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Fuzzy control system for variable rate irrigation using remote sensing

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ABSTRACT

Variable rate irrigation (VRI) is the capacity to spatially vary the depth of water application in a field to handle different types of soils, crops, and other conditions. Precise management zones must be developed to efficiently apply variable rate technologies. However, there is no universal method to determine management zones. Using speed control maps for the central pivot is one option. Thus, this study aims to develop an intelligent fuzzy inference system based on precision irrigation knowledge, i.e., a system that can create prescriptive maps to control the rotation speed of the central pivot. Satellite images are used in this study because remote sensing offers quick measurements and easy access to information on crops for large irrigation areas. Based on the VRI-prescribed map created using the intelligent decision-making system, the pivot can increase or decrease its speed, reaching the desired depth of application in a certain irrigation zone. Therefore, considering the spatial variability in the crop has made the strategy of speed control more realistic than traditional methods for crop management. The intelligent irrigation system pointed out areas with lower leaf development, indicating that the pivot must reduce its speed, thus increasing the water layer applied to that area. The existence of well-divided zones could be observed; each zone provides a specific value for the speed that the pivot must develop for decreasing or increasing the application of the water layer to the crop area. Three quarters of the total crop area had spatial variations during water application. The set point built by the developed system pointed out zones with a decreased speed in the order of 50%. From the viewpoint of a traditional control, the relay from pivot percent timer should have been adjusted from 70% to 35% whenever the central pivot passed over that specific area. The proposed system obtained values of 37% and 47% to adjust the pivot percent timer. Therefore, it is possible to affirm that traditional control models used for central-pivot irrigators do not support the necessary precision to meet the demands of speed control determined by the developed VRI systems. 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.

1. Introduction

The Food and Agriculture Organization (FAO) of the United Nations estimates that to meet food demands in 2050 agriculture production must at least double or triple in the next 40 years, and 80% of this increase must come from increasing the production. Considering the limited resources of our planet, reaching this goal will be challenging (FAO, 2016).

The adoption of irrigated agriculture enables increased productivity and the production of several crops (Borghetti, Silva, Nocko, Loyola, & Chianca, 2017). However, with the growing limitation of water resources, the use of water in agriculture must be more efficient to maintain the current levels of productivity in conjunction with the expansion of irrigated areas. Decisions for irrigation management require taking into consideration inter-related

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economic, physical, and biological variables, which are frequently difficult to foresee and over which there is little or no control (Herrera, Ibeas, & de la Sen, 2013). The decade-long search for automated solutions to improve agricultural application for more efficient use (Evans & King, 2012; Gilley, Mielke, & Wilhelm, 1983; Omary, Camp, & Sadler, 1997; Sadler, Camp, Evans, & Usrey, 1996) has resulted in the introduction of several solutions for agricultural inputs to conduct water application with spatial correction. Irrigation systems that operate using variable rate water application are required for a spatial water management to increase crop efficiency (Armindo, Botrel, & Garzella, 2011).

Decision support systems for irrigation and water conservation are used intensely for minimizing water application and maximizing yield. However, the numerical optimization of irrigation systems is computer-intensive and often requires simplification and discretization of the model (Dogan, Gumrukcuoglu, Sandalci, & Opan, 2010; Navarro-Hellín, Martínez-del-Rincon, Domingo-Miguel, Soto-Valles, & Torres-Sánchez, 2016). Furthermore, sensorial system and model integration do not reflect the natural flow of the environment (Voinov & Shugart, 2013), creating significant limitations in performance. Control systems also do not reflect or satisfy the requirements of the final users due to the lack of domain knowledge capture (McIntosh et al., 2011). The use of advanced control techniques is a promising possibility. Literature shows that these tools can significantly improve irrigation systems and efficient use of water resources (McCarthy, Hancock, & Raine, 2013; Romero, Muriel, García, & Muñoz de la Peña, 2012). The final challenge of an environmental and agricultural support system is to overcome the uncertainty related to data quality and difficulties in remote sensing of large areas (Dutta, Morshed, Aryal, D'Este, & Das, 2014; McCarthy et al., 2013). Moreover, the inter-related economic, physical, and biological variables are multi-attributed vaguely and in subjective terms.

A neat approach to deal with such uncertain situations is found in the fuzzy set theory, which has now reached a mature state for expansion and application. Zadeh's paper "Fuzzy Sets" was published in 1965; since then, the theory of fuzzy sets has been used for writing more realistic decision support models. Fuzzy logic can analyze the imprecise information and is efficient in decision-making for vague and uncertain phenomena (Kweon, 2012). Specialized systems that used fuzzy logic in its inception have been successfully applied to problems concerning decision, control, diagnose, and classification (Castillo & Melin, 2008) because they are capable of managing intrinsic complex reasoning in an application area. In agriculture, the interface of these systems allows a natural and straightforward use, as a planning tool for the manager and farmer. In irrigation systems, the interaction between components is not always accurately defined. Fuzzy logic can be used in such systems for extracting inferences from an inaccurate input and for solving problems in this area (Thangavadivelu & Colvin, 1997). An irrigation system based on the fuzzy logic with simple rules is more attractive to most farmers (Bahat, Inbar, Yaniv, & Schneider, 2000) since these systems do not require a precise measurement or a precise model, which may be very complicated and require considerable funds, resources and development time.

This study is based on the premise that irrigation problems do not require precise measures. The support system to the fuzzy decision is considered useful due to its interactive nature and flexible approach (Kumar & Rajkumar, 2014; Raju & Kumar, 2005); therefore, the integration of fuzzy logic and irrigation planning issues in the field is very effective. Herein, several control techniques for VRI have been presented, of which some use fuzzy inference and neural networks for setting the amount of water required for irrigation (Bing et al., 2015; Giusti & Marsili-Libelli, 2015; Papadopoulos, Kalivas, & Hatzichristos, 2011; Papageorgiou, Kokkinos, & Dikopoulou, 2016). Other techniques focus on determining when to irrigate and instruments that show spatial differences among sectors in the same crop area (Montalvo et al., 2013; Omid et al., 2010; Rafea, Hassen, & Hazman, 2003).

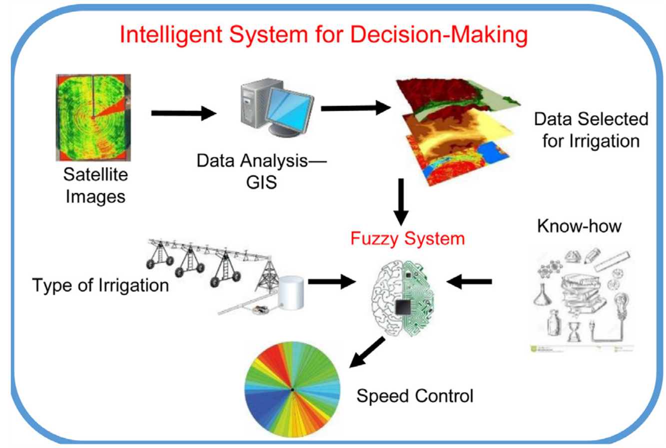

Fig. 1. Structure for the strategy of the intelligent irrigation system. *Source:* Author's archives.

However, all the techniques mentioned do not present control maps for the central pivot, as proposed herein. The problem examined herein is part of the crop production domain, approaching the issue of necessary decision-making for precision irrigation.

Therefore, the main objective of this study is to develop a fuzzy inference system that decides when to increase or decrease the speed of the central pivot by considering the spatial variability of the field and using little or imprecise information of the phenophase of the crop provided by satellite images.

2. Variable rate irrigation system (VRIS)

An intelligent irrigation system was developed by following the structure shown in Fig. 1. The structure of the proposed system allows the elaboration of the management map in a systematic, autonomous, and automatized way to control the irrigation system. The commercial systems used more frequently by farmers still cannot draw such a control map using the proposed technique.

