Research Article

DSS fertirrigation system: An Italian case study

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ABSTRACT

The proposed paper deals with a Decision Support System (DSS) conceived for agronomists and farm managers involved in the fertirrigation (FER) process. The DSS has been developed within the Smart District 4.0 (SD 4.0) project, funded with the contribution of the Italian Ministry of Economic Development (MISE), aiming to sustain the digitization process of the Italian Small and Medium Enterprises (SMEs). The DSS is part of an integrated framework, mainly including advanced services for blockchain traceability and agriculture planning, optimizing the cooperation among different actors, such as farmers, agronomists and fertilizer suppliers. The most relevant and challenging part of the platform consists of Machine Learning (ML) supervised and unsupervised algorithms with high performance, to optimize production and quality in viticulture. Specifically, the Probabilistic Neural Network (PNN) model provides the performance of time shortage prediction when compared with other ML algorithm performance. Finally, the clustering k-Means algorithm is applied to extract information about active substances, doses, time of shortage, adversities, and pathogen elements, useful to optimize a FER plan. All the analyzed algorithms are applied to an experimental dataset. The work starts with the design of the processes and of the information flow able to optimize grape supply chain and traceability, and then focuses on data analysis. The data analysis approach is suitable to formulate precision farming rules.

Keywords: Artificial Intelligence, Fertigation, Smart Agriculture, Blockchain, Precision farming.

INTRODUCTION

Fertirrigation (FER) is a growing field that is based on the mix of agricultural and technological knowledge and practice (Maloku *et al.,* 2020). The technological domain of the FER is based on the following elements: wireless sensors, soft computing and Internet of Things (IoT) (Njoroge *et al.,* 2018), analytics, Decision Support Systems (DSSs), cloud storage data (Power *et al.,* 2019), geographic information system-GIS, precision planting (Kumar *et al.,* 2017), global navigation satellite system (Marucci *et al.,* 2017). FER systems can be integrated with 5G technology (Razaak *et al.,* 2019). FER reduces the waste of resources (Sanghera *et al.,* 2020; *Sureshkumar et al.,* 2017). FER systems remove the presence of weeds from the soil (Lottes *et al.,* 2018; Olaniyi *et al.,* 2020). Robotization can boost the application of FER (Pretto *et al.,* 2019; Fawakherji *et al.,* 2021). FER improves the managerial efficiency of agricultural firms (Paustian *et al.,* 2017) increasing the productivity of the soil (Baek *et al.,* 2019). The usage of FER systems has a positive effect on promoting the efficiency of the nutrition method and the reduction of pollution (Septar *et al.,* 2019). The implementation of photovoltaic systems can also improve the efficiency of a FER system (Shamsuddin *et al.,* 2020; Abdullah *et al.,* 2020). The efficiency of FER systems can also be improved with the usage of IoT (Visconti *et al.,* 2020) and data management (Subić *et al.,* 2016). The application of information technology can have a positive impact on FER (Incrocci *et al.,* 2017) also in developing countries (Shraddha *et al.,* 2018; Jacobs *et al.,* 2018). Applications can also have a role FER management (Pérez-Castro *et al.,* 2017). The application of FER systems, based on robotization, data management and IoT (Zamora-Izquierdo *et al.,* 2019) has a positive role in reducing water scarcity (Rahman & Abidin *et al.,* 2018; Jiménez-Benítez *et al.,* 2020; Kachor *et al.,* 2019; Gaikwad *et al.,* 2020), diminution of water waste (Rahman & Buyamin *et al.,* 2018; Salvi *et al.,* 2017) and optimization of nutrients (Dong *et al.,* 2018; Karunanithy *et al.,* 2020). The application of FER techniques also has a positive impact on the ability to calculate the appropriate metrics for planning irrigation (Smith, 1992; Wu, 1992) and evapotranspiration (Allen *et al.,* 1998). The application of methods of estimation and prediction, can be optimized through the usage of statistical and computational methods based on Machine Learning (ML) (Choudhary *et al.,* 2019; Krupakar *et al.,* 2016). The application of fertilization plans is based on the estimation of quantities of fertilizers and nutrients present in the soil (Regar & Singh, 2014; Chuan & Zhao, 2016; Xu *et al.,* 2017; Brandoli *et al.,* 2021). The quantitative estimation of the mixture of fertilizers, water and nutrients is mainly based on statistical and computational methods i.e., ML (Chlingaryan *et al.,* 2018; Qin *et al.,* 2018; Nikoloski *et al.,* 2019; Pedersen *et al.,* 2019; Pohl *et al.,* 2017). To optimize the FER plan it is

also important to collect information about other variables such as: precipitation, temperature, humidity, pressure, dew point, wind speed, and intensity of solar radiation (Schlenker & Roberts, 2009; O'toole & Hatfield, 1983; Fritschen, 1967; Fischer, 1985). To perform an improved FER activity, it is necessary to gain the knowledge about the nutrients of the soil (Moreno & Garcia, 2018; Bondre & Mahagaonkar, 2019). Concerning irrigation and FER advances, specific methods can be adopted using DSS models based on data field detection (Massaro & Savino *et al.,* 2020; Massaro & Meuli *et al.,* 2018) and data fusion approaches (D'Accolti *et al.,* 2018). Another technology useful for the traceability of field production processes is the blockchain (Massaro & Maritati *et al.,* 2020). The described state of the art, highlights that the FER technologies and approaches can be different. For each crop can be developed specific approaches and technologies: the complexity is mainly to find the technology matching with the specific pilot case study, starting to the process optimizing. In this direction, a first step is to implement a software platform able to collect field data and actor's information. The basic principle to construct a FER DSS is to design and implement an information system platform, allowing the communication between different system actors such as agronomists, farmers, fertilizer suppliers, and analyzing collected data by means of specific methods and ML algorithms. Specifically, the study proposed in this paper is part of the Smart District 4.0 (SD 4.0) project, supported by the Italian Ministry of Economic Development (MISE), with the aim of stimulating the widespread digitization processes of SMEs in some typical sectors. In particular, as regards the Agro-Industrial sector, SD 4.0 has undertaken an experimental test case aimed at enhancing a solution for precision farming developed by Asepa Energy srl, a small company with high expertise and skill in industrial automation. Thanks to the proposed platform, it is possible to automate remotely combined cycles of irrigation and fertilization. The goals of the pilot case study of the project is to:

- Provide a single method of access to the various users of the system platform: farmers, agronomists, suppliers and possibly actors in the distribution chain, such as buyers, logisticians and consumers.
- Guarantee the certified traceability of field operations via blockchain;
- Guarantee the management of stocks in the warehouse, with the automatic supply of fertilizers;
- Allow the agronomist to be able to set the FER plan also in terms of proposals automatically generated and based on the updated status of the production site (sensors, weather, etc.) using automatic learning logics;
- Provide graphical dashboards useful for precision farming in the viticulture field.

