Decision Support Method to Assist Irrigation Management in Oil Palm Crops

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Abstract

In order to achieve optimum yields in oil palm, management practices should be tailored to the crop site agro-ecological conditions. Nevertheless, oil palm farmers often have to make decisions based on a limited knowledge base. Considering that water management is a critical aspect of oil palm crops, this paper describes an inference method for irrigation decision-making in oil palm supported on soil moisture and vapor pressure deficit data. Under an ideal scenario where this agrometeorological data is available through a Wireless Sensor Network (WSN) at a crop plot resolution, we formulated the method to prevent oil palm farmers to submit their crops to water deficit stress. The inference method was based on a Data Fusion technique called Dempster-Shafer Inference, which is convenient for the use of uncertain data with distinct levels of detail such as those present in a WSN. The outcome of fusing soil moisture and vapor pressure data was the estimation of the crop water status following the concept of Site-specific Agriculture. To evaluate the impact of the method on crop yield, we carried out two simulations. The first one on a WSNs simulator to generate the irrigation decisions according to the site-specific agrometeorological data collected from the WSN. The second one on a modeling framework to simulate the oil palm plot at the study site under two treatments: plot with irrigation managed by the inference method and plot without irrigation. Results showed a 27% increase in the production of bunches of fresh fruit between 2016 and 2017 in the treatment with irrigation. This indicates the enormous potential for developing decision-support systems for irrigation in oil palm and other crops.

Keywords

Decision making, Oil palm, Data fusion, Irrigation management, Wireless Sensor Networks, Site-specific agriculture.

1. Introduction

The use of climate science in agricultural planning can increase the capacity of farmers and agricultural planners to allocate resources effectively (FAO, 2010). However, it is necessary to tailor weather and climate information to a local level for individual farmers (FAO, 2015). Current information is inadequate to support effective decision making, and to a considerable extent, it is inaccessible to decision makers

(Lipper et al., 2014). Therefore, the gap between climate science and the application of information in the field must be closed, in the sense that farmers better understand the implications of their decisions (FAO, 2010).

In Colombia, palm oil industry is characterized by a population of more than 70% of small-scale farmers (FEDEPALMA, 2012), which have an average yield lower by 7 tons of fresh fruit bunches per hectare compared to large-scale farmers (FEDEPALMA, 2013). According to Fontanilla et al. (2015), thanks to the application of good practices in small-scale oil palm cultivations, crop yield can increase from 25 to 84%, and the net income of one grower per hectare can increase from 33 to 160% per year. Nevertheless, for oil palm, there are not many well-founded manuals that adequately describe how to grow and manage oil palm crops (Cock et al., 2016). Therefore, oil palm farmers frequently have to make decisions based on a limited knowledge base (Cock et al., 2016). Which is a real disadvantage because to achieve optimum yields in oil palm, it is necessary to adopt management practices tailored to the needs of the site, which are defined by their particular agro-ecological conditions (Paramananthan, 2003).

One opportunity in oil palm is to support irrigation. Since water deficit stress is highly adverse to crop yield, water management is a critical aspect of oil palm crops (Comte, Colin, Whalen, Grünberger, & Caliman, 2012), especially in areas where precipitation is below 100 mm per month (Paramananthan, 2003). As reported by Palat et al. (2008), in southern Thailand irrigation contributed to yield by increasing the production of fresh fruit bunches by 50%, in crops irrigated daily during the dry season. Then, the here proposed method is focused on assisting decision-making for irrigation management. This method will enable the development of systems that can proactively control irrigation based on the plot level agrometeorological conditions.

The purpose of this work was to address the challenge of bringing raw information to accessible, understandable and relevant information for decision making (Hansen & Coffey, 2011), in the context of oil palm plantations in Colombia, under an ideal scenario where agrometeorological information is available through wireless sensor networks. Consequently, the aim was to formulate a method that supports decision-making for irrigation management.

1.1. Irrigation decision-making in oil palm

According to Corley & Tinker (2016, p. 303), the decision on when to irrigate requires information on the degree of water deficit stress suffered by the palms. A way to estimate the stress is to calculate the soil water deficit, which can be solved with agrometeorological information on soil water reserves (Corley & Tinker, 2016, p. 303).

By knowing the water retention curve of the crop soil and establishing the water amount points that define water soil dynamics, the degree of water deficit stress can be determined as the difference between the volumetric water content –soil moisture– and the allowable soil water depletion point –critical deficit–. Then, irrigation should be activated when soil moisture reaches a value below the critical deficit because by that point plant functions such as growth or yield start to be affected (Corley & Tinker, 2016, p. 58; Evans, Cassel, & Sneed, 1996).

Nevertheless, stress due to water deficit is not only due to low water availability. The deficit can occur partially because the stomata of the oil palm are closed with the dry air, even when the soil moisture is not a restriction (Palat, Smith, & Corley, 2000), according to the works of Smith (1989) and Henson (1991). As reported by Dufrêne & Saugier (1993), this sensitivity of stomatal conductance due to changes in the vapor pressure deficit, VPD, occurs when VPD exceeded 1,8 kPa; at that point, photosynthesis declined. Hence, irrigation should not be activated when VPD reaches this value because palms photosynthetic rate begins to be limited and to decrease in an inversely proportional way (Dufrene & Saugier, 1993; Smith, 1989).

1.2. Wireless sensor networks for site-specific agriculture

Over recent years Wireless Sensor Networks (WSNs) have emerged as new sources of observations in agriculture, which allows agrometeorological information systems to operate with a variety of cost-effective, high-performance and reliable sensors (Mirhosseini, Barani, & Nezamabadi-pour, 2017). The general architecture of a WSN (Ian F. Akyildiz, Su, Sankarasubramaniam, & Cayirci, 2002; Culler & Hong, 2004; Yick, Mukherjeea, & Ghosal, 2008) consists of a set of autonomous devices spatially deployed, which collaboratively collect data on a particular phenomenon and transmit them wirelessly. Devices classified as node sensors (tens to thousands), a sink node and a Gateway. Sensor nodes are responsible for detecting, measuring, processing and sending the data of the phenomenon under study by multi-hop communication to the sink node (I. F. Akyildiz & Vuran, 2010; Ian F. Akyildiz et al., 2002). Then the data concentrated in the sink node, which have computational capabilities superior to sensor nodes, are forwarded to a Gateway to transmit it outside the network. Or data are sent to a base station that is a device directly connected to a computer, for dissemination and analysis.

By providing a new way to observe the crop and its environment (Ma, Zhou, Li, & Li, 2011), WSNs are already recognized as a powerful technology for the collection and processing of data in the domain of agriculture (Borgia, 2014) especially, under the concept of Site-specific agriculture. Initially, the concept was used as a synonym of Precision Agriculture (Johannsen & Carter, 2005). Thus, it was defined as the management of crops on a smaller spatial scale than that of the whole crop (Plant, 2001). However, these two concepts are currently differentiated (Andy Jarvis et al., 2013). It is affirmed that Precision Agriculture is responsible for crop management at a higher resolution within the plot guided by a factor, though Site-specific agriculture is responsible for the management of the crop plot guided by the combination of factors (Cock et al., 2011; Andy Jarvis et al., 2013). The reason is that, as indicated by Cock et al. (2011), for farmers in developing countries it is more important to manage their crops at the plot level rather than to refine the management of the crop within the plot.

This paper describes the development of a method for assisting irrigation decision-making in oil palm crops guided by the information provided from a WSN and then uses this method to demonstrate its effects on crop yield under the decision support provided.

2. Material and Methods

Based on the developed concepts above we formulated an inference method for irrigation decision-making in oil palm, under a scenario where agrometeorological information is available through a WSN. Also, we simulated the method to obtain irrigation decisions with agrometeorological information from one plot of a plantation site in Colombia, and we simulated the crop performance under the irrigation decisions taken at the first simulation.

