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Challenges and opportunities in precision irrigation decision-support systems for center pivots

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Abstract

Irrigation is critical to sustain agricultural productivity in dry or semi-dry environments, and center pivots, due to their versatility and ruggedness, are the most widely used irrigation systems. To effectively use center pivot irrigation systems, producers require tools to support their decision-making on when and how much water to irrigate. However, currently producers make these decisions primarily based on experience and/or limited information of weather. Ineffective use of irrigation systems can lead to overuse of water resources, compromise crop productivity, and directly reduce producers' economic return as well as bring negative impacts on environmental sustainability. In this paper, we surveyed existing precision irrigation research and tools from peer-reviewed literature, land-grant university extension and industry products, and U.S. patents. We focused on four challenge areas related to precision irrigation decision-support systems: (a) data availability and scalability, (b) quantification of plant water stress, (c) model uncertainties and constraints, and (d) producers' participation and motivation. We then identified opportunities to address the above four challenge areas: (a) increase the use of high spatial-temporal-resolution satellite fusion products and inexpensive sensor networks to scale up the adoption of precision irrigation decision-support systems; (b) use mechanistic quantification of 'plant water stress' as triggers to improve irrigation decision, by explicitly considering the interaction between soil water supply, atmospheric water demand, and plant physiological regulation; (c) constrain the process-based and statistical/machine learning models at each individual field using data-model fusion methods for scalable solutions; and (d) develop easy-to-use tools with flexibility, and increase governments' financial incentives and support. We conclude this review by laying out our vision for precision irrigation decision-support systems for center pivots that can achieve scalable, economical, reliable, and easy-to-use irrigation management for producers.

1. Introduction

Irrigation is critical to sustain agricultural production in dry or semi-dry climates and maintain the economy of these regions (Stubbs 2016, US GAO 2019). Irrigation systems include gravity, sprinkler, and micro-irrigation systems (figure 1), and among these, sprinkler irrigation systems, mainly center pivots, are used in ∼55% of the U.S. total irrigated lands (USDA 2017, US GAO 2019) (figure 1). For example, in 2015, 38% of corn and 25% of soybean production in the U.S. was produced with center pivots irrigation systems (Smidt *et al* 2019). Center pivot irrigation systems were invented by a farmer Frank Zybach in 1940 and patented 12 years later (Zybach 1952). In general, these systems have water that is pumped from the center of the field to overhead nozzles of different sizes located along a long pipe that rotates in a circular pattern and used to irrigate large fields. In the U.S., these irrigation systems were quickly adopted and used to irrigate row crops.

Efficient irrigation is essential to achieve sustainability of food production and regional water security (Lobell *et al* 2008, Griggs *et al* 2014, Grafton *et al* 2018, Li *et al* 2020). However, currently, producers determine the irrigation timing and amount of center pivots largely based on their personal experience and weather information. According to a survey, >75% of irrigation scheduling methods used by U.S. producers are based on rule-of-thumb procedures that include crop calendars, visual observation, and 'what the neighbors are doing?' (USDA 2017). Fewer than 25% of irrigation scheduling methods are science- and technology-based. Decisions based on rule-of-thumb methods could lead to over- or under-irrigation. Over-irrigation may raise concerns related to water scarcity and environmental sustainability. For example, the extensive irrigated areas in Kansas, California, and Arkansas (figure 1) have resulted in large groundwater level declines in the High Plains, Central Valley, and Mississippi Embayment aquifers, respectively (Marston *et al* 2015, McGuire 2017, US GAO 2019). Over-irrigation using groundwater may further increase soil salinity and sodicity in areas with shallow groundwater tables and excessive evaporation losses, which threatens soil health of these regions (Hillel 2000, Tanji 2002). Over-irrigation can also result in leaching and runoff of nutrient-enriched water, causing contamination to ground water (Power and Schepers 1989, Exner *et al* 2014). Conversely, under-irrigation does not sufficiently alleviate crop water stress, which usually leads to both yield and economic loss for producers. Compared with rule-of-thumb methods, science- and technology-based irrigation scheduling methods may increase crop profits and reduce environmental impacts by minimizing crop water stress.

Precision irrigation usually requires real-time information about soil water supply and crop water demand to determine optimal irrigation timing and varying amount in space, in order to reach predefined objectives such as the maximization of crop yield, resource use efficiency, or profitability (Sadler *et al* 2005, Smith 2011, US GAO 2019). Our study here will focus on discussing irrigation decision making tools for the majority of irrigation systems in the U.S., i.e. 'standard center pivots', where irrigation timing and amount are uniform across a field. In recent decades, some studies have reviewed specific aspects of precision irrigation decision-support systems, such as soil-based and/or plant-based irrigation scheduling methods and applications of remote sensing data and wireless technologies (Jones 2004, Fernández and Cuevas 2010, Pardossi and Incrocci 2011, Zaks and Kucharik 2011, Ha *et al* 2013, Haule and Michael 2014, Kansara *et al* 2015, Ihuoma and Madramootoo 2017, Foster *et al* 2019, Lakhwani *et al* 2019, Pathak *et al* 2019, Evett *et al* 2020, Gu *et al* 2020). However, few studies have provided holistic reviews and perspective of integrating different components of precision irrigation decision-support systems. With extensive progresses made in precision irrigation in both academia and industry, there is a lack of comprehensive reviews on existing challenges and opportunities.

This paper reviews recent advances and challenges, and envisions opportunities in precision irrigation decision-support systems for standard center pivots. We surveyed precision irrigation research from peer-reviewed literature, land-grant university extension and industry products, and U.S. patents. We identified challenges in data, decision-making approaches and criteria, and products used in current precision irrigation decision-support systems in this survey. We then proposed possible opportunities to address the corresponding challenges and bridge the gap between research and practice for precision irrigation decision-support systems, which we envision should be scalable, economical, reliable, and easy-to-use for producers. Although the survey is focused on the center pivot irrigation systems in the U.S, most of our review can be generally applied to different other types of irrigation systems at the global scale.

2. Recent advances in precision irrigation decision-support systems

2.1. Methods

The survey was performed using Web of Science, Google Scholar, Google, and Google patents with the keywords: irrigation scheduling, decision-making, decision-support, precision, and management. Based on the results, >200 in peer-reviewed literature, 17 precision irrigation products from the U.S. land-grant universities in table 1, 19 commercial precision irrigation products from industries in table 2, and more than 25 irrigation scheduling related patents from the survey, we identified data, decision-making

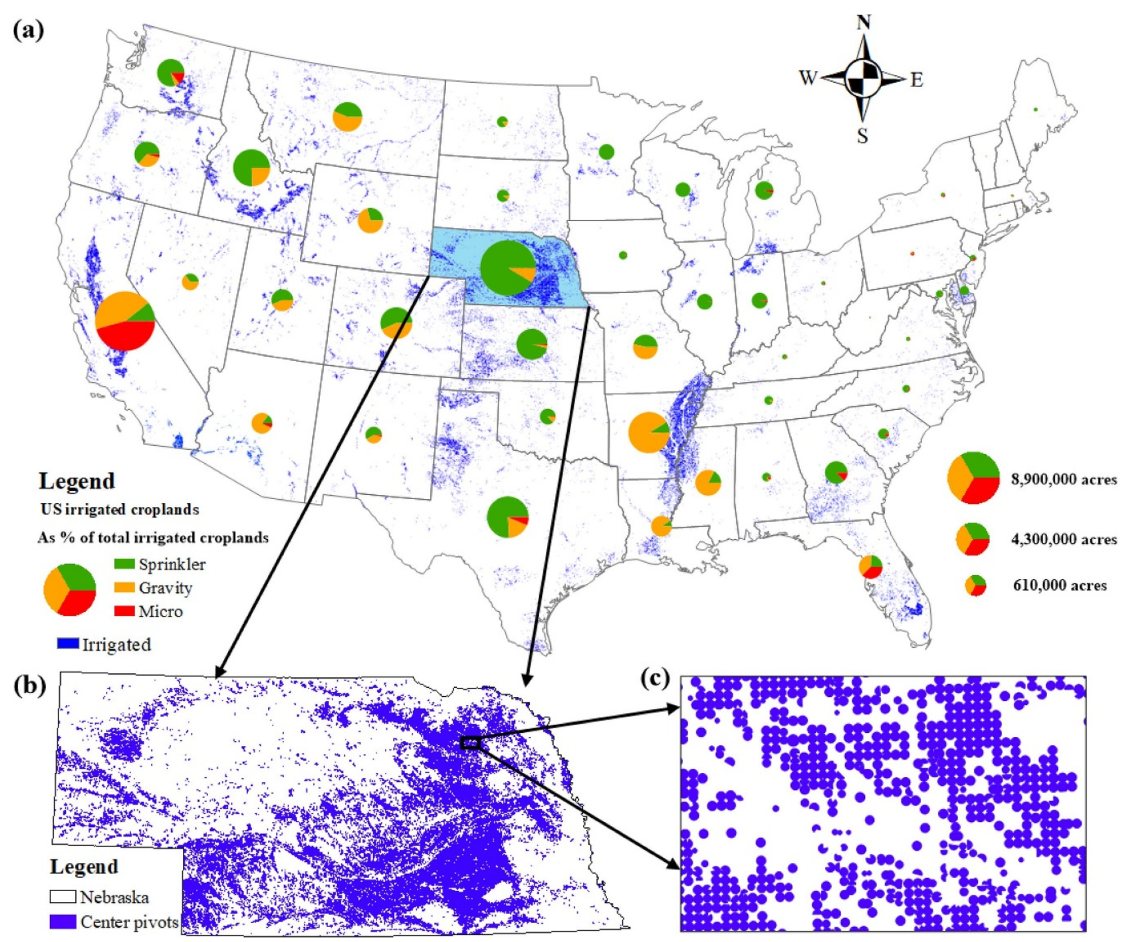

Figure 1. (a) Spatial distribution of irrigated croplands at 30 m resolution of sprinkler, gravity, and micro-irrigation by state for the Conterminous United States (CONUS) (USDA 2017, Xie *et al* 2019). The size of pie charts indicates the magnitude of irrigated croplands area. (b) Spatial distribution of center pivot irrigation systems in Nebraska (http://snr.unl.edu/data/geographygis/water.aspx). (c) Example of center pivots location in Nebraska.

approaches and criteria, and products used in current precision irrigation decision-support systems in three recent decades.

