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Abstract

The objective of this study is to develop an innovative system to assess the risk of pests using a fuzzy logic approach. The system is designed to provide farmers with an index representing an estimate of the risk of presence of Western Flower Thrips (WFT), *Frankliniella occidentalis* in a roses greenhouse. For this purpose, a modular knowledge-based decision support system has been designed. The major findings of our research are summarized in four points. First of all, the model is based on variables measured automatically via sensors and do not require human activity (damaged area of a leaf, sex ratio). Secondly, as the system is not only oriented toward experimentation and research centers but also farmers, the phenomenon of manual counting could be replaced by a predicted value. In addition, the novelty associated with the system is that it supplies a daily rather than a weekly estimate of WFT risk level. In so doing, the farmers could stay aware of the influence of daily weather conditions on its evolution. Finally, this study could be beneficial to help reduce the utilization of pesticides and decrease the percentage of production loss, due to continuous monitoring of the risk level in the greenhouse. Because the development of *F. occidentalis* is highly sensitive to climate change, and in order to enhance the assessment of pest risk, an approach, which combines data related to the type of rose, the duration of sunlight and meteorological conditions, was followed. Simulation results are displayed at the end to validate our approach.

Keywords: Expert Systems, Decision Making, Fuzzy Logic, Risk Assessment, Frankliniella Occidentalis, Integrated Pest Management, Roses Greenhouse

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1. Introduction

Western Flower Thrips is a devastating pest species originating from the North-West of America and Mexico [1]. This insect species attacks ornamental crops, trees, and vegetables, leading to enormous economical and agricultural losses [2]. It is very difficult to detect these insects with the naked eye at a premature stage because of their tiny size, high reproduction rate, and affinity to protected areas [3]. One method to improve early detection is to apply various control programs such as biological, chemical, physical and others [4]. The process is called Integrated Pest Management (IPM) [5]. Monitoring is a major technique in IPM to control WFT. It is defined as counting and estimating population densities of a pest species [6]. Monitoring could be also achieved by risk assessment. For so doing, Decision Support Systems (DSS) are designed for the purpose of forecasting risk values and providing early warning signals [7].

DSS are computer applications that can be viewed as Knowledge-Based (KB) systems which contemplate knowledge and expertise in a specific field to solve its associated problems [8]. There exist a lot of researches about the implementation of DSS in agriculture [9; 10], and especially for disease and pests detection. Prasad et al. [11] designed expert systems to identify and prevent rose diseases. Del Aguila et al. [12] presented a system to support decision making to reduce pesticide use depending on climate, plant characteristics and pest population variables. The results were reasonable to validate the model, but the authors found that the systems need to be extended. Aiello et al. [13] proposed a DSS based on multi-sensor network to evaluate the risk of spread of pests in a greenhouse, by computing the dew temperature and comparing it with leaf temperature. Sarma [14] developed a rule-based expert system to determine the infection of a rose crop by Black Spot, Botrytis Blight, Crown Gall, and other diseases. The system proved to have a good performance in identifying the roses' diseases. In general, those systems appeared to provide valuable results except that they are based on cases where symptoms of diseases/pests had appeared on the leaves.

Thrips monitoring has been also carried out using mathematical models in which many approaches have been proposed to estimate thrips' population. Wang [15] predicted the population dynamics of *F. occidentalis* in function of fecundity by females, sex ratio and larval mortality. Nothnagl et al. [16] estimated WFT populations on greenhouse grown chrysanthemum by considering the temperature, population density and food availability. Ogada et al. [17] introduced a deterministic model consisting of differential equation systems to estimate thrips population growth by incorporating the effect of Tomato Spotted Wilt Virus (TSWV) on its dynamic. The model required a huge number of variables to be constructed (18 variables). Besides, several insect modeling methods have been developed ([18; 19; 20] and therein). None of the models was established to provide a real-time daily estimate. They also required too many variables which are difficult to obtain by regular farmers (sex ratio, damage of leaf, fecundity of females, etc.). Many of these models were established under laboratory conditions, unconcerned with complexities arising from interactions inside the greenhouse [20; 21]. Besides, when sufficient data are not available, estimation using the aforementioned studies could be constrained. In our case, the available dataset is not big enough for automatic learning. However, knowledge and expertise in the field are accessible, and fuzzy logic is used to design an eligible DSS to estimate WFT risk level in a roses greenhouse.

Fuzzy logic is a computing technique based on the fuzzy set theory introduced by Lotfi Zadeh in 1965 [22]. This mathematical framework imitates human reasoning since it defines variables in linguistic terms. Fuzzy logic has been widely used in agriculture for many purposes [23; 24]. Ahlawat et al. [25] designed a fuzzy expert system for rose yield prediction depending on the climate and minerals concentrations. The model had a good estimation accuracy when calculating statistical indicators. Similarly, a fuzzy expert system was developed to maximize crop productivity while minimizing fertilizer use, based on climatic parameters as well as soil properties [26]. The results confirmed the usefulness of the system for maximizing crop productivity by taking into account soil profile, water quality, availability of primary and secondary micro-nutrients, seasonal factors and pest incidence. Fuzzy logic showed a solid performance for forecasting pest activity level in rice crops and Finger Millets [27]. Tilva et al. [28] used fuzzy logic to design a plant disease forecasting system based on meteorological data like- temperature, humidity, leaf wetness duration (LWD). Niega [29] simulated the effect of temperature, relative humidity, and wind speed on the Coconut Scale Insect (CSI) infestation. Kiani and Mamedov [30] combined image processing and fuzzy logic to identify the cause of disease on strawberry leaves.

