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Research Article

Modeling the Combined Effect of Fulvic Acid, Effective Microorganisms and Micro-Carbon on Olive Yield

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Abstract

Background and Objective: Biofertilizers are important inputs for the productivity of olive trees. The objective of the current study was to investigate the effect of fulvic acid, effective microorganisms and effective micro-carbon on the growth and yield of two olive cultivars. **Materials and Methods:** Two field experiments were carried out during the two successive seasons of 2020 and 2021 on "manzanillo and picual" cultivars olive trees (*Olea europaea* L.) at a private orchard located in village 4 west of Miniya, Egypt. The trees were treated with six treatments as follows: (T1) control (water only), (T2) fulvic acid was added under a drip irrigation system in the 1st week of March at 100 mL per tree, (T3) effective micro-organisms was added for each tree at 100 mL, (T4) fulvic acid+K MCT® (T5) effective micro-organisms+MCT®, (T6) fulvic acid+effective micro-organisms+K MCT® where K MCT® was sprayed 3 times at the 1st week of March (full bloom), at 1st week of May (starting fruit set stage) and at the last week of July in the third stage of fruit development (70% of final fruit size) at 500 ppm. **Results:** All treatments improved the nutrient status (N, P and K) of the leaves, other growth parameters, yield (kg/tree) and oil percentage than the control and the promised one is the using all together where gave high values at all examined parameters. **Conclusion:** Olive tree yield can be improved by the addition of fulvic acid+effective micro-organisms+K MCT® under semi-arid regions in upper Egypt.

Key words: Olive, manzanillo, picual, fulvic acid, E.M, K-MCT, yield, oil percentage

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Competing Interest: The authors have declared that no competing interest exists.

Data Availability: All relevant data are within the paper and its supporting information files.

INTRODUCTION

Olive (*Olea europaea* L.), commonly known as zayton in the Arabic Region, is a small woody and a long-lived tree that belongs to the Oleaceae family. Despite the olive tree being native to the Mediterranean Region, where 90% of the global olive cultivation exists, it has been cultivated in many countries worldwide such as Portugal, the USA, Southern Africa, Australia, Japan and China[1]. In Egypt, the area cultivated under olive in 2020 was estimated at 100,826 ha, which produced 932,927 tons[2]. Olive has high economic and nutritional values due to its high content of vitamin E and other strong antioxidants and monounsaturated fatty acids (oleic and palmitoleic), polyunsaturated fatty acids (linoleic and linolenic) and saturated fatty acids (palmitic, stearic and arachidic)[3]. Furthermore, it has many health benefits, especially against cardiovascular risks[4] and breast cancer[5].

Few studies have been conducted to improve olive production under arid conditions or in reclaimed lands using natural, organic or biological fertilizers[6,7]. In order to improve the sustainability and productivity of modern agriculture, these eco-friendly options are used in improving soil fertility, fertilizers efficiency, plant growth, nutrient uptake and/or tolerance to different stresses. Among the organic fertilizers, fulvic acid (FA), which is a natural humic substance produced by microbial hydrolysis of plant materials, was found to play a potential promoting role in the growth and production of different crops including sunflower[8]. Investigation on bio-stimulants such as micro-carbon fertilizers showed a considerable enhancement in the production of pepper crops treated with micro-carbon fertilizers, in addition, it improved plant adaptation under abiotic stresses[9]. The same results for enhanced grapes productivity under salinity stress were obtained by Fekry and Aboel-Anin[10]. Different bacterial and fungal bio-agents have shown a growth-promoting effect and resistance inducing activity against different biotic stresses on various crops[11,12]. In addition, other microorganisms can improve soil fertility and the availability of numerous nutrients for plant uptake. Effective microorganisms (EM), which are a mixture of beneficial bacteria and yeast, exhibited a promising growth-promoting activity on various crops. In this regard, Iriti *et al.*[13] reported that EM-treated bean plants showed high photosynthetic efficiency in their leaves and improved seed yield and quality, compared to the untreated plants.