2.2. Data used in precision irrigation

Data represents the basis of any precision management system. Multi-source data, including *in-situ* measurements, remotely sensing data, and gridded weather/climate/soil data (figure 2), are used for precision irrigation. *in-situ* sensors, e.g. soil/canopy temperature/weather sensors, can provide data with high accuracy but sometimes are expensive and labor-intensive to deploy those sensors. Soil sensors provide measurements of soil volumetric water content, water potential, salinity, and/or soil temperature, such as time-domain and frequency-domain reflectometer, capacitance probe, resistance probe, tensiometers, or cosmic-ray neutron sensor (Robinson *et al* 2003, Vaz *et al* 2013). The temperature sensors mainly are the infrared thermometer sensor, which can observe canopy or soil surface temperature. Weather sensors, largely deployed as weather stations, measure multiple meteorological variables, such as air temperature and humidity, solar radiation, wind speed and direction, barometric pressure, and precipitation. Producers have options to establish their own weather stations, but the cost is high and the current adoption is very low. On the other hand, public weather stations in the existing networks, such as National Oceanic and Atmospheric Administration managed by National Climate Data Center and state networks (e.g. mesonets) are usually not dense enough, often leading to tens of km or further away from a targeted irrigated field (Sassenrath *et al* 2013, Mun *et al* 2015).

Remote sensing data from satellites, airborne sensors, and unmanned aerial vehicles (UAVs) mainly characterize canopy conditions, such as vegetation indices, leaf area index (LAI), and canopy temperature (Guan *et al* 2016, Urban *et al* 2018, Kimm *et al* 2020b), and hydrological conditions, such as evapotranspiration (ET), rainfall, and soil moisture (Qiu *et al* 2016, Peng *et al* 2017, Guan *et al* 2018). Unlike *in-situ* data, satellite data provide information across space and time for large-scale applications. However, existing satellite technology has limited spatial and/or temporal resolutions for precision irrigation. For example, MODIS is in low-medium spatial (250 m–1 km) and daily temporal resolution;

Table 1. Examples of precision irrigation products from the U.S. land-grant universities.

Institution	Products	Data sources	Models	Crop type(s)	Irrigation triggering rules	Major functions
University of Nebraska–Lincoln	CornWater	Weather station	Hybrid-maize crop model	Corn	Soil moisture	Provide real-time irrigation management for the next 3 d (Han 2016, Payyala 2016)
	SoyWater	Weather station, soil sensors	SoySim crop model	Soybean	Soil moisture	Provide real-time irrigation management for the next 3 d (Gibson *et al* 2019, Specht and Yang 2017)
University of Idaho	Reference evapotranspiration calculator (Ref-ET)/mapping evapotranspiration at high resolution and internalized calibration (METRIC ET)	Weather station, ET maps	Penman–Monteith	—	Soil moisture	Use daily soil water balance and ET maps for irrigation (Allen *et al* 2007a, Santos *et al* 2008)
Colorado State University	WISE (water irrigation scheduler for efficient application)	Weather station, soil sensors	Penman–Monteith	Alfalfa, corn, potato and sugar beets	Soil moisture	Use ET and soil moisture measurements for irrigation (Andales *et al* 2014, Bartlett *et al* 2015)
	Irrigation scheduling	Colorado agricultural meteorological network (CoAgMet), atmometers, soil sensors	Penman–Monteith	—	Soil moisture	Use ET and soil water balance for irrigation, use soil moisture measurements to check occasionally (Broner 2005)
Purdue University/Michigan State University	Irris Scheduler	Weather station	Penman–Monteith	Corn, soybean, dry bean, green bean, etc.	Soil moisture	Use ET and soil water balance for irrigation (Brad and Phil 2017)
Kansas State University	KanSched	Weather station	Penman–Monteith	—	Soil moisture	Use ET and soil water balance for irrigation (Rogers 2012)
Montana State University	Dynamic tools irrigation scheduling	AGRIMET weather network, soil sensors	Penman–Monteith	—	Soil moisture	Use ET, soil moisture measurements, and soil water balance for irrigation (Carlson 2019)
Michigan State University/University of Minnesota	Irrigation scheduling checkbook method	Michigan agricultural weather network (MAWN)	Penman–Monteith	—	Soil moisture	Use ETo, crop coefficient curve, and soil moisture measurements for irrigation (Wright 2018)

Table 1. (Continued.)

Institution	Products	Data sources	Models	Crop type(s)	Irrigation triggering rules	Major functions
University of Missouri	Crop Water Use app	Weather station	Penman–Monteith	Corn, rice, soybean, and cotton	Soil moisture	Use ET and soil water balance for irrigation, use soil moisture measurements to check occasionally (Stevens 2014)
North Dakota State University	Web-based irrigation scheduling program on NDAWN	Weather station	Penman–Monteith	—	Soil moisture	Use ET and soil water balance for irrigation (Scherer and Morlock 2008)
University of Wisconsin-Madison	Wisconsin irrigation scheduling program (WISP)	UW-extension Ag weather network	Penman–Monteith	Blueberry, soybean, corn, etc.	Soil moisture	Use ET and soil water balance for irrigation (Curwen and Massie 1994, Sanford and Panuska 2015)
Texas A&M University	Dashboard for Irrigation Efficiency Management (DIEM)	Texas Tech mesonet network (weather station), soil sensors	DSSAT-CROPGRO-cotton model	Cotton, sorghum, and corn	Soil moisture	Provide irrigation scheduling based on real-time measurements and projected weather data (from historical weather records) (Bordovsky *et al* 2017)
University of California	iCrop (integrated crop water management model-driven decision support tool)	Gridded climate data (PRISM, NARR); weather stations (CIMIS, Kansas mesoscale network); soil data (SoilGrids from ISRIC)	DSSAT-CSM model	Corn, sorghum, cotton, tomatoes, trees, etc.	Soil moisture	Provide optimal irrigation scheduling considering in-season yield predictions (based on historical climate patterns) (Kisekka and Kim 2018)
	CropManage	CIMIS (weather, ETo maps), UC Davis California Soil Resource Lab (SoilWeb)	Penman–Monteith	Broccoli, cabbage, onions, strawberry, etc.	Soil moisture	Use ETo, crop coefficient curve, and soil moisture measurements for irrigation (Cahn 2019)
USDA-NRCS/Oregon State University	Irrigation management-online	Weather station, farm-specific information (crop, irrigation)	Penman–Monteith	Alfalfa, peas, potato, wheat	Soil moisture	Estimate soil moisture to forecast irrigation schedules (Irmak *et al* 2010)
Washington State University	Irrigation Scheduler	Weather station, soil sensors	Penman–Monteith	Fruit tree	Soil moisture	Use forecasted ETo, crop coefficient curve, and soil moisture measurements for one-week irrigation (Troy *et al* 2012)

Table 2. Examples of commercial precision irrigation products.

Industry	Products	Data sources	Models	Crop type(s)	Irrigation triggering rules	Major functions
Valley	AgSense	AgSense weather station, soil sensors	Penman–Monteith	—	Soil moisture	Use ETo, crop coefficient curve, and soil moisture measurements for irrigation (AgSense 2017)
	Irriger Connect	Satellite imaging (NDVI and soil humidity), soil sensors, weather station	Penman–Monteith	—	Soil moisture	Use ET and soil water balance for a week ahead irrigation scheduling with the weather forecast (IRRIGER 2018)
	Valley® Scheduling	Weather station, soil sensors	Penman–Monteith	—	Soil moisture	Use ET and soil water balance for a week ahead irrigation scheduling with the weather forecast (Valley 2017)
	Irrigation scheduling supervisory control and data acquisition (ISSCADA) system	Weather station, infrared thermometer (IRT) sensors, soil sensors	Penman–Monteith	Soybean	Integrated crop water stress index (iCWSI)	Use iCWSI for site-specific variable-rate irrigation, use soil moisture measurements to determine irrigation amount or fixed amount (Evett *et al* 2014; O'Shaughnessy *et al* 2018, O'Shaughnessy *et al* 2015)
Valley/Prospera	Autonomous crop management	Satellite imagery, soil sensors	Machine learning	—	Crop water stress index (CWSI)	Provide irrigation scheduling based on machine learning (Valley and Prospera 2019)
Lindsay	FieldNET Advisor™	Growsmart weather station	Machine learning	—	Soil moisture	Provide irrigation scheduling based on machine learning (Lindsay 2020)
John Deere	eAurora web central	Weather station	Penman–Monteith	—	ET	Use ET and soil water balance for irrigation (Deere 2018)
The Climate Corporation/Lindsay	Two-way data connectivity between Climate FieldView and FieldNET	Satellite images (vegetation maps, such as LAI), soil data, weather data	Machine learning	—	Soil moisture	Use satellite image, weather, and soil moisture to predict irrigation scheduling based on Climate FieldView platform (Climate Corporation 2017)
CropMetrics/CropX	Virtual Predictor/VO Grow	Weather station, soil sensors, aerial imagery, soil/topography maps	Penman–Monteith, crop model, machine learning	Corn, soybean, etc	Soil moisture	Use ET and soil water balance to provide one-week ahead irrigation forecast for variable rate irrigation (CropMetrics 2019)

Table 2. (Continued.)

