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Precision irrigation trends and perspectives: a review

Alice da Silva Gundim[1,2*] **Verônica Gaspar Martins Leite de Melo**[1] **Rubens Duarte Coelho**[1] **Janderson Pedro da Silva**[1] **Marcos Paulo Alves da Rocha**[1] **Ana Carolina Ferreira França**[1] **Ana Michele Pereira da Conceição**[1]

[1]Programa de Pós-graduação em Engenharia de Sistemas Agrícolas (PPGESA), Escola Superior de Agricultura "Luiz de Queiroz" (ESALQ), Universidade de São Paulo (USP), Piracicaba, SP, Brasil.
[2]Departamento de Engenharia de Biossistemas, Escola Superior de Agricultura "Luiz de Queiroz" (ESALQ), Universidade de São Paulo (USP), 13418-900, Piracicaba, SP, Brasil. E-mail: alice.gundim@usp.br. *Corresponding author.

ABSTRACT: In recent decades, research on precision irrigation driven by climate change has developed a multitude of strategies, methods and technologies to reduce water consumption in irrigation projects and to adapt to the increasing occurrence of water scarcity, agricultural droughts and competition between agricultural and industrial sectors for the use of water. In this context, the adoption of water-saving and application practices implies a multidisciplinary approach to accurately quantify the water needs of crops under different water availability and management practices. Thus, this review article presented a review of technologies and new trends in the context of precision irrigation, future perspectives and critically analyze notions and means to maintain high levels of land and water productivity, which minimize irrational water consumption at the field level.
Key words: precision agriculture, water management, water saving, irrigation technologies.

Tendências e perspectivas da irrigação de precisão: uma revisão

RESUMO: Nas últimas décadas pesquisas voltadas à irrigação de precisão, impulsionadas pelas mudanças climáticas, desenvolveram uma infinidade de estratégias, métodos e tecnologias para reduzir o consumo de água em projetos de irrigação, para adaptação à crescente ocorrência de escassez de água, secas agrícolas e competição entre os setores agrícolas e industriais pelo uso da água. Nesta conjuntura, a adoção de práticas de economia e aplicação de água, implica em uma abordagem multidisciplinar para a quantificação precisa das necessidades de água das culturas, sob diversas práticas de disponibilidade e manejo da água. Dessa forma, este artigo de revisão tem como objetivo apresentar uma revisão sobre as tecnologias e novas tendências no contexto da irrigação de precisão, as perspectivas futuras e analisar criticamente noções e meios para manter altos índices de produtividade da terra e da água, que minimizem o consumo de água irracional a nível de campo.
Palavras-chave: agricultura de precisão, gestão da água, economia de água, tecnologias na irrigação.

INTRODUCTION

Precision agriculture currently plays a significant role in the spatial and temporal management of the inputs involved in agricultural production. This science focused on the optimization of water resources in irrigated areas is called precision irrigation (PI), whose objective is to develop appropriate technologies to increase water productivity in irrigated agriculture through the application of water in precise and accurate amounts at the right time, according to the spatial and temporal variability of the irrigated areas (ABIOYE et al., 2020; BWAMBALE et al., 2023; ABAGALE & ANORNU, 2023; CAPRARO et al., 2018).

In addition, considering irrigation management, this is elaborated, according to soil, plant and climate information, which generate a large volume of data to be transformed into prescription maps of irrigation depths, based on the variability of soil attributes, landscape features and growing conditions (STONE et al., 2015).

In view of this, precision irrigation has tools capable of identifying contrasting spatial differences in an agricultural production area and establishing personalized management in a rational way in the field (CASANOVA et al., 2014; CORWIN, 2013; PAN et al., 2013).

The technologies being used, including in an integrated way, are as follows: automatic

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weather stations, remote sensing, global positioning system (GPS), geographic information systems (GIS) (BARKER et al., 2018; GIOTTO et al., 2016; MENDES et al., 2019; MILLER et al., 2017; NEUPANE & GUO, 2019), multispectral cameras, unmanned aerial vehicles (UAVs) (GAGO et al., 2015; MATESE & DI GENNARO, 2018), network of wireless sensors (WSN) (IBRAHIM et al., 2015), software (GOLDSTEIN et al., 2017; MCCARTHY et al., 2014), and plant growth and water flow simulation models (LIAKOS et al., 2019; LOZOYA et al., 2016; OLDONI & BASSOI, 2016; PEREA et al., 2017).

Therefore, in this review, we focused on strategies, methods, new technologies and trends that are available to farmers and professionals in the context of precision irrigation with a focus on optimizing water use.

Precision irrigation technologies and trends

Soil moisture sensors in agriculture

Irrigation management via soil moisture sensors has recently undergone several commercial innovations, many of which have been introduced by technology companies and independent research groups around the world (FERRAREZI et al., 2020). Many of these innovations are due to a significant decrease in the prices of monitoring equipment and data storage in digital agriculture. TIGLAO et al. (2020), who used a system of wireless sensors that cost half the price of commercial systems, achieved savings of 81% in water consumption applied in irrigation management.

Although, the accessibility of sensors has increased in recent years, their operation still has the same fundamentals based on physical, chemical and mechanical methods for the determination of information of interest, which can be obtained electrically, electromagnetically, optically, radiometrically, mechanically, acoustically, pneumatically or electrochemically, with the methods of electrical resistance (Boyoucus), tensiometry, neutron moderation and time domain reflectometry (TDR) being the most used to estimate the amount of water available in the soil (ZINKERNAGEL et al., 2020).