Following the main goals of the project, the results of the proposed work are discussed in the following steps:
- Design of the information system of the pilot case study describing in details dataflow architectures;

- Production process design by means of the Business Process Modeling Notation (BPMN) approach;
- The description of blockchain and platform FER planning dashboards;
- Comparison of different ML algorithm performances suitable for the prediction of the important variable of the time of shortage indicating company productivity;
- The adoption of the clustering k-Means model to provide graphical dashboards indicating the effectiveness of fertilizers.

METHODS

Architecture design

Figure 1 is illustrated the architecture of the FER system related to the case of study: the architecture indicates the data flow between the whole SD 4.0 platform involving field data of a central unit located in a field, and other data available in the cloud.

The DSS is integrated into the platform and processes different data such as weather data and predicted ones, products used for pathogens and adversities, product doses and times of shortage. As shown in the architecture of Figure 2, the field data transmission is enabled by MQ Telemetry Transport or Message Queue Telemetry Transport (MQTT) messages. Input sensor data and field information are processed by ML algorithms (core of the DSS system), providing fertilizer and irrigation recommendations and predictions.
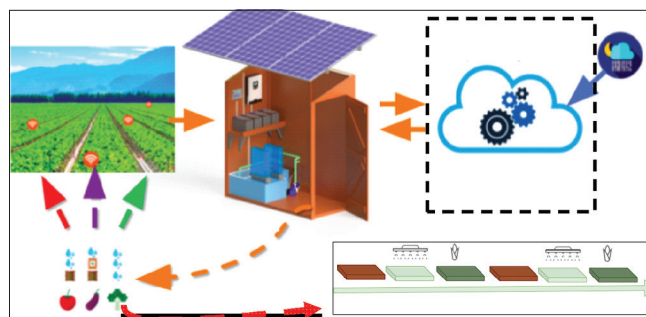

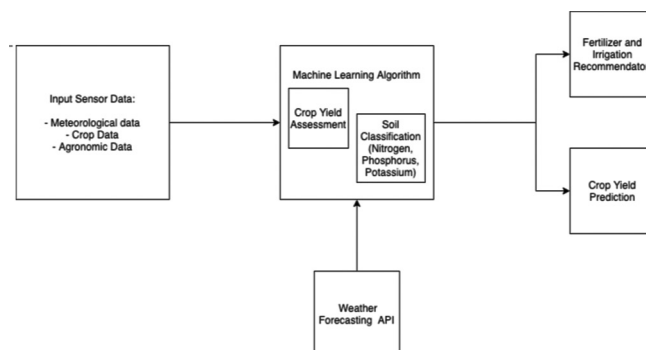**Figure 1:** Architecture of the SD 4.0 fertirrigation system.

Figure 2: Example of a ML DSS Model indicating a FER data processing approach.

BPMN processes

From the analysis of the AS-IS processes, substantially manual procedures are revealed which allow to trace field operations in a paper book. All the operating processes are not automatized, and the agronomist used a paper scheduling the FER procedures to perform. The actors involved in the optimized TO-BE processes are therefore substantially the same as those considered in the AS-IS processes, by adding the FER manager reading the DSS ML outputs. Furthermore, the new process has added to the registration (notarization) of information via blockchain.

All the actors involved in the new processes are therefore the FER manager, the agronomist, the farmer and the fertilizer manufacturing company providing commercial field treat-ment. In Figure 3 is illustrated the BPMN diagram of the first TO-BE use case, involving the various actors of the system. This diagram is based on the concept that, concerning the FER phases, there are three different methods:
- Manual fertigation: in this case the farmer can fertirrigate the field by activating the SD 4.0 system remotely using a mobile phone, sending the commands about the irrigation, the type of fertilizer and the doses to be used;
- Scheduled fertigation: the farmer can set up a calendar containing a FER plan by specifying information such as date, start time, end time, amount of water, type and amount of fertilizer to adopt;
- Automatic fertigation: in this case the SD 4.0 system proceeds with the automatic FER of the field, detecting

data from the field sensors and applying the FER model set.

The manual and the scheduled procedures are optimized by setting some threshold values able to control the FER process. The farmer and the agronomist pools complete the first case study: the farmer set doses, data, operating hour, and could enable the automatic FER plan, while, the agronomist creates and updates the FER model by suggesting to the farmer the actions to perform according to the results provided by the DSS.

The BPMN diagram of Figure 4 indicates the second use case describing the SD 4.0 platform's main functions of traceability of treatments via blockchain and inventory management. The use case is able to trace the life cycle of the product transcribing the related information useful also for agro-industrial companies which could manage and monitor the entire production chain, learn about the trend of crops and the cultivation techniques adopted by suppliers. In this use case, a notarization procedure is proposed by the farmer relating to any information on the products used (fertilizers) and any activity performed in the field (sowing date, seed type, position of the field, associated area, treatment date, etc.). Information notarization via blockchain, offers in the first instance the possibility to the final customer or supply chain operators, to retrieve all the information on a specific product by simply reading the QR code as packaging label of the purchased product. In the same formal model, the process of replenishing the fertilizer stocks is also managed based
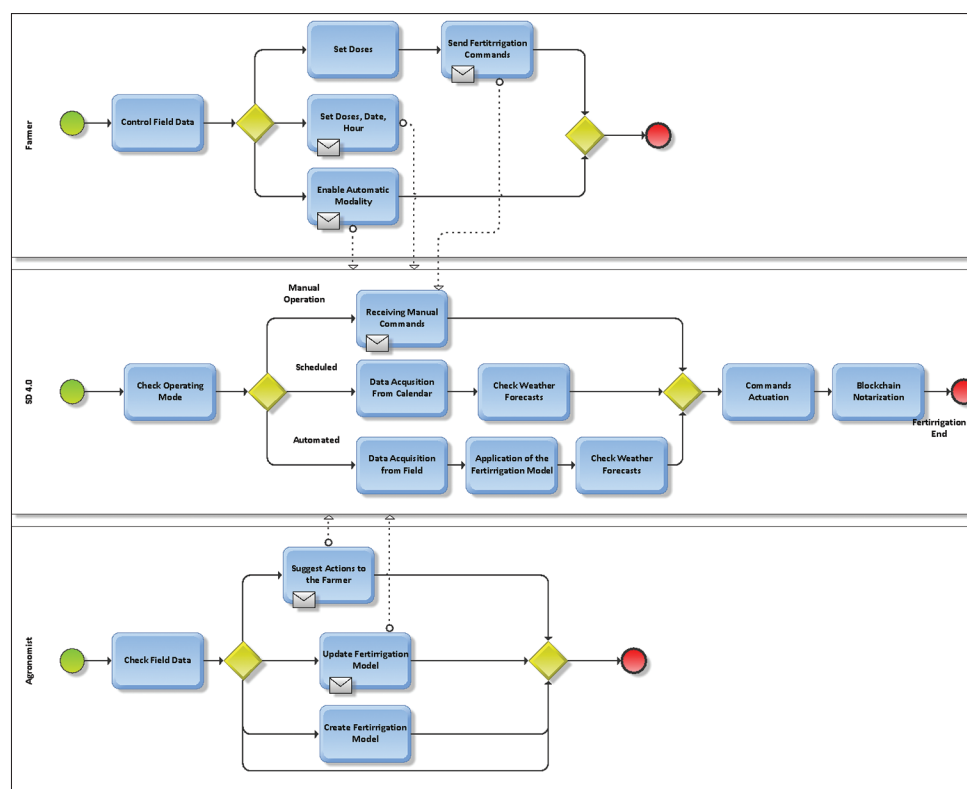

Figure 3: First use case: BPMN "TO BE" process involving different actors of the FER system.

on the trend in consumption related to their use during the season. The SD 4.0 platform receives the message, acquires all the information associated with the particular event ID from the DB, and notarizes them through blockchain. Then the platform updates the stocks and verifies the availability for other programmed FER plans. In the case of product unavailability, the platform automatically sends a notification to the fertilizer producer enabling the purchase process.