Industry	Products	Data sources	Models	Crop type(s)	Irrigation triggering rules	Major functions
Iteris	ClearAg's EvapoSmart	Global weather analysis and forecast system	Penman–Monteith	—	Soil moisture	Use ETo, crop coefficient curve, and soil moisture measurements for irrigation (iteris 2020)
	ClearAg's IMFocus	Global weather analysis and forecast system	Land surface model	—	Soil moisture	Use land surface model to track water and energy (iteris 2020)
LESCO®	Moisture Manager	Soil sensors	—	Lawns, etc.	Soil moisture	Use root zone soil moisture for irrigation scheduling (LESCO® 2018)
Observant	Irrigation scheduling	Observant weather monitoring, soil sensors	Penman–Monteith	—	Soil moisture	Use ETo, crop coefficient curve, and soil moisture measurements for irrigation (Observant 2019)
Agri-Valley Irrigation, LLC	Precision irrigation	Soil sensors	Penman–Monteith	—	Soil moisture	Use ET and soil water balance for a week ahead irrigation scheduling with the weather forecast (Agri-Valley Irrigation 2015)
GroGuru	Precision soil and irrigation monitoring system	Weather station, soil sensors for different depths (soil moisture, salinity, temperature)	Machine learning	Corn, etc.	Soil moisture	Use machine learning to predict irrigation scheduling (GroGuru 2019)
ARABLE	Arable Mark	Arable Mark all-in-one monitor (climate, plant, and soil data)	Machine learning	—	Soil moisture	Synthesize climate, plant, and soil data into water balance to produce irrigation (ARABLE 2018)
IrriWatch	IrriWatch	Remote sensing data (canopy temperature, solar radiation, crop leaf size, and photosynthesis)	Surface energy balance algorithm for land (SEBAL)	—	Soil moisture	Use remote sensing data to estimate ET and soil moisture by SEBAL for irrigation scheduling (Jaafar and Ahmad 2020)
HydroPoint	WeatherTRAK™	US weather stations (temperature, wind, solar radiation and humidity)	Not available	Turf and landscape plants	Daily ET	Estimate crop water use (ET) for irrigation scheduling (HydroPoint 2020)
Aspiring Universe	Agricultural intelligence	Remote sensing data (10-30m resolution, daily, cloud-free, gap-free ET/GPP/LAI)	Agroecosystem model	—	Daily ET, soil moisture	Use remote sensing data and process-based model to track field-scle soil moisture and ET for irrigation scheduling (Aspiring Universe 2020)

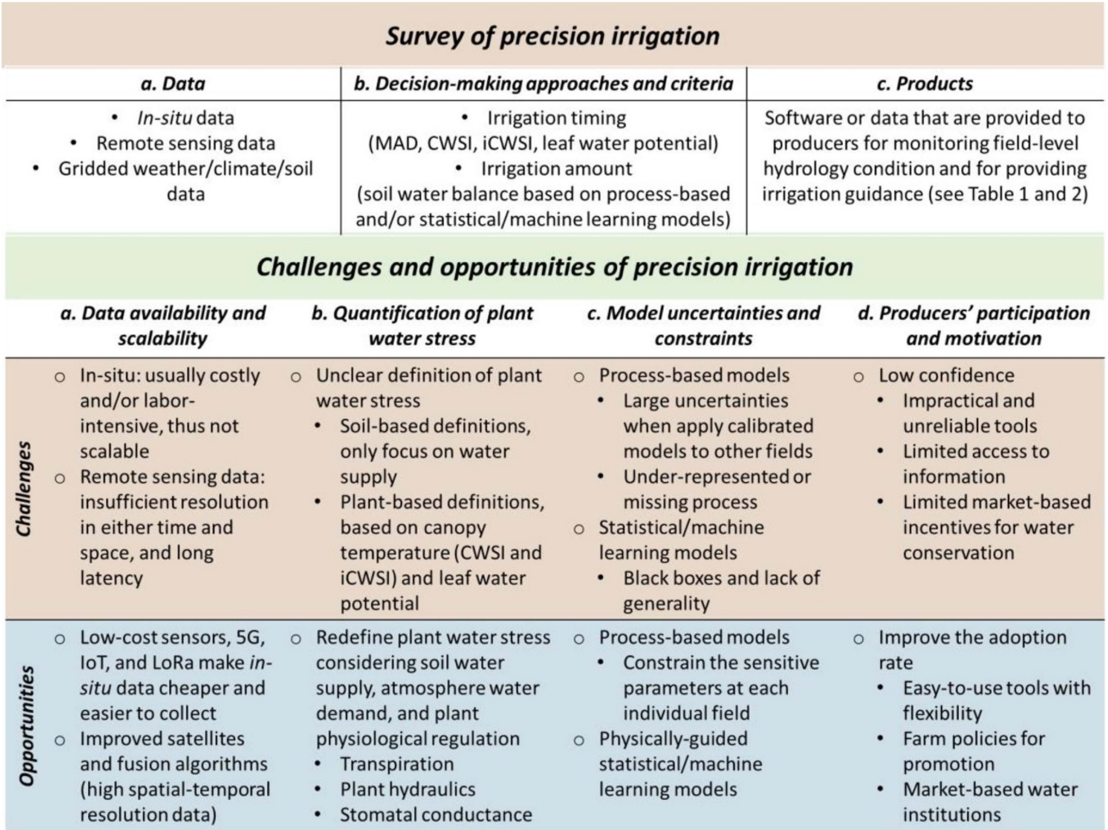

Figure 2. Summary of the recent advances, challenges, and opportunities of precision irrigation.

whereas, Landsat is in medium-high spatial resolution (30–60 m) but low temporal resolution (∼8 d). By contrast, airborne sensors and UAVs can provide data at higher spatial resolutions, e.g. ∼0.1 m, but require geometric and radiometric calibration, certified operators, and complex data processing, and thus they are usually cost-prohibitive. So far the most relevant remote sensing data for irrigation is ET, and there are various remote sensing-based ET models, e.g. atmosphere-land exchange inverse (ALEXI) (Anderson *et al* 2004), backward-averaged iterative two-source surface temperature and energy balance solution (BAITSSS) (Dhungel *et al* 2016), breathing earth system simulator (BESS) (Jiang and Ryu 2016), mapping evapotranspiration with internalized calibration (METRIC) (Allen *et al* 2007b), surface energy balance algorithm for land (SEBAL) (Bastiaanssen *et al* 1998), and their pros and cons have been reviewed in recent work (Zhang *et al* 2016, Jiang *et al* 2020a).

Finally, gridded weather/climate/soil data, such as NLDAS (Xia *et al* 2012), PUMET (Pan *et al* 2016), PRISM (Daly and Taylor 2001), DayMET (Thornton *et al* 2018), and SSURGO (NRCS 2017), are usually used as the forcing or parameters of land surface models to analyze the impact of irrigation (Devanand *et al* 2019, Xu *et al* 2019). Gridded weather/climate data can provide large-scale information, but usually have a coarse spatial resolution (>250 m) and cannot meet the field-level resolution and low latency requirements necessary for precision irrigation decision-support systems.

2.3. Decision-making approaches and criteria used in current precision irrigation decision-support systems

The major decision-making approaches for irrigation timing primarily depend on soil- and plant-based metrics (Elwin 1997, Jones 2004). Soil-based metrics determine irrigation timing based on soil moisture or soil moisture-derived metrics, such as maximum allowable depletion (MAD), which indicates the percentage of the available water capacity to which crops should be subjected. MAD is the most widely used precision irrigation decision-making method (Panda *et al* 2004, Lehmann *et al* 2013). Plant-based metrics mainly determine irrigation timing based on plant conditions, such as plant water conditions (e.g. leaf water potential) and/or canopy temperature, e.g. crop water stress index (CWSI) and integrated CWSI (iCWSI) (Jones 2004, Girona *et al* 2006). Leaf water potential, a direct measure of plant water status in terms of plant hydraulics, has been used by agronomists/consultants for the irrigation of high value crops, but this approach can be over-costly and unscalable for row crop (Jones 2004, Girona *et al* 2006). The CWSI and iCWSI provide irrigation-trigger information through the cooling effect due to plant transpiration, based on the normalized function of vapor pressure deficit (VPD) and temperature difference between canopy and air (Idso *et al* 1981, Jackson *et al* 1981, DeJonge *et al* 2015, O'Shaughnessy *et al* 2015).

The most widely adopted approach to determine how much water to apply is based on root-zone soil moisture. Given that soil moisture sensors are not available in most cases, the irrigation amount can be determined using soil water balance through two types of methods: the process-based models and statistical/machine learning models. Process-based models, including crop models, e.g. APSIM, AquaCrop, DSSAT, EPIC, Hybrid-Maize (Hammer *et al* 2002, Steduto *et al* 2009, Rosenzweig *et al* 2014, Peng *et al* 2020), hydrological models, e.g. SWAT (Chen *et al* 2018), and land surface models, e.g. Noah-MP, CLM, JULES, PALMS (Best *et al* 2011, Niu *et al* 2011, Yang *et al* 2011, Booker *et al* 2015, Peng *et al* 2018), can be used to simulate water balance and surface biophysical processes based on physical mechanisms with inputs of weather, soil, and/or satellite-based vegetation information. Statistical/machine learning models usually use empirical approaches to calculate soil water content and crop water use to determine the irrigation amount, and these empirical models require rich historical data to train and test the models to make them useful (Goldstein *et al* 2018). Furthermore, daily ET reports is also widely used for irrigation scheduling based on the estimation of daily crop water use (Lascano 2000, Lascano and van Bavel 2007, USDA 2017).

