Democratizing Data-Driven Agriculture Using Affordable Hardware

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The world needs to sustainably grow more food to feed the growing population of the planet. Data-driven agriculture is a promising technique that can help farmers be more productive, reduce costs, and enable adoption of sustainable agricultural practices. However, the adoption of data-driven agriculture is limited by a lack of affordable technologies, for broadband, sensing, imaging, and insights. In this article, we present an overview of Project FarmBeats, a research project that started in 2014 to increase the adoption of data-driven agricultural practices. We provide an overview of the various components of the FarmBeats architecture, and details of the hardware innovations.

The world's food production needs to increase by 50% by 2050 compared to 2010 levels to feed the growing population of the world.[1] Meeting this demand is challenging, given the limited amount of arable land, reduced quality of soil health, and receding water levels. This problem is even more severe if we consider the challenge of nourishing the world, instead of just feeding the world, without harming the planet.

One of the most promising approaches to address this challenge is data-driven agriculture. Using the latest advances in artificial intelligence (AI) and cloud computing, a farmer can be issued advisories, such as when to sow seed, and what pests are likely to occur in their farm. They can then use precision agriculture techniques to selectively apply farm inputs, such as water, nutrients, and pesticides. These advances will help the farmer become more profitable, reduce costs, as well as practice sustainable agriculture. This will also drive farm employment in the farm and the digital advisory ecosystem. According to the International Food Policy Research Institute, data-driven techniques can help us achieve this goal by increasing farm productivity by as much as 67% by 2050 and cutting down agricultural losses.[2]

Data-driven agriculture requires information about the farm. This is obtained from a variety of sources, including sensors, drones, tractors, weather stations, and satellite imagery. Field trials have shown that techniques that use sensor measurements to vary water application in the farm at a fine granularity (precision irrigation) can increase farm productivity by as much as 45% while reducing the water intake by 35%.[3] Similar techniques to vary other farm inputs like seeds and soil nutrients have proven to be beneficial. More recently, the advent of aerial imagery systems, such as drones, has enabled farmers to get richer sensor data from the farms. Drones can help farmers map their fields, monitor crop canopy remotely, and check for anomalies. Over time, all of these data can indicate useful practices and make suggestions based on previous crop cycles, resulting in higher yields, lower inputs, and less environmental impact.

While these techniques are promising, their adoption is limited to less than 20% of farmers, even in the United States, owing to the high cost of manual sensor data collection.[4] The adoption is much more limited in the low- and medium-income countries, where most farmers are smallholder farmers.[5]

One of the primary reasons for limited adoption of digital agriculture technologies is the cost of these solutions compared to their value to the farmers. Good-quality agriculture sensors cost over a few hundred dollars. Drones with cameras are commercially available for

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over $1,000. The network connection itself is expensive. Over three billion people worldwide are not using the Internet even though they are in coverage range. The challenge is compounded by the paying capacity of the farmers, who are severely financially constrained. More than half of farmers in the United States need a second income to stay afloat.[6] The situation is more dire for smallholder farmers. An average farmer in Sub-Saharan Africa makes less than $2 per day.[7]

In this article, we present a holistic approach for building a more affordable data-driven agriculture system. First, to reduce the cost of sensors, we are exploring new modalities of sensing, such as RF sensing, and ways to reliably use low-cost sensors. Our work, called Strobe, leverages Wi-Fi on existing smartphones to sense soil moisture and soil electrical conductivity (EC).[8] In another work, we propose the Fall-curve[9] to detect sensor failures. Second, for aerial imaging of small farms, we use tethered helium balloons as an alternative to more expensive drones.[10] Third, we reduce the number of sensors needed in a farm using multimodal AI. By combining aerial imagery and on-ground sensors, we need much fewer sensors to build heatmaps of farms.[4] Fourth, we reduce the cost of connectivity by leveraging a communication technology that uses empty TV spectrum to carry wireless signals.[11] Finally, instead of sending all the data to the cloud, we use edge computing—a computer in the farmer's house or office that is capable of operating offline.

