

# Al holds water: A case for Al-enabled water management in agriculture

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#### **Executive summary**

This white paper aims to bring to the forefront compelling new opportunities for artificial intelligence (AI) interventions to address the major challenges smallholder farmers face in water management. Improved water management has the potential to profoundly impact their income and yield, and is ripe for technological innovation.

There are a number of major challenges faced by smallholder farmers in water management, including those related to water access, water use efficiency and water replenishment. The underlying decisionmaking mindsets and behaviors of farmers makes addressing these challenges so difficult.

From our research and analysis, we've prioritized two opportunities in water management where we believe AI has significant potential to help: 1) assessing the water balance and improving crop selection and planning; and 2) optimizing irrigation scheduling.

In the context of the first opportunity, AI helps assess the water balance through improved hydrological modeling, particularly groundwater and surface water estimation. A key benefit of an improved water balance assessment is the potential to improve crop selection and planning, at the farmer, community and regional levels. Applications of AI to water balance assessment are prevalent in research communities, and basic estimation techniques are demonstrating impact. Leveraging AI to drive better estimations can amplify impact, as the estimation would be more precise, easier to replicate, and less reliant on burdensome operational efforts for data inputs.

In the context of the second opportunity, we see multiple AI approaches to measure soil water, including directly via sensors and indirectly via a soil water balance assessment, which help evaluate how much water should be supplied via irrigation. The research community has been actively exploring how AI can use a mix of data inputs to inform irrigation schedules, via AI models that draw on this mix of data inputs. Furthermore, some of these data inputs can be themselves be significantly enhanced via their own AI models. The richness and diversity of research exploration of AI to irrigation schedulingin combination with private sector activity that is ready to scale–make this opportunity particularly compelling.

We conclude with reflections on the common enablers that are needed to accelerate the ability for the Al approaches we've described to achieve impact.

# Introduction

Smallholder farmers, those owning less than 2 hectares of land and owning 84% of farms globally<sup>1</sup>, are among the most marginalized in the world, living in extreme poverty with an average income of ~\$3/day, and at a poverty rate greater than the national poverty rate in low- and middle-income nations.<sup>2</sup> Their agricultural challenges are significant and well known, and ultimately converge on the unfortunate conclusion that incomes will rarely be sufficient to make the occupation lucrative, and that agricultural employment and livelihoods are viewed as a default rather than a choice.

A complex network of organizations and initiatives is involved in supporting farmers, aiming to find better ways to improve their lives. The specific actors vary by country, but typically include a mix of:

- 1. Private sector agricultural value chain players, including input providers, off-takers, aggregators and processors
- 2. Public programs, often delivered through foundations, NGOs, nonprofits and community-based organizations
- 3. Government programs, at national, regional and local levels, anchored in ministries responsible for agriculture, natural resources and rural development, and often in partnership with academia
- 4. Technology innovators, particularly agtech (and fintech) start-ups and social enterprises

All of these actors appreciate the role and potential of technology innovation to support their efforts to help smallholder farmers, but the penetration of technology within each varies. Many programs with greater reach and scale, such as those led by governments, large NGOs or large value chain players, or those in partnership with mobile network operators, often rely on simple apps, IVR or SMS-based advisory services. Meanwhile, agtech innovators are often experimenting with more sophisticated technologies, but struggle to reach farmers at scale.

Across the landscape of technological innovations trying to address the challenges faced by smallholder farmers, few have achieved large-scale impact on their livelihoods, often losing momentum in execution, delivery and scale-up, or overlooking their most pressing needs as their communities and environments change. The sector is saturated with technological solutions, but the potential for artificial intelligence (AI) lies vastly unexplored. The fundamental potential of AI lies in its ability to offer personalized services at scale and at lower costs, which is exactly what agriculture needs. By understanding the needs of smallholder farmers, by identifying the right levers in the system to address them and by gauging their potential pathways to impact, we can utilize AI to deliver robust and viable solutions that improve on many of the technological innovations we currently see.

With this goal in mind, we identified water management as an area that holds considerable promise to positively impact the lives of smallholder farmers. Proper water management can lead to increases in income and yields for smallholder farmers, making it an important driver of increased profitability. However, smallholder farmers lack the knowledge and tools needed for efficient water management across each step of their journey, including in the context of water access, water use and water replenishment. This leads to suboptimal water management decisions, leading to lower income.

Through this white paper, we aim to bring to the forefront compelling new opportunities for AI interventions to address the major challenges smallholder farmers face in water management. Through our research and a series of workshops we hosted with water management experts, we've prioritized two opportunities for AI in water management. These opportunities span the farmer journey and ultimately help farmers make better decisions that will improve their income and livelihoods.