2.1. Study site

The agrometeorological data used for the method was based on data from an oil palm plantation located at "Palmar de la Vizcaína" Experiment Field Station, Santander, Colombia –6°58’ N; 73°42’ W–; at an altitude of 140 m with average conditions of 75% of relative humidity and 32°C of average daily temperature (Bayona-Rodríguez & Romero, 2016). A plot from the plantation was selected as study site under the criterium that agrometeorological data was especially available at that level of spatial resolution.

The selected plot has an area of 10 ha with seven-years-old oil palms, which were planted in a triangular distance of 9 m. The critical values for irrigation are 30% of soil moisture –specifically for the plot soil– and 1,8 kPa –general for oil palm–. Figure 1 shows an aerial photograph of the plot.

Figure 1. Location of the study site and a satellite image of the plot.

2.2. Variables for irrigation decision-making in oil palm

There were identified two variables to manage irrigation decision-making: soil moisture and vapor pressure deficit. The first one indicated in the form of volumetric water content, advises the necessity to irrigate oil palms. And the second one advises the moment to irrigate oil palms. After identifying these variables that determine the degree of water deficit stress, we assessed how often to value that degree and to make irrigation decisions; if it should be done hourly, daily, weekly or monthly. As reported by Corley & Tinker (2003, p. 299), the estimation of water deficit stress per week should be sufficient, since evapotranspiration per week is very unlikely to exceed 40 mm and the critical deficit in oil palm is higher than that. According to expert advice, data should be consolidated every three days at 6 o'clock in the morning and decide whether to or not to activate the irrigation for oil palms. Considering that soil moisture is more stable in time than vapor pressure deficit, at the term of making an irrigation decision soil moisture should be averaged with the data from the previous three days while vapor pressure deficit should be calculated with current air temperature and relative humidity data. Consequently, in Table 1, we present the management of variables for irrigation decision-making in oil palm.

Table 1. Variables in time to manage irrigation decisions in oil palm crops.

Resolution		Variable	Equation
Spatial	Temporal		
Plot	3-day average	Soil moisture	$\bar{\theta} = \frac{\sum_{i=1}^{N} \theta_i}{N}$ (1) where, $\bar{\theta}$ average soil water content [$m^3_{water}.m^{-3}_{soil}$] θ_i soil water content in a moment of time [$m^3_{water}.m^{-3}_{soil}$] N number of samples
	Current	Vapor pressure deficit	$VPD = e_s - e_a$ $VPD = 0{,}6108\, exp\left(\frac{17{,}27\, T}{T + 237{,}3}\right) - \left(0{,}6108\, exp\left(\frac{17{,}27\, T}{T + 237{,}3}\right) * \frac{RH}{100}\right)$ (2) $VPD = \left(0{,}6108\, exp\left(\frac{17{,}27\, T}{T + 237{,}3}\right)\right) * \left(1 - \frac{RH}{100}\right)$ where, *VPD* = vapor pressure deficit [kPa] e_s = saturation vapor pressure [kPa] e_a = actual vapor pressure [kPa] *T* = air temperature [°C] *RH* = relative humidity [%]

Given that WSNs can be deployed at a representative spatial scale, which translates into facilitating and improving the skills of farmers to accessing to data at the local level (Gutman & Robert, 2013; Wang, Zhang, & Wang, 2006) and that weather and climate conditions tend to show continuous variation without abrupt changes or discontinuities, unlike soils that can vary significantly over very small distances (Cock et al., 2011). We propose that irrigation decision-making in oil palm should be managed at the plot level and a WSN could be deployed per plot to collect soil moisture and vapor pressure data.

2.3. Specification of agrometeorological data

Considering that representative agrometeorological data is necessary for the method and that the selected plot does not count with a WSN, we used the available data from one source to recreate a scenario from the study site in which agrometeorological information is collected through a WSN.

The agrometeorological information was obtained from one micrometeorological station, Biomet 103, associated with an Eddy Covariance System (LI-COR Inc., 2011) installed at the plot. The station is equipped with sensors that observe the soil-plant-atmosphere relationship. The sensors make measurements every minute, except the wind speed that is measured at a rate of 10 Hz. As the station is located within the crop, it makes representative observations at the plot level since it intends to monitor and operationally support the local agricultural situation (WMO, 2010).

Both soil moisture and vapor pressure deficit data, the latter calculated with air temperature and relative humidity data, were used to generate datasets. Since the station is equipped with three sensors of soil moisture and one sensor of relative humidity and ambient temperature, there were created four datasets corresponding to the four records of sensors information. The datasets cover a time from August 20th of 2015 to May 31st of 2017.

Soil moisture datasets were created from averaging soil moisture over the three days before the time of the irrigation decision –6 am–, according to Equation (1). Moreover, the vapor pressure deficit dataset was created by calculating deficit with data from relative humidity and air temperature at the time of decision –6 a.m.– with Equation (2). As such, the first register of the datasets corresponds to August 23rd of 2015 at 6 o'clock in the morning.

2.4. Inference method

According to Bouma (1997), a challenge for science is to create methods that can characterize the spatiotemporal variability of crops in favor that farmers can use the information effectively to improve their management practices. Thus, there are required ways to bring raw information to accessible, understandable and relevant information for decision making (Hansen & Coffey, 2011). To address the challenge, we formulated the method using a technique from Data Fusion, a discipline that includes the application of techniques to support human or automated decision making (Boström et al., 2007).

Data Fusion (Gros, 1997), and specifically Multisensor Data Fusion (Hall & Llinas, 1997; Varshney, 2000), is a set of techniques that combine data from multiple sensors to provide higher value to information than the one that could be achieved using a single sensor. The definition of higher value can refer to the obtaining of higher precision, estimation, description, or quality of the information. The synergistic combination of data from sensors allows us to make inferences about information, hence improving the performance of a task by better understanding the current situation and better-supporting decisions (Nakamura, Loureiro, & Frery, 2007).

Inference techniques in Data Fusion are often applied to obtain decisions, on the knowledge of the perceived situation, which is provided by many sources. Inference refers to a transition from a proposition that is probably true to verification of its veracity (Farias et al., 2014; Nakamura et al., 2007). There are several techniques within the Data Fusion for the realization of inferences (Nakamura et al., 2007), among the most outstanding are the Bayesian Inference, the Dempster-Shafer Inference, and the Fuzzy Logic.

In the method, we used the Dempster-Shafer Inference technique over the other techniques because it provides a formalism to manage data uncertainty by expressing a degree of belief which supports or refutes a hypothesis (Gros, 1997). Furthermore, it allows combining data from sensors giving distinct levels of detail (Nakamura et al., 2007).

On the one hand, in a wireless sensor network, data comes from sensor nodes which observe physical properties that are continuously evolving in time. Hence, a sensor only gives us a snapshot of that evolution, which means that the measurements are not 100% true since the sensor provides an estimate of the measured physical property (Mitchell, 2012). Besides, sensor nodes are numerous devices that can fail (Abdelgawad & Bayoumi, 2012; Kulkarni, Forster, & Venayagamoorthy, 2011; Luo & Kay, 1989; Nakamura et al., 2007), which supposes errors in the measurements of the parameters and vulnerability to faults (Abdelgawad & Bayoumi, 2012).

On the other hand, according to the irrigation decision-making concept presented above, the variables that determine the degree of water deficit stress are soil moisture and vapor pressure deficit. These variables describe different physical quantities, therefore are expressed in different units of measurement and cannot be directly related. Nevertheless, as explained, their integration is a synergy that helps to understand the soil-plant-atmosphere relationship better and to establish the degree of hydric stress of oil palms to execute irrigation.

2.4.1. Dempster-Shafer Inference technique

This technique is based on the theory of the accumulation of evidence, formulated from the work of Dempster (1968, 2008), in the understanding and refinement of Fisher's approach to the inference of probability. Which was later formalized by Shafer (1976, 1992, 1996) towards a generalization of the Bayesian Inference.

