Precision Agriculture and Irrigation – Current U.S. perspectives

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Abstract. *Precision Agriculture (PA) as a conceptual framework for farming operations responds to the need to manage inter-field and intra-field variability on farms, within watersheds, regionally and internationally. How PA is used, the objectives involved, and the technologies that support it have changed substantially since the inception of modern PA in the 1980s when the U.S. Global Positioning System (GPS) became available for public use. Coupled with geographical information system (GIS) computer technologies that were first developed for satellite imagery, PA became a mainstream tool for farmers to plan site-specific agricultural operations, early on including fertilizer application, followed by seeding rate, seed variety, pesticide spraying and now site-specific irrigation. Equipment with GPS steering and position-aware supervisory control systems allowed pre-determined site-specific prescription maps to be downloaded into equipment and used, for example, to turn off a spraying system as it passed over a waterway. GPS-enabled harvesting equipment produced yield maps that were some of the first data to be used for site-specific management, often with confusing results due to a lack of co-varying field data and adequate decision support systems (DSS) based on how soil spatiotemporal properties influence plant development. This kind of passive and indirect PA has evolved, however, to provide more capable solutions that, for example, provide for variable rate application of fertilizers based on georeferenced soil sampling that leads to prescription maps of fertilizer need. Or for another example, spatially variable irrigation management based on 30-m resolution maps of crop water use based on multi-satellite sensor fusion. Many of the more successful PA technologies involve on-board sensor systems that feed data to embedded computing platforms that make on-the-fly adjustments to equipment. Such active and direct PA systems use modern technology that provides the ability, for instance, to turn spray equipment on in the presence of weeds and off otherwise, or to turn on variable rate irrigation nozzles where abiotic stress sensors indicate crop water stress. Such supervisory control and data acquisition (SCADA) systems rely on algorithms based on sophisticated understanding of biophysics and biological systems. Today the confluence of computing power, data acquisition and management infrastructure, new modeling paradigms, and spatial decision support systems ushers in new possibilities for PA. Providers of PA services now include government institutions from national to local levels, private providers (often using publically available data from government ground, aerial and satellite sensing systems), university extension systems and farmer cooperatives. Sources of data range from public domain to private data held by farmers or third parties. Questions around data standards, data sharing, data ownership, and public and private rights add further complexity to modern PA, but are actively being addressed by both public and private institutions.*

Keywords. Variable rate irrigation, evapotranspiration, decision support system, SCADA, soil water content, remote sensing, precision agriculture

Introduction

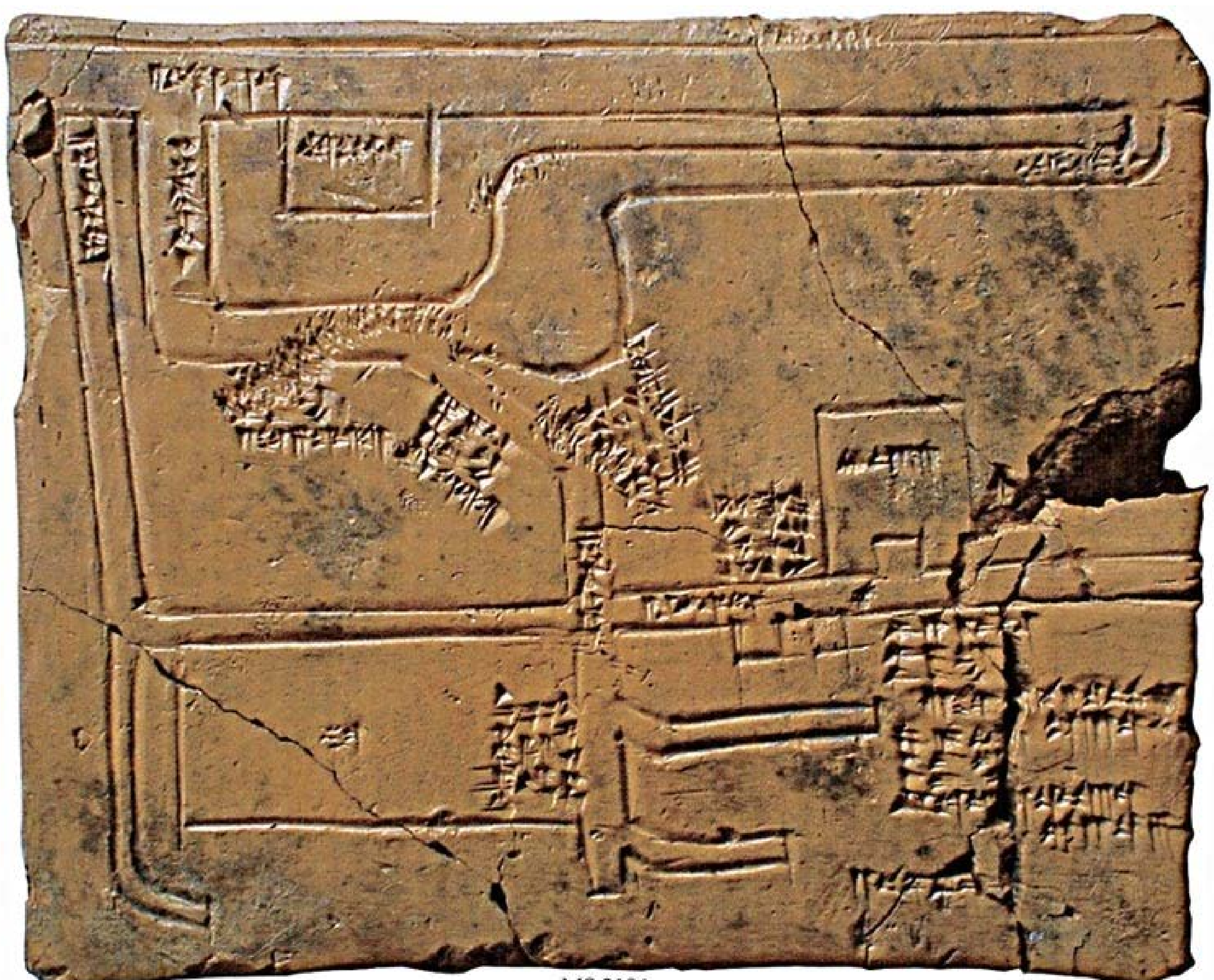
The basic premise of precision agriculture has been around since the first farmer decided to plant here, not there, to graze this area not that area, to irrigate that field not this one; and later on grew in complexity as farmers selected land races for specific environments. For example, farmers in West Africa have a wide variety of land races of sorghum and millet, some of which thrive in the wet lowlands while failing in the dry uplands, and vice versa. Similarly, farmers in the rice lands of Mali in the inland delta of the Niger River have a variety of rice landraces, some adapted to deeper flooding and planting in lower elevations and some adapted to less or intermittent flooding and planting at the upper edges of planting areas. Judicious selection and planting of these varieties helps farmers there grow rice successfully without terraforming to create level rice paddies, and allows considerable rice production despite inter-annual variations in flooding depth.

