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# Precision Irrigation Management

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## Introduction

Water is a crucial input for global food productivity in all aspects of agricultural production, from crop cultivation to livestock management to other aspects of the value chain (FAO, 2023). Irrigation remains vitally important in the United States and worldwide as a means to enhance agricultural productivity. Irrigation provides stability for agricultural productivity, enhances yield quantity and quality, and plays a vital role in sustaining production (Irmak 2023). Considering the negative impacts of climate change on agricultural production and management practices, especially in terms of increases in air temperature, vapor pressure deficit, and increased variability in precipitation timing, amount, and intensity, irrigation scheduling can be considered one of the most effective management tools to mitigate climate change impacts on the production of agricultural commodities, especially with respect to managing drought stress. Because drought and/or limited water resources are major limiting factors for food and fiber production worldwide, especially in dry regions, a substantial portion of the increase in crop production and crop water productivity (i.e., crop yield or biomass production per unit of irrigation or evapotranspiration) to meet the world's food and fiber demands will most likely stem from irrigated agriculture (Irmak 2015a, b). With the projected need of 60% more food production to achieve food security by 2050, the challenge is how to achieve this goal with the same or even reduced water resources without sacrificing water's other ecological services and functions. The challenge is elevated even further when other stressors to this resource, such as climate change, pollution, poor management and policy, and landscape alterations, are taken into consideration. Agriculture, which currently accounts for 70% of all water withdrawals globally, will be affected by these challenges, yet paradoxically, it holds the key(s) to the solution for food security and water scarcity in a rapidly changing world. Improving and expanding irrigated agriculture can directly increase food production (as compared with rainfed), mitigate yield decline during drought, improve the economic viability of existing cropland, and potentially reduce water usage in relatively inefficient systems. There is a concerted effort across the globe to perceive irrigation water use as part of the solution rather than a contributor to the environmental problem (ICID 2022). Thus, meeting the food and fiber demands of an increasing world population requires producing more commodities with equal or lesser resources, which requires enhancing crop water and nutrient productivity. These enhancements can aid in reducing within-field water losses and increasing crop production efficiency by applying the proper amount of water at the right time and at the right place in the production field utilizing precision irrigation technologies.

This paper discusses the role of irrigation technologies and complementary precision crop management in addressing these challenges in water resources and food production. First, the paper defines what precision irrigation entails, how it can improve performance efficiency, and the technologies that apply this concept to different irrigation systems. This includes gravity irrigation systems, which are considered the least efficient among all systems, yet are still used extensively in the western U.S. (Figure 1) and are the dominant irrigation method globally. Regardless of irrigation type, decision support systems and fertigation can improve the performance of irrigated production, which is discussed in the second chapter. This area is increasingly utilizing new technologies, such as soil water content sensors, mobile applications for water management, computer simulations, and evapotranspiration (ET) monitoring. This chapter is followed by discussions of the benefits these precision irrigation tools can provide. Chapter four discusses the state of adoption of precision irrigation technologies. Despite the promising opportunities and benefits, adoption is not yet at the optimum level in which irrigated agriculture can benefit from its maximum potential. Challenges and barriers to adoption will be discussed from different angles (sensors and sensing platforms) and sectors (integration and extension). Chapter five discusses other complementary technologies and themes related to precision irrigation, with the goal of bolstering the adoption rate and impact of these technologies to irrigated agriculture. The last chapter summarizes the benefits and risks (economic, environmental, and agronomic) of precision irrigation as well as future needs in research and extension/education.

## General Overview of Precision Irrigation

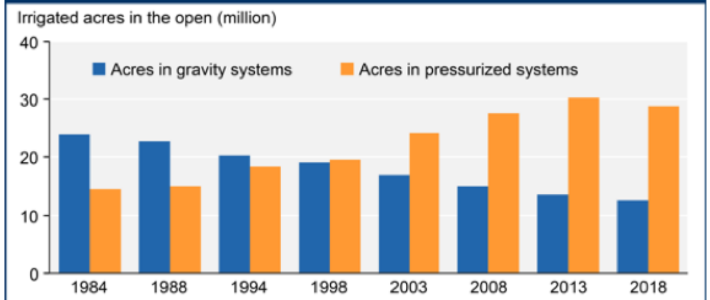
Irrigated agriculture is critical to meet the increasing demand for agricultural products. On a global scale, water used in agriculture represents roughly 70% of all water withdrawals (FAO 2020) and land dedicated to irrigated agriculture totals approximately 3.67 million km2 (Meier et al. 2018). Irrigated cropland produces double or triple the yields of rainfed crops in semiarid and arid regions (Musick et al. 1994; Norwood 1995; Evett et al. 2020a). However, today more than ever, water scarcity and water quality issues are challenging sustainable water management. The situation is greatly exacerbated by climate change, population growth, declining water resources, and competition for water from other users and economic sectors. Without irrigation, crop yields are unstable in areas where rainfall is unpredictable (Oweis et al., 1998; Lamb et al., 2011); subject to significant loss where rainfall is minimal, such as in semi-arid and arid regions (Klocke et al., 2012; O'Shaughnessy et al., 2014); and susceptible to substantial crop failure during periods of heat stress and drought (Lobell et al. 2013; Rippey 2015; Lesk et al. 2016; Otkin et al. 2016).

Using irrigation to improve the quantity and quality of grain yield is an essential agricultural practice (Sadler et al. 2005), especially in arid and semi-arid areas. The irrigation sector accounts for more than half of global freshwater consumption (Johansson et al. 2002). Yet, this water-demanding sector is compelled to optimize water usage more strategically due to the increased competition from expanded water-dependent industries (e.g., energy, mining, manufacturing, etc.), the increased public concern over water availability and quality, the rising cost of water and energy resources, and the increased frequency of extreme climate events.

Historically, irrigated agriculture in the United States was concentrated in the west; however, over the past 70 years, there has been a decline in irrigated acreage in this region and a shift of irrigated cropland eastwards and northwards into the Mississippi Delta, Southeast region and Northern Plains regions, respectively. Irrigation systems in the U.S. have become more efficient in recent years, mainly due to the widespread conversion from gravity flow to pressurized irrigation systems (USDA-NASS 2019). However, due to water scarcity, there is continuous pressure on the agricultural sector to improve irrigation application efficiency and yield per unit of water used by the crop (crop water productivity).

Site-specific water management, or delivering water to a specific location, has been in existence for thousands of years (Evett et al., 2020b) and can be achieved with gravity flow or pressurized irrigation systems. An example involving gravity flow systems is the automation and control of canal water to improve water management (Merkley et al. 1990) and overcome unreliable or uneven water distribution (Shahdany et al. 2018). In pressurized

**U.S. irrigated farmland acres in gravity and pressurized systems, 17 Western States, 1984-2018**




Note: Data are for acres irrigated in the open (i.e., area in greenhouses and other enclosed structures is not included). Gravity irrigation systems use on-field furrows or basins to advance water across the field surface through gravity-means only. Pressurized systems (e.g., center pivots) apply water under pressure through pipes or other tubing directly to crops. Pressurized irrigation includes acres irrigated by sprinkler and micro/drip irrigation systems. The 17 Western States are Arizona, California, Colorado, Idaho, Kansas, Montana, Nebraska, Nevada, New Mexico, North Dakota, Oklahoma, Oregon, South Dakota, Texas, Utah, Washington, and Wyoming.
Source: USDA, Economic Research Service using data from USDA, National Agricultural Statistics Service, Farm and Ranch Irrigation Survey (1984-2013) and Irrigation and Water Management Survey (2018).

systems, zone-controlled drip irrigation is used in vineyards and orchards to apply water during specific growth stages to improve fruit quality and water use efficiency (Katz et al., 2022). For sprinkler irrigation systems, moving line source systems, also known as traveling trickle (Howell and Phene 1983) or mobile drip irrigation (Kisekka et al. 2017; O'Shaughnessy and Colaizzi 2017), are under trial to investigate application efficiency and reduction in water losses from evaporation and high wind speeds. Most moving sprinkler irrigation systems can apply variable amounts of water laterally along the direction the irrigation system travels using speed control. Variable rate irrigation (VRI) hardware in the form of zone (a bank of sprinkler nozzles) or individual nozzle control allows watering rates to be varied along the lateral, as well in the direction of sprinkler movement. Prescription maps for VRI systems can be useful to customize application depths based on variable soil textures within a field or to withhold irrigation over non-arable areas, such as creeks, ponds or non-cropped areas, that are located within an irrigated field (Pierce 2010). Finally, greenhouse and vertical cultivation systems integrate automation and ecological control of the growing environment (temperature, light levels, humidity, carbon dioxide, etc.) with site-specific water and nutrient management for specialty crop production (Lu and Grundy 2017).

Precision irrigation (including variable rate irrigation) may include a variety of technologies and practices to achieve precise application rate, placement, and timing of irrigation water to a crop's root zone to optimize crop water use. With increased popularity and advancement in variable rate technologies, the concept of VRI is becoming more prominent (Sui et al., 2015; Evans et al., 2012; Corwin and Lesch, 2003). This approach aims to reduce water wastage and increase crop yield by controlling the application of water with the right amount at the right time (via a scheduling tool) and at the right location.

Various commercial VRI systems have been available for several years and have received increased attention from producers and irrigation specialists who search for innovative strategies to improve water productivity and conservation.

Research shows that VRI can achieve an average of 10-15% and up to 50% reduction in water consumption, depending on the efficiency of system components as well as the specifications of the irrigation sites, compared to uniform management (Council of Canadian Academies, 2013; Sadler et al., 2005). With the combination of other technologies, such as proximal soil sensing, global navigation satellite systems (GNSS), geographic information systems (GIS), and wireless data communication, VRI allows for fine-tuning the application of water to meet site-specific crop requirements. This subsequently helps to maximize crop yield and minimize water and/or energy consumption. Approximately 99% of VRI systems are designed to retrofit a center pivot irrigation system, which is more efficient and less labor-intensive than other types of moving irrigation systems (Evans et al., 2012).

In brief, a center pivot VRI system comprises a pivot rotating a pipe carrying multiple sprinkler nozzles centered in an agricultural field. Generally, two types of VRI systems are available: Speed Control (SC) and Zone Control (ZC) (Oliver et al., 2013). Speed Control keeps a constant water flow from nozzles while altering the pivot travel speed in angular increments as small as 1 degree. The application amount is then varied locally within each radial sector. Zone Control allows higher levels of irrigation control as the pie wedge-shaped sectors can be subdivided into smaller field segments by adding irrigation control zones along the lateral pivot arm. However, Zone Control is not restricted to subdividing the wedges and it should be able to handle roughly any shape of management zone, within the limits of the irrigation system design. The application amount is then allocated into each field segment, whose area is varied according to the size of angular increments, distance from the pivot point, and the number of control zones.

