Design of an Autonomous Ag Platform Capable of Field Scale Data Collection in Support of Artificial Intelligence

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Abstract. *Pivot+ is intended to serve as an innovative, multi-user research platform dedicated to the autonomous monitoring, analysis, and manipulation of crops and inputs at an individual plant scale, covering extensive areas. It effectively addresses many constraints that have historically limited large-scale agricultural sensor and robotic research. This achievement would be possible by augmenting well-established center pivot technology, known for its autonomy, with robust power infrastructure, high-speed fiber, and wireless networking capabilities. The system would also include environmentally controlled and protected cabinets to house non-field-hardened sensors, data servers, and research sensors and systems, enabling remote data access.*

Pivot+ would enable collaborative, field-scale research for agricultural sensors, communications, robotics, and machine learning applications, including micro-meteorology, phenotyping, soil and water interactions, and cropping systems management. A potential installation would cover a 115-acre area, facilitating numerous parallel experiments. Data collection would occur at regular 90-minute intervals, with the pivot operating in diverse weather and lighting conditions. Researchers can leverage high-resolution soil order, drainage class, elevation, slope, and topographic position classifiers to tailor site-specific experiments. The outcome would be a wealth of high-resolution temporal and spatial observations, yielding the high-quality datasets demanded by modern AI and machine learning methodologies. This paper covers a conceptual design of Pivot+ and discusses its potential impacts on several important research areas.

Keywords. *Artificial Intelligence, Machine Learning, Datasets, Precision Agriculture, Pivot*

1. Introduction

The functional adoption of artificial intelligence (AI) in agriculture has the profound potential to revolutionize crop management and address the incredibly difficult challenges of environmental stewardship and global food security. However, the market has only seen a limited number of commercially viable AI solutions, which tend to be somewhat limited in their scope of operation. The reason is simple: AI efficacy is strongly dependent upon not just large, but also high-quality datasets that capture the totality of interactions between the variables of interest. For cropping systems, this means measuring the combined effects of soil, water, plants, and environmental factors over long spans of time, weather patterns, and locations. Furthermore, even after data is collected and an algorithm design is complete, deployment and testing in field conditions is just as challenging as the initial data collection was (Liu, 2020). Traditional agriculture research mechanisms are severely limited by the scale of farming and the feasibility of high-density sampling and model validation. As a result, the development of robust AI models is at best difficult, and at worst, not yet possible.

To address these issues, we propose Pivot+: an innovative multi-user research platform designed to facilitate autonomous, field-scale data collection. Deploying well-established center pivot irrigation technology, augmented with state-of-the-art networking and sensor capabilities, the platform would produce continuous, high-resolution monitoring and manipulation of the entire cropping system. The coverage area is extensive and made up by a mix of several different water, soil, and land topology factors. This would not only address the modern constraints of agricultural sensor and robotic research but could become a core infrastructural piece toward the design, development, and deployment of AI and machine learning (ML) applications in plant, environmental, and soil sciences.

This paper details a design proposal for Pivot+ at the Purdue University Agronomy Center for Research and Education (ACRE) farm. This device would encompass a 115 acre sensor and cropping system interaction network, complete with dense underground tiling for tile water runoff analysis, high-resolution LiDAR of the soil topology, and robust soil type mapping and historical sampling. The large operation area allows for the execution of numerous parallel research experiments, each with precise control of field trials. The result would be a wealth of temporal and spatial data that is crucial for the advancement of AI and ML research aimed at optimizing corn and soybean management practices, improved yield predictions, lowering environmental impacts, and enhancing the resilience of agricultural systems to climate variability.

2. Background

There are several prominent research devices with similar objectives, but to the best of our knowledge, there is truly no comparable instrument to Pivot+ in the world. Many universities conduct sensor-based research on movable platforms carried by UAS/UAVs, gantries, and both custom and commercially available farm equipment. While these solutions do collect data required for AI and ML objectives, they are often limited to too small an area or are too labor-intensive to collect data at the required spatial scale and temporal density; sometimes, both concerns apply. That said, research has begun to address considerable challenges in this domain, such as shrinking sensor size, isolating platform motion from the sensor, reduced power requirements, and increasing robustness to outdoor conditions. Additionally, researchers have laid the algorithmic groundwork for processing and leveraging such data. It is the combination of this progress and recent major advancements in AI that makes Pivot+ so timely. Some examples of existing prior art follow.

While UAS/UAVs have become a very popular tool for collecting image-based phenotyping data, they have proven to be less than ideal solutions. Aerial image scanning tends to result in lower resolution compared to ground-based systems and therefore captures fewer details. They are highly impacted by environmental conditions like wind, rain, and lighting, limiting their operation to clear weather days. Additionally, UAS/UAVs struggle with flight times and ranges, making it difficult to scan large areas. Lastly, they require a skilled operator and regulatory compliance to fly them, making scanning operations a logistically complex process.

To address these issues, some researchers have explored fixed gantry systems that not only increase data quality but can also be made autonomous so scanning may happen at any time. Purdue uses a small gantry that moves over a plot of much less than one acre (Ma et al., 2021a; Ma et al., 2021b). Useful research has been conducted with this system, but the scale is far too small to support more than one research group at a time. At a slightly larger scale, the LemnaTec Field Scanalyzer has been successfully deployed at locations such as Rothamsted Research (Virlet et al., 2017) and TERRA-REF. While new phenomena in plant sensing are being discovered and comprehensive open datasets published (LeBauer et al., 2021), the limited scale of roughly one acre is still much too small to support dozens of independent experiments across many soil types, topologies, and genetic factors. Pivot+ intends to cover an area more than 10 times larger than TERRA-REF and autonomously support many simultaneous users.