2.4. Existing products developed for precision irrigation decision support

Based on the multi-source data, decision-making approaches and criteria used in precision irrigation, many products have been developed to provide precision irrigation decision support for producers. We have listed some examples of precision irrigation decision support products from the U.S. land-grant universities and industries (tables 1 and 2). The combination of reference ET (ET_o), crop coefficient (K_c), and soil water stress coefficient (K_s) is the most widely used empirical method to estimate crop water use, i.e. $ET = ET_o \times K_c \times K_s$. There are many approaches to calculate ET_o, reference ET for a short crop with a height of 0.12 m (similar to grass), using meteorological data, such as FAO Penman–Monteith method (Allen *et al* 1998, Walter *et al* 2000, Allen 2009). The majority of products incorporate crop water use (i.e. ET) to soil water balance to infer soil moisture for irrigation scheduling, such as METRIC ET, WISE, and CropManage. Besides, some products can also provide irrigation scheduling with lead time of a few days with weather forecasts, such as CornWater and SoyWater developed by University of Nebraska–Lincoln.

3. Challenges and opportunities for precision irrigation decision-support systems

Based on current precision irrigation research, we identified four critical challenge areas and corresponding opportunities (figure 2) to improve precision irrigation decision-support systems for the center pivots in the U.S.: (a) data availability and scalability; (b) quantification of plant water stress; (c) model uncertainties and constraints; and (d) producers' participation and motivation. With these challenges and opportunities, our proposed precision irrigation decision-support system for center pivots, which includes three components: data acquisition, modeling and analytics, and decision-making support (figure 3), should be scalable, economical, reliable, and easy-to-use for producers.

3.1. Data availability and scalability

One major challenge regarding data need for precision irrigation is the lack of field-level resolution and high-accuracy data for scaled-up applications. Here we first reviewed the challenges of different existing approaches, and then discussed the opportunities to obtain scalable and high-accuracy data that can be acquired in every field at large regions for precision irrigation.

3.1.1. Challenges

Here we identify three challenges from *in-situ*, satellite-based vegetation, and satellite-based ET and soil moisture data in data availability and scalability (figure 2).

3.1.1.1. In-situ *data*

Existing *in-situ* sensors in the market are generally expensive or at least not sufficiently cheap to enable wide adoption. They also typically need to be installed and removed before and after the growing season for row-crops, resulting in extra labor costs. Though *in-situ* sensors usually provide high-quality measurements, these measurements are from a single point and thus often have limitations in capturing spatial heterogeneity of a whole field (Geesing *et al* 2004, Dong *et al* 2013, Irmak *et al* 2014, Rudnick *et al* 2015, Vuran *et al* 2018). Large public *in-situ* networks are available to provide long-term datasets from the National Soil Moisture Network and state mesonets, but these network stations are usually deployed in natural landscapes, away from crop fields, thus they have to rely on interpolation for precision irrigation but with significant uncertainty (Mauget and Leiker 2010).

3.1.1.2. Satellite-based vegetation data

To enable precision irrigation decision, field-level resolution and high frequency are needed for remote

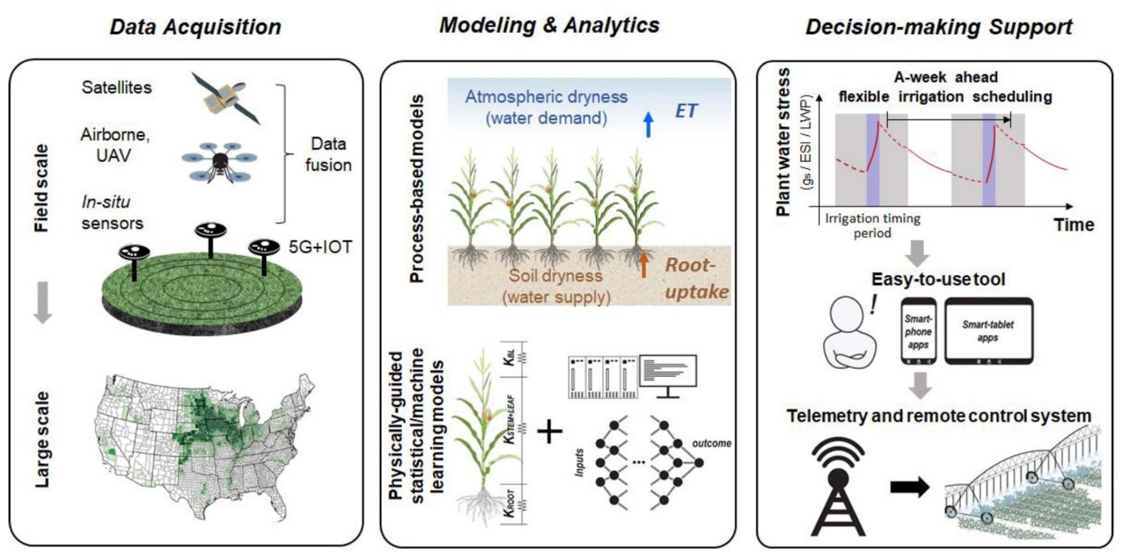

Figure 3. Proposed systematic framework of precision irrigation decision-support system for center pivots.

sensing data. However, conventional satellite-based datasets on vegetation conditions, e.g. LAI and land surface temperature (LST), cannot fulfill high resolutions in space and time simultaneously; and some satellite-derived products have inherent limitations, such as insufficient accuracy and significant time latency (table 3). These drawbacks limit their applications to provide real-time and field-resolution data to determine irrigation scheduling for precision irrigation.

3.1.1.3. Satellite-based ET and soil moisture data

Continuous real-time estimation of ET and soil moisture, which indicate crop water use and soil water supply for crops in irrigation decision-making tools, remains a major challenge at fine scales with high accuracy for precision irrigation. Current operational soil moisture products only have coarse resolutions and could not fulfill the field-level irrigation needs; to make them useful, they need to be downscaled to high resolutions in both space and time, which adds large uncertainties (table 3). Specifically, current satellite-based soil moisture products based on passive microwave remote sensing are still limited to coarse resolutions (e.g. >10 kms in SMAP L3 and SMOS L3 products) and are only sensitive to shallow soil depth (<0.05 m) (Entekhabi *et al* 2010, Chan *et al* 2016); the above limitations make these data not useful for field-scale precision irrigation. The existing operational ET data either has coarse resolutions or not effective under cloudy days. For example, ALEXI/DisALEXI and METRIC ET products are based on energy balance approaches, which retrieve clear-sky ET from satellite-observed LST and fill ET gaps for cloudy-sky days, and thus are considerably affected by atmospheric conditions, thus limiting its practical uses (Allen *et al* 2007a, Cammalleri *et al* 2013, Li *et al* 2017, Anderson *et al* 2018, Ma *et al* 2018).

3.1.2. Opportunities

3.1.2.1. In-situ *data*

First, continuous development of soil moisture sensor is needed to reduce the cost while achieve the robust performance (Montzka *et al* 2020). Second, more *in-situ* measurements from low-cost sensors can be combined to fill in the critical data gap for essential plant and environmental conditions. For example, *in-situ* LAI measurements, along with some other environmental variables, such as air temperature and humidity, now can be acquired from low-cost sensors; these measurements can provide significant constraints to improve ET estimations for irrigation scheduling. Economic cameras, such as PhenoCam, point-and-shoot cameras and smartphones, and spectral reflectance sensors, have been deployed to track vegetation phenology, such as LAI, and productivity (Ryu *et al* 2010, 2012, Francone *et al* 2014, Richardson *et al* 2018, Yan *et al* 2019). Furthermore, recent advances in microcomputers and microcontrollers have improved the ability to intelligently integrate low-cost sensors and provide a comprehensive solution for crop growth monitoring (Kim *et al* 2019). Third, some mobile sensors may also contribute to fill the gaps of spatial and temporal sampling, such as putting the roving cosmic-ray neutron sensors on trucks to sample soil moisture at a regional scale (Franz *et al* 2015, Schrön *et al* 2018). Additionally, new technologies, such as 5G networks, Internet of Things (IoT), Long Range communication devices, and edge computing, can further speed up the development of wireless sensing networks (WSNs), which can possibly make it less expensive and easier to provide scalable *in-situ* data for precision irrigation.

3.1.2.2. Satellite-based vegetation data

For remote sensing data for vegetation conditions, improved satellite technologies/algorithms and data

Table 3. Some examples of satellite-based products of LAI, LST, ET, soil moisture, and precipitation.