> *IN THIS ARTICLE, WE PRESENT A HOLISTIC APPROACH FOR BUILDING A MORE AFFORDABLE DATA-DRIVEN AGRICULTURE SYSTEM.*

The above mentioned technologies were developed as part of the FarmBeats research project at Microsoft. The goal of FarmBeats is to democratize data-driven agriculture, such that any farmer can augment their knowledge of the farm, with data, and data-driven insights. As part of this initiative, we are developing new technologies, spanning AI, cloud, data, IoT, edge, robotics, networking, and hardware, to make data-driven agriculture more affordable. In this article, we will discuss the innovations in hardware, and the open questions.

DATA-DRIVEN AGRICULTURE: EXISTING APPROACHES AND CHALLENGES

Perhaps the biggest innovation in the last century, which led to the Green Revolution, is the use of genetic engineering. For example, genetically modified organism (GMO) soybean seeds are genetically engineered to handle pesticides better, and can also be planted much closer to each other. Although these innovations have helped, further increase in yield is needed to meet the growing demand.

Data-Driven Agriculture

Data can augment a farmer's knowledge about their farm, and AI on that data can provide insights to the farmer. A promising data-driven technique is precision agriculture, which treats the farm as heterogeneous (land, livestock, fisheries, etc.), and uses variable treatment throughout the farm, such as variable seeding, fertilizer application, lime application, irrigation, feeding, among others. Precision agriculture is good for the overall farming ecosystem. It improves yield, reduces operating expenses, and is also good for the environment. For example, by only irrigating areas that need water, the farmer gets a healthy crop, and by not using water where it is not needed, the farmer saves money, while preventing surface runoff, and nutrient leaching. Similarly, by applying fertilizer only where needed, the farmer saves cost, and limits the damage caused by overfertilization. For livestock, adapting the feed for each animal using precision nutrition can help increase productivity for meat or dairy.

In addition to precision agriculture, data can also help a farmer with other digital advisories, such as planning what to grow, when to plant seeds, and when to harvest based on market prices and logistics overheads. Data-driven agriculture can also help a farmer create the right market linkages, provide access to financial tools and insurance, and help with agricultural research and development.

Data-driven tools can help farmers adapt to climate change. Farmers take a lot of actions based on past weather conditions. An unexpected change, either in temperature or precipitation, will significantly impact a farmer's yield. Data-driven techniques can predict these changes and provide timely notifications to the farmer. In addition, agriculture can be a potential solution to climate change, by helping sequester carbon in soil. However, this requires the use of regenerative agricultural practices, such as no till, or reduced till, cover cropping, and nutrient management. The use of digital technologies can help a farmer adopt regenerative agricultural practices, without sacrificing profitability.

Existing Approaches

Agronomists have studied various aspects of precision agriculture, from defining more accurate management