Microirrigation technologies (microspray, surface drip, and subsurface drip irrigation) also have advanced capabilities for precise placement, timing, and rates of irrigation. According to Lamm, et al. (2021), subsurface drip irrigation (SDI) has continued to expand in recent years with development and ongoing research of technologies and management strategies for application to an expanding variety of crops. Despite some persistent challenges, there is still opportunity for further expansion of SDI. Variable rate drip irrigation is now being used in vineyards to apply precise amounts of irrigation to specific irrigation zones, reducing variability in yield and quality (Nadav and Schweitzer, 2017). Research is also underway to develop variable rate drip emitters that can be controlled remotely to enable field-scale variable rate drip irrigation systems (AL-agele et al., 2021). With good design, installation, maintenance and management, microirrigation systems offer potential for achieving high application efficiency and application uniformity, and hence precision in placement and rate of applied water.

Spatially variable crop water needs can result from differences in microclimate, field topography, soil physical properties such as soil texture, apparent electrical conductivity, salinity, and pest or disease infestation (Smith et al. 2009). Precision irrigation technologies combine site-specific irrigation systems with sensor feedback to detect differences in crop water status in space and time (over a growing season) (Figure 2). These technologies, when managed and functioning properly, apply water in the right location, at the right time, and in the right amount. Several academic, government, and private institutions are independently developing precision irrigation systems in the U.S. (Evett et al. 2020c; Zhang et al. 2021) and working with farmers to increase adoption of water-smart technologies (Bondesan et al. 2019; Ortiz et al. 2021). Information from the sensors provides input for models or algorithms whose outcomes can be used to predict crop growth, monitor crop status, or schedule irrigations. Pressurized systems in the form of moving sprinklers or microirrigation systems also are generally well-suited to automation, offering relatively easy application with emerging "smart" irrigation technologies and controllers. An example is the ARSPivot software (Andrade et al 2020) integrated with the Irrigation Scheduling Supervisory Control and Data Acquisition (ISSCADA) system (Evett et al. 2020), which uses sensor feedback to recommend scientific irrigation requirements.

## Utilization and Benefits of Precision Irrigation Technologies

Precision irrigation technologies implemented alone or in combination with improved cultivars could be used in water-limited regions to improve crop water productivity or crop quality. For example, precision irrigation in vineyards or orchards could improve the quality of fruit and raise the value of the product (Bahat et al. 2019; Cohen et al. 2021). Precision irrigation technologies typically incorporate automation and control by monitoring crop or soil water status, predicting when to apply an irrigation, and automatically turning the irrigation system "on" and "off", thereby offering convenience and time savings to farmers. The application of precise amounts of water to exact locations within an open field or in a controlled environment could be more cost-effective and environmentally favorable than uniform application of water. Other potential benefits of precision irrigation include minimizing water wastage, aiding in compliance with regulatory requirements for water allocation, and improving yield per unit of water applied where water is limited. Smart irrigation systems could help develop strategies to mitigate unpredictable rainfall and increase the resilience of irrigated agriculture from climate change by enabling adaptive control. However,

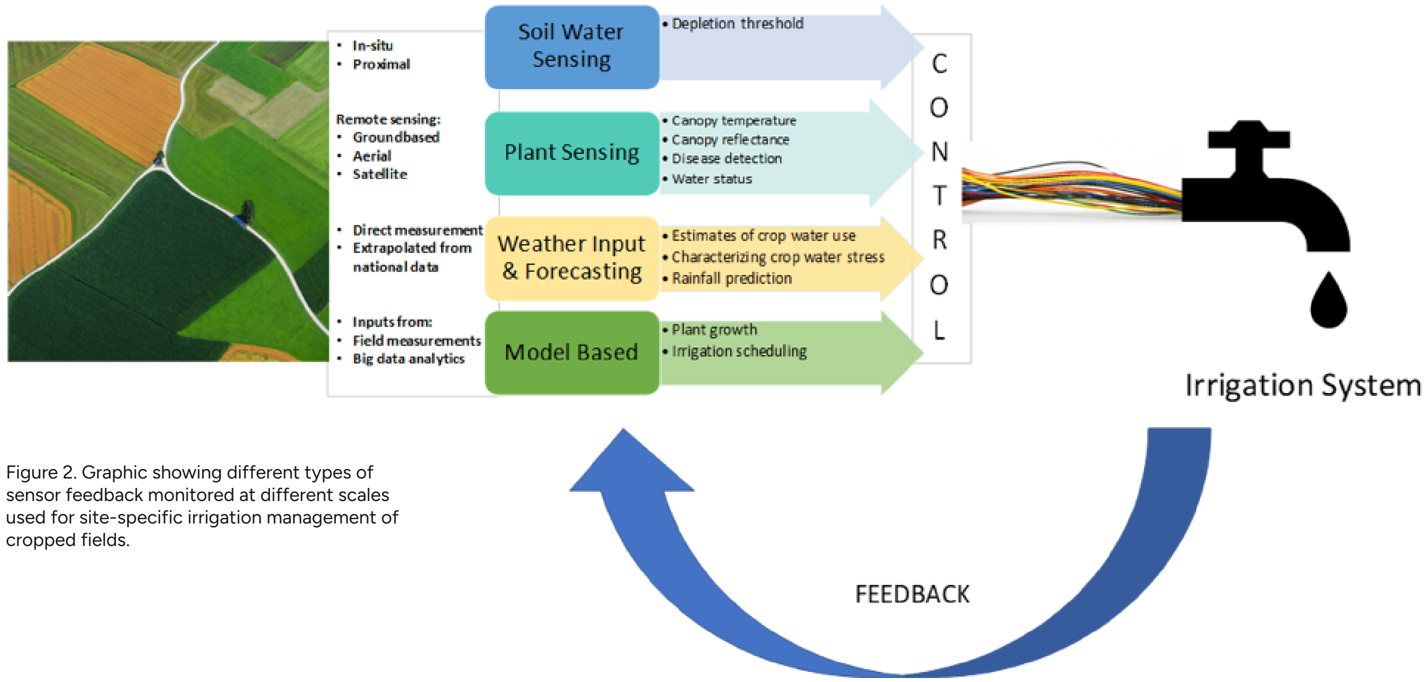



Figure 2. Graphic showing different types of sensor feedback monitored at different scales used for site-specific irrigation management of cropped fields.

the economic return versus the cost of VRI and precision irrigation technologies must be carefully considered (Sharma and Irmak 2020; O'Donnell et al. 2023), not only at the agronomic or irrigation engineering and crop science fields, but also in production fields. Their implications for economic and environmental services also need to be quantified, demonstrated, and disseminated for a wider adoption (Irmak et al. 2012).

## Decision Support Systems for Precision Irrigation

### Irrigation scheduling technology

The amount of water required to maximize yield and/or crop water productivity varies depending on the crop, the growth stage of the crop, and the environmental demand. Precision irrigation systems can be managed to adapt water applications to different crop growth stages or crop evapotranspiration requirements within the growing season. Adaptation requires fundamental information provided by the farmer (crop type, planting date, soil type, water stress thresholds, and soil water depletion thresholds) to predict crop growth stages. Data collected from sensors, such as soil water content, plant (canopy) water stress sensors, and nearby weather data, can be used to adjust irrigation control strategies throughout the growing season (McCarthy et al. 2010 a, b). Adaptative irrigation control strategies could also use historical information to predict rainfall and help manage irrigation timing.

### Management zones

Management zones (MZ) are areas within a field that have similar features and can be treated in a like manner or managed as a separate area. The boundaries of an MZ can be static or dynamic. As of today, most MZ are static, meaning that the physical boundaries of the zones remain the same over time. These zones are typically established based on physical soil textural or hydraulic properties, soil electrical conductivity maps, topographical or digital elevation maps, and historical yield data (Bevington et al. 2019, Cohen et al. 2021). Although MZ boundaries may be static, prescription maps for these areas can be dynamic to address changes in crop water status over time. It is also possible that MZ boundaries can be dynamic when using aerial or satellite imagery; however, software development is needed to downscale the new boundaries into a format that is usable by a moving irrigation system or by developing variable rate emitters for drip irrigation systems.

Whether management zones are static or dynamic, it is necessary to upload MZ boundaries to the irrigation controller or the nutrient application equipment. Different methods can be used to delineate MZs; examples include manual methods by overlaying a semi-transparent gridded map of a field over a Google Earth image and using GIS mapping software to draw MZ boundaries based on physical features of areas that do not yield well or are non-arable. Statistical methods, such as kriging, cluster analysis, and multivariate regression, can be used to partition spatially variable data into homogeneous clusters to develop MZs within in a field (Fraisse et al. 2001; Basso et al. 2007; Haghverdi, et al. 2015; Peeters et al. 2015; Bevington et al. 2019; Ohani-Levi et al. 2019). Statistical methods can also be used to provide the optimal number of MZs in a field, a value that is usually based on economics (Figure 3). Satellite and drone imagery has been very useful in providing attributes used in MZ delineation. The attributes include hydraulic conductivity curves; soil physical properties (texture, bulk density); water retention curves; shallow and deep soil apparent electrical conductivity (ECa); canopy and bare soil reflectance measurements; crop yield maps; non-invasive soil information; soil properties; digital elevation mapping; and terrain information (Morata, 2020; Flint et al., 2023). However, all these variables are very difficult to map at usable spatial resolution and their beneficial utilization for MZ delineation can result in variable successes.

The boundaries of a MZ that can be effectively managed by center pivot or linear move irrigation systems equipped for VRI are influenced by the way in which different manufacturers implement VRI for their irrigation systems. Some manufacturers use an underlying grid of trapezoids (for center pivot systems) or rectangles (for linear move systems); the areas correspond to the smallest areas for which irrigation amounts can be individually controlled by the VRI system. An MZ for a VRI system using an underlying grid can be created by grouping a set of areas with similar characteristics. Thus, the boundary of the MZ will be determined by the outer perimeter of all the grouped areas that are part of the MZ (Figure 3). Other manufacturers use a different approach, where an MZ is delimited by a set of points that correspond to the corners of the MZ. The geographic coordinates of this set of points must be obtained to generate the MZ.

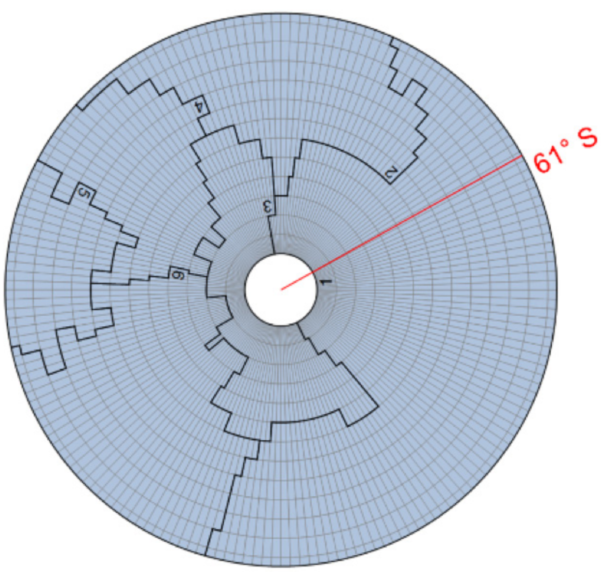



Figure 3. Grid of trapezoids upon which six Management Zones (MZs) were generated using the ARSPivot software (Andrade et al. 2020) by grouping six sets of trapezoids with similar characteristics. The red line represents the angular position (61°) of a center pivot Variable Rate Irrigation (VRI) system.