The most common and simple sensors that use indirect (non-destructive) methods to measure soil moisture are resistive sensors that work by monitoring the variation in electrical resistance between two electrodes embedded in the soil. Advantages of their use include low acquisition cost, simple sensor operation and easy availability in the market; as a disadvantage, they do not have high accuracy in soil moisture readings. Models such as FC-28 and SEN0114 are found on the market. The other sensors are capacitive, such as the SHT10 and EC-5 models; they work by measuring the dielectric constant of the soil by the time elapsed after emitting an electromagnetic pulse generated by metal rods embedded in the soil. These sensors have the advantage of high accuracy in readings; however, due to the construction of their sophisticated and expensive electronic components, their acquisition costs can be high (GASCH et al., 2017; GOMES et al., 2017; MATOS et al., 2017). Other models found on the market include Decagon 10HS, Meter TEROS-12 (also measures temperature and electrical conductivity), Sentek Drill & Drop (measuring moisture, temperature and salinity every 10 cm) and Watermark 200SS (measures the tension of water held in the soil in kPa).

Due to the wide variety of methods for obtaining data and the very nature of construction of humidity sensors, a series of usage characteristics and recommendations for each field condition can be specified in each specific situation ZINKERNAGEL et al. (2020).

One of the biggest advantages of using soil moisture sensors is linked to irrigation management, since monitoring the amount of water in the soil is a direct indication of the irrigation needs of an agricultural area (HAMAMI & NASSEREDDINE, 2020).This applicability can be observed in research carried out by O'SHAUGHNESSY et al. (2020) in the state of Texas, USA, studying the productivity of *Sorgum bicolor* L., in which the productivity of irrigation water was quantified based on three different management methodologies, via plant-based thermal patterns, via soil-based neutron probe measurements, and a hybrid method combining plant and soil monitoring over a period of three consecutive years. The researchers reported that in the periods of joint use of monitoring methods (hybrid method), there was a consistent increase in the accumulation of biomass, resulting in both productivity gains per unit of area and water savings.

EL-NAGGAR et al. (2020), in an experiment in New Zealand with bean and pea crops under two irrigation management methods, via climatological water balance and via capacitive soil moisture sensors (FDR) coupled with radiofrequency data transmission systems (IoT), observed a difference in the volume of water applied and at the beginning of irrigation operations, resulting in savings between 27–44% of the volume of water used in areas managed with soil moisture sensors. This result was attributed to the imprecision of the balance methodology of water in predicting the effects of poor soil drainage, especially resulting from the presence of a physical impediment in the soil profile, which underestimates the real volume of water available to the plants.

In addition to monitoring, the use of sensors also encompasses the use of automation in irrigation systems, as can be seen in a study carried out by CONESA et al. (2021), where the use of an automatic irrigation system based on capacitance sensors (FDR) showed better results in the efficiency of water use, resulting in a decrease in the irrigation depth compared to methods based on monitoring the evapotranspiration of the water reference (ET_o) and in the use of crop coefficients (Kc) in the literature. JAISWAL & BALLAL (2020) used an automatic system based on soil and climate sensors operating with fuzzy logic to control the flow of the irrigation system, achieving a smaller volume of water between 45% and 30%, respectively, as well as lower irrigation costs, when compared to the flood irrigation system.

According to DOMÍNGUEZ-NIÑO et al. (2020), the use of sensors in agriculture also allows a better understanding of the real situation of humidity in different areas with plants in different stages of growth, since monitoring via sensors takes place directly at the place of interest and not in a generalized way, such as in climate monitoring, which often considers irrigation sites based on a single stage of plant growth.

The automation of irrigation systems based on soil sensors associated with the use of IoT technologies can be observed in the research of BARKUNAN et al. (2019) in which the soil moisture and climate monitoring sensors were connected through a microcontroller capable of sending messages to the operator's smartphone, providing information on the soil moisture conditions and the beginning of the irrigation period. This is possible through the use of *wireless communication devices* that allow data transfer between applications without cables.

The use of a wireless sensor network is very important in precision irrigation because, according to irrigation management, extension of the area to be irrigated and producer preferences, it is necessary to use spatially distributed sensor mesh to attend to data collection remotely from several irrigated sectors, for example. Cabe points out that the choice of type of *wireless device* must consider the range of the device. For example, a *Bluetooth device,* model HC-06, with an SPP usage profile (*Serial Port Profile*), has a maximum distance of 10 m between connected devices, with a point-to-point connection. Another model, the *XBee* XB24-Z7WIT-004, of *ZigBee specification*, uses radiofrequency signals for communication and low operating power, with a range limit of about 100 m, which allows point-to-point and multipoint connections, making it possible to form a *mesh network of wireless* devices.

Challenges in the application of sensors for soil moisture monitoring

One of the challenges for using FDR or TDR sensors in soil water monitoring is the relationship between factory calibration and sensor installation orientation in the soil profile (vertical or horizontal), which can cause systematic variations in the humidity readings.

This effect was observed by CHEN et al. (2019a),who when comparing a capacity sensor and three TDR sensors in three positions on the ground, observed a significant variation in the readings of water content in the soil under irrigation, concluding that, in general, for sensors with factory calibration, the vertical orientation presents greater precision when compared to horizontal orientation, attributing this phenomenon to the greater disruption in the soil that the installation in the horizontal position of the sensor causes at the time of installation of the sensor. They suggested that irrigators should follow the positioning that manufacturers recommend for their equipment.

However, SHARMA et al. (2017) pointed out that, not infrequently, the calibration of sensors provided by manufacturers can overestimate the volume of water in the soil and that, although they may be suitable for soils of similar texture, they often do not consider factors such as type, amount of organic matter and apparent density of the soil, which influence the dielectric properties, making a local calibration necessary for better accuracy in the readings.