2.1. Data

2.1.1. Normalized difference vegetation index (NDVI) and canopy temperature

Vegetation indexes generated from the data gathered by remote sensing constitute an important tool for monitoring natural or anthropogenic changes in the use and coverage of the land. These indexes have been used to estimate several vegetation patterns, such as leaf area index and green biomass quantity, as well as in the evaluation of soil use and the maintenance and recovery of degraded areas (Okin, 2007). Information from satellite images and values from the normalized difference vegetation index (NDVI) reading, which is an essential parameter for irrigation maintenance, were used and adjusted according to local conditions. Irrigation management through the plant shows the complexity inherent to the visualization of the symptoms of water deficit, which are difficult to detect. In certain occasions, problems are discovered when it is too late, i.e., when their effects have already compromised the production and quality of the product. Usually, these symptoms are related to the color tone of leaves, leaf curling, and leaf angle. However, a correlation between NDVI values and the basal crop coefficient (Kc) (Hunsaker, Barnes, Clarke, Fitzgerald, & Pinter, 2005; and Kamble, Kilic, & Hubbard, 2013) can be established since a strong correlation exists between estimated Kc (Kc-

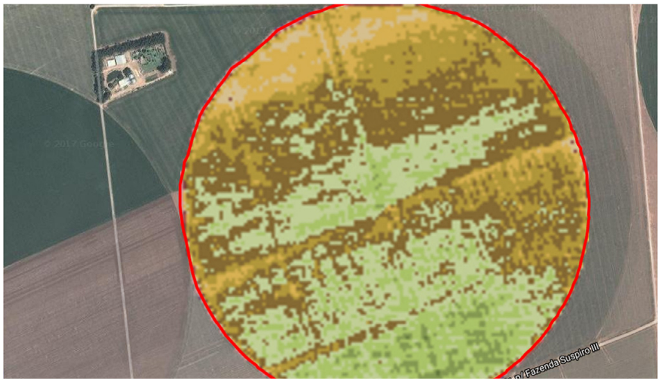

Fig. 2. Snapshot of the i-ekbase visual interactive system based on big data integration over large farming areas. *Source:* adapted from i-ekbase system.

NDVI) and observed Kc (Allen, Pereira, Raes, & Smith, 1998/FAO-56) in corn and soy crops for guiding irrigation times in the season.

The use of canopy temperature and infrared thermometry is another way to relate to the development of the crop through remote sensing. A plant under water stress has decreased transpiration and would typically show a higher temperature than a plant that is not under stress (Bellvert, Zarco-Tejada, Girona, & Fereres, 2014), a trait that could be used as a powerful tool to monitor and quantify water stress. Canopy temperature increases when solar radiation is absorbed (Idso & Baker, 1967), but it cools down when the latent energy or transpiration is used for evaporating water instead of cooling plant surfaces. Further, algorithms based on canopy temperature are strongly correlated with quantifiable results from crops (Colaizzi, O'Shaughnessy, Evett, & Howell, 2012), such as yield, water efficiency use, seasonal evapotranspiration, leaf water potential at noon, irrigation rates, and damage caused by herbicides.

2.2. Satellite imagery

The Intelligent Environmental Knowledgeable system (i-ekbase)[1] is an autonomous big data analytics engine running a CLOUD system. i-ekbase is an easy-to-use fully automated geographic information system (GIS). It primarily focuses on precision agricultural and biodiversity monitoring applications, automatically integrating data from various satellites with local weather data, farmers' knowledge, and applying Machine Learning techniques to create a data-driven future for global agriculture (Dutta et al., 2014). Fig. 2 illustrates the i-ekbase visual interactive system based on big data integration over large farming areas.

The i-ekbase is regularizing satellite remote sensing for all-purpose precision agricultural monitoring on a mobile device, for greater benefit to global agriculture community, and for increasing agriculture business profitability. The system services provide weekly or daily large area-wise resource management map products, including normalized vegetation index (NDVI), soil moisture, biomass, surface temperature, vegetation landscape maps for supporting remote digital scouting, large area-wise farm monitoring and decision support system, and rapid intervention of a management issue.

Herein, we used the i-ekbase system for capturing timely remote sensing imagery on the study site using Landsat (with a spatial resolution of 15 m) and Sentinel (with a spatial resolution of 10 m) satellites. Data were captured for 12 months for developing the experimental system.

[1] http://iekbase.com/.

Data that compose this image have over 14 thousand geo-referential points, which indicate a raster type structure, containing in each point or pixel that attributes for agricultural analysis. Given the size of the data, only a few lines are shown in Table 1. Different types of software are available on the market, which can generate maps from .shp,.kml, or CSV archives, such as Surfer (Golden Software, Inc.), ArcView (ESRI), and Global Mapper (Global Mapper), all requiring payment. QGIS is an open code licensed under General Public License GNU and will be used herein for pre-processing and editing the archive provided by the web tool i-ekbase.

After collecting the remote sensing data using the web tool i-ekbase (Table 1), the information is pre-processed to filter the data that are not required by the decision-making system. Thus, only canopy temperature, upper layer soil moisture, NDVI, and coordinates are considered (Table 2).

For applying this approach on a commercial scale, remote sensing data required to describe the soil–plant–atmosphere relation can be acquired from satellite images (Moran, Inoue, & Barnes, 1997) and airplanes (Fitzgerald, Lesch, Barnes, & Luckett, 2006; Wood, Taylor, & Godwin, 2003). However, high costs, spatial resolution, data frequency and data availability (Pinter et al., 2003; Trout, Johnson, & Gartung, 2008), as well as satellite cloudless images (Barker, Heeren, Neale, & Rudnick, 2018) are challenges for the correct execution of models based on remote sensing; these factors can limit the efficiency of VRI management in real time.

Remote sensing data that accurately describe the soil–plant–atmosphere relationship was selected for the intelligent irrigation system at the crop location. In this stage, accurately choosing the best data is fundamental to ensure that the results are calculated correctly. A simple but promising approach uses culture coefficients from normalized differentiated variation indexes, combined with local climate data, to assume the amount of ETc (evapotranspiration) of variable crops almost at real time (Er-Raki et al., 2007; Gonzalez-Dugo & Mateos, 2008; Hunsaker et al., 2005).

With some consideration of the daily meteorological conditions, models based on remote sensing can be used in studies of water relations (Barker et al., 2018) in the soil–plant–atmosphere system and could become an easy-to-use and fast response tool. Canopy temperature is also an important parameter to manage irrigation and must be adjusted according to local crop conditions. From the location selected for cultivation and the type of crop to be irrigated, in relation to the data linked to the type of plant, a crop coefficient will be used together with information from satellite images. In this case, NDVI reading, upper layer soil moisture, and canopy temperature values will be used.

2.3. Crop area

The crop area is a farm at Primavera do Leste, Mato Grosso state, Brazil, latitude 15°14′24.73′′S and longitude 54°0′53.29′′W. This area contains several crops, such as soy, cotton, and "safrinha" corn, irrigated by a central pivot. The delimited area is 140 ha, with a radius of 667 m (see Fig. 3). The area delimited by the red circle is irrigated with a central pivot, and the information used in this study is for a cultivation cycle of "safrinha" corn in 2015/2016. To irrigate "safrinha" corn means to provide minimum water conditions for the development of the crop. Corn is highly sensitive to drought. Therefore, the occurrence of a period of lower water intake by plants in critical moments for the development of the crop, from flowering to physiological maturation, can lead to the lower yield. For maximum yield, corn plantation needs approximately 650 mm of water (Bergamaschi et al., 2001) during its cycle,

Table 1
Data exported from the web tool i-ekbase.

Latitude	Longitude	Canopy nitrogen (%)	Leaf area index (m^2/m^2)	NDVI (%)	Biomass (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

Source: adapted from the i-ekbase system (2017).

Table 2
Pre-processed data.

Latitude	Longitude	NDVI (%)	Upper layer 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

Source: adapted from the i-ekbase system (2017).

Fig. 3. Images from the area under study. *Source:* Author's archives.

which varies from 110 to 140 days in hybrids with an average cycle.

Plant development is made evident by the images captured by remote sensing during growth. After analyzing the NDVI values contained in Fig. 4, the similarity among values attributed to crop coefficient (Kc) can be verified (Hunsaker et al., 2005; and Kamble et al., 2013). As the crop develops, the leaf area increases, which makes it possible to establish a NDVI relationship.