## Soil water content and plant stress monitoring

### Soil water monitoring

Precision irrigation scheduling based on soil water sensing involves monitoring soil water content in the root zone—at two or more depths, in the case of soil water sensors—until a pre-established threshold is reached. Irrigation water is then applied to replenish soil water depletion in each management zone. Soil tension (matric potential) is not directly measured but is a surrogate variable strongly influenced by, for example, permittivity, resistance, travel time of broadband step pulse, neutron intensity, etc. Soil water sensors can also be used to track root water uptake dynamics characterized by sharp declines in water content during the day and negligible changes in soil water at night. Examples of commercially available soil water sensors include soil water potential sensors (tensiometers), resistivity-based sensors (e.g., gypsum block), capacitance sensors, sensor-based on time-domain (TDR), and frequency domain reflectometry (FDR). Neutron probes are the most accurate method to measure soil water content as a low-level radioactive source is lowered into an access tube near the plant's root system and measurements are taken at multiple depths. Neutron probes are primarily used only in research and not in production fields because of the extensive labor involved in using the instruments, their high cost, and the regulations related to radioactive material (source). Passive neutron probe sensors called cosmic ray neutron sensing are beginning to be commercialized. The advantage of this sensor is that it has a footprint scale of a few hundred meters.

Since soil water content is not measured directly, site-specific calibration must be done for each sensor to convert a surrogate soil variable to soil water content. Another disadvantage of most commercially available sensors is that they sense a very small soil volume, which results in variability between sensor replicates, making interpretation very difficult. While the science behind how these different sensors operate has not changed for decades, significant improvements in electronics and data communication protocols have resulted in lower costs and seamless real-time monitoring (Kisekka et al. 2022). However, most growers use soil water sensor data to qualitatively assess trends in soil water dynamics, but not to determine actual soil water content. Because precision irrigation requires recommendations for irrigation depths and often involves multiple MZ, the challenges are to determine the optimum number of soil moisture sensors to install in each MZ and to provide actionable information. There are many soil moisture sensor companies and the industry has evolved. One trend has some ag tech companies that sell data service charging growers an annual or seasonal subscription to access soil water data (e.g., Hortau, Irrometer Company, Sentek Technologies, METER, GroPoint, Acclima Inc., etc.) or receive irrigation scheduling recommendations (GoAnna Ag, GroGuru, Prospera).

In agricultural production and natural ecosystem fields, heterogeneity in soil moisture can exist due to numerous factors, including landscape/topography; cropping system/vegetation types and their characteristics; soil physical, chemical, and hydraulic properties; meteorological/climate variables, especially non-uniform distribution of precipitation; intended or unintended (wind drift, sprinkler malfunction, etc.) non-uniform irrigation applications; soil management practices, including tillage management; nutrient management; and other variables (Irmak et al., 2022;

Wilson et al., 2004). Thus, in addition to soil water sensing technology performance and adaptability in different soil types, spatial variability should be accounted for in various agronomic management practices, including practicing effective irrigation management (Irmak et al., 2022).

**Soil-water and plant stress monitoring**

Precision irrigation scheduling based on plant water status monitoring involves the use of sensors that measure water stress directly (e.g., pressure chamber) or indirectly (e.g., dendrometers). Plant water status monitoring for precision irrigation is commonly used in specialty woody perennial crops, e.g., almonds, citrus, pecans, and grapes, as well as agronomic row crops such as soybean, maize, sorghum. Midday stem water potential (SWP) has been proven as the best indicator of plant water status because it integrates soil factors for the entire root zone and environmental conditions (Fulton et al. 2014). SWP measures the water tension in the plant; low stem values are related to low sap-flow velocities and can be caused by low soil moisture (Kume et al., 2007). SWP is dynamic and is not only affected by soil water content but also environmental conditions and management. SWP changes diurnally and seasonally, and it is a more difficult method to develop absolute general thresholds for triggering precision irrigation events as compared with monitoring soil water content. For this reason, SWP measurements should be benchmarked against a reference or baseline SWP for non-water stressed trees under the same environment (Kisekka 2022). Measurements of midday SWP are usually collected around solar noon or between 1 and 3 p.m. when SWP is minimum (i.e., most negative). In some crops, such as grapes, leaf water potential (LWP) is used. LWP does not require placing a leaf into an aluminum bag before placing it in the pressure chamber and tends to be quicker to measure. However, it is more sensitive to atmospheric demand and tends to be more variable compared to SWP. Although SWP is preferred, measurement of midday SWP is labor-intensive, which has contributed to its lack of widespread adoption in precision irrigation.

To overcome this challenge, recent research and development has focused on making sensors that can continuously measure SWP. These sensors can be broadly categorized into osmometers and micro-tensiometers. The osmometer sensors measure pressure changes due to changes in osmosis of the chamber fluid. The sensor has a semi-permeable membrane that allows water movement between the tree xylem and the sensor fluid chamber (Meron et al., 2015). The change in pressure measured by the sensor can be interpreted in terms of stem water potential. Other types of SWP sensors act as micro-tensiometers. Micro-tensiometers are based on tensiometry, a technique for measuring the chemical potential of stretched liquid water based on a thermodynamic equilibrium between the stretched water and its vapor (Pagay, 2014). An example of microtensiometer SWP is the FloroPulse stem water potential sensor (Kisekka, 2022). Overall, research has shown good agreement between SWP sensors and the pressure chamber, which is used as the scientific benchmark for SWP monitoring.

Plant water status monitoring for implementing precision irrigation scheduling can also be accomplished using dendrometers. Dendrometers measure the mean daily shrinkage (MDS). MDS refers to the difference between daily maximum and minimum trunk diameter. Soil water depletion or more demand from weather causes the trunk to shrink more each day. Research in almonds has shown dendrometers to be good indicator of plant water stress. An example of a commercially available dendrometer for precision irrigation is Phytech Ltd. (https://www.phytech.com/). Other types of sensors that have been successfully used to monitor water stress include sap flow gauges that have been commercialized to support operational precision irrigation scheduling (e.g., TreetoScope). However, data from sap flow gauges can be variable, making it difficult to extract insights to inform precision irrigation scheduling.

While SWP and dendrometers have been used successfully in precision irrigation management, they are more commonly used in high-value crop production. Monitoring canopy temperature remotely using thermal sensing has been a longstanding practice to characterize crop water stress by converting the data into a thermal stress index. Popular indices are the crop water stress index (CWSI) (Meyers et al. 2019; Drechsler et al. 2019), the DANS index (degrees above non-stressed plants) (DeJonge et al., 2015), and the TTT method (time-temperature threshold) (Wanjura et al., 1995). Remotely sensed thermal data can be captured from satellite, aerial, or ground-based platforms; regardless of the platform, data must be geolocated. While the CWSI can be an effective tool for quantification of plant water stress level and can aid irrigation decisions, Irmak et al. (2000) showed that this method is primarily effective in determining irrigation timing and yield estimation rather than providing guidance or recommendations for irrigation amount. Thermal imagery from satellite sensors has been used to estimate regional crop water use (evapotranspiration). While satellite imagery may be too coarse for precision irrigation scheduling on individual farms, algorithms have been developed to downscale the information to the sub-field scale (Ha et al. 2013; Wang et al. 2017), and thermal imagers mounted on unmanned air vehicles provide imagery at a higher resolution (Lacerda et al. 2022). However, with all platforms, a software with functional algorithm(s) interface is needed to translate the acquired data into watering rates using a format compatible with the variable rate irrigation controller. While plant-based measurements typically signal crop water status sooner than soil water status, the use of plant-based sensors is not popular among producers.

## Water management apps

Significant progress has been made both by university research and extension programs, as well as the commercial irrigation industry in the U.S., to develop irrigation management apps that are either web- or smartphone-based. With minimum inputs desired from the user, such as location, planting/harvesting dates, crops, and irrigation system characteristics, these apps can simulate the soil water balance by retrieving public weather and soils data to provide real-time irrigation scheduling prescriptions. Some of these apps are aimed at eliminating the need for installing weather monitoring or soil moisture sensors at the site, although provisions to add such instrumentations into the app may exist. To enhance the predictive accuracy, however, some of the apps are specifically designed to process field-measured soil moisture data/information to provide more effective and representative recommendations (rather than relying on modeling) for a specific field condition (Irmak 2010; Bordovsky et al. 2017; Irmak 2023). The accuracies achieved in decision-making by relying on university-developed irrigation management apps have been evaluated against ground truth data in contrasting conditions (Andales et al. 2014; Bordovsky et al. 2017; Brad and Phil 2017; Cahn et al. 2015; Carlson 2019; Han 2016; Irmak et al. 2010; Kisekka and Kim 2018; Migliaccio et al. 2015; Peters et al. 2013; Rogers 2012; Sanford and Panuska 2015; Scherer and Morlock 2008; Stevens 2014; Vellidis et al. 2016; Wright 2018; Irmak 2023). These decision tools are welcomed by local producers as a free-of-cost irrigation management solution that can be used either singularly or to complement other solutions, such as soil and plant moisture sensors. Some commercially available irrigation apps can further streamline irrigation management by allowing the smartphone to communicate with multiple irrigation systems on the farm. This integration of devices has been saving substantial time and fuel that otherwise would have been spent by the producer for manual irrigation operations, justifying investment on irrigation app subscriptions.

High spatial variability of rainfall is somewhat challenging to be measured by the limited to moderate spatial distribution of weather monitoring networks, hindering robustness of app simulations (Migliaccio et al. 2015). There is significant future promise for irrigation management apps to incorporate real-time crop feedback into simulations, as remotely sensed soil and crop status information becomes cheaper and more accessible. The short-term weather forecasts can also be effectively used in irrigation decision support apps. Additionally, advances in data analytics by employing machine learning algorithms may overcome the need for otherwise complex parameterization of soil water balance models.