- 1. Assess the water balance and improve crop selection and planning.
- 2. Optimize irrigation scheduling.

While these two opportunities have traditionally been viewed as difficult to solve, we believe AI has significant potential in each of them for impact, which we will highlight in the following sections. We will identify the specific challenges within each that AI is well positioned to solve, and also share examples from research and the real world to help make our case for AI's potential.

We hope that this white paper will be useful to a range of stakeholders that are vital in implementing AI solutions. Our aim is to get donors and investors who are interested in technology-related agricultural programs excited about AI possibilities, and generate enthusiasm amongst technology innovators who are curious in unlocking newer pathways for AI exploration in agriculture. We hope to reach agribusinesses and agricultural programs who are looking to incorporate AI-based water management solutions into their activities, and finally we wish to create a compelling case for governments to consider the potential of AI in water use policies and efficient water usage schemes. This white paper is the result of a collaboration between the Wadhwani Institute for Artificial Intelligence, IDH and Dalberg Design

#### The Wadhwani Institute for Artificial Intelligence

is an independent nonprofit institute developing AI-based solutions for underserved communities in developing countries. We co-create processes with diverse partners to scale our solutions widely and sustainably.

The IDH Sustainable Trade Initiative convenes companies, CSOs, governments and others in publicprivate partnerships, and drives the joint design, co-funding and prototyping of economically viable approaches to realize green and inclusive growth at scale.

#### Dalberg Design

partners with leading organizations to bring people to the table so they can design solutions to the challenges and opportunities that affect their day to day lives. We seek to advance creative potential-the capacity for creative problem solving and the human right to co-create solutions that address the needs of communities

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# Why water managment in agriculture?

Globally agriculture is the biggest consumer of water resources<sup>3</sup>; however only a fraction of the water diverted for agriculture is effectively used for crop growth, with the rest drained, evapotranspired or run off. The increasing global scarcity of water due to climate change and water depletion poses new challenges for food production, processing and preparation, energy, industry, other economic sectors, as well as our ecology and general livelihood. Accounting for 70% of global water withdrawal<sup>4</sup>, agriculture is both the cause and victim of water scarcity<sup>5</sup>, thus making it a crucial component in addressing the water crisis. The impact of improved water management is profound. Studies have shown improved water management can lead to a 42% increase in income and 50% increase in yields for smallholder farmers.<sup>6,7</sup> Moreover, the improvement in water management required to achieve this impact is quite reasonable. For example, studies have shown that under rainfed conditions, a 50% yield rise is achieved through just one supplementary round of irrigation in the dry period.<sup>8</sup>

#### 2.1 - Water management challenges

The threat posed by degradation of water resources on livelihoods dependent on agriculture is acutely experienced by smallholder farmers. They already face many challenges that contribute to difficulties in making the right agricultural decisions that benefit their farms and their families, including inconsistent access to markets, lack of quality inputs, poor agronomic training and support, limited access to labour, transportation and finance, and higher vulnerability to shocks. Water scarcity aggravates their challenges.

Globally, poor water availability and management are common causes for both low farm productivity (the performance of crops) as well as low crop intensity (the sowing of additional crops). Studies have shown that access to irrigation can increase farm productivity by up to 40%, and even higher for certain crops such as wheat.<sup>9</sup> Yet in Africa, only 6% percent of the total area of the region is under cultivation, and of this cultivated area, only 6% is under irrigation.<sup>10</sup> In India, due to low crop intensity caused by lack of water for harvesting, 60% of agricultural land remains unused for 4-6 months.<sup>11</sup> Unarguably, better water management in agriculture is pivotal to increase farmers' income. In order to cultivate crops, a farmer needs to first gain access to water, which helps them plan their crops appropriately. Thereafter, they need to water their crops efficiently, during crop cultivation. And finally, a farmer needs to consider replenishing water for the next cropping cycle. Across this journey, there are several challenges that smallholder farmers face. While farmers understand that water issues affect many of their agricultural decisions, they struggle to understand the impacts of water issues on profitability in a precise way, leading to suboptimal water management behaviors and practices.

#### Key farmer challenges in water management

#### Water access

- Lack of accessible data on weather prediction
- Low monitoring of groundwater depletion
- Lack of aquifer and groundwater mapping
- Unavailability of timely water
  resources (e.g., canals, borewells)

These challenges prohibit smallholder farmers from understanding the availability of water, thus impacting their crop planning and irrigation. Smallholder farmers are also highly vulnerable to the shocks from increasing yet unpredictable droughts and floods inflicted by climate change.