For the positioning of sensors in soil layers of different textures, KARGAS & SOULIS (2019) observed interesting results, concluding that for the correct management of irrigation in productive areas, it is necessary to use a different sensor for each soil layer or a single sensor installed in the middle portion of the root system that is in contact with both layers simultaneously.

SILVA et al. (2018), in a study on banana, observed that the ideal positioning of the sensors may not be constant throughout the development of the plant; that is, the most representative position for the sensor to read the soil moisture may vary along with the phenological stage of the plant.

Other factors such as salinity, soil textural class and temperature where the sensor is installed can also affect the accuracy of soil moisture monitoring, which may limit the use of these sensors in areas with higher temperatures, such as semi-arid and arid regions, or the use of reused water in irrigation (CARDENAS-LAILHACAR & DUKES, 2015; INCROCCI et al., 2019; OATES et al., 2017).

Naturally, the use of soil moisture sensors in agriculture results in a large amount of data for analysis. It is possible to observe a growing trend in researches that use data science techniques to interpret the readings of these sensors based on artificial intelligence techniques.

Researches such as the one by GOLDSTEIN et al. (2017) trained several machine learning algorithms in the interpretation of a series of climatic and soil data to propose assertive recommendations for the management of irrigation in the field based on data storage in cloud computing.

Using more robust computational techniques, such as "neural networks" it is possible to employ a network of sensors for the precise determination of soil moisture, resulting not only in more homogeneous irrigation in the areas but also in water and electrical energy savings through the best use of the pumping system (DURSUN & ÖZDEN, 2016).

The use of mobile sensor systems, together with graphical software, to better understand the determination and monitoring of soil moisture distribution; although, in smaller quantities, also expands the options for new research areas and future applications at the field level (SHAN et al., 2019).

Finally, the development of the following new types of sensors demonstrate industrial innovations to be used in future research: *mm-sized soil moisture sensors* (ZHOU et al., 2019), which have the ability to perform better monitoring of water distribution in the soil profile; *perforated coaxial cylinder* (CHEN et al., 2019c), capable of monitoring both soil water volume and temperature; *thick film conductivity sensors* (SOPHOCLEOUS et al., 2020), capable of monitoring changes in soil structure through changes in conductivity and soil water content; and a *Fiber Bragg Grating sensor* (ZHANG et al., 2019), developed for monitoring water pressure in the field.

Use of satellites and spectral sensors for precision irrigation

Advances in spectroscopy have allowed the execution of specific analyses of different types of materials in a non-destructive and fast way, revealing valuable information through the energy reflection of the targets (LILLESAND & KIEFER, 1994).

Spectral sensor technology has been used to efficiently generate information on a large time–space scale. Data collected in the field with point equipment can be, in some cases, more accurate, while cost, speed and practicality are advantages of spectral sensors coupled to satellites or UAVs to capture information spatially distributed over large areas. The remote data analyzed allow considerations about photosynthesis, physiological disturbances, phenology and water interactions in real time, which are fundamental for water planning and management (KARTHIKEYAN et al., 2020).

Satellites and sensors

There are currently several satellites in operation that perform this type of work remotely: MODIS, Landsat 7, Landsat 8 and Sentinel 2A. The great acceptance of this technology is because they are free products, with good spatiotemporal resolution and radiometric quality and with ease of data integration with APIs.

The data generated by satellites can be useful in several applications at the irrigation level. VANINO et al. (2018) combined meteorological data with data captured by the sensors of the Sentinel 2A satellite to estimate the leaf area index and surface albedo to use this information to calculate the evapotranspiration of tomato crops and validate it through comparison with evapotranspiration data obtained by the soil–water balance. The results of this research showed the satisfactory suitability of the Sentinel 2A satellite to determine water demand. SHADMAN et al. (2017) used thermal band data from the Landsat 8 satellite to estimate water stress in sugarcane plants through the crop water stress index (CWSI). According to the author, the data capacity of the satellite sensors was positive and sufficient to carry out monitoring via remote sensing of the water stress of sugarcane without the need for auxiliary soil data.

MARINO et al. (2014) evaluated spectral differences in tomato leaves located in 3 irrigated regions, classifying them as high (H), medium (M) and low (L) in terms of water use and efficiency; NETO et al. (2017) evaluated the spectral reflectance in the visible (VIS) and near-infrared region (NIR) of sunflower leaves in water deficit to obtain models capable of estimating the status of water and chlorophyll. CHEMURA et al. (2017) used information from VIS and NIR to create a machine learning model using the random forest algorithm to predict the water content in the plant in the coffee crop. All studies were conclusive and showed variations in spectral identity in relation to variations in water content in plants.

In precision irrigation, indices generated from orbital satellites have been mainly used to:

(a) monitor irrigation systems in macro-regions; (b) adapt local crop coefficients for a better calculation of plant evapotranspiration; and (c) estimate vegetative metrics such as plant density, coverage fraction (fc) and leaf area index (FRENCH et al., 2020).

According to CHEN et al. (2018), many studies focus only on mapping the extent of irrigated areas without considering important information that could also be extracted with the use of remote sensing, such as the amount of water with drawn from the system and the frequency and time of irrigation.

Different levels of decision can be used in irrigated macro-regions using satellite systems, since it is possible to track the temporal growth of crops, deriving this information in basal coefficients that allow a better estimate of regional evapotranspiration. Thus, GONZÁLEZ-DUGO et al. (2013) developed a methodology called MINARET (*monitoring irrigated agriculture* ET), which uses Landsat data capable of constantly monitoring the water consumption of different irrigated crops. MASELLI et al. (2020) used meteorological data together with Sentinel 2A data to estimate evapotranspiration in monitoring irrigated areas in the Italian semi-arid region.