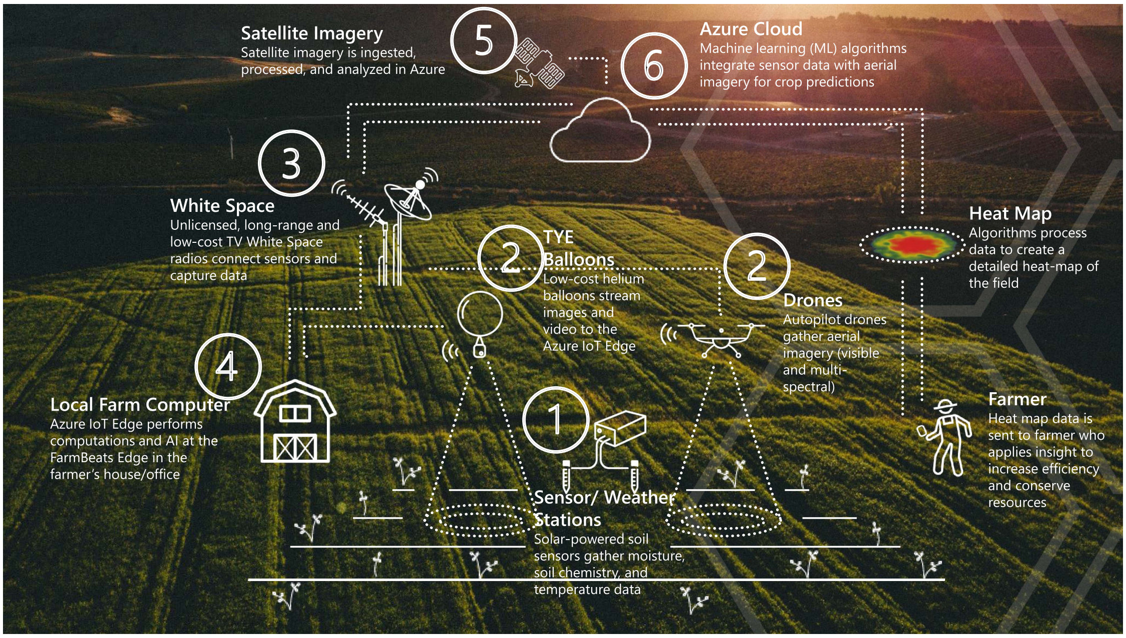

FIGURE 1. Different components of the FarmBeats research program. This includes innovations in hardware, systems, AI, computer vision, networking, and other research areas. In this article, we present the innovations in hardware.

zones, to improving prescription, to leveraging soil science, and plant physiology techniques. Remote sensing from satellite imagery and soil samples from the lab are the most commonly used data-driven techniques. Recent work has looked at technologies for gathering data from farms. Researchers have built specialized sensors, for measuring nutrients, water levels, and other such sensors. Practitioners have started using drones to get a spatial view of the farm, and mesh networks to gather data from sensors in the farm.

Challenges

We note that despite the promise of data-driven agriculture, it has not been widely adopted. For example, only 13% of small holder farmers in Sub-Saharan Africa have registered for digital services, and less than that are active.[12]

Even in the United States, precision agriculture is still in its infancy. The primary reason is cost and inaccuracy. Satellite data are sparse, with coarse spatial resolution, and lack temporal data below the clouds. On-farm data collection technologies are expensive to provide the return of investment (ROI) to the grower. Several commercial products build management zones, but they are often unable to capture the spatial and temporal variations in the field caused by climatic and soil variations. This variation is even more for soil organic carbon, which needs to be monitored for agricultural emissions and carbon sequestration.

FarmBeats: A PLATFORM FOR DIGITAL AGRICULTURE

FarmBeats was started as a research project in Microsoft Research in 2014, with a goal to enable data-driven agriculture. Since then, parts of the research have been shipped as a Microsoft product called Azure FarmBeats.[13] Organizations such as Land O'Lakes[14] and USDA ARS[15] have since announced partnerships on Azure FarmBeats for their agricultural products.

The FarmBeats research system is innovating on the end-to-end system for digital agriculture, as shown in Figure 1. We work with partners to prototype agricultural services for farmers. Given any farm, which could be a polygon or a shape file, the system captures large amounts of data about the farm, from a variety of data sources, including sensors, drones, tractors, cameras, satellites, and weather stations. This includes both temporal, spatial, and historical data. The system then uses AI to combine these data in new ways to fill in gaps, and make predictions of what is likely to happen in the farm. This abstraction is available via APIs to partners, who then use their detailed agricultural knowledge to develop agricultural insights for growers.

The research system described in Figure 1 works as follows:

1) *Sensors:* The system recommends sensor locations based on knowledge of the farm. These are regions where the farmer should place the sensors.

Our research includes ways to reduce the cost of sensing using Wi-Fi signals on smartphones,[8] and improve the fault tolerance of sensors.[9]

2) *Aerial imaging:* Drones are used to capture imagery from large parts of the farm, and to spray chemicals and water. We have researched ways to improve the battery life of drones, and intelligent path planning.[4] We have also invented a low-cost way to image farms using smartphones with battery packs mounted on tethered helium balloons.[10]
3) *Networks:* Since large areas in the farm do not have Internet access, and even if they do get a wireless signal reception, the connection is not affordable. We use a new technology that uses unused TV channels to send and receive data.[11] Antennas on a farmer's house or office send and receive signals over several miles, providing low cost, high-speed connectivity over long distances. In addition, we have come up with a new radio design for low-power, long-range, narrowband operation in the TV spectrum.
4) *Edge compute:* Not all the data generated in the farm need to be sent to the cloud. In some cases, it is extremely prohibitive. For example, a drone can generate several gigabytes of data in tens of minutes. Transmitting these data to the cloud over a few Mbps Internet connection will take extremely long. Instead, we perform large amounts of compute on a PC form factor device in the farmer's house or office.[4] We have also invented a new technique to send large amounts of data from the edge to the cloud by first identifying parts of the image that are more important, and then selectively sending the subframe fragments using progressive compression.[16]
5) *Satellite imagery:* One of the key sources of data for a farm is from satellite imagery. FarmBeats ingests current and historical satellite data about a farm. One of the challenges in satellite imagery is clouds. Since over 70% of satellite data are covered by clouds, it is difficult to observe the farm through the clouds. We have invented a new technique, called SpaceEye, that combines imagery from optical satellites with RF signals from RADAR satellites to reconstruct satellite imagery below the clouds, with high accuracy.[17]
6) *AI and computer vision:* We use AI on farm data to a) fill in gaps in collected data, and b) predict likely outcomes. Both of these are performed at the edge and in the cloud. We merge data across multiple data streams, such as sensors and aerial imagery, sensors and weather stations, drones and satellites, etc. For example, using multimodal techniques, we are able to combine local sensor data with weather station data to make very hyperlocal predictions of weather in the farm.[18] We also use computer vision techniques to build 3-D orthomosaics, and create aerial timelapses.[19]