This process is also described by Hunsaker et al. (2005), with relations for calculating the basal crop coefficient (Kcb) for cotton as a function of NDVI. When each of the development phases of the crop is analyzed, two distinct areas are evident: one with little growth and another with average growth. From this differentiation, it is possible to build a water demand map as well as speed control maps. For the preliminary analysis, the daily average precipitation data made available by National Institute of Meteorology[2] (INMET) were used. Data were collected from April to September 2016 in the municipality of Primavera do Leste, Mato Grosso state, Brazil. Fig. 5 illustrates the obtained data. Finally, precipitation readings recorded during the development of the crop under study corroborate with the premise of water stress due to the lack of rain, which would indicate the possibility of complementing the water demand with irrigation.

2.4. Fuzzy systems

Over the last 20 years, fuzzy systems have attracted considerable attention and have met great applicability in the agricultural domain, helping farmers to make the right decisions for their crops (Papageorgiou et al., 2016). For example, Bahat et al. (2000) proposed a solution for an irrigation controller based on the fuzzy logic methodology with simple rules, making the system more attractive for farmers. Raj and Kumar (2005) observed that the integration of fuzzy logic and real-world irrigation planning problems are very useful, particularly with multiple specialists in a subjective data environment.

Upon using fuzzy systems for decision-making concerning irrigation, Zhang, Fei, Wei, Congcong, and Yuewei (2011) reported that fuzzy logic does not require all the relevant information for solving the problem of water in irrigation. Bing, Huifeng, and Xia (2015) developed a fuzzy system of decision-making for solving uncertainties and non-linearity of the irrigation system, and the model showed high precision.

The system of fuzzy inference proposed by Almeida, Vieira, Marques, Kiperstok, and Cardoso (2013), in turn, provided a conceptual approach based on the multi-criteria decision-making process. This approach relates water use to environmental factors, such as drought, water exploration index, water use, population density, and wastewater treatment index, resulting in warnings about future water supply. Irrigation based on the fuzzy inference system presents better results than traditional methods. The fuzzy system will be used to infer the variations in the linear movement speed of the pivot according to satellite images. An intelligent system was developed, manipulating various data-driven approaches to create a control map.

Due to the nature of the management of the study area, fuzzy systems are used herein to aid irrigation decision-making. Because a farmer's decisions are purely intuitive and knowledge-based gained over years of work, we chose not to describe the way the farm works explicitly. Another critical piece in the farmer's

[2] https://www.agritempo.gov.br/agritempo/jsp/Grafico/graficoMicrorregiao.jsp?siglaUF=MT.

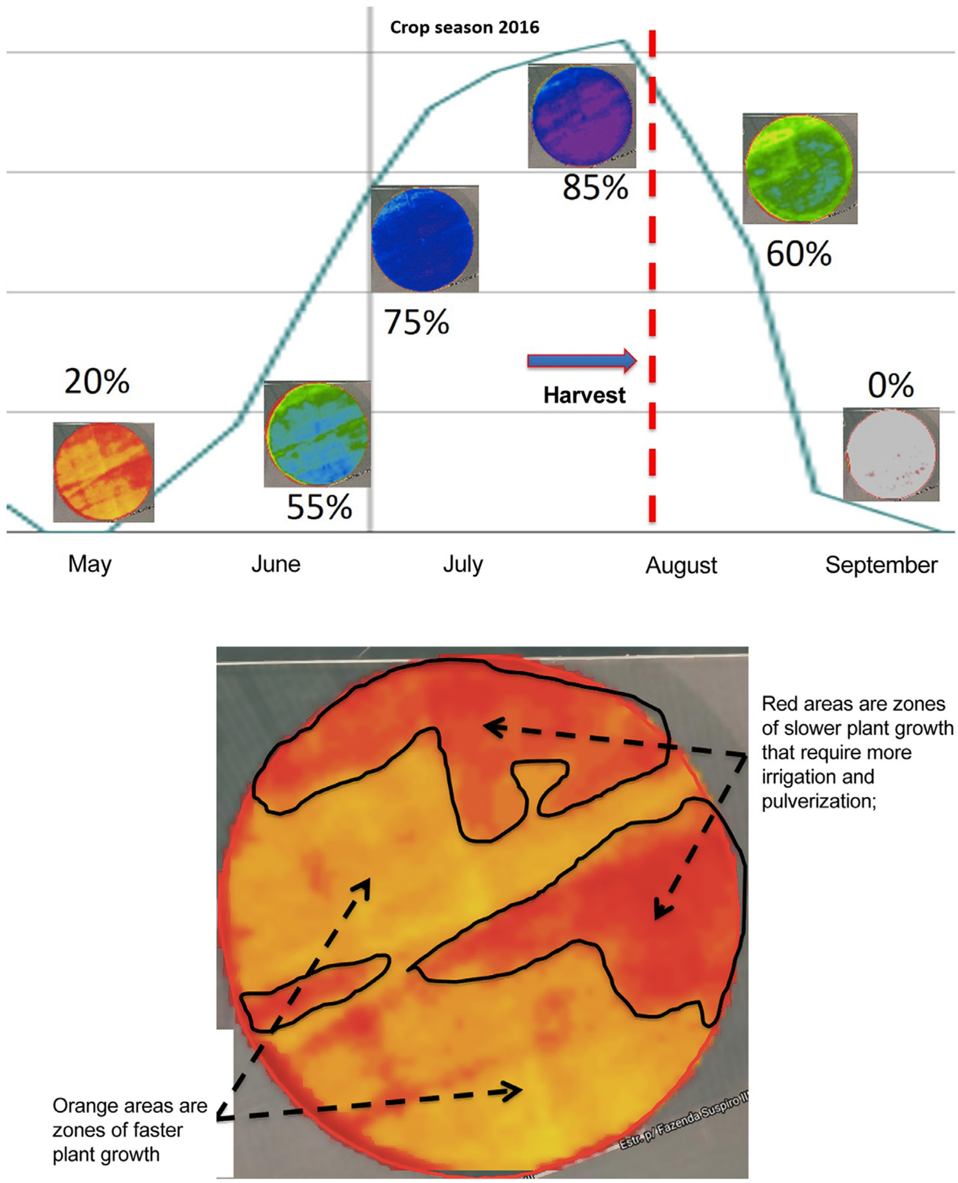

Fig. 4. NDVI variation in a crop cycle. *Source:* Author's archives.

routine was that the pivot utilized extensive amount of time to perform a full turn. However, the central pivot irrigation system should operate 21 h a day, with 3 h for maintenance because high electricity prices are charged by the utility. Three input variables were used (NDVI, upper layer soil moisture, and canopy temperature) to infer the speed, which the central pivot has to reach to improve the irrigation level within the crop area, and to find an adequate speed for the pivot movement in relation to the amount of water coming out of the sprinklers.

Futhermore, a decision unit or inference machine is implemented using the Mamdani method to conduct the rule-based inference operations with crisp input and crisp output. Mamdani fuzzy systems use fuzzy sets as a consequent rule; therefore, the inference method for a set of conjunctive rules for the rth rule will be given by the following condition:

$$If\ x_1\ is\ A_1^k\ and\ x_2\ is\ A_2^k,\ then\ y^k\ is\ B^k\ for\ k = 1, 2, 3, \cdots, r. \quad (1)$$

Within the objective proposed for the developed system, once linguistic variables are applied to the output of fuzzy inference systems, it becomes fitter for modeling the human reflection process.

Table 3
Fuzzy set input for the fuzzy inference system.

Input variables	Linguistic variables		
	Low	Average	High
Canopy Temperature [°C]	<14	14< ϕ <27	>24
Upper Layer Soil Moisture [%]	<14	12< ϕ <24	>21
NDVI [%]	<16	12< ϕ <27	>27

Source: Authors.

By doing so, the interface of the system becomes more straightforward and natural. In the first stage of development, the water layer provided by the irrigation system is considered constant. The database that defines the association functions of sets used in the fuzzy rules is implemented according to Table 3 and Fig. 6.