Obtaining evapotranspiration values with greater precision is a fundamental factor, as it is a key parameter in the water and energy balance equation. FAO bulletin 56 states that crop evapotranspiration (ETc) can be calculated by multiplying the reference evapotranspiration (ETo) and a specific crop coefficient (Kc) (ALLEN et al., 1998).

Although, the coefficients provided by the FAO are general, throughout the growing season, there are variations in crop characteristics, so the parameter is intrinsically linked to species, variety, plant population density, phenology, water availability, climate and other factors. Therefore, a standard Kc may not well represent some localities, causing less reliable estimates and directly impacting good water use (MOKHTARIA et al., 2018). In recent years, several works have contributed to more accurate irrigation, developing methods to estimate Kc or Kcb (basal crop coefficient) and considering vegetation indices, which are considered great phenological thermometers, called Kc-VI (ALAM et al., 2018; CAMPOS et al., 2017). Still, more recently, PEREIRA et al. (2021) published a newsletter (Updates and forward to the FAO56 crop water requirements method - Case studies using ground and remote sensing data; applications to update and upgrade the FAO56 method) with updates of these coefficients through a collection of several studies, with the use of new tools, such as remote sensing and IoT, which bring more precision to the calculation of the water needs of crops, which are important advances for precision irrigation.

FRENCH et al. (2020), using data from Landsat and Sentinel mission satellites, determined a Kc-VI used to calculate wheat evapotranspiration. The experiment was carried out in the American southwest, and it was concluded that the best values of Kc and ETc were obtained in the middle of the season until the end of senescence, while at a time point sooner than 60 days after planting, a high and overestimated ETc was observed due to the low coverage canopy at the time, which contributed to the low reflectivity of the plants.

Electromagnetic approach applied to the determination of the spatial variability of the water status of plants in the field based on UAVs

Four components must be considered before selecting the appropriate UAV for IP (GAGO et al., 2015): experimental design, type of data to be obtained, data acquisition, and data processing and results. In addition to UAVs, sensors are essential for the quality of the images obtained. Decision-making regarding the type of camera to be used depends directly on the project objective. The cameras embedded in UAVs most used in the IP concept aiming intelligent management of water are thermal, multispectral, hyperspectral, RGB and near infrared (NIR) cameras.

To monitor biotic and abiotic stress, thermal (1 band) and hyperspectral (100–250 bands) cameras are recommended, while multispectral (6–12 bands) and RGB cameras (3 bands) are indicated for growth and biomass assessment (ADÃO et al., 2017). High-resolution RGB cameras are traditionally used in agroforestry applications; however, they lack the precision and spectral range to trace the material characteristics that hyperspectral and multispectral cameras can provide.

SUSIČ et al. (2018) demonstrated the potential of using hyperspectral images ranging from 400 to 2500 nm to assess the water deficit status in tomato plants. ZARCO-TEJADA et al. (2012) used UAV-based hyperspectral and thermal cameras to assess water stress levels in citrus crops and confirmed a link between PRI and canopy temperature. Recently, LOGGENBERG et al. (2018) used hyperspectral technology combined with machine learning to discriminate between water-stressed and non-stressed vines.

Hyperspectral imaging cameras generally capture more detail in spatial and spectral ranges compared to other cameras. LOGGENBERG et al.

(2018) observed that the main limiting factor in the application of hyperspectral data is the inherent issue of dimensionality, which results in reduced precision. In addition, hyperspectral cameras are very expensive and complex (ELVANIDI et al., 2018), which limits their expeditious and wide application, especially in commercial agriculture.

Multispectral cameras are composed of multiple sensors with high-quality filters that can simultaneously capture images using different wave frequencies. They can record both the light spectrum that is visible to the human eye and the non-visible spectrum; thus, these cameras allow for much more accurate measurements of plant health and phenological status than conventional cameras (RGB) (KHANAL et al., 2017).

Multispectral and hyperspectral cameras do not have a resolution comparable to traditional RGB cameras, which causes some initial frustration for users new to the spectral area accustomed to traditional high-resolution images. The resolution of RGB cameras is in the range of 20–120 MB, while multispectral and hyperspectral cameras have a resolution between 0.2–3 MB.

According to POBLETE et al. (2017), plant water status is not accurately predicted using multispectral imaging between the 500 and 800 nm spectral bands due to the lack of sensitivity to water content; however, wavelengths greater than 800 nm are best for this purpose.

RALLO et al. (2014) observed that satisfactory estimation of leaf water potential at leaf and canopy levels can be obtained using vegetation indices based on the NIR shortwave infrared domain, with specific optimization of the “central bands.”

Recently, some researchers have developed artificial neural network (ANN) models derived from multispectral images to predict the spatial variability of water potential in agricultural crops. ROMERO et al. (2018) classified the water status of the vine based on 10 vegetation indices (VI) using bands of Red, Green, Red-Edge, and NIR wavelengths and found that there were no significant relationships between individual VIs, with values of correlation lower than 0.3 for almost all the studied indices.

There is a very specific spectral band called RedEdge, which lies between red and infrared, has excellent correlation with chlorophyll fluorescence and effectively differentiates between healthy and senescent vegetation (MATESE & DI GENNARO, 2018). There is already a range of specific multispectral cameras for use embedded in UAVs (MATESE & DI GENNARO, 2018). Among them, Tetracam, Airinov and Micasense camera manufacturers can be highlighted.

