

# We are IntechOpen, the world's leading publisher of Open Access books Built by scientists, for scientists

4,800

Open access books available

122,000

International authors and editors

135M

Downloads

Our authors are among the

154

Countries delivered to

TOP 1%

most cited scientists

12.2%

Contributors from top 500 universities



WEB OF SCIENCE™

Selection of our books indexed in the Book Citation Index  
in Web of Science™ Core Collection (BKCI)

Interested in publishing with us?  
Contact [book.department@intechopen.com](mailto:book.department@intechopen.com)

Numbers displayed above are based on latest data collected.  
For more information visit [www.intechopen.com](http://www.intechopen.com)



# Integrating Remote Sensing Data into Fuzzy Control System for Variable Rate Irrigation Estimates

*Willians Ribeiro Mendes, Fábio Meneghetti U. Araújo  
and Salah Er-Raki*

## Abstract

Variable rate irrigation (VRI) is the capacity to vary the depth of water application in a field spatially. Developing precise management zones is necessary to efficient variable rate irrigation technologies. Intelligent fuzzy inference system based on precision irrigation knowledge, i.e., a system capable of creating prescriptive maps to control the rotation speed of the central pivot. Based on the VRI-prescribed map created by the intelligent system of decision-making, the pivot can increase or decrease its speed, reaching the desired depth of application in a certain irrigation zone. Therefore, this strategy of speed control is more realistic compared to traditional methods. Results indicate that data from the edaphoclimatic variables, when well fitted to the fuzzy logic, can solve uncertainties and non-linearities of an irrigation system and establish a control model for high-precision irrigation. Because remote sensing provides quick measurements and easy access to crop information for large irrigation areas, images will be used as inputs. The developed fuzzy system for pivot control is original and innovative. Furthermore, the artificial intelligent systems can be applied widely in agricultural areas, so the results were favorable to the continuity of studies on precision irrigation and application of the fuzzy logic in precision agriculture.

**Keywords:** fuzzy control, variable rate irrigation, center pivot control, remote sensing, decision support system

## 1. Introduction

Availability of water is one of the basic conditions for life on planet Earth. However, it is a limited resource, currently at risk of extinction. Global population growth, climate change and demand from several economic sectors such as industry and agriculture put into question the availability of drinking water to all living beings on planet. In particular, irrigated farming is one of the sectors that consume more water per day, and can reach 90,000 liters/hectare, while the average consumption per capita in Brazil is 162 liters per day [1].

The United Nations Food and Agriculture Organization (FAO) predicts that global demand for food by the year 2050 will increase by at least 60% above 2006 levels, and in order to meet this demand it would need to double or triple agricultural production. However, most of the food production increase must have come

from yield increases [2]. According to [3], the adoption of irrigated agriculture makes it possible to increase productivity and diversify agricultural crops. However, there is a limitation in water resources and, therefore, the use of water in agriculture needs to be more efficient.

The [4–6] present an overview of precision agriculture. The authors state that the term can be used in everything that refers to activities performed more accurately by means of electronic systems; however, they make a note regarding the applications of inputs uniformly, which would be only conventional systems and not deal with the spatial variability of crops. Automation and instrumentation solutions are required for better application of inputs, and in order to achieve a distinct water management in each sector of a planted area, irrigation systems must perform water application taking into account the spatial variability of the crop and the soil so that the maximum efficiency of the crop can be reached [7].

Authors such as [8–13] discuss some solutions for water application using spatial correction and conclude that the central or linear pivot or irrigator are particularly suited to the precision irrigation condition, especially because of their current levels of automation and large area reached by the pivot. However, the major limitation for the adoption of irrigation that complies with spatial and time variability, usually called variable rate irrigation, is associated with the development of great irrigation management.

The availability of sensors is currently a constraint to the automation of irrigation control, and it is expected that the requirements of advanced process control for irrigation also fosters the development of new sensors. In [14] brings a review of the existing literature on advanced process control in irrigation and its requirements of sensors and adaptability to the field conditions, besides discussing the obstacles in area sensing.

In order to deliver detailed spatial and temporal information regarding soil and crop response to varied management practices and dynamic environmental conditions, and to avoid the time-consuming process for installing and maintaining sensors over each field, the use of remote sensing techniques has been improving in precision agriculture [15, 16]. According to the authors, remote sensing images are already widely used and proved to do a good prediction on required irrigation amount for each type of crops. Remote sensing by satellite has been very promising in on-field monitoring, but still presents problems such as accuracy, cloud coverage, and the high cost to obtain good spatial resolution [17].

The application of process control techniques for variable rate irrigation has recently been reviewed in [18–24]. Artificial intelligence (AI) can be applied in an interdisciplinary way, besides bringing about a paradigm shift of how we understand agriculture today. Solutions in AI technology not only enable farmers to do more with less, but also improve quality and ensure a faster introduction into the market.

AI technologies assist farmers in soil analysis and crop health, among others, besides saving time and allowing them to grow the right crop at each season, thereby maximizing the crop production. In this context, tools with knowledge representation and reasoning about imprecision present as a feasible alternative. In this way, fuzzy logic allows intelligent computational systems to “reason”, considering aspects inherent to uncertainty and realistic processes. Moreover, it is a very interesting methodology to be applied in decision making, because it is possible to model perceptions and preferences similar to the style of a human being.

Decision support systems are tools that can be used in fuzzy set theory [25] to provide a conceptual framework for representing knowledge and reasoning about imprecision and consequent uncertainty. The fuzzy set provides adequate tools for

modeling and dealing with expert rules [26]. By modeling linguistic variables in the form of fuzzy sets, it was possible to transform expert rules into mathematical terms, and in addition, fuzzy set theory offers a wide variety of operators that can aggregate and combine these rules. The application of linguistic variables and fuzzy conjunction methods provide an adequate method to model the human reflection process and, in so doing, make the interface of these systems simpler and more natural as planning tool on the farm by the manager or farmer.

The fuzzy decision support system is considered useful due to its interactive nature, flexibility in approach and evolution of the graphical characteristics, and can be adopted for any similar situation to classify the alternatives. More often, ambiguity in agricultural decision-making is aggravated by inaccuracy and intuition. The ability of fuzzy systems to deal with complex systems can help farmers to make better decisions in agricultural processes [27]. There is a very significant advantage in using fuzzy decision-making systems for the variable rate irrigation process: the advantage of not needing the full amount of relevant information by simply selecting the variables that play the role of the irrigation calculation according to [28].

This chapter is organized as follows, the present section aims to contribute to a refinement of the studies on the application of fuzzy control systems for the exploration of precision irrigation modeling and management. In the next section, we provide a literature review of the latest related research, divided into three subsections, namely: (a) the most important concepts for understanding the main characteristics in a central pivot irrigation system; (b) concepts fundamental to the understanding of fuzzy logic, relevant to the structuring and development of the intelligent irrigation system and (c) remote sensing. In Section 3, we thoroughly describe the basic mathematical framework that involves the three techniques. Finally, a representative case study on the intelligent control of variable rate irrigation systems is presented.

## 2. Precision agriculture

Available bibliographies give different names to describe the concept of precision agriculture such as spatially prescriptive agriculture, computer farming, satellite farming, high technology for sustainable agriculture, soil specific crop management or site-specific crop management. It is considered a revolutionary approach to improving resource management and sustainable agricultural development and is a promising technology. [29–33].

Precision agriculture studies were started in countries such as the USA, Canada, Australia, and Germany, besides the Western Europe, in the mid-1980s, and only began to receive great interest as a new experimental tool in the 1990s [29]. In [34] is define the specific management of a study zone as the electronic monitoring and control applied to data collection, information processing and decision support for the temporal and spatial allocation of inputs for agricultural production. The specific control zone, as shown in **Figure 1**, is spatially defined by soil elements, crop type, pests and other elements required for efficient management of inputs.

Technologies on agricultural production are expected to impact in two areas: profitability for producers and ecological/environmental for the public. Increased costs with water, fertilizer and pesticides, coupled with environmental concerns, lead to a growing acceptance of the concept of specific management of an operating zone.



**Figure 1.**

Different management zones within the same planting area. Source: Embrapa. (<https://www.macroprograma1.cnptia.embrapa.br/redeap2>).

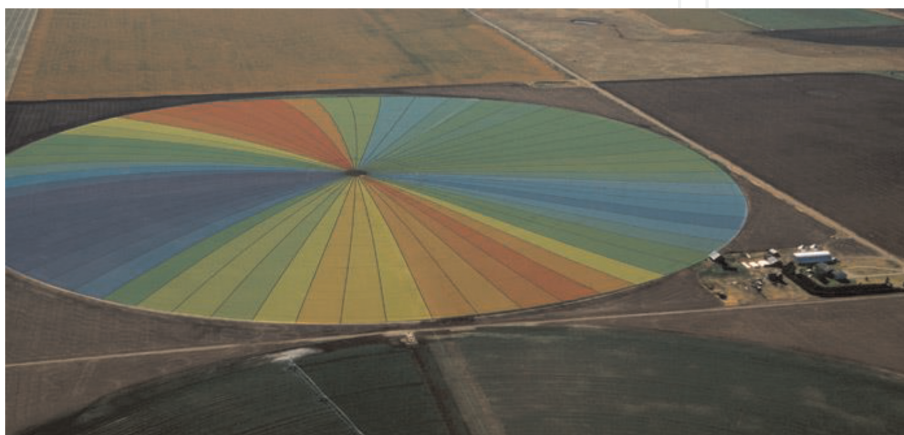
## 2.1 Variable rate irrigation (VRI)

Variable rate irrigation (VRI) is a specific management tool used to apply the adequate amount of water in the sectors or zones of a planting area, for example **Figure 2**, presents control regions where the zones in reddish colors need more water, and those of bluish colors are with the humidity within the limits that the plant needs. The development of the prescription of variable rate irrigation is a field of active research, studied in [13, 14, 35].

Once established, prescriptions can, within a management variability, remain fixed, or these zones can dynamically change a small number of times during a growing season. Characteristics of crops and soil type are the main factors that contribute to determine the space and time variability of a planted area. This information is incorporated into a geographic information systems (GIS) database and, therefore, used for interpretation and decision support [36].

### 2.1.1 Irrigation system

Irrigation systems are a set of techniques aimed to distribute water to crops in adequate quantities in order to promote appropriate plant development with a



**Figure 2.**

Spatial variability of irrigation water needs. Source: VALLEY. (<http://ww2.valleyirrigation.com/valley-irrigation/pt/tecnologia-de-comando/reg-a-de-taxa-vari%C3%A1vel/vri-controle-de-velocidade>).

minimum of water consumption [37]. Irrigation systems can be divided into two subsystems: catchment and application subsystem. The way the water is applied depends on different methods of application, and each has its specificities. They are divided into three groups: surface irrigation, localized irrigation, and sprinkler irrigation.

- Surface irrigation: the water from the distribution system (channels and pipes) to any point of infiltration within the area to be irrigated is made directly on the surface of the soil. They are classified as infiltration furrows and flooding or submersion;
- Localized irrigation: the water is applied directly on the root area, with small intensity and high frequency. Classified as: micro-sprinkler and drip;

Sprinkler irrigation is the method of irrigation in which water is sprayed on the surface of the land, like a rainfall, because the water jet is fractioned in drops. They are classified as: conventional spraying, central pivot, self-propelled, and linear system. Since this is the scope of this chapter, central pivot irrigation will be further detailed.

### *2.1.2 Central pivot*

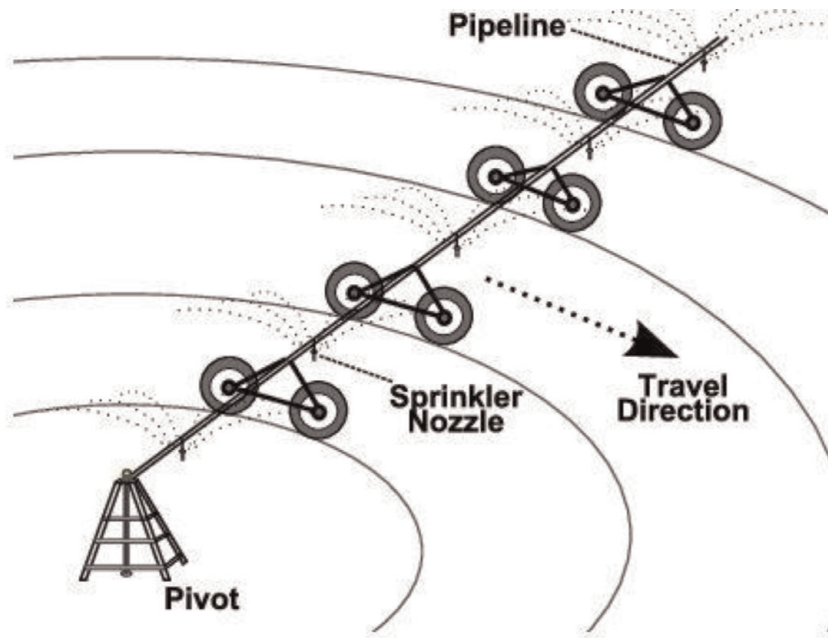
Among the sprinkler systems, the central pivot has been used with relative success due to the lower labor demand [37, 38]. It was first built in 1948 by Frank L. Zybach, who sent the invention for analysis, finally patented in 1952 in Colorado, United States (see **Figure 3**). In 1954, Zybach sold the manufacturing rights to the American company Valley, located in the State of Nebraska. In 1968, the Lindsay Company also started to produce pivots, and currently both companies share the leadership of the world market of pivots.

