



Strategic Foresight to Applications of Artificial Intelligence to Achieve Water-related Sustainable Development Goals

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EXECUTIVE SUMMARY

This report uses strategic foresight to study applications of Artificial Intelligence (AI) to achieve water-related Sustainable Development Goals (SDGs). The report discusses motivations, applications, and opportunities related to the adoption of AI for sustainable development. AI is a thriving field, that aims to build systems that function intelligently and independently. The global market size of AI, currently valued at USD 2 trillion, is forecasted to contribute USD 16 trillion to the global economy by 2030. AI is expected to drive the next era of technological and economic development, similar to past developments such as the industrial revolution, the silicon chip era, and the emergence of smart devices. Strategic foresight uses insight about the future state of an industry to guide present-day decision-making. It is used as a tool in policy planning for assessing the potential impact of AI in fulfilling water-related SDGs. The foresight highlights findings from relevant literature and an expert panel, concluding with suggestions and policy recommendations for consideration by national Governments, and other relevant stakeholders.

The Report shows that: the AI-enabled innovation in the water sector is estimated to contribute USD 200 billion in value to the global economy by 2030. Current applications of AI in the water sector include i) predictive maintenance of water infrastructure, ii) forecasting water demand and consumption, iii) monitoring the health and environmental impacts of water reservoirs and dams, iv) tracking water quality, and v) monitoring and predicting water-related disasters. These applications contribute to achieving water-related SDG targets, specifically 3, 6, 11, and 15.

The rate of adoption of AI-based solutions in predictive maintenance of water infrastructure has accelerated as AI becomes increasingly accessible, and data analytics and smart sensors become more efficient and affordable. The global market for AI-enabled water leakage detection systems is expected to grow by approximately 4.9% each year over the next five years and is expected to be valued at USD 660 million in 2024, from USD 500 million in 2019.

Deep learning technology is an AI function that imitates the workings of the human brain in processing data and creating patterns for use in decision making. It has enabled a new generation of water management systems, which can generate short-term (daily) and long-term (annual) forecasts. This technology is available to countries that want to conserve water resources, and the associated economic value, by increasing the operational efficiency of water management systems.

As more water storage reservoirs are planned in Asia and South America, AI-based techniques are being successfully implemented to accurately predict the impacts of reservoir development and operation. AI will also be used to predict and manage water-related extremes at national and regional levels. These applications are expected to reduce environmental and community impact.

Water quality monitoring has been the most significantly impacted by AI, relative to other applications in water management. AI is used in monitoring the quality of water samples collected at diverse locations, large water bodies, and flowing water in real time. The applications of AI in water quality monitoring will increase as cost-effective, portable water quality monitoring devices become available to end-users in households, restaurants, and various public locations. These devices can be attached to smart phones to analyze water samples in real-time and detect viruses that are 100 times smaller than bacteria.

In 2018, water-related disasters (cyclones, floods, and droughts) caused an economic loss of USD 137 billion. Due to the increasing frequency of water-related disasters, there is increased urgency to adopt AI technology to better enable water-related disaster forecasting, impact assessment, and societal resilience.

AI can be used to forecast water-related disasters with higher accuracy, frequency, and lead time relative to non-AI methods, allowing for focused management of post-disaster activity. Applications of AI in water management have the potential to mitigate significant economic loss, preserve communities and ecosystems, and decrease mortality associated with water-related disaster.

The report recommends that:

- Policymakers should conduct holistic assessments of social, economic, and cultural factors before AI adoption in the water sector, as prospective applications of AI are case-specific. It is also important to conduct baseline studies to measure the implementation capacity, return on investment, and impact of intervention.
- To ensure positive development outcomes, policies regarding the use of AI for water-related challenges should be coupled with capacity and infrastructure development policies. Capacity development policies need to address the AI and Information and Communications Technology (ICT) needs for the AI-related skill development of all water-related stakeholders. Infrastructure development policies should address the underlying requirements of computation, energy, data generation, and storage. The sequencing of these policies is critical.
- To mitigate the predicted job displacement that will accompany AI-led innovation in the water sector, policies should direct investments towards enabling a skilled workforce by developing water sector-related education at all levels. This skilled workforce should be strategically placed to offset dependency on the private sector.
- Water-related challenges are cross-cutting running from grassroots to the global level and require an understanding of the water ecosystem. It is important for countries connected by major rivers and watersheds to collaborate in developing policies that advance the use of AI to address common water-related challenges.
- A council or agency with representation from all stakeholders should be constituted at the national level, to allow for the successful adoption of AI by water agencies. This council or agency should be tasked with the development of policies, guidelines, and codes of conduct for the adoption of AI in the water-sector.

These key policy recommendations can be used as primary guidelines for the development of strategies and plans to use AI to help achieve water-related SDGs.

Keywords: *Artificial Intelligence, deep learning, machine learning, Sustainable Development Goals, strategic foresight, disruptive technologies*

INTRODUCTION

We are living in an age where ecological change is dominated by human activity (UNFCCC, 2017). The emerging consequences of this are reflected in biodiversity loss, rising ocean temperatures, water extremes, deforestation and air and water pollution (IPCC, 2019). We are simultaneously standing in the age of information and technology, accumulating knowledge at unprecedented rates.

A turning point is approaching where we must decide how to use the amassing information and technology at our disposal, to slow or even reverse the growing environmental strain for future generations. Impacts and initiatives recorded at various scales show that emerging disruptive technology is being used to propel the digital transformation from conserving, monitoring, and evaluating Earth's resources, to decarbonising the energy and transport sectors.