Tetracam’s modular cameras can be mounted in different arrangements, depending on which bands you want to capture and which bandwidths. Airinov’sagro Sensor has 4 bands and has been used by the famous eBee AG, the version of the fixed-wing UAV for agricultural applications in Switzerland Sensefly (MATESE & DI GENNARO, 2018). The American Micasense manufactures the RedEdge sensor, a multispectral camera that simultaneously captures 5 different narrow-width bands and a more recent dual camera that captures 10 spectral bands. In addition to the RGB bands of the visible spectrum, the camera also captures the NIR in the non-visible spectrum and the RedEdge, a spectral band that is positioned exactly on the threshold between the visible and the non-visible. In addition to increasing the sensitivity of certain indices, it is with this spectral band that certain diseases and crop pests can be identified (DEVIA et al., 2019).

DEVIA et al. (2019) studied biomass production in rice crops using multispectral imaging. The authors presented a method for biomass estimation using near-infrared (NIR) images captured at different crop scales. The approach estimated the biomass of large areas of the crop with an average correlation of 0.76 in relation to the traditional manual destructive method.

KITIĆ et al. (2019) proposed a low-cost portable active multispectral optical device for accurate detection of plant stress and to perform field mapping called Plant-O-Meter. The device has an integrated multispectral source that comprises light in four more indicative wavelengths (850, 630, 535 and 465 nm) and allows the simultaneous illumination of the entire plant. Sequential illumination and detection provide fast reflectance measurements, which are transmitted by wireless to Android-powered devices for data processing and storage. The device was tested under laboratory conditions by comparing Plant-O-Meter measurements with imaging results from a SPECIM hyperspectral camera and a GreenSeeker handheld device under field conditions. The comparison revealed comparable performance, showing a strong correlation in both the hyperspectral (R2 = 0.997) and portable GreenSeeker (R2 = 0.954) from the laboratory measurements and R2 = 0.886 for the field experiments), indicating that the device exhibited strong potential for accurate stress measurements.

The scientific articles reviewed in this research, referring to the use of different spectral technologies in agriculture, indicate the types of multispectral and thermal cameras used by the scientific community for the rapid detection of water stress in culture.

Artificial intelligence in precision agriculture

Due to climatic uncertainties, the growing demand for food and the rapid expansion of the population, the agricultural sector is increasingly dependent on the use of new technologies to obtain higher yields in a sustainable way with each harvest. In this context, artificial intelligence (AI) is increasingly developing applications in agriculture aiming productivity gains in a precise and effective way, avoiding the waste of resources (SHAIKH et al., 2022).

In recent decades, researchers have strived to allow computers to extract enough information from raw data to model the real world. To achieve this, many have turned to machine learning algorithms to capture a large amount of information and automatically discover the representations needed to detect or classify input patterns and solve the various problems and needs of the agricultural sector (KHALIL & ABDULLAEV, 2021). Machine learning algorithms are computation models with particular properties such as learning, generalizing, grouping or organizing data. They consist of distributed structures formed by a large number of very simplified processing units connected to each other. Intelligent behavior occurs through the interactions of the neural network processing units (CANZIANI et al., 2016). The first neural networks to achieve widespread repercussions were based on unsupervised pre-training. However, it was the rediscovery of convolutional neural networks (CNN) (LECUN et al., 1998) that made this topic one of the main topics in machine learning, parallel processing technologies in GPUs (Graphal Processor Unit) and large databases that allowed these networks to be used fully. With the good performance being demonstrated by such models, other areas of knowledge besides the area of computing have been using these models for different purposes, as in the area of agricultural sciences since the 1990s with the pioneering work of MCQUEEN et al. (1995), in which the authors investigated the use of machine learning techniques existing at the time for some problems in agriculture and horticulture and presented a case study to infer management rules for some invasive plants. Recent research has used PCN-type networks (pulse-coupled networks) for the separation of wheat grains and to evaluate the physical characteristics of the soil and the growth of the cultures, concluding after field experiments that the developed model assisted in choosing the crop that best suited the evaluated soil (SHAIKH et al., 2022).

Works that involve not only agronomic data but also other technologies, such as satellite images, have been developed, such as the classification of management areas using satellite images (KHALIL & ABDULLAEV, 2021). In the context of the use of neural networks for agriculture and with the advent of cheaper computing resources combined with the new sensors that are being developed, proposals that increasingly use cutting-edge technological resources are noted (SOBAYO et al., 2018).

As a tool to aid strategic decision making, smart agriculture has emerged as a new scientific area that employs, among other technologies, machine learning algorithms to assess and monitor the conditions of growing areas, such as soil and weather conditions, leading to more accurate results (LIAKOS et al., 2018).

BACHOUR et al. (2015) used a methodology that combines wavelet mult-iresolution analysis with the MVRVM algorithm (multivariate relevance vector machine) to predict 16 days of ETo. More recently, deep learning (DL) is a machine learning technique that has shown good results in solving agricultural problems. KAMILARIS & PRENAFETA-BOLDÚ (2018) presented a review of 40 relevant studies in the area and found that, in addition to improvements in the performance of classification/prediction problems, DL also reduced resource engineering in many of the works.

For crop management, for example, yield predictions can be made from satellite images, as presented by KHALIL & ABDULLAEV (2021). In this research, the authors concluded that it is possible to predict wheat yield from image processing with supervised Kohonen networks. Another beneficial activity is pest and disease control, where the spraying of pesticides is now directed only to the affected plants, reducing financial and environmental costs (JIAO et al., 2022).