Dataset variable	Product name	Platform	Spatial resolution	Temporal resolution	Latency	Reference(s)
LAI	AVH15C1	NOAA/AVHRR	0.05°	Daily	1 d	Claverie *et al* (2016)
	GEOV3	PROBA-V	1/360°	10 d	10 d	Camacho *et al* (2016)
	MCD15A3H	MODIS	500 m	8 d	5 d	Yan *et al* (2016)
	VNP15A2H	SNPP/VIIRS	500 m	8 d	2 weeks	Knyazikhin and Myneni (2017)
LST	MOD/MYD11 A1	MODIS	1 km	Daily	1 d	Wan *et al* (2015)
	MYD21A1	MODIS	1 km	Daily	4 weeks	Hulley (2017)
	ECO2LSTE	ECOSTRESS	70 m	Irregular	2 d	Hook and Hulley (2019)
	Landsat	Landsat	30 m	16 d	8 d	Cook *et al* (2014)
	GOES-R LSTC	GOES-R	2 km	Hourly	Real time	Schmit *et al* (2017)
	VNP21A1	SNPP VIIRS	1 km	Daily	8 weeks	Liu *et al* (2015)
	Sentinel3_SL_2_LST	Sentinel-3	1 km	Daily	Real time	Sobrino *et al* (2016)
ET	MOD/MYD16A2	MODIS	500 m	8 d	3 weeks	Cleugh *et al* (2007)
	PML-V2	MODIS	500 m	8 d	Not operational	Zhang *et al* (2019)
	BESS	MODIS	1 km	8 d	Not operational	Jiang and Ryu (2016)
	FLUXCOM	MODIS	1 km	8 d	Not operational	Jung *et al* (2019)
	GLASS	MODIS	0.05°	8 d	Not operational	Yuan *et al* (2010)
	GLEAM v3a	MODIS	0.25°	Daily	Not operational	Martens *et al* (2017)
	ALEXI	GOES-R	4 km	Daily	Not available	Anderson *et al* (2007)
	PT-JPL	ECOSTRESS	56 m	Irregular	1 week	Fisher *et al* (2020)

(Continued)

Table 3. (Continued.)

Dataset variable	Product name	Platform	Spatial resolution	Temporal resolution	Latency	Reference(s)
Soil moisture	SMAP	SMAP	36 km (SMAP_L2/3_SM_P), 9 km (SMAP_L2/3_SM_P_E, SMAP_L4_SM), 3 km (SMAP_L2_SM_SP)	Daily or 3 h	1–3 d	Chan *et al* (2016), Entekhabi *et al* (2010), and Reichle *et al* (2017)
	SMOS	SMOS	15/25 km	Daily	6 h to 7 d	Al Bitar *et al* (2017)
	ASMR2 L3	ASMR2	10 km	Daily	1 d	Jeu and Owe (2014)
	SSM/I	SSM/I	25 km	Daily	1 d	Paloscia *et al* (2001)
	SMOPS	ASCAT, SMOS, GMI, SMAP, AMSR2, Wind-Sat	25 km	Daily	1 d	Zhan *et al* (2011)
Precipitation	TRMM	TRMM	0.25°	3 h	8 h	Iguchi *et al* (2000)
	GPM	GPM	0.1°	30 min	4 h	Huffman *et al* (2015)
	GOES-R	GOES-R	4 km	15 min	2 h	Loto'aniu *et al* (2019)
	PERSIANN	GOES-8, GOES-10, GMS-5, Metsat-6, Metsat-7, TRMM, NOAA-15, −16, −17, DMSP F13, F14, F15	0.25°	6 h	2 d	Ashouri *et al* (2015)
	CHIRPS V2.0	CCD	0.05°	Daily	3 weeks	Funk *et al* (2015)
	CMORPH V1.0	SSM/I, AMSU-B, AMSR-E, TMI	0.07°	30 min	2 h	Joyce *et al* (2004)
	MSWEP	CMORPH, Grid-Sat, GSMaP, TMPA	0.25°	3 h	4 h	Beck *et al* (2019)

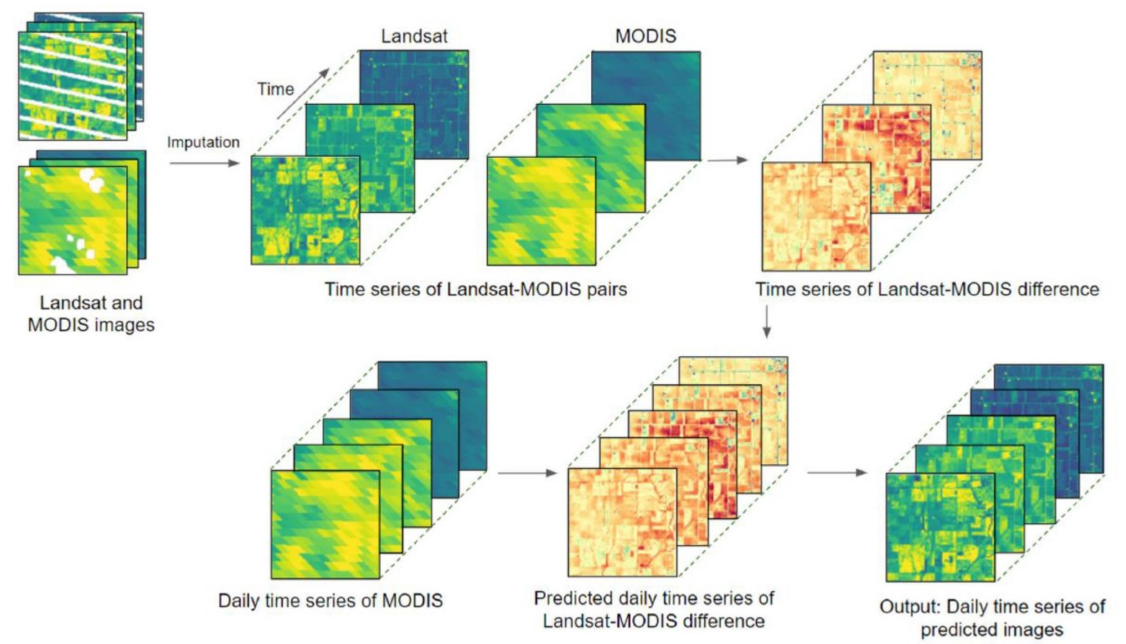

Figure 4. Overview of the fusion method of STAIR (Reprinted from Luo *et al* 2018, Copyright (2018), with permission from Elsevier).

fusion methods (figures 2 and 3) can help to provide high spatial-temporal resolution products directly. Notably, satellite datasets with high resolutions in both space and time, e.g. daily, 3 m resolution Planet Labs data, are emerging and becoming available; though whether these data can be commercially viable for irrigation products is still unclear. Alternatively, satellite fusion algorithms, such as the SaTellite dAta IntegRation (STAIR) fusion method (figure 4) (Luo *et al* 2018, 2020), have been developed to fuse various satellite data together, e.g. Landsat, MODIS, and Sentinel-2, to enable the operational and real-time generation of a 10–30 m, daily and cloud-/gap-free data product for surface reflectance, which has significantly advanced the field-scale and real-time monitoring of crop conditions (Jiang *et al* 2020a, Kimm *et al* 2020b).

3.1.2.3. Satellite-based ET and soil moisture data

High-resolution and operational ET and soil moisture products, once become available, can enable precision irrigation scheduling at the field level and low costs without *in-situ* sensors. Notable, the recently developed BESS-STAIR ET product, generated by a satellite-driven water-carbon-energy coupled biophysical model BESS combined with the STAIR fusion data, not only has a high spatial-temporal resolution (daily, 30 m) under all-sky conditions, but also has demonstrated a high performance in estimating field-level ET when benchmarked with 12 eddy-covariance flux sites across the U.S. Corn Belt (figure 5) (Jiang *et al* 2020a). It indicates that BESS-STAIR ET has potential for applications in field-level precision irrigation, and also has scalability to regional and global scales. Besides, high-resolution LST products could also be incorporated into the BESS model as constraints to improve BESS-STAIR ET's performance in near future. Some other existing programs, such as OpenET (Hall *et al* 2020), also have plans to offer satellite-based ET data, but unless real-time and field-level ET data can be provided, the promise to resolve precision irrigation cannot be fulfilled.

For field-scale soil moisture, leveraging recent advances in mobile proximal sensing, high-resolution satellite remote sensing and downscaling, model-data fusion, ground sensing networks, machine learning and data mining techniques may provide promising solutions. Several proximal sensing techniques (Babaeian *et al* 2019), such as cosmic ray neutron sensing, can be powerful in mapping field-scale soil moisture when mounted on mobile platforms (Franz *et al* 2015, Schrön *et al* 2018). Higher resolution soil moisture estimation can also be achieved through synergic use of both active and passive microwave remote sensing (Das *et al* 2019) or spatial downscaling (Peng *et al* 2017). Field-scale soil moisture simulation can also be improved with model-data fusion. Soil moisture is highly connected with some other land surface state and flux variables, such as ET and LST. The recently developed satellite-based 30 m BESS-STAIR ET (Jiang *et al* 2020a), ECOSTRESS-based ET (Anderson *et al* 2020) and LST (Hook and Hulley 2019) can be used to constrain the hydrological models through model-data fusion methods and thus to better infer field-scale soil moisture. The soil parameters in the hydrological models, which are an important source of uncertainty in field-scale soil

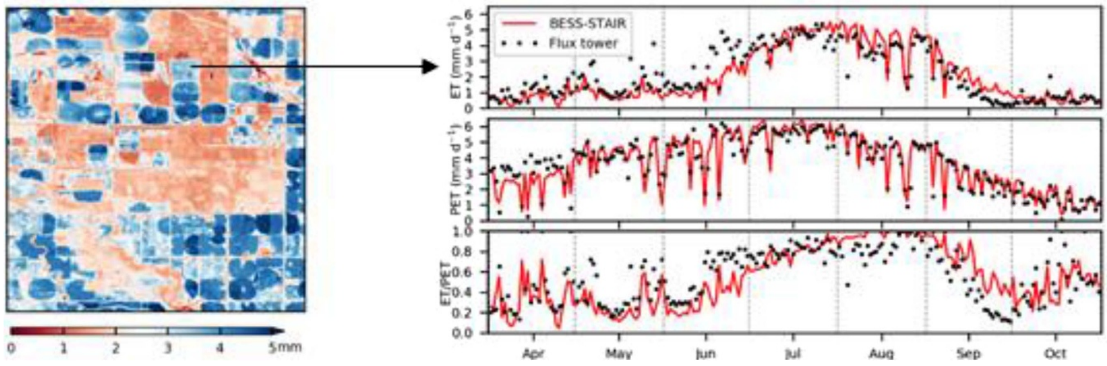

Figure 5. BESS-STAIR performance. Left: a daily ET map in eastern Nebraska. Right: time series comparison of ET, potential ET (PET), calculated by the Priestley–Taylor equation to measure the atmospheric demand, and ET/PET between BESS-STAIR daily estimations and flux tower measurements in 2012 (Jiang *et al* 2020a).