Site-specific water management likewise found its genesis in the selection of areas for drainage to ameliorate waterlogged soils and the sizing of fields and basins for irrigation according to the perceived infiltration rates in specific parts of the landscape. Because they create structures that persist over long periods and because the land areas affected are relatively large, these irrigation and drainage design practices are not recognized as precision agriculture, even though they are site specific and often based on precise topographic and geophysical data. Mapping of irrigation systems dates back at least to ancient Babylonia, almost 4,000 years (Fig. 1). With the advent of GIS, GPS and modern sensing and irrigation application systems, attitudes about the role of irrigation systems in PA are now changing.

Modern PA began in the 1980s when the GPS became available for public use. Coupled with GIS computer technologies, PA became a mainstream tool for farmers to plan site-specific agricultural operations. Equipment with GPS steering and position-aware supervisory control systems allowed application prescription maps to be downloaded into equipment, for example to turn off a moving irrigation system as it passed over a rock outcrop. GPS-enabled harvesting equipment produced yield maps that were used for site-specific management, often with confusing results due to a lack of co-varying data on soil and landscape properties and lack of adequate decision support systems (DSS) based on how soil spatiotemporal properties and landscape influence plant development.

Many of the more successful PA technologies involve on-board sensor systems allowing on the fly adjustments to equipment, for example to turn spray equipment on in the presence of weeds and off otherwise, or to turn on variable rate irrigation nozzles where abiotic stress sensors indicate crop water stress. These supervisory control and data acquisition (SCADA) based systems are multiplying rapidly and include systems that automatically thin fruit tree blossoms according to bloom density as a system moves through an orchard. Key to these PA systems are wireless data transmission, wireless sensor networks and the internet-of-things (IOT) in which every sensor is a georeferenced node in a larger network, and in which subnetworks are integrated into the internet. Although many successful SCADA systems rely on wireless sensor networks and georeferencing, many are not IOT enabled, although the potential exists. As systems are connected to the internet, issues of data ownership, already extant, become even more prevalent.

Today the confluence of computing power, data acquisition and management infrastructure, new modeling paradigms, and spatial decision support systems ushers in new possibilities for PA. For example, satellite data, initially not deemed useful for PA due to poor temporal and spatial resolution, are now used in computational systems that fuse data from satellites with different spatial and temporal resolutions and with different spectral imagers to provide daily evapotranspiration maps with 30-m resolution (Anderson et al., 2017). Providers of PA services now include government institutions, private providers (often using publically available data from state and federal government on-the-ground, aerial and satellite sensing systems), university extension systems and farmer cooperatives. Sources of data range from public domain to private data held by farmers or third parties. Questions around data sharing, data ownership and public and private rights add further complexity to modern PA. The IT sphere now has such importance to PA that some see PA as, “a suite of IT based tools which allow farmers to electronically monitor soil and crop conditions and analyze treatment options” (Aubert et al., 2012).



MS 3196

Figure 1. Map on clay tablet of canals and irrigation systems west of Euphrates. Named are Euphrates and three canals. Lengths, widths and depths of the canals are given. Source: The Schøyen Collection, MS 3196, http://www.schoyencollection.com/24-smaller-collections/maps/map-irrigation-ms-3196. (visited on 4 Sept 2017).