In Figure 5 is illustrated the third use case involving the "core" actor of the agronomist, enabling processes of creating and updating the FER plan. The goal of this use case is to create an intelligent and automatic FER system through the use of ML techniques, maximizing crop yields. The factors contributing to the crop yield are the environmental factors such as meteorological factors (rainfall, temperature, humidity, air pressure, dew point, wind speed, intensity of solar radiation), culture factors (type of crop, morphological composition of the soil, evapotranspiration conditions), and agronomic factors (quantity of fertilizer or water used in the last irrigation, estimated shortage time). The FER model is set using a calendar, where for each FER event the agronomist will have to specify the related information.

PLATFORM FRAMEWORK

The Unified Modeling Language (UML) scheme of Figure 6 indicates the Use Case Diagram (UCD), including all system functions and actors, and shows SD 4.0 platform data flow. In the diagram is distinguished the data warehouse system (Google Cloud BigQuery), and the relationships between all actors. As main DSS outputs are indicated in the figure the stock management indicators, the intelligent FER plan, the weather forecasting and data clustering dashboards. Figure 6 is representative of the BPMN "TO BE" process in Figure 5. The DSS "core" is constituted by the Konstanz Information Miner (KNIME) artificial intelligence algorithms. The adopted

KNIME workflows are objects oriented Graphical User Interfaces (GUIs) suitable for industrial applications (Massaro & Galiano, 2020; Massaro, 2021; Massaro et al., 2018). More details will be provided in the *Results* section.

RESULTS

SD 4.0 frontend implemented interfaces

The SD 4.0 platform is developed by using different technologies embedded into a unique framework. In particular, the Ethereum technology is adopted to include notarized information into blockchain blocks and to trace product transactions. In Figure 7 is illustrated a screenshot of the frontend interface controlling blockchain data.

The frontend interface related to SD 4.0 initial FER plan creation is shown in the Figure 8.

When a FER plan is created a unique Identification number (ID) is associated with each FER event. In Figure 9 is illustrated the Graphical User Interface (GUI), composed of the different fields structuring a FER plan.

The output of the created event is summarized by the layout interface of Figure 10.

DSS data processing of the experimental dataset

Some functions of the DSS are forecasting and the data clustering supporting agronomists to define FER plans. The experimental dataset concerns two years of FER process, related to three fields used for three grape typologies (Red Globe, Italia, Selvatico), and contains the following attributes for a total number of 94 records:
- Time: sampling time of the experimental dataset;
- Time of Shortage (key parameter expressing field activity and consecutively productivity): waiting time for further field operations;
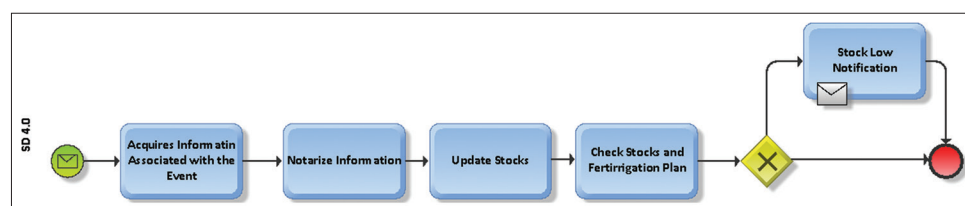

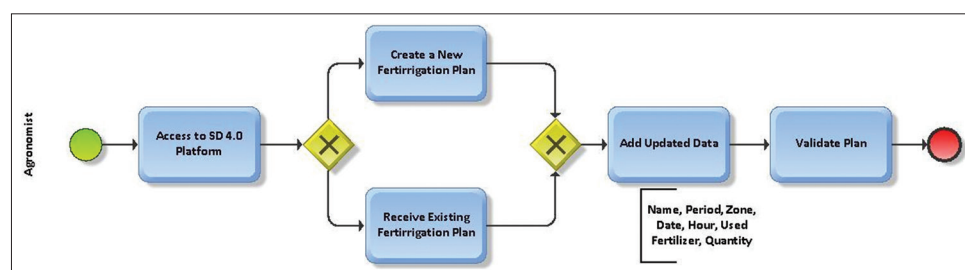**Figure 4:** Second use case: BPMN "TO BE" of the SD 4.0 platform.

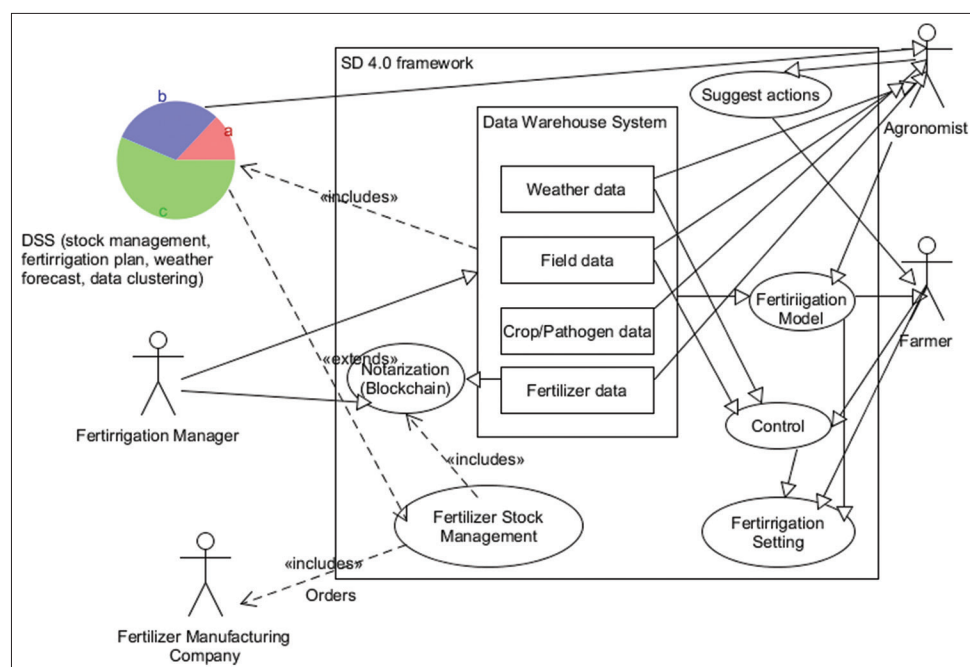**Figure 5:** Third use case: BPMN "TO BE" process associated to the agronomist.