The community has also developed mobile vehicles that can carry sensor packages into a field. Examples of these systems include Purdue's PhenoRover (Lin et al., 2021) and the Australian Plant Phenomics Facility's FieldExplorer (Sutton, 2020). While these systems provide unprecedented resolution in the captured data, they still struggle to unlock the high spatial and temporal density needed for AI and ML models. Capable of scanning larger areas due to their mobility, the small scanning swath and dependency on a human driver ultimately limit their utility at scale.

Finally, it is worth mentioning the many developments within indoor phenomics facilities. These systems can reliably produce very high-quality and well-controlled phenomics data in fully automated ways. Examples include the Purdue Alumni Seed Phenotyping Facility, Nebraska-Lincoln PhenoSphere, Iowa State Enviratron, and the Australian Plant Phenomics Facility. However, these facilities are limited by the growth that an indoor chamber can facilitate, lack many of the soil-water interactions that heavily influence outdoor cropping systems, and focus on a very small number of plants at any given time.

3. Pivot+ at Purdue ACRE

The design and concept of Pivot+ proposed in this paper is envisioned to be installed at the Purdue ACRE farm. The primary purpose of this paper is to communicate the design and benefits it would provide to researchers. The authors aim to build a community of researchers around the concept and seek to fund and construct at least one Pivot+ system.

The base of Pivot+ is a rotating center-pivot irrigation gantry, similar structures shown in Figure 1, integrated with high-speed fiber networking and computing. This shared, field-scale platform would support research on agricultural sensors, sensor communications, robotics, and AI/ML applications in phenotyping, cropping systems management, micro-meteorology, and more. An irrigation gantry was chosen due to its design maturity, economies of scale, and robust autonomy, resulting in a cost-effective and reliable platform suitable for hosting research.

The gantry's control provides precision experimental access to nearly any location within its coverage area. For ACRE, that would be approximately a 115-acre radius covering both large-scale fields and some small-scale research plots, as shown in Figure 2. With integrated power and extensive gigabit-per-second networking, Pivot+ can support dozens of simultaneous users whose experiments need to scan thousands of potential plots multiple times per day or night, in all weather conditions, year-round.

Fig 1. Photos of similar center-pivot style gantries. Top: front view of a gantry is full height corn (Lumin Osity). Bottom: lengthwise view of gantry (Leslie Cross).

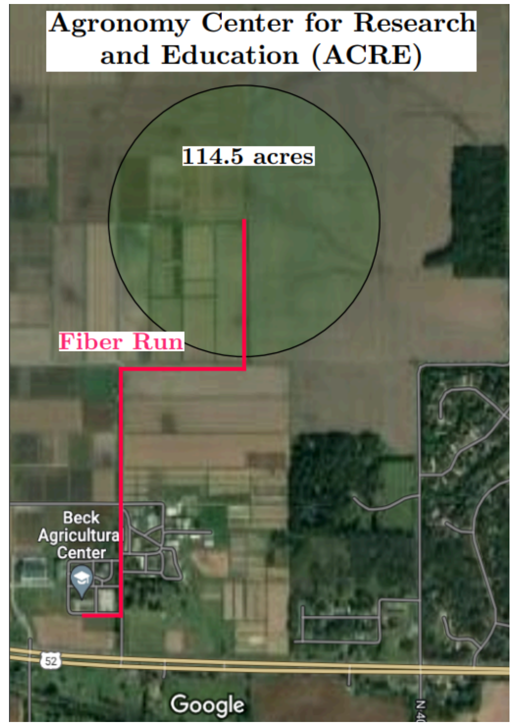


Fig 2. The envisioned location for Pivot+ at Purdue ACRE farm, including a potential buried fiber backhaul.

Pivot+ can be broken down into four major subsystems, which are detailed in the sections below. The first is the center pivot gantry, which has already been introduced. The second is a fiber trunk, which would provide wired, ultra-high bandwidth, ultra-reliable connectivity at any point along the gantry's 384 m (1260 ft) radius. The third is the tower package, which consists of climate-controlled cabinets placed on each of the seven towers. These cabinets allow the use of commercial-grade networking and vastly simplify the design of user experimental sensors, computing, and networking hardware, which no longer needs to be "hardened" for outdoor deployment. Each cabinet would be directly wired into the fiber trunk. Finally, the fourth subsystem is the pivot package, which supports high-power edge computing for immediate local data processing, as well as a high-capacity direct connection to the Purdue campus network through buried fiber (shown in Figure 2). This connection would provide experimental users with high-speed internet access to their field experiments.

Pivot+ could break many bottlenecks that limit capacity for agricultural sensor and robotic research at scale. By solving problems of data backhaul and precision field access, it would allow research on sensor systems, signal processing, and machine learning to proceed independently of research on autonomous UAV/UAS and machine platforms, freeing sensor research from limits on bandwidth, payload, operation time, visibility, weather, and the requirement for human operators.

To our knowledge, this integration of a movable pivot gantry, fiber networking, and computing would create the world's largest agricultural robotic sensing platform. By scale and ease of use, it would go a long way toward democratizing research and, as a by-product, it would pave the way for vastly expanded sensing capabilities within existing pivot systems that water more than 50 million acres in the United States and around the world.