## Decision support systems for variable rate irrigation Platforms for ET monitoring

Evapotranspiration (ET) is the largest component of the soil water budget in any terrestrial ecosystem, including agricultural fields. Thus, accurate determination of crop ET becomes a necessary precursor to efficient irrigation management, especially when relying on soil water budget techniques. Crop ET can be indirectly or directly measured using sophisticated instrumentation, such as Eddy Covariance systems, Bowen Ratio Energy Balance Systems, lysimeters, scintillometry, sap flow gauges, stable isotopes, etc. The use of such techniques, however, is limited to research applications, being complex, costly, and requiring substantial time investment. Typically, crop ET is estimated using mathematical formulations that integrate the atmosphere's demand for water (demand side) with soil and crop condition (supply side). For irrigation management applications, the two-step method reported in FAO-56 (Allen et al. 1998) and more recently outlined by Jensen and Allen (2016) is widely used by practitioners. This procedure is heavily employed in data-scarce environments by assuming crop growth and water uptake patterns. Since a lack of precise soil and crop monitoring is generally typical of commercial production environments, the two-step approach is one of the tools to tracking ET in irrigation scheduling and is frequently used in water management apps. ET determination using the two-step approach has been shown to improve significantly when site-specific data on soil and crop conditions are incorporated (Pereira et al. 2020; Kimball et al. 2019; El-Naggar et al. 2020). For accurate crop ET determination, one of the central requirements is robust estimates of evaporative demand of the atmosphere, often represented by reference evapotranspiration (ETo). Within the Unites States, this need is effectively fulfilled by ET networks constituting geographically distributed automated agricultural weather stations. These stations are supposed to be properly sited over unstressed grass or alfalfa-reference surfaces, instrumented to measure air temperatures, solar radiation, relative humidity, and wind speeds, and rigorously maintained (ASABE engineering practice standard EP501.1 2015). Some major ET networks in the U.S. are California Irrigation Management Information System, the Arizona Meteorological Network, High Plains Regional Climate Center, New Mexico State University Climate Center, Colorado Agricultural Meteorological Network, North Dakota Agricultural Weather Network, Kansas Mesonet, Oklahoma Mesonet, and Missouri Agricultural Weather Station Network. Sub-field scale crop ET estimates are critical for precision irrigation management and much progress has been made in this direction by employing in-field mounted sensor systems (Andrade et al. 2020; Peters and Evett 2008; Payero and Irmak 2006), unoccupied aerial systems (Mokari et al. 2022; Nieto et al. 2019; Chavez et al. 2020), and satellite platforms (Xue et al. 2020; Mateos et al. 2013; Bhatti et al. 2020; Melton et al. 2012; Senay 2018). Proximal and remote-mounted sensors detect electromagnetic radiation reflected from soils and crops and estimate the degree of water stress for better informed ET estimation. Integrating Landsat images with different ET algorithms, field-specific crop ET information for the western U.S. has recently become available to the public via the OpenET (Melton et al. 2021) program, where users can retrieve current and recent historical ensembles of crop ET for their fields.

## Role of computer simulation and data assimilation

According to the most recent Irrigation and Water Management Survey (USDA 2018), crop simulation models are the least used scientifically-based irrigation scheduling tools among irrigators in the United States. The main obstacles to adopting crop simulation models for operational precision irrigation scheduling are the absence of evidence that these models provide a return on investment and the complexity associated with their implementation in real farm situations.

Irrigation scheduling models based on simple IF-THEN rules (i.e., irrigate if situation X happens) that in some implicit fashion reflect our understanding of the system have been around for decades. The drawbacks of these types of models are that the rules tend to be very complex and are crop- and soil-dependent. In other words, this approach tends to provide a solution to a specific problem rather than a generic framework that can be applied to other crops/locations with minimal adjustments. Crop model-based irrigation scheduling can overcome this limitation by providing a more generalizable framework. But crop model imperfections due to model structure or parameter uncertainty are commonly pointed out as the main obstacles to implementation of crop model-based optimization in precision irrigation. Real-time data assimilation of crop or soil measurements has been shown to improve models' predictive power, and associated irrigation decisions. Linker and Kisekka (2022) showed that assimilating LAI alone significantly improved irrigation outcomes of a model-based irrigation optimization framework. To advance the use of crop simulation models in precision irrigation, future work should focus on combining model-based optimization and real-time data assimilation.

**Deficit irrigation**

Globally, irrigated agriculture is experiencing competition from municipal, industrial, and environmental needs for water, and decline in freshwater supplies (Porkka et al. 2016; Richter 2016). In water-limited areas such as the western U.S., water consumption for irrigation can exceed water supplies from surface and groundwater resources, and competing interests can increase water prices. Water markets allow farmers to transfer water to other higher value users during critical periods of water shortages (Richter 2016; Szeptycki and Pilz 2017). To optimize overall farm economy, farmers can practice deficit irrigation, which is an effective tool to apply less water than what is required to fully meet crop needs, resulting in lower yields (or quality) but maximized net income. The principle behind deficit irrigation is to change the goal from maximum yields and gross income per area to acceptable yields that maximize water productivity and economic gain while operating within the water supply constraints posed by limited or expensive water. Drought tolerance of a crop can vary by phenological stage, and hence an important precursor to effectively implementing deficit irrigation strategy is precise knowledge of crop response to water limitations. This response is represented using a crop water production function, which establishes a relationship between marketable yield and total crop ET (Stewart et al. 1977; Hexem and Heady 1978; Doorenbos and Kassam 1979; Taylor et al. 1983). Also important is conducting an economic assessment of the tradeoffs expected between yield and water costs (English 1990; English and Raja 1996; Trout et al. 2020; Trout and Manning 2019). Global meta-analyses have confirmed across experimental conditions that higher water productivity can be achieved under deficit irrigation, including cotton (Cheng et al. 2021), wheat (Yu et al. 2020), maize (Allakonon et al. 2022), tree fruit (Tong et al. 2022; Adu et al. 2019), and vegetables (Singh et al. 2021; Adu et al. 2019). With fiercer pressure on water resources and more intense and longer droughts projected across global irrigated agroecosystems, deficit irrigation will enable producers to stabilize returns in an uncertain future.

## An Economic Approach to Optimize the Spatial Scale of Water Management Using Variable Rate Irrigation

According to Walton et al. (2010), the adaptation or abandonment of a technology depends on whether it can create desirable and continued economic returns. Currently, the economic advantage of VRI technology is still uncertain with limited supporting evidence due to (1) the complexity of assessing the monetary value of various VRI water management and hardware options as compared with revenue from potential yield increase or water savings, and (2) the variation of crop, soil, environment, and technology. Understanding the relationships between soil, water, and crop yield is key and the most challenging task.

Yield response to water availability, known as the water production function (or yield response function), has been studied for over fifty years for the purpose of improving water productivity. This response can be divided into two phases: deficit irrigation and surplus irrigation or waterlogging (Hanna 2006; Mannocchi and Mecarelli 1994). Under water deficiency, crop yield increases with increased amounts of irrigation water until the maximum yield is achieved (Schneekloth et al. 2009; Brumbelow and Georgakakos 2007; Al-Jamal et al. 2000). The minimum amount of water that can achieve the maximum yield is referred to as the yield-maximizing irrigation amount. The proper timing of the irrigation through an effective irrigation scheduling plays a very important role in this process as well. Yield declines once irrigation water exceeds the yield-maximizing value. Intensive efforts have been made to obtain yield increase response under water deficiency (Al-Jamal et al. 2000). Yield increase following a quadratic function has been reported for corn, onion, cotton, maize, wheat, and forage crops (Kiani and Abbasi 2012; Quiroga et al. 2011; McCuistion et al. 2009; Garcia-Vila et al. 2009; Jalota et al. 2006; Cetin and Bilgel 2002; Howell et al. 1995). Because soil type; elevation and its derivatives, such as slope; aspect; topographic wetness index (TWI); flow direction; flow length; and catchment area affect yield variability, these factors must be included when assessing whether a VRI system may improve economic returns.

Through field experiments, Sharma and Irmak (2020) conducted economic comparisons of VRI with fixed (uniform) rate irrigation (FRI) and no irrigation (NI) in combination with three nitrogen application strategies of fixed (uniform) rate fertigation (FRF), variable rate fertigation (VRF), and pre-plant nitrogen (PP) management for maize (Zea mays L.). For the economic analyses, the average initial investment of the irrigation system and necessary VRI technology, salvage value of the system, total capital investment, total fixed cost, net present value (NPV), and internal rate of return (IRR) were quantified by considering numerous factors/variables, including interest rate, production input cost, longevity of the system, insurance cost, ownership cost, and salvage value. Soil types and irrigation management strategies (treatments) had significant impact on grain yield and thus on profitability, NPV, IRR, and irrigation system payback period. Net income from FRI management was significantly higher than VRI management in all soil types. The nitrogen treatments did not affect net income in any of the growing seasons. The FRI management strategy had a positive NPV in all soil types, whereas VRI management in soil types S2 (Hastings silty clay loam) and S3 (Hastings silt loam) had negative NPVs. The negative NPV indicates that the present value of the costs exceeds the present value of future profits at the assumed discount rate (5%). Sharma and Irmak (2021a) quantified and compared the soil-water dynamics, including available water (AW), and ETc during vegetative and reproductive growth periods of VRI, FRI, and NI under FRF, VRF, and PP nitrogen management in three different soil types. Sharma and Irmak (2021b) quantified and compared maize growth and development [leaf area index (LAI) and plant height], grain yield, crop evapotranspiration (ETc), irrigation-yield production functions (IYPF), evapotranspiration-yield production functions (ETYPF), and crop water productivity (CWP) under VRI, FRI, and NI at fixed rate fertigation (FRF), VRF, and pre-plant nitrogen (PP) management in the same environment and under the same agronomic management practices. The VRF treatment used 20% less fertilizer as compared with PP and FRF treatment without significantly ($P > 0.05$) reducing the grain yield. In the higher elevation soil S1, the grain yield was not significantly different ($P > 0.05$) between FRI and VRI treatments. However, in S2 and S3, which have lower elevation, yield in FRI was 43% and 55% greater than the yield in VRI, respectively. On average, under VRI management total irrigation amount was 24% lower than FRI in S1, with only 4% reduction in yield as compared with FRI. Soil type impacted the response of maize grain yield to ETc and the responses also varied between FRI and VRI. They concluded that, in most cases, FRI had superior performance in terms of maintaining optimum crop yield and reducing yield variations than VRI. VRI management based on soil water status has the potential to maintain maize grain yield and improve CWP as compared with FRI in certain conditions or soil types, such as in S1 Crete silt loam. However, further research is needed to validate/justify its adoption for the fields with significant spatial soil heterogeneity (both in horizontal and vertical domains) and to understand the economics of VRI-VRF systems.

## Economic assessment of irrigation management

The decision to adopt new technology is very crucial to the economics of the farming business. To determine if optimizing water usage by intensifying irrigation control (i.e., adding more control zones over a pivot arm) with a VRI system was a financially justified decision, a partial budgeting analysis of irrigation management was conducted and demonstrated. Partial budgeting evaluates the financial effects of the business resources that will be changed (Dalsted and Gutierrez, 1990). In the case of irrigation management, the resource that needs to be optimized is the amount of irrigation water. Note that this water optimization was achieved by allocating irrigation water to smaller field segments to minimize water wastage.