Figure 6: UML UCD diagram of the whole DSS of the FER system.

Figure 7: Ethereum blockchain GUI indicating node transaction list.

- Pesticide Doses: quantity of pesticide doses expresses in g/L;
- Pathogen/adversity element: Red Spider (Ragnetto Rosso), Downy Mildew (Peronospora), Moth (Tignoletta), Frankinella Occidentalis, Powdery Mildew (Oidio), Gray Mold (Muffa Grigia), Catch Moth (Cattura Tignola), Leafhoppers (Cicalina);
- Commercial fertilizer typology (Sercadis, DUORO 100 EC, Fluxapyroxad, Forum 50 Wp, Quantum, Tiovit jet, CAL-EX 1,9 EW, Penconanzolo, Topas 10 EC, Abamectina, Cimoxanil, Folpet, Geoxe, Karathane star, Mevaxil M, Microthiol disperss, Mildicut, Rame, Reindan 22, Rufast e Flo, Trap test, Affirm, Belpromec, Brodoflow new, Cerexil M Dg, Cloripirifos-metile, Corner MZ, Cyazofarmin Fosfonato di Disodio. Dicarzol 50 SP, Dimetomorf, Fludioxonil, Laotta, Metalaxyl M Mancozeb, Meptyldinocap, Moxyl 45 WG, Optix 80 disperss, Poltiglia disperss, R6 Albis, Ridomil Gold MZ Pepite, Sacron 45 WG, Sundek, Support 10 EC, Vite for WG 80, Tiogel WG, Vertimec EC, Vite for WG 80, Vitene Ultra SC, Zolfo Bagnabile).
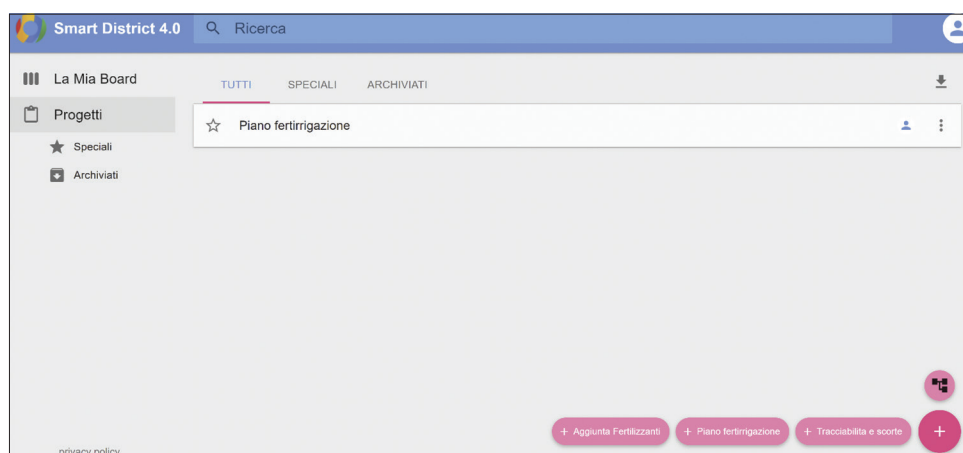
Figure 8: SD 4.0 platform: initial graphical user interface of the FER plan creation.
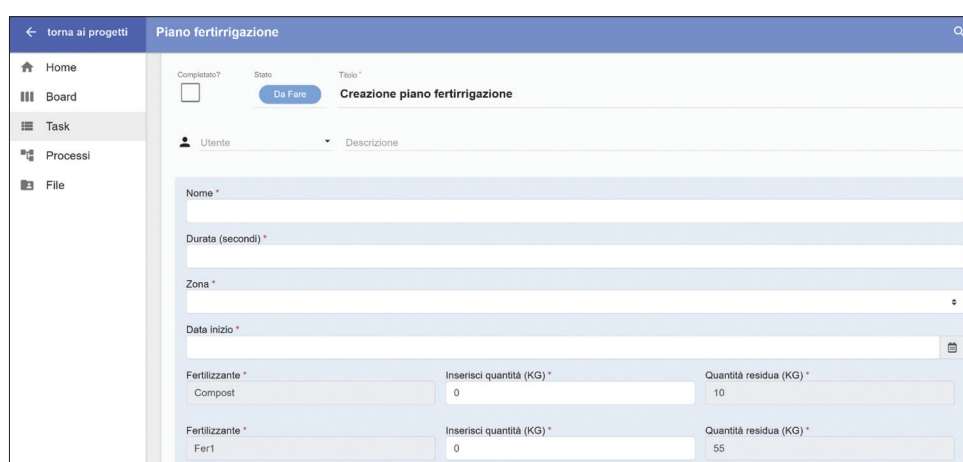

Figure 9: SD 4.0 platform: GUI of the construction of the FER plan.

Figure 10: Output of the FER plan.

- Active substance of the fertilizer (Clorpirifos Metile, Penconazolo [Penconazole], Topas 10 EC [Penconazole based], Abamectina [Abamectin], Dimetomorfo [Dimetomorph], Nordox Energy [Copper based], Cobre Nordox [Cu$_2$O based], Sundex, Rame [Copper], Geoxe [fludioxonil based], Emamectina Benzoato [Emamectin Benzoate], Zolfo Bagnabile [Wettable Sulfur], Fludioxonil,

Tiovit Jet [formulated based on technologically advanced sulfur], Abamectina [Abamectin], Acrinatrina [Acrinatrin], Cimoxanil, Fosetil-Al [Aluminum ethylphosphite based], Fluopicolide+Fosetil-Al, Mancozeb Metalaxyl-m, Tartrate-resistant acid phosphatase [Trap] test, Formentate, Fluxapyroxad, Sercadis [Fluxapyroxad based], Folpet, Folpan 80 WG [Folpet based], Meptyldinocap, Karathane Star [Meptyldinocap based], Vitene Ultra SC, CAL-EX 1,9 EW [Abamectin based], Mildicut [Cyazofamid and Disodium Phosphonate based], Cyazofamid Fosfonato di Disodio [Cyazofamid Disodium Phosphonate], Sacron 45 WG [CIMOXANIL based], Carexil M DG [Metalaxyl and Mancozeb based], Penconazole, DUORO 100 EC [Penconazole based], Forum 50 Wp [DIMETOMORF based]);

Where some commercial fertilizers have the same name as the active substances. The dataset is sorted by date. A first approach to analyze experimental data, is to find the best supervised algorithm for forecasting. In Table 1 are listed the performance indicators of Artificial Neural Network (ANN)-Multilayer Perceptron (MLP), Fuzzy Rule, Probabilistic Neural Network (PNN), Simple Regression Tree, Gradient Boosted