The speed of the lateral displacement of a central pivot is controlled in the last tower, which is established by a timer, installed in the central control box of the pivot, which controls the time of activation and the stop of the motor of the last tower. For example, the condition in which the motor standstill time is equal to the movement time corresponds to the setting of 50% of the maximum speed set by the timer control percentage. At maximum speed of 100%, the motor of the last tower is continuously moving [37, 39].

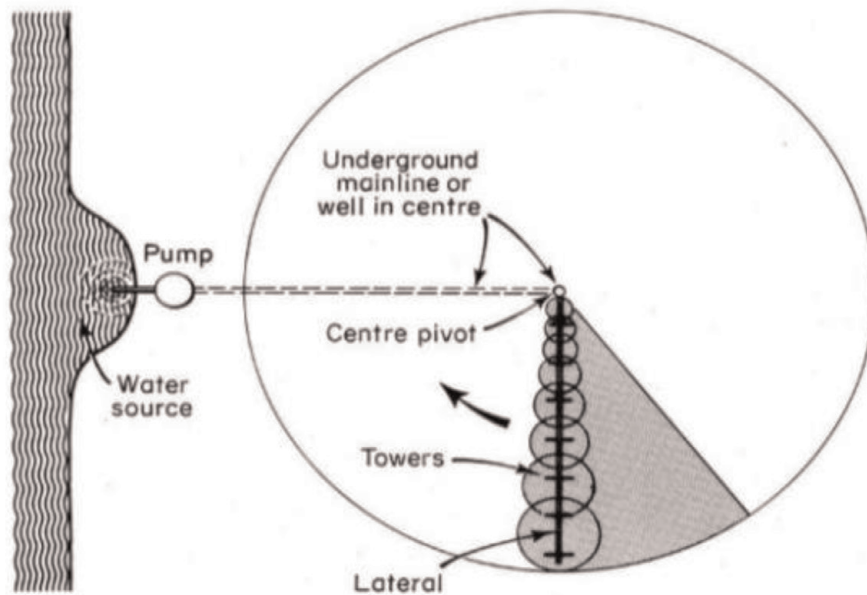
Irrigated agriculture does not allow reductions in crop productivity due to lack or excess of applied water. The application of little water (deficit irrigation) can be an obvious waste, since production could not obtain the expected benefit. On the other hand, the excessive application is much more destructive, because soil saturation occurs, which prevents its aeration and leaches the nutrients, inducing a higher rate of evaporation and salinization [40]. So, it is important to develop an irrigation scheduling program for deciding when and how much to irrigate. For this purpose, we used the fuzzy logic system to simulate the amount and the frequency of irrigation needed.

## **2.2 Fuzzy logic**

Fuzzy sets theory was introduced in 1965 by the Iranian mathematician Lotfi Asker Zadeh, a professor at the University of Berkley, USA [41], especially intended to offer a mathematical treatment to some subjective linguistic terms such as “approximately” and “around”, among others. This would be a first step in programming and storing vague concepts in computers, making it possible to produce calculations with inaccurate information, such as the human being [42].



a)



b)

**Figure 3.** Structure of a central pivot. (a) Basic components, and (b) irrigated land. Source: Adapted from [38].

In other words, while decision making in classical theory would be like Eq. (1), fuzzy logic would be like Eq. (2) [43].

$$f(x) = \begin{cases} 1 & \text{if, and only if, } x \in A \\ 0 & \text{if, and only if, } x \notin A \end{cases} \quad (1)$$

$$f(x) = \begin{cases} 1 & \text{if, and only if, } x \in A \\ 0 & \text{if, and only if, } x \notin A \\ 0 \leq \mu(x) \leq 1 & \text{if } x \text{ partial membership to } A \end{cases} \quad (2)$$

The most evident characteristic of fuzzy logic is to consider that between two values (zero and one) there may be intermediate values, and these values are

analyzed according to a degree of pertinence, which indicates the level that the information belongs to a specific set in a universe of discourse, according to [44].

Fuzzy set theory provides a method for manipulating sets whose boundaries are imprecise rather than restricted. The uncertainty of an element, that is, its fractional degree of pertinence, can be conceived as a measure of possibility, in other words, the possibility that an element is a member of the set [42].

### 2.2.1 Fuzzy inference systems

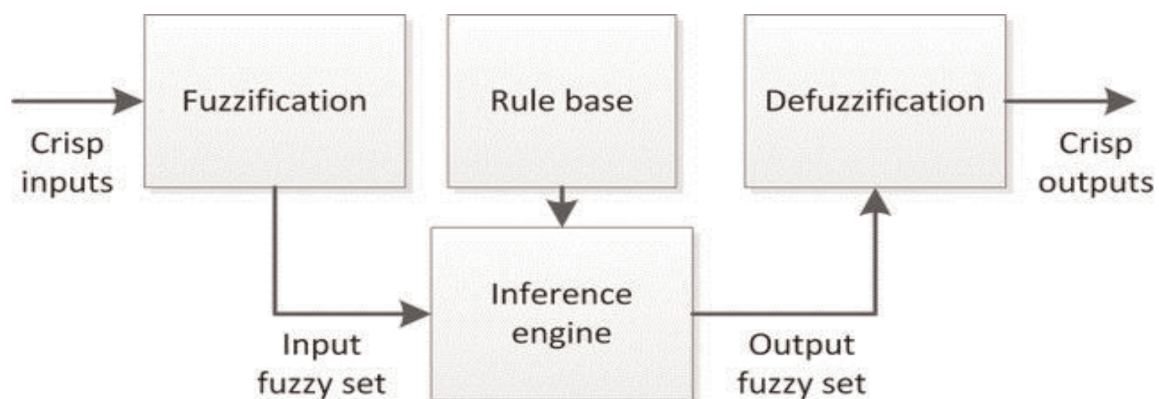
In many practical systems, relevant information comes from two sources: human experts, who describe their knowledge about the system in natural languages, and sensory measures and mathematical models proposed according to physical laws. An important task, therefore, is to combine these two types of information into systems designs [45].

The fuzzy inference system consists of a fuzzification interface, a rule base, a database, a decision-making unit or inference unit, and finally a defuzzification interface. The functional blocks are shown in **Figure 4**.

The function of each block is:

- A rule base containing a number of “if-then” fuzzy rules;
- A database that defines the functions of association of fuzzy sets used in fuzzy rules;
- A decision unit that performs rule inference operations;
- A fuzzification interface that transforms crisp inputs into degrees of correspondence with linguistic values;
- A defuzzification interface that transforms the fuzzy results of the inference into a crisp output.

Based on natural language, a fuzzy logic system is simple to understand and enables the representation and processing of human knowledge in a computer. The inputs, outputs, and fuzzy logic rules are easy to modify. These fuzzy logic features make it particularly well suited for use in a decision support system and is able to assist in the construction of vague rate-based irrigation control maps based on results of an imaging system in real time or by prescriptive maps based on the soil-plant-atmosphere transfer.



**Figure 4.**  
*Fuzzy inference system. Source: Adapted from Ross [46].*



### 2.2.2 Mamdani inference method

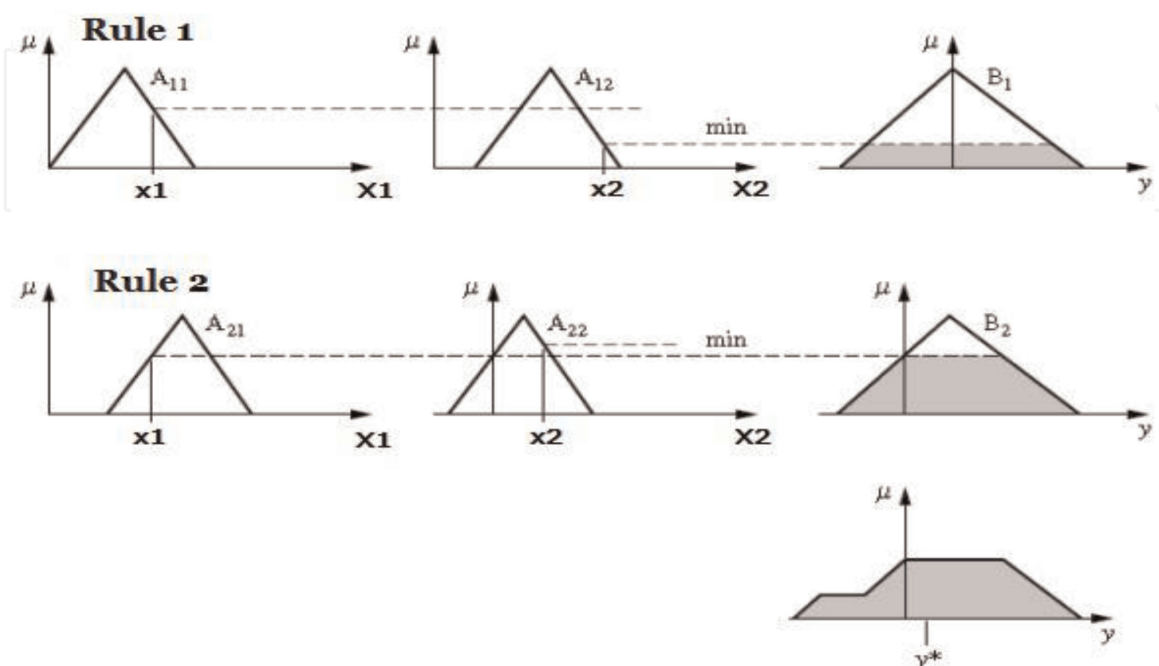
Developed by Mamdani [47], the inference method is the most common in practice and literature. To begin the general view of this idea, it is considered a simple system of two rules, where each rule comprises two antecedents and one consequent. The graphic procedures herein illustrated can be easily extended and maintained for fuzzy rule bases or fuzzy systems with any number of antecedents and consequents. Two different cases of two-input Mamdani systems are considered, where the inputs to the system are scalar values and a max-min inference method is used. Thus, the Mamdani inference method for a set of conjunctive rules for  $r_{th}$  rules are given by Eq. (3):

$$\text{if } x_1 \text{ is } A_1^k \text{ and } x_2 \text{ is } A_2^k \text{ then } y^k \text{ is } B^k \text{ for } k = 1, 2, \dots, r \quad (3)$$

This equation has a very simple graphical interpretation, exemplified in **Figure 5**, and illustrates graphical analysis of two rules, where symbols A11 and A12 refer to the first and second fuzzy antecedents of the first rule, respectively, and symbol B1 refers to the consequent fuzzy of the first rule. The symbols A21 and A22 refer to the first and second fuzzy antecedents, respectively, of the second rule, and the symbol B2 refers to the consequent fuzzy of the second rule.

### 2.2.3 Takagi-Sugeno-Kang inference method (TSK)

Although originally proposed by Takagi and Sugeno [48], this method is also known in the literature as Takagi-Sugeno-Kang (TSK) model. This is due to the subsequent works by Sugeno and Kang [49] related to methodologies developed to identify this type of model. The fuzzy TSK model consists of an inference system capable of describing, in an exact or approximate way, non-linear dynamic systems through a set of linear, locally valid dynamic systems, smoothly interpolated, non-linear and convex. A typical rule in a Sugeno model, which has two inputs,  $x$  and  $y$ , and one output  $z$ , is in the form of Eq. (4).