Remote sensing data allow building the universe of discourse for each input variable and therefore change the database into linguistic variables, as shown in Table 3. Each input was previously limited to the discourse universe in question and associated to the grade of membership in each fuzzy set through specialized knowledge. Therefore, to obtain the grade of membership of a certain

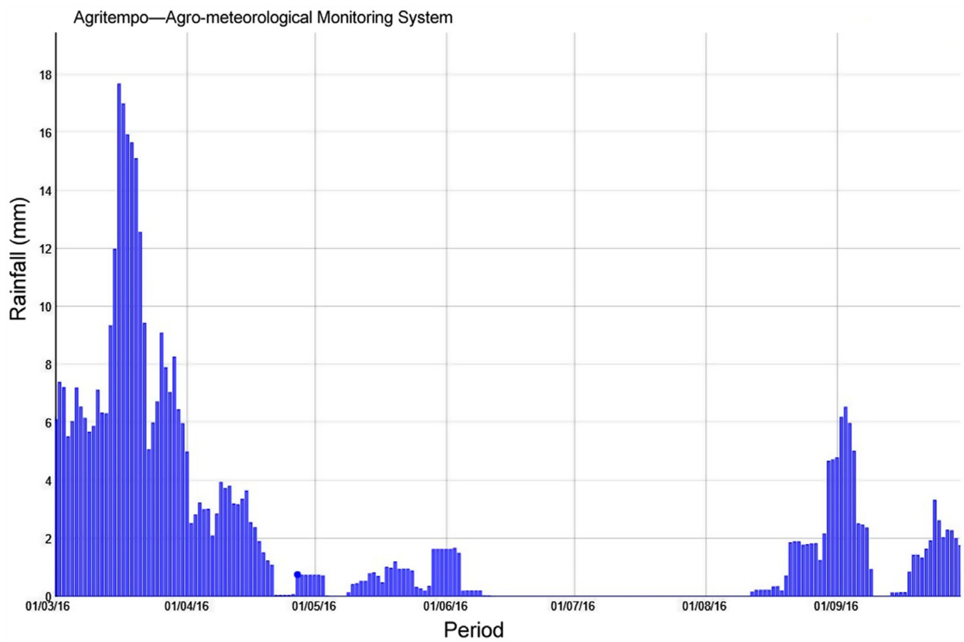

Fig. 5. Average precipitation obtained in 2016. *Source:* Agritempo—Agro-meteorological Monitoring System.

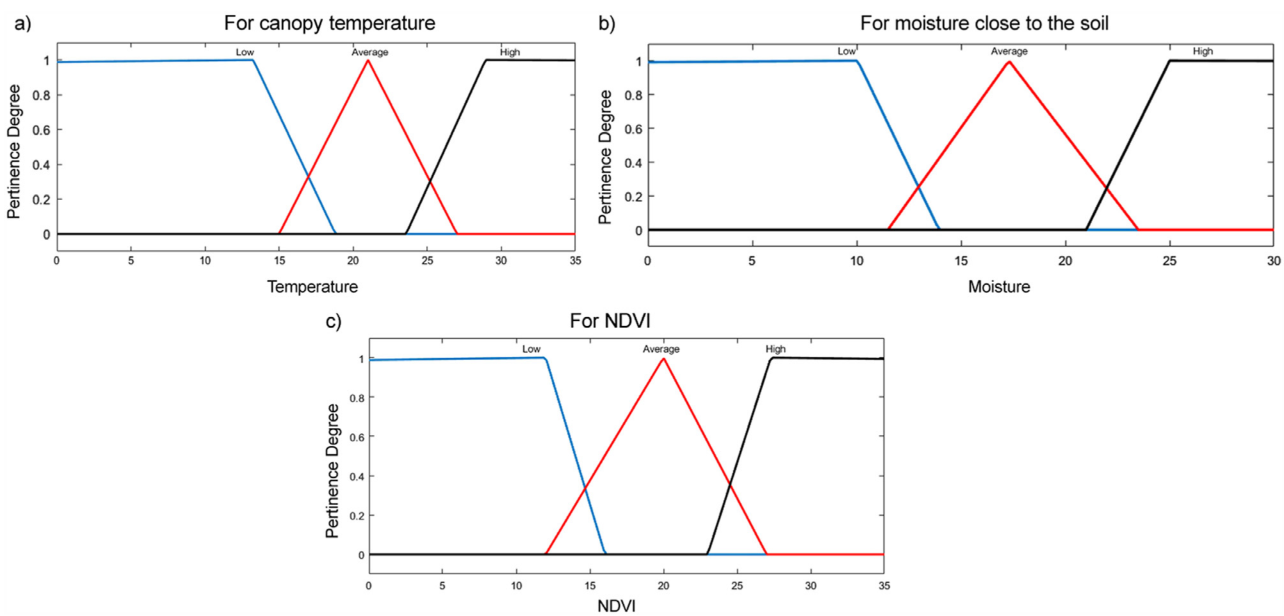

Fig. 6. Membership functions corresponding to each system input. *Source:* Author's archives.

crisp input, one must search for this value in the fuzzy system knowledge.

The *fuzzification* of the decision-making system in Fig. 6 helps to visualize the corresponding membership functions, considering these intervals as the discourse universe of the variables. Triangular membership functions were chosen because they simplify the calculation of the fuzzy inference mechanism and couple to the fuzzy rules IF-THEN (Wang, 1997). Well distributed triangular membership functions change input data into fuzzy values (low, average, and high), as shown in Fig. 6a, as well as values for soil moist and NDVI (Fig. 6b and c, respectively).

Fuzzy outputs, which represent the rotation speed of the central pivot, were built from five linguistic variables: very low (MB), low (B), normal (N), high (A), and very high (MA). All the sets were interpreted based on their membership functions, as shown in Fig. 7. Several defuzzification methods have been proposed (Dubois & Prade, 2000), of which CENTROID (area center or center of gravity) is more widely used. For this method, a clear value of the output variable is calculated by finding the variable for the center of gravity of the association function for the fuzzy value (Jang, Sun, & Mizutani, 1997) as follows:

$$u^* = \frac{\sum_{j=1}^{N} u_i \times u_{out}(u_i)}{\sum_{j=1}^{N} u_{out}(u_i)}, \tag{2}$$

where $u_{out}(u_i)$ is the area of a grade of membership modified by the fuzzy inference result and u_i is the position of the centroid of the individual membership functions.

Finally, the fuzzy rule relating to rotation speed contains 27 rules, as summarized in Table 3. Therefore, the reading of the

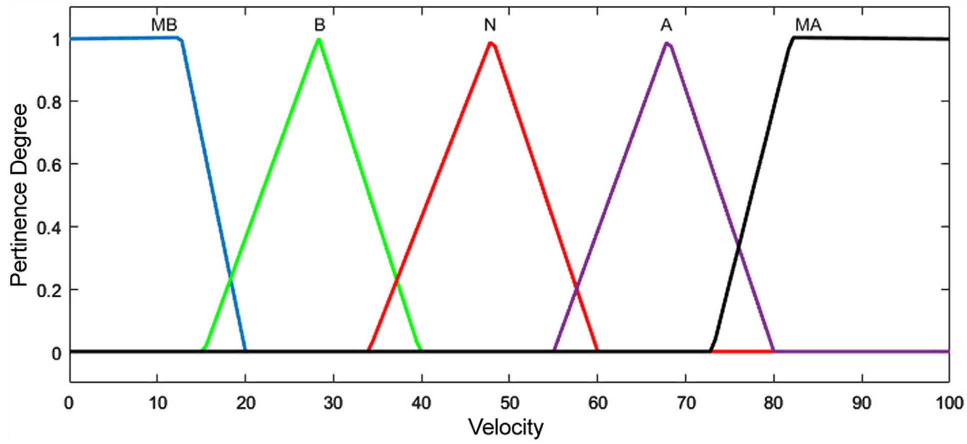

Fig. 7. Membership functions for the speed corresponding to the stage of *defuzzification.* Membership functions (Velocity). *Source:* Author's archives.

Table 4
Fuzzy rules for speed control of the central pivot.