We note that the architecture in Figure 1 is not designed to be grower facing. It is meant for other AgTech researchers to incorporate their agronomic expertise with the data collection and AI capabilities of FarmBeats. In the rest of this article, we discuss the hardware innovations in components 1–4 of Figure 1.

RELIABLE, LOW-COST SENSING

Existing sensing technologies in a farm are expensive. They also require a lot of sensors in the farm, which further drives up costs. Our research has focused on ways to significantly bring down the cost of sensing by:

1) leveraging other forms of sensing, which are more commonly available, such as RF;
2) making low-cost sensors more reliable by detecting faults early;
3) using AI/ML techniques to enable low-cost sensors to function as more powerful weather stations;[18]
4) reducing the number of sensors needed in a farm by combining sensors with multispectral imagery from drones and satellites.[4,13]

We discuss the first two technologies in the following sections.

Sensing Using RF

Several technologies for measuring soil moisture and EC have been invented in the last few decades, including direct sensing techniques, which require soil to be extracted and dried out, as well as indirect sensing methods that measure surrogate properties of soil moisture and EC, such as capacitance, electrical, and nuclear response. However, their adoption is limited by the cost and accuracy. Even sub-1000 dollar sensors can fail to accurately measure soil EC and moisture. Our work, Strobe, leverages RF signals in existing Wi-Fi bands to bring down the cost to tens of dollars as well as achieving comparable performance to more expensive soil sensors.[8]

RF-based soil sensing is enabled by the phenomenon that RF waves propagate slower and attenuate more in soil than in air because of soil's larger permittivity and EC than air. Unlike prior RF-based solutions such as ground-penetrating radars and time-domain reflectometry that require a wide bandwidth from hundreds of megahertz to a few gigahertz to achieve high accuracy, Strobe only exploits the 70 MHz of the available Wi-Fi spectrum in 2.4 GHz. Strobe overcomes the key challenge of limited bandwidth using a novel multiantenna technique. With a linear antenna array, Strobe measures the relative propagation time and amplitude of Wi-Fi signals received by different antennas, and then converts them to soil moisture and EC. Strobe can work with commodity multiantenna Wi-Fi cards, which brings down the cost to be tens of dollars. We expect the cost to be lower when the system is manufactured at a larger scale, e.g., tens of thousands of devices.

Reliable Sensors

Sensor hardware for agriculture, especially low-cost sensors, are prone to faults as they are exposed to harsh outdoor environments. Water, humidity, extreme temperatures, and insufficient power can all lead to faulty sensor hardware and, in turn, corrupt data. There are several real-world scenarios where existing data-centric and heuristic-based approaches have limitations in sensor fault detection. Our work, Fall-curve, focuses on identifying and isolating defective sensor hardware at the edge.[9]

We exploit a unique hardware signature where the signature of a working sensor is distinct from a faulty one. To save power in an IoT device, a common practice is to power off the sensor when the data collection is not required. We observe that when a sensor is powered off, its output voltage signal gradually falls down to zero following a curve. The Fall-curve is exhibited due to the presence of active and parasitic capacitances in the sensor hardware. Consequently, the curve is unique to each sensor, i.e., its hardware components. Therefore, any hardware malfunction results in a different shape of the curve.