Examples of PA

There are essentially two paradigms for PA: (1) A passive/indirect method in which data are collected/assembled to produce maps of various state variables, which are then used to guide PA; and (2) An active and typically direct method in which sensor subsystems are parts of SCADA systems that process the data using algorithms to guide control of machinery for input and practice applications. These SCADA systems typically embody a DSS, often one that automatically generates a spatiotemporal prescription for action, which can likewise, but not necessarily, be automatically applied. Examples of the first paradigm include the numerous private and public organizations, including large agribusinesses such as Monsanto/Bayer, Cargill and John Deere, as well as a plethora of smaller businesses, that are involved in collecting high resolution spatiotemporal data from farms, evaluating the data, and providing value-added services that promise to increase yield, optimize input use and increase profitability and sustainability through spatially- and temporally-varying application of agricultural inputs and practices. Examples of the second paradigm include sensor feedback systems, such as herbicide sprayers, fertilizer application systems, and plant and soil feedback based irrigation systems, which automatically acquire sensor data, analyze the data to determine actions, and direct machinery to carry out the actions.

Prescription Fertilization. Site-specific fertilizer application was the earliest widely adopted example of PA practices in the US, and typically still follows the passive/indirect paradigm. Presently, the 4R concept (Right source, Right rate, Right time, Right place) is used to both promote and explain the importance of precision fertilizer management for increased nutrient use efficiency and decreased environmental impact (Sposari and Flis, 2017). In 2016 the USDA Economic Research Service (ERS) reported that nearly half of U.S. corn and soybean growers used GPS yield monitoring, greater than 20% used yield maps, and 16-19% used GPS soil fertility mapping (Schimmelpfennig, 2016). Of these, 20% used variable rate fertilization; but this practice was applied on 26% of corn and 34% of soybean acres, which indicates that adoption was greater on larger farms. Since 2011, yearly surveys of agricultural retail service providers by Purdue University showed increasing adoption of GPS soil mapping, yield monitoring and soil bulk electrical conductivity (EC) mapping (Erickson and Lowenberg-Deboer, 2017). Soil sampling with GPS mapping is more highly adopted than other practices and is closely tied to adoption of variable rate fertilizer application (Griffin et al., 2016); both farmers and dealers report positive returns on investments in PA fertilizer practices and equipment (Erickson and Lowenberg-Deboer, 2017). PA fertilizer practices are most commonly applied to corn, soybean and wheat in the US (Snyder, 2016).

Despite much research on the use of optical sensors of canopy reflectance for guiding fertilizer applications, this is still considered an advanced and emerging technology that is most often used later in the growing season to guide supplemental fertilizer applications (Snyder, 2016). While N-sensors may improve profitability by preventing over- and under-fertilization, the literature reports mixed results (Ondoua and Walsh, 2017). Like other methods, PA nitrogen fertilization guided by sensors fails when something other than N (most commonly water) is limiting. As with other PA technologies, the availability of precision application equipment outstrips the availability of DSS and the multiple sources of data required to make DSS reliable and the outcomes of following DSS-based application prescriptions successful.

Prescription Irrigation. A recent example in site-specific variable-rate irrigation (VRI) is the Irrigation Scheduling Supervisory Control and Data Acquisition (ISSCADA) system of Evett et al. (2014) (Fig. 2). This is an example of the active/direct PA paradigm. Motivated by the rapid increase in pressurized irrigation systems amenable to control in the US, and designed to work with linear move and center pivot irrigation systems that cover 65% of U.S. irrigated lands, this system uses plant sensors mounted on the irrigation system lateral pipe to scan plant water stress in the field and produce maps prescribing variable rate irrigation according to stress level (O'Shaughnessy et al., 2015).