Fuzzy inputs			Fuzzy outputs
NDVI	Canopy temperature	Upper layer soil moisture	Rotation speed
Low	Low	Low	Low
Low	Low	Average	Low
⋮	⋮	⋮	⋮
Low	Low	High	Very Low
Low	Average	High	Very Low
⋮	⋮	⋮	⋮
Average	Average	Low	Normal
Average	Average	Average	Normal
Average	Average	High	High
⋮	⋮	⋮	⋮
Average	High	Average	High
High	Low	Average	Very High
High	Low	High	Very High

Source: Authors.

first line, for example, is IF NDVI = Low AND Canopy Temperature = Low AND Soil Moisture = Low THEN Rotation Speed = Low. This set of rules is based on basic knowledge of irrigation, according to the methodology adopted in Bernardo, Soares, and Mantovani (2006) and Silva and Azevedo (1998).

The rules were elaborated with the connective "AND" and are based on the premise that little leaf growth is due to water deficit in the soil (Boyer, 1968; Hsiao, 1973; Wright, 1977) along with high canopy temperature, which indicates low evapotranspiration, in other words, plants under water stress. Values of moisture close to the soil given by the web tool are local readings of spots with fewer leaves, making it possible to estimate its value.

3. Results and discussion

3.1. Control maps for pivot rotation speed

For mapping the speed control system herein, eight crop areas were stipulated with a level of ambiguity regarding the impact of the variable application rate (Feinerman & Voet, 2000), given that an increase in the flexibility of input application through field subdivision in a higher number of management unities did not necessarily lead to a reduction in the total (optimal) water use. The images showing different growth stages of the plantation were analyzed. The development stage [Kc-Development] was the one that presented the highest water stress in different planted areas, as shown in Table 5. Furthermore, performing the analysis of critical point was essential to demonstrate the applicability of fuzzy systems to create the control maps.

The information extracted after pre-processing remote sensing data was NDVI, canopy temperature, and upper layer soil moisture. These values are the input data set for the fuzzy system, which is capable of inferring percentages for the central pivot rotation speed motion. The case study corresponds to the sampling of two readings obtained from different dates of the crop cycle: the first on June 15, 2016 and the second on June 28, 2016.

Table 5
Analysis of the best dates for the case study.

Growth stage	Crop coefficients [Kc]	Input data satellite imagery	Walter stress detect	Case study
Emergence 2 leaves 4–6 leaves	Initial	May 2016	Less critical	Lower leaf
6–8 leaves 10–12 leaves 12–16 leaves	Development	June 2016	Critical	June 15 June 28
Tassel emerging Pollination and silks Blister Milk stage	Mid-Season	July 2016	No Critical	Out of scope
Dough Dent Beginning black layer Maturity	Late-Season	August 2016	No Critical	Out of scope

Adapted from Ritchie, S.W., J. J. Hanway, and G. O. Benson. 1993. How a corn plant develops. Spec. Rep. 48 (revised). Iowa State Univ. of Sc. and Technol. Coop. Ext. Serv., Ames, IA.

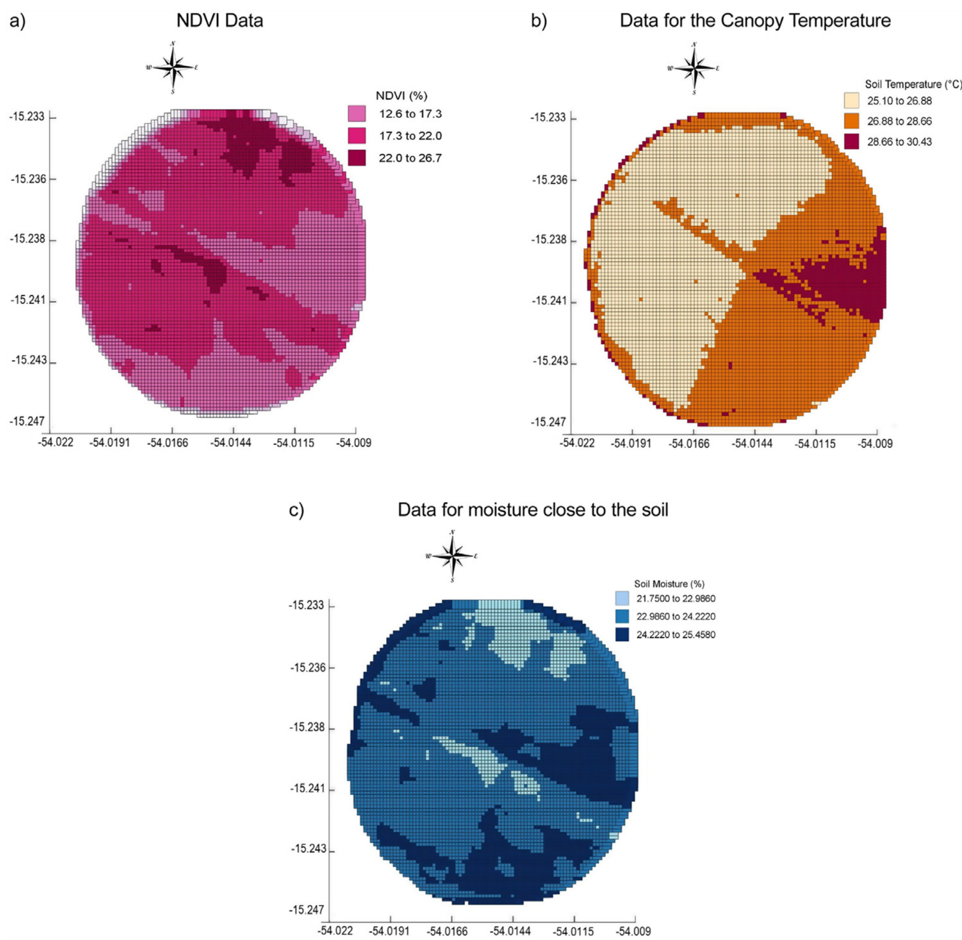

Fig. 8. Input data in the fuzzy inference system. *Source:* Author's archives.

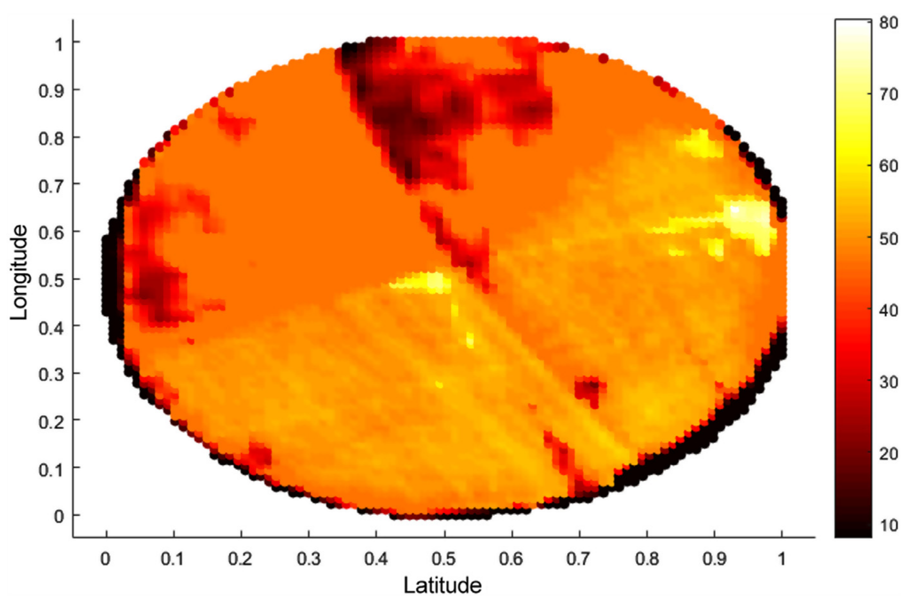

Fig. 9. Output data for the fuzzy inference system: rotation speed of the central pivot. *Source:* Author's archives.