#### Water use efficiency

- High dependency on water heavy crops
- Lack of information about sustainable irrigation practises
- Inability to track water consumption

These challenges make it difficult for smallholder farmers to adopt efficient means of water use, such as borewells and irrigation products. In the absence of reliable information about irrigation efficiency, farmers look at broad historical patterns and community precedent which are often inaccurate.

Water replenishment

- Lack of information about sustainable practices amongst farmers, such as rain-water harvesting
- Low efficiency of government schemes to promote such practises
- Lack of infrastructure needed to implement sustainable practices

These challenges result in farmers making decisions on water usage without consideration for seasonal replenishment patterns, leaving them unprepared to deal with erratic weather conditions due to climate change.

Addressing these challenges can maximize income potential and profitability, but farmers don't make decisions based on precise income and profitability assessments or calculations, for several reasons summarized in the figure below. For any water management solution to truly help smallholder farmers, we must understand and account for the behaviours that influence their decision making process.

#### Anchoring on quanitifiable drivers Historical patterns Smallholder farmers' outlook for profitability typically Farmers' decisions are strongly influenced by their emphasizes more easily quantifiable drivers (e.g., prior experience (including any agronomic training market prices, labour costs, transportation/off-taking they may have received). For example, those who have costs, processing/aggregation costs) over drivers that experienced shocks in past seasons (e.g., droughts, are harder for them to quantify (e.g., weather, water, soil pests, diseases) will make agricultural decisions that conditions, pest and disease risk, etc.). This prevents reduce their risk of exposure in the current season. This them from adapting a macro approach in planning their leaves smallholder farmers unprepared to face the rise crop cycles. in unpredictable weather patterns or address the more complex challenges. **Community precedents Government and agricultural recommendations** Farmers' decisions are strongly influenced by the Farmers' decisions are also strongly influenced by behaviors and practices that are popular in their government policies and programs that may be communities. These are shared and communicated relevant to their circumstances. Farmers trust that through village governing bodies, farmer organizations these recommendations are grounded in the right (collectives/coops/SHGs), extension service providers, rationalization, but rarely have visibility into the agro-dealers, community-based organizations, or underlying assumptions or thinking. Some of these community-level NGO programs. These decisions are policies and recommendations, despite having good often not based on rigorous assessment of benefits and intentions, may not be based on recent scientific rationale, data or analysis. Farmers are also influenced by input providers, agro-dealers and retailers, particularly those in their local communities who they trust, but similarly, their recommendations are also rarely based **Bias towards individual short term benefits** on the rigorous scientific rationale or analysis. Due to stringent resources and lack of appropriate planning tools, farmers prioritize maximizing their short-term, individual benefits over longer-term, collective group benefits.

# The case for AI in water management

#### 3.1 - What is AI?

Artificial Intelligence (AI) refers to the ability of a computer program to perform tasks commonly associated with intelligent beings. AI solutions attempt to provide smart recommendations or predictions based on the inputs provided to them. These inputs can take many forms, including time series data like rainfall patterns, farmer's past yields, and images, amongst others. Similarly, the outputs can be recommendations or predictions that can take many forms, such as forecasts for next year's rainfall, yield projections, or objects detected within an image.

Standard computer algorithms take inputs to produce the required outputs using a logical model. For example, the profit of a business is calculated using revenues and costs across business streams. These revenue and cost inputs feed a logical model that produces the output, the profit.

Artificial Intelligence is a type of algorithm that learns to create this logic from data. For example, historical rainfall and other meteorological data are routinely used to train models to forecast weather. In agriculture, images of pests are used to train models that are able to detect and classify the type of pest. This training enables AI to translate new data into new insights.



The power of AI lies in its ability to scale exponentially, yet in a targeted way. If there are countless variations of individual images of pests on a farm, countless standard algorithms would be needed to account for all of them. But an AI algorithm would find patterns across images and be able to identify the specific pests in a given farm based on a new image that had never been seen before. Similarly, offering hyper-local weather forecasts would be impossible using standard algorithms, as they would need to account for the individual conditions of every location. But an AI algorithm could identify patterns to be able to make predictions at any level of granularity. For these reasons, the advent of AI in agriculture is a game-changer.

#### **Data inputs**

Al algorithms learn to make decisions by being trained on data, which can come from any number of sources. This data should carry sufficient information about the expected output. Better data leads to better outputs, which means data needs to be accurate, available at required frequencies and levels of granularity, and diverse. Al algorithms' performance is always as good as the quality of the data used to train them.