In Dempster-Shafer Inference technique (Farias et al., 2014; Gros, 1997; Khaleghi, Khamis, Karray, & Razavi, 2013; Nakamura et al., 2007), the Θ represents the set of possible states that describe a system, $\Theta = \{\theta_1, \dots, \theta_N\}$, where each element of the set is exclusive in the sense that the system can only be found in a state at a given moment, and that the set of 2^Θ represents all possible subsets of Θ, whose elements are the hypotheses. The Dempster-Shafer theory assigns the mass function m to each hypothesis H of 2^Θ, which represents the possible propositions regarding the state of the system. According to the mass function, $m: 2^\Theta \rightarrow [0,1]$, it is satisfied that the mass function of an empty set is zero:

$$m(\emptyset) = 0 \tag{3}$$

Also, the mass function of a hypothesis H is greater than or equal to zero:

$$m(H) \geq 0, \quad \forall H \in 2^\Theta \tag{4}$$

And the sum of the mass function of all the hypotheses is equal to 1 as:

$$\sum_{H \in 2^\Theta} m(H) = 1 \tag{5}$$

The confidence interval in a hypothesis H, is defined as the range between its belief and its plausibility as $[\mathrm{Bel}(H), \mathrm{Pl}(H)]$, which is the true belief about the hypothesis H.

The belief in a hypothesis H, the belief function $\mathrm{Bel}: 2^\Theta \rightarrow [0,1]$ over Θ, is:

$$\mathrm{Bel}(H) = \sum_{A \subseteq H} m(A) \tag{6}$$

Where $\mathrm{Bel}(\emptyset) = 1$ and $\mathrm{Bel}(\Theta) = 1$. And the doubt in a hypothesis H is expressed according to the belief function as:

$$\mathrm{Do}(H) = \mathrm{Bel}(\neg H) = \sum_{A \subseteq \neg H} m(A) \tag{7}$$

The plausibility of a hypothesis H, the plausibility function $\mathrm{pl}: 2^{\Theta} \rightarrow [0,1]$ over Θ, is defined as:

$$\mathrm{Pl}(H) = 1 - \mathrm{Do}(H) = \sum_{A \cap H = \emptyset} m(A) \tag{8}$$

To combine the evidence provided by dissimilar sources over a hypothesis H, there is a combination rule which integrates the effects of two mass functions m_1 and m_2, as:

$$m_1 \oplus m_2(\mathrm{H}) = \frac{\sum_{A \cap B = H} m_1(A) m_2(B)}{1 - \sum_{A \cap B = \emptyset} m_1(A) m_2(B)} \tag{9}$$

Where the combination of mass functions of an empty set is zero:

$$m_1 \oplus m_2(\emptyset) = 0 \tag{10}$$

As an advantage, Dempster-Shafer Inference technique allows grasping ignorance or an inability to distinguish between possible states so that probabilities over a state are associated only when support information is available. In the theory of probability, Bayesian Inference, this would be treated in a very different way by assigning an equal or uniform probability to each possible state. The use of the discernment framework, as the set Θ is called, allows for a much richer representation of beliefs.

2.4.2. Estimating the crop water status

Irrigation management is fundamentally based on making decisions about whether YES or NOT to irrigate. Thus, this decision can be reduced to a process of inference about the state of the crop: given a set of possible states, it is necessary to infer what the actual state of the crop is. Since it is only needed to water when it is necessary and adequate to irrigate, in agreement with the irrigation decision-making concept in oil palm, the states of the crop can refer to NORMAL (N) and $\mathrm{CRITICAL}$ (C). The first refers when the plants have sufficient soil moisture or when the environmental conditions are not appropriate of watering. And the second refers when the plants have insufficient soil moisture, and environmental conditions are optimal for watering. Thus, the discernment framework is the set $\Theta = \{\mathrm{N}, \mathrm{C}\}$. And the quantity of hypothesis is $2^{\Theta} = 2^2 = 4$, being the hypothesis set $H(\Theta) = (\emptyset, \mathrm{N}, \mathrm{C}, \{\mathrm{N}, \mathrm{C}\})$.

The Dempster-Shafer Inference technique works with pieces of evidence, which are represented by mass functions. Therefore, to formulate the method it is necessary to translate the agrometeorological variables that indicate the need and time of irrigation: soil moisture during the last three days and vapor pressure deficit, into mass functions to be fused using the Dempster-Shafer combination rule. In line with what was reported in Section 1.1 on irrigation decision-making in oil palm and with the critical values for the plot, the mass functions of the method are defined below.

When soil moisture decreases, $0\% \leq \bar{\theta} < 30\%$, it means that there is a non-zero belief that water is needed for the crop. Also, when $\bar{\theta}$ tends to 0%, this belief increases. Therefore, to translate $\bar{\theta}$ into evidence, we define the mass function $m_1: 2^{\Theta} \rightarrow [0,1]$ for the hypothesis set as follows:

$$
\begin{gathered}
m_1(C) = \begin{cases} (1-\bar{\theta}), & 0\% \leq \bar{\theta} < 30\% \\ 0, & \bar{\theta} \geq 30\% \end{cases} \\
m_1(N) = 1 - m_1(C) \\
m_1(\{\mathrm{N}, \mathrm{C}\}) = 0 \\
m_1(\emptyset) = 0
\end{gathered}
\tag{11}
$$

The above means that soil moisture establishes a state:

- CRITICAL of a need for irrigation, when soil moisture is less than 30%.
- NORMAL of no-need for irrigation, complementary to the CRITICAL state, when the soil moisture is greater than or equal to 30%.
- And that the hypothesis of {N, C} has a mass equal to 0, since soil moisture during the last three days cannot define a state of non-belief on ′NORMAL (N) or CRITICAL (C)′.

Moreover, when the vapor pressure deficit decreases, $VPD < 1{,}8\ kPa$, means that there is a non-zero belief that it is appropriate to irrigate the crop. Also, when VPD tends to 0, this belief increases. Therefore, to translate VPD into evidence, we define the mass function $m_2: 2^{\Theta} \rightarrow [0,1]$ for the hypothesis set as follows:

$$
\begin{gathered}
m_2(\mathrm{C}) = \begin{cases} \left(1 - \frac{VPD}{1{,}8}\right)^{w}, & VPD < 1{,}8 \\ 0, & VPD \geq 1{,}8 \end{cases} \\
m_2(\mathrm{N}) = 1 - m_2(\mathrm{C}) \\
m_2(\{\mathrm{N}, \mathrm{C}\}) = 0 \\
m_2(\emptyset) = 0
\end{gathered}
\tag{12}
$$

Where $w = 1.75$. This weight is given to $m_2(\mathrm{C})$ with the goal that the belief assigned by this mass has a smaller impact on the decision of irrigation. The reason is that this weight softens the response of the method at estimating a CRITICAL state by the 'moment' factor because the 'need' factor must be more decisive in the management of irrigation.

According to the mass function due to vapor pressure deficit, a state is established:

- CRITICAL of a right moment for irrigation, when the vapor pressure deficit is less than 1,8 kPa.
- NORMAL of a no-right moment for irrigation, complementary to the CRITICAL state, when the vapor pressure deficit is greater than or equal to 1,8 kPa.
- And that the hypothesis of $\{N, C\}$ has a mass equal to 0, because the vapor pressure deficit cannot define a state of nonbelief about 'NORMAL (N) or CRITICAL (C)'.

To estimate the state of the crop that decides whether or not irrigation should be activated: (i) the beliefs assigned by m_1 and m_2 are combined using the Dempster-Shafer combination rule; (ii) the belief and plausibility of each hypothesis (NORMAL (N) and $\mathrm{CRITICAL}$ (C)) con are calculated with respect to $m_1 \oplus m_2$; (iii) the most plausible state is chosen; if both states are equally plausible, the most credible is chosen; if both states are equally plausible and credible, the NORMAL (N) state is chosen. Finally, if it is inferred that the state of the crop is $\mathrm{CRITICAL}$ (C), the decision is that YES, it is suitable irrigating the plot. On the contrary, if it is inferred that the state of the crop is NORMAL (N), the decision is that NOT, it is not suitable irrigating the plot.