Table 1: Standard hyperparameters adopted for the comparison

Sintesi dei risultati degli algoritmi utilizzati per il machine learning e le predictions							
N	**Algorithm**	**R^2**	**Mean Absolute Error**	**Mean Squared Error**	**Root Mean Squared Error**	**Mean Signed Difference**	**Mean Absolute Percentage Error**
1	ANN-MLP	0,30822949	0,142123791	0,026213761	0,161906643	-0,00192817	NaN
2	Fuzzy Rule	-0,3403142	0,161945813	0,050789497	0,225365252	-0,001	NaN
3	PNN	0,06621973	0,103448276	0,035384412	0,188107449	-0,043103448	NaN
4	Simple Regression Tree	0,01911545	0,129187192	0,037169369	0,192793592	-0,031486043	NaN
5	Gradient Boosted Trees	0,03640951	0,126700633	0,036514033	0,191086453	-0,033643815	NaN
6	Linear Regression	-0,049649	0,175470263	0,039775112	0,199436987	-0,042182583	NaN

Table 2: Standard hyperparameters adopted for the comparison of different ML algorithms

Algorithm Hyperparameters		
Algorithm	**Hyperparameters**	
PNN	Missing values	Best Guess
	ShrinK after commit	Yes
	Use class with max coverage	No
	Maximum number of Epochs	42
ANN-MLP	Maximum number of iterations	100
	Number of Hidden Layers	1
	Number of Hidden Neurons per Layer	10
	Ignore Missing Values	No
	Use seed for random initialization	No
Fuzzy Rule	Missing values	Best Guess
	ShrinK after commit	Yes
	Use class with max coverage	Yes
	Maximum no. Epochs	42
Simple Regression Tree	Enable Highlighting	2.000
	Missing value handling	XGBoost
	Limit number of levels (tree depth)	10
	Minimum split node size	1
	Minimum node size	5
Gradient Boosted Trees	Limit number of levels (tree depth)	4
	Number of models	100
	Learning rate	0,1
Linear Regression	Predefined Offset Value	0
	Missing Values in Input Data	Fail on observing missing values
	Scatter Plot View-First Row	1
	Scatter Plot View-Row Count	20.000

Trees, and Linear Regression algorithms. The performance is estimated by adopting Konstanz Information Miner (KNIME) workflow [59] using the standard hyperparameters indicated in Table 2 (parameters provided by the KNIME tool as default parameters).

In order to optimize the metric for the best performance estimation, it is defined the *BestAlgorithm* of Eq. (1), defins the final algorithm ranking. By observing the results of Table 3, the PNN algorithm represents the best algorithm for the fixed hyperparameters. Different results can be achieved by changing hyperparameters by adopting an approach based on error minimization (Massaro *et al.,* 2018), but the proposed method is useful to find a primary an algorithm

suitable for the experimental dataset, by considering also the *BestAlgorithm* indicator able to address the choice by estimating the sum of the Mean Absolute Error (MAE), Means Squared Error (MSE), and Root Mean Squared Error (RMSE).

$$\begin{aligned} \mathit{BestAlgorithm} = &MinRanking(MeanAbsoluteError) + MinRanking(MeanSquaredError) \\ &+ MinRanking(RootMeanSquaredError) \end{aligned} \quad (1)$$

In Figure 11 is illustrated the KNIME workflow implementing PNN algorithm composed by the following blocks (workflow objects):

- Excel Reader: reader of dataset exported from BigQuery datawarehouse in the local repository;
- Table Manipulator: block used for the data type setting (attributes as string, double, etc.);
- Column Filter: block selecting the attributes to analyze (for the specific case of the algorithm comparison are considered the key attributes of Time of Shortage and Pesticide Doses);
- Normalizer: block able to normalize the attribute values to average strong data oscillations and, consecutively, reducing error during the calculus;
- Partitioning: block splitting the experimental dataset into training and testing dataset (for the comparison is adopted 70 % of the dataset for the training, and 30 % of the dataset for the testing);
- PNN Learner: algorithm training block;
- PNN Predictor: algorithms testing block;
- Numerical Scorer: block providing error indicators of Table 1.

The forecasting is performed by considering the key attributes of pesticide dose, and time of shortage. For example Figure 12 is illustrated the trend of the Pesticide dose during two operation years, where more records can coincide with the same data explaining why the second season appears to be longer.

The Time Shortage trends related to the two analyzed seasons, and to the prediction of the third year, are plotted in Figure 13: the days are limited to a period range between 10 and 35 days with some peaks observed in the first year and in the predicted one. The result of Figure 13 proves that for the three analyzed grape fields the human work is and will be controlled (correct execution of the FER plan).

The second approach adopted for data analysis is to find data clusters supporting dataset reading, and providing information about precision farming for the specific case study.

Table 3: Ranking related to the tested algorithms using the *BestAlgorithm* indicator

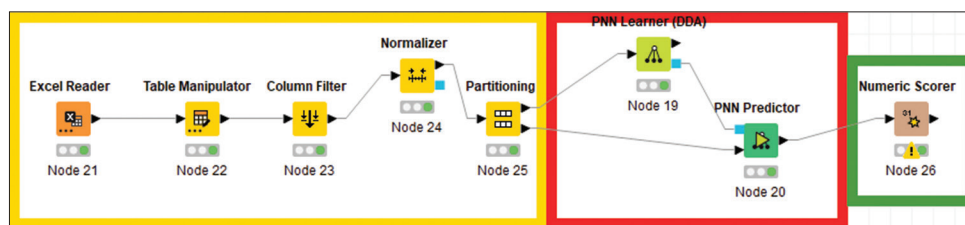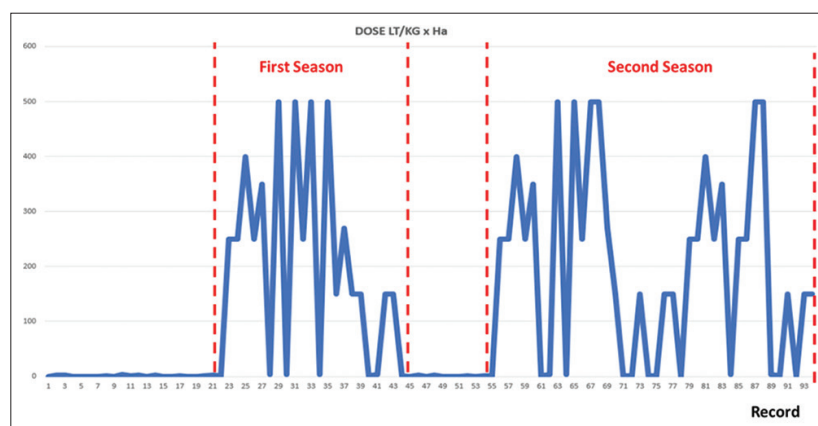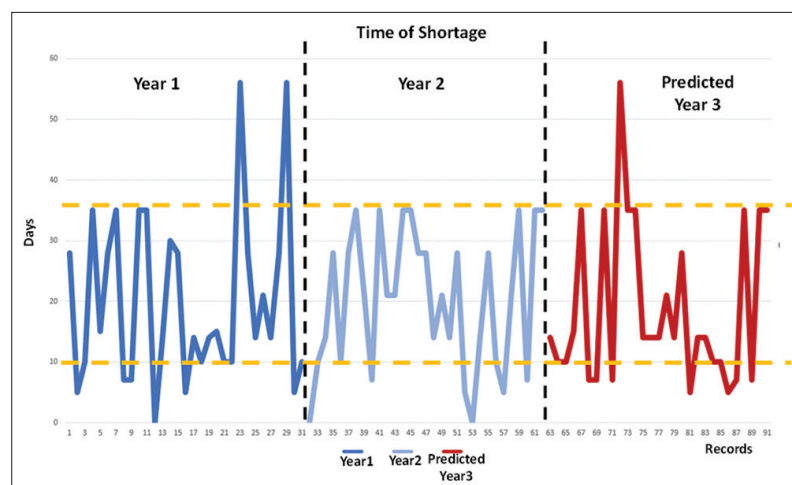| Rank	Algorithms	Mean Absolute Error		Mean Squared Error		Root Mean Squared Error		Totale	
		Ranking degli algoritmi in base alla minimizzazione degli errori.							
1	PNN	★	1	★	2	★	2	☆	5
2	ANN-MLP	☆	4	★	1	★	1	☆	6
3	Gradient Boosted Trees	★	2	☆	3	☆	3	★	8
4	Simple Regression Tree	☆	3	☆	4	☆	4	★	11
5	Linear Regression	☆	6	☆	5	☆	5	★	16
6	Fuzzy Rule	☆	5	☆	6	☆	6	★	17