In water management, certain data inputs like groundwater levels and rainfall have several publicly maintained datasets, but these are not always available at local levels (i.e., only at state / village levels), and are often tracked less frequently (quarterly or yearly).

More generally, agriculture is a data-rich field, but the data is difficult to effectively access and use: it is often siloed in private organizations, its quality is inconsistent, and data sharing arrangements are limited. Al innovators often must develop new approaches to data collection to train their models, which can be time-consuming and operationally difficult. Technologies such as remote sensing and IoT have bridged gap by providing real-time soil and weather data, although IoT hardware is not affordable by poor farmers.

#### **AI algorithms**

AI systems take data as inputs, and train on them to create meaningful outputs. There are various types of AI algorithms, but the one that's used most extensively is called "supervised learning". In supervised learning, data is labeled with descriptors that it wants the machine to learn an association about. For example, the image of a pest trap is labeled with the type of pest it contains; the algorithm then learns to associate that pest with latent qualities of the image, such that new images with similar qualities can be automatically labelled as also containing that type of pest. In supervised learning, the aim is to train the AI algorithm to predict the label from the input signal using many inputoutput pairs. To get an AI algorithm to perform as desired, usually a lot of data is required, which is often a bottleneck to build AI algorithms in agricultural contexts. Another challenge is annotation, which is the creation of the inputoutput pairs in the data for the model to learn. Continuing the pest example, in order for the AI algorithm to detect a type of pest, they are first trained with tagged pest images. The tagging of images involves locating the pests on the image and naming them. This tagging is a manual task, which can be costly and error-prone.

#### Outputs

What emerges from an AI algorithm is an output that has the potential to be used to improve insights, analyses, forecasts, or recommendations that help make better decisions. In practice, this output typically forms a part of a product such as an app, website or tool, which can be used by farmers and other various stakeholders to make much smarter decisions.

Making an AI-based product useful and accessible can also be a challenge, like many technological innovations. Many farmers still don't have smartphones. Connectivity remains a recurring challenge, particularly in remote rural areas. Deploying AI-based recommendation systems in high-stakes agricultural decision making also introduces challenges of inexplicability, biases and trust, particularly if recommendations deviate from historical practice and precedent.

#### 3.3 - How can Al improve water management?

We have prioritized two opportunities for AI in water management which ultimately help farmers make better decisions that will improve their income and livelihoods:

- 1. Assess the water balance and improve crop planning
- 2. Optimize irrigation scheduling

We have selected these due to the potential of AI to overcome some of the key data issues within each, specifically by helping to make better use of more accessible data. AI also has the potential to aid the process of estimation through some level of automation, thereby improving the quality of the emerging insights, recommendations and forecasts in a way that directly and materially benefits farmers, eventually at scale. Recognizing AI is still a very experimental field, we've also selected these opportunities based on AI activity in each. The first opportunity is being actively explored in research communities worldwide, showing strong promise though early evidence in lab settings. We foresee this activity accelerating into more pilots and real-world experiments. The second opportunity is more mature, with a handful of case studies demonstrating impact at limited scale, which is an indicator of broader market potential. We envision accelerating these into more programs and initiatives worldwide.

# Opportunity 1: Assess the water balance and improve crop planning

Water balance assessment, also known as water budgeting, is an approach that helps decision-makers plan around water deficits or excess based on an understanding of the historical, current and predicted water availability and requirements in an area. It is used at several levels of decision-making around water resources, including at village, district, state and national levels.

Numerous stakeholders are typically involved in calculating water balance assessments. Agricultural and environmental research communities play a central role. For example in India, organizations such as the Madras Institute of Development Studies and the University of Calcutta have attempted to build water budgets on district levels through research projects. However, these efforts and are not easy to scale across geographies and replicate across different time periods.<sup>12</sup>

Not surprisingly, numerous studies show that there is considerable local variation in water resource availability and use.<sup>13</sup> Accurate water balance assessments are helpful in multiple ways. For farmers, they help inform crop selection and the potential for multiple crops. For villages and districts, they help plan locations and community engagement around shared resources such as farm ponds. For states, they help inform crop plans, irrigation projects and farmer incentive schemes, in addition to supporting other needs like fishery planning.

#### 4.1 - The challenge of assessing the water balance

There are several challenges in carrying out a water balance assessment. To understand them, we must first understand the process of calculating the water balance.