In this study, we aim at assisting farmers to monitor WFT in order to aid in the early disclose of perilous conditions for the development of thrips. One of the main strengths of the suggested system is that it provides a daily risk index. This advantage could be very substantial for

IPM because it could help farmers to employ appropriate strategies based on the displayed signal. Also, we are interested in developing a model to predict thrips' populations in a roses greenhouse, relying on a small number of variables.

The objectives of this work are to avoid yield loss, to optimize the production by reducing the use of pesticides, and to help the farmer fight effectively against pests. Another interest, which could be taken into account in this study is to help the farmer replace manual counting of thrips by an estimated value [31; 32]. The proposed DSS considers two different configurations (related to the metabolism of thrips in accordance with weather conditions) for risk level estimation using fuzzy logic. As this project is a collaboration between the University of Toulon and the Technical Institute of Horticulture (ASTREDHOR), the obtained results were validated by experts with whom we collaborate with, at the Syndicate of the Regional Center for Application and Horticultural Demonstration (SCRADH), its station in Hyères, France.

The rest of paper is organized as follows. Section 2 is dedicated to present the materials and methods in which we introduce the place of the study, the data and the proposed model. Section 3 includes the experimental results, the demonstration of a confidence index and a supervision interface. Section 4 presents a discussion about the findings of this research. At the end, a general conclusion is given.

2. Materials and Methods

2.1. Experimentation's site description

Hyères is a major city in the south-east of France, known for its importance in producing roses in the French Riviera. The SCRADH, latitude 43° 6' 55.9836" N, longitude 6° 9' 11.663" E, is a center that conducts experiments and research programs in the horticultural sector in Hyères. They have been carrying out experimental protocols on greenhouse crop production systems, then validating the technical and economic feasibility of new production concepts. Their inquiries and explorations are concerned with adopting appropriate strategies to control WFT, which has been an unpleasant pest for many years. A high percentage of crop loss has been observed (100% at some periods) due to WFT. The experimental greenhouse (300 m^2) consists of 6 benches (B1 to B6) of 24m long each, each carrying 6 plots (Fig. 1) (36 plots in total). Each plot (parcel) measures $4m \times 1m = 4m^2$ and contains about 34 rose-plants of same variety, for instance, Milva 2A, Samourai, Amaretto, Penny Lane, etc. The plants size varies between [0.5m, 2m] and the average size of the plants is about 1.5m. None of the plants was withered and replaced during the data acquisition period.

Figure 1: Distribution of plots in the greenhouse

2.2. Data acquisition

Data provided by the SCRADH consists of weather data measured by sensors and pest population data measured by manual counting. The data correspond to the period between October 15th 2012 and April 30th 2014.

2.2.1. Weather data

Weather data consists of internal greenhouse temperature Ti ($^\circ C$) and relative humidity RH (%), external temperature Te ($^\circ C$), global solar radiation Rad (W/m^2), and external wind speed Wspeed (m/s). The sampling time is 1 hour. The weather station is a PRIVA E-measuring box. The sensors inside the greenhouse are those of Ti and RH. Those outside the greenhouse correspond to Te, Rad and Wspeed.

2.2.2. Insect population data

The pest data is the weekly count of WFT individuals. For each plot, 4-5 plants were randomly selected, with 1.5 meters in between. The hypothesis is that 4-5 plants provide an idea about the population of thrips on other plants, and so, there is no need to inspect them all. Engineers at SCRADH counted the number of WFT individuals inside the rosebuds (of the selected plants) at harvesting (commercial) stage by threshing each rosebud on a white paper. The number of WFT in each flower plot tr_i is classified into 4 classes: 0, 1, 2, and 3, respectively corresponding to the total absence, existence of 1, 2, and 3 and more WFT individuals (Fig. 2).

Figure 2: A piece of raw data sampled on the 2nd week of 2013

Let n_i be the frequency (number of repetitions) of each class tr_i. Since $tr_3 = 3$

corresponds to the existence of 3 and more thrips, then its frequency is considered more significant than the others. For example, even if the counted population is 1000, it is marked 3. When we compute the mean, there will be a loss of information, and the relevant value is not a good representative. Fig. 3 shows the frequencies of each class tr_i during the study period. It is trivial that even though tr_0 has the highest frequency, but it actually corresponds to the absence of thrips.

Figure 3: Yearly count of each class tr_i

For a realistic and logical demonstration, each n_i is associated with a certain weight w_i, such that $w_0 = w_1 = w_2 = 0.1$ and $w_3 = 0.7 = 1-(w_0 + w_1 + w_2)$. The weights were proposed by the SCRADH's engineers following their expertise, but they could be adjusted depending on strong knowledge in the field. The measured risk level of WFT in the greenhouse $\in [0,3]$ is attained as shown below (Eq. (1)):

$$thrips\ level = \frac{\sum_{i=0}^{3} w_i n_i tr_i}{\sum_{i=0}^{3} w_i n_i} \qquad (1)$$

As an example, on week 19 in 2013, 0 thrips individuals was detected in 20 plots, only 1 thrips in 8 plots, 2 individuals in 3 plots, and 3 and more in 5 plots (Table 1). We remind that $tr_3 = 3$ corresponds to the presence of 3 and more thrips, and that its frequency $n_3 = 5$ is way more important than others classes.