**Figure 5.** Interpretation of the Mamdani method. Source: Adapted from Ross [46].

$$\text{if } x \text{ is } A \text{ and } y \text{ is } B \text{ then } z \text{ is } z = f(x, y) \quad (4)$$

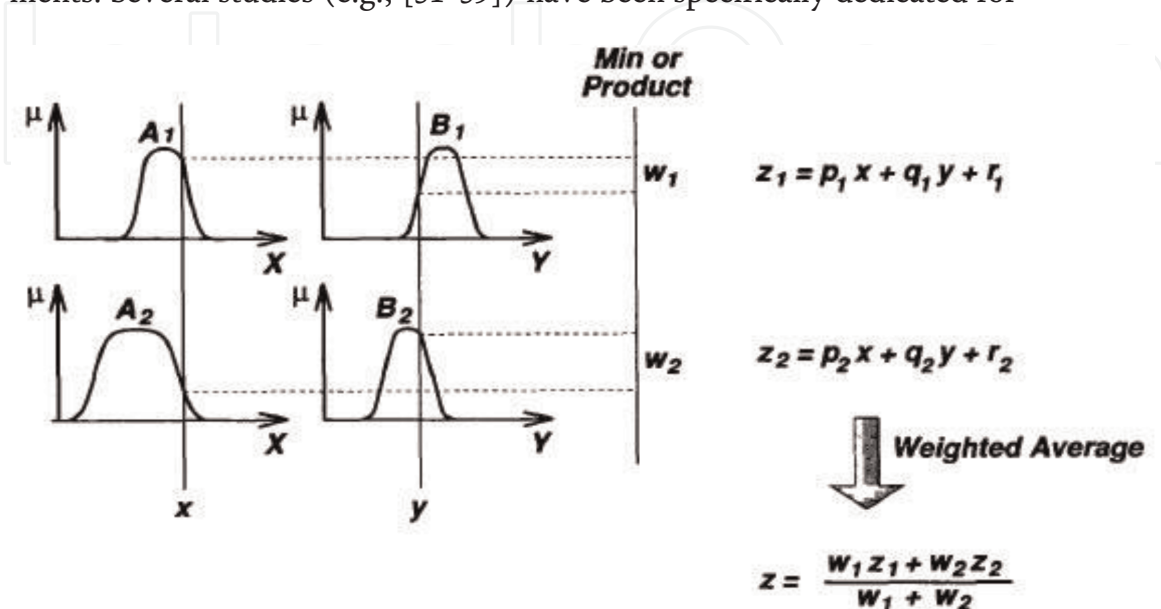
Usually,  $f(x, y)$  is a polynomial function at the  $x$  and  $y$  inputs, but it can be any general function as long as it describes the output of the system within the fuzzy region specified in the antecedent of the rule to which it is applied. When  $f(x, y)$  is a constant, the inference system is called a zero-order Sugeno model, which is a special case of the Mamdani system, in which the consequent of each rule is specified as a singleton fuzzy [50]. Each rule, in Sugeno model has an output given by a function. Due to this, the result is obtained through a weighted average, thus avoiding the time spent with the defuzzification process necessary in the Mamdani model. **Figure 6** illustrates the concept of the TSK model.

### 2.3 Remote sensing

Remote sensing technologies are being used more and more often in the precision agricultural applications. This is because that the variables (crop stress, soil type, disease,) to be measured and controlled are very disperse in remote areas with limited wireless communications or no power supply. Also, the measurements of each variable at spatial and temporal scale are expensive and time-consuming for installing and maintaining sensors over each field. Sensors can be multispectral cameras on Satellites or mounted on Unmanned Aerial Vehicle (UAV, or “drones”). In this chapter, we focalized on the using of satellites images for agricultural applications.

Remote sensing imagery can be used for mapping soil properties, classification of crop species (land use), detection of crop water stress, monitoring of irrigation, and predicting of crop yield. The use of remote sensing in precision agriculture depends principally on the spatial, temporal, radiometric and spectral resolution. Satellite remote sensing has shown a very strong potential for irrigation management at large scale through using a different data (optical, thermal and radar) acquired from different satellites.

Optical reflectances in red and near infrared (0.4–12.5  $\mu\text{m}$ ) have the potential to access the vegetation indices (VI) that are directly related the different crop parameters like crop coefficient (Kc) used in estimating the crop water requirements. Several studies (e.g., [51–59]) have been specifically dedicated for



**Figure 6.**  
 Graphic interpretation of the Sugeno method. Source: Adapted from [50].

estimating  $K_c$  from Normalized Difference Vegetation Index NDVI [60] and Soil Adjusted Vegetation Index SAVI [61].

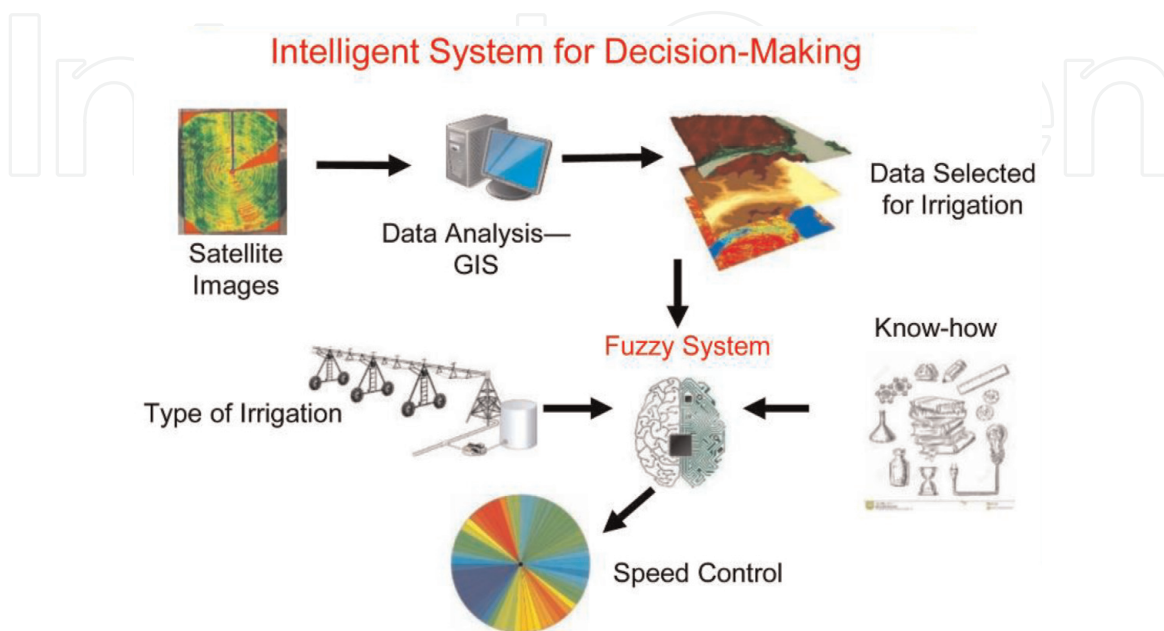
For thermal data, land surface temperature (LST) derived from thermal infrared remote sensing data have been used in a variety of applications such as, among others, climate studies [62, 63], the monitoring of crop water consumption and water stress detection [64–67], vegetation monitoring [68, 69], soil moisture estimation [70–72]. Canopy temperature has long been recognized as a good indicator for crop water status and as a potential tool for irrigation scheduling. Stomatal closure is one of the first responses to plant water stress that causes a decrease in plant transpiration and thus an increase in plant temperature. An increase in plant temperature is a sign that the vegetation is undergoing water stress. The crop water stress index (CWSI) is the most frequently used index to quantify the crop water stress based on canopy surface temperature [73].

Regarding the radar images, a significant effort has been recently dedicated to exploit these images to estimate soil moisture (SM) due to (i) the high-spatial resolution achievable by synthetic aperture radars (SAR) and (ii) the advent of SAR data available at high-temporal resolution. Especially, the Sentinel-1 (S1) constellation (composed of two satellites S1-A and S1-B) potentially provides SAR data at 20 m resolution every 3 days [74]. Thus, numerous studies have investigated and exploited the sensitivity of the radar signal to SM [70, 75–80].

### 3. Methods

The present stage shed light on the form that the construction of the proposed system is given, presenting as each fundamental characteristic of an irrigation project is appropriate to be added to the basic elements of fuzzy system.

The development of the intelligent irrigation system follows the structure shown in **Figure 7**. The structure of the proposed system enables the elaboration of a systematic, autonomous and automated management map to control an irrigation system. The output values of the intelligent system will be the inputs of the central pivot movement speed control and the sprinkle valve opening control.



**Figure 7.**  
*Structure for intelligent irrigation system strategy.*

However, it is important to emphasize that the commercial systems most used by farmers are not yet capable of elaborating this type of control map in the same way proposed by this work.

### 3.1 Geographic information system

Over the last decade, new information technologies, such as the geographic positioning system (GPS) and the geographic information system (GIS) have been introduced, which enabled to reduce the scale of management to the field level [81]. There are different software programs available in the market that can create maps from data point files, such as Surfer (GoldenSoftware, Inc.), ArcView (ESRI) and Global Mapper (Global Mapper).

The free QGIS<sup>1</sup> software will be used in this work for pre-processing and editing the file provided by the i-ekbase web-tool. QGIS is an open source geographic information system (GIS), licensed under GNU General Public License. It is an official open source geospatial foundation (OSGeo) project that runs on Linux, Unix, Mac OSX, Windows and Android, and supports several formats of vectors, rasters, databases and functionalities. QGIS has a plug-in infrastructure, and it is possible to add new features by writing plug-ins in C++ or Python.

#### 3.1.1 Vegetation indices

As mentioned above, vegetation indices generated from remote sensing data are an important tool for the monitoring of natural or anthropogenic changes in land use and land cover. These rates have been used to estimate several vegetation parameters such as leaf area index (LAI) and amount of green biomass, as well as in the evaluation of land use and management and the recovery of degraded areas [82].

In this study, satellite image information was used, and in this case, the reading values of NDVI—Normalized Difference Vegetation Index—is defined as the difference between Near infra-red and red reflectances divided by its sum. It measures the vegetative cover and its color on the land surface over wide areas. Dense and green vegetation absorbs strongly the red wavelengths of sunlight and reflect in the near-infrared wavelengths resulting high values of NDVI, near to 1. For bare soil (no vegetation), NDVI values are between 0 and 0.14 depending on the moisture and roughness of soil. The practice of plant irrigation management has inherent complexity in visualizing the symptoms of water deficit, which are difficult to detect. On some occasions, they are discovered very late, that is, when observed, their effects have already compromised the production or quality of the product. Usually these symptoms are related to leaves coloring, leaf winding, leaf angle, etc.

However, it is possible to establish a correlation between the values of NDVI and the crop coefficient (Kc), [83, 84]. The estimated Kc values (Kc-NDVI) and the Kc values observed in Allen [85] for maize and soybean crops to guide the irrigation schedule during the season. Another way of relating the development of the plantation by means of remote sensing is the use of canopy temperature and infrared thermometry. A plant under water stress reduces transpiration and typically presents a higher temperature than the non-stressed crop [86], which can be a powerful tool for monitoring and quantifying water stress.

Canopy temperature increases when solar radiation is absorbed [87] but, is cooled when latent energy or sweating is used to evaporate water instead of heating plant surfaces. Algorithms based on canopy temperature are strongly correlated

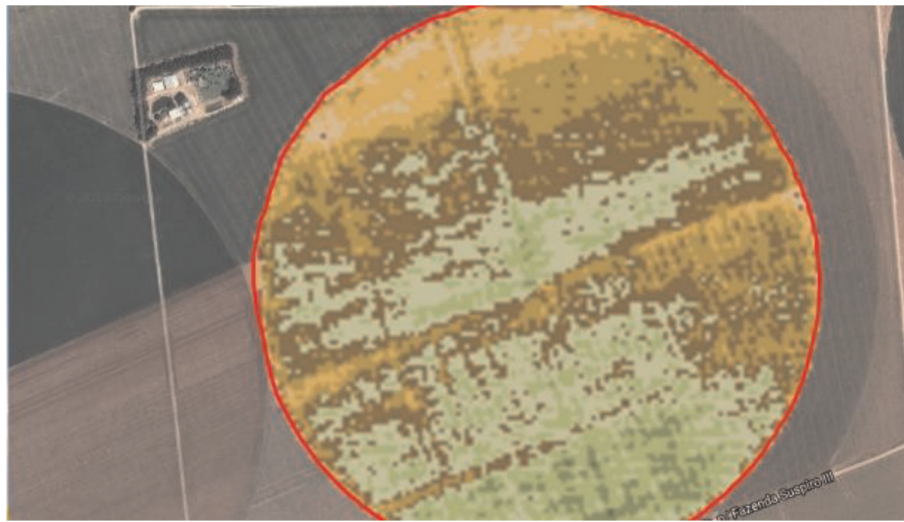
---

<sup>1</sup> <http://www.qgis.org/en/site/>

with quantifiable crop yields [88], such as productivity, water use efficiency, seasonal evapotranspiration, leaf water potential at noon time, irrigation rates and damage caused by herbicides.