The water balance is dictated by the water availability and requirements of a certain region. Sources of water could be either from the surface, groundwater, or rainfall (which recharges groundwater or surface water). After estimating availability, requirements of industrial and domestic use are estimated and subtracted from the available water to determine the water availability for agriculture.

In summary, the water available for agriculture = available groundwater + available surface water domestic requirements - industrial requirements.

Techniques for estimating the water balance range from simple 'back of the envelope' estimates to highly complex computer-based models. Accurate estimation requires a sound knowledge of hydrological models and access to quality-controlled data inputs.

For example, one common method called SCS-CN (Soil Conservation Service - Curve Number) requires parameters such as soil texture, land use and land cover, antecedent moisture condition, slope, and rainfall to estimate surface runoff depth. These are often sampled across a period of time from certain locations, and therefore may not adequately portray the picture for an entire region. Additionally, many processes for collecting this data are still operational, timeconsuming, and require manual interventions which are prone to human error, making them unscalable.

Another approach to estimate groundwater availability called the WLF (water level fluctuation) method measures fluctuations in depth to groundwater between rainfall events. This approach relies on extrapolating data from numerous groundwater measurement sites (e.g., 105 distinct sites for a research study in West Bengal<sup>14</sup>). This approach has significant data quality concerns, as data collection is not automated, piezometric sensors are expensive to install and maintain across sites, and travel by government bodies to visit sites is time-consuming and expensive.<sup>15</sup>

There are three main challenges faced in the calculation of the water balance:

- 1. It is a complex process, requiring the expertise of scientists to be carried out effectively.
- 2. There is a lack of high quality, localized data inputs that make the water balance assessment relevant for a certain area.
- 3. The process is time-consuming, operationally heavy, and difficult to scale or repeat.

These challenges are quite significant, but not impossible to overcome. We believe that AI can help.

#### 4.2 - How can AI help assess the water balance?

Recently, a significant amount of research has been carried out into the development and application of AIbased techniques for hydrological modeling. Hydrological modeling seeks to understand complex, dynamic and nonlinear systems, where the underlying physical relationships are not fully understood and the available data are noisy, incomplete and/or unquantifiable. As such, AI techniques may provide a promising alternative, or complement, to traditional process-based or statistical type of approaches.<sup>16</sup>

#### AI to estimate groundwater availability

The knowledge of groundwater table fluctuations is important in agricultural lands as well as in studies related to groundwater utilization and management levels. With the help of a time series model created with algorithms called SVMs (support-vector machines) and ANNs (artificial neural networks), South Korean researchers forecasted groundwater level in wells near coastal regions. They used previous data on groundwater levels, tide levels and precipitation as vectors. Water table levels, rainfall and evapotranspiration data across a period of 8 years were used to train and test the models. They found that their models could be employed successfully in forecasting water table level fluctuations up to 7 days beyond data records.<sup>17</sup> Such forecasts can help ease the complexity of water balance assessment calculations.

#### AI to estimate surface water availability

Applying AI models to remote sensing or satellite imagery data has come a long way in helping to solve the data availability challenge. Remote sensing data coupled with modelling is now able to provide highly accurate, frequent and localized inputs on several weather and soil parameters. For example, researchers at University of Texas, Austin, have been able to leverage deep learning and LandSat images to predict surface water availability through computer vision and convolutional neural networks. The model was tested globally and focused on its ability to learn features at the global scale; independent of the type of terrain and the atmospheric conditions.<sup>18</sup>

These applications of AI to estimate groundwater and surface water availability are quite fertile areas of research, with numerous such examples of successful algorithms emerging worldwide. We believe this demonstrates strong potential for pushing these algorithms further toward real-world solutions, incorporated into products, services, programs and policies at larger scales. Crop selection and planning today is strongly informed by ease of access to markets and sales prices, as these are core drivers of income. Farmers want to maximize their profits, so tend to choose crops that require lowercost inputs and that are higher yield. However, there is an imprecise understanding of profitability given the range of factors that influence yield volume, costs and market prices. **The influences of water availability, quality and usage are often overlooked, as they are hard to measure or understand precisely.** 

Farmers select crops based on their rainfall expectation from regional forecasts and historic precedents, but do not account for microclimate variations on their farms, or consider climate change inflicted weather changes such as drought or floods that increase or reduce access to rain water. Irrigated farmers select crops depending on their understanding of the irrigation needs; however they don't have an understanding of their actual water use during irrigation, sustainability of irrigation sources such as borewells, their actual recharge potential, or the cost of powering irrigation solutions. Such issues tend to result in individualist biases such as not pursuing a second crop and taking up water-guzzling crops with short term benefits. Often, traditional and community practice also dictate what farmers choose to grow in a season, which helps reduce the perceived impact of poor crop selection, masking it in a community decision.