An advantage of using the Fall-curve is that the fault can be identified at the end IoT device without any contextual knowledge and historic sensor data. To do so, we use a lightweight nearest neighbor search algorithm running in the end IoT device. A dictionary of polynomial feature vectors extracted from the Fall-curves of nonfaulty sensors is prestored in the IoT device. The search is conducted on this dictionary against feature vectors extracted from the Fall-curve of the connected sensor.

AFFORDABLE NETWORKING

Connecting sensors, drones, and other devices in rural areas is challenging. Solutions, such as satellite or cellular connectivity,[20] are expensive. Carriers have little incentive to deploy expensive towers in regions that are so sparsely populated. While there are point-to-point connectivity solutions to bring broadband to a farmer's home, they are not sufficient to connect devices in the farm. In fact, a recent study by the USDA concluded that close to 75% of the farmland in the United States does not have Internet connectivity.

FIGURE 2. TV white space antenna and broadband radio in a farm in Eastern Washington.

Broadband in the Farm

In addition to other technologies, we use the TV white spaces (TVWS)[11] to connect the farm. This technology refers to unused TV spectrum, in the very high frequency (VHF) and ultrahigh frequency (UHF) bands, which are legal to use in the United States, Canada, and several countries worldwide. Devices using this technology consult with a database to determine the available channels at a location, and operate in an available TV channel. Since this spectrum is in the lower frequencies, the signals can propagate much farther than signals in 2.4 GHz or 900 MHz of the spectrum, and also through dense leaves and crop canopies. For example, recent deployments in Africa have links operating at over 2 Mbps at 10 km when transmitting at 1 W.[11] Furthermore, earlier this year, the Federal Communications Commission (FCC) approved the TVWS devices to operate at up to 10-W EIRP in rural areas, enabling extremely long-range networks.

Even though there are few free TV channels in metropolitan cities, the rural areas, where most farms are located, have more than 100-MHz TV spectrum. Given this large available bandwidth, we are able to support several devices, including high-bandwidth devices, such as cameras, operating at long distances using a single gateway device. Furthermore, since these devices operate in unlicensed spectrum, their cost is significantly less than comparable cellular networks.[11] Farmers can set up the TVWS radio and antenna, as shown in Figure 2, to connect several miles around a farm.

FIGURE 3. FarmBeats IoT radio utilizes TV white spaces for long-range communication.

Connecting Sensors

LoRa and SIGFOX IoT networks operate around the 2.4-GHz or 900-MHz band, which have limited propagation through crops and canopies. They can operate in 400-MHz "semilicensed band" in the United States, but that needs coordination with a local agency to get a very small sliver—12.5 KHz—of the spectrum, which can support very few sensors.

We propose the use of TVWS spectrum, which is abundantly available in rural areas, for IoT communication. It offers very long-range connectivity over tens of miles, even through crops and canopies. As part of the FarmBeats system, we designed and implemented a narrowband IoT radio that can operate in this spectrum (as seen in Figure 3). This opens the door for very large-scale network deployments where a single base station can support hundreds of devices across tens of miles.

Although our IoT radio offers longer range, it consists of low-cost off-the-shelf hardware components. It enables low-power LoRa communication over the TVWS spectrum by incorporating the SX1276 chip from Semtech as the LoRa (de)modulator. We modified the RF filters to operate outside the industry, scientific, and medical (ISM) band, including the VHF and UHF TV spectrum. The TV spectrum has strict regulatory restrictions on side-channel leakage and harmonics of the signal to protect the primary user from the harmful interference. It is also very wideband compared to the 900-MHz ISM band, and separate filters are required to operate in different bands within this spectrum. We designed a software configurable logarithmic periodic filter that enables narrowband communication in a continuous spectrum starting from 150 to 960 MHz including VHF, UHF, and ISM bands. The filter design limits the side-channel leakage and harmonics in other bands within the spectrum. We modified the base LoRa media access control (MAC) protocol, such that these transmissions do not interfere with existing TV reception. We provided our results to the FCC, including the design, and in November 2020, for the first time, the FCC approved regulations for use of IoT devices in the TVWS spectrum.

FIGURE 4. TYE deployment on the Dancing Crow Farm in Carnation, WA, USA.