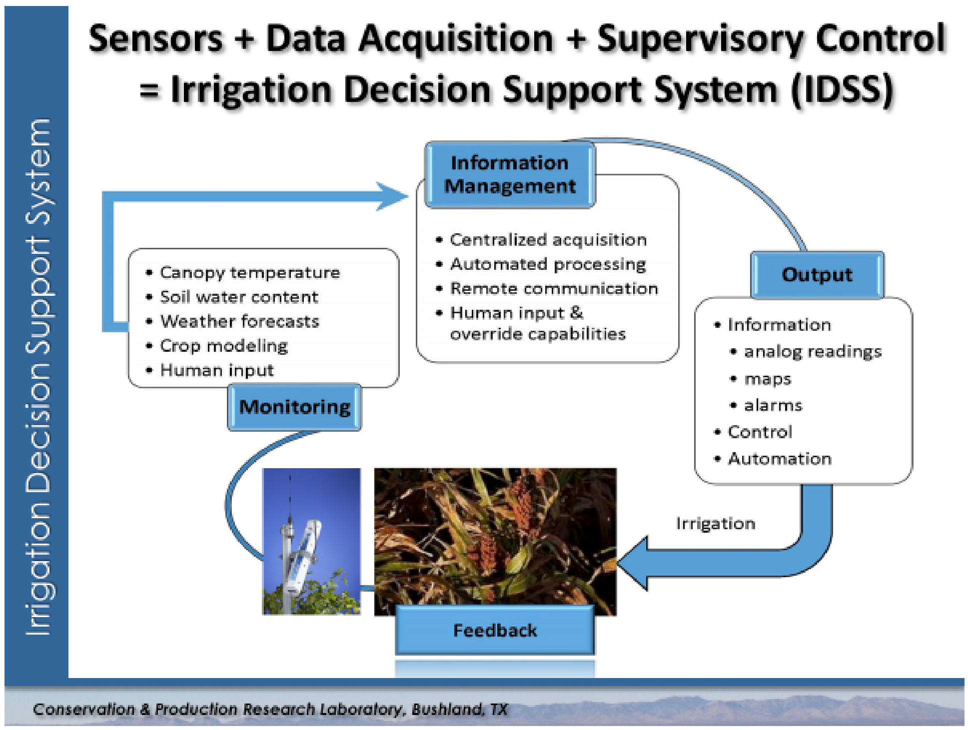


Figure 2. The sensing, information management, prescription mapping, irrigation control, and plant feedback loop for an Irrigation Scheduling Supervisory Control and Data Acquisition System that directs a variable rate center pivot irrigation system to apply water when, where and in the quantity needed.

A subset of sensors is fixed in the field for reference stress sensing and soil water sensors are buried to provide feedback on irrigation effects in the soil. Data from all crop and soil sensors and from weather sensors is automatically collected wirelessly by an embedded computer at the irrigation system pivot point. Novel algorithms allow conversion of plant stress measurements taken at one time of day in a specific location in the field to a diurnal curve of plant stress, which is then converted to an integrated crop water stress index for the day. This process is repeated for each control zone, producing a map of crop water stress (Fig. 3, Left). Control zones may be as small as 2 degrees of arc with radial increments defined by adjacent pairs of crop sensors pointing at the control zone from opposite sides (to control for sun angle and sensor zenith angle effects). The crop water stress map is converted into a prescription map defining irrigation amounts for each control zone (Fig. 3, Right), which may automatically guide the irrigation system, or be modified by the irrigation manager before automatic application. The infrared thermometer sensors and sensor network were commercialized from research prototypes (O'Shaughnessy et al., 2013), and the soil water sensors were also developed with a commercial partner (Evett et al., 2015; Schwartz et al., 2016). This amounts to a 3R system for irrigation: Right place, Right amount, and Right time; and it results in improved crop water productivity for several field crops in the U.S. Great Plains (cotton, maize, sorghum, soybean) (O'Shaughnessy et al., 2016).

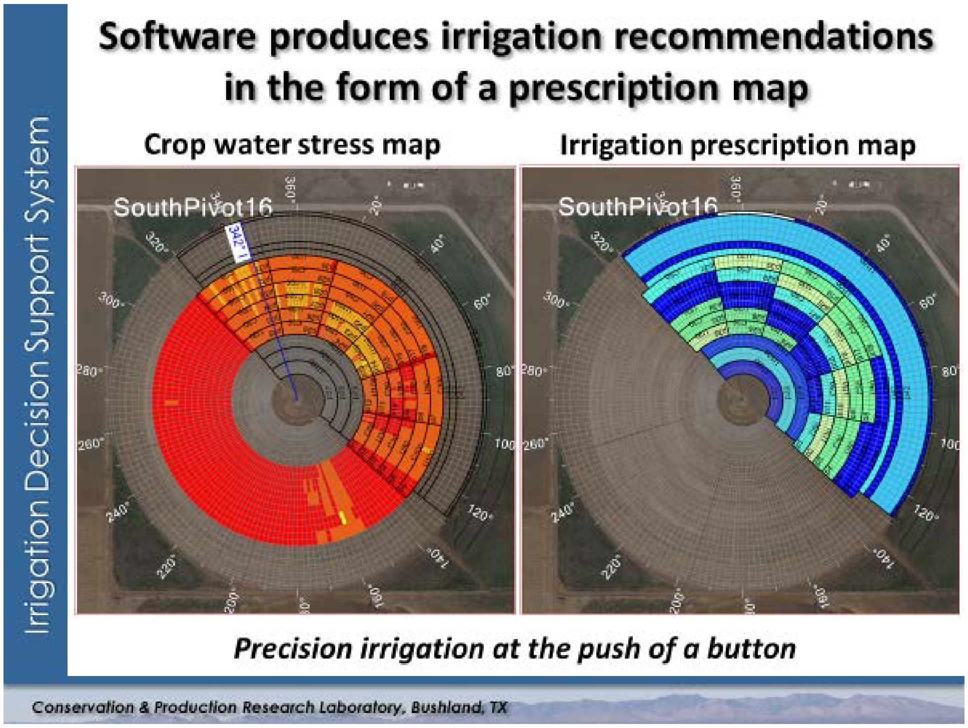


Figure 3. (Left) a crop water stress map produced from canopy temperature data acquired by a wireless infrared thermometer system deployed on a center pivot irrigation system lateral. The lower left half of the field was fallowed. (Right) An irrigation prescription map automatically produced by the ISSCADA DSS system from those data.