Better water balance assessments that are available and updated regularly-every season at a minimum-could improve their crop planning. On a farm level, farmers could choose their crops better, and have a view on ability to harvest a second crop in a year. On a district level, village panchayats could plan communities activities to save water. Regional governments can plan activities like local seed distribution and acreage per crop based on the water balance. They may also explore incentive schemes, such as credit plans to promote specific crops in partnership with lending institutions, or direct-to-farmer / direct-to-coop incentives to promote less water-thirsty crops.

#### CASE STUDY

FAQ's program in Andhra Pradesh - The impact of water balance assessment on crop planning<sup>19</sup>

<u>Challenge</u>: In Andhra Pradesh, farmers are plagued by recurrent drought year after year. They have been drilling deeper and deeper for water to support cultivation of thirsty, high-value crops promising greater returns but involving greater risks. Agriculture has become increasingly water-intensive and expensive. A key to solving this problem is to enable rural communities to understand the groundwater system so they can deliberate among themselves and make appropriate decisions, leading to better investments and efficient management of their water resources.

<u>Solution approach</u>: Crop-water budget exercises can be carried out every year by farmers themselves to reduce risks of crop failure and identify opportunities for sustainable production. Groundwater management committees (GMCs) within a hydrological unit come together and work out an appropriate cropping system given their estimate of the total groundwater resources available. Under this system, crop-water balances are prepared and farmers take action depending on the groundwater deficits. The Food and Agriculture Organisation pioneered this approach in 2006 in the state. Under this pilot, farmers met every 15 days to discuss topics such as hydrological measurements, water recharge, water availability and appropriate cropping systems, water use efficiency, organic farming methods, institutional linkages and gender issues in water management.

Results: Farmers witnessed at least 33% water savings in some areas.

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Applications of AI to water balance assessment are prevalent in research communities, and basic estimation techniques are demonstrating impact. Leveraging AI to drive better estimations can amplify impact, as the estimation would be more precise, easier to replicate, and less reliant on burdensome operational efforts for data inputs. AI researchers should work with groundwater management committees to source better data and leverage remote sensing approaches, for example, to help accelerate the benefits of improved water balance on crop planning and other areas.

# Opportunity 2: Optimize irrigation scheduling

Irrigation scheduling is the process of determining the optimal time to water crops and the optimal quantity of water to be used during irrigation. Every crop has a set of agronomic practices, which explain how much water is required at each crop stage. These have been documented and are generally available to farmers via local service providers, but farmers also use their intuition and traditional, community knowledge to water their crops. For example, they may touch the soil to feel the moisture content and provide water accordingly.

Limited understanding of the correlation between irrigation patterns and profitability drivers hold farmers back from making informed irrigation schedules. Like with crop selection, farmers tend to rely on historic evidence for deciding irrigation schedules. While past irrigation practices may be appropriate for some crops, even slight changes in seed varieties can require different irrigation approaches, leading to under- or over-irrigation. In some locations, such as states like Punjab and Haryana in India where irrigation and electricity are heavily subsidized, farmers routinely over-irrigate their fields, leading to low land fertility. Studies in India have shown that efficient irrigation can increase yields by up to 40% and decrease water use by 20-30%.<sup>20</sup>

Irrigation also has a significant collective action problem. Farmer organizations such as collectives, coops and SHGs make group decisions on irrigation strategies, timelines and quantities that individual farmers using shared irrigation resources are supposed to adhere to. But in practice, farmers are not incentivized to irrigate for collective benefit, so tend to over-irrigate their own farms using limited water resources.

#### 5.1 The challenge of optimizing irrigation scheduling

The process of irrigation scheduling typically involves two approaches, both of which start by attempting to measure soil water. Monitoring a farm's soil water level helps evaluate how much water should be supplied via irrigation at each stage of the crop lifecycle to maintain balance.

Approach 1: The first approach is to directly monitor soil water by using soil moisture sensors.

Approach 2: The second approach is to use other data sources (such as weather data or crop stage) to estimate for soil water in the rooting depth by a soil water balance approach.

This approach is usually referred to as weather-based or evapotranspiration (ETc)-based irrigation scheduling (or more simply, the water balance method). After

determining the soil water, parameters such as soil texture, soil structure, soil moisture and evapotranspiration are used to define the infiltration rate of water in the soil. These in turn inform the *field capacity*, when the water and air contents of the soil are considered to be ideal for crop growth, as well as the *permanent wilting point*, when the soil water content is at the stage when the plant dies.