3.1 Gantry Platform: The center pivot

The initial Pivot+ design work required knowledge of the pivot irrigator details. To proceed with the concept design, the system was modeled on the commercially available Valley Irrigation 8000 series center pivot irrigator with seven "high-profile" towers; however, other products and vendors could be used. In this case, the tower interspan is 54.8 m (180 ft) with approximately 3.5 m (12 ft) of vertical clearance at the lowest point between spans.

By default, a 480 Volt (V) three-phase power at 45 Amps (A) per phase electrical circuit is used to run the electric motors in each of the seven towers. In addition, an independent 5 A, 120 V single-phase circuit is available for control systems. Pivot+ specifies extra electrical power capacity for the gantry to allow power for servers, network switches, HVAC, research user equipment.

These pivots are designed to carry heavy loads, and the additional weight of the climate-controlled cabinets, servers, switches, and sensors is less than 10 percent of the standard water load, well within the design margin of the structure. The basic structure and mounting of cabinets, cabling, networking, and sensing are shown in Figure 3.

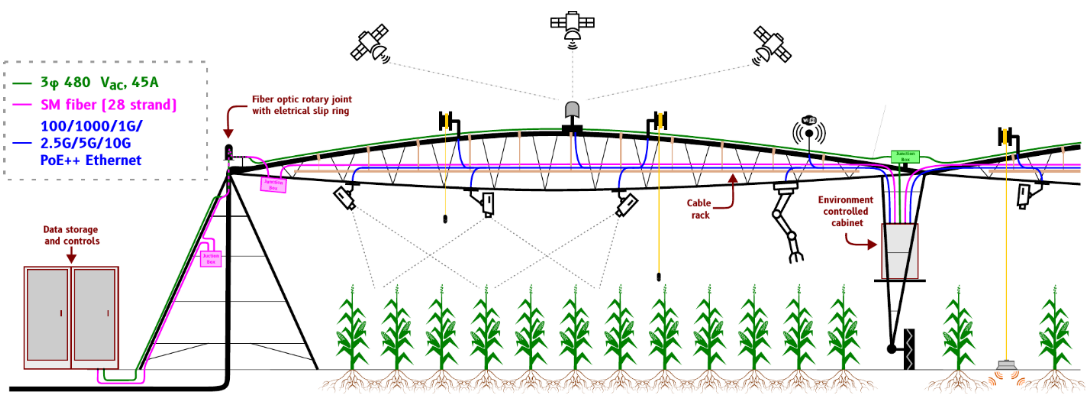


Fig 3. Pivot gantry conceptual diagram illustrating pivot point, towers, climate control cabinets, and cabling.

The gantry footprint is divided into seven annular regions separated by wheel tracks. Powered by high-speed variable frequency drives and programmable control, the speed and direction of rotation can be controlled every 2 degrees of angle. The gantry can complete a fully autonomous revolution in 90 minutes (1.5 hours), compared to the nearly 24 hours it would take an operator to drive a 4-row research-grade sprayer carrying sensors over the same 115 acres at 6.5 km/h (4 mph), not accounting for turnarounds or other maneuvers.

The 2-degree steps of wheel control divide the land underneath into annular quadrants ranging from 37 to 687 square meters (400 to 7,400 square feet, or 0.01 to 0.17 acre) in size. By strategically placing sensor packages along the length of the gantry, trade-offs between scanning speed and acres covered per revolution can be managed on an experiment-by-experiment basis.

3.2 Fiber Trunk: Fiber cable and optical rotary joint

The gantry would carry 28 strands of single-mode optical fiber, which is enough for 14 bi-directional links or at least two full-bandwidth fiber optic connections between each tower and the pivot package. However, all fibers would be patched into all towers, so the individual strands can be unequally allocated across the towers if so dictated by experiment or user need. The network interconnections of the fiber trunk, pivot package, tower packages, and user devices are shown in Figure 4.

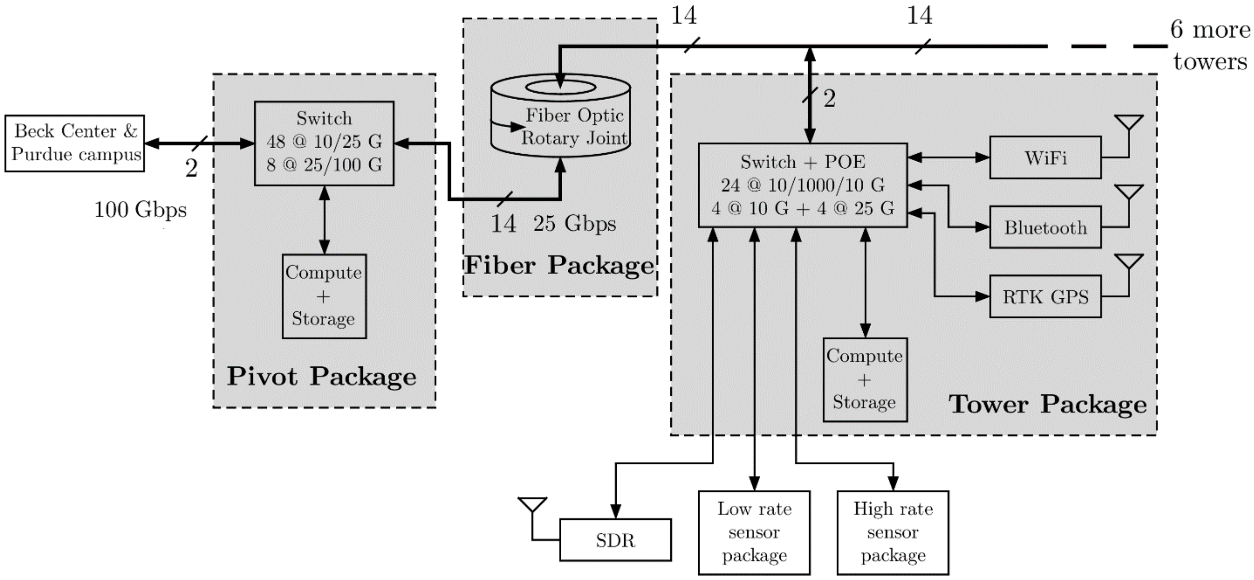


Fig 4. Pivot gantry conceptual diagram illustrating network architecture.