Figure 11: KNIME workflow applied to the experimental dataset, implementing PNN algorithm.

Figure 12: Dose data trend collected into two operation years (2019-2020). The dose refers to a specific active substance.

Figure 13: Time of Shortage (labelled class) trend related the period from May to August (2019-2020).
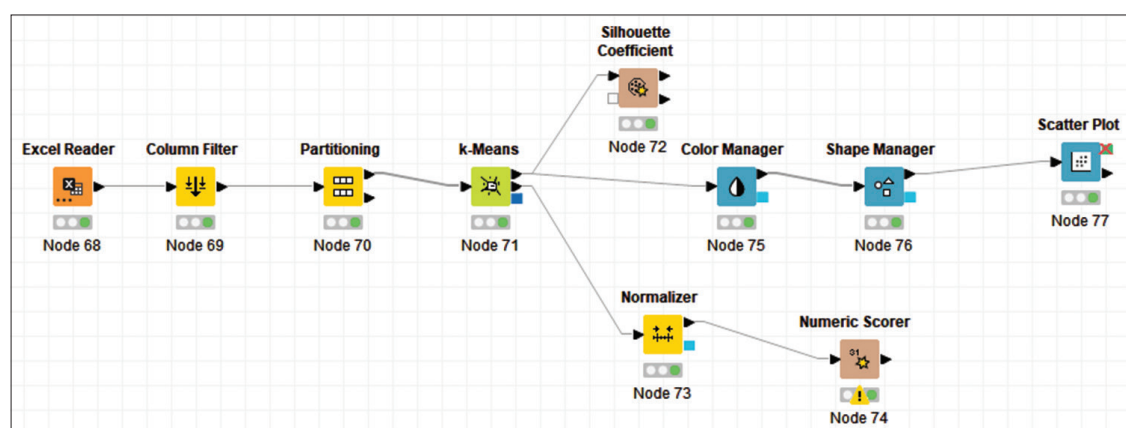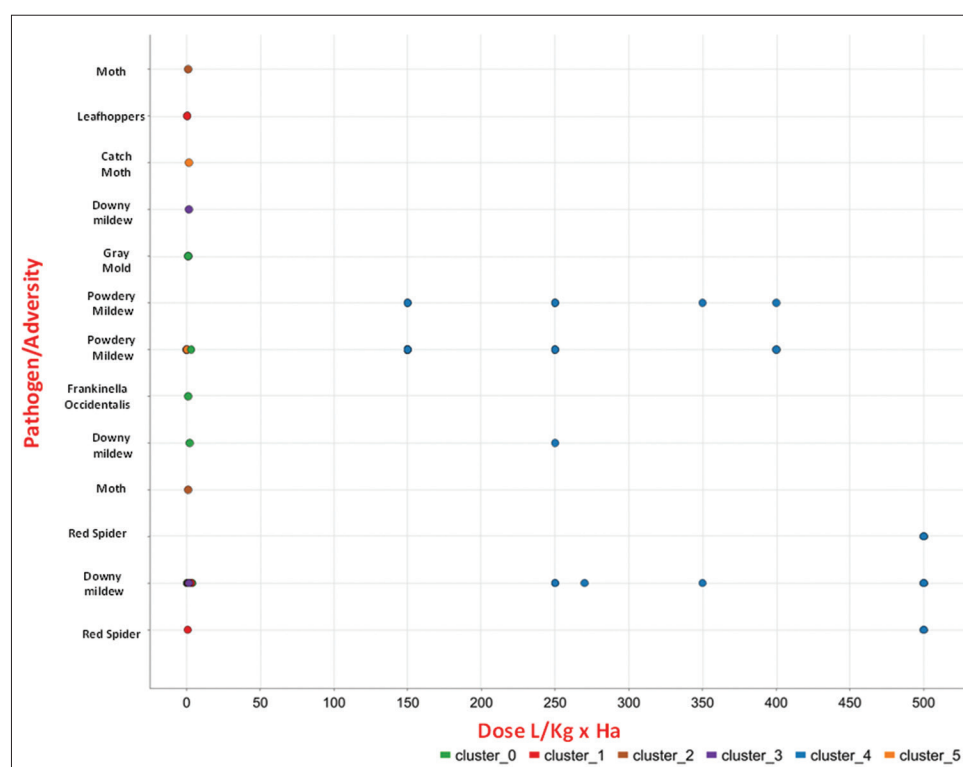
Table 4: Silhouette coefficients estimated for k = 5, k = 6, and k = 7

Silhouette Coefficient (SC)			
Cluster	SC for k=5 (5 cluster)	SC for k=6 (6 cluster)	SC for k=7 (7 cluster)
0	0,414	0,414	0,392
1	0,073	0,580	0,580
2	0,981	0,981	0
3	0,365	1	1
4	0,901	0,364	0,364
5	//	0,901	1
6	//	//	0,979
overall	0,403	0,506	0,495

In order to obtain DSS graphical dashboards, the KNIME workflow of Figure 14 is adopted implementing the k-Means algorithm. The choice of the cluster number k is defined by estimating the Silhouette Coefficient (SC) (Aranganayagi *et al.*, 2007). The estimated SCs are listed in Table 4: a good approach is to select the k number providing the best overall SC number for the case of k =6.