2.5. Inference method simulation

The proposed method was simulated assuming as the simulation scenario the oil palm plot with a WSN deployed to acquire local and representative data from the crop; the WNS data was recreated from the datasets generated on soil moisture and vapor pressure deficit from the plot at the study site.

For the simulation, Castalia program was used, this is "an open-source simulator for wireless sensor networks and body area networks which is widely used in the academic and research community" (Pediaditakis, Tselishchev, & Boulis, 2010). According to its creators, Pham, Pediaditakis, & Boulis (2007), the reason for creating Castalia is that before there was not a simulator that, in fact, could recreate precise communication models -wireless channels and radio models- and that was also reliable and fast. Given this need, Castalia was ideally suited for the design and validation of algorithms and protocols, in addition to being relatively easy to use (Pediaditakis et al., 2010). The main reason for using Castalia in this work is that it allows the simulation of the WSN and the inference method indifferent of a particular WSN platform, and also allows the recreation of physical processes in a very flexible way.

Castalia was used in its version 3.2 (Boulis, 2011) running on OMNeT++ in its version 4.4.1 (OpenSim Ltd., 2014). Table 2 summarizes the main configurations made for the simulation. In this work, a square area corresponding to the plot was recreated with a WSN deployed. The network counted with 72 sensor nodes organized in a grid of 9 x 8 and connected in a tree topography by the routing protocol of Gnawali et al. (2009).

Table 2. Configuration of the simulation in Castalia for the validation of the inference method.

Simulation parameter	Value
Deployment area –plot–	317 m x 316 m (approx. 10 ha)
Number of nodes	1 sink node and 72 sensor nodes
Sensor nodes deployment	A grid of 9 nodes x 8 nodes
Sink node location	Center of the deployment area
Communication standard	IEEE 802.15.4
Routing protocol	Collection Tree Protocol – CTP implemented by Colesanti & Santini (2012)
RF transceiver	CC2420 of Texas Instruments
Packet rate –data rate–	Approximately one packet sent every 900 seconds

Since soil moisture varies in space much more than air temperature and relative humidity; the first variable is conditioned by factors such as soil type and topography, whereas the second and third variables are widely established in the atmosphere for the plot. The 72 sensor nodes in the simulation were arranged to monitor the heterogeneous behavior of soil moisture in the plot, while only one sensor node was arranged to monitor the air temperature and relative humidity –to calculate the vapor pressure deficit–. Also, a physical process module was configured in Castalia to recreate the soil moisture behavior with the three soil moisture datasets transformed into three information sources. This module is based on a model, in which an arbitrary number of information sources influence is diffused over space (Boulis, 2011).

In Castalia, an information source is a string of snapshots. Each snapshot describes: time [s], position *x* [m], position *y* [m], and value of the physical property. The three datasets created from the soil moisture sensors were organized into three strings of snapshots. Since the sensors at the micrometeorological station are static, that is, position *x* and position *y* are fixated, but we had to recreate the soil moisture in the entire 10-ha plot, a fictitious location was defined for each snapshot with random numbers within the area of deployment. Thus, each soil moisture snapshot was located at a new point in the plot.

The measurement of each sensor node over a physical property is defined by Equation (13) (Boulis, 2011), which implies that a measurement keeps a spatial correlation with all information sources. Because the effect of multiple sources is additive, each soil moisture measurement is the sum of the values provided by the three information sources. Consequently, to avoid multiplying the soil moisture measurements by three, the soil moisture values at the datasets were divided into three when creating the strings of snapshots.

$$V(p,t) = \sum_{all\ sources\ i} \frac{V_i(t)}{\left(\left(K * d_i(p,t)\right) + 1\right)^a} + N(0,\sigma) \tag{13}$$

where,

$V(p,t)$ = value of the physical process at point p, at time t

$V_i(t)$ = value of the i^{th} source at time t

$d_i(p,t)$ = distance of point p from the i^{th} source at time t

K, a are parameters that determine how is the value from a source diffused

$N(0,\sigma)$ is a zero-mean Gaussian random variable with standard deviation σ

The p point is the location of the sensor node within the deployment area, which in this case is related to the deployment in the grid of 9 x 8. The parameters K, a and σ are configurable in the module. It was defined $K = 0$ and $a = 1$; then the division factor is 1 and the value defined by the information source is maintained. And $\sigma = 0.2$, to introduce the lowest noise in the measurements and keep them as faithful as possible to the real soil moisture data.

Before using the 72 sensor nodes as data sources whose information is translated into beliefs with the method, the plot was divided into three zones. Hence, the soil moisture measurements were consolidated by zone. Consequently, the set of sensor nodes was divided into three subsets –each related to a zone– and their measurements were averaged. In the end, for the inference method applied every three days at 6 in the morning, four values entered: three average soil moisture values –an average for each zone– and one value from vapor pressure deficit. Based on these values, the estimation of the crop water status at the plot was inferred.

2.6. Oil palm yield simulation

The irrigation decisions derived from the inference method were translated into irrigation operations in a modeling framework to evaluate its impact on crop yield. In this way, the plot at the study site was taken to simulation to compare two irrigation treatments, namely: plot with irrigation managed by the inference method and plot without irrigation.

For the simulation of the oil palm plot, the Agricultural Production Systems sIMulator (APSIM) software was used. This program offers a modeling framework for agricultural and livestock systems, developed with high standards from science and software engineering, internationally recognized (APSIM Initiative, n.d.; Holzworth et al., 2014).

The APSIM model for oil palm was developed by Huth et al. (2014) and based on that this crop simulation was developed. The model uses widely tested submodels for the water, carbon and nutrient cycle, and based on these makes predictions of oil palm growth and crop yield per unit area (Nelson, Banabas, Huth, & Webb, 2015). In addition to estimating the use of resources and the flow of organic matter for the palm (Okoro et al., 2017). This model simulates the growth of leaves, stem, root and fresh fruit bunches in response to the inputs of the model, which are, mainly, data from the daily weather report, soil information and crop management practices.

The primary resources used for the simulation are described below.

2.6.1. APSIM oil palm model from Huth et al. (2014)

Based on data from three sites in Papua New Guinea, the authors tested the model for oil palm under the modular system of APSIM. The growth of the crop is calculated based on solar radiation, water availability, temperature, and nitrogen concentration.

For this simulation, two treatments were compared –plot with irrigation and plot without irrigation – with the same input data, except the first treatment, which included irrigation operations derived from the decisions of the inference method, while the second did not include irrigation operations.

2.6.2. Daily weather report data

The climate variables used for the simulation were: solar radiation [$MJ.m^2$], maximum temperature [°C], minimum temperature [°C], and precipitation [mm]. Since the simulation requires this data from year 1 of sowing, which for the case of the plot is 2011, it was necessary to use data from a weather station of the National Institute of Hydrology, Meteorology, and Environmental Studies –known as IDEAM–, installed in the study site. The daily weather records go from January 1st of 2011 to December 31st of 2017.

2.6.3. Soil data

Because soil information about the plot at the study site was not available, the parameters and soil data of the oil palm crop in Sangara at Papua New Guinea (Huth et al., 2014) were used. This site has a sandy clay loam of soil type. Some specific changes to the characteristics of the soil-water phase are indicated in Table 3.

Table 3. Parameters configured for the simulation in APSIM of the oil palm plot.

Parameter	Value
Simulation time	01/01/2011 a 31/12/2017
Sowing day	01/01/2011
Planting density [palms/ha]	143
Initial volumetric water content	27%, evenly distributed
Fraction of water in layers of soil	
0 - 10 cm	0,320
10 - 30 cm	0,320
30 - 60cm	0,320
60 - 90 cm	0,320
90 - 120 cm	0,320

2.6.4. Crop management data

In the case of fertilization at the plot, Table 4 presents the fertilization operations entered in the simulation model. This information was recreated from factual information on fertilizers, dates, and quantities applied in the years 2016 and 2017; for the previous years, there was no information available. Also, only the fertilizers that provide nitrogen were considered, since the model only takes into account the cycle of this nutrient in the growth and development of oil palm.