Table 1: Counting of WFT individuals on week 19 of the year 2013

tr_i	0	1	2	3	total
n_i	20	8	3	5	36
w_i	0.1	0.1	0.1	0.7	1

Accordingly, the measured level of WFT on week 19 of the year 2013 is:

$$thrips\ level_{week19} = \frac{0.1\times 20\times 0+0.1\times 8\times 1+0.1\times 3\times 2+0.7\times 5\times 3}{0.1\times 20+0.1\times 8+0.1\times 3+0.7\times 5} = 1.8 \tag{2}$$

Fig. 4 presents the risk values of WFT on all the other weeks of the study, calculated following the same method as the one shown as above (Eq. (1)). Each value is defined and interpreted as the risk level of WFT and not the mean value. We are currently working on a method to transform this value into an approximated value of WFT individuals.

Figure 4: WFT weekly risk levels calculated from Eq. (1)

2.2.3. Static data

Thrips are sensitive to season variations [33; 34]. Consequently, the season is represented by the luminosity duration (hours), computed as the time difference between sunrise and sunset. Based on their expertise, SCRADH’s engineers observed that rosebushes with multi-bud stems are not favorable for hosting WFT as single-bud stems are. Hence, we thought about choosing this static variable to take place in the estimation process.

Fig. 5 shows the structure of our system which is based on an innovative DSS [35]. The system begins with sensing and ends with actions; a database is derived from data related to the environment as explained in the above paragraph. The so-formed database is subjected to analysis and modeling with the assistance of SCRADH’s experts. The results are interpreted and beneficial pieces of advice are induced and transferred to an end-user in order to support the decision makings and the actions executed within the crop environment. Finally, after carrying out these actions, the crop environment is monitored to begin a new cycle of information flow and so on.

Figure 5: Scheme of an innovative DSS [35]

Aiming at understanding the effect of meteorological parameters on the development of thrips, and reducing the complexity that could appear in designing our system, we intend to analyze the data (section 2.3).

2.3. Data Analysis

Data analysis is performed through a Principal Component Analysis (PCA) [36]. It is a technique used to determine the correlation between two or more variables and to reduce the size of a correlated data set without losing much information. The new variables are uncorrelated and called principal components, where each principal component is a linear combination of the original variables [37].

Let X be $n \times p$ data matrix where n is the number of samples and p the number of variables. This matrix X is centered and scaled in order to avoid the loss of information that might be caused by disparate scales or units of variables. Let V be the covariance matrix associated to X. Determine the eigenvalues $\lambda_1, \lambda_2, \dots, \lambda_p$ and their corresponding eigenvectors $u_1, u_2, \dots, u_p$ of the covariance matrix V. These eigenvectors are defined as the principal components (PCs) of a dataset. The number of PC's is determined by retaining the PC's that account for a certain percentage of the explained variance. This quantity is measured as follows:

$$W(PC_j) = \frac{\lambda_j}{\sum_{j=i}^{p} \lambda_j} \times 100 \tag{3}$$

We can also determine the correlation coefficient (C_j) between each variable and the principal components as follows:

$$C_j = \sqrt{\lambda_j} \times u_j \tag{4}$$

This calculation helps us plot the correlation circle which considers that two variables are correlated if their positioning in the correlation circle is close to each other and to the circumference of that circle. In this study, PCA is used to determine the influence of Ti, Te, RH, Rad, and Wspeed on the development of thrips level. We note that the weekly average values of the previous variables are used for PCA which serves as a tool to choose the variables for our system.

2.4. Knowledge elicitation using fuzzy logic

Fuzzy logic has found widespread applications in control systems, expert systems, pattern recognition, decision-making and many others. This approach is based on the computation of the degrees of truth (membership values). It is a generalization of the classical logic (0 or 1) in which each element belonging to the fuzzy set can have a membership value in the interval $[0,1]$. As data collected from the field could involve uncertainty and imprecision, fuzzy expert systems are designed upon human knowledge and reasoning to deal with such issues. A fuzzy system is composed of four blocks; Fuzzification, Knowledge base, Inference Engine, and Defuzzification (Fig. 6).

- Fuzzification: Crisp data are transformed into linguistic values in which each variable is characterized by a name, reference set (universe of discourse), and membership functions.
- Knowledge Base (Database and Rule Base): Relations between inputs and outputs are defined throughout some rules provided by expert knowledge.
- Inference Engine (Reasoning): Inference operations are performed on the rules to draw conclusions. For each rule, a fuzzy subset is defined for each output variable. Those subsets are aggregated using composition.
- Defuzzification: Fuzzy output set is converted into a crisp output.

Figure 6: Fuzzy reasoning principle

Knowing that a knowledge-based system becomes more complex depending on the amount of information to be processed, our system is designed in a hierarchical and modular way to avoid this dilemma [38]. Our system consists of 7 modules as shown in Fig. 7. The first two modules are adapted to estimate the MicroClimate Risk Factor (MCRF) and the Meteorological Risk Factor (MRF) issued from internal greenhouse temperature, humidity and external solar radiation. Modules 3 and 4 allow to evaluate the Static Risk Factor (SRF) corresponding to sunshine duration and the type of roses in the greenhouse, using an adequate function. The Weighted Risk Factor (WRF) is measured in function of MRF and SRF via a mathematical function in module 5. The WRF is modified in module 6 due to human intervention (for example: pruning, massive harvesting, etc.), resulting in the so-called Weighted Risk Factor after Intervention (WRFaI). The role of the last module is to predict the Total Risk Factor (TRF) the next day depending on ℓ previous observations. In what follows, we provide a comprehensive description of each unit pointed out above.