DISCUSSION

By fixing k = 6 are estimated the clustering dashboards plot two variables for each graph. Reading the dashboards of Figures 15-19, the information resumed in Table 5 has been achieved, useful to optimize a FER plan.

Figure 14: KNIME workflow implementing k-Means algorithm.

Figure 15: Clusters defined by Pathogen/Adversity versus Pesticide Dose (k=6).
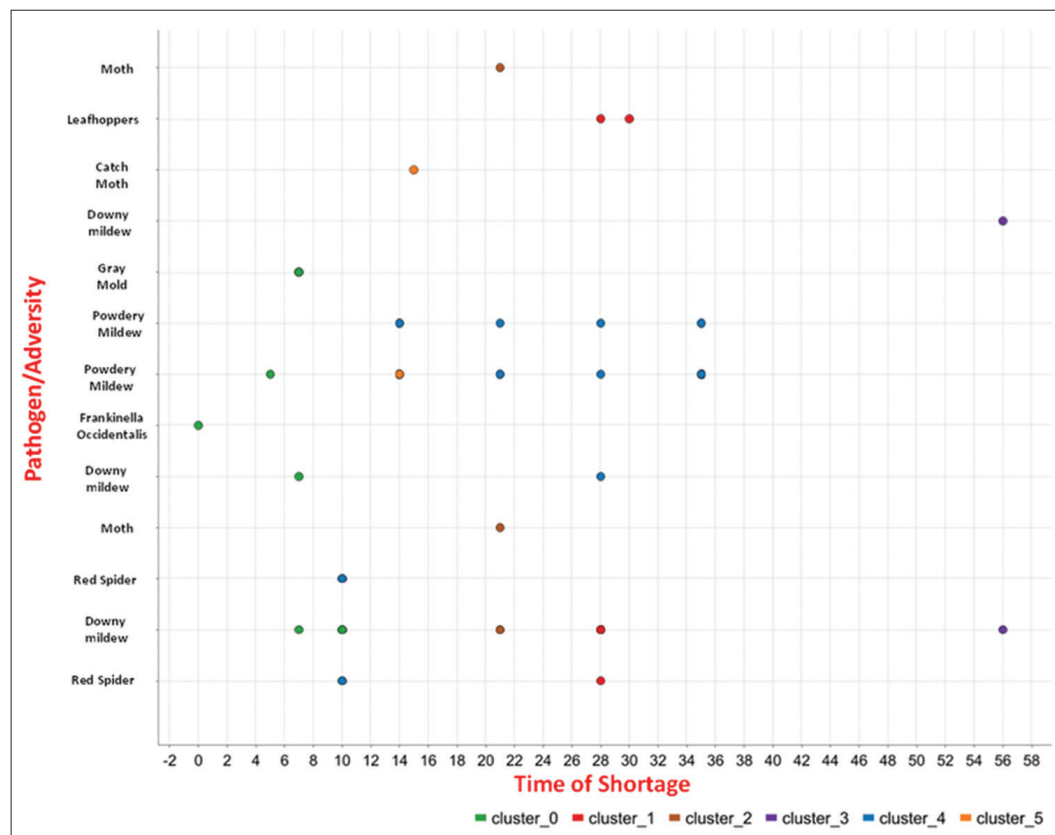
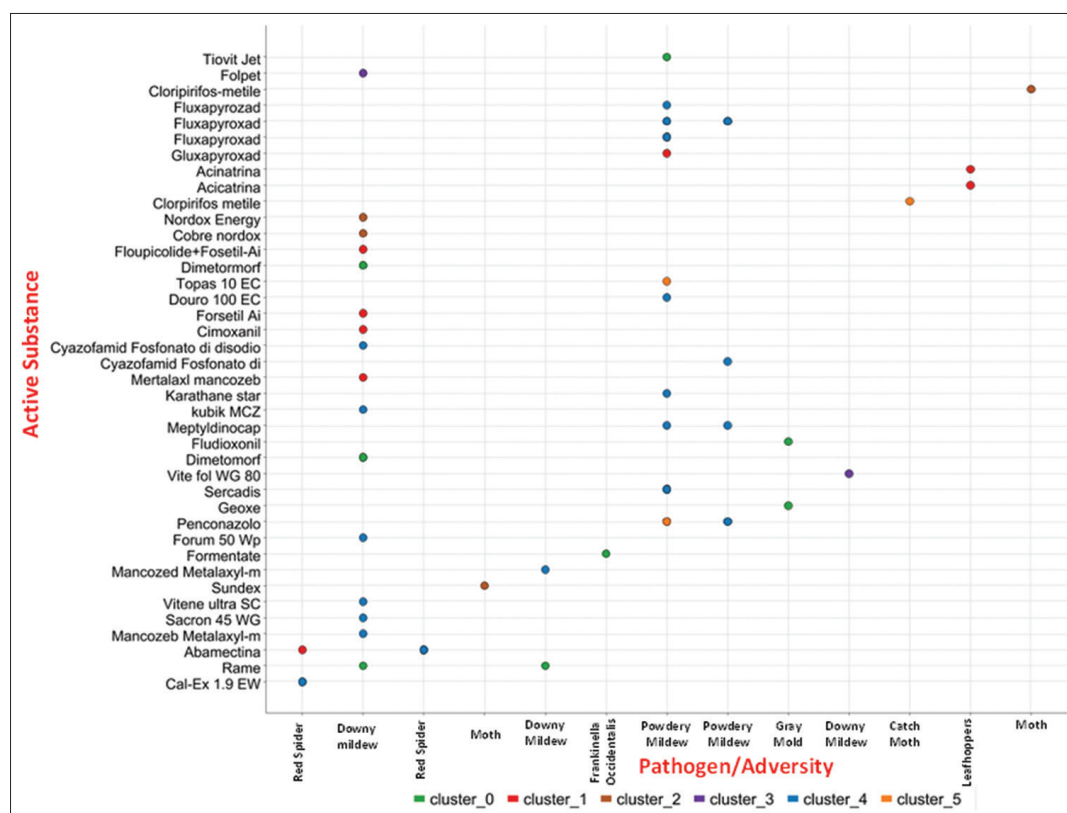**Figure 16:** Clusters defined by Pathogen/Adversity versus Time of Shortage (k=6).