3.2. Case study on June 15th, 2016

The input set for the intelligent fuzzy system is the analyzed and processed data on canopy temperature, moisture close to the soil, and NDVI (see Table 2) illustrated in Fig. 8a–c. The input, as shown in Fig. 8, was organized according to the linguistic variables of the fuzzy system and separated by tones for better visualization. Due to the nature of the central pivot speed control equipment, the output given by the fuzzy system was in percentage values. The per centimeter, which was responsible for rotational speed control,

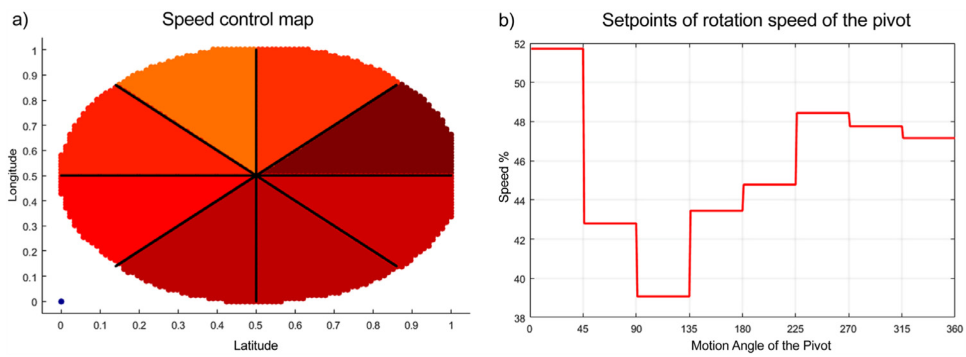

Fig. 10. Map for the pivot rotation speed control. *Source:* Author's archives.

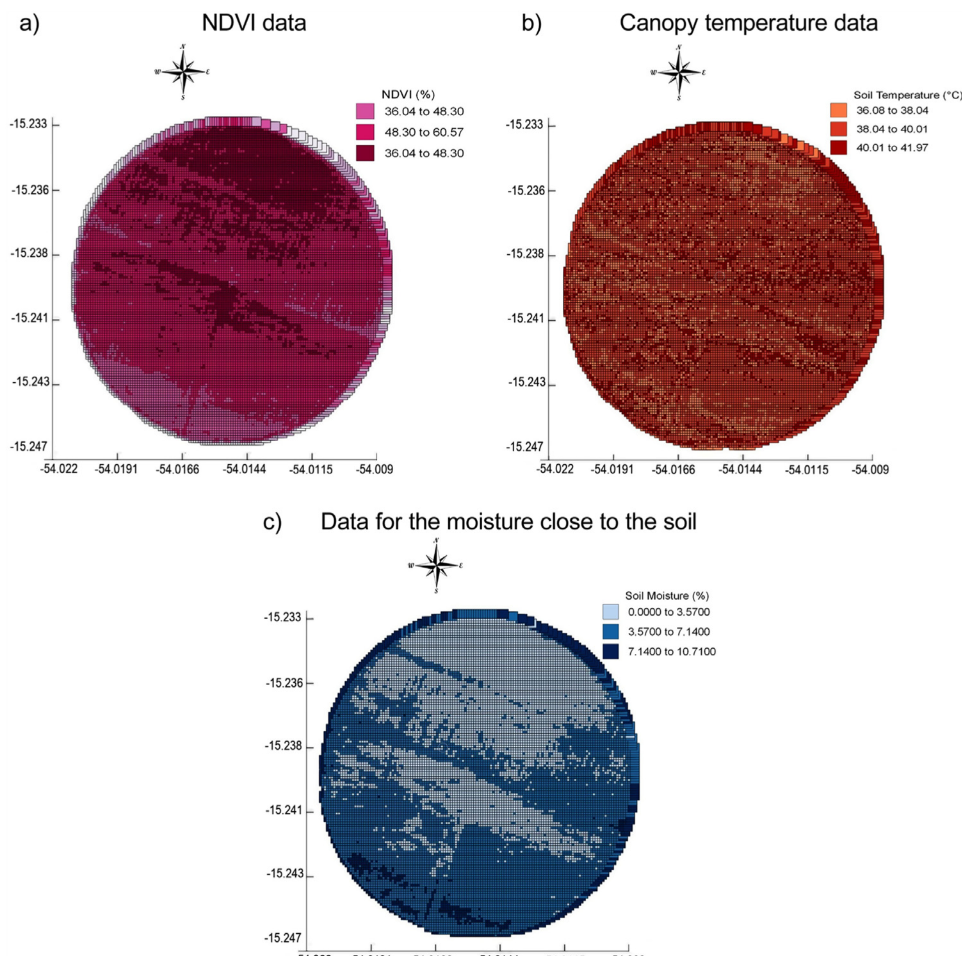

Fig. 11. Input data for the fuzzy inference system. *Source:* Author's archives.

used only the reference percentage of rotation in relation to the time of 60 s. Thus, for the values of 50% (represented in orange in Fig. 9), the control made the pivot stay in operation for 30 s and off for 30 s. The intelligent system obtained the result shown in Fig. 9, which illustrates different regions within the area, with different values for the pivot rotation speed.

Analysis of the input data identified the existence of two broad areas with lower leaf development, which could indicate a lack of water for development. After processing input data, the intelligent irrigation system showed these areas of lower leaf development in a more intense red tone. This indicates that the pivot must reduce its speed, thus increasing the water layer in that specific location, because the rotation speed of the pivot determines the level of the water layer applied. A thinner water layer is applied with higher speed and a higher application of water in the soil occurs with lower rotation speed (Valín, Cameira, Teodoro, & Pereira, 2012).

The expected result was the creation of control maps; in this case, it was possible to determine the reference speed values for eight initially programmed zones, as shown in Fig. 10. Moreover, areas that present different colors in Fig. 9 are shown in the control map result, which illustrates the existence of well-divided zones. In each one, a specific value is observed for the speed that the pivot must reach to increase or decrease the water layer in the crop area.

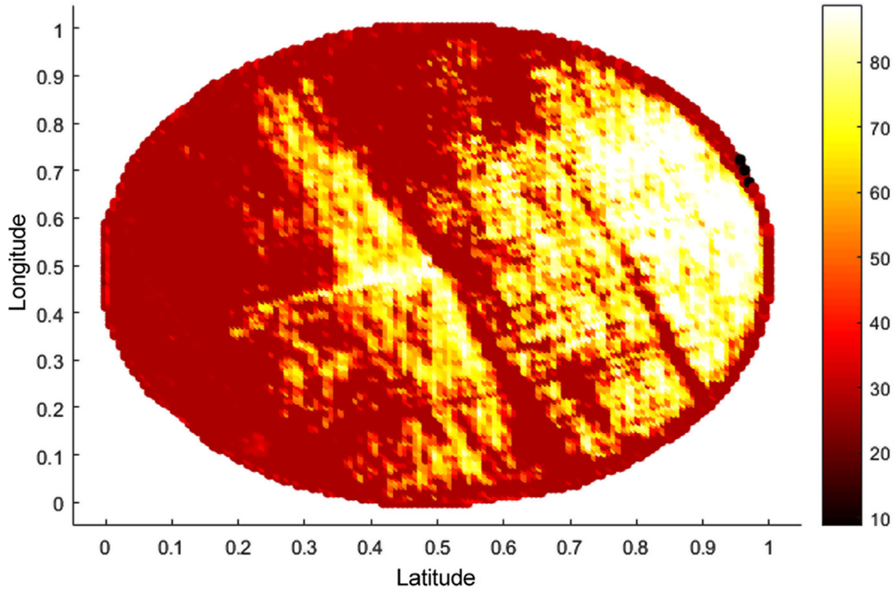

Fig. 12. Output data for the fuzzy inference system: speed rotation for the pivot. *Source:* Author's archives.

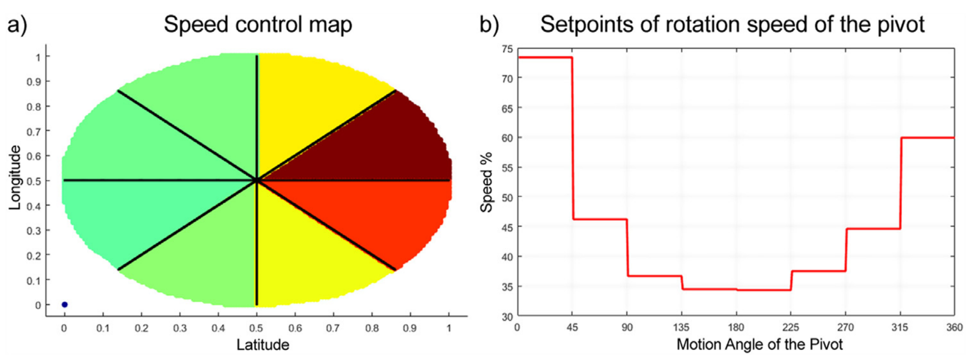

Fig. 13. Map for the rotation speed control of the pivot. *Source:* Author's archives.