Due to the continuous rotation nature of a center pivot gantry, passing cables from outside the gantry to it is nontrivial. A physical wire would wind around the pivot base and eventually break. Existing pivots utilize slip couplings to solve this problem for both water and electrical services. Pivot+ presents a new challenge now that a high-strand fiber optic cable must also pass through this rotation point.

Fiber optic rotary joints (FORJ) are optical-mechanical systems that allow multiple independent strands of optical fibers to pass through a rotating mechanical joint, similar to a slip coupling but for fiber. They have been in commercial use for more than 40 years in medical CT scanners, submersible sensing, rotating antenna radar systems, wind turbines, and oil exploration (Dorsey, 1982; Dorsey & O'Brien, 2019). However, to our knowledge, they have not yet been applied in rotating irrigation gantries. The Pivot+ gantry would deploy an integrated fiber/electrical rotary joint which can pass all 28 fiber strands and sufficient power for both the pivot's 480 V three-phase and 120 V single-phase circuits.

3.3 Tower Package: Experment interface and sensor networking along the gantry

Each of the seven towers would carry a climate-controlled 26 rack unit (RU) NEMA 4 cabinets containing an optical patch panel and a transformer to step down the 480 V three-phase main for powering HVAC, servers, switches, sensors, and power-over-ethernet (POE) equipment. The optical patch panel allows any fiber pair to be used at any tower for simplicity and robustness. Refer to the networking architecture of the system shown in Figure 4 for more detail.

While each NEMA 4 cabinet is identical, the hardware they contain is provisioned to support user experiments operating out of a particular one. In its most basic form, a tower cabinet would contain a PoE switch, a WiFi access point, an RTK GPS receiver to precisely locate each tower, and an ISOBlue machine telematics server running the Avena software stack (Balmos et al., 2022). Avena would be the primary software used to interact with the gantry control system, host user experiment programs, and stream and store data.

The cabinet switch is provisioned with twenty-four 100/1000/10 Gbps PoE access ports, four 10 Gbps access ports for particularly high-bandwidth sensor nodes, and four 25 Gbps uplink ports available for fiber termination. The cabinets are sized to provide ample space for the hardware associated with user experiments and for future upgrades to switching and computing. When a user experiment is installed in a tower cabinet and/or on the gantry, it would be primarily connected and powered by PoE (although traditional 120V outlets and Wi-Fi would also be available). Therefore, though some integration with Avena software, sensor systems would automatically turn on when the gantry is in motion, and autonomously collect, process, and store data to the researcher’s private storage, exactly as it would in the lab.

Dedicated HVAC units would independently cool and heat the internal space for year-round operation. In addition, the cabinets are environmentally sealed from dust and inclement weather. User hardware, which may have traditionally been considered lab-only due to its delicate nature or lack of proper environmental protections, would now be easily brought to the field, further lowering the barrier to researching in outdoor cropping systems.

3.4 Pivot Package: Network interface at the pivot point

The pivot package is responsible for interfacing between the gantry's integrated electronic system and the rest of the world, as depicted in Figure 4. This would be accomplished in two ways: 1) a small climate-controlled field-side server room capable of hosting the fiber trunk switch, large form factor servers, GPU processing nodes, and high-capacity disk arrays, and 2) a new fiber connection to the Purdue campus network, its data centers, and Internet peering. The field-side server room would be directly connected to the tower packages via the fiber trunk, ensuring no reasonable networking bottleneck between the computing hosted field-side and sensors deployed on the gantry itself.

If all the switches on the seven pivot towers were operating at maximum uplink bandwidth, the combined optical bit rate passing through the FORJ towards Purdue would be 350 Gbps (7 × 2 × 25). Currently, the backhaul available to bring data from the pivot to campus operates through two 10 Gbps links, resulting in a peak-to-average ratio of 17.5-to-1. Today’s technology would easily allow upgrading this connection to 100 Gbps links, which would lower the peak-to-average ratio to about 1.75-to-1.

There are two reasons for overselling the network on the gantry compared to the backhaul bandwidth. First, by over-provisioning the fiber trunk, we allow inter-tower communications without limiting the bandwidth needed for gantry-to-campus or gantry-to-Internet traffic. We foresee the potential for very high-bandwidth inter-tower communications when experiments span multiple towers and require real-time coordination based on sensor readings. Secondly, the field-side server room is provisioned to allow for considerable computing and storage that can pre-process user data to compress measurements, detect events, compute sufficient statistics, and generally reduce the aggregate bandwidth needed back to campus or the Internet.