LOW-COST SMALL-SCALE AERIAL IMAGING

In spite of recent advances in unmanned aerial vehicle (UAV) technology, a few factors limit their adoption for smallholder farmers. First, UAVs consume a large amount of power to stay afloat, resulting in very short battery life (few tens of minutes for most commercial UAVs). Second, there are several regulatory restrictions associated with UAV usage. Finally, UAVs require high capital investment. Commercial quadrotors that can last for 30 min and are reliable outdoors cost over $1,000. This is further compounded by the fact that the UAV batteries have finite charge cycles and need to be replaced frequently if the UAV is used often.

In a previous work,[10] we present a long-term low-cost aerial imagery platform called TYE (for Tethered eYE). TYE is a tethered aerial camera that floats in the air, at a few hundreds of feet, due to the lift provided by a balloon, as shown in Figure 4. We utilize a lighter-than-air gas (such as helium) filled reusable tethered balloon system to carry a payload (a camera and some additional hardware). Unlike UAVs, TYE is low cost, does not suffer from regulatory restrictions, and can last for several days. TYE operates in two different modes: 1) Static-TYE, where the balloon is tethered to a stationary point, for long-term unmanned aerial imagery applications, such as surveillance and crowd monitoring; and 2) Mobile-TYE, where the tether is movable, for spatial mapping applications that require TYE to map a large area, such as crop canopy estimation in farms. Raw visual imagery from TYE is extremely hard for humans to view and understand.

The balloons are highly susceptible to arbitrary lateral motion and camera rotations induced by wind. This constantly changes the field of view of the TYE camera across subsequent frames. To overcome this problem, we designed a custom mount to reduce camera mobility, and leverage the gyroscope to eliminate frames with extreme motion. We then utilize techniques from computer vision to correct for the camera motion in software. As a result, TYE produces consistent views for the user as if the camera was stable in the air, in spite of arbitrary physical camera motions.

While long-term imagery applications of TYE do not require any human involvement, the spatial mapping application for aerial imagery of a farm requires TYE to be maneuverable like drones. Thus, Mobile-TYE requires a person to move the balloon around while holding the tether. In this mode, wind-induced motion of the balloon causes the balloon-path to be uncorrelated with the human path. This leads to novel path planning challenges, since most area-coverage algorithms are designed for UAVs that can follow tight global positioning system (GPS)-controlled paths by exerting turbine forces to counter the force of wind. In order to overcome this challenge, we propose a novel path-planning algorithm that ensures area coverage, with minimum human motion, in spite of balloon motion caused by wind. Furthermore, we implemented this algorithm as a mobile application for the user to keep adapting their path in response to the balloon motion.

We have implemented TYE as a software–hardware system, using helium balloons. We support two camera designs: a GoPro and a smartphone. Furthermore, we evaluated the feasibility of TYE in two different applications: 1) aerial survey of crops in agriculture (both static-TYE and mobile-TYE) and 2) flood monitoring to identify the flow of water in a flood (static-TYE).

AI FOR AFFORDABILITY

In addition to reducing the cost of hardware, AI can help make digital agriculture affordable by 1) reducing the number of sensors needed, and making sensors and drones more functional using multimodal AI, by combining with other sources of data, such as weather station data, or satellite imagery; and 2) improving the ROI in on-farm hardware by using AI to advise farmers for optimal strategies on seeding, spraying, harvesting, and trading decisions to make farming more sustainable and profitable (see Kumar *et al.*'s work[21]).

Multimodal AI on Farms

Inference based on multimodal data provide a more holistic perspective of the farm. Our work develops some key technologies to combine multiple modalities: 1) combining multiple temporal data streams (such as on-farm sensors with weather stations) representing various geospatial scales; and 2) combining spatial datastream (such as drone or satellite imagery) with temporal datastream (e.g., from sensors) sampled at various temporal resolutions.

Consider a specific scenario—It is springtime in Eastern Washington, USA, and the temperature is slightly above freezing. A farmer is preparing to fertilize their fields of wheat and lentils as winter runoff and frost are nearly finished. The plants are susceptible to fertilizer at freezing temperatures, so the farmer checks forecasts from the local weather station, which is about 50 miles away. The three-day outlook shows temperatures above freezing. The farmer rents equipment and starts fertilizing the farm. But at night, the temperature in parts of the fields drops below freezing and kills around 20% of the crops. This is unfortunately a common situation on farms, since climatic parameters can vary over short distances and even between sections of the farm.