Table 4. Characteristics of fertilizers applied, and fertilization operations configured in the simulation of the oil palm plot in APSIM.

Fertilizer	Chemical and percentage composition	Commercial reference
Nitrax-S	NH_4 NO_3 P_2O_5 S: 17.5% - 10.5% - 4% - 6%	(Yara International ASA, 2017)
DAP	NH_4 P_2O_5: 18% - 46%	(Fertiberia, 2017)
Urea	Urea: 46%	-
Date of application	Fertilizer	Dose [kg.ha]
27/05/2016	Nitrax-S	110,11
21/05/2016	DAP	20,02
09/06/2016	Nitrax-S	46,904
07/10/2016	DAP	95,81
10/10/2016	Urea	31,46
20/12/2016	Nitrax-S	95,81
21/01/2017	DAP	31,46
12/04/2017	Nitrax-S	85,8
24/04/2017	DAP	28,6
22/09/2017	Nitrax-S	54,34
03/11/2017	DAP	25,74
20/10/2017	Urea	85,80
20/12/2017	Nitrax-S	67,21
23/12/2017	DAP	30,03

Moreover, in the case of irrigation, for the treatment of plot with irrigation, irrigation operations were created between August 20th of 2015 to May 31st of 2017, according to the decisions resulting from the application of the inference method in the first simulation. The decision to 'YES, it is suitable irrigating the plot' resulted in the application of 15 mm of water, whereas the decision to 'NOT, it is not suitable irrigating the plot' resulted in the application of 0 mm of water. Considering that the irrigation events were decided every three days, a level of water of 15 mm is sufficient to compensate the evapotranspiration in that period if it was necessary to irrigate.

3. Results and discussion

This section presents the most relevant results of the simulation of the inference method for irrigation management with the available agrometeorological information of the plot.

3.1. Irrigation decisions

The relationship between the average soil moisture and the vapor pressure deficit with the decisions taken is valued.

Figure 2 to Figure 8 depict the averages of soil moisture, the vapor pressure deficit and the irrigation decision taken by date. The left vertical axis is the percentage of soil moisture, and the right vertical axis is the vapor pressure deficit in kPa and the decision taken. For the latter, a 1 value means YES to irrigate and a 0 value means NO to irrigate. Thus, for example, in Figure 2, for October 10th of 2015, the soil moisture averages were below 25%, the steam pressure deficit was 0 kPa and the decision was YES to irrigate. In October 13th of 2015, the soil moisture averages were above 30%, the vapor pressure deficit was 0 kPa and the decision was NO to irrigate.

As observed in the figures, that the three averages of soil moisture were below 30% ensured that the decision made was YES to irrigate. Here the question about what was the incidence of vapor pressure deficit in the irrigation decision arises. According to the agrometeorological information received from the study site, the vapor pressure deficit at 6 o'clock in the morning never exceeded 0.4315 kPa –March 31st of 2016–, that is, at that time the deficit always infers a $CRITICAL$ state of the crop and supports a positive irrigation decision. While critical values of vapor pressure deficit –greater than or equal to 1,8 kPa– were only reached between 1:30 p.m. and 10:45 p.m. in the study site. If the irrigation decision were made between those hours, the vapor pressure deficit would have real competition in the irrigation decision-making process.

Overall, the time lapse in which the crop was inferred in a $NORMAL$ state was greater than the time lapse when the crop was inferred in a $CRITICAL$ state. For example, throughout period 5 –Figure 6–, sufficient soil moisture was maintained for crop growth and crop yield, thus ensuring a permanent $NORMAL$ state. The periods with the most marked dry seasons were 1, 2, 3 and 6 –Figure 2, Figure 3, Figure 4, and Figure 7–, where at least half of the time the crop was in a $CRITICAL$ state. On the other hand, periods 4 and 7 –Figure 5and Figure 8– were dominated by seasons marked with a soil moisture above the critical value –30%–, which are most likely related to rainy seasons. Inclusively, in the figures, it can be recognized that the decisions of YES to irrigate were persistent between the months of December to March-April, which are summer months for the Colombian region where the study site is located. In fact, according to Lascano (1998), this region usually suffers a dry season between the months of November to April that affects crop yield.

The averages of the soil moisture measurements –recreated from the three datasets– varied from 10% to 45%. Meanwhile, the records of the three sensors varied from 6% to 65%. This indicates that the agrometeorological information of the micrometeorological station was useful at representing a WSN monitoring the plot. However, the ideal scenario to validate the inference method for irrigation management would be one in which the plot is monitored by a WSN. Whose measurements are subject to uncertainty and where the Dempster- Shafer technique helps manage the inaccurate data derived from it.

One more question that arose was, decided YES to irrigate, when to stop watering? The deactivation of irrigation was not addressed in the inference method since the main purpose was to decide whether to water or not. In general, in irrigation systems, this issue is handled in two ways, by time or by a condition. That is, the irrigation is stopped after a pre-defined time, or, the irrigation is stopped when a variable reaches a condition. In the work of Amaral et al. (2016), palm oil crops are irrigated with micro-sprinkler every four days for four hours during the summer season. In works on irrigation management systems supported by WSNs, the deactivation strategic differed. For example, in Gutierrez et al. (2015), and, Mitralexis & Goumopoulos (2015) irrigation stops after a predetermined time. And in Coates et al. (2013), Mafuta et al. (2013), and, Sales et al. (2015), irrigation is stopped when it is satisfied a conditional value. Bearing in mind that irrigation management is optimal if it is based on data collected in real time, it is estimated as a future work of the method to establish a deactivation strategy that includes: increasing the sampling frequency of soil moisture and vapor pressure deficit while irrigation is active and stopping irrigation if a threshold value –to be determined– of soil moisture is reached or if the critical value of the vapor pressure deficit is reached –1,8 kPa–.

Figure 2. Irrigation decisions in relation to the average soil moisture in the 3 zones of the plot and the vapor pressure deficit for period 1.

Figure 3. Irrigation decisions in relation to the average soil moisture in the 3 zones of the plot and the vapor pressure deficit for period 2.