In water and soil management, important practices have been developed not only to increase crop productivity but also to use these resources efficiently. PATIL & DEKA (2016) used the extreme learning algorithm to estimate the weekly evapotranspiration of a crop in India. In soil management, GU et al. (2021) presented a new method for estimating soil moisture based on ANN models. ANN shave also been the subject of scientific investigations in the field of irrigation engineering to estimate the localized pressure drop caused by connectors and special parts present in irrigation systems. According to ELNESR & ALAZBA (2017), the use of neural networks presents a powerful tool for estimating the load loss caused by initial connectors when compared to the use of empirical models. KADHEM et al. (2017) used a neural network to predict wind speed data with chronological and seasonal characteristics. The authors concluded that the neural network was able to portray variations in wind speed with good performance during the different seasons of the year. LIU et al. (2018) developed a wind speed prediction model based on WPD (wavelet packet decomposition), CNN (convolutional neural network) and CNNLSTM (convolutional long short-term memory network). To verify the prediction performance of the proposed model, it was compared with 8 neural models widely used by the scientific community. The authors concluded that the proposed model is robust and effective in predicting wind speed time series.

Definition of management zones in precision irrigation

One way to manage physical, chemical and/or biological variations within a growing area is through the delineation of management zones (ZM). Management zones are sub-areas within a cultivation area that have similar characteristics but differ to a certain degree from the others in such a way that a particular agronomic management is justified to be adopted in each of them (KITCHEN et al., 2005).

For management zones to be determined, it is necessary to obtain data from the area of interest, which can be of various types, such as crop productivity, soil physical and chemical properties, topography, vegetation indices, and aerial images. From these individual or combined data, thematic maps are created, and this spatial information is then interpreted. In this context, BAZZI et al. (2018) used soil property data to define management zones, such as soil texture and apparent electrical conductivity. YAO et al. (2014) used soil physicochemical properties and crop yield data and determined management zones.

Generally, irrigation is carried out uniformly in a cultivated area, regardless of the spatial characteristics of that area. In the field, the water content in the soil is not homogeneous due to its spatial variability, which ranges from crop development, difference in relief and variation of soil hydraulic properties and rainfall distribution. Thus, the proper use of irrigation in each management zone reduces the volume of water used in the irrigation system, as there is an increase in efficiency that provides growth in productivity, reducing nutrient leaching and water waste. Management zones are used to optimize irrigated areas, where a heterogeneous area is separated into homogeneous zones and irrigation management will be the same in these regions (LIANG et al., 2016; PEREA et al., 2017).

For XIANG et al. (2007), cluster analyses and empirical analyses are the categories in which most of the methods used to define management zones are inserted. Since the empirical methods are simpler, based on specialized knowledge and on the distribution of productivity in the production areas, in this way, it is possible to divide a heterogeneous area into homogeneous sub-areas. However, cluster analysis is a more complex, less subjective method that uses multiple variables during the establishment of management zones. In cluster analysis methods, data points in a cropping area are divided into different classes, where the similarities between the points are evaluated to define the classes, and with that, the management zones are defined (GAVIOLI et al., 2019; LI et al., 2007).

To define management zones, several factors and data are often used; in this case, a multivariate analysis was used to define the zones. OLDONI et al. (2019) also used geostatistical and multivariate analyses to determine management zones in a peach orchard, with a clustering approach on both soil (soil texture, water content, organic matter content) and plant (amount of fruit per tree, average fruit weight, total soluble solute content) for differentiated management.

Another form of multivariate geospatial analysis is kriging factor analysis, a data interpolation method that identifies variability and was used in the study by BEVINGTON et al. (2019), where soil properties and hydraulic parameters were measured to define management zones using kriging factor analysis and the fuzzy-c means algorithm. CHEN et al. (2019b) used an RGB camera attached to a UAV to determine the plant cover and vigor of the peanut and cotton canopy through the green–red vegetation index to determine management zones in Italy, used as indicators of irrigation uniformity, which they also served as an indication for the application of variable rate irrigation (VRI) in a pivot system. In the research by SCHENATTO et al. (2017), management zones were also created using the fuzzy-c means algorithm, focusing on soil characteristics, such as elevation, slope, density, organic matter, clay and sand contents, and plant attributes, such as yield.

In the study by ANASTASIOU et al. (2019), multivariate geostatistical techniques were also used to unite the multitemporal data from a multiband radiometer and a geophysical sensor and thus delimit the management zones of a vineyard, considering the electrical conductivity of the soil and canopy area. OHANA-LEVI et al. (2019) used a weighted multivariate spatial clustering model to determine irrigation management zones in a vineyard. Management zones were determined using a multivariate k-means cluster, and machine learning and spatial statistics were also used to analyze the variables, which comprised soil properties, terrain characteristics and environmental impact.

Another tool used to collect data and define management zones is the proximal sensing of the soil, based on electromagnetic induction techniques, radiometry and fluorimetry (CASTANEDO, 2013). In the research by CASTRIGNANÒ et al. (2017), proximal and remote sensors were used in a tomato growing area, and there was integration with multivariate geostatistical data to define management zones based on the electrical conductivity of the soil, which was measured at different frequencies, sensor polarizations and depths. Likewise, MOUAZEN et al. (2014) used a soil sensor to measure electrical conductivity, soil water holding capacity, available water, organic matter, density, clay content and organic carbon, establishing a multi-sensor and data fusion approach to delineating management zones for site-specific irrigation, best addressed in section 1 of this review.