Under the partial budgeting concept, the economic assessment of irrigation management was conducted by evaluating the net return, financial loss, and capital investment in water optimization across different levels of irrigation control.

**Net return of irrigation management**

The net return from irrigation management was calculated as the difference between the additional income and the cost of altering the amount of applied water. Under this concept, the net return of water optimization was expressed as:

$$r_Q = \sum_{i=1}^{n} [p_Y Y_i - (c_W + c_E) Q] a_i$$

in which $r_Q$ was the net return of a given field segment delineated under a specific uniform level of irrigation control ($\$\bullet yr^{-1}$), Q was the total irrigation amount applied to this segment ($mm\bullet yr^{-1}$), n was the number of elementary field areas (interpolation pixels) within this segment, $Y_i$ was the yield of $i^{th}$ elementary field area ($t\bullet ha^{-1}\bullet yr^{-1}$) within this segment responding to Q, $a_i$ was the size of $i^{th}$ elementary field area (ha), $p_Y$ was the price of grain yield ($\$\bullet t^{-1}$), $c_W$ was the cost of irrigation water ($\$\bullet mm^{-1}\bullet ha^{-1}$), and $c^E$ was the cost of energy for pumping water ($\$\bullet mm^{-1}\bullet ha^{-1}$).

Using the equation above, the optimum net return $r_{Q_{opt}}$ was obtained when the optimum irrigation amount $Q_{opt}$ was applied. In this case study, the amount of $Q_{opt}$ for a particular segment was determined by testing different values of Q with an increment of ΔQ until the maximum net return was achieved. After selecting the optimum irrigation amount for each field segment, the optimum net return of a given field under a specific level of irrigation control was expressed as:

$$R_{opt} = \sum_{j=1}^{m} r_{Q_{opt_j}}$$

in which $R_{opt}$ was the optimum net return for a field under a specific level of irrigation control ($\$\bullet yr_{-1}$), $r_{Q_{optj}}$ was the optimum net return of $j^{th}$ segment within this field ($\$\bullet yr^{-1}$), and m was the number of irrigation segments.

### Economic loss of irrigation management

Maximizing the net return of water optimization by subdividing a field into an infinite number of small segments is not practical due to the complexity and potential uncertainty involved in such management. Naturally, enlarging segment areas with low irrigation control results in greater deviation from the maximum (theoretical) attainable net return due to sub-optimal water usage. Such economic deviation was quantified using:

$$L = \frac{R_{opt_{max}} - R_{opt}}{A}$$

in which L was the economic loss of a specific level of irrigation control ($\$\cdot ha^{-1}\cdot yr^{-1}$), $R_{opt_{max}}$ was the maximum attainable net return for a given field when considering segment areas were as small as the elementary field areas (interpolation pixels) ($\$\cdot yr^{-1}$), and A was the total area of the field (ha).

### Capital investment in irrigation management

To achieve water optimization through different levels of irrigation control, costs of control systems need to be evaluated. Such expenditures were quantified using:

$$C = \frac{C_{CPIS} + C_{iSC} + C_{iZC} + n_{ZC} \cdot c_{ZC}}{A}\, dy$$

in which C was the capital investment of a specific level of irrigation control ($\$\cdot ha^{-1}\cdot yr^{-1}$), $C_{CPIS}$ was the cost of a center pivot irrigation system (\$), $C_{iSC}$ was the cost of initiating angular adjustment of water application (zone control) (\$), $C_{iZC}$ was the cost of initiating zonal adjustment of water application (\$), $n_{ZC}$ was the number of control zones, $c_{ZC}$ was the cost of each additional control zone ($\$\cdot zone^{-1}$), dy was the prorate coefficient to annualize capital investment over given number of years (20) at a specific interest and cost depreciation rates.

The sum of L and C constitutes the economic disadvantage of irrigation management to the end producer. Thus, the goal of decision-making is to identify the level of irrigation control that minimizes the sum of L and C among all alternatives.

### Sensitivity and profitability analysis

To evaluate the economic opportunity of irrigation management under different fields and financial conditions, a sensitivity analysis was also performed. The relative net return was calculated as a deviation of net return when varying nominal input values one-at-a-time to a maximum of ±40%.

Moreover, the relative profitability was calculated to evaluate the conditions under which adopting irrigation management was economically viable. The profitability was the difference between the net return and the capital investment. By subtracting the profitability of the non-irrigation management, the relative profitability of a specific level of irrigation control was determined.

### Levels of irrigation control

A total of 62 scenarios, grouped into no irrigation (NI), uniform management (UM), speed control (SC), and zone control (ZC) were proposed in this case study to represent different levels of irrigation control. Two SC scenarios represented a pivot rotating at 2° and 10° fixed rate angular increments. Fifty-eight ZC combined these two angular increments, with a pivot arm subdivided into up to 30 sprinkler banks (or control zones) to deliver different irrigation rates simultaneously. Although the length of each independently controlled bank is typically defined by field anomalies and general field patterns, in this case study, it was assumed that the field segments that could receive different water rates were similar in size across the entire field. This means the lengths of the sprinkler bank towards the center of the pivot are longer than those towards the edge of the field. With 62 scenarios, the number of individual irrigation rates (or field segments) within a field could range from 1 (e.g., UI) to 5,400 (e.g., 2°-30 ZC: 2° angular increments with 30 sprinkler banks). Figure 4 illustrates three irrigation scenarios for a center pivot system with a lateral length of 289 m. The innermost circular area (0.24 ha with a 27.6 m radius) was excluded from evaluation, as generally this area is either not irrigated or under-irrigated..

### Demonstration of the application

To highlight the tool's strength in the accounting field and to address heterogeneity in decision-making regarding irrigation strategy, a detailed field characterization of water status was necessary to present the impact of water optimization on profits. For that, an example data fieldand a list of assumptions (Huang et al., 2015) were used.

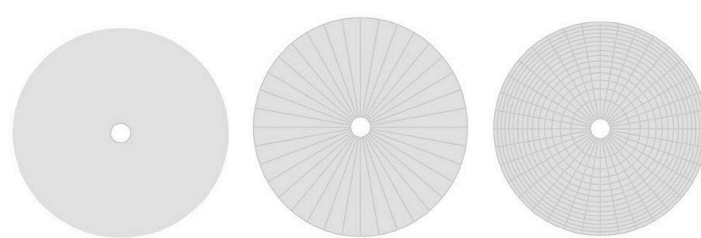


Figure 4. Illustrations of three irrigation management scenarios: UM (left), 4° SC (middle), 4°-15 ZC (right).

### Example data field and field characterization

A circular agricultural field at the Alberta Irrigation Technology Center (AITC) in Lethbridge, southern Alberta, Canada (Figure 5) was selected as an example to demonstrate the model's performance. The field was under semi-arid climate conditions, and hard red spring wheat was grown. A five-tower center-pivot VRI system with a span length of 289 m and 129 sprinklers, manufactured by Valley® Irrigation, has been installed to provide irrigation water. This system allowed the water rate of each sprinkler to be altered down to every 2° rotation increment. The total area under this pivot system was approximately 27 ha;. The north-eastern quarter of the field) was not under observation to avoid interrupting farming operations. The innermost circular area (approximately 27.6 m in radius) was excluded, leaving a total area under evaluation of approximately 20 ha. Full details of the field experiment are available in Yari et al. (2017).

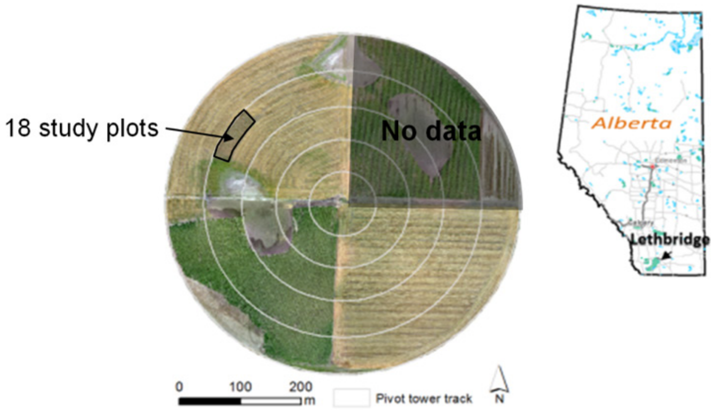



Figure 5. A field case study located at the Alberta Irrigation Technology Center (AITC) in Lethbridge, Alberta, Canada, was used as an example in this case study.

A detailed field characterization of the potential water stress status was conducted using ECa and a topographic survey. The Veris® 3100 EC Surveyor (1 Hz reading and approximately 10 m intervals between passes) was used to obtain ECa measurements. An RTK GPS receiver (1 Hz sampling rate and approximately 5 m spacing between passes) was used to collect topographic measurements. ECa measurements ranged from 17 to 175 mS•m−1. Field elevation ranged from 903 to 907 m. Although ECa served as a proxy for water stress potential (WSP) and elevation was used to simulate landscape-induced water-logging susceptibility, these two variables could be replaced with other data sources that provide high-resolution water-status information.

To represent field characteristics of elementary field areas, geospatial processing was performed on the dense sensing measurements (e.g., ECa and elevation). An ordinary kriging interpolation method was used to create interpolated ECa and topographic maps. The topographic map was converted to a topography wetness index (TWI) surface using the open-source GIS software SAGA (Böhner and Conrad, 2009). This software provides comprehensive algorithms for processing various elements (such as multidirectional convergence flow, catchment area, etc.) required to estimate potential soil moisture variability induced by landscape position (Silva et al., 2014), which facilitated part of the data analysis in this case study. TWI was a unit-less value; the larger values represent a relatively higher tendency for water accumulation (e.g., lowland), and the smaller values represent a relative relatively lower tendency (e.g., highland):

$$TWI = ln\left(\frac{A_S}{\tan(\beta)}\right)$$

In which As was the ratio of catchment area over cell width in slope direction, and $\beta$ was the slope in the steepest downslope direction of the terrain (°).

The ECa and TWI surface maps were synthesized and converted into a vector-based map (i.e., square polygons) consisting of multiple 3-by-3 m grids to represent the confined elementary field areas. Each area was subjected to a pair of ECa and TWI values;. 3-m spatial resolution was chosen because it was the smallest distance between two sensor measurements. This map was used to create irrigation segments according to 62 management scenarios using the software ArcGIS™ developed by ESRI (2014). Figure 6 illustrates an irrigation segment from scenario 10°-5 ZC with a color scheme over elementary field areas showing the variability of ECa. Each confined elementary field area contained attributes of polygon ID, segment ID, management ID, ECa, and TWI. This information was stored as tabular data to estimate yield response and irrigation management profits using the R programming language (R Development Core Team, 2016).