moisture simulation, can also be estimated through model-data fusions methods when proper field-scale measurements are available. With emerging technologies like WSNs and IoTs (Kiani and Seyyedabbasi 2018), more ground-based soil moisture observations will become available (Quiring *et al* 2016), which provides an opportunity for data-driven prediction of soil moisture. State-of-the-art data mining techniques based on a network of coevolving time series (Cai *et al* 2015, Hairi *et al* 2019) can simultaneously capture the structural topology and temporal dynamics of multiple time series for the temporal and spatial patterns of soil moisture and its correlation with other variables. Meanwhile, the emerging physics-guided machine learning approaches (de Bézenac *et al* 2019, Reichstein *et al* 2019, Yang *et al* 2019), which can integrate hyper-resolution hydrological modeling with advanced machine learning algorithms, may also shed light on field-scale soil moisture estimation.

3.2. Quantification of plant water stress

A fundamental question about precision irrigation is 'what is plant water stress and how to quantify it?'. Answering this question requires us to fully consider the soil–plant–atmosphere continuum (SPAC). Only after this question is answered, optimal methods could be developed around the correct concepts.

3.2.1. Challenges

'Plant water stress' is a critical concept to indicate the water shortage status of plants, based on which we can create irrigation triggering rules. There are various definitions of 'plant water stress', for example, based on soil moisture and/or plant conditions, including canopy temperature and/or leaf water potential (Jones 1990, 2004, 2007, Rodríguez-Iturbe and Porporato 2005, Möller *et al* 2007).

3.2.1.1. Soil-based concepts

Soil-based metrics are the most widely used methods for irrigation decision-making, such as MAD (see tables 1 and 2, figures 6(d) and 8(e)). These metrics are based on the available water in the root-zone for root water uptake to indicate plant water stress. It is worth noting that these soil-based metrics largely only reflect water supply and they do not consider atmospheric water demand. Since agricultural drought in the U.S. Corn Belt is both driven by soil water deficit and atmospheric dryness characterized by high VPD (Lobell *et al* 2014, Zhou *et al* 2020, Kimm *et al* 2020a), it could be inappropriate to quantify plant water stress solely based on soil moisture.

3.2.1.2. Plant-based concepts

Canopy temperature and leaf water potential are often used for irrigation management (figures 6(a), (e) and 8(a), (b)). Canopy temperature reflects plant water stress indirectly through canopy energy balance, such that a reduction of ET leads to reduced evaporative cooling, and thus higher canopy temperature given the same net energy (Idso *et al* 1981, Jackson *et al* 1981, DeJonge *et al* 2015, O'Shaughnessy *et al* 2015). However, canopy temperature derived metrics, such as CWSI and iCWSI, which can be measured from proximal, airborne, or satellite thermal sensors at the canopy scale, contain non-negligible uncertainty due to the empirical calculation methods, and are also prone to weather conditions, i.e. no observations during cloudy days for satellite products. The empirical calculation methods usually use the empirical upper and lower limits of the temperature difference between canopy and air to estimate CWSI and iCWSI based on the standardized temperature difference, resulting in irreducible uncertainty and error.

Leaf water potential, a more rigorous measure of plant water stress based on plant hydraulics, can indicate plant's internal water stress directly, but it is relatively cumbersome and labor-intensive to measure (Jones 2004, Girona *et al* 2006). The traditional measurements of leaf water potential via pressure chambers are reliable but require destructive leaf sampling and could be time-consuming (Boyer 1967, Ritchie and Hinckley 1975, Turner 1988), while the

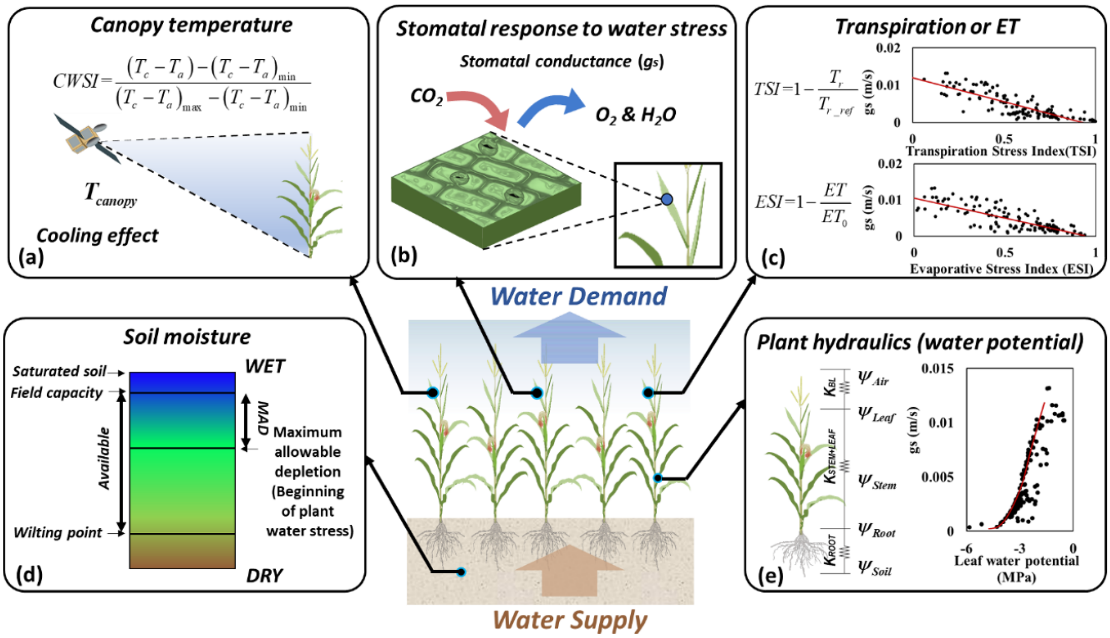

Figure 6. Conceptual scheme of five possible aspects to define plant water stress. (a) CWSI based on canopy temperature. (b) Stomatal conductance considering stomatal response to water stress. (c) TSI or ESI based on transpiration or ET. (d) Soil moisture-based metric: MAD. (e) Leaf water potential based on plant hydraulics. ET denotes the crop water use considering the limitation from soil water supply; ET_o denotes reference ET calculated by the Penman–Monteith equation for a short crop, grass (0.12 m).

psychrometric methods (Richards and Ogata 1958, Barrs 1964, Pérez et al 2011) are non-destructive but expensive and require sophisticated equipment and high level of technical skill. Thus, economically it is not viable and scalable to use these methods for row crops, which have much lower value than fruit and vegetables.

3.2.2. Opportunities

We interpret 'plant water stress' as a joint contribution of soil water supply (i.e. root-zone soil moisture) and atmospheric water demand (i.e. VPD), mediated by plant physiological regulations (Rigden et al 2020, Kimm et al 2020a) (figure 3). Both low soil moisture and high VPD can lead to plant water stress, and different plants may have different physiological responses and water use strategies (Sinclair et al 1984, Sinclair 2005, 2012, Katul et al 2012). Thus, plant water stress should be defined and quantified holistically based on the interplay between soil water supply, atmospheric water demand, and plant physiological regulations, i.e. SPAC concept, for irrigation scheduling. We propose three definitions based on transpiration, plant hydraulics, and stomatal conductance (figures 2 and 6).

3.2.2.1. Transpiration

We can define 'plant water stress' from the perspective of transpiration (figure 6(c)). As transpiration can be limited by soil water deficit and/or downregulated stomatal conductance due to atmospheric aridity, actual transpiration (Tr) is achieved as the minimum of atmospheric water demand and soil water supply (Sinclair et al 1984, Sinclair 2012), with the former defined as transpiration when soil moisture is non-limiting with the same vegetation conditions, i.e. reference transpiration, Tr_ref, and the latter defined as root water uptake given limited soil moisture. Thus, the ratio of Tr (with plant water stress) and Tr_ref (without plant water stress) can be used to indicate plant water stress, here we define it as transpiration stress index (TSI) (figure 6(c)). However, in practice it is difficult to obtain direct measurements of Tr and Tr_ref. Though there are multiple ET partitioning approaches that can separate evaporation and Tr, such as process-based models (Stoy et al 2019), energy balance (Kool et al 2016), remote sensing products (Talsma et al 2018), or geochemical signatures (Al-Oqaili et al 2020), these methods contain relatively large uncertainties, which limits the accurate calculation of TSI in real-world applications. Alternatively, we could use the ratio of actual ET and reference ET (ET_o), i.e. evaporative stress index (ESI) (Anderson et al 2011), as an approximation of TSI to indicate plant water stress for precision irrigation (figure 6(c)). ESI, which has been extensively used to quantify agricultural drought in long-term baseline conditions (Anderson et al 2011, 2016), can be derived from remote sensing, e.g. ECOSTRESS ESI_PT-JPL (Fisher et al 2020) and BESS-STAIR ET (Jiang et al 2020a), and/or process-based models.