To define management zones, low-cost remote sensing data are viable options (section 2 of this review), where spatiotemporal information on the biological and physical parameters of vegetation are used (FONTANET et al., 2018). FONTANET et al. (2020) used remote sensing to define management zones in a corn planting area, analyzing normalized difference vegetation index (NDVI) time series by remote sensing, soil moisture sensors, and root zone simulation predictions. GOBBO et al. (2019) also used NDVI in defining management zones in corn plantations and combined it with soil texture data to create irrigation management zones.

In the research by GEORGI et al. (2017), remote sensing was used together with an automatic delineation algorithm. An automatic segmentation algorithm was developed using multispectral satellite data, which is a cheaper method for defining management zones.

We emphasized that the creation of management zones for irrigation is not strictly associated with the application of water at a varied rate but rather in specific fields or areas and not exclusively on a lateral line of an irrigation system. The creation of these zones can help in the sizing of localized irrigation systems, enabling the differentiation of water needs by sector, such as ZM, which differs from SS-VRI (site-specific variable rate sprinkler).

Another point to consider is the limitations of the use of remote sensing to create ZM. FONTANET et al. (2020) suggested the integration of spatial and temporal information, since there are soil and/or plant attributes with spatial differences that also change over time; that is, they are not static. For example, the NDVI must be combined with a measurement of available soil water to dynamically delineate both space and time ZM for irrigation.

Irrigation systems with variable water application rates

Irrigated agriculture is one of the agricultural activities with the highest consumption of fresh water in the world. In this sense, precision irrigation is an important tool for the development of profitable and sustainable agriculture (DU et al., 2015; MATEOS & ARAUS, 2016).

Thus, as discussed in the previous section, the creation of irrigation management zones is essential to increase the efficiency of the application and use of water in the field. Within this tool, Site-specific Variable Rate Irrigation (SS-VRI) is a management method that consists of applying water according to spatial variability due to characteristics, such as soil and culture; and therefore, through rational application, it is possible to increase water conservation and productivity, in addition to reducing the leaching rate of nutrients and agrochemicals and optimizing inputs (DU et al., 2015; MATEOS & ARAUS, 2016).

SS-VRI differs from conventional sprinkler systems and requires variable rate sprinklers, which are based mainly on pulse modulation, angle of departure and arrival points, and sprinkler head (SADLER et al., 2005).The main research covers linear and center pivot sprinkler systems due to the level of automation and coverage of the cultivation area through a single side tube (ADEYEMI et al., 2017). However, this type of management has already been studied for other types of irrigation methods, such as drip, considering the challenges of directionality and the invariable rate of lateral lines (LINKER, 2020). Therefore, the main commercial equipment developed thus far is linked to central pivot and linear mechanized sprinkler irrigation.

The greatest success of implementing VRI in center pivot systems, and the focus of this review, is that it allows: first, the control of the travel speed of the center pivot, allowing the variation of water application/infiltration depth by sector, and second, controlling the variation of water application by zone; that is, it allows the differentiation of irrigation rates along the lateral pipeline (ANDRADE et al., 2020; O'SHAUGHNESSY et al., 2019; SUI & YAN, 2017).

SOBENKO et al. (2018) developed a sprinkler with flow adjustment through the cross section based on an iris mechanism controlled by a stepper motor using a deterministic model for flow prediction, but the idealized nozzle discharge coefficient (0.60) was below the average values (0.90–0.92) observed in conventional fixed nozzles.

The management of SS-VRI can be carried out efficiently in several ways, such as monitoring the soil moisture content, a subject discussed in greater depth in sections 1 and 4. For this, the positioning and number of sensors should be chosen with care so that the generated data are representative of the area under cultivation. Through analyses of variance and temporal stability of soil water content monitored by a neutron probe, BARKER et al. (2017) concluded that for management zones divided to minimize variations within the zones, the number of sensors may be more important than their position in the area. In addition, due to the high cost of a number of sensors, a partnership between modeling and monitoring soil water is proposed. In a similar study focusing on the placement of soil sensors, ZHAO et al. (2017) stated that the clay percentile of management zones should be considered for the placement of sensors.

The use of spectral images obtained via satellite or unmanned aerial vehicles (UAVs) has been used in the management of variable-rate irrigation systems. The principle of this use is based on understanding the spectral response of the leaf, which is applied at the canopy level and is used to establish management zones (HANK et al., 2018). MENDES et al. (2019), using images obtained from satellites, carried out the mapping of areas considering the variability for the application of variable-rate irrigation depths via the central pivot system. With the same objective, SHI et al. (2019), with the help of unmanned aerial vehicles (UAVs), obtained multispectral images of the vegetation and used vegetation indices to determine the spatial variability and constitution of homogeneous areas. Similar work was developed by BHATTI et al. (2020), in which the comparison of multispectral images obtained by UAV and satellites was performed to evaluate the response of crops to variable irrigation based on canopy temperature and surface energy balance modeling. More examples of the use of images in precision irrigation are mentioned in sections 2 and 3.

Despite all the benefits, the uptake of SS-VRI systems has grown slowly. The main justifications for this are that this type of management requires qualified technical assistance, and the acquisition of the necessary equipment still has a high cost, requiring a careful analysis of the economic viability of production (ABIOYE et al., 2020). To assist in these matters, simulation models are viable options for assessing the response of crops to different irrigation management methods.

MCCARTHY et al. (2014) used a model called VARIwise based on the predictive control model methodology to evaluate the performance of cotton cultures grown on a center pivot with variable application rate irrigation compared to conventional systems. In most results, simulations of precision irrigation performance had superior results. In a similar research, THORP (2019) carried out a long-term evaluation through simulations using the same crop under soil variability parameters to analyze the advantages of the system. However, modeling applied to precision irrigation can be complex because it deals with the dynamics of water in soil. The following topic discusses in-depth examples of models and applications of modeling in irrigated agriculture.