Disruptive technology is an innovation that significantly alters the way that consumers, industries, or businesses operate. A disruptive technology sweeps away the systems or habits it replaces because it has attributes that are recognizably superior (Smith, 2019).

Despite the growing use of disruptive technology in various fields of sustainability science, their incorporation by public agencies remains poor (IIASA, 2019). The demand for public discourse regarding the widespread use of disruptive technologies in global sustainability and climate change action has been expressed at various platforms and summits (German Advisory Council on Global Change (WBGU), 2019; Independent Group of Scientists, 2019).

Establishing a public discourse is challenging due to the evolving nature of disruptive technologies, and the localisation of climate change-related challenges. Public agencies around the world are using strategic foresight to address these problems (UNDP Global Centre for Public Service Excellence, 2015).

This report uses the horizon scanning method of strategic foresight to assess the possible benefits

and challenges of employing artificial intelligence (AI) technology to achieve water-related SDGs. The scan consists of the desk review of 270 research articles, the opinions from 8 domain experts, and a review of 25 strategic foresights and digital transformation reports.

Strategic Foresight is a systematic approach to looking beyond current expectations and taking into account a variety of plausible future developments in order to identify implications for policies today (OECD, 2019).

Horizon Scanning seeks and researches signals of change in the present and their potential future impacts (OECD, 2019).

This report is divided into five chapters. Chapter 1 highlights the need for a strategic foresight and discusses the data and methods used in the report. Chapter 2 discusses AI, its evolution, features, and current state and trends.

Proponents for the integration of AI in water-related SDGs are discussed in chapter 3. Chapter 4 focuses on the uptake of AI for water-related SDGs in five key areas: i) predictive maintenance of water infrastructure, ii) predicting water demand and consumption, iii) monitoring water reservoirs and dams, iv) monitoring water quality and v) monitoring and predicting water-related disasters. The representative applications, opportunities, foresight and policy recommendations are presented for each of the key areas. Further, the representative applications are the AI-related verticals in the water sector developed and deployed by either public, private entities or through public-private partnership. In addition, the chapter closes with a list of challenges and suggestions for AI developments to achieve water-related SDGs.

Chapter 5 presents a list of key policy recommendations to prompt the adoption of AI in the water sector at the national level. These policy recommendations are the primary output of this strategic foresight. As a product of strategic foresight, this report does not aim to define a plan, but rather support the development of strategies and plans to use AI to help achieve water-related

SDGs. UNU-INWEH has a service delivery model in place to assist interested agencies in developing strategies and plans to adopt AI for all key areas discussed, at national or sub-national level.

ABOUT ARTIFICIAL INTELLIGENCE

AI is a thriving field, that aims to build systems that function intelligently and independently. We encounter these systems daily, e.g. smart device weather apps that feature weather tracking systems, web-based information portals like Google Search or Yahoo, virtual assistants like Siri and Alexa, featured movie and music suggestions on YouTube and Netflix, and automated AI-based customer service systems used by banks, airlines, online stores, and other industries.

AI has the ability to reason and understand natural language, images, and patterns in data of any spatiotemporal form with algorithms (Kumar et al. 2016). It has the ability to interpret data, learn from it, and utilise it to accomplish objectives (Kaplan and Haenlein 2019).

While AI technology was previously primarily applied in computer science, it now encompasses several other fields which collaborate with each other such as biology, neuroscience, engineering, environment, education, robotics, biomechanics, material sciences, economics, healthcare, and business management applications (Huang and Rust, 2018; Parkes and Wellman, 2015; Wiljer and Hakim, 2019).

The AI global market will grow at 5% annually and will contribute approximately USD 16 trillion to the global economy in 2030 (Verweij and Rao, 2017).

The current global market size of AI is USD 2 trillion (Louis Columbus, 2018). The AI market includes the producers and consumers of systems (intelligence systems, decision support processing, hybrid systems, fuzzy systems) and the involved technology (machine learning, robotics, image processing, speech recognition, natural language processing and cognitive computing) - (Inkwood Research, 2019). AI is forecasted to contribute

USD 16 trillion to the global economy by 2030, more than the current output of China and India (Verweij and Rao, 2017). This growth will result from increased industrial productivity and consumption from personalised retail services.

The emergence of AI is expected to have a net positive impact on the achievement of the SDGs (Vinuesa et al., 2020). The SDGS are dynamic, complex and interconnected, AI in its various forms – machine learning, natural language processing, predictive analytics and more can bring great efficiencies, speed and intelligence required to solves complex SDG related tasks and processes (Michael and Rosie, 2019).

DRIVERS OF ADOPTION OF ARTIFICIAL INTELLIGENCE FOR SUSTAINABLE DEVELOPMENT

Access to Infrastructure and Technology

The majority of AI frameworks and libraries are being developed through the use of open standards, open data, and open innovation initiatives. The adoption of the open-source framework has led to the development of a collaborative innovation process, which has enabled the development of solutions addressing SDGs. Development agencies, academic institutions, and organisations at all scales have contributed to nurturing and adopting the open-source framework in AI (United Nations Technology Innovation Labs, 2019)

Access to Quality Datasets

The last decade and a half has seen an exponential increase in structured and unstructured data volume. According to IBM, 2.5 quintillion bytes of unstructured data is created every day (IBM, 2013). A large proportion of specialised data sources are stored under a centralised framework, inaccessible and costly for use in training AI models. However, there is a continuous drive to replace centralised data sources with datasets created under the open government initiative, research grants, and through non-profit organisations. These decentralised initiatives of data creation, sharing, and storage provide critical, quality seed data required to train AI models for SDGs.