Figure 7: Architecture of the proposed system

2.4.1. Meteorological Risk Factor

The evaluation of the MRF depends on the average values of daily weather conditions (internal temperature ($\overline{Ti}$), internal humidity ($\overline{RH}$) and global solar radiation ($\overline{Rad}$)), and is fulfilled through modules 1 and 2 using fuzzy logic [39]. The universes of discourse, membership functions and fuzzy rules are selected by referring to cited peer-reviewed literature and depending on SCRADH's expertise and knowledge. Triangular and trapezoidal membership functions were used for the inputs of each module because they facilitate the calculation of degree of truth, and simplify the choice of universe of discourse for each membership function. The outputs of fuzzy modules were fuzzified by singleton membership functions to avoid the complexity of estimation. Defuzzification has been carried out via the centroid method (weighted average for singletons) using the Mamdani max-min inference approach. For all the figures in Section 2.4.1, the x-axis represents the universe of discourse and the y-axis gives the degrees of belonging.

2.4.1.1. Design of a microclimate risk fuzzy classifier (module 1) In the first module, we estimate the risk of development of thrips rising from the microclimate inside the greenhouse. This module consists of two input parameters (internal temperature and internal relative humidity) and one output parameter (MicroClimate Risk Factor). For the fuzzification of internal temperature having $[10^{\circ}C, 40^{\circ}C]$ as universe of discourse, we consider three membership functions [33; 40]: Cold ($<15^{\circ}C$), Warm ($\in[23^{\circ}C, 29^{\circ}C]$), and Hot($>34^{\circ}C$) as viewed in Fig. 8a. The second input, internal humidity $[40\%, 100\%]$ is decomposed into three membership functions [40; 41]: Moderate ($\in[40\%, 50\%]$), Slightly High ($\in[60\%, 80\%]$), and High ($>90\%$) as shown in Fig. 8b.

The output of the microclimate risk classifier is respresented by three singleton membership functions each representing a level of risk: Low (0) , Moderate (1.5) and High (3) (Fig. 9).

Figure 8: a) Fuzzification of the input: Internal Temperature and b) Fuzzification of the input: Internal Humidity

Figure 9: Fuzzification of the classifier: MicroClimate Risk Factor

Table 2 includes the set of fuzzy rules (rulebase). We perform the centroid defuzzification method using Mamdani max-min inference approach.

Table 2: Set of rules of the fuzzy classifier: MicroClimate Risk

Internal Temperature	Internal Humidity	MicroClimate Risk Factor
Cold	Moderate	Low
Cold	Slightly High	Low
Cold	High	Low
Warm	Moderate	Moderate
Warm	Slightly High	High
Warm	High	Moderate
Hot	Moderate	Low
Hot	Slightly High	Low
Hot	High	Low

2.4.1.2. Design of a meteorological risk fuzzy classifier (module 2) When weather conditions become less favorable, then thrips population decreases [42]. On the contrary, data collected by SCRADH show an increase in the population during the third quarter of 2013, which contradicts the information above. This contradiction is due to the fact that the metabolism of thrips changes from one semester to another (winter-spring and summer-autumn) due to weather conditions and the intensity of thrips population. Such complexity makes it difficult to estimate WFT risk level using the same model during the two semesters. We therefore consider two models: one for the winter-spring semester (W-Sp) and another one for the summer-autumn (S-A) period. The difference between the two models is that the W-Sp model is preceded by a cold period (autumn), while the S-A model is preceded by a warm period (spring). The system switches from one model to another depending on the ephemeris (Fig. 10).

Figure 10: Switch between the two models (module 2)

The calculation of the Meteorological Risk Factor takes into account two inputs: the MicroClimate Risk Factor and solar radiation. The input MicroClimate Risk Factor is decomposed according to Fig. 11a.

W-Sp Model Our expertise allowed us to deduce that when solar radiation increases, then thrips population increases. To fuzzify solar radiation, we consider three functions of belonging: Weak ($< 100\, W/m^2$), Moderate ($\in [150, 250]\, W/m^2$) and Strong ($> 300\, W/m^2$) (Fig. 11b). The output of the meteorological risk fuzzy classifier is defined by five membership functions, each corresponding to a level of risk: Null (0), Small (0.75), Medium (1.5), High (2.25) and Extreme (3)(Fig. 12). Accordingly, as shown in Table 3, the decomposition involves a set of nine rules.

Figure 11: a) Fuzzification of the input: MicroClimate Risk Factor and b) Fuzzification of the input: Solar Radiation

Figure 12: Fuzzification of the classifier: Meteorological Risk Factor

S-A Model Thanks to the reasoning and knowledge provided by SCRADH, we were able to define the set of rules presented in the Table 3. We can simply say that despite similar weather conditions in the first and third quarters of the year, the evolution of thrips is not the same. As we mentioned earlier, even if the weather conditions become less favorable in the fall, they will have a significant effect on thrips evolution because they already exist in the greenhouse.