The ISSCADA system puts the PA sensors, IT system and application equipment in the hands of the producer. Although it can make use of secondary data such as SSURGO (NRCS, 2017) soil mapping units or soil EC maps to fine tune prescriptions, it doesn't require them.

A contrasting PA irrigation system is the newly developed "pixelated" irrigation management system used in vineyards in California (Semmens et al., 2015; Xia et al., 2016). This system is of the passive/indirect type. Data from multiple satellite remote sensing platforms is fused to produce daily, 30-m pixels of surface temperature and reflectance, which are combined with local microclimate data to produce evapotranspiration (ET—crop water use) data (Anderson et al., 2012; Cammalleri et al., 2013, 2014). In trials in California, daily 30-m data of vineyard ET were used to manage vineyard irrigation systems, reducing spatial variation of crop water status and yield, and improving crop quality. Expected operational products of this USDA-ARS-NASA collaboration, called GRAPEX, include datacubes of daily ET at 30-m resolution for selected growing areas (Fig. 4). E.J. Gallo Co. has developed a toolkit for using ET datacubes to determine the start of the irrigation season and weekly irrigation recommendations (Fig. 5). As a result of this work, ARS developed an ET toolkit that has been used in South Dakota, Maryland, Nebraska, North Carolina, and elsewhere to help solve site specific water management problems (Sun et al., 2017; Yang et al., 2017a,b,c)

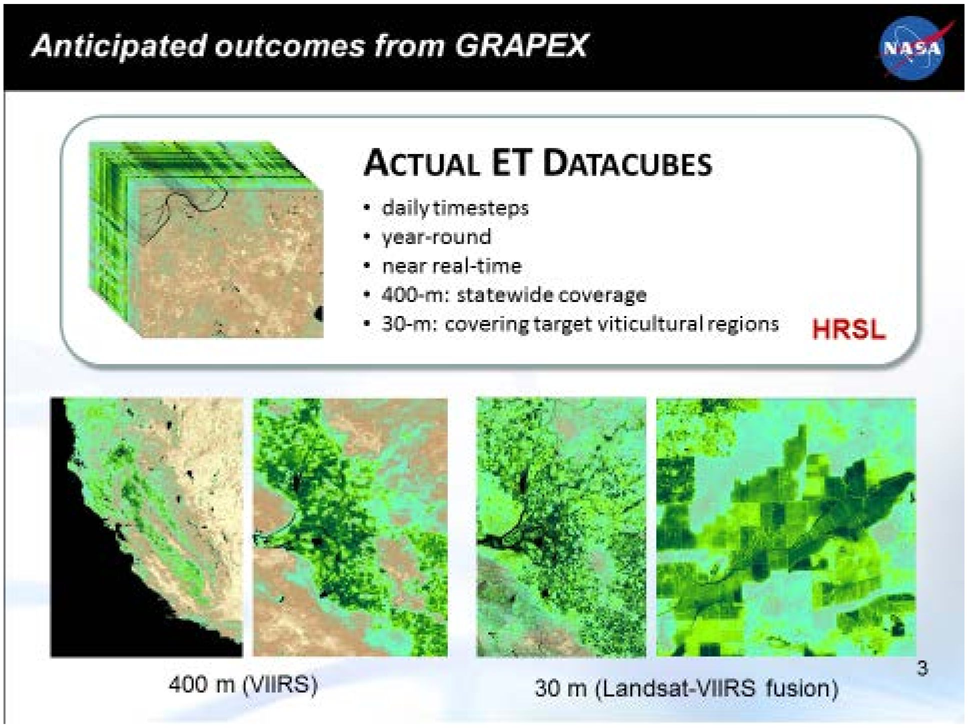


Figure 4. From left to right: California state-wide daily ET image at 400-m resolution, detail of the Napa Valley, same detail of the NAPA Valley but at 30-m resolution, and a closer look at a few vineyards and other fields at 30-m resolution.