### 3.1.2 Satellite images

In order to study satellite images, data will be provided by a specialized company, by means of its intelligent environmental knowledgebase (i-ekbase), and made available via web tool, with limited and free use, for research related to the topic. The web tool will provide data from the area chosen initially for the study. The intelligent environmental knowledgebase (i-ekbase)<sup>2</sup> is an autonomous Big Data Analytics engine with a CLOUD system, and a fully automated geographic information system (GIS) [89]. **Figure 8** illustrates an example image provided by the i-ekbase tool, while **Table 1** shows the data generated by the web tool in the CSV (Comma Separated Values) format.



**Figure 8.** Land surface temperature image by the i-ekbase web tool. Source: Adapted from the i-ekbase system.

Lat	Long	Canopy nitrogen (%)	Leaf area index (m <sup>2</sup> /m <sup>2</sup> )	NDVI (%)	Bio-mass (tn/ha)	Soil salinity (dS/m)	Soil moisture (%)	Canopy temp. (°C)
-15.2464	-54.0157	0.0	0.0	13.49	0.0	3.35	13.52	36.48
-15.2464	-54.0156	0.09	0.0	15.24	0.14	3.32	13.19	36.81
-15.2464	-54.0155	0.41	0.0	15.36	0.15	3.39	13.93	36.07
-15.2464	-54.0159	3.36	0.0	22.76	0.76	3.16	11.61	38.39
-15.2464	-54.0158	4.96	0.0	26.68	1.09	3.10	11.00	39.00
-15.2463	-54.0162	7.37	0.0	31.78	1.52	2.87	8.65	41.35
-15.2463	-54.0162	9.30	1.0	36.34	1.89	2.80	8.03	38.97
-15.2463	-54.0161	11.59	1.0	41.42	2.32	2.68	6.84	40.16

**Table 1.** Data exported by the i-ekbase web tool. Source: Adapted from the i-ekbase system.

<sup>2</sup> <http://iekbase.com/>

The i-ekbase system services provide larges area-wise resource management maps, with supporting remote digital scouting for decision support systems and rapid intervention of issues. For developing the experimental system were processed 12 months of Data, these remote sensing imageries were acquired by Landsat (with a spatial resolution of 30 m, but for this experiment the Data was upscale to 10 m) and Sentinel (with a spatial resolution of 10 m) satellites. Data that constitute this image have more than 14,000 georeferenced points, containing at each point or pixel the attributes of the agricultural analysis. Due to the extension of the data, only a few lines are shown in **Table 1**.

In order to apply this approach to the commercial field scale, the remote sensing data required to describe the soil-plant-atmosphere relationship can be acquired from satellite [90] and aircraft images [91, 92]. However, high costs, spatial resolution, data frequency and data availability [93, 94], in addition to cloudless satellite imagery, are a challenge for the correct execution of models based on remote sensing [95]. These issues can limit the efficiency of real-time variable rate irrigation management.

From the remote sensing data, those that best describe the soil-plant-atmosphere relationship for the intelligent irrigation system of the plantation site will be selected. In this phase, the correct selection of these data is fundamental to correctly calculate the results. A simple but promising approach uses crop coefficients derived from the normalized difference vegetation index (NDVI) along with local climate data to infer quantities of evapotranspiration (ET<sub>c</sub>) from variable crops almost in real time [57, 83, 96].

Based on the choice of planting site and type of crop to be irrigated, in relation to plant type data, the crop coefficient will be used along with information from the satellite images. In this case, the reading values of NDVI, near soil moisture and vegetative canopy temperature will be used. The latter is an important parameter for irrigation management and should be adjusted according to local growing conditions.

### **3.2 Location of the study**

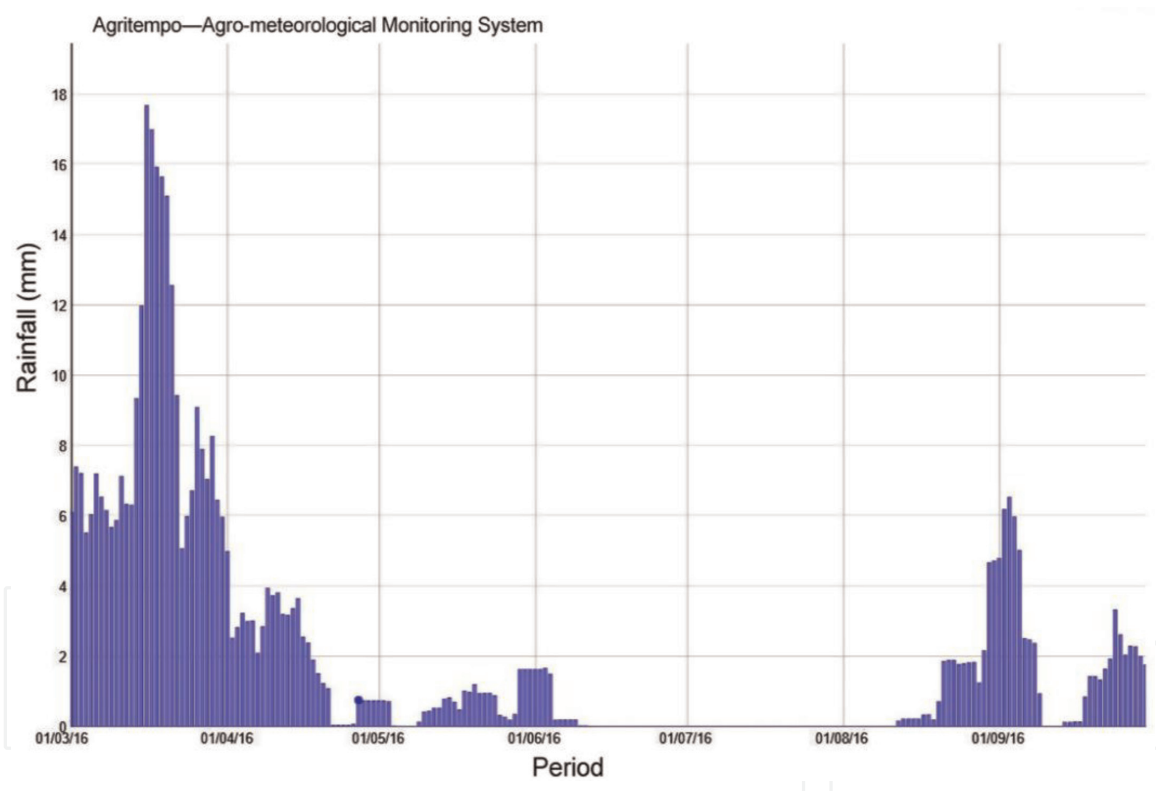
The study site is a farm located in the municipality of Primavera do Leste, MT, latitude 15° 14'24.73 "S and longitude 54 ° 0'53.29" W. This site has areas of cultivation irrigated by central pivot, and the crops planted are soybean, cotton and second-crop corn. The delimited area presents a total of 140 ha, in a radius of 667 m, see **Figure 9**. The area delimited by the red circle has central pivot irrigation, and the information used in the case study is from a 2015/2016 second-crop corn cycle. Irrigation in maize crop means to meet the minimum water requirements for the development of the crop.

Maize expresses high sensitivity to droughts. Therefore, the incidence of periods with reduction of the water supply to the plants at critical moments of the development of the crop, from flowering to physiological ripeness, can cause a direct reduction in the final harvest. In order to obtain maximum output, maize planting requires approximately 650 mm of water during its cycle [97], which can vary from 110 to 140 days in medium-cycle hybrids. For this preliminary analysis, data on daily average precipitation were used, provided by INMET (National Institute of Meteorology), from April to September 2016, to the city of Primavera do Leste, in the State of Mato Grosso, Brazil. **Figure 10** shows the data obtained.

These readings recorded during the development of the plantation under study corroborate the supposition of water stress due to lack of rainfall (from June to September), which would indicate the possibility of complementing water demand by irrigation.



**Figure 9.**  
*RGB images of the location of study area in in the municipality of primavera do Leste, state of Mato Grosso, Brazil.*

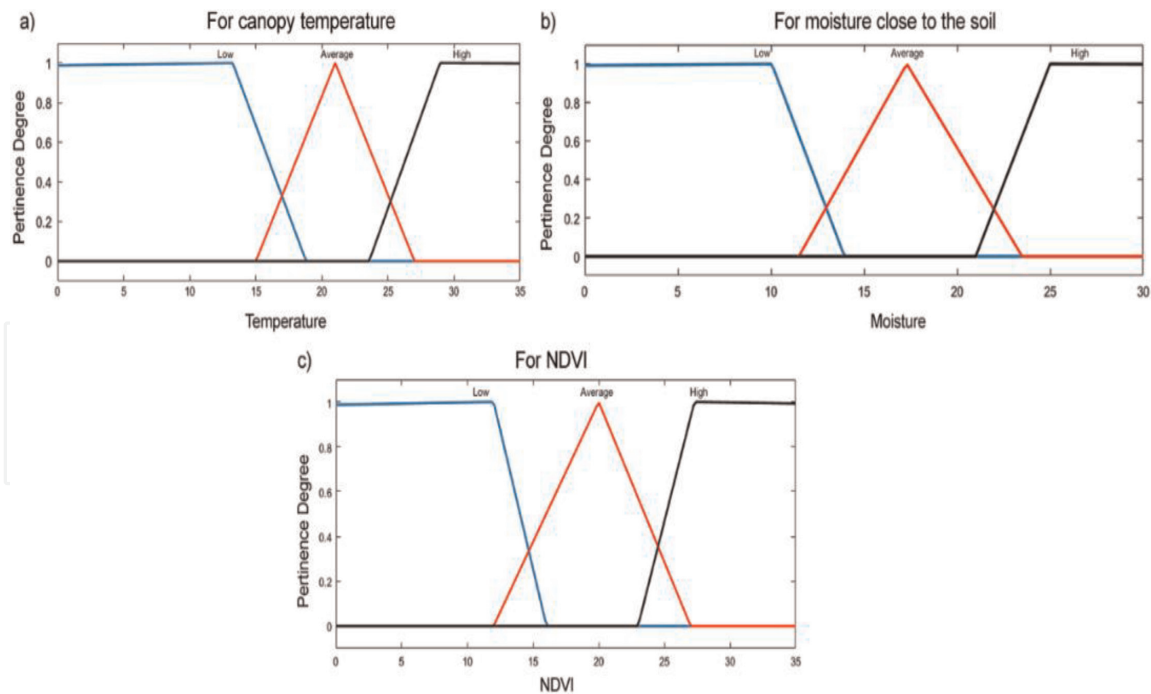


**Figure 10.**  
*Daily average precipitations obtained in the period of 2016. Fonte: INMET.*

### 3.3 Fuzzy systems

In this step, a fuzzy system will be used, which in this case will be capable to infer the variations of linear speeds of the pivot according to the images provided by the satellite. For the creation of the control map, a system with artificial intelligence will be developed, capable of manipulating data and knowledge.

Three input variables (NDVI, near-soil moisture and canopy temperature) were used to infer the speed that the pivot should have to improve the level of irrigation within the management area, so that an adequate speed could be found for the



**Figure 11.** Corresponding membership functions for each system entry, (a) canopy temperature, (b) upper layer soil moisture, (c) NDVI.

Input variables	Linguistic variables		
	Low	Average	High
Canopy temperature (°C)	<14	$14 < \phi < 27$	>24
Upper layer soil moisture (%)	<14	$12 < \phi < 24$	>21
NDVI (%)	<16	$12 < \phi < 27$	>27

**Table 2.** Fuzzy input set for the fuzzy inference system.

movement of the pivot in relation to the amount of water sprayed by the sprinklers. The decision unit or inference machine to perform rule-based inference operations will be implemented using the Mamdani method, with crisp inputs and crisp output value<sup>3</sup>.

In this first stage of development, the water depth that the irrigation system provides will be considered constant, and the database, which defines the functions of association of the sets used in the fuzzy rules, will be implemented as shown in **Table 2** and **Figure 11**.

With the remote sensing data, it is possible to construct the universes of discourse of each input variable and thus transform the database into linguistic variables, such as those presented in the table above. Each of these inputs was previously limited in the universe of discourse in question and associated with a degree of pertinence in each fuzzy set by means of specialist knowledge. In this manner, in order to obtain the degree of pertinence of a given crisp input, it is necessary to search for this value in the knowledge base of the fuzzy system. The fuzzification of the decision-making system is shown in **Figure 11**, and it is possible

<sup>3</sup> <https://www.agritempo.gov.br/agritempo/jsp/Grafico/graficoMicrorregiao.jsp?siglaUF=MT>



to visualize the corresponding membership functions, considering these intervals as the universe of discourse of these variables.

Triangular membership functions were chosen because they simplify the calculation of the fuzzy inference mechanism. Well distributed triangular membership functions transform the input values into fuzzy values (low, medium and high), as shown in **Figure 5**, as well as the values of soil moisture and NDVI (**Figure 11b** and **c**, respectively). The fuzzy output set, which represents the rotational speed of the central pivot, was built on five linguistic variables: very low (VL), low (L), normal (N), high (H) and very high (VH). These sets were interpreted by means of their degrees of pertinence, illustrated in **Figure 12**.