Table 3: Set of rules of the fuzzy classifier: Meteorological Risk

MicroClimate Risk Factor	Solar radiation	MRF (W-Sp model)	MRF (S-A model)
Low	Weak	Null	Medium
Low	Moderate	Small	Medium
Low	Strong	Medium	High
Moderate	Weak	Small	High
Moderate	Moderate	Small	Medium
Moderate	Strong	Medium	Extreme
High	Weak	High	High
High	Moderate	High	High
High	Strong	Extreme	Extreme

2.4.2. Static Risk Factor

In module 3, we determine the weighting coefficient related to luminosity. This coefficient is integrated in the computation of the Static Risk Factor (the risk issued from the photoperiod and stem type) in module 4, which acts as a multiplying coefficient to the output of module 2.

2.4.2.1. Coefficient of luminosity: photoperiod (module 3) Photoperiod is an important factor that influences the morphological and phenotypic characteristic of thrips [33]. The development of thrips is directly correlated with the photoperiod, in which the biotic potential increases with photoperiod extension [43]. Whittaker and Kirk [34] found that long days promoted a faster development of thrips, particularly between early May and late June. According to SCRADH's expertise and [44; 45], the largest WFT populations have been observed between May and July. This implies that WFT populations vary with respect to the season. The reproduction rate of WFT becomes very high between week 19 (end of May) and week 27 (end of June) because the meteorological conditions are optimal, so the risk of infestation also increases. We propose a coefficient the could mimic this situation. This coefficient increases the risk realistically in terms of luminosity duration. The proposed coefficient is limited to a maximum value of 1.6 (maximal duration of sunshine = 16 hours divided by 10) to avoid bad estimation.

Let z be the duration of sunshine. Consequently, the coefficient $K_1(z)$ linked up to the W-Sp model, is defined by the following function:

$$K_1(z) = \begin{cases} \dfrac{z}{10}, & z \geq c \\ 1, & otherwise \end{cases} \tag{5}$$

where $c = \min(z)_{week \in [19,27]} = 14.5$ hours.

In the last quarter, thrips have already developed, so the season will not play an important role in their development. Thus, the coefficient for the S-A model is given by:

$$K_2(z) = 1$$

2.4.2.2. Static risk (module 4) Experts at SCRADH observed that WFT are more attracted to single-bud rose bushes (uni-flower) than to multi-buds ones (multi-flower). Let U be the type of the rose plant such that $U = 0$ if multi-flower and $U = 1$ if uni-flower. The Static Risk Factor for the two models is evaluated as:

$$\phi_i(K_i(z),U) = \begin{cases} \dfrac{K_i(z)}{K_i(z)+\alpha}, & U=0 \\ K_i(z), & U=1 \end{cases} \tag{6}$$

for $i = 1,2$ and $\alpha \in \mathbb{R}^{*+}$. The value of α is determined by the expert regarding the importance of the type "multi-flower" in determining the risk level.

Finally, the Static Risk Factor will become $SRF = \phi_i(K_i(z),U)$.

2.4.3. Weighted Risk Factor (module 5)

The evaluation of the Weighted Risk Factor is obtained in module 5 by multiplying the Static Risk Factor and the Meteorological Risk Factor.

$$WRF = MRF \times SRF \tag{7}$$

2.4.4. Intervention (module 6)

In module 6, the system is adjusted via a function upon human intervention, i.e, Dishooting (DS) (the rosebuds are broken so the plants accumulate nutrients), pruning (PR), and massive harvesting (MH). SCRADH's experts observed a remarkable decrease in WFT populations up to 10% of the initial population before harvesting. They also noticed that pruning caused the elimination of about 50% of WFT density. Accordingly, throughout the massive harvest and pruning, the risk is updated daily as shown below:

$$WRFaI(PR, MH, WRF) = \begin{cases} 0.5 \times WRF & PR = 1 \\ 0.1 \times WRF & MH = 1 \\ WRF & otherwise \end{cases} \tag{8}$$

Pertaining to Dishooting, the experts at SCRADH explain that this intervention is performed on a weekly basis given the number of weeks. Dihsooting leads to the removal of equal sub-populations of thrips every week. Hence, we can define a coefficient to model this action as follows:

$$WRFaI(DS, WRF) = \frac{s-1}{s} \times WRF \quad DS = 1 \tag{9}$$

where $s > 1$ is the number of weeks planned at prior for Dishooting.

2.4.5. Prediction of the WFT risk level (module 7)

We intend now to predict the Total Risk Factor (WFT risk level) over a certain number of previous days. The prediction is performed in module 7 using the Moving Average method. Moving Average (MA) is a time series method used in forecasting and smoothing [46]. It is based on predicting the average value of a variable at day $t+1$ by considering the most recent ℓ observations until a certain day t. The TRF is calculated as shown below:

$$\begin{aligned} TRF_{t+1}(\ell) &= \frac{1}{\ell}\sum_{i=1}^{\ell} WRFaI_{t-(\ell-i)} \\ &= \frac{WRFaI_{t-(\ell-1)} + \ldots + WRFaI_{t}}{\ell} \end{aligned} \tag{10}$$

MA is used to smoothen the WRFaI.

2.5. Evaluation of Models Performance

The goodness-of-fit of the model was evaluated by the mean square error (MSE). It indicates the accuracy of prediction by calculating the difference between measured and predicted values. It is defined as follows [47]:

$$MSE = \frac{1}{N}\sum_{n=1}^{N}(\hat{y}_n - y_n)^2 \tag{11}$$

where $\hat{y}_n$ and y_n are respective predicted and measured WFT levels for the n^{th} data entry, and $\bar{y}_n$ is the average of y_n.