To validate the basis of reasonable sensing bandwidth, we consider the demand created by Purdue’s PhenoRover system, which is a multi-spectral sensing system mounted on an agricultural spraying platform. The standard PhenoRover sensor package includes RGB Flea cameras, a Velodyne VLP 32C, the Headwall MV system, which covers the VNIR (up to 1000 nm wavelength), and a thermal camera. When the PhenoRover runs at ACRE, it produces about 20 GB per acre. Translating that data demand to the situation at hand, we note that Pivot+ sweeps over about 76 acres per hour at top speed. This translates to a roughly 3.5 Gbps, which is easily within the range of the planned networking capacity and provides considerable headroom for growth as sensing technology further develops.

3.5 Description of study area

A potential site with a significant proportion of small and large plots was selected for Pivot+ at ACRE. ACRE is located mostly on low relief (~9m) up-sloping gently from southeast to north. It is part of the till plains from Wisconsin age (15,000-20,000 years), making most of soils parent material from old deposits of till and outwash. The loess deposit in this area is creating silty loam and silty clay loam textures. The dominant soil order in ACRE is Mollisols, specifically Aquolls which correlates with the seasonal high-water table. This general information can be found in the report on *soil survey of Tippecanoe* by the US Department of Agriculture (USDA) and National Resources Conservation service (NRCS) (1998). The pivot site is on the east side of ACRE. The relief in this site is 2.5m with higher slopes in the south-west quadrant and in the north or the area under upper semicircle. These areas are observed in the LiDAR elevation map, see Figure 5. The 1m spatial resolution LiDAR data for this study was obtained from the 3DEP program of US geographical Survey (USGS) hosted by The National Map website. The slopes in this figure were calculated from the downloaded digital elevation map resampled at 10m^2 resolution for better visual representation. Each grid's slope is shown by black arrows pointing in the direction of the negative gradient. The size of these arrows represents the slope magnitude. Other elevation-derived land classification indices such as topographic position index (TPI), convexity etc., help identify the site's terrain features. TPI for the pivot site was calculated from elevation data at 10m^2 resolution. The moving window method used window size 9px for this calculation. This TPI was used as a base to overlay existing drain tiles at this site, see Figure 6. These drain tiles are a mixture of new uniform tiling as seen in the small plots in the southwestern quadrant and older Pre-ACRE tiles in the rest of the section. These tiles along with terrain factors are key in studying the flow of water at the pivot site.

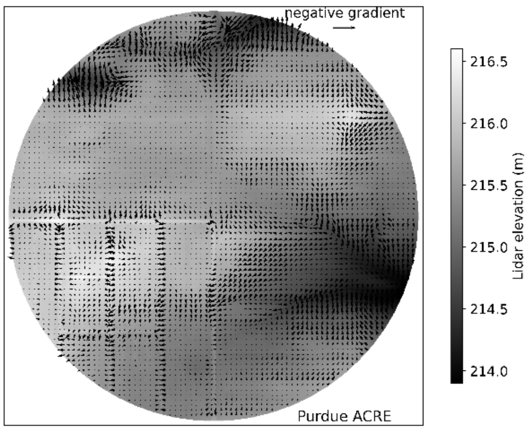


Fig. 5. Elevation, slope and aspect of prospective pivot site at ACRE.

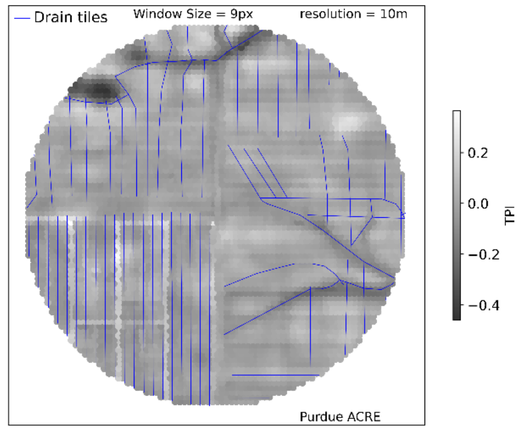


Fig. 6. TPI overlayed with drain tiles of the prospective pivot site at ACRE.

The Soil Survey Geographic database (SSURGO) database was leveraged to study the soil characteristics of the prospective pivot site. The SSURGO database is maintained by the soil survey staff (2021). The dominant soil series at the location are Chalmers, Brenton, Pella and Milford, see Figure 7(a). The official soil series description by soil survey staff (2011) describes Chalmers soil with the taxonomic class *fine-silty, mixed, super-active, mesic Typic Endoaquolls*. This suggests that the soil in the Chalmers polygon has predominantly fine-silty soil texture, with a mixed mineral class. A mixed mineral class suggests an absence of any dominant mineral. It is super-active in its cation exchange capacity and has a mesic soil temperature regime. The soil temperature ranges from 8°C to 15°C in the mesic temperature regime. The overall character of Chalmers is of a typical aquic Mollisol. These have high water tables throughout the year and are made up of thick dark topsoil high in organic material. Prairies are the native vegetation of Chalmers soils and when artificially drained, it supports mainly corn and soybean crops. Mollisols, the soil order of Chalmers, in Indiana, are remnants of glaciated lands in the north and are maintained with artificial drainage when used as croplands. Pella soil series is from the same taxonomic class as Chalmers, but unlike Chalmers, it is formed on depressional areas of ancient lake plains, outwash plains, and till plains. They also have carbonates in the top 102 cm (about 3.35 ft) of topsoil which is absent in Chalmers. Milford is from *fine, mixed, superactive, mesic Typic Endoaquolls* taxonomic class. These are formed on low broad summits and depressions in ancient glacial lakes. Milford has a higher clay content than both Pella and Chalmers. Brenton soil belongs to the *fine-silty, mixed, superactive, mesic Aquic Argiudolls* taxonomic class. These are formed on outwash plains and stream terraces where the relief is relatively smooth. The overall clay content is less than Pella's and the same as Milford's.