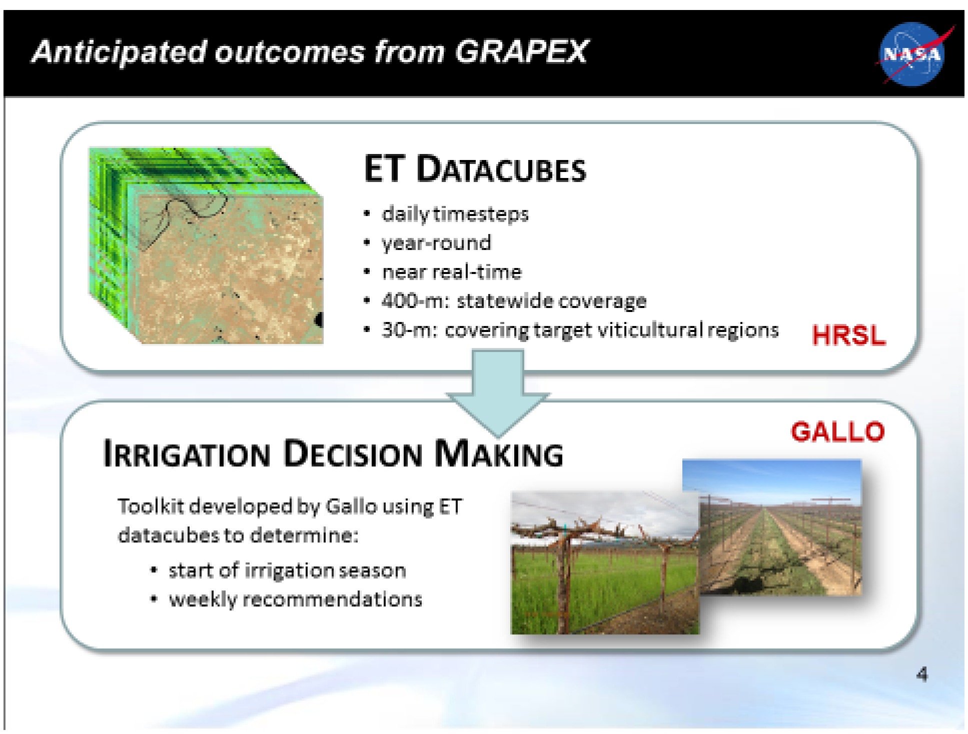


Figure 5. ET datacubes are made available at daily time steps in near real time and with 30-m resolution in targeted growing areas. E.J. Gallo has developed a toolkit for using ET datacubes to determine the start of the irrigation season and weekly irrigation recommendations.

PA for Other Specialty Crops. Specialty crop production, including grapes, accounts for greater than 38% of U.S. crop value production (USDA-NASS, 2015), and tree fruit production accounts for 39% of that production (USDA-NASS, 2014). But specialty crop production is labor intensive and thus costly, while labor availability varies inter-annually. Fruit thinning is one of the most costly steps in production, but ensures profitable production through optimal fruit size and quality. The same is true for crops such as lettuce, which is why precision planting and thinning systems are also being increasingly developed and put into practice in the US (Shearer and Pitla, 2014), and new ones are being developed (Lyons et al., 2015).

A new paradigm for PA – G × E × M

The consideration of plant genetics, environmental factors, and management practices in research on sustainable farming systems has led to the paradigm of G × E × M research (Hatfield and Walthall, 2015), which harkens back to the very beginnings of farmer recognition of environmentally-adapted land races and the management practice of spatial sensitivity in planting them. The G × E × M paradigm also looks forward to new technologies of rapid plant breeding; big data sets that include spatial and temporal landscape, soil, plant and weather data; and modern computing power applied to data analysis, agroecosystems modelling, and development and application of algorithms for decision making in the near term and even real time.

USDA-ARS is using the G × E × M paradigm and is extending it with a post-harvest component that relates strongly to the first three through yield quality, value and the production system's relationship to socioeconomics: G × E × M × S. The paradigm is a key part of USDA-ARS's Long Term Agroecosystem Research (LTAR) network research plan and is taking hold in other ARS national programs due to its power to guide research objectives to outcomes that are productive for stakeholders because it takes into account the entire farming operation and physical and hydrologic landscapes. These outcomes are naturally realized through PA because of its power to manage inputs in relation to the crop and environment in space and time to produce the crop yield and quality desired.

Because G × E × M × S research pulls in large amounts of interrelated environmental, genetic, management and yield and quality data, it produces large data sets that are well suited for use in developing and testing simulation models and sub-models of several kinds – crop growth and yield, canopy and cover development, canopy reflectance-emittance-temperature, soil water balance and plant water uptake, energy and water balance, and so forth. While crop simulation models are notoriously unreliable for real-time, site-specific prediction (e.g., Webber et al., 2017), the use of near real-time data assimilation techniques can render them sufficiently accurate for management purposes, with the added advantage of being able to predict at least short term future outcomes of applied management practices. When used with data assimilation, simulation models become the basis for PA decision support systems.

The accuracy and usefulness of simulation models is also improved through use of large data sets in multi-model comparison studies that explore the reasons for model inaccuracies and lead to model improvements (Liu et al., 2016; Webber et al., 2017). The Agricultural Model Intercomparison and Improvement Project (AgMIP, http://www.agmip.org/) is demonstrating how G × E × M datasets can lead to better understanding of model deficiencies and to model improvements (e.g., Maiorano et al., 2017; Pauli et al., 2017; Wang et al., 2017). This international research effort is strongly supported by UKaid and USDA, plus a variety of in-kind contributions by universities and other organizations internationally. Although not directly intended to support PA, the potential for AgMIP to improve PA DSS is clear, particularly when improved models are combined with wireless sensor networks.

Role of IT, including “big data”

Data standards for Information Technology (IT).
A primary problem with data that could be used in PA DSS is that data follow either one of many disparate data standards that exist today, or no accepted standard at all. For example, a datum as simple as soil water content has no meaning for crop management unless one knows at what depth the reading was taken, the support volume for the reading, where the reading was taken, and what the error limits of the datum are. Similarly for crop canopy temperature data, which may be used to guide irrigation, a datum has no utility for that purpose unless one knows whether the view was oblique (and at what angle) or nadir, the zenith angle it was taken at, the time of day and day of year (sun angle effects), the area covered, the crop growth stage (for estimation of soil background interference), and the error limits. Beyond these data characteristics, users need to know units of reported measurements; the metadata should include details of what was actually measured as well as what was reported. For example, many soil water sensors report volumetric water content, but none measure that; they measure either in the frequency or time domains; and knowing which can tell the user a lot about data reliability. We are living in a data Babel – shades of ancient Babylonia.