3. Results

3.1. Experimental Results of Principal Component Analysis

PCA results show that around 82% of the total variance was explained by the first two principal components (Fig. 13a). The x-axis represents the principal components and the y-axis represents their eigenvalues. Fig. 13b presents the correlation circle in the plane 1*2, in which the x-axis (respectively y-axis) represents the correlation between the variables and the first principal component PC1 (resp. the second principal component PC2). The plot shows the existence of a good correlation between thrips and Ti, Te, Rad, whereas the correlation is less important with HR ($\angle(HR, thrips) \approx 114^\circ$ with a correlation coefficient =-0.4), and very weak with Wspeed ($\angle(Wspeed, thrips) \approx 94^\circ$ with a correlation coefficient =-0.07).

Figure 13: a) Percentage of variability for each PC and b) Correlation circle in plane 1*2.

We can therefore define three groups of variables, G1={Ti, Te, Thrips, Rad}, G2={Wspeed}, and G3={HR}. A linear regression model was developed to verify the choice of the variables based on the PCA decomposition. Consequently, the highest determination coefficient ($R^2 = 0.65$) was scored by the model including Ti, HR and Rad, where all the variables appeared to be significant (Ti: $p-value < 0.001$, Rad: $p-value < 0.01$ and RH: $p-value < 0.05$). Those variables are chosen based on PCA, linear regression and experts knowledge, as their influence on the development of WFT is well recognized. They are also used to construct the set of rules of the proposed system (section 2.4).

3.2. Evaluation of the fuzzy system

We verified the risk identification method on real measured data provided by the SCRADH. The results are presented in two parts. We present in section 3.2.1 the data used for the estimation of the moving average and then in section 3.2.2 the results obtained for the evaluation of the TRF and the intermediate factors.

3.2.1. Data

The data provided by SCRADH are from October 15th 2012 to April 30th 2014. The roses in the greenhouse are uni-flower type (U=1), then $SRF = K_i(z)$. The first step was to determine the range of data in the moving average. Based on the life cycle of thrips which varies from 7 to 15 days [3] contingent upon weather conditions, we tested 4 data ranges: 7, 10 and 14 days, and daily. We found that MA(14) (Moving Average over the last 14 observations) predicts the TRF with the smallest mean squared error (MSE=0.11). Therefore, the following results take into account an estimated 14-day moving average.

3.2.2. The Risk Factors

In this section, we show an illustration of the functionality of the system on 5 different days. With this choice of days, we wanted to test our method on identical days a year apart, in different seasons. Days 70 and 435 correspond to December 10th and days 145 and 510 to February 26th. To show the functionality of our system in the summer, we chose day D275 (June 26th 2013, day belonging to the beginning of the S-A model). Fig. 14 shows the values of $\overline{Ti}$, $\overline{RH}$ and $\overline{Rad}$ over the period of the study. We notice that favorable conditions are observed between days 250 and 330 (May-July), especially for relative humidity which shows a significant variation when compared to the other days. Table 4 shows the climatic conditions (Fig. 14) and the values of the risk factors on the five days considered.

Table 4: Climatic conditions and distinct risk values (2012-2014)

Day	D70	D145	D275	D435	D510
$\overline{Ti}$ $(^{\circ}C)$	19	19	25	19	19
$\overline{HR}$ (%)	88	72	71	87	82
MCRF	**1.3**	**1.5**	**3**	**1.1**	**1.5**
$\overline{Rad}$ (W/m^2)	96	63	330	75	136
MRF	2.1	0.7	**3**	**2.1**	0.8
SRF	**1**	**1**	**1.5**	**1**	**1**
WRF	**2.1**	**0.7**	3	**2.1**	**0.8**
TRF	**2**	**0.3**	**2.8**	**1.9**	**0.2**

These results are consistent when comparing actual weather conditions to those conducive to the development of thrips Ti $\in [23^{\circ}C, 29^{\circ}C]$, HR $\in [60\%, 80\%]$ and Rad $> 300\,W/m^2$ for the S-A model. The method indicates a very high risk of thrips (TRF=2.8). This result is confirmed by weather conditions (Ti= $25^{\circ}C$, HR= 71% and Rad= $330\,W/m^2$) that are ideal for the presence of thrips. Likewise for the day D75 (December 10, 2012, day belonging to the model S-A), the weather conditions (Ti= $19^{\circ}C$, HR= 88% and Rad= 96 W/m^2) is favorable to the presence of thrips; which is confirmed by the TRF value of 2. Fig. 15 shows the comparison between the estimated (dotted-blue) and measured (solid-black) thrips level. It is important to note that there is currently no method for estimating thrips risk level in real time. Nowadays, due to the fact that warning tools available to farmers are quite limited, experimentation centers in the French Riviera, SCRADH-Hyères, and others, warn farmers in the region about prosperous conditions to pest evolution through sending text messages. For the validation of our approach, the comparison was realized on weekly samples (Table 5), because in-situ measurements are done once a week. For instance, the TRF on week 11 equals 1.9 and the measured value is 1.9. As well as, on week 22, our system estimates a value of 0.6, whereas the measured value was 0.7 (Table 5).

Figure 14: Average daily values of (a) internal temperature (b) internal humidity (c) solar radiation (October 1st 2012-April 30th 2014.)