**Nominal values for assumed conditions**

Table 1 lists the nominal values and variables used to demonstrate the outcomes of the economic assessment. It should be noted that under no circumstances should these values be considered as the most certain estimates. These values were used to represent a specific case of field ECa and elevation, and, to specify model boundary conditions for yield response to irrigation, the cost of water and energy, the price of grain yield, and the cost of the irrigation system. Note that, the values of $C_{CPIS}$, $C_{iSC}$, $C_{iZC}$, and $c_{ZC}$ were based on the model of the mentioned VRI system from Valley® Irrigation in 2013. Thus, the actual number may change. Nevertheless, the economic assessment tool is highly flexible and can be easily performed with any alternative set of input values.

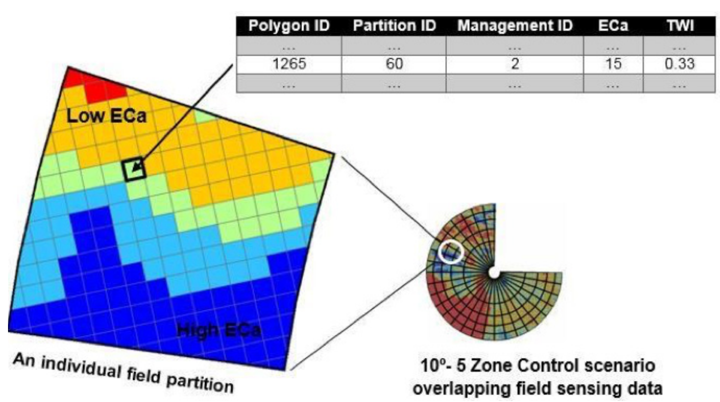



Figure 6. Example of an irrigation partition from one of the 62 management scenarios with a color scheme showing ECa.

| Model variable | Value | Model variable | Value | Model variable | Value |
|---|---|---|---|---|---|
| $Q_{YmaxDry}$ | 400 mm | $Q_{YmaxWet}$ | 100 mm | A | 20 ha |
| $TWI_{High}$ | 0 | $TWI_{Low}$ | 1 | $C_{CPIS}$ | $100,000 |
| $ECa_{Dry}$ | 35 mS • m$^{-1}$ | $ECa_{Wet}$ | 65 mS • m$^{-1}$ | $C_{iSC}$ | $5,000 |
| $Y_{max}$ | 9 t • ha$^{-1}$ | $Y_{0Dry}$ | 0 t • ha$^{-1}$ | $C_{iZC}$ | $9,000 |
| $Y_{waterlogIHigh}$ | 4.5 t • ha$^{-1}$ | $Y_{waterlogwlLow}$ | 0 t • ha$^{-1}$ | $c_{ZC}$ | $2,000 |
| $c_E$ | $0.4 mm$^{-1}$ • ha$^{-1}$ | $c_W$ | $0.5 mm$^{-1}$• ha$^{-1}$ | Years | 20 |
| $p_Y$ | $180 t$^{-1}$ | $\Delta Q$ | 10 mm | $d_y$ | 6.17% |

Table 1. The input values of model variables used in the economic assessment.

### Testing of input values

During 2013 and 2014, eighteen plots (approximately 180 m$^2$ each) were created to study yield response to irrigation treatments (Table 2). At these plots, water was applied at various depths (mm), grain yields of hard red spring wheat (t•ha−1) were measured, and soil samples were collected. According to this table, soil ECa was relatively higher at plots one to eight. Total irrigation amounts for the two experimental years were very similar. No yield was observed in plots one to five in both years due to flooding and heavy rainfall; however, in the remaining plots, the yield in 2014 was higher.

Figure 7 illustrates the relatively higher ECa measurements across plots one to eight, which coincided with the conditions of excessive water accumulation due to flooding. As shown, each experimental plot overlaps approximately twenty elementary field areas (i.e., 3 m by 3 m), which 20 elementary field areas (i.e., 3 m by 3 m), implying 20 different yield response functions.

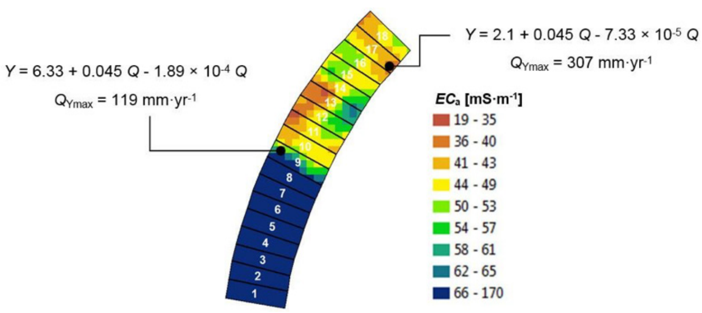



Figure 7. Illustration of eighteen study plots and two simulated yield response functions.

To evaluate whether the given assumptions could yield comparable results, a yield simulation was conducted for the 18 study plots. Under various experimental water application depths (Table 2), eighteen simulated yields were calculated using the given field assumptions and spatially dynamic yield response functions.. Figure 8 illustrates the correlation between experimental and simulated yields for the two study years, with R2 values above 0.7, indicating that the input conditions yielded similar responses to irrigation. The model successfully distinguished zero-yield plots (i.e., one to six) where soil ECa values were relatively higher. The observed experimental yield at plots seven and eight, however, was inconsistent with the simulated results. Nevertheless, this result shows that the selected input values for this example field were effective.

Table 4 summarizes the results of the economic assessment under 62 irrigation scenarios. Net returns, financial losses, capital investments, and economic disadvantages of irrigation management were calculated. The net return was estimated to be 1,348 ($•yr−1) when each irrigation segment was measured at 3 m by 3 m. According to the

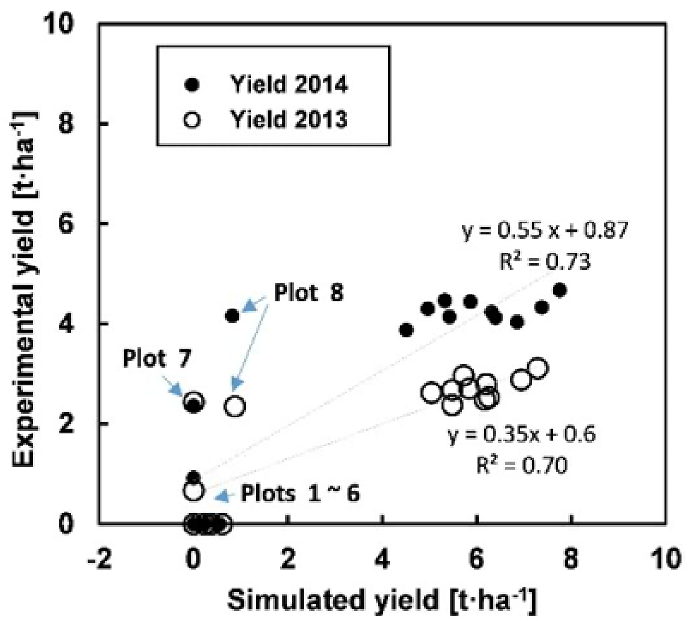



Figure 8. Correlation between simulated and experimental yields for 18 study plots.

| Plot | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **ECa (0-30cm) [dS • m$^{-1}$]** | 3.5 | 3.7 | 3.4 | 4.3 | 3.8 | 5.8 | 5.2 | 3.1 | 1.1 | 0.7 | 0.6 | 0.8 | 0.7 | 0.7 | 1.1 | 0.7 | 1.3 | 3.1 |
| **Irrigation 2013 [mm • yr$^{-1}$]** | 76 | 76 | 102 | 127 | 102 | 76 | 127 | 102 | 127 | 102 | 102 | 76 | 127 | 127 | 76 | 102 | 127 | 76 |
| **Irrigation 2014 [mm • yr$^{-1}$]** | 61 | 61 | 107 | 152 | 107 | 61 | 152 | 107 | 152 | 107 | 107 | 61 | 152 | 152 | 61 | 107 | 152 | 61 |
| **Yield 2013 [t • ha$^{-1}$]** | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.7 | 2.4 | 2.4 | 2.4 | 2.5 | 3.0 | 2.7 | 2.9 | 3.1 | 2.7 | 2.5 | 2.8 | 2.6 |
| **Yield 2014 [t • ha$^{-1}$]** | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.9 | 2.4 | 4.2 | 4.1 | 4.2 | 4.4 | 4.3 | 4.3 | 4.3 | 4.5 | 4.1 | 4.0 | 3.9 |

Table 3. ECa, irrigation treatments, and grain yield of eighteen study plots.

results, the net return increased with increasing levels of irrigation control (water optimization), with the highest and lowest values being under 2°-30 ZC and NI, respectively. In other words, intensifying irrigation management from no to advanced control reduced economic losses from 917 to 39 ($\$ \cdot ha^{-1} \cdot yr^{-1}$). Comparing economic losses between the two angular increment sizes under ZC management, it was found that using 2° angular increments could reduce financial losses by 12%. Although 2°-30 ZC showed the lowest economic loss, the optimal management level was 2°-10 ZC after accounting for the required capital investment.

Figure 9 illustrates the economic loss, capital investment, and economic disadvantage (i.e., the sum of economic loss and capital investment) as a function of irrigation control level. The economic loss decreased sharply from NI to UM when irrigation practice was introduced, and then continued to decline with increasing levels of VRI control. The magnitude of decrease in the economic loss was greater under 2° angular control than that of 10°. This result was anticipated, as irrigation management under 2° angular control better matched local needs than under 10°, because the irrigation segment area defined under the former control was 80% smaller than that determined under the latter.

The economic disadvantage declined with the introduction of VRI. However, after the optimal VRI 10-control-zones were reached, the economic disadvantage increased due to higher capital investment. This observation was only valid for the cost model of the mentioned VRI technology. As marketing strategies for parts pricing and technical support often vary among manufacturers, the overall economic outcomes are expected to change when considering VRI systems other than the one used in the case study. Generally, irrigation management involving a greater number of VRI control zones becomes economically optimal when the economic disadvantage (primarily due to capital investment) associated with each added control zoneremains relatively low.

As illustrated in Figure 10, net return was highly sensitive to the maximum yield, the model boundary condition ECa (which defined the field's wet and dry conditions), the yield-maximizing irrigation amounts under dry conditions, and the price of yield. The graph showed that when soil water storage potential (represented using $ECa_{wWet)}$ or precipitation was relatively higher, the incremental increase of net return was higher under UM scenario. Regardless of management options, implementing irrigation to crops with high yield, low water demand, and high market price was a profitable strategy. Within the given range of nominal values, the cost of energy and water did not influence the net return as much as other variables.