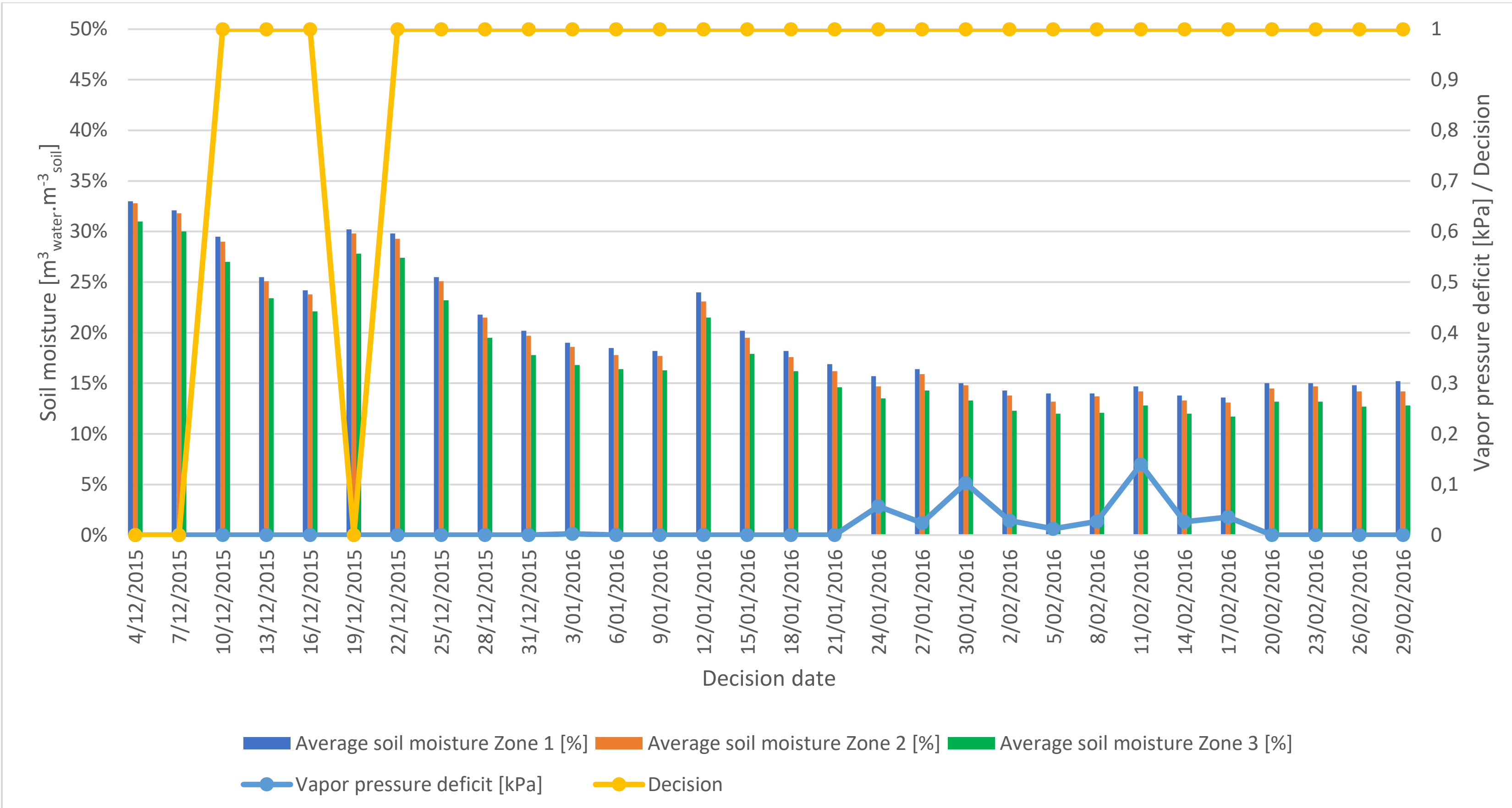


Figure 4. Irrigation decisions in relation to the average soil moisture in the 3 zones of the plot and the vapor pressure deficit for period 3.

Figure 5. Irrigation decisions in relation to the average soil moisture in the 3 zones of the plot and the vapor pressure deficit for period 4.

Figure 6. Irrigation decisions in relation to the average soil moisture in the 3 zones of the plot and the vapor pressure deficit for period 5.

Figure 7. Irrigation decisions in relation to the average soil moisture in the 3 zones of the plot and the vapor pressure deficit for period 6.

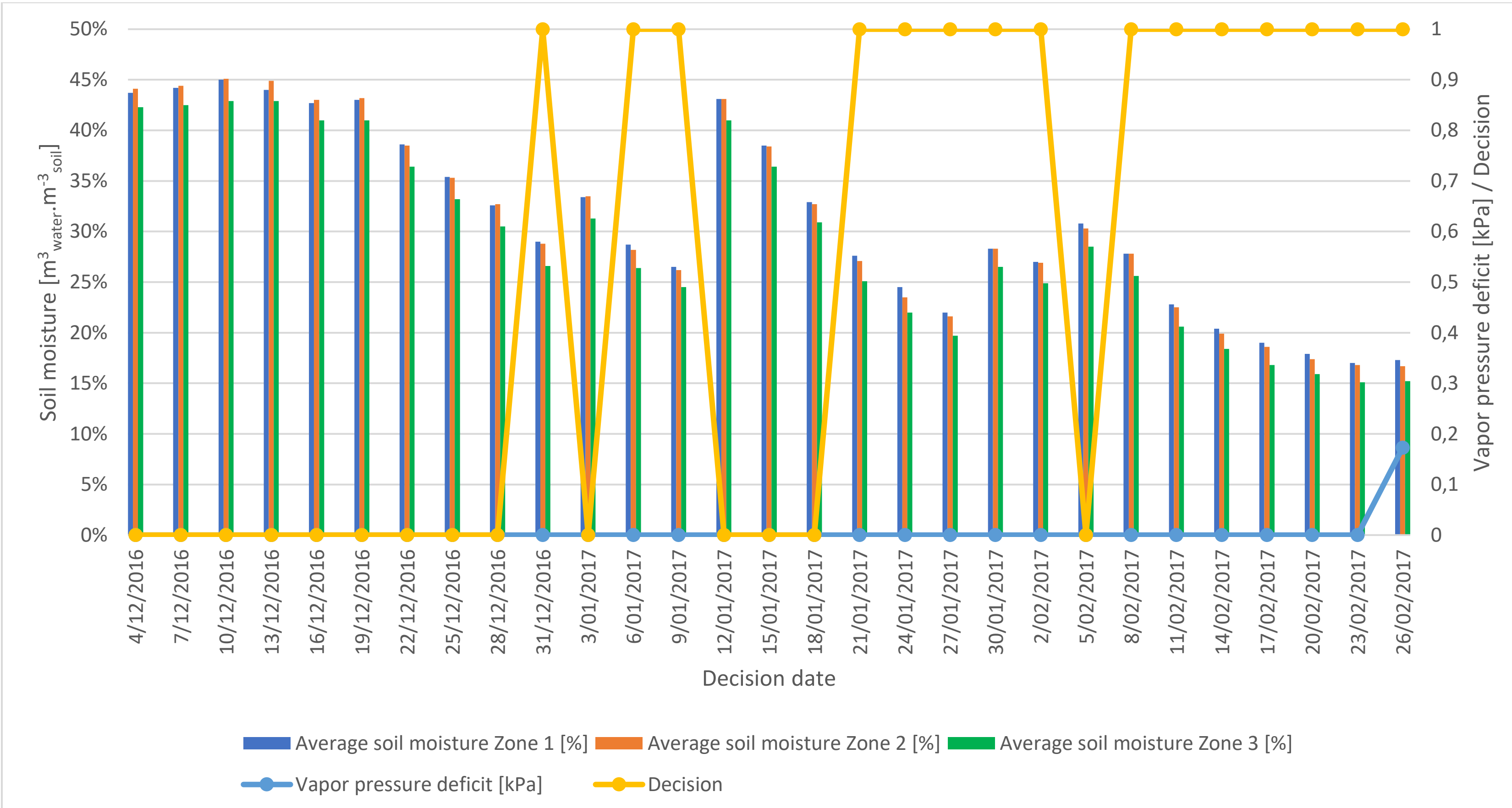


Figure 8. Irrigation decisions in relation to the average soil moisture in the 3 zones of the plot and the vapor pressure deficit for period 7.

3.2. Oil palm yield

The relationship between precipitation, irrigation decisions, and crop yield was assessed for the two scenarios: with irrigation and without irrigation.

Figure 9 presents the annual crop yield reported by APSIM regarding precipitation, irrigation water, and fertilization at the plot. The left vertical axis is the crop yield, in tons of fresh fruit bunches –FFB– per hectare per year. Moreover, the right vertical axis is the water level in millimeters of annual precipitation and irrigation. Also, the right vertical axis is the amount of fertilizer applied in kilograms per hectare per year. For instance, in 2015 the precipitation was 3386 mm.year^{-1}, the irrigation was 360 mm.year^{-1} –for the scenario with irrigation–, the fertilization was 0 kg.ha^{-1}.year^{-1} and the crop yield for the two scenarios –with irrigation and without irrigation– was 4 t_{FFB}.ha^{-1}.year^{-1}.