The individual plots of the soil's physical characteristics are important in understanding the water holding capacity of soils. The soil in this site is made up of till and loess parent material see Figure 7(b). Loess is made up of silt deposited by wind and till consists mainly of gravitationally deposited soil by glaciers. Loess parent material is defined by a depth of ~50 cm (about 1.64 ft) of silt. The soil texture of loess and till plains are silty. Figure 7(c) shows the silty soil textures of the pivot site. These soil properties also contribute to the classification of drainage classes. The drainage classes of pivot site are shown in Figure 7(d). The somewhat poorly drained class which is better drained than the poorly drained class are in the same areas as silt loam and loess. The poorly drained classes coincide with clayey texture of the areas with silty clay loam texture.

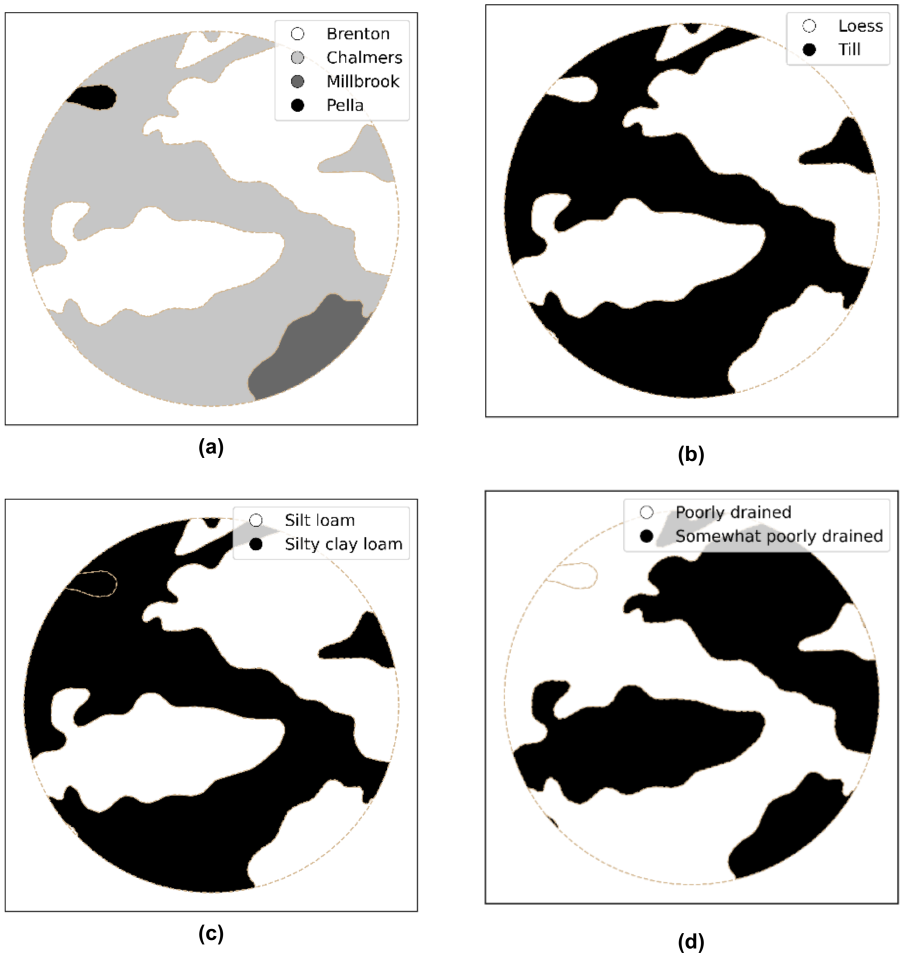


Fig. 7. Soil physical properties are illustrated in (a) soil series, (b) parent material, (c) soil texture, and (d) drainage class.

4. New Research Enabled

The Pivot+ will benefit numerous research areas, including applied machine learning and artificial intelligence, meteorology, remote sensing, agricultural robotics, and distributed communications.

As part of the base operation of Pivot+, "standard" sensor packages would be deployed along the entire length of the pivot. This sensor suite would scan every acre that the gantry covers during each pass it makes (excluding certain areas containing proprietary or protected field trials and other similar constraints). The result will be one of the most complete, open, and high-density spatial and temporal datasets over a range of soil, water, and weather observations. Combined with the soil and topology data outlined in section 3.5 and a carefully managed planting and field operation log (Buckmaster et al., 2024), Pivot+ could become a primary data source for agricultural innovations.

4.1 Applied machine learning and artificial intelligence

One area of interest is the early detection of critical events or decision points in cropping system operations, such as irrigation, herbicide, and fertilization decisions, which must react to seasonal changes. Recently, AI techniques have been developed for change point detection in various fields, such as computer vision for autonomous transportation (Gao et al., 2018). Pivot+ datasets will enable research into automated decision point detection for agriculture.

For example, detecting emerging crop insect infestations (Wen & Guyer, 2012). Early signs of infestation, such as markers of initial insect presence or changes in soil composition, could be identified by analyzing patterns from the visible and infrared sensor packages.

Pivot+ also provides a considerable opportunity to advance fast AI/ML solutions, with support to real-time cropping system operations. Tower infrastructure enables researchers to quickly iterate and experiment with techniques to accelerate computation speed and reduce hardware requirements. For instance, pre-processing sensor video data down to simpler signals that could be used within decision point modeling techniques that have been developed to extract recurring subsequences from time series data (Brinton et al., 2016; Brinton et al., 2017). This significantly reduces overall computational complexity compared to processing raw video.