This science has been brought to market by several agtech start-ups who provide solutions for precision irrigation e.g., Vinsense, Jain Irrigation, Netafim etc. They use the first approach, deploying sensors to estimate water requirements. Such systems, though promising, are difficult to scale given the investments required, mainly due to the cost of sensors and their installation and maintenance. The second approach requires extensive data collection and is at best, an estimate and hence often less precise. The University of Minnesota has created spreadsheet models to help farmers do this themselves.<sup>23</sup> Farmers need to monitor the crop's growth, identify soil textures in the rooting zone, observe and log the maximum air temperature each day, measure and log the rainfall or irrigation applied to the field, and then the model calculate evapotranspiration and water deficit. But such models require farmers to monitor field parameters manually 3 times a week, and be proficient in technological skills. Additionally, these are estimates and are often affected by weather conditions more than what it accounts for.

#### 5.2 How can AI help optimize irrigation scheduling?

As discussed earlier, there are several data inputs required to make a decision on when and how much to irrigate. The role of AI is fundamentally one of using a mix of data inputs to inform irrigation schedules, as visualized below.



The research community has been very active exploring AI applications to irrigation scheduling.<sup>21</sup> As examples:

- Data on soil moisture, soil type, product type and time interval were used as input parameters for an Artificial Neural Network which was trained to provide outputs that determined the water requirement of the plant and the irrigation time intervals. The system was tested in a strawberry orchard of 1000 m2 in the Serik district of Antalya, Turkey. The trial achieved a 20.46% water saving and 23.9% energy saving.<sup>22</sup>
- 2. Researchers in New Zealand built a model that uses daily rainfall and potential evapotranspiration (PET) estimates to predict changes in the water content in two overlapping soil zones. By validation against 11 historical data sets, the model was shown to give accurate predictions of soil water deficit across a range of New Zealand flat-land pastoral soils. The model parameters can be easily estimated from commonly available soil properties (soil order classification, and available water holding capacity) without the need for additional site-specific calibration.<sup>24</sup>

AI-inspired irrigation scheduling is also seeing real-world commercial application, an exciting development for the field. One such case study is shared below.



#### GramworkX - IoT data to provide irrigation schedules<sup>25</sup>

<u>Challenge</u>: Weather and water are important aspects that impact yields. However, farmers are restricted by scant data and a poor decision support system. For example, farmers use drip irrigation technologies to improve water use efficiencies, yet they do not know when and how much to irrigate.

<u>Solution approach</u>: GramworkX developed an IOT- and AI-enabled smart farm resource management tool, which helps farmers guide, optimize and monitor utilization of water. This device reads critical farm parameters such as atmospheric temperature, pressure, humidity, rainfall and soil moisture every 10 minutes, which it sends to the cloud on an hourly basis. A machine learning algorithm then provides irrigation and other predictions available to farmers through a mobile app.

They measured irrigation requirements across 2 regions for the same crop (tomatoes), and studied growth across two fields (with drip irrigation and similar acreage) in AP and MH, to understand irrigation requirement patterns and any difference caused by weather parameters. The study showed that water requirements in MH were higher based on modeling of temperatures and wind speed.<sup>26</sup>

Results: The solution has scaled across 6 states in India.

A second opportunity for AI in irrigation scheduling is to help with data challenges. The lack of localized, cheap, high resolution, high frequency, and accurate data are common challenges that restrict scaling of solutions. AI can identify soil type and texture or estimate water volumes in wells or ponds from smartphone images. Remote sensing approaches can be used to identify soil moisture levels, detect vegetation, measure groundwater levels and predict weather. For irrigation scheduling purposes, AI models typically need multiple data inputs, some of which themselves can be significantly enhanced via their own AI models, as depicted below.<sup>27</sup>



A handful of AI innovators have also developed solutions that are on the market in various countries, one of which we've described below. Although these have not achieved true scale yet, they have advanced beyond the research ecosystem.

#### CASE STUDY

Conserwater - Using remote sensing data to model soil moisture<sup>28</sup>

<u>Challenge</u>: Farms need more frequent advisory on irrigation, and other soil nutrient deficiencies. Sensors require capital investment and maintenance, and aren't scalable across farmers.