Access to Computing Power

In the last couple of decades, computational power has been valuable for scientific exploration, providing the ability to analyze data and run complex models (Gomes et al., 2019). This computational power has evolved from desktop machines to cloud-based plug and use affordable computing resources. AI has benefited from this evolution as more complex models can be executed on the cloud, with substantially lower required cost and time. Many governments and regional agencies have set up cloud-based computation clusters, which are accessible to researchers and non-profit organisation to run computation tasks, contributing to the robust and quick development of AI solutions for SDGs (Independent Group of Scientists, 2019).

Access to Complete AI Solutions

The SDGs have benefited from the increased accessibility of AI. AI models are now available as readily deployable packages, avoiding the traditional pitfalls of AI technology adoption, such as onboarding of AI domain experts, time-consuming system integration, and lack of transparency (Dasgupta and Wendler, 2019).

ARTIFICIAL INTELLIGENCE IN THE CONTEXT OF WATER-RELATED SUSTAINABLE DEVELOPMENT GOALS

Artificial Intelligence, Big data, and the Internet of Things (IoT) are becoming increasingly prominent in the water industry (Raconteur, 2016). Making water systems (water distribution, water storage, and wastewater collection and treatment systems) more resilient and efficient is essential to reduce the implications of water shortages and crises that will be induced by global climate change. The AI-enabled innovations and interventions in the water sector are estimated to have a positive impact of USD 200 billion in 2030, which will be 0.04% -0.2% of the global GDP (Microsoft and PricewaterhouseCoopers 2019). This impact may appear small when compared to AI's influence on other industries and SDGs, but this involvement will play a vital role in preserving freshwater resources, forests, and oceans.

The AI-enabled innovations and interventions in the water sector are estimated to have a positive impact of USD 200 billion in 2030 - (Microsoft and PricewaterhouseCoopers 2019).

The key areas where AI is expected to have influence in the water sector are listed below, with the representative AI applications, opportunities, foresight and policy suggestions for each key area. The applications and case studies can be used to gauge the current state of the technology adoption, whereas the opportunities, foresight, and policy suggestions can be used during the policy formulation process. Figure 1 lists the SDG targets that each of the key areas is contributing to.

Predictive Maintenance of Water Infrastructure

The fourth industrial revolution, termed maintenance 4.0 in the water sector (Lasi et al., 2014), is propelled by AI. This revolution is a shift from preventive maintenance systems of scheduled inspections and maintenance of the water infrastructure, to predictive maintenance which uses intelligent-sensor-physical systems to monitor water infrastructure and schedule inspection and maintenance based on asset condition. Predictive maintenance is being used for water supply network, wastewater infrastructure maintenance, and non-revenue water (water that is pumped and then lost or unaccounted for) tracking. As the global water utility network faces the challenge of increased demand, falling revenues, and climate change, there is increased investment by the public and private sector in predictive maintenance. These investments support maintenance 4.0 through mitigation efforts by funding the development and upkeep of water infrastructure. The rate of adoption for AI-based solutions in water infrastructure management and maintenance is accelerating, as AI becomes increasingly accessible, and data analytics and smart sensors become widely more efficient and affordable. The global utility AI-IoT industry is currently valued at USD 4 billion, and is expected to grow to USD 15 billion by 2024, with an expected annual growth rate of 20% (Global Market Insights, 2019). This expected growth and investment will not only help to renew and replace the aging water and wastewater infrastructure,

SDG Targets

		3.3	3.9	6.1	6.3	6.4	6.5	6.6	11.5	15.1
Key areas	Predictive maintenance of water infrastructure			●	●	●				
	Predicting water demand and consumption			●		●	●			●
	Monitoring water reservoirs and dams					●	●	●		●
	Monitoring water quality	●	●	●	●					
	Monitoring and predicting water-related disasters								●	

SDG 3
 SDG 6
 SDG 11
 SDG 15

Target 3.3: by 2030, end the epidemics of AIDS, tuberculosis, malaria, and neglected tropical diseases and combat hepatitis, water-borne diseases, and other communicable diseases

Target 3.9: by 2030, substantially reduce the number of deaths and illnesses from hazardous chemicals and air, water, and soil pollution and contamination

Target 6.1: by 2030, achieve universal and equitable access to safe and affordable drinking water for all

Target 6.3: by 2030, improve water quality by reducing pollution, eliminating dumping and minimising release of hazardous chemicals and materials, halving the proportion of untreated wastewater and substantially increasing recycling and safe reuse globally

Target 6.4: by 2030, substantially increase water-use efficiency across all sectors and ensure sustainable withdrawals and supply of freshwater to address water scarcity and substantially reduce the number of people suffering from water scarcity

Target 6.5: by 2030, implement integrated water resources management at all levels, including through transboundary cooperation as appropriate

Target 6.6: by 2030, protect and restore water-related ecosystems, including mountains, forests, wetlands, rivers, aquifers and lakes

Target 11.5: by 2030, significantly reduce the number of deaths and the number of people affected and substantially decrease the direct economic losses relative to global gross domestic product caused by disasters, including water-related disasters, with a focus on protecting the poor and people in vulnerable situations

Target 15.1: by 2030, ensure the conservation, restoration and sustainable use of terrestrial and inland freshwater ecosystems and their services, in particular forests, wetlands, mountains and drylands, in line with obligations under international agreements

Figure 1: Key areas of AI applications and the SDG targets

but also help in ensuring long-term water availability, watershed and water source protection, and emergency preparedness.