Application of data standards and data management plans are not keeping up with the Internet cloud and the IOT that encompasses rapidly burgeoning wired and wireless sensor networks. Traditional sources of environmental data—national weather networks (daily, subdaily); state and regional weather networks (daily and often subdaily); and hydrologic networks--are being surpassed by new soil moisture networks; ecosystem and agroecosystem research networks; satellite platforms (biweekly to daily and subdaily); data fusion systems applied to satellite data; genomics and plant breeding programs; ad hoc and commercially proprietary sensing and data manipulation networks; etc.

Nonetheless, bright spots are emerging. The USDA-ARS LTAR network has adopted data standards, including metadata standards, similar to those of EPA and USGS. All U.S. federal government data standards are transitioning to the ISO suite of standards; ISO 19115 and its accompanying standards will replace prior standards as the official metadata standard for U.S. federal agencies. Data management planning is now required for all USDA-ARS research projects, and for those funded by USDA National Institute of Food and Agriculture (NIFA), as well as most other federal agencies. In the commercial sector, AgGateway (http://www.aggateway.org/), a non-profit with greater than 230 member companies, is a leader in PA data standards, including the SPADE (Standardized Precision Ag Data Exchange) project creating standards for data exchange between farm management systems and field equipment. Its Precision Ag Irrigation Language (PAIL) project sets standards for field data used to develop irrigation management plans, operate irrigation equipment according to plans, and record the results (Ferreyra et al., 2017). AgGateway works with standards groups, including GS1, ASABE, AEF, OAGi and USDA. The AgGateway Global Network is a non-profit recently formed to expand the successful AgGateway collaborative framework outside the US.

Because of the rich, rapidly expanding and changing commercial sector of data providers, interpreters and users, data standards are key for interoperability of the sensors, IT systems, DSS and SCADA systems that provide value in the agricultural market through mechanized PA. Many potential partners inhabit this space: USDA, universities and cooperative extension, NOAA, NASA, USGS, DOE, NEON, FLUX-NET and many others. Turning potential to actual partners is the business of an ad-hoc consortium of many players, including commodity groups, Farmers Business Network, Field to Market, Ag Data Coalition, Ag Gateway, Open Ag Data Alliance, and private data integrators. Because a substantial part of these data are collected using systems that farmers own, or are observations made using government resources that relate directly to privately owned land, issues of data ownership and privacy arise. Some U.S. farm groups have suggested that USDA become the repository for such data, with appropriate privacy safeguards in place.

Future directions in research and technology transfer

Research

Almost every aspect of agricultural research has some application in precision agriculture. Geostatistical investigations of soil and plant attributes have long been established, but inclusion of temporal variations involves the application of ever more sophisticated models of plant growth and yield in response to the environment, management and dynamics of water and nutrients. As noted previously, supercomputing holds promise for not only the more deterministic simulation modeling approaches, but also for investigation of overall system behavior and identification of key variables through hypercube data analyses by means of network analysis methods.

AgMIP is one example of ongoing research needs in agricultural modeling (Rosenzweig et al., 2013); and it has yielded new insights into the need for not only better simulation models but also better data to support the development and testing of those models. For example, of 46 models tested, none was consistent in accurately simulating crop ET using high quality data sets. Since ET is a key covariate with yield, and one that is sensitive to climate forcing, it is of great interest to get this right. And because data are increasingly available at appropriate spatial and temporal resolutions for in-field management, the potential application to PA is clear.

There is much yet to be done in the development of sensors that can help identify plant biotic and abiotic stresses more accurately and quickly, at low cost and with low power consumption. The assembling of these sensors into wireless networks that are themselves low cost and low power yet reliable over long distances is a continuing challenge, but greatly aided by technology coming out of the smart phone industry. New wireless data transmission protocols and commercial systems are announced almost weekly. Increasingly, agricultural research requires true interdisciplinary teams that include crop physiologists, soil scientists, computational scientists, proximal and remote sensing scientists, agricultural and biological engineers, and electrical engineers. Such teams will be needed to develop the next generation of more capable GPS-guided SCADA systems for PA.

Unmanned aircraft (UA), also known as unmanned aerial vehicles (UAV), are increasingly used for crop, pest and irrigation systems management in the US. There were more than 1.1 million UAs in the US in 2016, and the FAA estimates that number will at least triple by 2021. Commercial UAs numbered approximately 42,000 in 2016 and are expected to number at least 442,000 by 2021—and may number as much as 1.6 million. Rules and waivers are in place to allow UA use in agriculture. Low cost UAs are the result of a confluence of miniaturized electromechanical technologies similar to those that allow low-cost wireless sensor networks: microelectromechanical systems (MEMs) sensors (gyros, accelerometers, etc.), GPS modules, low power-long range (LoRa) radios, and multi-band cameras. Thanks to a competitive smart phone market, these technologies have become very inexpensive and small, yet powerful. Research progress is rapid in both university and private venues, aided by an open-source community sharing computer code such as DIY Drones (http://diydrones.com/), and by 3-D printers for rapid prototyping and production, also with an open-source user community. Code for image stitching, orthogonal correction and image processing is readily available. While imaging fields is increasingly easy and inexpensive, even on a daily basis, there are continuing impediments to progress in delivering useful PA DSS. These include sensor calibration, image correction, image analysis and reliable decision support generation software. However, in many cases images are directly useful, for example in showing problems with an irrigation system, or a pest incursion.