Table 4. Economic assessment of 62 irrigation management scenarios.

| Scenarios | Zone | Revenues | | Cost of Error | | Cost of technology | Total Cost | |
|---|---|---|---|---|---|---|---|---|
| | | 2° | 10° | 2° | 10° | | 2° | 10° |
| UM | n/a | 1,006 | | | 381 | 309 | 689 | |
| SC | n/a | 1,041 | 1,041 | 346 | 346 | 324 | 670 | 670 |
| ZC | 2 | 1,151 | 1,126 | 236 | 260 | 336 | 572 | 597 |
| - | 3 | 1,193 | 1,165 | 194 | 221 | 343 | 536 | 564 |
| - | 4 | 1,218 | 1,186 | 168 | 200 | 349 | 517 | 549 |
| - | 5 | 1,249 | 1,209 | 138 | 178 | 355 | 493 | 533 |
| - | 6 | 1,266 | 1,220 | 120 | 166 | 361 | 481 | 527 |
| - | 7 | 1,276 | 1,232 | 110 | 155 | 367 | 478 | 522 |
| - | 8 | 1,287 | 1,238 | 100 | 148 | 373 | 473 | 522 |
| - | 9 | 1,295 | 1,246 | 91 | 141 | 380 | 471 | 520 |
| - | 10 | 1,306 | 1,254 | 81 | 133 | 386 | 466 | 519 |
| - | 11 | 1,308 | 1,257 | 78 | 130 | 392 | 470 | 521 |
| - | 12 | 1,312 | 1,258 | 75 | 128 | 398 | 473 | 526 |
| - | 13 | 1,319 | 1,265 | 68 | 122 | 404 | 472 | 526 |
| - | 14 | 1,323 | 1,266 | 63 | 120 | 410 | 474 | 531 |
| - | 15 | 1,325 | 1,270 | 61 | 117 | 417 | 478 | 533 |
| - | 16 | 1,328 | 1,272 | 59 | 115 | 423 | 482 | 537 |
| - | 17 | 1,329 | 1,272 | 58 | 114 | 429 | 487 | 543 |
| - | 18 | 1,333 | 1,275 | 54 | 112 | 435 | 489 | 547 |
| - | 19 | 1,337 | 1,279 | 50 | 107 | 441 | 491 | 549 |
| - | 20 | 1,339 | 1,279 | 48 | 107 | 447 | 495 | 555 |
| - | 21 | 1,340 | 1,281 | 47 | 106 | 454 | 501 | 559 |
| - | 22 | 1,341 | 1,283 | 45 | 103 | 460 | 505 | 563 |
| - | 23 | 1,341 | 1,283 | 46 | 104 | 466 | 512 | 570 |
| - | 24 | 1,342 | 1,282 | 45 | 104 | 472 | 517 | 576 |
| - | 25 | 1,343 | 1,283 | 44 | 104 | 478 | 522 | 582 |
| - | 26 | 1,344 | 1,283 | 43 | 103 | 484 | 528 | 588 |
| - | 27 | 1,345 | 1,285 | 42 | 102 | 491 | 532 | 592 |
| - | 28 | 1,347 | 1,285 | 40 | 101 | 497 | 537 | 598 |
| - | 29 | 1,347 | 1,286 | 39 | 100 | 503 | 542 | 603 |
| - | 30 | 1,348 | 1,287 | 39 | 99 | 509 | 548 | 609 |

Unit: $\$ \cdot ha^{-1}yr^{-1}$

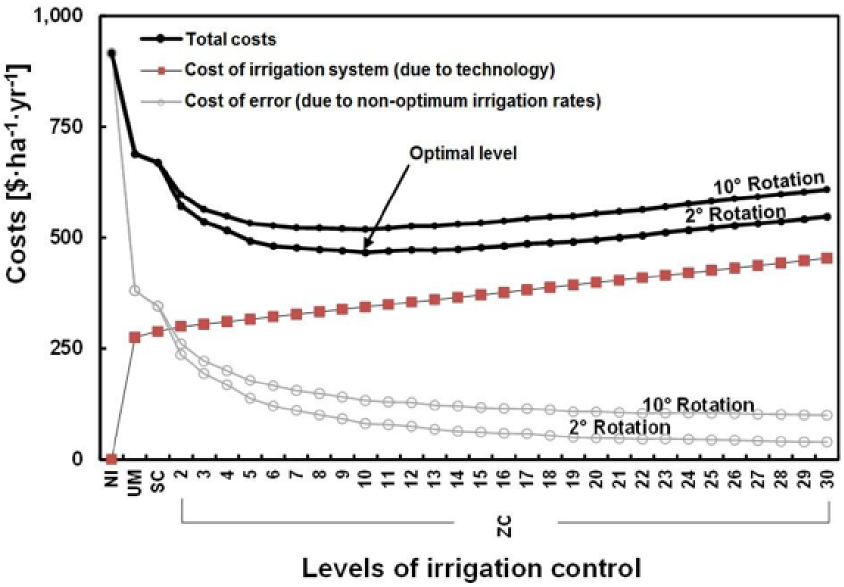



Figure 9. Costs associated with different levels of irrigation control: NI (no irrigation), UM (uniform management), SC (VRI speed control), and ZC (VRI zone control)

As indicated in Figure 11, implementing irrigation management was profitable when the yield price was greater than 108 $\$\cdot t^{-1}$ and/or the maximum yield was higher than 5 $t\cdot ha^{-1}$. s market price and yield of the selected crop increased, the profitability of VRI Zone control reached up to \$ 200$\cdot ha^{-1}\cdot yr^{-1}$ higher than that for uniform management. However, when the minimum attainable yield under dry conditions exceeded 4 $t\cdot ha^{-1}$, applying additional water to the crop was not an economically viable strategy regardless of management options.

As for the effect of soil water storage conditions (represented using by ECa) on profitability, it was shown that uniform management resulted in no profitability when ECa at the wettest locations was below 50 $mS\cdot m^{-1}$. Besides, the four management options would result in an additional \$ 200$\cdot ha^{-1}$ in profitability annually, with ECa measurements at the driest locations increasing by up to 40%. Moreover, adopting irrigation management for a crop whose yield-maximizing water requirement in dry locations was as high as 520 mm annually (including rainfall) remained economically viable.

Finally, the profitability of irrigation investment fluctuated widely across management options, with spatial variability in field characteristics, soil-crop-water relationships, crop prices, and water and energy costs. The results showed that increasing the level of irrigation control using an advanced VRI system appeared to be an excellent approach to improve water productivity by spatially adjusting application amounts according to local needs, regardless of environmental and financial factors. However, in terms of optimizing irrigation profitability, the economic assessment revealed that quantifying the value of irrigation management was an essential component in the economicdecision-making. Using proximal soil sensing technology to obtain dense geospatial data at low cost proved an efficient method for characterizing field heterogeneity. Although ECa and topographical data as proxies for soil properties associated with irrigation management, incorporating additional or alternative field measurements could help compare different outcomes. The theoretical formulation of the crop-water-soil relationship was found to be highly effective, providing a universal formula that can be customized site-specifically based on field measurements. Using the default field data resolution (3 by 3 m) to generate numerous spatially dynamic water response functions for the economic assessment of the 20-ha example field was not computationally intensive. But a similar evaluation has not been tested for larger fields.

Nevertheless, this generic algorithm for the water response function was spatially dynamic, unlike the general empirical approach. The incorporated algorithms can be further fine-tuned using crop models , such as AquaCrop, to improve characterization of a given target field. Such a test was not yet complete in this study. Moreover, the results suggested that crop commodity prices had a much greater impact on irrigation profitability than the commodity prices of water and energy. This finding might be underestimated, as the tested range for the commodity value of natural resources might be smaller than the actual market fluctuations. Because global political dynamics and climate highly influence commodity prices, they should be closely monitored to reduce long-term financial risks.

Based on these results, it is concluded thatrealizing the full potential of VRI technology requires an economic assessment before implementation. The proposed economic assessment tool effectively incorporated agronomic and economic factors while adopting VRI technology to optimize crop irrigation profitability and water management. The model is flexible, and its architecture accommodates a range of environmental and economic input parameters. The comparison of 62 irrigation scenarios using the 20-ha example field showed the greater benefit of raising VRI control to the point where the pivot was subdivided into 10 independently operated irrigation control zones. Further intensification of VRI indicated economic disadvantages, with relatively high capital investment compared with the acquired yield and cost benefits. Yet, this result was valid only under the specific assumptions and input setting.

The advantage of this assessment tool for irrigation management is its generic approach, which can be automatically adjusted by the tool based on field conditions. Further development of this tool includes the evaluation of applicability under a broader range of field characteristics, the incorporation of various crop-water-soil relationships, and the consideration of potential monetary risks. With a robust economic assessment tool, irrigation managers can identify investment options, estimate profitability, anticipate potential financial risks, and achieve operational stability.

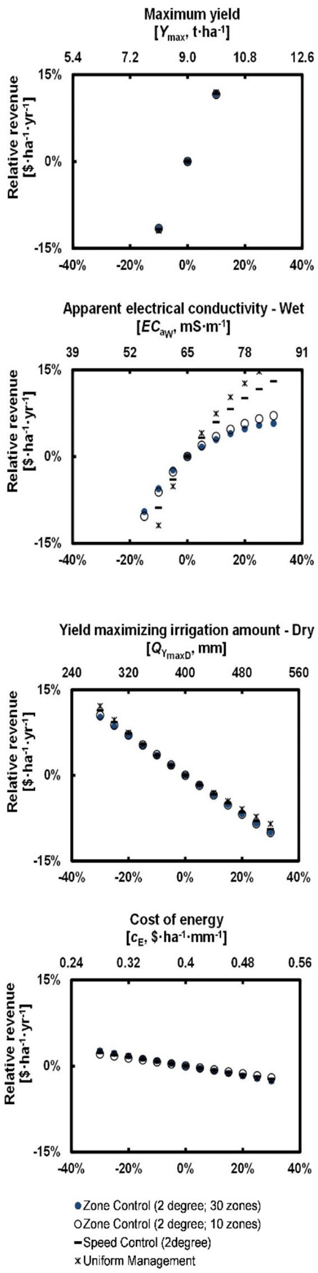



Figure 10. Sensitivity of field revenue to different values of variable input.