In Figure 10, the same results are presented monthly. The left vertical axis and the right vertical axis refer to the same units in Figure 33, but per month. Hence, for example, for March of 2016, the precipitation was 182 mm.month^{-1}, the irrigation was 150 mm.month^{-1} –for the scenario with irrigation–, the fertilization was 0 kg.ha^{-1}.month$^{-1,}$ and crop yield for the scenario with irrigation was 30 t_{FFB}.ha^{-1}.month^{-1} and for the scenario without irrigation was 26 t_{FFB}.ha^{-1}.month^{-1}.

As shown in Figure 9 and as reported by Goh (2000), Paramananthan (2003), and Paramananthan, Chew & Goh (2000), regarding the climatic suitability classification for oil palm productivity, the year 2016 had an inadequate aptitude as low precipitations occurred. On the other hand, the other years were in the adequate range when having annual precipitations from 1700 up to 3000 mm.year^{-1}. Except for the year 2015, which exceeded 3300 mm.year^{-1}, that is, it was a moderately suitable year of productivity. Hence, it calls attention that this year was applied 360 mm.year^{-1} of water for irrigation. While for the years 2016 and 2017, the water used for irrigation was justified since these years had precipitations below 2000 mm.year^{-1}; in other words, years with slightly limited precipitation for productivity.

To better understand what happened in the last three years, 2015, 2016 and 2017, Figure 10 presents received precipitation and irrigation applied monthly. Although the year 2015 far exceeded the adequate annual amount of precipitation, in reality, the rainfalls focused on the first half of the year. The second semester of 2015 had comparatively less rainfall and is also the time from which irrigation decisions begin to be made by the inference method -August 20th of 2015-, which is why the application of water for irrigation is observed from that moment on. In regard of 2016, this was a crucial year for the implementation of irrigation because it had precipitations below 1000 mm.year^{-1}. In total, in 2016, 645 mm.year^{-1} of irrigation water was applied; an amount higher than 2017 when 270 mm.year^{-1} was applied.

Figure 9. Annual yield of the oil palm plot, with irrigation and without irrigation, in relation to precipitation, irrigation, and fertilization.

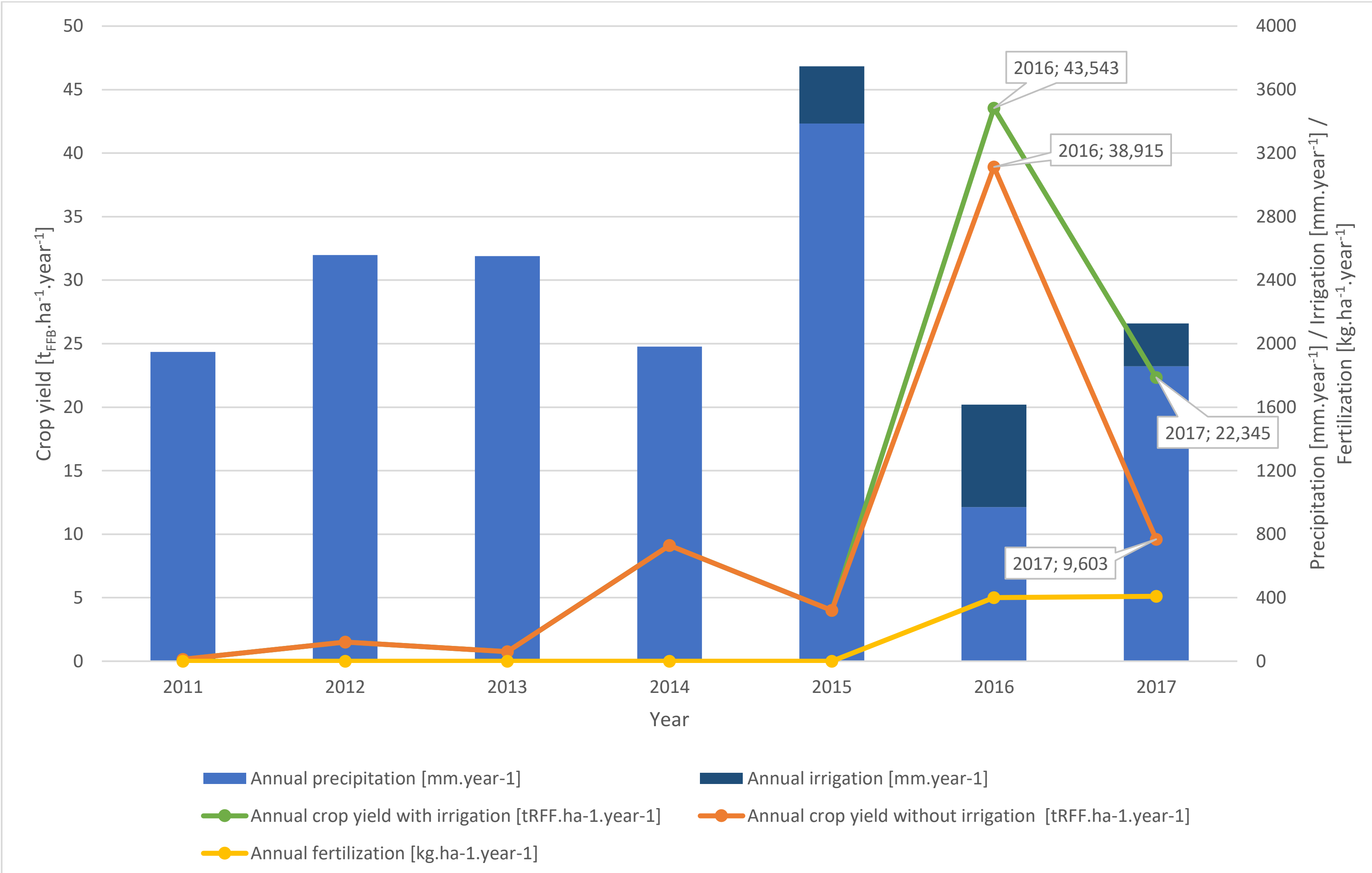
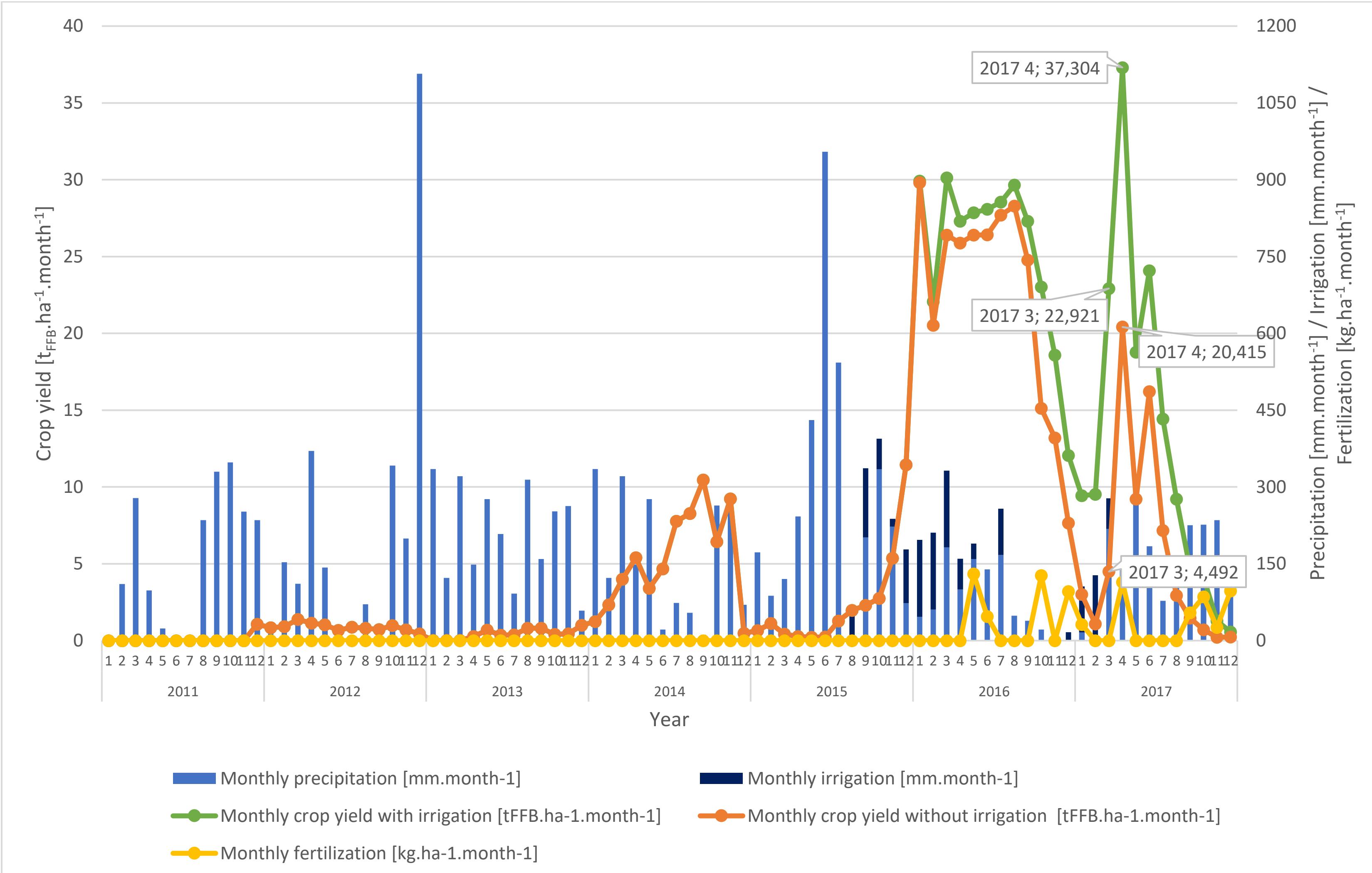