While most wireless sensor networks operate with sensors above ground or embedded in the soil surface, there is increasing interest in sensing networks beneath the soil surface that can characterize the state and dynamics of chemical, physical and biological aspects of the rhizosphere. An upcoming National Science Foundation-sponsored workshop on the "Subterranean MacroScope" will focus on the many problems involved in developing the needed sensors and communications networks (https://ime.uchicago.edu/subterranean_macroscope/). Disciplines involved include microbiology, genomics, biochemistry, plant and microbial physiology, physical chemistry, biophysics, soil physics, MEMS, microfluidics and electrical engineering.

Technology transfer

The commercial sector is increasingly involved in PA technical transfer because most PA technologies are too complex for on-farm development. Manufacturers are involved in every phase to produce and market sensors and sensor network systems, build SCADA systems into agricultural equipment and produce and sell the equipment, often through dealers who to varying degrees take on the role of system support. This is also true in the development and marketing of new crop varieties that fit environmental and management scenarios and may be useful in PA planting systems. Commercial entities are increasingly active in the provision of actionable PA data and prescriptions to farmers. Companies such as Climate Corporation assemble data from multiple public sources (Landsat and other satellites, NOAA weather data, NRCS SURGGO soils data, etc.) and use large computing systems and statistical analysis to deliver recommendations. Many companies are providing aerial imagery at high resolution and in multiple visible and infrared light bands to guide PA farming, although data interpretation and decision support still are a work in progress.

NGOs are increasingly providing assistance for PA. Trade Industry groups such as the Irrigation Association provide certified training at their annual meetings and via webinar. Scientific societies are involved through their meetings and outreach to the commercial sector. For example, the American Society of Agronomy is currently developing a Precision Agriculture specialization within its Certified Crop Advisor (CCA) training program that reaches several thousand crop consultants in North America.

Cooperative extension also plays a role. In the US, cooperative extension was the predominant paradigm for transferring technology to farmers in the 1900s. Today, extension is hampered by budget cuts and to some degree cut out of the picture due to the expanding role of commerce. There are still valid roles for extension however, in conducting public trials of new PA DSS technologies, running publicly accessible demonstration farms, developing cost-benefit analyses of technology adoption, and publishing guides on new technologies.

Keys to Future Success

A 2016 Roundtable hosted by USDA-ARS's Office of International Research Programs and the International Society of Precision Agriculture identified 10 keys to ensuring successful DSS for PA (Yost et al., Submitted):

- Increase research documentation of PA outcomes
- Enhance funding for PA research
- Facilitate public-private partnerships
- Develop more IP-neutral relationships between public and private research
- Improve involvement of NGOs and others in PA research and application efforts
- Generate more PA projects that encompass the four goals of sustainable agriculture
- Achieve better balance between basic and applied research, short and long term funding, and small versus large grants
- Include more stakeholder involvement and retrospective assessments
- Enhance research relevance to smallholder farms, especially internationally
- Continue regular roundtable discussions

While these higher level concerns are certainly important considerations, it will be the constant process of developing and testing sensors and sensing networks, IT systems and software, and control systems and application hardware, coupled with a robust and open user community, that develops useful PA DSS and application technologies.

Conclusion

The fundamentals of precision agriculture were employed thousands of years ago in manual fashion, but it is only since circa 1980 that GPS technology has allowed easy and efficient mapping of soil, landscape and crop properties that can be used to guide precision application of practices and inputs. Originally conceived as a passive/indirect process of first measuring and mapping the state variables of interest, then using the map to make decisions about PA practices, PA today involves practices using a mix of the older paradigm and a newer one of active and direct response to variations in crop and environmental properties detected using sensor networks, often wireless, and often on the go. The definition of what PA is has been greatly widened by the availability of inexpensive, wireless and often mobile sensors, coupled with modern IT, sophisticated algorithms for data processing and decision support, and computer control systems guiding machinery to apply practices and inputs. Renewed focus on sensors of soil chemical, physical, biological and microbiological properties in the rhizosphere, and ways to wirelessly transmit data out of the soil, promise to engender the next generation of sensing systems for guiding PA. The great increase in data from private and public sources is opening up new avenues for both PA research and application. Simulation model improvements are proceeding and future models promise to be competent enough to be the internal engines of PA decision support systems, particularly if they are made self-correcting through assimilation of data from the plethora of internet-of-things sensors. Because most PA technology will be manufactured and made available to farmers through retailers, technology transfer is steadily moving from the public to the private sector, but there remains a place for public sector technology transfer, both from research to commercial production, and by extension services field testing, demonstrating and analyzing the economics of the new technologies.

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