Modeling agricultural crops and their interaction with the prescription of variable water depths in precision irrigation

Extreme drought events have increased in intensity in recent decades and predictions from agrometeorological modeling indicate that climate extremes of drought will become more frequent and prolonged due to a set of factors, among which global warming stands out (IPCC, 2018).

Agriculture is one of the human activities most dependent on climatic conditions, especially traditional rainfed crops, so the development of studies to evaluate the effects of these on agricultural production is important. However, carrying out field experiments becomes limiting due to a series of factors, such as manpower, available time and financial resources. An alternative or complementary solution is the use of agricultural modeling to forecast the development of agricultural crops in new climate scenarios.

Crop simulation models are based on biophysical processes to make estimates such as growth, development and production, based on physiological characteristics of the crop in question and environmental variables (MONTEITH, 1996). Understanding these models becomes the conceptual basis for modeling agricultural crops.

Mechanistic models, based on the physics and physiological processes of plants, become allies in the development of teaching, research and crop management. Among them, the DSSAT (*Decision Support System for Agrotechnology Transfer*) presents a set of models developed for several important crops, such as corn and soybean (JONES et al., 2003).

In a review of the opportunities and approaches for modeling spatial variations of water at the field level, TENREIRO et al. (2020) pointed out that, among the irrigation methods, there are three ways to simulate irrigation applications in crop models: a) determination of a calendar by the user; b) an irrigation program based on the water capacity of the soil, applying constant or variable rates; and c) through a schedule based on multiple criteria, such as the phenological stage of the crop, water content in the soil, restrictions on the availability of water and type of cultural management. These methodologies have the potential to calculate the varied rate of irrigation to be provided to plants, "when," "where" and "how much" they need, resulting in the optimization of the use of this water resource (HAGHVERDI et al., 2016), thus validating the three ways to simulate field-level irrigation applications in the models.

In the literature, the prescription of variable irrigation depths follows two methodologies: a) make individual use of crop simulation models or hydrological models, which focus on the movement of water in the soil and b) make combined use of these two models.

The DSSAT model, because it is a simulation of cultivation, is advantageous in the study of irrigation management scenarios, as presented by MALIK & DECHMI (2019) in a study carried out in Spain with different cultures. They evaluated two scenarios, one based on irrigation applied by producers and another on irrigation adjusted to the water demand of the crop, with crop and soil data collected for model calibration and validation. The authors reported up to a 27% reduction in the application of irrigation depths. Similar researches are presented by CAMARGO & KEMANIAN (2016), PEREZ-ORTOLA et al. (2015) and XIANGXIANG et al. (2013).

Another well-established model is APSIM, which also focuses on modeling agricultural crops and assesses the impacts of different crop management practices, including irrigation (AMARASINGHA et al., 2015; DUTTA et al., 2020).

PEREA et al. (2017), for example, carried out an integrative modeling coupling a deterministic model of water application with the Aquacrop model, simulating the impacts of heterogeneous irrigation caused by wind drift and pressure variation in the irrigation system. They concluded that variable-rate irrigation was the best method in all scenarios of pressure variation in the system to save water and increase onion yield.

ROY et al. (2019) also proposed the integration of crop and hydrological models using HYDRUS-2D software and DSSAT to identify the most appropriate irrigation management to maximize water use efficiency through precision irrigation using retention technology of subsurface water, together with a computational procedure of evolutionary multi-objective optimization to link the two models. The authors concluded that the optimization procedure reduced water use and increased corn yield prediction by 6-fold compared to non-optimized and randomized irrigation management without subsurface water retention membrane. For the combination of models, another proposal developed by GARCÍA-VILA & FERERES (2012), in which they combined the AquaCrop model with an economic optimization model, identified irrigation strategies and predicted their impact on income. in which the simulated results indicated that the best strategy under water restrictions combined the planting of crops with low water use in part of the area as a way of making more water available for the most profitable crops and with the greatest water need.

In this review, several premises involving precision irrigation were addressed, from the use of soil sensors, remote sensing, artificial intelligence, management zones for irrigation, and variable-rate irrigation to agricultural modeling in view of optimizing the use of water resources. However, there are other techniques and technologies used in RI that help in the efficient use of both water and energy resources, such as the use of wastewater (IBEKWE et al., 2018; SHANNAG et al., 2021; VERGINE et al., 2016), solar panels to reduce energy costs with water pumping and automation in irrigation systems (GRANT et al., 2022; SINGH et al., 2021) and the use of microorganisms (fungi and bacteria) to mitigate damage caused by water deficit (ASHWIN et al., 2022).

CONCLUSION

This review of trends and prospects for precision irrigation for irrigation monitoring and management is based on relevant past and current research work that has contributed to achieving greater water savings in agriculture. It is hoped that this review article has given a broad overview of research trends and generated new ideas for readers on implementation and execution approaches to choosing the best smart irrigation strategy, paying attention to the fact that the combination of monitoring methods via soil, plant and climate is the most assertive strategy to increase the energy efficiency of water use in irrigated fields. However, it results in a large volume of data to be analyzed, making it necessary to use algorithms based on artificial intelligence, which promotes a fast and efficient monitoring system of the collected data, aiming the assertive recommendation of irrigation at a variable rate in the area irrigated to save water and energy so as not to overload the irrigating farmer with the daily decision in determining the irrigation dose.

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The authors declare no conflicts of interest. The founding sponsors had no role in the design of the study; in the writing of the manuscript; or in the decision to publish the results.

AUTHORS' CONTRIBUTIONS

All authors critically reviewed the manuscript and approved the final version.

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