Figure 15: Estimated vs measured WFT level (October 15 2012-April 15th 2014)

Table 5: Predicted and Measured Risk Values-System without bio-control agents

Week	W11	W22	W40	W50	W65	W74
Measured	**1.9**	**0.7**	**2.6**	**1.5**	**0.2**	**0.7**
Predicted TRF	**1.9**	**0.6**	**2.8**	**1.6**	**0.2**	**0.6**

Nevertheless, we can see in Fig. 15 that despite some dispersions between the estimated values and those measured (especially for the year 2012, phenomenon coming from conducting diverse experiments and treatment strategies), our results are compatible. The global performance of the model was evaluated by the mean squared error (MSE=0.11). This statistic confirms the coherency of our results and the robustness of our model.

3.2.3. Confidence index

Confidence indices are used in expert systems to determine the reliability (validity) of a predicted value of a system [48]. Due to uncertainty, those values might not be so accurate; hence, we aim to measure how true they are [49]. Some studies in the literature encourage using confidence intervals, whereas others consider precise indices, depending on the application and its objectives. Mahini et al. [50] proposed a CI based on the knowledge derived from the rule-base (outputs) of their fuzzy expert system for predicting space weather. Another confidence factor was used in [51] to detect human diseases with real time diagnosis. The factor worked well for some diseases but was less effective to detect others. In [52], authors considered the confidence factor as the degree of belief associated with the rule. Confidence intervals were used in [53] to determine the certainty of the values predicted by a skin disease diagnosis expert system. One of the most important aspects of our system is to provide an estimate in real time (by day), so that the user could respond at an early stage. In this presented study, we are interested in measuring the truth of the estimated values of the system, therefore we will determine the Confidence Index (CI).

As the system is based on daily data, then the CI has to be computed in a similar manner. Because sensor driven data could involve uncertainty, our role is to evaluate at prior the effect of uncertainty on the forecast, just as Météo-France does. We have arbitrary chosen $\pm$ 5% uncertainty for temperature, humidity and solar radiation sensors. The decision process is as follows: despite this uncertainty, if the estimates are close to each other, then the prediction is reliable. Whereas if the results are contradictory onto one another, the prediction is slightly reliable.

The greenhouse comprises three sensors, each with 3 possibilities. As an example, the 3 options for the temperature's sensor are $\overline{T}$, $\overline{T}-5\%\overline{T}$ ($\overline{T} \searrow$) and $\overline{T}+5\%\overline{T}$ ($\overline{T} \nearrow$). Henceforth, we define $3^3 = 27$ combinations of variables as shown in Table 6, in which a value of 1 indicates the selection of variable and 0 stands for the option of not choosing it. For instance, case C1 is the case where the three sensors incorporates no uncertainty, and case C2 corresponds to its negative presence in the solar radiation sensor. The determination procedure of the confidence index is as follows:

1. Estimate the Total Risk Factor (TRF) for each of the above combinations (C1,…,C27).
2. Calculate the dispersion E_j between TRF_1 and TRF_j, $j = 2,\ldots,27$, such that $E_j = TRF_j - TRF_1$.
3. Calculate the percentage of confidence $(PCI_j(\%))$ corresponding to each dispersion E_j such that $PCI_j(\%) = \left[1 - \frac{E_j}{max(thrips\ level)}\right] \times 100 = \left[1 - \frac{E_j}{3}\right] \times 100$, $\forall$ $j = 2,\ldots,27$.
4. Select the minimal value of $PCI_j(\%)$ to be the confidence index CI, $CI = min(PCI_j)\ \forall j = 2,\ldots,27$.

Table 6: Possible cases of uncertainties

Cases	$\overline{T}$	$\overline{T}\searrow$	$\overline{T}\nearrow$	$\overline{RH}$	$\overline{RH}\searrow$	$\overline{RH}\nearrow$	$\overline{Rad}$	$\overline{Rad}\searrow$	$\overline{Rad}\nearrow$
C1	1	0	0	1	0	0	1	0	0
C2	1	0	0	1	0	0	0	1	0
C3	1	0	0	1	0	0	0	0	1
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
C25	0	0	1	0	0	1	1	0	0
C26	0	0	1	0	0	1	0	1	0
C27	0	0	1	0	0	1	0	0	1

The motivation behind calculating the confidence index in this way is to anticipate all the probable cases of uncertainty. In addition, the minimal percentage of confidence is adopted because it represents the worst scenario of uncertainty. CI is supposed to range between 0% and 100% ($CI \in [0\%, 100\%]$). If the estimation is reliable, then $CI \in [80\%, 100\%]$. When $CI \in [60\%, 80\%[$, the predicted value is considered slightly reliable. Once $CI \in [40\%, 60\%[$, the system points out low reliability. Whenever the confidence index indicates a value less than 40% , we conclude that the system is unstable and we can't count on its performance. However, it is very rare to obtain a value less than 40%, unless the sensors are broken down. A graphical interface was established using SIMULINK (Fig. 16). The developed intuitive interface allows users to easily track and monitor the thrips risk level according to input data.

Figure 16: Supervision Interface

It incorporates three sub-windows. The first one to the left (Risk of tomorrow) comprises a gauge which exhibits the severity of risk through colored intervals, a display case indicating next day's risk, and another one to show the confidence index associated with the predicted value. The sub-window to the right shows the severity of thrips evolution during the week, so that the farmer can follow up on the risk's evaluation. In the below window, thrips development trend is displayed to alert the user about the variation of risk from one day to another.