Applications

1. AI-enabled water supply network in Singapore, Asia

The Public Utilities Board in Singapore has used AI and smart sensors to establish an effective and sustainable water supply management system. The system uses data from smart sensors inferred by AI for leaks and fault detection in the utility network and preventive maintenance, in addition to other real-time monitoring. The system monitors utility lines connecting household connections, reclamation plants, desalination plants, duplex pipelines, water reservoirs, and other core integral infrastructure.

Singapore National Water Agency's R&D projects repository: <http://bit.ly/2PsvaBe>

2. A virtual water network - HydrolQ, Kenya, Africa

In Africa, 50% of the water supplied by utilities is lost before reaching the end-user. This is due to feeble infrastructure, intentional pipeline damage, and poor maintenance culture. In Kenya, HydrolQ has developed a household level solution to monitor leaks/faults, water pressure, and water quality. The system uses AI, coupled with smart sensors and payment automation, enabling household customers to pay for the consumed quantity only.

HyrdolQ's specification sheet: <http://bit.ly/2Pt6VTt>

3. Assessing condition and risk of drinking water distribution main in the USA

Fracta, a USA based company, is helping water utility management agencies adopt AI-based solutions for better management of water infrastructure. Their solutions help to assess the condition and risk of drinking water distribution mains by using machine learning algorithms to calculate the Likelihood of Failure (LOF). The system enables decision-makers to assess water infrastructure and make informed choices regarding repairs and replacements. The company currently covers 847 miles of utility lines in the USA and has so far helped agencies cut costs by USD 4 million. The company is aiming to

solve the water main problem in North America, evaluated at USD 1 trillion.

Overview of AI powered tools used by Fracta: <http://bit.ly/2P6hiLi>, <http://bit.ly/2LmoQIK>

4. Sewer monitoring using AI in the USA

SmartCover Systems, a USA based company, monitors water and wastewater infrastructure using AI. The system, coupled with IoT solutions, continuously measures, acquires and communicates data through satellite communications. It has the ability to measure blockages, detect stormwater infiltration, and provide real-time maintenance updates using AI-based trend analysis. Cities such as Hawthorne and Escondido in California, as well as major drinking water and sewage utilities such as the San Antonio Water System in Bexar County, Texas, have used SmartCover Systems, resulting in a significant decrease in wastewater production.

Overview of SmartCover's result dashboard: <http://bit.ly/2DIJlWr>

Opportunities and Foresight

- The global volume of non-revenue water is estimated to be 346 million m³, costing approximately USD 39 billion. AI-IoT driven solutions developed through the collaboration of the public and private sectors can help to tap into this non-revenue water (Liemberger and Wyatt 2019).
- AI has been adopted by less than 20% of public and private water management agencies to monitor and optimise the water utility network (Mercer, 2016). There is abundant room for investment and growth by the public and private sectors.
- The real-time Internet of Things (IoT) integrated network has matured into technology that provides the critical data link to future machine learning/AI software. The global market for AI-IoT enabled water leakage detection systems is expected to grow by approximately 4.9% per year over the next five years and is expected to be valued at USD 660 million in 2024, from USD 500 million in 2019 (360 Research Report, 2019).
- Advancement in AI models, sensors, and robotics will allow for the development of mobile repair bots which will be able to detect and fix leakages. In the case of major

leakages, a swarm of these bots would be deployed to the site.

Policy Recommendations

- Provincial and federal governments should develop regulatory frameworks for local water agencies, requiring them to measure all costs and benefits of leak detection and incorporate these data into their investment decisions.
- Technology and engineering firms are advancing the ability to detect and predict water leaks. Provincial and federal governments should revise their water management frameworks, to integrate these advances, to contribute to economic prosperity and enhance environmental protection.
- Provincial and federal governments should develop the organisational capacity to allow local water agencies to adopt AI based solution for the maintenance of water infrastructure.
- Local governments should adopt data driven approaches coupled with AI to develop real time sewage control and management tools and strategies.

Predicting Water Demand and Consumption

AI-IoT enabled water management systems allows facility managers to monitor water consumption and demand and analyze water system performance in real-time (Water Intelligence 2019). Addressing data related to water consumption and demand with deep learning technology has enabled a new generation of water management systems, which can generate short-term (daily) and long-term (annual) forecasts. Short-term forecasts are used for the efficient management of water stored in reservoirs, along with the associated infrastructure. Long-term forecasts are used to design and upgrade water networks (Antunes et al., 2018).

Applications

1. Forecasting water demand at the district level in Spain

In Spain, the Spanish Ministry of Economy and Competitiveness has deployed an Artificial Neural Network (ANN) based water demand forecasting system. The system couples ANN with Bayesian framework and Genetic Algorithms (GA), to provide short-term daily forecasting of water

irrigation demand. The system has improved the prediction accuracy by 11% when compared to non-AI based models.

Research paper discussing the algorithm and forecasting results: <http://bit.ly/2PjdpmG>

2. Smart water grid for urban water supply and management system in Australia

In South East Queensland, Australia a smart water grid has been deployed as an integrated system for managing and securing the urban water supply. The grid uses AI to enable water consumption and demand forecasting to address water reservoirs and dams, water treatment installations, desalination plants, water pumping stations, and household customers. The smart grid manages up to USD 7.6 billion of water infrastructure, and a water volume of 400 million m³ per year.

