impacts depends on other predicted variables (e.g. duration, drought intensity, etc.)	Self-learning methods based on deep and machine learning algorithms, but little accuracy so far. Integration of multi-sensor predictive modelling as a possible avenue

Source: (Hanadé Houmma et al., 2022[177]).

Impact assessment

Water excess (flood)

The **floodam-agri tool** allows the estimation of flood damage at the plot level. It models yield losses and short-term management strategies based on knowledge from agricultural experts from the region under study. The tool estimates the damage as a variation in added value resulting from a flood in terms of product loss (yield) and intermediate consumption. It was set up for the construction of damage functions on a national scale in France as part of cost-benefit analyses for the evaluation of flood management projects (Modjeska and Brémond, 2022[94]).

AGRIDE-c, a conceptual model for the estimation of flood damage to crops. AGRIDE-c is a synthetic, expert-based model relying on the investigation of flood damage mechanisms and related economic impacts to agricultural crops. It adopts a coupled approach considering the physical damage to crops (i.e. yield reduction as a function of hazard and vulnerability features) and its economic implications in terms of loss of revenue and variation in production costs, which also depend on farmer's alleviation strategy after the flood. The general framework can be adapted and replicated in different regions. Takes into account types of crops, climatic region, crop calendars, flood damage mechanisms, crop yields and prices, cultivation practices and related costs); this is one of the main added values of AGRIDE-c, which makes it suitable to be adapted and/or transferred to other regions (Molinari et al., 2019[95]).

The study “Agricultural flood vulnerability assessment and risk quantification in Iowa” uses the Agricultural Flood Damage Analysis Model (AGDAM), crop layer raster datasets and flood inundation maps to assess agricultural flood risk in the state, focusing on corn, soybean and alfalfa crops. It stresses the importance of high-quality crop information and flood inundation data for the accurate estimation of agricultural loss quantification. It finds that terrain-based flood mapping products (Height Above the Nearest Drainage, HAND) perform better than FEMA maps for agricultural flood loss analysis (Yildirim and Demir, 2022[184]).

A continuous consequence/probability diagram may be a suitable technique to assess risk. For the hazards considered (e.g. flood, drought, salinity), risk is divided in three levels in the consequence/probability diagram corresponding to different bands: a) high risk (red band), where the level of risk is considered intolerable and risk treatment is essential whatever its cost; b) medium risk (yellow band), where the risk is considered tolerable; c) low risk (green band), where the level of risk is considered negligible, so no risk treatment measures are needed. Risk tolerance limits depend on the study area characteristics and should be defined based on information from past events and risk owner judgement. After establishing the risk context for the area where the approach is applied, hazard scenarios based on historical data and stakeholder’s information have to be defined to support risk assessment. Consequence descriptors are evaluated for the defined scenarios and risk levels are determined, compared and evaluated against risk criteria and tolerance limits previously defined. Results provide scientifically supported information to help stakeholders and risk owners to discuss the acceptability of the risk magnitude. The consequence descriptors can be evaluated through the analysis of model results, and historical and monitoring data. The tool uses hazard scenarios and numerical models to assess risk. This is combined with historical data and stakeholders’ input to define the risk context including risk management objectives (Freire et al., 2021[185]).

Water resource assessment

Software, models

The **Soil and Water Assessment Tool (SWAT)** is one of the most widely used watershed scale tools to simulate the quality and quantity of surface and ground water (Bieger et al., 2016[186]). The tool can predict the effect of soil, land use and management on water quantity and quality across different spatial and temporal scales and under different climate scenarios. It is computationally efficient and requires input data that is usually available. As an open-source software, its algorithms are available to all, which has led to continued iteration and development of the tool. Despite its demonstrated flexibility and effectiveness, several weaknesses and limitations of the model remain.

Water Evaluation and Adaptation Planning (WEAP) is a software tool for integrated water resources planning. WEAP integrates demand-side factors such as water use patterns, equipment efficiencies, re-use strategies, costs, and water allocation schemes with supply-side components such as stream flow, groundwater resources, reservoirs and water transfers (WEAP, 2025[187]). As a result, the tool can be used to examine alternative water development, management and policy options. WEAP operates on the basic principle of a water balance and can be applied to diverse systems, including agricultural systems. WEAP provides a system for maintaining water demand and supply information as well as the capability to simulate a broad range of natural and engineered components, including rainfall runoff, baseflow, groundwater recharge, water conservation, allocation priorities, pollution, and ecosystem needs. A financial analysis module allows cost-benefit comparisons.

The **Dynamic Water Resources Assessment Tool (DWAT)** developed by the WMO assesses the sources, extent, dependability and quality of water resources. It can be used to assess land-use changes within a basin over time, and impacts on water availability under different scenarios including climate change. DWAT uses a distributed conceptual scheme for water cycle analysis and contains sub-algorithms, such as evapotranspiration, infiltration, watershed runoff, groundwater movement, and channel routing (World Meteorological Organization, 2025[188]).

Water footprint

Tuninetti et al (2019[189]) combine data on water use efficiencies (crop water footprint, CWF) and crop water consumption (water footprint) with a “water debt” (WD) indicator that captures the time needed for soil moisture, surface water and groundwater to replenish: the **“water debt repayment time” indicator**. The water debt repayment time quantifies the local mismatch between water use and availability. This Water Debt indicator “allows one to discriminate two countries showing the same water use efficiency and producing nearly the same amount of crop but generating a different impact on water resource depending on the local water availability”.

OECD Food, Agriculture and Fisheries Papers

Anticipating and monitoring water risks for agriculture

No. 226

This paper examines water risks for agriculture and outlines a typology of tools to support public authorities in anticipating, monitoring and assessing these risks. Agriculture faces multiple water risks including shortage, excess and poor water quality, alongside systemic risks from degraded freshwater systems and a destabilised water cycle. Monitoring and anticipating these risks is critical to sustaining agricultural production and protecting freshwater resources. Given the diverse water risks and decision contexts, the sector requires a suite of tools tailored to different risks and temporal and spatial scales. The relevance of specific tools depends on decisions being taken, with the highest value achieved when tools inform choices with high or irreversible costs. While technological progress is driving rapid tool development, gaps and challenges remain. Public authorities have a central role in promoting a robust data environment, while taking a long-term, holistic perspective to build systemic resilience.