3.2.2.2. Leaf/stem water potential

We also can define 'plant water stress' using leaf/stem water potential based on plant hydraulics (figure 6(e)). Plant hydraulics is the fundamental theory that connects soil water supply and atmospheric water demand (Dixon and Joly 1895, Tyree 1997, 2003, Taiz and Zeiger 2006, Stroock *et al* 2014), and can realistically represent the path of water flow from the soil through the plant substrate to the atmosphere driven by the potential gradient (Anderegg 2015). When plant water stress is caused by soil water deficit and atmospheric aridity, either independently or collectively, a substantial drop in leaf/stem water potential can be observed, and consequently with a reduction in sap flow. Thus, leaf and stem water potentials can be used as metrics to quantify plant water stress (figure 6(e)). However, measurements of leaf and stem water potentials are labor-intensive and expensive to use for precision irrigation. Thus, accurately modeling plant hydraulic control and water transport in the SPAC to estimate plant hydraulic traits, e.g. leaf/stem/root water potential and hydraulic conductance, becomes the key to the quantification of plant water stress in practice. To manage the complexities of plant hydraulic models, some highly uncertain parameters can potentially be constrained using various measurements through data-model fusion approaches (referred to section 3.3), and some processes can also be simplified for crops, e.g. neglecting plant water storage (Salomón *et al* 2017), to enable efficient and scalable adoption of this method.

3.2.2.3. Stomatal conductance (G_s)

We can also define 'plant water stress' in terms of G_s (figures 6(b), 7 and 8), which reflects the physiological regulation of the uptake of atmospheric CO_2 for photosynthesis and water loss through transpiration (Ball *et al* 1987, Medlyn *et al* 2011). Stomatal regulations are co-regulated by water supply (soil moisture) and demand (VPD) (figure 6(b) and the co-regulation pattern in figure 7) (Lin *et al* 2018, Kimm *et al* 2020a). G_s decreases with VPD given a certain soil moisture, and increases with soil moisture given a certain VPD (figure 7). Besides, the strong relationship between CWP, CWSI, ESI, TSI, MAD and G_s indicates that different plant water stress metrics (CWP, CWSI, ESI, TSI, MAD) all reflect the information of G_s (figure 8). Thus, stomatal conductance is the most effective indicator of plant water stress based on the co-regulation from soil moisture and VPD. However, quantifying 'plant water stress' in terms of G_s is difficult, since we do not have a direct measure of actual G_s in practice at the canopy level—we can only do it at the leaf level. Thus, the above approach may have to rely on either process-based models or observation derived proxies, such as inversed Penman–Monteith equation and semi-empirical G_s models (Ball *et al* 1987, Allen *et al* 1998, Leinonen *et al* 2006, Damour *et al* 2010, Medlyn *et al* 2011, Gago *et al* 2016, Buckley 2017, Kimm *et al* 2020a). The effectiveness of the above modeling or proxy approaches remains to be investigated, but the promise lies in leveraging scalable field-level measurements (e.g. from novel satellite products, see section 3.1.2) with models through data-model fusion approaches to estimate G_s and then make irrigation decision guidance.

3.3. Model uncertainties and constraints

With the data availability and 'plant water stress' definitions clarified, process-based models and/or statistical/machine learning models can be used to simulate the SPAC system for irrigation scheduling. Both two types of models can involve significant uncertainties if not properly used, thus data-model fusion methods should be used to constrain models at each individual field, using field-scale measurements (figure 2).

3.3.1. Challenges

3.3.1.1. Process-based models

Uncertainties of the process-based models (referred to section 2.3) can come from model inputs, parameters, and structures. Beven and Freer (2001) and Liu and Gupta (2007) have provided some detailed discussions on these aspects. Here we only discuss our unique perspective related to two major challenges. The first challenge is that scalable precision irrigation through process-based models requires us to have accurate simulations at each individual field in large regions. Process-based models usually can be calibrated at fields with rich data. Many practitioners assume that a model that has been calibrated at one or a few locations can be applied directly to other random sites. However, this approach in general does not work. The reasons are two-folds: first, when applying a model to a new site, many site-specific input data is not available, such as management practices and soil characteristics, which can lead to large errors in the simulations. Second, there are some site-specific model parameters remaining unknown and using predefined values may lead to large uncertainties. To possibly resolve this issue, we need to calibrate the process-based models at each individual field. The challenge thus is how to get the required field-level measurements for the calibration at each individual field. Computation burden also exists when we want to constrain each individual field using the process-based models.

The second challenge is the under-represented or missed critical processes in the current models. One typical example is the linear/nonlinear response functions of G_s to soil moisture used in many current land surface models, such as in NOAH-MP model (Niu *et al* 2011), JULES model (Best *et al* 2011), and CTESSEL model (Boussetta *et al* 2013). These linear/nonlinear soil moisture-based water stress functions only consider soil water supply but ignore atmospheric

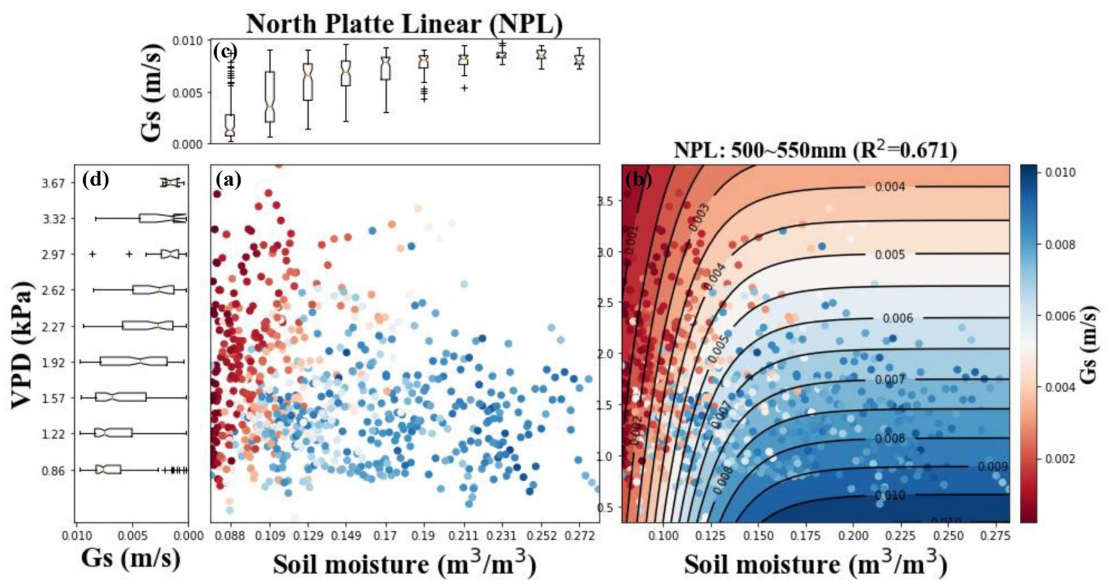

Figure 7. Soil moisture and VPD's co-regulation on G_s of maize at one site (North Platte Linear, NPL: 41.09° N; 100.78° W) in central Nebraska. (a) Scatter plots of daily soil moisture, VPD, and G_s during peak growing season (July and August) from 2001 to 2019 based on the simulation from an advanced process-based model (*ecosys*). (b) Contour of G_s as a function of soil moisture and VPD using equation (4) in Kimm *et al* (2020a). (c), (d) Two box plots show the variation of G_s with soil moisture and VPD.

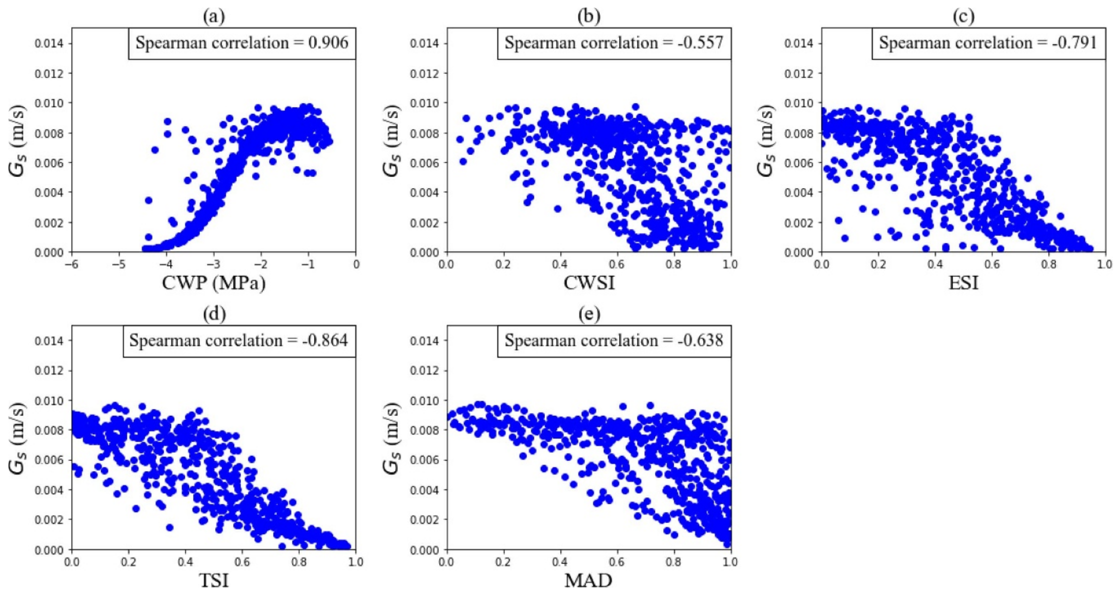

Figure 8. The performance of five metrics (CWP, CWSI, ESI, TSI, and MAD) interpreting G_s of maize during peak growing season (July and August) from 2001 to 2019 at one site (NPL: 41.09° N; 100.78° W) in central Nebraska based on the simulation from an advanced process-based model (*ecosys*). (a) CWP: canopy water potential; (b) CWSI: crop water stress index; (c) ESI: evaporative stress index; (d) TSI: transpiration stress index; and (e) MAD: maximum allowable depletion.

water demand, thus these models have been found to overestimate soil moisture impacts on G_s, thus overestimated loss of ET with decreasing soil moisture (Ukkola *et al* 2016, Lei *et al* 2018). Few models consider the complicated interaction between surface water and groundwater, which is critical for the conjunctive use of these two sources for optimal irrigation in regions with active surface water and groundwater interactions (Singh *et al* 2016). Besides, ignoring these active interactions may also lead to large uncertainties of the subsurface hydrological conditions.