Overview of SEQ water grid: <http://bit.ly/2th13nt>

3. Multi-level forecasting in Southern California, USA

The Metropolitan Water District of Southern California uses an ANN-based model to forecast population and economic growth affecting drinking water demand (CDM Smith, 2019). These forecasts are used to promote water conservation measures and manage water supply. The model generates the forecast for 18 million customers and 26 retailers, in addition to managing the supply from local resources.

The Metropolitan Water District of Southern California's water planning R&D document repository : <http://bit.ly/2rUn4rT>

4. Modular modeling based forecasting in London, UK

Thames Water, the UK's largest water and wastewater service company, uses AI to predict population growth, the number of households that are located in water resource zones, and water consumption. These predictions are used to assess the impact on per capita water consumption, total demand for policy options (metering program, innovative tariffs), and the non-domestic water demand. Thames Water serves 13.5 million customers in London and supplies an average of 2.6 million m³ of water per day.

Thames Water's smart water initiatives: <http://bit.ly/38DaY74>

Opportunities and Foresight

- The majority of water agencies in the developed world use AI-based models for forecasting water demand and consumption. These forecasting models can be implemented in countries wanting to adopt and localise forecasting models.
- The robust AI-based water consumption forecasting model based on quality data will allow for increased operational efficiency of water management agencies and help to conserve valuable water and monetary resources.

Policy Recommendations

- Federal and provincial governments should publish and continually update detailed guidelines and benchmarked data and algorithms for preparing AI-enabled water management systems, that forecast short-term and long-term water demand and consumption for household, industrial, and commercial use.
- Water management agencies should revise their water management plans to integrate AI for short- and long-term water demand and consumption forecasts. These forecasts should be used to ensure the short-term and long-term balance between water demand and available resources, as well as to determine emergency management plans for extreme weather events. These urban water management plans should be updated every 5 years.

Monitoring Water Reservoirs and Dams

Globally, there are approximately 7,320 water reservoirs and associated dams which have a global reservoir storage of 6700 km³ (Global Water Systems Project, 2013). Another 3,700 major dams are either planned or under construction, primarily in countries with emerging economies (Zarfl et al., 2015). With this increasing trend in water reservoir construction in Asia and South America (Reality Check team BBC News, 2018), AI-based techniques are being successfully introduced in reservoir operations and decision making. Water resource aspects that are being predicted using modern

AI methods include rainfall, sediment, streamflow water quality, evapotranspiration, and water level. Each of these components are being forecasted with varying accuracy based on the data available and the AI technique employed.

Applications

1. Locating dams with high hazard potential, USA

In the USA, 18% of the dams are categorised as having high hazard potential (if they fail, there could be associated mortality). 20,000 of these high hazard dams are in need of repair with an estimated cost of USD 20 billion. The Columbia Water Center is using AI, geospatial data, and climate models to pinpoint the riskiest dams. This use of AI is guiding decision-makers through the process of repairing and decommissioning dams. Deep learning is being used to analyze the climate data from 1970 to 2019 to recognise which patterns of moisture and circulation translate to rain. The deep learning model is able to predict "rain" or "no rain" with 95 percent accuracy. This rain forecast is coupled with elevation maps, dam heights, dam storage capacity, and runoff calculations to predict whether the rain could overtop the dam, and the impact this would have on dam health.

Web-article on using AI to locate risky dams: <https://bit.ly/3bvDF7m>

2. Shrinking dam's greenhouse gas emission in the Amazon

There are currently 150 hydropower dams and another 350 proposed for the Amazon basin, which encompasses parts of Brazil, Ecuador, Peru and Bolivia. A Cornell University led team has developed an AI-based computational tool which uses a multi-objective optimisation framework to analyze the dams' impact in terms of greenhouse gas (GHG) emissions per unit of electricity generated (carbon intensity). The output from this tool will help South American governments and organisations make informed decisions that balance the benefits and disadvantages of each dam. Using these tools, the researchers can identify the combination of dams which would produce the lowest amount of GHG emissions for a given energy output target. The analysis is done for 20-year and 100-year time frames. The tool computes highly accurate solutions in near real time.

Research paper discussing the algorithm and results: <https://go.nature.com/2OKKPeI>

3. Real time dam monitoring, UK

The Real Time Infrastructure Management (RTIM) system was jointly developed by HR Wallington and Siemens. It enables scenarios of levee or dam failure based on real time information for emergency management. RTIM uses cloud computing, sensor technology and AI driven predictive modelling. The predictive model analyzes the data feeds from a system of sensors installed at the dam and looks for anomalies that it cannot explain. These anomalies are flagged as information, warnings or alarms and relayed to dam managers for investigation and action. RTIM can manage data feeds from multiple sensors installed at several sites. Dwr Cymru Welsh Water is the first UK company to install RTIM at the Llugwy dam.

Research paper discussing the real time monitoring tool and its application: <https://bit.ly/2Hiinfu>

4. Smart dam monitoring, Italy

Enel green Power has developed a smart dam monitoring system (DMS) which monitors dam water level, water temperature, and air temperature in real time. An AI based model is the backbone of the DMS, which combines dam deformation and stress parameters with environmental parameters to monitor dam health in real time. In the case of an anomaly, the system activates an alarm to notify specialist engineers, enabling guided decision-making. The Riolutano Dam in Italy is one of the first dams where DMS is installed and in operation.