Figure 10. Monthly yield of the oil palm plot, with irrigation and without irrigation, in relation to precipitation, irrigation, and fertilization.



Taking into account that not only the annual amount of precipitation is essential, but the distribution of the same, with a minimum monthly requirement of 100 $mm.month^{-1}$ (Paramananthan, 2003). Moreover, taking into account that soil moisture is one of the agrometeorological variables from which the irrigation decisions of the inference method are derived, which is mainly determined by the climate in the two or three previous months (Cock et al., 2016). It can be better understood that in the second half of 2016, despite the low precipitations, no more water was applied for irrigation and that the low water reserves in soil began until the beginning of 2017.

Likewise, it can be better understood that although the year 2015 had greater precipitations than 2017 –3386 $mm.year^{-1}$ and 1857 $mm.year^{-1}$, respectively–, in the former, more water was applied for irrigation than in the latter. Initially in 2015, as already mentioned, the rains were more intense in the first semester than in the second semester, whereas in 2017 precipitations were better distributed throughout the year. That is, soil moisture was more stable, and that ensured a lower number of positive irrigation decisions. Besides, irrigation decisions only operated until May 31st of 2017 –only agrometeorological information of the lot was available to this day– and therefore no more water was accumulated for irrigation that year.

On fertilization, it is evident in Figure 9 and Figure 10 that only fertilizing operations were carried out between May of 2016 and December of 2017, with an annual application of around 400 $kg.ha^{-1}.year^{-1}$. From year 1 to year 5, no fertilization operations were recorded according to the information provided on the plot. Worryingly enough, the recommended range for nitrogen –the only nutrient considered by the crop model– for immature palms can range from 48 to 90 $kg.ha^{-1}.year^{-1}$ (Bessou et al., 2017; Choo et al., 2011), while in mature palms it can range from 56 to 191 $kg.ha^{-1}.year^{-1}$ (Foster, 2003). Without considering that the application of fertilization is particular to each cultivation site (Caliman et al., 2004), and in that sense, the application rate should be adjusted to the soil conditions of the plot.

Still, according to Mosquera et al. (2017), fertilization participates in the costs of maintenance of the crop since year 1 and is in fact, the cost of greater participation in the cultivation of oil palm. Then it is believed that the lack of information on fertilization is due to a lack of record and not to an absence of fertilizers in the crop. What is certain is that the lack of information on fertilization in the simulation model from year 1 to year 5 –2011 to 2015– affected the predicted crop yield. Moreover, this introduces the uncertainty of how much the fertilization factor led to a delay and decrease in the production of fresh fruit bunches. To provide further reliability to the predictions on the crop outcomes more information about fertilization should be gathered.

Regarding the projected crop yield in the plot under the two treatments, although water for irrigation begins to be applied in August of 2015, it is from January 2016 when differences are marked in favor of the scenario with irrigation. The reason is that the fructification in palm oil is continuous, then there are always delayed effects of soil water deficit in yield (Carr, 2011) and also, delayed effects of irrigation on yield. Knowing that losses in crop yield depend on when the deficit occurs in relation to the stage of development of the inflorescence (Turner, 1977), it is established that the same happens with yield gains due to irrigation.

When observing the period between December of 2015 and March of 2016 –Figure 3 and Figure 4– as a time of water deficit –soil moisture below 30%–, and observing March and April of 2017 –Figure 10– as the months with the greatest yield differences between the two treatments, the delay in the effect of drought and irrigation on yield is even clearer. In these months, yield differences of 18.4 $t.ha^{-1}.month^{-1}$ and 16.8 $t.ha^{-1}.month^{-1}$ between treatments were reached. However, as reported by Turner (1977), the effects of drought on yield occur 21 to 26 months later.

By classification, the study site has suitable climatic conditions for oil palm productivity. Except for the year 2016, which was a year impacted by the El Niño climate phenomenon according to the drought reported between the end of 2015 and the beginning of 2016 (MADR, 2015, 2016). This suitability means that in the study site the benefit of irrigation is discreet compared to that which could be established in places with more marked and extensive dry periods, which does happen in plantations located in northern Colombian region, where the dry period usually extends between November to July (Lascano & Munévar, 2000).

As expected, the simulation estimated a higher crop yield for the plot under irrigation treatment, which demonstrates the usefulness of the inference method in supporting decision making. Plus, the positive impact on crop management due to the inference method. Between treatments, as shown in Figure 9, in 2016 the estimated yield difference was 4.6 $t.ha^{-1}.year^{-1}$ and for 2017 was 12.7 $t.ha^{-1}.year^{-1}$. This results in a 27% increase in the production of bunches of fresh fruit between 2016 and 2017, which allows us to affirm that the method has great potential for the palm agroindustry in Colombia and in other countries where the oil palm also develops.

4. Conclusions

The challenge of bringing raw information to accessible, understandable and relevant information for decision making was addressed in this work. Under an ideal scenario where agrometeorological information is available through a WSN at an oil palm plot, we formulated an inference method to assist decision-making for irrigation management. Without using an advanced technique, the inference method is based on Dempster-Shafer Inference, a technique close to human perception and reasoning. The inference method is supported on agronomic evidence such as the degree of water deficit stress and the stomata closing to estimate the crop water status. The simulation carried out to establish the impact of the method on crop yield, indicates that the irrigation managed by the method contributed positively to oil palm plot by increasing 27% the production of bunches of fresh fruit. Since palm farmers do not have many well-founded manuals that adequately describe how to grow and manage the crop and frequently have to make decisions based on a limited knowledge base, this method could enable the development of decision support systems that can proactively control irrigation according to the plot level agrometeorological conditions.

Furthermore, the formulated inference method –a new method for local and representative agrometeorological information processing– is the first approach from Data Fusion to support decision-making in the management of oil palm crops. And it allows that WSNs, a low-cost technology, can be better exploited for the collection of information and the search for an added value of the information. Not to mention that the inference method can be applied to other crops since its formulation is based on generic agronomic evidence, which gives it a potential impact beyond the oil palm agroindustry.

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