3.3.1.2. Statistical/machine learning models

The first challenge is that statistical/machine learning models are usually seen as 'black boxes', which lack the physical mechanisms related to water cycle and irrigation (Torres *et al* 2011, Goumopoulos *et al* 2014, Navarro-Hellín *et al* 2016, Romero *et al* 2018).

It is difficult to trace the highly variable hydrological and vegetation conditions using 'black boxes' machine learning algorithms. Another challenge is the data scarcity for the training of statistical/machine learning models at every individual field. The statistical/machine learning models can be trained at data-rich fields, while they cannot be extrapolated to other fields due to the lack of generality (Goldstein *et al* 2018, Romero *et al* 2018).

3.3.2. Opportunities

3.3.2.1. Process-based models

Regarding the first challenge, process-based models should be constrained at each individual field by integrating the field-level measurements into data-model fusion methods for scalability. From the perspective of data, field-level measurements can be acquired by economic sensors and/or satellite remote sensing (see section 3.1.2). Advanced satellite remote sensing technologies nowadays can accurately estimate crop conditions (e.g. LAI and GPP) (Wu *et al* 2020, Jiang *et al* 2020b, Kimm *et al* 2020b) and hydrological conditions (e.g. ET) (Jiang *et al* 2020a), making field-level information available. From the perspective of model, sensitive analysis should be applied first to screen out the most sensitive model parameters. Then, the most sensitive parameters need to be constrained for each individual field using field-level measurements (Yang *et al* 2020). There are many data-model fusion methods that can be used to integrate data and model for model constrains at each individual field, including calibration (e.g. Bayesian inference) and/or data assimilation. Detailed applications of these methods are referred to Houska *et al* (2014) and Liu and Gupta (2007). Regarding the computational cost, surrogate models, based on machine learning methods, can be applied to improve the calibration efficiency (Wang *et al* 2014, Zhang *et al* 2017).

Regarding the second challenge of the under-represented or missed critical processes, we envision the following opportunities for model. Improved quantification of plant water stress following the supply-demand concept and hydraulic functions (referred to section 3.2.2) should be incorporated into the process-based models to replace the original soil moisture-based water stress functions. The interactions between surface water and groundwater should also be incorporated into the process-based models at regions where the groundwater level is shallow and consequently active interactions happen. It can not only improve the simulation of subsurface hydrological conditions for precision irrigation with possible subsurface measurements from low-cost subsurface sensors, but also can contribute to the sustainable irrigation with the conjunctive use of surface water and groundwater (Wu *et al* 2016).

3.3.2.2. Statistical/machine learning models

The nature of 'black boxes' can be potentially resolved by the emerging physics-guided statistical/machine learning models. Physics-guided statistical/machine learning models mainly incorporate some physical laws, such as water and energy balance, into original 'black boxes' to improve the traceability and prediction performance (de Bézenac *et al* 2019, Reichstein *et al* 2019, Yang *et al* 2019) (figure 3). For the limitation of data scarcity for model training, the growth of rich data from *in-situ* sensors and remote sensing (e.g. satellites, airborne sensors, and UAVs) can effectively enhance the training of statistical/machine learning models (see section 3.1.2). Besides, integrating process-based models with statistical/machine learning models will also help alleviate the limitation of data scarcity (Shen 2018, Shen *et al* 2018).

3.4. Producers' participation and motivation

Now following the discussion of data, mechanisms, and modeling in precision irrigation, we focus on the producers' participation and motivation that is needed to promote precision irrigation decision-support systems. According to USDA in 2017, producers' adoption rate of precision irrigation decision-support systems was less than 25%, and their adoption decision is largely depended on whether the expected benefits outweighed the adoption costs (USDA 2017, US GAO 2019).

3.4.1. Challenges

Producers have low confidence in precision irrigation decision-support systems, and also have concerns in data privacy (Cox 1996). It is generally recognized that there are three challenges to the producers' participation and motivation (figure 2).

3.4.1.1. Impractical and unreliable tools

Many of the existing precision irrigation tools lack the proper user interface and are difficult to use, leading to poor user experience (Mir and Quadri 2009). Furthermore, the accuracy underlying these tools are in general low, and thus producers are reluctant to use them (Cox 1996, Mir and Quadri 2009, US GAO 2019). Besides, most current precision irrigation decision-support systems assume that producers follow the recommended irrigation decisions strictly for each recommended irrigation event, and give producers no flexibility on the recommended irrigation timing (US GAO 2019).

3.4.1.2. Limited access to information

Producers in general have limited access to information on the development of new precision irrigation decision-support systems. The tools developed by land-grant university extensions are mainly applied in experimental fields for research, rather than for practical applications; while those from industries are promoted to large-scale producers, rather than those with medium to small-sized farms. Besides, there is limited expertise to help producers to set up and maintain the precision irrigation decision-support systems (Mir and Quadri 2009, US GAO 2019).

3.4.1.3. Limited market-based incentives for water conservation

There is limited reliance on economic instruments, such as water pricing, water trading, and caps on water use, for managing water scarcity (Moore 1991, Olmstead and Stavins 2009). Additionally, sustained investments have not been made in governance and adequate institutional capacity to manage conflicts and adapt to changing conditions. The establishment of water markets could encourage water conservation, increase the value of water and induce public and private investments in irrigation efficiency (Rosegrant *et al* 1995, Johansson *et al* 2002).

3.4.2. Opportunities

Regarding the low confidence from producers on precision irrigation decision-support systems, three types of measures could be used to increase the producers' adoption rate (figure 2).

3.4.2.1. Easy-to-use tools with flexibility

Accuracy and easy-to-use are the basic features affecting the adoption rate of precision irrigation tools (Keil *et al* 1995, Mir and Quadri 2009). Use of these tools can be validated using some historical extreme weather events (such as drought), and the performance can be shown to producers (figure 3). Besides, tools should be provided with easy-to-use interfaces. Additionally, dynamic decision-making in precision irrigation tools can provide some flexibility for producers. For example, multiple solutions of irrigation timing (the gray region in figure 3) can be recommended together, and producers can select the favored one or decide not to irrigate. If producers decide not to irrigate, the new and updated irrigation scheduling should be provided rapidly based on updated soil and plant conditions. The frequent interactions between producers and these tools can give producers more flexibility and improve the accuracy of irrigation scheduling.

3.4.2.2. Farm policies for promotion

The government can develop farm policies to promote precision irrigation decision-support systems. For example, the government can provide more education and training about these systems and their impact on water sustainability through extension and partnerships with private companies. Incentives can also be provided to the tool developers to encourage them to deliver technologies and/or perform as consultants to provide the support for the tool users (producers). Subsidies can also be provided for early adopters, i.e. higher risk tolerance, to encourage producers to adopt precision irrigation decision-support systems.

3.4.2.3. Market-based water institutions

Additionally, market-based water institutions, such as water markets with caps on water withdrawals and the ability to trade water across users, will provide incentives for adopting technologies that increase resource use efficiency (Garrick *et al* 2020). Subsidies to reduce the upfront costs of precision technologies can also promote adoption, particularly if producers have high discount rates. Enhanced resource use efficiency can however create financial incentives to increase economic return; thus, market-based solutions in favor of precision irrigation systems should be promised as a joint effort of governments, industry, and producers.

3.4.2.4. Extension to the existing center pivots

Except for the above three types of measures, producers can also add telemetry to allow remote control or automatic control of the center pivots (figure 3). Producers can receive alerts by e-mail and/or text messages about decision-making information and any potential problems online. With the above suggested opportunities, precision irrigation decision-support systems can be promoted to producers with the existing standard center pivots.

4. Concluding remarks

This systematic review focuses on precision irrigation research, identifies critical challenges and opportunities in four areas, which can be treated as the research directions of precision irrigation decision-support systems in the future, thus bridging the gap between research and practice. With more efforts in these research directions, our envisioned precision irrigation decision-support system (figure 3) can be applied universally and cost-effectively using the recent advanced technologies at each individual field in large regions.

(a) **Data availability and scalability.** High spatial-temporal-resolution satellite fusion products and low-cost sensor networks are emerging and should be used to scale up the adoption of precision irrigation decision-support systems.
(b) **Quantification of plant water stress.** Mechanistic quantification of 'plant water stress' is suggested as triggers to improve irrigation decision, by explicitly considering the interaction between soil water supply, atmospheric water demand, and plant physiological regulation.
(c) **Model uncertainties and constraints**. The process-based and statistical/machine learning models should be constrained at each individual

field using field-scale measurements and data-model fusion methods to investigate plant water relations for scalable precision irrigation.

(d) **Producers' participation and motivation**: Easy-to-use tools should be developed with flexibility, and governments' financial incentives and support should also be increased to improve adoption rates of new irrigation technologies.

Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

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