EGP's online report on smart dam monitoring: <https://bit.ly/2UJ4DIW>

5. Preserving Lake Sulunga using the Africa Regional Data Cube (ARDC), Tanzania

The Africa Regional Data Cube (ARDC) is helping the Government of Tanzania assess water extent and improve water policies to protect Lake Sulunga and the communities who depend on it for water, food, and income. ARDC uses water observations from Space Algorithm (WOFS) to get extents of water change and create animations for engagement with policy makers (Killough, 2019).

An online report discussing tools and results: <https://bit.ly/3aLYf2C>

Opportunities and Foresight

- It is expected that with advances in AI models and better quality of training data, AI could be used in the feasibility and design stage of reservoirs, to accurately predict their impact on the environment and the local community. This will help to bring transparency to the reservoir construction industry.
- As the reservoirs become part of national and regional water grids, AI will be used to predict and manage water-related extremes at national and regional levels.
- AI will be used to assist the decision-making process regarding the construction or decommissioning of reservoirs, based on groundwater outcomes, economic productivity, migration, and urban growth.

Policy Recommendations

- Reservoir design policies and guidelines should ensure the installation of a sufficient number of sensors and measurement gauges to meet current and future data needs. This will aid AI models to accurately predict the critical parameters required for reservoir management.
- To address transparency related issues around reservoirs, national and regional water management agencies should develop policies to ensure the use of open data and open AI-based tools, to study the impacts of reservoirs before and after commissioning.
- National and regional water management agencies should build organisational capacity to develop and deploy AI models that monitor water reservoirs and dams.

Monitoring Water Quality

Poor water quality is one of the main challenges faced in the 21st century, with one out of every nine people worldwide obtaining drinking water from unimproved and unsafe sources (WHO, UNICEF, 2015). Additionally, 90% of sewage in developing countries is discharged untreated directly into water bodies (UNESCO WWAP, 2015). It is important that disruptive technologies are used to address these water quality-related challenges.

Water quality monitoring has benefited the most from the adoption of AI, relative to all other application areas discussed in this report. Globally, AI is being used to address an array of spatial and temporal water quality-related challenges. The applications of AI for water quality can be categorised as:

- *Real-time water quality monitoring using AI and IoT*

AI-IoT based solutions are being used to enable frequent data collection and forecasting networks for real-time water quality monitoring. These systems are usually deployed upstream of water supplies, to monitor and forecast dissolved oxygen and total organic carbon. The forecasts range from short term (hourly) to seasonal (rainy and non-rainy).

- *Water quality monitoring based on sampling*

The advancements in AI-based pattern recognition and sensor image quality has allowed for the rapid detection of bacterial contaminants in water. AI-based tools are providing an alternative to manual and time-intensive processes of mapping color-based indicators, previously used to identify the level of certain contaminants, diseases, and infections.

- *Large water body quality monitoring using AI and remote sensing (satellite imagery)*

AI is being used to classify satellite imagery for remotely located watersheds and remote sensing of water bodies where it is not possible to install sensors to collect water samples. This method enables the identification of changes or trends in water quality over time. Typical monitoring parameters in the category include total suspended solids, chlorophyll-a, diffuse attenuation coefficient, sea surface temperature, and fluorescence line-height.

Applications

1. Clean Water AI

Clean water AI is one of the groundbreaking systems using AI to achieve water quality related SDGs. The system was developed in the USA and uses IoT and Convolution Neural Network (CNN) to perform real-time analysis and identify contaminants such

as bacteria, without an internet link. The system uses inexpensive and commercial off-the-shelf components. Currently, the clean water AI kit is available for USD 500. This price is expected to decrease in the future, with global adoption and advancement in AI technology.

Clean water AI's demo (video): <http://bit.ly/35smaRT>

2. Prediction of water quality in Iran

The Support Vector Machines (SVM) model is used to identify the Water Quality Index (WQI) in the Sefidrud basin in Iran. This inference was based on water samples collected and analyzed in the laboratory. The SVM models are able to analyze 87% of the total water quality index variability. In addition to developing the water quality index, the results from SVM can be used to improve river management for water quality.

Research paper discussing the algorithm and results from the field: <http://bit.ly/2PcB5sH>

3. Satellite-based water quality monitoring in Africa.

SERVIR has leveraged the power of deep learning, with satellite information, to access the historical water quality changes of inland and trans-boundary lakes in Kenya, Malawi, Rwanda, Tanzania, and Uganda. Information relating to chlorophyll-a, lake surface temperature, and suspended matter is provided through a web-based decision information system. The system is being used to develop and support efforts to control pollutants which contribute to poor water quality.

SERVIR Global's service catalogue: <http://bit.ly/2RXvmtN>

4. Prediction of groundwater quality in India

ANN and Multiple Linear Regression (MLR) modeling are used in assessing the water quality index (WQI) of groundwater suitable for drinking, from the Shivganga River basin. The WQI is based on physicochemical parameters such as pH, EC, TDS, TH, Ca, Mg, Na, K, Cl, HCO₃, SO₄, NO₃, and PO₄. The model was successfully tested in the pre- and post-monsoon seasons and could be implemented in other regional locations to monitor groundwater quality.

Research paper discussing the algorithm and results: <http://bit.ly/2Pt7xZh>

5. Increasing safe drinking water using satellite data in Ghana

The Water Resources Commission in Ghana is using the Africa Regional Data Cube (ARDC) to assess and improve water quality in the Weija Reservoir, one of the main sources of freshwater for the city of Accra and its peri-urban areas. In this scenario, ARDC uses various algorithms, such as the NASA Chlorophyll-A detecting algorithm (Werdell, et al., 2018).