<u>Solution approach</u>: ConserWater uses satellite data, weather data, topography, and other factors along with geospatial deep learning techniques to predict irrigation water needs to the level of accuracy of soil sensors. They use a variety of public satellites (NASA, ESA, JAXA) and private satellites, with wavelengths ranging from UV to radio waves.

Results: The performance of the solution was measured against soil sensors, as well as soil moisture estimation techniques. Its irrigation schedules showed more effectiveness during these trials. The solution has now scaled across 8 countries (USA, India, Israel, Mexico, Brazil, Kenya, South Africa, Indonesia, Australia).

The richness and diversity of research exploration of AI to irrigation scheduling in combination with private sector activity that is ready to scale make this opportunity particularly compelling. We see a large opportunity area in using AI to replace or account for hardware sensors and serve as data inputs. Several companies have started using remote sensing data (e.g., Fasal, ConserWater), seeing significant scope in optimising for resolution and accuracy of the predictions provided.

There are complementary areas of AI and irrigation exploration that lend further weight to this opportunity. For example, smartphone-based spectrometry for soil texture and soil nutrients is an upcoming field and large opportunity area. Fertigation, the addition of fertilizer and mineral inputs into irrigation systems, is another burgeoning field within the irrigation space, and one where AI has already demonstrated its ability to have impact<sup>28</sup>.

## Conclusions

For each of the water management opportunities we've described, we see strong potential for AI-based innovations to help solve the underlying data issues and offer more targeted, personalized and relevant insights and recommendations to improve the lives of farmers. But for any AI innovation to come to life and achieve impact at scale, we need an ecosystem that creates the right conditions for success, and will need to commit to a range of investments and efforts to help the ecosystem get there. A number of common enablers will accelerate the ability for the AI approaches we've described to achieve the impact we strive for.

#### **Participatory data acquisition**

Water management in agriculture lacks data that is reliable, timely and sufficient, the lynchpins for successful Al solutions. We need to explore new approaches for data acquisition by enabling crowd-sourced and participatory mechanisms, which can help collect "ground truth" data needed for AI models. For example, farmers could be provided with low-tech tools and the required training to gather groundwater data through participatory mapping (e.g., via farmer-friendly piezometre tubes) and to assess soil moisture (through soil testing kits or sensors). Local officials can be better incentivized to track borewell usage. Hyper-local data on rainfall and other weather indicators can be made available through various remote sensing technologies.

#### **Evolved technology environment**

There is a need to facilitate access to the collected data by developing agricultural data stacks or hubs to consolidate agricultural data owned by government bodies, programs and private companies. We need a new set of policies and frameworks for data ownership, privacy and protection and should create incentives and build infrastructure for sharing information (e.g., public/private clouds with appropriate computational capacity). For example, Ethiopia's ATA (Agricultural Transformation Agency) and Kenya's KALRO (Kenya Agricultural & Livestock Research Organization) are investing significantly in development of agricultural data hubs consolidating their own data, global data sets and local partner data to better support technology innovation across the ecosystem.

#### **Better farmer adoption**

To increase uptake amongst farmers, we need mechanisms to build trust and awareness about new technologies and their potential to create impact for their farms and livelihoods. Innovations need to be grounded in the realities of smallholder farmers lives and their immediate context to be relevant and convincing to farmers. New technologies should account for low literacy and access, with due consideration for appropriate delivery channels. Incentive mechanisms can be put in place to overcome low willingness to pay and make solutions affordable. The complete farmer journey around any product or solution, from awareness to onboarding to sustained engagement, needs to be carefully designed and choreographed. Numerous agricultural innovators worldwide have been leveraging human-centered design and behavioral design methodologies to ensure new products, services and programs account for these concerns. For example, Safaricom's DigiFarm bundled service platform in Kenya, Kheyti's greenhouse offering in India, and myAgro's layaway-based input solution in Senegal have all used farmer personas and journey mapping approaches to help refine and focus their product offerings to drive greater reach and engagement.

#### **Building viable solutions**

For solutions to scale and secure the required financing, more efforts are required to demonstrate their value proposition, business case and commercialization potential. Partnership models such as PPPs, donor-driven innovation support and market strategies such as product bundling should be employed across the agtech ecosystem to bring AI solutions from the research community to market. For example, the New Zealand irrigation scheduling model shared above shows strong potential for public sector partnerships to expand reach and integration into innovative private sector services.

As with any new technology innovation, getting these enablers right will take time and effort. We hope collective action across the ecosystem will help accelerate the process of converting AI in water management from research experiments to real-world impact. Donors, technology innovators, agribusiness and agricultural programs, and governments all have the role to play in making this happen.

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