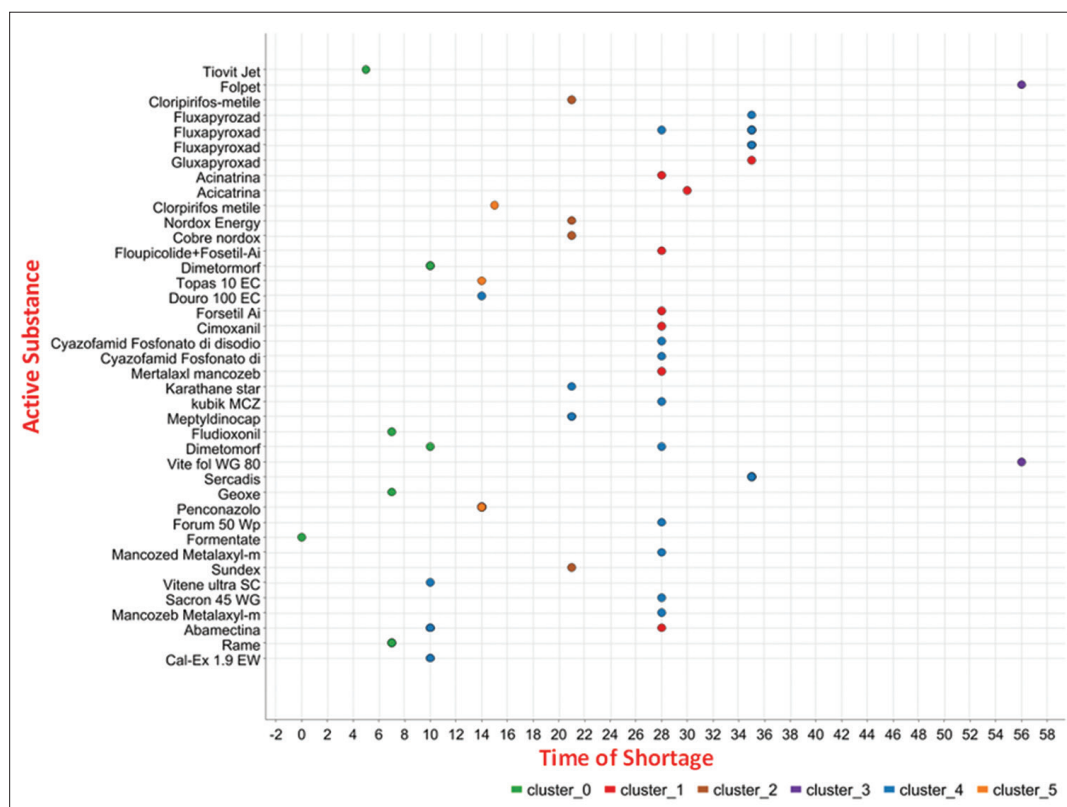**Figure 17:** Clusters defined by active substance versus Pathogen/Adversity (k=6).

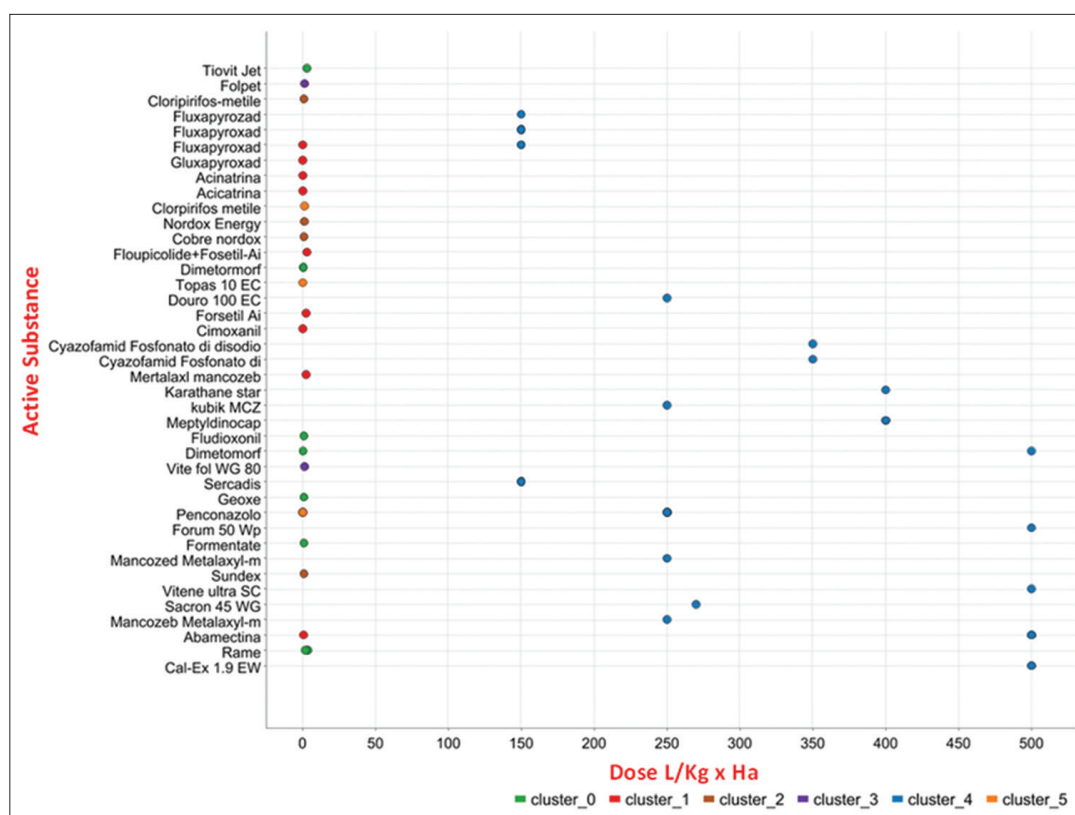**Figure 18:** Clusters defined by active substance versus time of shortage (k=6).

Figure 19: Clusters defined by active substance versus Pesticide Dose (k=6).

Table 5: Comments of the outputs of the clustering dashboards.

Dashboard	Extracted information
Pathogen/Adversity versus Pesticide Dose [Figure 15]	Moth, Leafhoppers, Catch Moth, Gray Mold, Downy Mildew, and Frankinella Occidentalis require low doses.
Pathogen/Adversity versus Time of Shortage [Figure 16]	Time of shortage usually does not overcome the 35 days for each pathogen and adversity, except for Downy Mildey (more resistance of Downy Mildey [61]).
Active Substance versus Pathogen/Adversity (Figure 17)	More active substances are associated only to Downy Mildew and Powdery Mildew (are tried more active substances because there is no clear solution).
Active Substance versus Time of Shortage [Figure 18]	The time of shortage usually does not overcome the 35 days using each active substance.
Active Substance versus Pesticide Dose [Figure 19]	Only few substances do not require big doses (Tivot Jet, Folpet, Cloripirifos-metile, Gluxapyroxad, Acinatrina, Nordox Energy, Cobre Nordox, Fluopicolide+Fosetil-Al, Topas 10 EC): more efficiency or aggressive substances requiring low doses.

CONCLUSIONS

The proposed work discusses the results of a project based on the technological improvement of a company working in FER. By Adopting a software platform, new processes are implemented to formulate FER plans according to data analysis criteria. In this direction, DSS dashboards of supervised and unsupervised algorithms provide a further tool supporting agronomist decisions focused on the analysis of key parameters such as adopted active substances and related doses, time of shortage and adversity or pathogen elements. The paper is oriented to describe the data flow of the pilot case study showing methods and approaches useful for data processing and data analysis. The proposed methods can be extended to other typologies of cultures requiring precision farming, and to Industry 4.0 systems.

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