An online report discussing AI powered tool and its applications: <https://bit.ly/3bVS2kQ>

Opportunities and Foresight

- Cost-effective portable devices will be available, that can be attached to smartphones to analyze water samples in real-time, without the need of internet connection.
- Global AI model training data for all known water contaminants would be available under the open data framework.
- AI-IoT enabled water quality monitoring devices will be installed by end-users at households, restaurants, and public spaces to monitor known water contaminants. These devices will have the ability to detect viruses that are 100 times smaller than bacteria.
- It will soon be possible to measure and monitor the water quality for large water bodies using satellite imagery with higher frequency (daily or weekly) and accuracy.

Policy Recommendations

- National water and health policymakers should develop and update water quality monitoring frameworks to enable AI-based monitoring and forecasting of water quality at all spatial (large water bodies to households) and temporal (hourly, daily, weekly and monthly) scales.
- Policies should be framed to facilitate the development of national and regional open-access water quality databases, that contain the physical features and color patterns of all known water contaminants. An incentive based scheme should be introduced for local stakeholders, prompting them to install and manage measurement instruments.

Monitoring and Predicting Water-related Disasters

Water-Related Disasters (WRD) (cyclones, floods, and droughts) account for an overwhelming 90% of natural disasters. Since the year 2000 through to the end of 2018, a total of 5,338 WRD have been reported, leading to over 326,000 fatalities and economic losses of more than USD 1.7 trillion globally. Floods account for about 54 % of all WRDs (Perera et al., 2019). In 2018 alone, WRD have caused an economic loss of USD 137 billion (Podlaha and Bowen 2018). The magnitude of water-related economic loss is expected to increase yearly, due to the increasing frequency and intensity of severe weather events attributed to climate change, such as drought periods, heavy rainfall, and heatwaves.

There is an increasing need to advance the trend of AI adoption, to provide tools for water-related disaster forecasting, impact assessment, and societal resilience. These AI-based tools are powered by the large-scale transboundary water-related disaster data that is available under open-access.

Applications

1. Wet weather optimisation using AI in Ohio, USA

An AI-enabled wet weather management system combines meteorological data with real-time data from IoT on water levels, flow, and storage capacity across stormwater and combined sewer collection networks. This helps to monitor the utility network and optimise capacity during wet weather events, to reduce flooding and overflows.

Metropolitan Sewer District of Greater Cincinnati's project page: <http://bit.ly/35oxhLM>

2. Flood forecasting in India

Google, through its Google Public Alerts program in India, is using AI to issue flood alerts. The alert system uses data from historical flood events, river level readings, terrain, and elevation as the training data for its model. The system is also able to indicate the predicted severity of the flood.

Google's project blog on the flood forecasting initiative: <https://bit.ly/2XlQ4q6>

3. Flood forecasting with limited water level data in Japan

Fujitsu, under its Human Centric AI Zinrai, has developed an AI-powered flood forecasting system. Local governments in Japan are facing the challenge of flood damage because of localised heavy rains. These cloud bursts of concentrated downpour cause sudden water level increase in small rivers which run through urban areas. Current flood forecasting is limited to large rivers in Japan, as smaller rivers do not have sufficient water level sensor technology installed to monitor the water levels and flow. The Fujitsu system is able to overcome this bottleneck and can predict water levels at any given time, with the additional ability to forecast for several hours.

An online report discussing the tool, outputs and expected impacts: <http://bit.ly/38JfTn9>

4. Rapid Hurricane Assessment

NASA and Development Seed have developed a deep learning-based hurricane intensity estimator. The system uses satellite imagery as its training data to deliver live hurricane speeds. This allows NASA to prepare estimates for various agencies in the span of an hour, as compared to the previous 6-hour period. The system was recently used to successfully track Hurricane Harvey.

Research paper discussing the algorithm and its applications: <http://bit.ly/38NdPub>

5. Simulation system for assessing industry damage of flood

The University of Tokyo has developed a simulation system for assessing the damage to industrial supply chains after a large-scale urban flood. This simulation system is based on multi-agent deep reinforcement learning and helps companies to develop and optimise action plans to be executed during the recovery process.

Research paper discussing the algorithm and simulation results: <https://bit.ly/2xSDAvg>

Opportunities and Foresight

- Historical disaster data-gaps can be filled from satellite imagery inventories available at national and global levels.

- AI will be used to forecast water-related disasters with higher accuracy, frequency and lead time, allowing for focused management of post-disaster activities.
- AI will be used to generate rich information data streams for publicly available weather and disaster forecasts, including real-time depth, direction, and water speed.
- AI will be used to accurately simulate the impacts of water-related disasters. These simulations will be a critical to the development of mitigation strategies and resilience building measures.
- AI will be used by urban development and management agencies to better monitor and forecast water-related disasters accurately in urban environments.

Policy Recommendations

- Natural disaster management agencies and regional agencies working in the disaster management sector should develop policies to collect and publish historic water-related disaster data. This would provide critical training data to help improve the accuracy of AI models.
- National disaster management agencies should use AI to generate periodic risk maps. These risk maps should be based on dynamic databases, which continuously record how urban centers are evolving and growing.