More broadly, researchers could transfer data collected by Pivot+ to external computing resources and apply deep learning techniques directly. For example, prior work in wireless signal classification has found that Convolutional Recurrent Neural Networks (CRNNs) achieve robust predictive performance when trained using time series data (Sahay et al., 2020; Sahay et al., 2021). Significant progress could be made on AI/ML methodologies encompassing tasks such as irrigation decision-making (Glória et al., 2021) to crop yield mapping (Schueller, 2021).

Finally, researchers could investigate decentralized AI/ML techniques, which are important in agriculture due to the heterogeneity in connectivity across rural edge devices (Chiang & Zhang, 2016; Hosseinalipour et al., 2020). Ideally, model training and inference would be carried out intelligently across these devices, minimizing upstream and downstream transmissions. With Pivot+, researchers can explore how farm devices may cooperatively compute by pooling their resources, operating locally on their data, and later combining results through techniques such as stochastic gradient descent-based distributed learning (Elgabli et al., 2020) or federated learning (Wang et al., 2019; Azam et al., 2021).

4.2 Micro-meteorological studies

The Pivot+ instrument will enhance our ability to measure and model momentum, heat, and mass fluxes in the surface boundary layer at field scale over diverse agricultural surfaces. It will provide a unique framework for understanding the spatial and temporal variability of many biophysical processes, compared to traditional methods used to determine mass, momentum, and heat fluxes from meadows (Kunz et al., 2020), cropped land (Flesch & Grant, 1991; Gao et al., 2004; Schmitz & Grant, 2009; Schäfer et al., 2012; Grant & Omonode, 2018; Lin et al., 2020), and agricultural operations (Grant et al., 2022).

A key issue in micrometeorology is understanding the spatial and temporal variability in turbulent fluxes of heat, mass, and momentum in the surface boundary layer. This variability limits the applicability of point measurements and needs to be assessed to properly bound the fluxes of mass (such as H2O, CH4, NH3, and N2O) and heat out of the canopy. While mean flux measurement theory is well developed, little is known about the spatial variability of these fluxes and the confidence intervals for flux estimates. Understanding this variability would require many instrument locations in a field, which is practically difficult to achieve in an operating cropping system. Pivot+ could help remove this limitation by installing gas instrumentation on the Pivot+ gantry, enabling the exploration of spatial variability in horizontal and vertical fluxes without disturbing the crops or field operations. Combining this with spatial variability in soil moisture and plant stress will help validate models for crop water stress, crop water use, and N-use efficiency.

4.3 Remote sensing for plant breeding and cropping systems

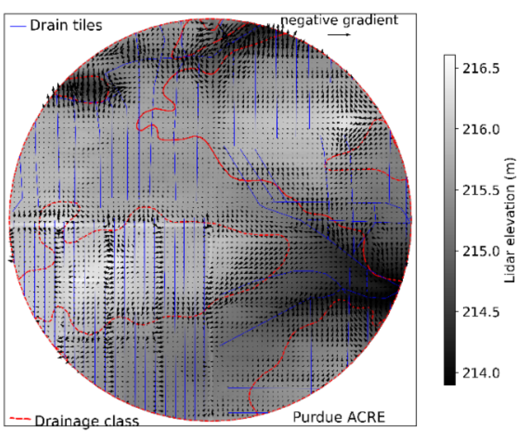
Researchers have extensive experience in data acquisition from RGB, LiDAR, and hyperspectral sensors on integrated UAVs and high-clearance tractors (Masjedi et al., 2020; Karami et al., 2021; Nazeri et al., 2021). This experience has shown the value of multiresolution systems, but traditional wheel-based systems have limitations in traversing fields under various environmental conditions. These systems are restricted to operating under the canopy or with attached booms, which are difficult to compensate for in motion. Additionally, both wheel-based and UAV systems are limited to a single acquisition per day, even when conditions are favorable. Pivot+ offers a physically stable system that can accommodate a wide range of sensors without the weight or packaging limitations of UAVs.

4.4 Soil, water, and yield interactions

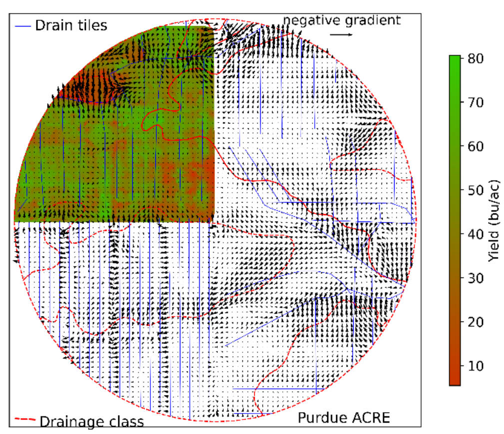
The study of the combined effects of terrain's influence on water flow and soil's water holding capacity can be more thoroughly pursued using Pivot+. Such studies are advocated by agricultural researchers such as Moral et al. (2010), Yao et al. (2014), Friasse et al. (2001), Samouëlian et al. (2005), Kumhálová et al. (2011), and Mallarino et al. (2004). The datasets created by Pivot+ will also facilitate the integration of weather effects over time.