To address this problem and others, we developed DeepMC, a multiscale encoder–decoder framework to combine weather station forecasts (which is collected and predicted at a coarser geo-spatial scale) with sensor data (which is collected at a highly localized geo-spatial scale) to predict microclimates on the farm. This framework is called DeepMC (see Kumar *et al.*'s work[18]). DeepMC predicts various microclimate parameters with over 90% accuracy at IoT sensor locations deployed in farms around the world.

Some of our other work on multimodal AI focuses on spatiotemporal data sets. We combine multispectral spatial datastreams collected through either satellites or drones with IoT sensor-based temporal data sets to generate high-resolution heatmaps of soil and crop parameters on the farm. Large number of sensors on the farm create operational challenges for operating machinery on farms, in addition to the added cost of procuring and maintaining sensors on the farm. We keep the deployed sensors at the minimum by computing the optimal sensors needed for the desired resolution of the predicted outcomes. In addition, the technique is also used to generate heatmaps for various soil and crop parameters such as soil moisture, soil temperature, and soil nutrient content on the farm. Our technique uses a fusion mechanism to combine spatial data sets with temporal signals sampled at various temporal resolutions.[4]

Optimal Advisories

Farmers synthesize various parameters to make operational decisions on the farm. Typically, these decisions can be categorized into three groups:

1) *Strategic:* These are decisions based on long-term impact and are not dependent on day-to-day variabilities, such as resource allocation—how many workers to hire? What crops to grow in which section for this year?
2) *Tactical:* Scheduling decisions that are based on day-to-day operations—such as when and where to spray?
3) *Real-time:* Decision that are dependent on real-time feedback: such as operational automation—flight planning for drones, tractors, etc.

Most of these decisions are made under various uncertainties—nature, human, or machinery related. We developed a sequential decision making framework to advise operations on the farm by taking in insights collected by the FarmBeats system and compute optimal actions for strategic, tactical, and real-time decision-making. This system solves for optimal strategies by combining farm-specific guidelines with natural, market, and policy-based rules with signal dynamics. These AI technologies help democratize agriculture by bringing actionable insurgents and advisories in the hands of individual users in an affordable and quality manner.[21]

SUMMARY AND FUTURE WORK

Innovations in hardware can help democratize digital agriculture. Low-cost sensors can be made more fault tolerant using Fall-curves. Alternative sensing methodologies, such as RF sensing using Wi-Fi, can enable any farmer with a smartphone to get data about their farm. Low-cost imaging will help growers to get aerial data at low cost, and new low-cost networking techniques, such as the use of unused TV channels, can further bring down the cost of existing solutions by not relying on satellite connectivity. AI techniques can also reduce the need for expensive sensors, and also reduce the number of sensors needed in the farm.

However, we note that we have only scratched the surface in making sensing of the farm more affordable. A lot more innovation is needed, in technology, business, and policy, to further reduce costs, and increase adoption of digital agriculture techniques.

On the technology side, we need to develop more inexpensive forms of sensing. Recent work on using microelectromechanical systems (MEMS) sensors for sensing soil, and audio sensors for measuring rain, are very promising. In addition to sensors, we need lower cost and energy efficient drones that can reduce the overhead in procuring aerial imagery. Cloud and AI that can reach to all farmers worldwide, for example, using an affordable edge. Furthermore, research is needed on user interfaces, to make digital agriculture more usable by farmers who operate devices with soiled hands, and are often not the most technology savvy.

> *SIMILAR TO SUBSIDIES FOR IRRIGATION AND FARM EQUIPMENT, THERE NEEDS TO BE SUBSIDIES FOR DIGITAL TECHNOLOGIES, TO DRIVE THE ADOPTION OF DIGITAL AGRICULTURE TECHNOLOGIES.*

Business and policy innovation are also needed to further increase the adoption of digital agriculture solutions. New business models, such as sensing as a service, in which people on the field can carry a sensor to different parts of the farm instead of using multiple sensors, or new business models where farmers get paid to use digital techniques, can help drive adoption. Similarly, policy innovation is needed as well. Similar to subsidies for irrigation and farm equipment, there needs to be subsidies for digital technologies, to drive the adoption of digital agriculture technologies.

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