Challenges and Suggestions

As listed above, adopting AI to achieve water-related SDG targets has numerous advantages and opportunities. However, there are also challenges that need to be discussed at various policy development platforms. This section lists the challenges and suggestions which can be used to initiate the policy dialogue.

Challenges

- There is a strong divide between the North and South hemispheres in AI-related knowledge generation and technology adoption for the water sector. Seven of the ten leading countries in AI and water-related research are developed countries. No country from Africa is featured on the list. There is also a lack of knowledge and skill sharing among countries at the regional level (Mehmood, 2019).

- There is a lack of engagement, awareness, and prioritisation by local governments, regional agencies, and academia to promote and use AI for water-related challenges. This lack of initiative is driven by the industrial-era perspective present in the majority of organisations responsible for developing or adopting innovative solutions. This structural limitation is the major constraint regarding the acceptance of positive disruption by AI on workflows (Abbosh et al., 2017).
 - Lack of capacity building policies and measures to generate human resources which are proficient in AI as well as are water-domain experts is one of the most common constraints being faced in developing nations. There is also an absence of platforms that facilitate cross-fertilisation of ideas between technologists, water domain experts, and the public sector at national and regional levels. However, most of the water-related issues that could benefit from AI based innovative solutions exist at regional and local levels (Markow et al., 2017).
 - There is a lack of resources and funding for AI-related innovations and solutions in the water sector. These include a shortage of upfront investment in infrastructure, hiring of experts, and re-training of available human resources (The International Development Innovation Alliance, 2019).
 - In the absence of an AI regulatory framework, decisions are being made at the individual level, resulting in knowledge and data gaps. This challenge is further propelled by a lack of understanding of AI capabilities in the water sector by policy or decision-makers, resulting in the development of solutions and decision making in silos (Paul et al., 2018).
 - A large quantity of quality data is needed to train AI applications. Water-related data capturing, storing, and sharing mechanisms are still lacking in the majority of the developing world. This is further complicated by a lack of data ownership and licensing related issues.
2. Knowledge portals should be established at national and regional levels to share AI knowledge relating to the water sector. These portals would help in facilitating partnerships and identifying future trends.
 3. Agencies and institutions should be encouraged to share trends and applications of AI in the water sector at political forums of sustainable development and national and regional sustainability reports.
 4. National capacity development and action plans should focus on intermediate and long-term goals to generate human resources in AI. These development plans should address knowledge gaps by initiating capacity development programs at higher education and vocational training institutes. These plans should also be structured around organisational models fit to facilitate digital disruptions and focus on pooling and sharing resources for capacity building programs.
 5. Academia should be integrated with the public-private partnerships of AI in the water sector, to ensure that developments in AI are demand-driven and cater to societal needs.
 6. Platforms should be established to facilitate dialogue between the government and industry sectors, academia, and civil society to develop holistic AI-based solutions that address water-related issues.
 7. Data gaps should be addressed by developing policies based on open-source frameworks. These policies should be transboundary in nature. The data should be managed in a decentralised manner, preventing the monopolisation of data and data-related services.

Suggestions

1. National and regional water agencies should develop regulatory frameworks and action plans to initiate and contribute to the development of AI-based solutions at various levels in the water sector.

POLICY RECOMMENDATIONS

This section presents a list of key policy recommendations to prompt the adoption of AI in the water sector at the national level. These policy recommendations are the primary output of this strategic foresight and can be used as primary guidelines for the development of strategies and plans to use AI to help achieve water-related SDGs.

AI models, tools, and technologies need localisation before adoption

Water-related challenges and opportunities vary by country and region, with varying levels of implementation capacity and available infrastructure to address the challenges and opportunities afforded by AI. Before adopting AI to address water-related challenges, it is important to conduct baseline studies to measure the implementation capacity, return on investment, and impact of the intervention. Policymakers should conduct a holistic assessment of social, economic, and cultural factors before AI adoption in water industries.

AI for water-based interventions need support to ensure development outcomes

To ensure positive development outcomes, policies regarding the use of AI for water-related challenges should be coupled with capacity development and infrastructure development policies. Capacity development policies need to address the AI and ICT needs for the skill development of all water-related stakeholders. These capacity development policies should also facilitate transdisciplinary and interdisciplinary research and development. Infrastructure development policies should address the underlying requirements of computation, energy, data generation, and storage. The sequencing of these policies is critical.

Facilitate cross-cutting collaborations

Water-related challenges are cross-cutting, running from grassroots to the global level. It is important for countries connected by major rivers and watersheds to collaborate in developing policies that advance the use of AI to address common water-related challenges.

Build a skilled workforce

To mitigate the predicted job displacement that will accompany AI-led innovation in the water sector, policies should direct investments towards enabling a skilled workforce by developing water sector-related education at all levels. This skilled workforce should be strategically placed to offset the dependency on the private sector. Employment opportunities for skilled workers in the water industry should expand in the public sector, to decrease dependency on the private sector.

AI for water-based interventions need flexible policies to adopt new models and frameworks

Policies should be designed to adapt to the new AI models and frameworks. Deep learning and generalised intelligence will facilitate the development of more efficient solutions that address water-related challenges. Policies should be flexible enough to adopt these advancements quickly. Conducting frequent foresight could help in developing such flexible policies.

Drive AI adoption and create enabling environment through a centralised agency

A council or agency with representation from all stakeholders should be constituted at the national level, to allow for the successful adoption of AI by water agencies. This council or agency should be tasked with the development of policies, guidelines, and codes of conduct for the adoption of AI in the water-sector.

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