Corwin et al. (2006) studied vectorized topographic data to complete the triad of monitoring soil fertility, weather variability, and agro-management effects (from gantry robots) for accurate yield prediction. Pivot+'s vectorized topography-weather-agromanagement dataset would enable proper usage of AI/ML and other techniques in advancing research on modeling cropping parameters.

An example of such an integrated analysis is shown in Figure 8. The high-resolution terrain factors elevation and slope were calculated at 1 m² grids. This gridded elevation data was used to sample georeferenced soil properties to create a vector of pedogeomorphological characteristics for each 1 m² grid. Figure 8(a) shows the drain tiles overlaid on the topographic map at the prospective Pivot+ installation site at ACRE. The topographic factors included in this plot are elevation, slope, aspect, and soil drainage classification. These factors influence soil water availability, which is crucial for field homogeneity. Figure 8(b) illustrates the results of adding yield to the vectorized topographic features. The soybean yield in the northwest quarter of the field is from 2015. This vectorized dataset can facilitate multivariate yield prediction research in precision agriculture.



(a)



(b)

Fig. 8. Integrated terrain, soil (a) and (b) added yield dataset are illustrated.

4.5 Ag robotics for scouting, sampling, precision sensing, and treatments

Traditionally, crop monitoring and assessment has been achieved through costly, labor-intensive, and time-consuming processes like scouting, manual sampling, and documenting farm conditions. Robotic platforms carried by unmanned vehicles have emerged as a viable approach for precision agriculture practices (Manish et al., 2021; Kim et al., 2022). However, GNSS signals and high-bandwidth communications needed for traditional navigation methods are typically unreliable inside and under crop canopies.

Pivot+ can address this by providing a platform for robotic arms mounted above the crop, enabling fully autonomous plant tissue sampling, insect scouting, precision monitoring, and targeted application of water, fertilizer, herbicides, and more. The robotic control systems could leverage the Pivot+ data network to access built-in gantry localization via RTK GPS. Previously, this was accomplished by SLAM algorithms with cameras like RGB-D tracking cameras and 2D/3D LiDAR sensors, such as P-AgBot (Kim et al., 2022). However, SLAM is challenging for in-crop robots due to the uniform environment.

By freeing the robotic arm's computing power from localization tasks, we can employ more advanced ML-based algorithms for plant identification, segmentation, precision sensing, insect scouting, and product application tasks (Li et al., 2022).

4.6 Communication, computing, and networking

The stable and constantly available communication and computing architecture of Pivot+ provides a robust, reliable, and easily reconfigurable platform for on-site evaluation of distributed communication, computing, and networking solutions. Specifically, the high-speed backbone could enable accurate synchronization among software defined radios (SDRs), allowing a system designer to isolate the impact of distributed synchronization protocols from other signal processing components in the system. One example is the distributed full- or half-duplex relay schemes (Riihonen et al., 2011). With full span of the gantry, researchers could emulate multi-hop environments. Combining with SDRs of multiple antennas, the system is perfectly positioned to evaluate state-of-the-art low-latency MIMO relay solutions (Wang et al., 2017; Ogbe et al., 2020; Ogbe et al., 2019). The evaluation can be done either with perfect optical-fiber-based synchronization for an idealized setting or with a practical distributed synchronization protocol (Rogalin et al., 2014) in place.

In addition to applications in relay communications, the sheer size of the gantry allows it to act as a large distributed antenna array, upon which new experiments of distributed MIMO can be designed with applications in range extension (Kim et al., 2021), interference suppression, and signal localization (Garcia et al., 2017) at a much bigger physical scale, especially when complemented with existing communication/computing equipment at the nearby farm facilities for more interactive experiments.

Pivot+ will support various IoT field sensors. In addition to the intended Ag applications, the gantry can also be used as a platform for general IoT sensor network experiments. Specific examples include joint physical-layer and network-layer designs (Khreishah et al., 2009), opportunistic routing (Kuo & Wang, 2017), sleep/wake scheduling for battery and for wireless powered devices (Wu et al., 2009), delay-tolerant communications (Zhang, 2006), signal processing and network protocols for IoT multiple-access solutions (Wei et al., 2019), communications with underground sensors via near-field inductive coupling (Arakawa et al., 2018a; Arakawa et al., 2019; Arakawa et al., 2020) or ground-penetrating radar transduction (Vanjari et al., 2007), and remote powering of passive underground sensors (Arakawa et al., 2018b).

One of the latest frontiers of communication and computing is the machine-learning-aided channel equalization and communication co-design. The large, reliable, moving structure of the gantry can be used as a data collecting device that reliably measures the on-site at-scale wireless channel conditions together with live weather data. This would serve as the much-needed training set for new ML-based innovation on rural wireless communication (Shlezinger et al., 2020).

5. Summary

The design of the Pivot+ leads to an innovative multi-user research platform that facilitates autonomous monitoring, analysis, and manipulation of crops and inputs at the plant scale over extensive areas (115 acres) and supports multiple users with numerous parallel experiments. This platform addresses the limitations of traditional agricultural sensor and robotic research by leveraging established center pivot irrigation technology, augmented with robust power infrastructure, high-speed fiber, and wireless networking capabilities.

Environmentally controlled cabinet enclosures allow users to bring research-grade equipment directly to the field and scan the cropping system at 90-minute intervals, any time of day and in any weather conditions. As a result, Pivot+ supports extensive research on agricultural sensors, sensor communications, robotics, and machine learning applications, including micro-meteorology, phenotyping, and crop systems management. The outcome will include innovative new research results and large numbers of high-quality datasets essential to modern AI and machine learning methodologies.

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