For example, by considering the period from June 19th to June 25th 2013 (where the system switches from model W-Sp to model S-A on June 21), we observe in the first window that the risk of June 26th is predicted to be approximately 2.9 with 98% confidence indicating a very severe situation (red color). The window to the right shows an extreme evolution between 19 and 25 June. Regarding the trend, the first arrow to the right exhibits a constant average trend of evolution between June 19th and June 25th, indicating that the variation of risk at this period doesn't imply a significant decrease or increase. The fourth downward-facing arrow explains that the risk decreased significantly on June 22nd 2013. Therefore, the trend of evolution has been decreasing from June 16th to June 22nd 2013 on average; similarly for the other arrows. Eventually, this supervision interface serves as an aiding tool for farmers to facilitate monitoring their greenhouses.

4. Discussion

The results in this research were obtained upon data collected from an experimental greenhouse, during a production period. The strengths of the model is that it is friendly-applicable by end-users. In addition, it relies on a small number of variables, and it helps optimize the production and its cost (yield/pesticides). Also, the model depends on real-time data, so it is self-adaptive to meteorological perturbations and seasonal variations. On the other hand, it entails some disadvantages. As seen in Fig. 15, the system was sensitive to missing knowledge, in which it was not capable of providing precise estimates between weeks 2 and 10. The achievement of study's objectives (potential of decreasing the use of pesticides and yield loss) is the most useful part for the end-user.

Based on the theoretical concepts used in this study, a supervision interface is created. Depending on the displayed prediction, the end-user will take appropriate decisions. Since the system provides daily information, spraying pesticides could be replaced with other IPM strategies (biological, cultural, etc...), and we therefore expect a reduced pulverization of chemicals.

The possible interactions between agronomic factors such as the plant variety, fertilization, irrigation were not considered in the development of the model due to the following reasons. Whatever the variety of the plant is, WFT will always exist . Although some varieties could be less sensitive to WFT, but as there are other sensitive varieties in the greenhouse, then WFT will move and fly from one plant to another. Hence, there is no sense in choosing this variable. When the size of the plant increases, it becomes a better host for WFT. The major difficulty while monitoring

WFT is that they are invisible because their nests are inside the rosebuds. Fertilization and irrigation are correlated with the plant size. 160mg/l of Nitrogen and Phosphorus, and 320 mg/l of potassium are added per plant. The amount of Potassium is as twice as that of nitrogen and phosphorus so that an equilibrium of minerals is attained. Plants are irrigated at least once a day in which 250ml of water per plant are added. In the presence of heat and sun (hot periods), irrigation could be applied up until 10 times per day so that plants will never suffer from water stress (plants are always in phytological activities such as evapotranspiration, photosynthesis, etc). Finally, those agronomic factors play an important role in defining the health and size of the plant. The larger the plant is, the more WFT individuals. Linking this up to our study, since we selected the flower buds at commercial stage (harvesting stage), our sampling method is independent of those agronomic factors.

One method to define thresholds for risk assessment is the Lhoste-Drouineau-Bages (LDB) method [54; 55]. In the absence of symptoms, if 10 WFT individuals per 150 m^2 are counted, then the threshold is reached (5% of agronomic loss); therefore, biological control is reinforced. Nevertheless, as we stated before, the monitoring of such kind of pests is very difficult through visualization (naked eye) because they are tiny insects (1-2 mm) and they have a thigmotactic behavior. The regular method adopted for defining the threshold is the appearance of symptoms on the crops. As soon as the first symptom is observed, rose growers intervene rapidly (the same day or during the week). However, this method is very limited because organisms are inside the rosebuds and their development is at maximal levels when climatic conditions are favorable.

5. Conclusion

In this study, we proposed a decision support system to pest risk assessment in a greenhouse producing roses. The work is based on data analysis, fuzzy logic theory and time series prediction. Our system provides a daily risk index based on the average values of internal temperature, internal humidity and solar radiation, exact duration of luminosity and type of rose. One of the great advantages of our system is that even if the data is uncertain, we can easily reveal risky conditions. We proposed a novel confidence index that supports decision makings, and an interface to keep the farmers aware of thrips risk level. Results showed a good performance of the system in determining the risk level of pest infection in a greenhouse by taking into account a small number of variables. The entire work has been validated and approved by experts at SCRADH.

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Abstract :
The objective of this study is to develop an innovative system to assess the risk of pests using a fuzzy logic approach. The system is designed to provide farmers with an index representing an estimate of the risk of presence of Western Flower Thrips (Frankliniella occidentalis) in a roses greenhouse. For this purpose, a modular knowledge-based decision support system has been designed. The major findings of our research are summarized in four points. First of all, the model is based on variables measured automatically via sensors and do not require human activity (damaged area of a leaf, sex ratio). Secondly, as the system is not only oriented toward experimentation and research centers but also farmers, the phenomenon of manual counting could be replaced by a predicted value. In addition, the novelty associated with the system is that it supplies a daily rather than a weekly estimate of WFT risk level. In so doing, the farmers could stay aware about the influence of daily weather conditions on its evolution. Finally, this study could be beneficial to help reduce the utilization of pesticides and decrease the percentage of production loss, due to continuous monitoring of the risk level in the greenhouse. Because the development of F. occidentalis is highly sensitive to climate change, an approach that combines data related to the type of rose, the duration of sunlight and meteorological conditions, enhances the assessment of pest risk.   Simulation results are displayed at the end to validate our approach.