The result shown in Fig. 9b corresponds to reference values, which must be sent to the pivot controller, since the control system of these works with a percentage of the speed rotation, known as the percentimeter.

3.3. *Case study on June 28th, 2016*

Data analyzed and processed by the SIG can be used as inputs for the fuzzy intelligent system. Fig. 11 shows the NDVI images, temperature images, and soil moisture images.

The case study on June 28th included the values of input variables for the fuzzy system with linguistic definitions necessary for interpretation.

The intelligent system of irrigation obtained the result shown in Fig. 12, which illustrates different regions within the crop area with different values of pivot rotation. A higher rotation speed implies the application of a thinner water layer, and a lower rotation speed leads to more water application in the soil, given that the application flow is kept constant in the sprinklers.

Once the satellite images are compared again, NDVI and canopy temperature are essential for the decision-making process of the intelligent irrigation system. The large areas with a lower leaf development could indicate a lack of water for development. In the case of the output of the intelligent irrigation system, more intense red areas indicate that the pivot must reduce its speed.

In this study, the reference values of the rotation speed of the pivot for the eight initially programmed zones of irrigation were determined, as shown in Fig. 13. In this result, the areas with different colors in Fig. 12 are the result of the control map constructed and are shown in Fig. 13. Irrigation zones were well divided, which makes it possible to see an absolute value for the rotation speed of each pivot, increasing and decreasing the water layer applied to the cultivation area. The result shown in Fig. 13b corresponds to reference values to be sent to the pivot controller.

4. Conclusion

The developed fuzzy system for irrigation control is original and innovative. No similar discussion in the scientific literature about speed control maps of the central pivot was found. Furthermore, there is no information available on commercial systems that can autonomously build this type of map. Experiments demonstrated the potential effectiveness of the pivot operation based on the differences between velocities by management zones. The system follows the definition of VRI; once the speed changes, there are changes in the amount of supplied water. In this context, fuzzy logic can be applied widely in agricultural areas; therefore, a decision support system can be build that has the knowledge of precision irrigation.

The implementation of fuzzy logic decision support system was successful to develop prescription maps for VRI with central pivots. However, a broader and commercial application will depend on the integration of data collection systems, management strategies, and hardware control. In other words, the fuzzy logic model performed as expected, providing excellent results. However, the reliability of data sources (NDVI, surface soil water, and canopy temperature) to develop a reliable prescription map is the scope of future study. The future study will focus on the field implementations and determine whether any additional data (different types of data, high-quality data, and/or more frequent data) will be required for developing the map.

In this analysis, the rotation speed control extracted through inference does not consider the volume of the water layer to be applied. The interpretation given by the fuzzy system is as follows: where there is variation in the plant growth, there will be variation in water demand. To solve this, more data should be collected to validate the system for various scenarios in near future. The results were favorable to the continuity of studies on precision irrigation and application of the fuzzy logic for creating central pivots irrigation systems maps. Future research should implement this decision support system into field trials to evaluate its ability to reduce irrigation pumping and/or improve crop yield.

Contributorship statement

The authors Willians Ribeiro Mendes, Fábio Meneghetti U. Araújo, Ritaban Dutta, and Derek M. Heeren; declare that they are responsible for the preparation of the manuscript entitled FUZZY CONTROL SYSTEM FOR VARIABLE RATE IRRIGATION USING REMOTE SENSING. Below are described each contribution:

Willians Ribeiro Mendes, conceived the original idea; designed the model and the computational framework and analysed the data and carried out the implementation. And wrote the manuscript with input from all authors.

Ritaban Dutta, and Derek M. Heeren, analyzed the experimental data, drafted the manuscript and contributed to the design and implementation of the research, to the analysis of the results and to the writing of the manuscript.

Fábio Meneghetti U. Araújo conceived the study and were in charge of overall direction and planning. And supervised the findings of this work.

All authors discussed the results and contributed to the final manuscript.

Thus, they declare that they had sufficient participation in the work to assume responsibility for the total content.

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References

Allen, R. G., Pereira, L. S., Raes, D., & Smith, M. (1998). *Crop evapotranspiration-guidelines for computing crop water requirements, irrigation and drain* (p. 300). Rome, Italy: FAO. Paper No. 56.

Almeida, G., Vieira, J., Marques, A. S., Kiperstok, A., & Cardoso, A. (2013). Estimating the potential water reuse based on fuzzy reasoning. *Journal of Environmental Management, 128*, 883–892.

Armindo, R. A., Botrel, T. A., & Garzella, T. C. (2011). Flow rate sprinkler development for site-specific irrigation. *Irrigation Science, 29*, 233–240.

Bahat, M., Inbar, G., Yaniv, O., & Schneider, M. (2000a). A fuzzy irrigation controller system. *Engineering Applications of Artificial Intelligence, 13*, 137–145.

Barker, J. B., Heeren, D. M., Neale, C. M. U., & Rudnick, D. R. (2018). Evaluation of variable rate irrigation using a remote-sensing-based model. *Agricultural Water Management, 203*, 63–74.

Bellvert, J., Zarco-Tejada, P. J., Girona, J., & Fereres, E. (2014). 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, 15*, 361–376.

Bergamaschi, H., Dalmago, G. A., Bergonci, J. I., Bianchi, C. A. M., Muller, A. G., Comiran, F., et al. (2004). Distribuição hídrica no período crítico do milho e produção de grãos. *Pesquisa Agropecuária Brasileira, Brasília, 39*, 831–839 (Water Distribution in the critical period of corn and grain production. *Brazilian Agropecuary Research, Brasilia*, 39, 831–839.

Bernardo, S., Soares, A. A., & Mantovani, E. C. (2006). *Manual de irrigação* (p. 625). Viçosa: UFV. p. (Irrigation Manual, 8th edition, Ed. UFV, Vicosa, 625p.).

Bing, Z., Huifeng, J., & Xia, H. (2015). Study on corn water saving irrigation decision–making model. *Advance Journal of Food Science and Technology, 9*, 9–12.

Borghetti, J. R., Silva, W. L. C., Nocko, H. R., Loyola, L. N., & Chianca, G. K. (2017). *Agricultura irrigada sustentável no Brasil: identificação de áreas prioritárias* p. 243 (Sustainable irrigated agriculture in Brazil: Identification of priority areas. 243p.).

Boyer, J. S. (1968). Relationship of water potential to growth of leaves. *Plant Physiology, 43*, 1056–1062.

Castillo, O., & Melin, P. (2008). *Type-2 fuzzy logic: Theory and applications* (pp. 5–28). Berlin Heidelberg: Springer-Verlag. https://doi.org/10.1007/978-3-540-76284-3.

Colaizzi, P. D., O'Shaughnessy, S. A., Evett, S. R., & Howell, T. A. (2012). Using plant canopy temperature to improve irrigated crop management. *24th Annual central plains irrigation conference CPIA, Colby KS*.

Dogan, E., Gumrukcuoglu, M., Sandalci, M., & Opan, M. (2010). Modelling of evaporation from the reservoir of Yuvacik dam using adaptive neuro-fuzzy inference systems. *Engineering Applications of Artificial Intelligence, 23*, 961–967.

Dubois, D., & Prade, H. (2000). *Fundamentals of fuzzy sets* (p. 647). Norwell, MA: Kluwer.

Dutta, R., Morshed, A., Aryal, J., D'Este, C., & Das, A. (2014). Development of an intelligent environmental knowledge system for sustainable agricultural decision support. *Environmental Modelling & Software, 52*, 264–272.

Er-Raki, S., Chehbouni, A., Guemouria, N., Duchemin, B., Ezzahar, J., & Hadria, R. (2007). Combining FAO-56 model and ground-based remote sensing to estimate water consumptions of wheat crops in a semi-arid region. *Agricultural Water Management, 87*, 41–54.

Evans, R. G., & King, B. A. (2012). Site-specific sprinkler irrigation in a water-limited future. *Transactions of the ASABE–Advances in Irrigation, 55*, 493–504.