If the center of gravity method is used for defuzzification, the fuzzy set produced after aggregation will be a numerical output composed of the union of all rule contributions. This calculation is made according to Eq. (5):

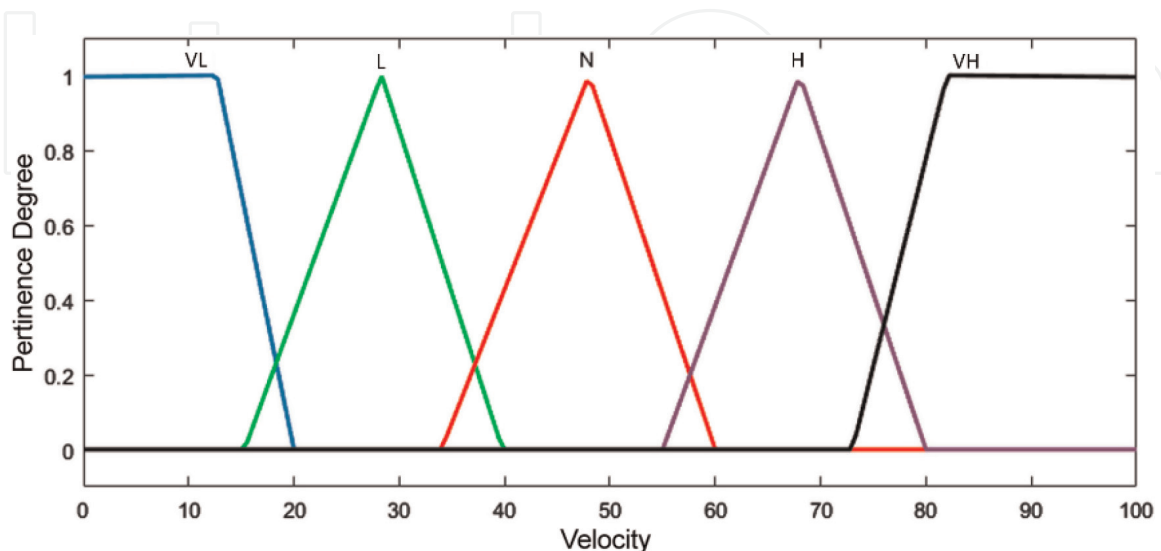
$$\mu^* = \frac{\sum_{i=1}^n \mu_i \cdot \mu_{out}(\mu_i)}{\sum_{i=1}^n \mu_{out}(\mu_i)} \quad (5)$$

The values  $\mu_{out}(\mu_i)$  represent the area of a pertinence function modified by the result of fuzzy inference, and  $(\mu_i)$  is the position of the centroid of the individual pertinence function.

Finally, the basis of fuzzy rules IF-THEN was elaborated and presented in **Table 3**, the fuzzy rule relating to rotation speed contains 27 rules, thus, the Mamdani inference method for a set of conjunctive rules is given by Eq. (3), for example: IF NDVI is Low AND Canopy temperature is Low AND Near-soil moisture is Low THEN Rotation Speed is Low.

This set of rules is based on the basic knowledge about irrigation, according to a methodology adopted by [37, 39].

The rules were constructed with the connective “AND”, and are based on the supposition that where there is little leaf growth, there is soil water deficit. Together with the characteristic of the high canopy temperature, indicating a lower evapotranspiration, that is, water stress of the plants, the values of near-soil moisture provided by the web tool are readings of the locations where there are few leaves, and it is possible to estimate their value.



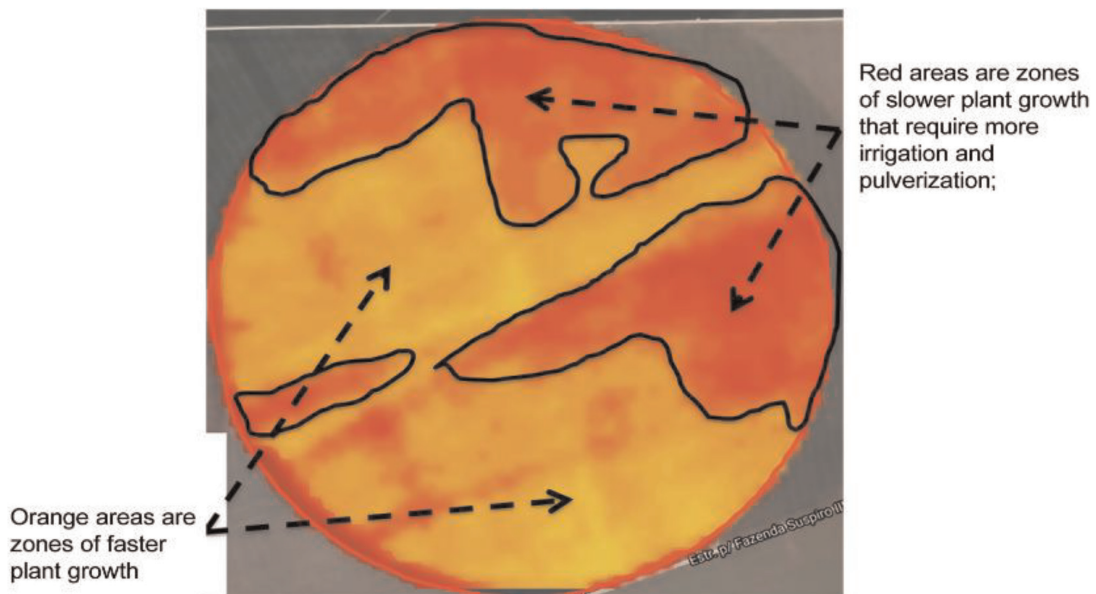
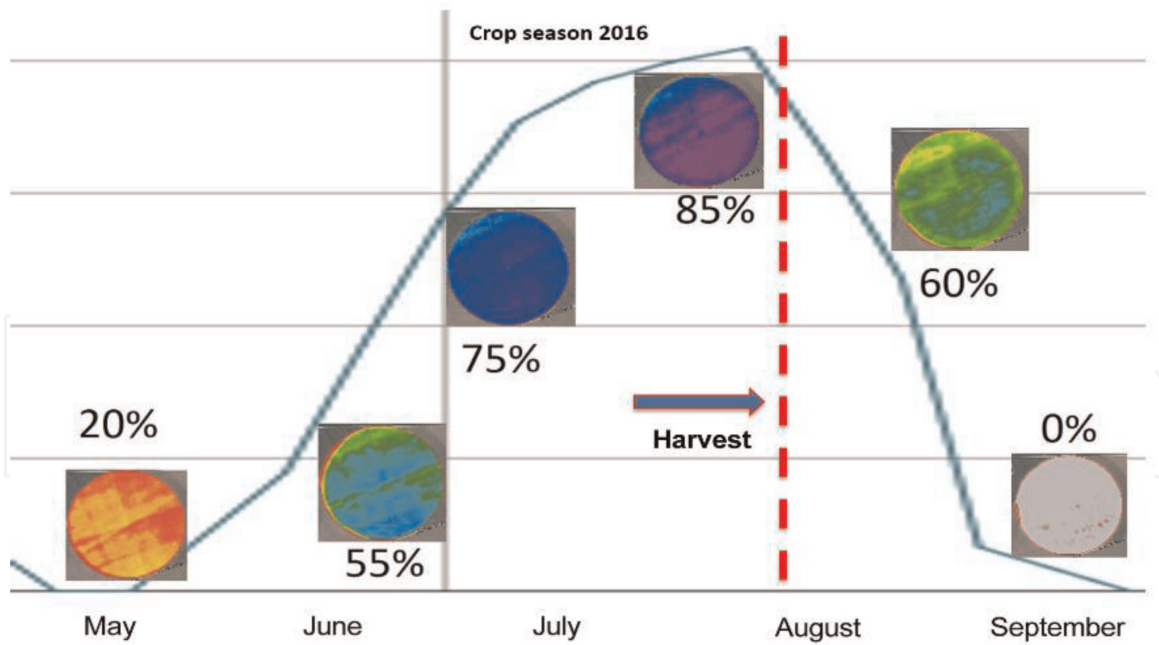
**Figure 12.** Function of pertinence of the speed corresponding to the defuzzification of the system.

Inputs			Output	
NDVI	Temperature	Near-soil moisture	Rotation speed	
Low	Low	Low	Low	
		Medium	Low	
		High	Very low	
	Medium	Low	Low	Low
			Medium	Low
			High	Very low
		High	Low	Low
			Medium	Low
			High	Very low
Medium	Low	Low	Normal	
		Medium	Normal	
		High	High	
	Medium	Low	Low	Normal
			Medium	Normal
			High	High
		High	Low	Low
			Medium	Normal
			High	Normal
High	Low	Low	High	
		Medium	Very high	
		High	Very high	
	Medium	Low	Low	Very high
			Medium	Very high
			High	Very high
		High	Low	Very high
			Medium	Very high
			High	Very high

**Table 3.**  
 Fuzzy rules for central pivot speed control.

#### 4. Control maps of central pivot motion speed

The development of the crop is evidenced captured by the images throughout the crop, and the information contained in this sensing is the NDVI values. By analyzing the information contained in **Figure 13**, it is possible to verify the similarity between the values attributed to Kc. It is noticed that as the crop evolves, the greater the exposure of the leaf area, and thus it is possible to establish a relation of NDVI. This process is described in [56], with ratios to calculate the base crop coefficient (Kcb) for cotton as a function of NDVI. When we look closely at each stage of the development of the plantation, two distinct areas are noticed: one with



**Figure 13.**  
Variation of NDVI in one crop cycle.

little growth and the other with normal growth. From this type of differentiation, it is possible to construct water demand maps, as well as speed control maps.

Data contained in this remote sensing are described in **Table 4**. In this configuration, the table presents the preprocessed data, near-soil temperature, soil moisture, and NDVI, besides latitude and longitude.

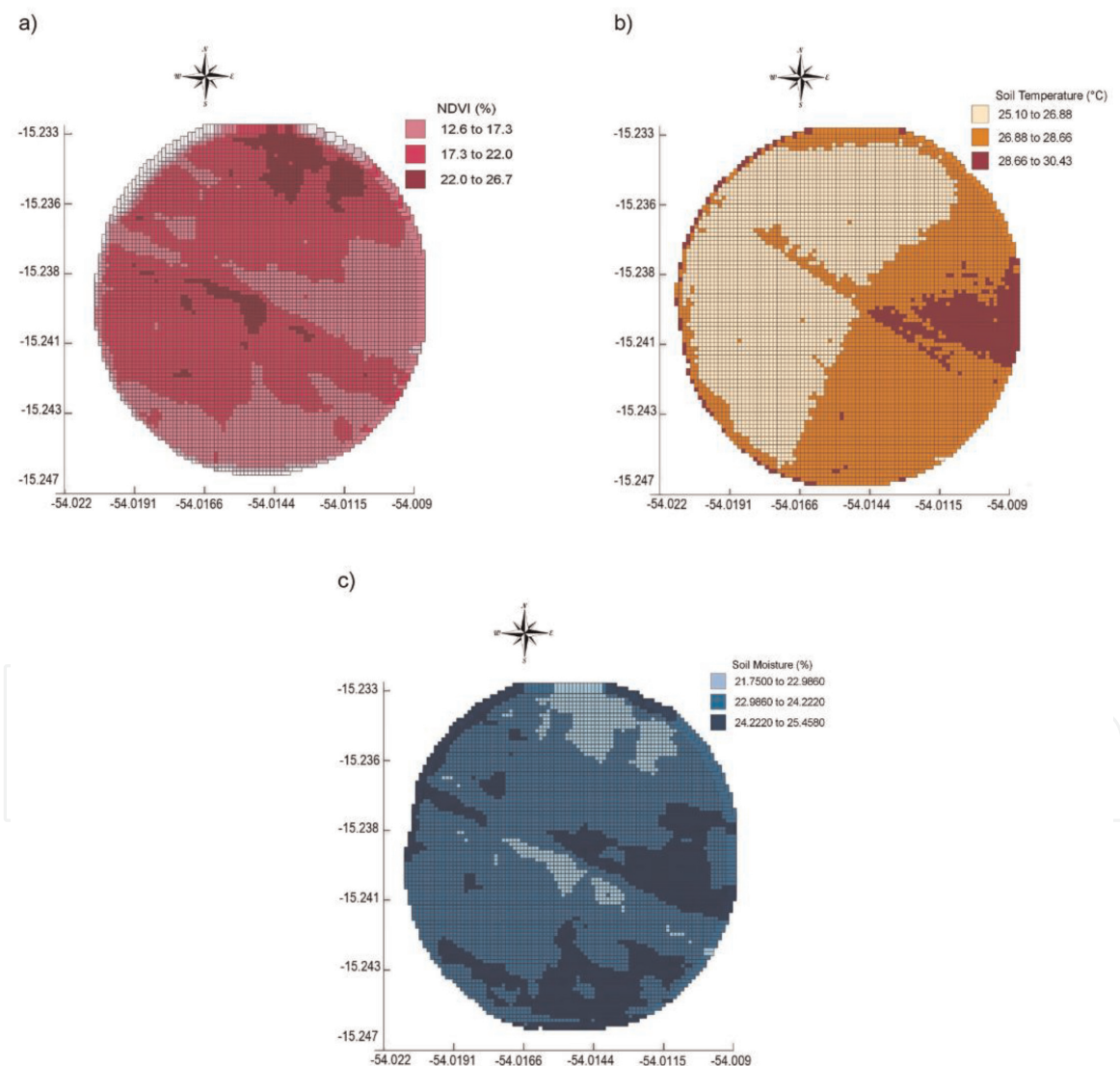
#### 4.1 Case study on June 15th, 2016

Canopy temperature, near-soil moisture and NDVI data, analyzed and processed, will be the set of inputs for the intelligent fuzzy system. The following are illustrated in **Figure 14**: (a) NDVI images, (b) temperature images, and (c) soil moisture images.