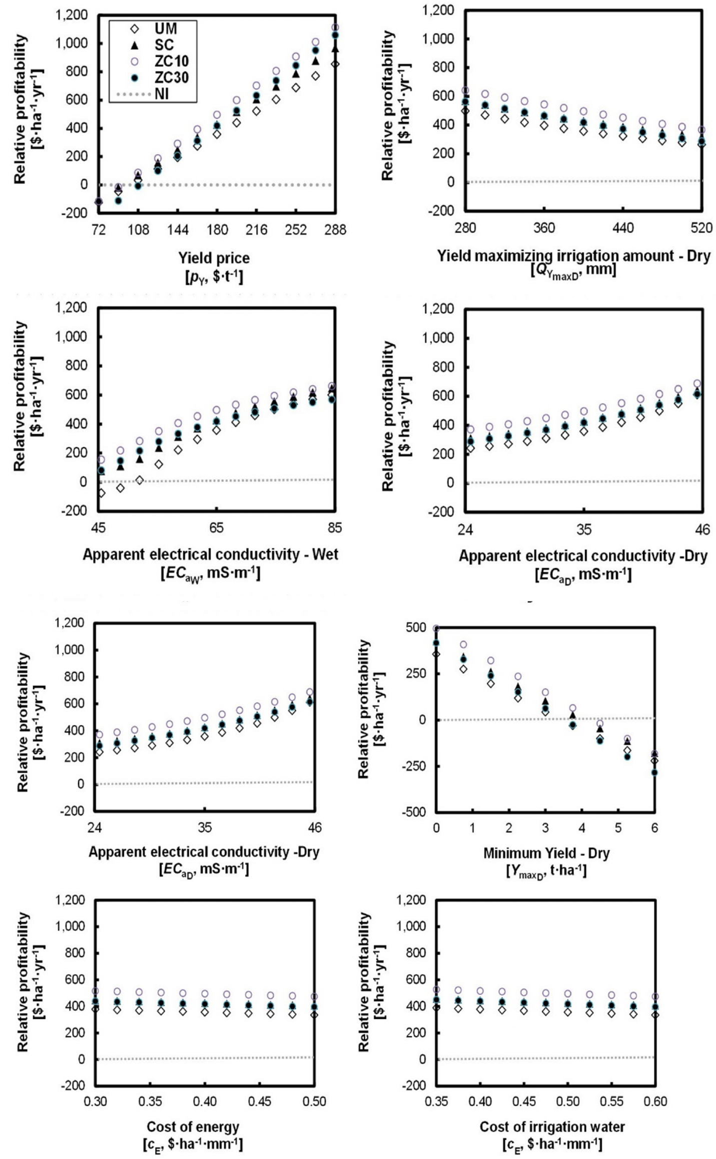



Figure 11. Economic benefits of selected irrigation management scenarios over no irrigation under different field and financial conditions.

## Complementary Technologies and Themes to Precision (Smart) Irrigation

Digital agricultural solutions and smart farming systems are under development in several countries. A smart farming system could include various precision agricultural technologies, including precision irrigation. The smart farming concept describes a system where smart sensing and monitoring systems function with information communication technologies to increase the economic yield of crop and/or livestock production and optimize farm inputs, processes, and profits (Wolfert et al. 2017). The concept extends to the transportation, distribution, and retail phases of the food supply chain (Nukala et al. 2016; Idoje et al. 2021).

Within the smart farming framework, existing complementary technologies that could facilitate the integration of control and decision-making for precision irrigation systems in open fields and in controlled environments require fast, reliable internet connections. This is necessary to link farming processes for optimal water management, reliable sensor network systems that provide feedback on plant water and nutrient status, cloud computing systems that enable the collection and access of real-time data and information, big data analytics for decision support, and predictive analytics for weather and markets (Maraveas et al. 2022). The internet of things for precision agriculture (IoT4Ag) (Kagan et al. 2022) could enable the monitoring of plant, soil, water, and weather data and inform data-driven models, and big data analytics that will employ artificial intelligence (AI) to monitor and predict water stress (King and Shellie 2016), water quality (Chen et al. 2020), and control irrigation scheduling (Romero et al. 2012). Big data analytics are a major component in many ongoing agricultural projects, including the classification of land cover changes, forecasting rainfall, snow melt and severe weather events, and estimating evapotranspiration with limited instrumentation (Kamilaris et al. 2017).

An example of a precision irrigation technology that integrates different types of sensing systems and data analytics for irrigation management decision support is the Irrigation Scheduling Supervisory Control and Data Acquisition System (ISSCADAS) (Evett et al. 2020) (Figure 12). The ISSCADAS uses weather data and canopy temperature data collected throughout a field using a network of wireless canopy temperature sensors mounted on a center pivot irrigation system to generate precision irrigation prescription maps based on the estimation of plant water stress (O'Shaughnessy et al. 2010). A network of soil water sensors connected to the internet of things (IoT) (Thompson et al. 2021) can be used in combination with canopy temperature sensors to generate precision irrigation prescription maps based on the estimation of plant stress and soil water status. The combined use of canopy temperature and soil water sensors can also improve precision irrigation management using the ISSCADAS in humid (Stone et al. 2019) and semi-arid (O'Shaughnessy et al. 2020) environments. AI algorithms can be used to estimate canopy temperatures in situations where canopy temperatures cannot be measured because the center pivot cannot move due to a malfunction or cannot traverse the field within a reasonable amount of time. The canopy temperatures estimated by AI algorithms can be used to generate precision irrigation prescription maps based on plant stress to add redundancy to the ISSCADAS (Andrade et al. 2022).

While smart farming could lead to more sustainable agricultural production, there are barriers to its progress and adoption. These include limited accessible and reliable internet connectivity in rural areas (Mark et al. 2016; O'Grady et al. 2019; Strover et al. 2021); upfront costs for sensor systems, up-to-date infrastructure for data transmission, and hardware for automated control; lack of expertise to analyze data; data governance; and incompatibilities within the collection of integrated technologies (Wolfert et al. 2017; El Bilali and Allahyari 2018; Drewery et al. 2019).

## Future Needs

Precision irrigation, when properly designed and implemented, can offer significant benefits for producing agricultural commodities with reduced inputs and enables utilizing resources efficiently, which can contribute to the sustainability of agricultural productivity. This management strategy can be effective in production fields that have considerable spatial variability in terms of soil types, soil properties, slope, and other soil and terrain characteristics. It can provide significant advantages over traditional irrigation management strategies, especially in water-limiting regions. Thus, precision irrigation technology can be one of the effective tools for using natural resources efficiently to produce sufficient food and fiber for a rapidly growing world population, especially in light of climate change, which negatively impacts agricultural production globally. While precision irrigation technology has been established and demonstrated to be beneficial for agricultural production, this technology is primarily utilized in research and demonstration platforms. Its adoption in large- or small-scale agricultural production fields is necessary to achieve or realize the aforementioned contributions in terms of food and fiber production with limited input by accounting for spatial attributes of production fields. Specifically, to realize the maximum benefits of precision irrigation technology, the following current and future needs have been suggested:

(i) Precision irrigation technologies are adaptable to sprinkler, gravity (surface), and microirrigation (including surface and subsurface drip) methods and can provide considerable increase in crop water productivity. While the focus of precision irrigation has been on sprinkler and microirrigation methods, there are effective and practical tools that could enable implementation of precision irrigation in gravity (surface, including furrow, irrigation) systems, which needs further research and demonstration as surface irrigation is by far the most dominant irrigation method globally.

(ii) While precision irrigation has shown in research and demonstration fields that it is a viable technology that

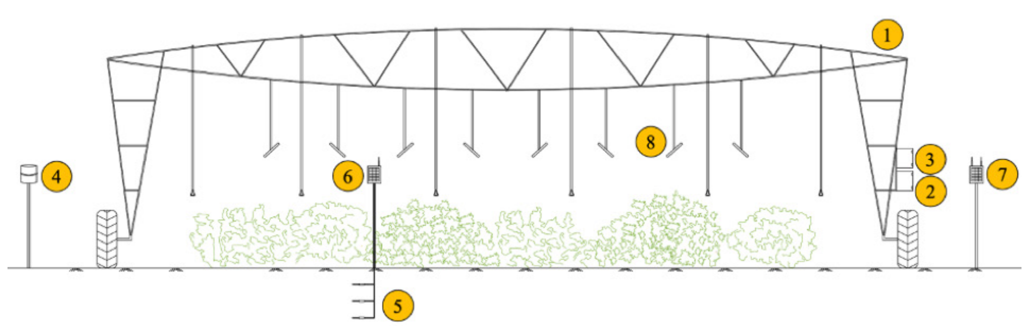



Figure 12. Schematic of a (1) self-propelled sprinkler irrigation system and a network of sensing systems supporting its irrigation management. The irrigation system is operated by a (2) control panel. Recommended precision irrigation prescription maps are generated automatically by an Irrigation Scheduling Supervisory Control and Data Acquisition System (ISSCADAS). The ISSCADAS runs continuously on (3) an embedded computer mounted next to the control panel and automatically collects and processes data obtained from a (4) weather station, a (5) network of soil water sensors reporting data to a (6) node- (7) gateway system connected to the internet of things (IoT), and a (8) wireless network of canopy temperature sensors distributed along the irrigation system's frame.

can contribute to the sustainable utilization of natural resources for production, well-coordinated efforts to better understand the impediments for adoption in growers' fields and enable the successful implementation of this technology in large scale production fields are necessary. Accomplishing these goals requires the participation and partnership of academicians, researchers, private industry, state and federal water management agencies, irrigation practitioners, growers and their advisors, and other agricultural professionals.

(iii) Because crop physiology, development, and response to different spatial variability can change with soil type, climate, management practices, and numerous other factors, the research, demonstration, and analyses of viability, as well as the effectiveness of precision irrigation technology in different soil types, climatic conditions, and under different types and magnitude of spatial variabilities, must continue.

(iv) The management zone delineation and associated algorithms (based on electrical conductivity, and other soil characteristics variables/indices) and their implementation in data acquisition systems in terms of irrigation timing and amount decision-making need further investigation to enhance the suitability of methods for different cropping systems, soil, and terrain characteristics.

(v) The use of soil moisture-sensing technologies, evapotranspiration-based irrigation scheduling, and plant characteristics-based irrigation scheduling, as well as how these technologies can be used with precision irrigation methods to further enhance crop productivity, needs further research, demonstration, and dissemination.

(vi) Potential design, operational, and management-related drawbacks, and potential challenges in terms of implementing precision irrigation technologies under different climatic, soil ,,and management conditions need to be openly communicated/disseminated so that these challenges can be addressed to enhance the effectiveness of precision irrigation.

(vii) Crop water and nitrogen productivity responses to precision irrigation (including variable rate irrigation) under different production and management settings need to be documented for local conditions, as these relationships may not be transferable between the locations or regions that have different crop production environments and management.

(viii) The benefits and positive impacts and implications of large-scale adoption, as well as economic and environmental benefits of precision irrigation technologies, need to be better documented and effectively communicated to stakeholders, decision- and policymakers, and all partners and professionals involved in small- or large-scale irrigated agricultural production, planning, management, and forecasting. This need is becoming more critical as the negative impacts of climate change, limitations in water resources availability, water quality degradation for agricultural irrigation, competition for water between different sectors, and other factors impose (and will continue to impose) stress on irrigation agriculture to meet the food and fiber demand of a rapidly growing world population. Technology development, and perhaps more importantly, implementation of technologies in production fields, will definitely aid in mitigating the negative impacts of climate change and other external factors/challenges on irrigated crop production and enable the sustainability of irrigated agricultural production.

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