FAO. (2016). *The state of food and agriculture. Climate change, agriculture and food security*: 2016. Rome: Food and Agriculture Organization of the United Nations.

Feinerman, E., & Voet, H. (2000). Site-specific management of agricultural inputs: an illustration for variable-rate irrigation. *European Review of Agricultural Economics, 27*, 17–37.

Fitzgerald, G. J., Lesch, S. M., Barnes, E. M., & Luckett, W. E. (2006). Directed sampling using remote sensing with a response surface sampling design for site-specific agriculture. *Computers and Electronics in Agriculture, 53*, 98–112.

Gilley, J. R., Mielke, L. N., & Wilhelm, W. W. (1983). An experimental center-pivot irrigation system for reduced energy crop production studies. *Transactions of ASAE, 26*, 1375–1379.

Giusti, E., & Marsili-Libelli, S. (2015). A fuzzy decision support system for irrigation and water conservation in agriculture. *Environmental Modelling & Software, 63*, 73–86.

González-Dugo, M. P., & Mateos, L. (2008). Spectral vegetation indices for benchmarking water productivity of irrigated cotton and sugarbeet crops. *Agricultural Water Management, 95*, 48–58.

Herrera, J., Ibeas, A., & de la Sen, M. (2013). Identification and control of integrative MIMO systems using pattern search algorithms: An application to irrigation channels. *Engineering Applications of Artificial Intelligence, 26*, 334–346.

Hsiao, T. C. (1973). Plant responses to water stress. *Annual Reviews of Plant Physiology, 24*, 519–570. doi:10.1146/annurev.pp.24.060173.002511.

Hunsaker, D. J., Barnes, E. M., Clarke, T. R., Fitzgerald, G. J., & Pinter, P. J. (2005). Cotton irrigation scheduling using remotely sensed and FAO-56 basal crop coefficients. *Transactions of ASAE, 48*, 1395–1407.

Idso, S. B., & Baker, D. G. (1967). Relative importance of reradiation, convection and transpiration in heat transfer from plants. *Plant Physiology, 42*, 631–640.

Jang, R. J. S., Sun, C. T., & Mizutani, E. (1997). *Neuro-fuzzy and soft computing*. Upper Saddle River: Prentice-Hall.

Kamble, B., Kilic, A., & Hubbard, K. (2013). Estimating crop coefficients using remote sensing-based vegetation index. *Remote Sensing, 5*, 1588–1602.

Kumar, S. U., & Rajkumar, A. (2014). Multicriterion fuzzy decision making in irrigation planning. *International Journal of Scientific and Research Publications-IJSRP, 4*, 1–7.

Kweon, G. (2012). Delineation of site-specific productivity zones using soil properties and topographic attributes with a fuzzy logic system. *Biosystems Engineering, 112*, 261–277.

McCarthy, A. C., Hancock, N. H., & Raine, S. R. (2013). Advanced process control of irrigation: The current state and an analysis to aid future development. *Irrigation Science, 31*, 183–192.

McIntosh, B. S., Ascough, J. C., Twery, M., Chew, J., Elmahdi, A., Haase, D., et al. (2011). Environmental Decision Support Systems EDSS development: Challenges and best practices. *Environmental Modelling & Software, 26*, 1389–1402.
Montalvo, M., Guerrero, J. M., Romeo, J., Emmi, L., Guijarro, M., & Pajares, G. (2013). Automatic expert system for weeds/crops identification in images from maize fields. *Expert Systems with Applications, 40*(1), 75–82.
Moran, M. S., Inoue, Y., & Barnes, E. M. (1997). Opportunities and limitations for image-based remote sensing in precision crop management. *Remote Sensing of Environment, 61*, 319–346.
Navarro-Hellín, H., Martínez-del-Rincon, J., Domingo-Miguel, R., Soto-Valles, F., & Torres-Sánchez, R. (2016). A decision support system for managing irrigation in agriculture. *Computers and Electronics in Agriculture, 124*, 121–131.
Okin, G. S. (2007). Relative spectral mixture analysis—A multitemporal index of total vegetation cover. *Remote Sensing of Environment, 106*, 467–479.
Omary, M., Camp, C. R., & Sadler, E. J. (1997). Center pivot irrigation system modification to provide variable water application depths. *Applied Engineering in Agriculture, 13*, 235–239.
Omid, M., Lashgari, M., Mobli, H., Alimardani, R., Mohtasebi, S., & Hesamifard, R. (2010). Design of fuzzy logic control system incorporating human expert knowledge for combine harvester. *Expert Systems with Applications, 37*(10), 7080–7085.
Papadopoulos, A., Kalivas, D., & Hatzichristos, T. (2011). Decision support system for nitrogen fertilization using fuzzy theory. *Computers and Electronics in Agriculture, 78*, 130–139.
Papageorgiou, E. I., Kokkinos, K., & Dikopoulou, Z. (2016). Fuzzy sets in agriculture. In C. Kahraman, U. Kaymak, & A. Yazici (Eds.), *Fuzzy logic in its 50th year. Studies in fuzziness and soft computing* (p. 341). Cham: Springer. https://doi.org/10.1007/978-3-319-31093-0_10.
Pinter, P. J., Hatfield, J. L., Schepers, J. S., Barnes, E. M., Moran, M. S., Daughtry, C. S., et al. (2003). Remote sensing for crop management. *Photogrammetric Engineering & Remote Sensing, 69*, 647–664.
Rafea, A., Hassen, H., & Hazman, M. (2003). Automatic knowledge acquisition tool for irrigation and fertilization expert systems. *Expert Systems with Applications, 24*(1), 49–57.
Raju, K. S., & Kumar, D. N. (2005). Fuzzy multicriterion decision making in irrigation planning. *Irrigation and Drainage, 54*, 455–465.
Romero, R., Muriel, J. L., García, I., & Muñoz de la Peña, D. (2012). Research on automatic irrigation control: State of the art and recent results. *Agricultural Water Management, 114*, 59–66.
Sadler, E. J., Camp, C. R., Evans, D. E., & Usrey, L. J. (1996). A site-specific center pivot irrigation system for highly-variable Coastal Plain soils. In P. C. Robert, R. H. Rust, & W. E. Larson (Eds.), *Proceedings of the third international conference on precision agriculture* (pp. 827–834). Madison, WI: Am. Soc. Agron..
Silva, E. M. da, & Azevedo, J. A. (1998). *Dimensionamento da lateral de irrigação do pivô central* p. 54 EMBRAPA-CPAC, Documentos 71(Lateral dimensioning for central pivot irrigation. EMBRAPA-CPAC, Documents 71. 54p.).
Thangavadivelu, S., & Colvin, T. S. (1997). Fuzzy-logic-based decision support system for scheduling tillage operations. *Engineering Applications of Artificial Intelligence, 10*, 463–472.
Trout, T. J., Johnson, L. F., & Gartung, J. (2008). Remote sensing of canopy cover in horticultural crops. *HortScience, 43*, 333–337.
Valín, M. I., Cameira, M. R., Teodoro, P. R., & Pereira, L. S. (2012). DEPIVOT: A model for center-pivot design and evaluation. *Computers and Electronics in Agriculture, 87*, 159–170.
Voinov, A., & Shugart, H. H. (2013). Integronsters," integral and integrated modeling. *Environmental Modelling & Software, 39*, 149–158.
Wang, L. X. (1997). A course in fuzzy systems and control. Prentice Hall PTR. 2.ª ed.
Wood, G. A., Taylor, J. C., & Godwin, R. J. (2003). Calibration methodology for mapping within-field crop variability using remote sensing. *Biosystems Engineering, 84*, 409–423.
Wright, S. T. C. (1977). The relationship between leaf water potential (ψ_{leaf}) and the levels of abscisic acid and ethylene in excised wheat leaves. *Planta, 134*, 183–189.
Zadeh, L. A. (1965). Fuzzy sets. *Information and Control, 8*, 338–353.
Zhang, H. Y., Fei, L., Wei, Z., Congcong, M., & Yuewei, C. (2011). The fuzzy decision-making method of irrigation amount based on ET and soil water potential. *International Conference on Electronics, Communications and Control (ICECC)*, 2927–2931.