The inputs, as shown in **Figure 14**, are arranged according to the linguistic variables of the fuzzy system and separated by tonalities for better visualization.

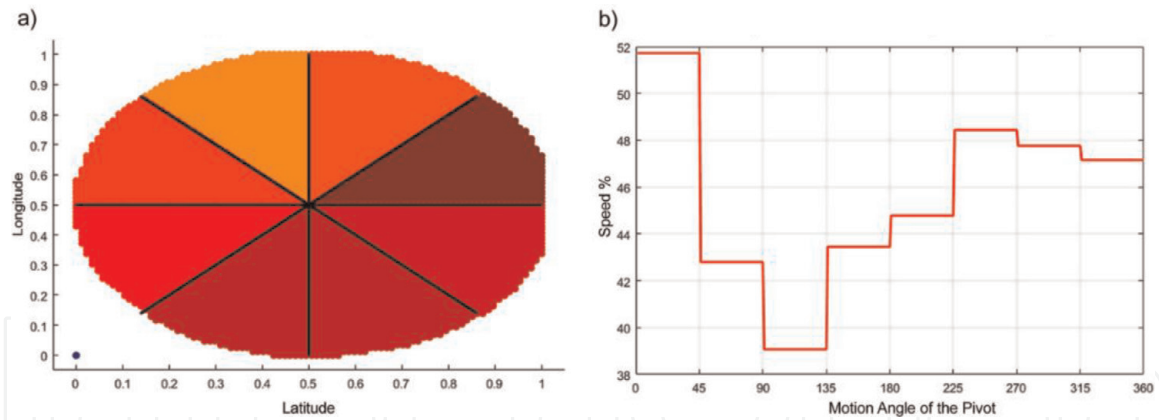
Lat	Long	NDVI (%)	Near-soil moisture (%)	Canopy temperature (°C)
-15.2463	-54.0157	5.96	25.75	30.75
-15.2463	-54.0156	6.49	25.68	30.24
-15.2463	-54.0154	6.67	25.68	30.03
-15.2463	-54.0153	6.85	25.68	30.19
-15.2463	-54.0152	6.66	25.8	30.63
-15.2463	-54.015	6.47	25.92	30.67
-15.2463	-54.0149	6.82	25.84	30.44
-15.2463	-54.0142	7.01	25.77	29.33
-15.2463	-54.0141	6.37	25.88	29.58

**Table 4.**  
 Pre-processed data.



**Figure 14.**  
 Input data from the fuzzy inference system, (a) NDVI data, (b) canopy temperature data, (c) near-soil moisture data.

The intelligent system gave the result shown in **Figure 15**, where it is possible to verify different regions within the area, with different values for the pivot rotation speed. The indirect relationship between the pivot rotation speed and the level of the applied water depth implies a smaller applied water depth in a higher speed, and



**Figure 15.** Control map of pivot rotating speed, (a) speed control map, (b) pivot turning speed setpoints.

a higher water application in the soil in a lower rotation speed [98]. When analyzing the input data, it is possible to identify two large areas with a lower leaf development, which may indicate a lack of water for development. After processing this input data, the intelligent irrigation system indicates that these areas with lower leaf development, in a redder color, indicate that the pivot should reduce its speed and thus increase the water depth in that area.

The expected result is the creation of control maps, and in this case, it was possible to determine the speed reference values for the eight zones initially programmed. The areas that presented different coloration in **Figure 14** are in the control map result. It is possible to verify well divided zones, and in each one there is a determined value for the speed that the pivot must develop to decrease or increase the water depth in the cropped area. The result shown in **Figure 15b** corresponds to the reference values that should be sent to the pivot controller, since the control systems of these devices work with percentage of rotation speed.

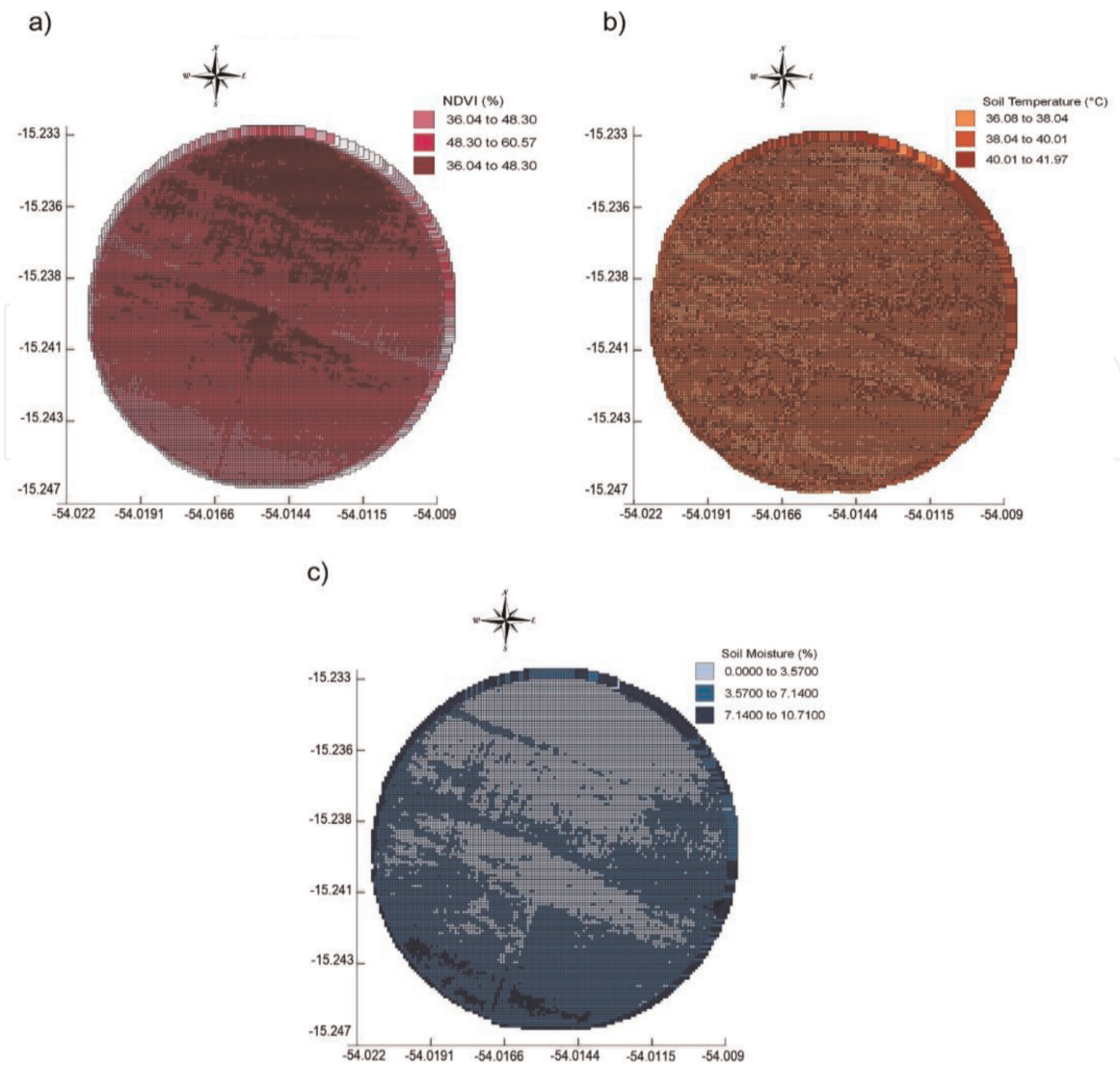
#### 4.2 Case study on June 28th, 2016

The data analyzed and processed by the GIS were used as inputs to the intelligent fuzzy system. They are illustrated in **Figure 16**: (a) NDVI images, (b) temperature images and (c) soil moisture images.

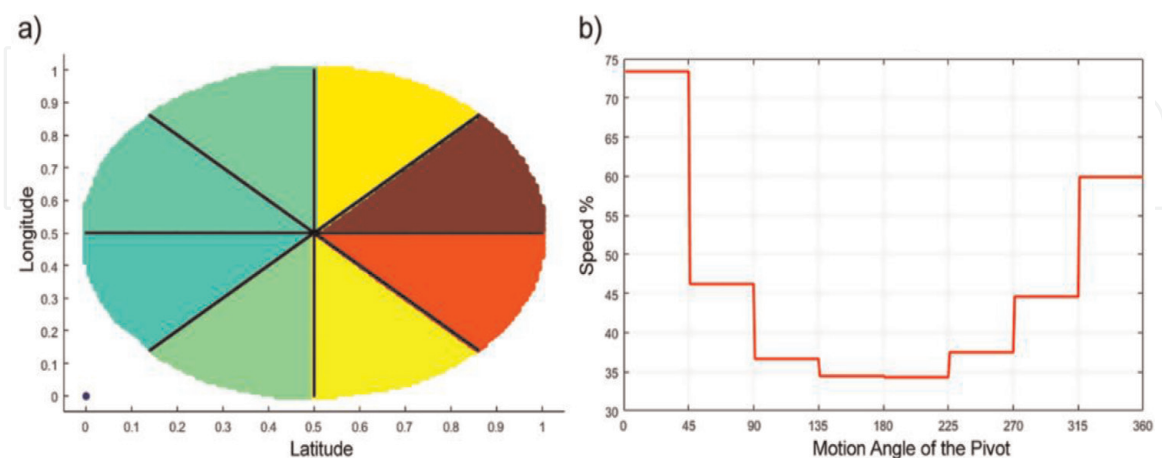
Similar to the previous case study, the study of June 28 presents the values of the input variables of the fuzzy system with the linguistic definitions necessary for interpretation. The results of the intelligent irrigation system are shown in **Figure 17**, where is also possible to observe different regions within the crop area, with different values for the pivot rotation speed. A higher speed of rotation implies a smaller applied water depth, and with a lower speed of rotation, there is a greater application of water to the soil, if the application flow is kept constant by the sprinklers.

When comparing satellite images once again, it is seen that NDVI and canopy temperature are essential for the decision-making of the intelligent irrigation system. It is possible to see that there are large areas with a lower leaf development, which may indicate a lack of water for development. In the case of intelligent irrigation system output, areas in a redder color indicate that the pivot should slow down.

The expected result is the creation of the control maps, and for this study it was possible to find the reference values of the central pivot rotation speed for the eight irrigation zones initially programmed, shown in **Figure 17**. In this result, it is also possible to identify the areas that presented different colors in **Figure 16**.



**Figure 16.** Input data from the fuzzy inference system, (a) NDVI data, (b) canopy temperature data, (c) near-soil moisture.



**Figure 17.** Pivot rotating speed control map, (a) speed control map, (b) pivot rotation speed setpoints.

The irrigation management zones are fairly divided, and in each one a value is determined for the pivot rotation speed, decreasing or increasing the water depth applied to the crop area. The result in **Figure 17b** corresponds to the reference values to be sent to the pivot controller.

## **5. Conclusions**

The fuzzy control system for irrigation developed is original and ground breaking, and there is no literature about a rotation speed control map for center pivot in the same approach presented in this work. In addition, there is no available information that commercial systems can build this type of map autonomously.

The experiments point to the efficiency result for pivot operation, since it is possible to note differences between the speeds per management zone that could be employed in the pivot. The system follows the definition of variable rate irrigation, since when changing the speed, the amount of water applied also changes.

In this context, it was observed that the fuzzy logic can be widely used in farming, and it is feasible to aggregate precision irrigation knowledge with the formulation of a decision support system. The implementation was successful for the application of variable rate water to central pivots. However, a broader commercial application depends on the integration of data collection systems, management strategies, and hardware control.

These studies were motivated by a broader research effort on the applications of fuzzy systems in agriculture. In addition, fuzzy control applied in variable rate irrigation (VRI) was explored in this domain in order to provide a better understanding of the relation between agricultural factors involving complexity and uncertainty and solutions with A.I. technologies. Future development and application of these methodologies in agricultural engineering are required especially in the context of decision support in precision irrigation. The results are favorable to the continuity of the studies on precision irrigation and application of the fuzzy logic for the development of control maps for central pivots irrigation systems.

## **Acknowledgements**

The authors thank the Federal Institute of Education, Science and Technology of Mato Grosso—IFMT—for the financial support, and to the Post-Graduation Program in Electrical and Computer Engineering of the Federal University of Rio Grande do Norte—PPGEEC/UFRN—for the technical and administrative support. Finally, we thank the Coordination of Improvement of Higher Education Personnel—Ministry of Education (Capes—MEC) for granting the PRODOUTORAL scholarship to the corresponding author.

## **Conflict of interest**

The authors declare no conflict of interest.

IntechOpen

## Author details

Willians Ribeiro Mendes<sup>1\*</sup>, Fábio Meneghetti U. Araújo<sup>2</sup> and Salah Er-Raki<sup>3,4</sup>

1 Control Engineering and Automation Department, Federal Institute of Education, Science and Technology of Mato Grosso—IFMT, Mato Grosso, Brazil


2 Computer Engineering and Automation Department, Federal University of Rio Grande do Norte, University Campus Lagoa Nova, Natal, Rio Grande do Norte, Brazil

3 LP2M2E, Département de Physique Appliquée, Faculté des Sciences et Senvolvimen Techniques, Université Cadi Ayyad, Marrakech, Morocco

4 Center for Remote Sensing Application (CRSA), University Mohammed VI Polytechnic (UM6P), Benguerir, Morocco

\*Address all correspondence to: [willians.mendes@pdl.ifmt.edu.br](mailto:willians.mendes@pdl.ifmt.edu.br)

## IntechOpen

© 2019 The Author(s). Licensee IntechOpen. This chapter is distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/3.0>), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited. 



## References

- [1] ANA. Agência Nacional de Águas (Brasil). Levantamento da Agricultura Irrigada Por Pivôs Centrais no Brasil-2014: Relatório síntese/Agência Nacional de Águas. Vol. il. Brasília: ANA; 2016. p. 33. ISBN: 978-85-8210-034-9
- [2] FAO. The State of Food and Agriculture. Climate Change, Agriculture and Food Security. Rome: Food and Agriculture Organization of the United Nations; 2016
- [3] Christofidis D. Água na produção de Alimentos: O Papel da irrigação no Alcance Do Desenvolvimento sustentável. Brasília: Universidade de Brasília; 2005. p. 29
- [4] Balastreire LA. A Estado-da-Arte da Agricultura de Precisão no Brasil. Ed. Vol. 1. Piracicaba; 2000
- [5] Brase T. Precision Agriculture. Boston, United States: Cengage Delmar Learning Publishers Inc; 2005:288. ISBN-13: 978-1-40188-105-4
- [6] Srinivasan A. Handbook of Precision Agriculture: Principles and Applications. Binghamton, NY: CRC Press Taylor & Francis Group; 2006. ISBN-13: 978-1-56022-954-4
- [7] Bernardi AC. Agricultura de precisão: Resultados de Um Novo Olhar. Brasília-DF: Embrapa; 2014. 596 p. Available from: <http://ainfo.cnptia.embrapa.br/digital/bitstream/item/113993/1/Agricultura-de-precisao-2014.pdf>. ISBN 978-85-7035-352-8
- [8] Gilley JR, Mielke LN, Wilhelm NN. An experimental center-pivot irrigation system for reduced energy crop production studies. Transactions of ASAE. 1983;26(5):1375-1379
- [9] Bright JC. Optimal control of irrigation system: An analysis of water Allocation Rules [thesis]. University of Canterbury: Department of Agricultural Engineering; 1986
- [10] Fraisse CW, Heermann DF, Duke HR. Modified linear move system for experimental water application. In: Advances in Planning, Design, and Management of Irrigation Systems as Related to Sustainable Land Use. Vol. 1. Lueven, Belgium: Center for Irrigation Engineering, K. U. Leuven; 1993. pp. 367-376
- [11] Sadler EJ, Camp CR, Evans DE, Usrey LJ. A site-specific center pivot irrigation system for highly-variable Coastal Plain soils. In: Robert PC, Rust RH, Larson WE, editors. Proceedings of the Third International Conference on Precision Agriculture. Madison, Wis: Am. Soc. of Agron; 1996. pp. 827-834
- [12] Evans RG. If you Build it, Will it Work? Testing Precision Center-Pivot Irrigation. GPS World Magazine, Eugene; 1997. pp. 10-17
- [13] Evans RG, King BA. Site-specific sprinkler irrigation in a water-limited future. Transactions of the ASABE—Advances in Irrigation. 2012;55:493-504
- [14] McCarthy AC, Hancock NH, Raine SR. Advanced process control of irrigation: The current state and an analysis to aid future development. In: Irrigation Science. Vol. 31. Springer-Verlag; 2013. pp. 183-192. DOI: 10.1007/s00271-011-0313-1
- [15] Er-Raki S, Chehbouni A, Duchemin B. Combining satellite remote sensing data with the FAO-56 dual approach for water use mapping in irrigated wheat fields of a semi-arid region. Remote Sensing. 2010;2(1):375-387
- [16] Amazirh A, Er-Raki S, Chehbouni A, Rivalland V, Diarra A, Khabba S, et al. Modified penman–Monteith

equation for monitoring evapotranspiration of wheat crop: Relationship between the surface resistance and remotely sensed stress index. *Biosystems Engineering*. 2017; **164**:68-84. DOI: 10.1016/j.biosystemseng.2017.09.015

[17] Deguise JC, McNairn H. Hyperspectral remote sensing for precision agriculture. In: *Proceedings of Fifth International Conference on Precision Agriculture (CD)*; 16-19 July; Bloomington: MN, USA; 2000

[18] McCarthy AC, Hancock NH, Raine SR. Real-time data requirements for model-based adaptive control of irrigation scheduling in cotton. *Australian Journal of Multi-Disciplinary Engineering*. 2011;**8**(2):189-206. ISSN 1448-8388

[19] Boutraa T, Akhkha A, Alshuaibi A, Atta R. Evaluation of the effectiveness of an automated irrigation system using wheat crops. *Agriculture and Biology Journal of North America*. 2011;**2**(1): 80-88

[20] Caceres R, Casadesus J, Marfa O. Adaptation of an automatic irrigation control tray system for outdoor nurseries. *Biosystems Engineering*. 2007;**96**:419-425

[21] Miranda FR, Yoder RE, Wilkerson JB, Odhiambo LO. An autonomous controller for site-specific management of fixed irrigation systems. *Computers and Electronics in Agriculture*. 2005;**48**: 183-197

[22] Luthra SK, Kaledhonkar MJ, Singh OP, Tyagi NK. Design and development of an auto irrigation system. *Agricultural Water Management*. 1997; **33**:169-181

[23] Colaizzi PD, Evett SR, Agam N, Schwartz RC, Kustas WP, Cosh MH, et al. Soil heat flux calculation for sunlit and shaded surfaces under row crops: 2.

Model test. *Agricultural and Forest Meteorology*. 2016:129-140. DOI: 10.1016/j.agrformet.2015.10.009

[24] Anom SW, Shibusawa S, Sao A, Sakai K, Sato H, Hirako S, et al. Soil parameter maps using the real-time spectrophotometer. In: *Proceedings of Fifth International Conference on Precision Agriculture (CD)*; 16-19 July; Bloomington: MN, USA. 2000

[25] Dubois D, Prade H. *Fuzzy Sets and Systems: Theory and Applications*. New York: Academic Press; 1980

[26] Rommelfanger HJ. Fuzzy logic-based processing of expert rules used for checking the credit solvency of small business firms or for supporting analytic procedures of auditors. In: Ribeiro RR, editor. *Soft Computing in Financial Engineering*. Vol. 37. Heidelberg: Physica-Verlag; 1999. pp. 1-244

[27] Dubey S, Pandey RK, Gautam SS. Literature review on fuzzy expert system in agriculture. *International Journal of Soft Computing and Engineering (IJSCE)*. 2013;**2**(6)

[28] Zhang HY, Fei L, Wei Z, Congcong M, Yuewei C. The fuzzy decision-making method of irrigation amount based on ET and soil water potential. In: *International Conference on Electronics, Communications and Control (ICECC)*; 2011. 2927-2931

[29] Werner A, Jarfe A. *Precision Agriculture, Herausforderung an Integrative Forschung, Entwicklung Und Anwendung in der Praxis*. Proceedings 2002. Darmstadt, Germany: Kuratorium für Technik und Bauwesen in der Landwirtschaft e.V. (KTBL); ISBN: 3-9808279-0-9

[30] Domsch H, Giebel A. Electrical conductivity of soils typical for the state of Brandenburg in Germany. In: *3rd European Conf. on Precision*

Agriculture; 18–20 June; Montpellier: France. 2001. pp. 373-378

[31] Sparovek G, Schnug E. Soil tillage and precision agriculture: A theoretical case study for erosion control in Brazilian sugarcane production. *Soil and Tillage Research*. 2001;61(1–2):47-54

[32] Heermann DF, Wallender WW, Bos MG. Irrigation efficiency and uniformity. In: Hoffman GJ, Howell TA, Solomon KH, editors. *Management of Farm Irrigation Systems*. 2nd print. Michigan: St. Joseph, ASAE; 1992. pp. 125-149

[33] Mulla DJ, Schepers JS. Key processes and properties for site-specific soil and crop management. In: Pierce FJ, Sadler EJ, editors. *The State of Site-Specific Management for Agriculture*. Madison, WI: ASA, CSSA, SSSA; 1997. pp. 1-18

[34] Lowenberg-Deboer J, Swinton SM. Economics of site-specific management in agronomic crops. In: Pierce FJ, Sadler EJ, editors. *The State of Site-Specific Management for Agriculture*. Madison WI: ASACSSA-SSSA; 1997. pp. 369-396

[35] Torre-Neto A, Schueller JK, Haman DZ. Networked sensing and valve actuation for spatially variable microsprinkler irrigation. In: Presented at the July 2000 ASAE International Meeting; Milwaukee, WI: Paper No. 001158. ASAE; 2950 Niles Rd. St. Joseph, MI; 2000

[36] Grisso R, Alley M, McClellan P, Brann D, Donohue S. *Precision Farming: A Comprehensive Approach*. Virginia Cooperative Extension; 2009. Available from: <http://pubs.ext.vt.edu/442/442-500/442-500.html>

[37] Bernardo S, Soares AA, Mantovani EC. *Manual de Irrigação*. 8a edição ed. Viçosa: Imprensa Universitária; 2006. p. 625

[38] da Silva JGF, Coelho EF. Irrigação do mamoeiro. In: Martins D, Dos S, Costa

A, de F, da S, editors. *A Cultura Do Mamoeiro: Tecnologia de produção*. Vitória, ES: INCAPER; 2003. pp. 161-197

[39] da Silva EM, de Azevedo JA. Dimensionamento da Lateral de irrigação Do pivô Central. Planaltina: EMBRAPA-CPAC; 1998. p. 54

[40] Reichardt K. *A Água Em Sistemas Agrícolas*. Piracicaba: Editora Manole; 1990. p. 188

[41] Zadeh LA. Fuzzy sets. *Information and Control*. 1965;8:338-353

[42] Simões MG, Shaw IS. *Controle e Modelagem Fuzzy*. 2a ed. São Paulo: Editora Edgard Blucher Ltda; 2007

[43] Dubois D, Ostasiewicz W, Prade H. Fuzzy Sets: History and Basic Notions. In: Dubois D, Prade H, editors. *Fundamentals of Fuzzy Sets*. The Handbooks of Fuzzy Sets Series. Boston, MA: Springer; 2000;7:21-124. [https://doi.org/10.1007/978-1-4615-4429-6\\_2](https://doi.org/10.1007/978-1-4615-4429-6_2)

[44] Barros LC, Bassanezi RC. *Tópicos de Lógica Fuzzy Com Aplicações Em Biomatemática*. Campinas, SP: UNICAMP/IMECC; 2006

[45] Henderson H. *Encyclopedia of computer science and technology*. Facts on File. Rev. ed., New York; 2009. pp. 203-204. ISBN-13: 978-0-8160-6382-6

[46] Ross TJ. *Fuzzy Logic with Engineering Applications*. Handbook. 2nd.Ed ed. USA: John Wiley & Sons, Ltd. University of New Mexico; 2004. p. 628

[47] Mamdani EH, Assilian S. An experiment in linguistic synthesis with a fuzzy logic controller. *International Journal of Man-Machine Studies*. 1975;7: 1-13

[48] TAKAGI T, SUGENO M. Fuzzy identification of systems and its applications to modeling and control.

IEEE Transactions on Systems, Man, and Cybernetics. 1985;**SMC-15**(1): 116-132

[49] Sugeno ME, Kang GT. Structure identification of fuzzy model. *Fuzzy Sets and Systems*. 1986;**28**:329-346

[50] Jang J-SR, Sun C-T, Mizutani E. *Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence*. Prentice Hall; 1997

[51] Jackson RD, Idso SB, Reginato RJ, Pinter PJ Jr. Remotely sensed crop temperatures and reflectances as inputs to irrigation scheduling. In: *Irrigation and Drainage Special Conference Proceedings*; 23–25 July. Boise: Idaho, ASCE New York; 1980. pp. 390-397

[52] Bausch WC, Neale CMU. Crop coefficients derived from reflected canopy radiation: A concept. *Transactions of ASAE*. 1987;**30**(3): 703-709

[53] Neale CMU, Bausch WC, Heerman DF. Development of reflectance-based crop coefficients for corn. *Transactions of ASAE*. 1989;**32**(6):1891-1899

[54] Choudhury BJ, Ahmed NU, Idso SB, Reginato RJ, Daughtry CST. Relations between evaporation coefficients and vegetation indices studies by model simulations. *Remote Sensing of Environment*. 1994;**50**:1-17

[55] Hunsaker DJ, Pinter PJ Jr, Barnes EM, Kimball BA. Estimating cotton evapotranspiration crop coefficients with a multispectral vegetation index. *Irrigation Science*. 2003;**22**:95-104

[56] Hunsaker DJ, Pinter PJ Jr, Kimball BA. Wheat basal crop coefficients determined by normalized difference vegetation index. *Irrigation Science*. 2005;**24**:1-14

[57] Er-Raki S, Chehbouni A, Guemouria N, Duchemin B, Ezzahar J, Hadria R. Combining FAO-56 model and ground-

based remote sensing to estimate water consumptions of wheat crops in a semi-arid region. *Agricultural Water Management*. 2007;**87**:41-54

[58] Er-raki S, Rodriguez JC, Garatuza-Payan J, Watts CJ, Chehbouni A. Determination of crop evapotranspiration of table grapes in a semi-arid region of Northwest Mexico using multi-spectral vegetation index. *Agricultural Water Management*. 2013; **122**:12-19. DOI: 10.1016/j.agwat.2013.02.007

[59] Diarra A, Jarlan L, Er-Raki S, Le Page M, Aouade G, Tavernier A, et al. Performance of the two-source energy budget (TSEB) model for the monitoring of evapotranspiration over irrigated annual crops in North Africa. *Agricultural Water Management*. 2017; **193**:71-88. DOI: 10.1016/j.agwat.2017.08.007

[60] Rouse JW, Haas RH, Schell JA, Deering DW, Harlan JC. Monitoring the Vernal Advancement and Retrogradation of Natural Vegetation. Greenbelt MD: NASA/GSFC, Type III, Final report; 1974. pp. 1-371

[61] Huete AR. A soil-adjusted vegetation index (SAVI). *Remote Sensing of Environment*. 1988;**25**: 295-309

[62] Hansen J, Ruedy R, Sato M, Lo K. Global surface temperature change. *Reviews of Geophysics*. 2010; **48**(4):1-29. DOI: 10.1029/2010RG000345

[63] Kustas W, Anderson M. Advances in thermal infrared remote sensing for land surface modeling. *Agricultural and Forest Meteorology*. 2009;**149**: 2071-2081. DOI: 10.1016/j.agrformet.2009.05.016

[64] Bastiaanssen WGM, Menenti M, Feddes RA, Holtslag AAM. A remote sensing surface energy balance

- algorithm for land (SEBAL). *Journal of Hydrology*. 1998;**212-213**:198-212
- [65] Boulet G, Chehbouni A, Gentine P, Duchemin B, Ezzahar J, Hadria R. Monitoring water stress using time series of observed to unstressed surface temperature difference. *Agricultural and Forest Meteorology*. 2007;**146**: 159-172. DOI: 10.1016/j.agrformet.2007.05.012
- [66] Er-Raki S, Amazirh A, Ayyoub A, Khabba S, Merlin O, Ezzahar J, et al. Integrating thermal surface temperature into penman-Monteith model for estimating evapotranspiration and crop water stress of orange orchard in semi-arid region. *Acta Horticulturae*. 2018; **208**:120-131. DOI: 10.17660/ActaHortic.2018.1197.12
- [67] Olivera-Guerra L, Merlin O, Er-Raki S, Khabba S, Escorihuela MJ. Estimating the water budget components of irrigated crops: Combining the FAO-56 dual crop coefficient with surface temperature and vegetation index data. *Agricultural Water Management*. 2018; **208**:120-131. DOI: 10.1016/j.agwat.2018.06.014
- [68] Kogan FN. Operational space technology for global vegetation assessment. *Bulletin of the American Meteorological Society*. 2001;**82**: 1949-1964. DOI: 10.1175/15200477(2001)082<1949:OSTFGV>2.3.CO;2
- [69] Williamson HD. Evaluation of middle and thermal infrared radiance in indices used to estimate GLAI. *International Journal of Remote Sensing*. 1988;**9**:275-283. DOI: 10.1080/01431168808954851
- [70] Amazirh A, Merlin O, Er-raki S, Gao Q, Rivalland V, Malbeteau Y, et al. Retrieving surface soil moisture at high spatio-temporal resolution from a synergy between Sentinel-1 radar and Landsat thermal data: A study case over bare soil. *Remote Sensing of Environment*. 2018;**211**:321-337. DOI: 10.1016/j.rse.2018.04.013
- [71] Merlin O, Duchemin B, Hagolle O, Jacob F, Coudert B, Chehbouni G, et al. Disaggregation of MODIS surface temperature over an agricultural area using a time series of Formosat-2 images. *Remote Sensing of Environment*. 2010;**114**:2500-2512. DOI: 10.1016/j.rse.2010.05.025
- [72] Sandholt I, Rasmussen K, Andersen J. A simple interpretation of the surface temperature/vegetation index space for assessment of surface moisture status. *Remote Sensing of Environment*. 2002; **79**:213-224. DOI: 10.1016/S0034-4257(01)00274-7
- [73] Moran MS, Clarke TR, Inoue Y, Vidal A. Estimating crop water deficit using the relation between surface-air temperature and spectral vegetation index. *Remote Sensing of Environment*. 1994;**49**:246-263. DOI: 10.1016/0034-4257(94)90020-5
- [74] Torres R, Snoeij P, Geudtner D, Bibby D, Davidson M, Attema E, et al. GMES Sentinel-1 mission. *Remote Sensing of Environment*. 2012;**120**:9-24. DOI: 10.1016/j.rse.2011.05.028
- [75] Baghdadi N, Gaultier S, King C. Retrieving surface roughness and soil moisture from synthetic aperture radar (SAR) data using neural networks. *Canadian Journal of Remote Sensing*. 2002;**28**(5):701-711. DOI: 10.5589/m02-066
- [76] Baghdadi N, Holah N, Zribi M. Soil moisture estimation using multi-incidence and multi-polarization ASAR data. *International Journal of Remote Sensing*. 2006;**27**:1907-1920. DOI: 10.1080/01431160500239032
- [77] Holah N, Baghdadi N, Zribi M, Bruand A, King C. Potential of ASAR/ENVISAT for the characterization of soil surface parameters over bare

- agricultural fields. *Remote Sensing of Environment*. 2005;**96**(1):78-86. DOI: 10.1016/j.rse.2005.01.008
- [78] Srivastava HS, Patel P, Manchanda ML, Adiga S. Use of multiincidence angle RADARSAT-1 SAR data to incorporate the effect of surface roughness in soil moisture estimation. *IEEE Transactions on Geoscience and Remote Sensing*. 2003. DOI: 10.1109/TGRS.2003.813356
- [79] Zribi M, Baghdadi N, Holah N, Fafin O. New methodology for soil surface moisture estimation and its application to ENVISAT-ASAR multi-incidence data inversion. *Remote Sensing of Environment*. 2005;**96**(3-4):485-496. DOI: 10.1016/j.rse.2005.04.005
- [80] Vereecken H, Huisman JA, Bogaen H, Vanderborght J, Vrugt JA, Hopmans JW. On the value of soil moisture measurements in vadose zone hydrology: A review. *Water Resources Research*. 2008;**44**:1-21. DOI: 10.1029/2008WR006829
- [81] Blackmore BS, Griepentrog HW. A future view of precision farming. In: *Proc. PreAgro Precision Agriculture Conf. Munchenberg, Gemrnay: Centre for Agricultural Landscape and Land Use Research (ZALF)*; 2002. pp. 131-145
- [82] Okin GS. Relative spectral mixture analysis: A multitemporal index of total vegetation cover. *Remote Sensing of Environment*. 2007;**106**:467-479. DOI: 10.1016/j.rse.2006.09.018. Toulouse
- [83] González-Dugo MP, Mateos L. Spectral vegetation indices for benchmarking water productivity of irrigated cotton and sugarbeet crops. *Agricultural Water Management*. 2008;**95**:48-58
- [84] Kamble B, Kilic A, Hubbard K. Estimating crop coefficients using remote sensing-based vegetation index. *Remote Sensing*. 2013;**5**:1588-1602. New York
- [85] Allen RG, Pereira LS, Raes D, Smith M. *Crop Evapotranspiration-Guidelines for Computing Crop Water Requirements, Irrigation and Drain*, Paper No. 56. Rome, Italy: FAO; 1998. p. 300
- [86] Bellvert J, Zarco-Tejada PJ, Girona J, Fereres E. Mapping crop water stress index in a "pinot-noir" vineyard: Comparing ground measurements with thermal remote sensing imagery from an unmanned aerial vehicle. *Precision Agriculture*. 2014;**15**:361-376
- [87] Idso SB, Baker DG. Relative importance of reradiation, convection and transpiration in heat transfer from plants. *Plant Physiology*. 1967;**42**: 631-640
- [88] Colaizzi PD, O'shaughnessy SA, Evett SR, Howell TA. Using plant canopy temperature to improve irrigated crop management. In: *24th Annual Central Plains Irrigation Conference*. Colby KS: CPIA; 2012
- [89] Dutta R, Morshed A, Aryal J, D'este C, Das A. Development of an intelligent environmental knowledge system for sustainable agricultural decision support. *Environmental Modelling & Software*. 2014;**52**:264-272
- [90] Moran MS, Inoue Y, Barnes EM. Opportunities and limitations for image-based remote sensing in precision crop management. *Remote Sensing of Environment*. 1997;**61**:319-346
- [91] Wood GA, Taylor JC, Godwin RJ. Calibration methodology for mapping within-field crop variability using remote sensing. *Biosystems Engineering*. 2003;**84**:409-423
- [92] Fitzgerald GJ, Lesch SM, Barnes EM, Lueckett WE. Directed sampling using remote sensing with a response

surface sampling design for site-specific agriculture. *Computers and Electronics in Agriculture*. 2006;**53**:98-112

[93] Pinter PJ Jr, Hatfield JL, Schepers JS, Barnes EM, Moran MS, Daughtry CS, et al. Remote sensing for crop management. *Photogrammetric Engineering & Remote Sensing*. 2003;**69**:647-664

[94] Trout TJ, Johnson LF, Gartung J. Remote sensing of canopy cover in horticultural crops. *HortScience*. 2008;**43**:333-337

[95] Barker JB, Heeren DM, Neale CMU, Rudnick DR. Evaluation of variable rate irrigation using a remote-sensing-based model. *Agricultural Water Management*. 2018;**203**:63-74

[96] Hunsaker DJ, Barnes EM, Clarke TR, Fitzgerald GJ, Pinter PJ Jr. Cotton irrigation scheduling using remotely sensed and FAO-56 basal crop coefficients. *Transactions of ASAE*. 2005;**48**:1395-1407

[97] Bergamaschi H, Dalmago GA, Bergonci JI, Bianchi CAM, Muller AG, Comiran F, et al. Distribuição hídrica no período crítico do milho e produção de grãos. *Pesquisa Agropecuária Brasileira*, Brasília. 2004;**39**:831-839

[98] Valín MI, Cameira MR, Teodoro PR, Pereira LS. DEPIVOT: A model for center-pivot design and evaluation. *Computers and Electronics in Agriculture*. 2012;**87**:159-170