Machine learning (ML) is a collection of techniques that are used for making accurate predictions of data[14]. Random forest (RF) is a non-parametric and supervised machine learning algorithm[15]. The RF consists of a number of decision trees, where each tree splits by selecting random inputs and fits a random bootstrap sample of the data[16]. The RF was selected to be applied in the present study due to its good prediction performance. In addition, it has many advantages such as (1) It can be used for both classification and regression, (2) It can handle high-dimensional data, especially when non-linear and interactions effects among inputs exist and (3) It can be used effectively for ranking the inputs according to their importance to the output.

This study aimed to (1) Investigated the effects of single and combined applications of FA, EM and Micro Carbon Technology® (MCT) on growth and yield parameters of olive trees (cvs. Manzanilla and Picual) under semi-arid conditions and (2) Modeling these effects using machine learning.

MATERIALS AND METHODS

Two field experiments were conducted during the seasons of 2020 and 2021 on two olive cultivars, Manzanillo and Picual (*Olea europaea* L.), at a private orchard located on village 4 west of Miniya, Upper Egypt.

Fertilizers and olive cultivars: Organic and bio-fertilizers used in this study were purchased as follows: FA (Diamond Co., USA), MCT (Humagrow, USA) and EM (effective micro-organisms). Olive trees (cvs. Manzanilla and Picual) were used in the field experiment.

Field experiments: The field experiment was performed at olive trees farm located in 4th village, West Samalut, Minya, Egypt. Thirty-six trees (cvs. Manzanilla and Picual, 18 each cultivar) of uniform vigor, 15 years old. The trees were free of diseases and free of insect damages, grown in sandy soil and irrigated with a drip irrigation system. The soil characteristics were as follows: Sandy texture, organic matter (0.5%), pH (7.8), electrical conductivity (1.7 dSm), calcium carbonate (3.5%), total N (0.08%), available P (2.1 ppm) and available K (85 ppm). Salinity of irrigation water was 2500 ppm. The trees were spaced at 6×6 m and received the same horticulture practices as recommended by the Egyptian Ministry of Agriculture. This experimental work was included six treatments each one replicated 3 times and the treatments for each cultivar were as follow, 1: Control (water sprayed trees), 2: Fulvic acid as a soil addition, 3: Effective microorganisms as a soil addition, 4: Fulvic acid+MCT, 5: Effective microorganisms+MCT and 6: Fulvic acid+effective microorganisms+MCT.

Each treatment was replicated three times, one tree per each. Fulvic acid, EM and MCT were added three times 1st week of March (full bloom), at 1st week of May (starting fruit set stage) and at the last week of July in the third stage of fruit development (70% of final fruit size) at 50 mL per tree for all.

Growth parameters evaluation: In each season, the growth parameters of olive trees were evaluated for the number of shoots per branch, shoot length (cm), number of leaves per shoot, leaf dry weight (g) and leaf area (cm^2).

Biochemical analyses of olive leaves: At the harvest, samples of leaves from each treatment of the two olive cultivars were taken and chlorophyll content (a and b) was measured using a spectrophotometer (Unico, Model UV2150, Dayton, New Jersey, USA). Furthermore, nitrogen content in olive leaves was estimated using the modified Kjeldahl method[18,19]. While total phosphorous content in the leaves was measured using vanadium phosphomolybdate method[17,18] via a spectrophotometer (Unico, Model UV2150, Dayton, New Jersey, USA) and potassium content in olive leaves was measured according to AOAC[18] via a flame photometer (Systonic, Model S-935, Haryana, India). Leaf water content of olive leaf was measured by the determination of fresh and dry weights. For each treatment, three replicates were applied.

Yield and its components: In each season at the harvest time, the length of inflorescence (cm), number of flowers per inflorescence, initial fruit sitting, fruit retention (%) and the average yield per tree (kg) were determined. In addition, fruit oil (%) was estimated.

Statistical analyses: The achieved results were statistically analyzed using R software ver. 4.2.3. (R Core Team, 2023)[19]. Data was first tested for normality and subjected to ANOVA. Means were compared using Tukey's HSD test at $p \leq 0.05$ based on one-way ANOVA.

Random forest model: The RF was tuned by changing some parameters to optimize the performance of prediction. These parameters included a number of trees (ntree), the minimum number of data points at a leaf (nodesize), which is used for preventing overfitting and the maximum number of randomly selected inputs (mtry) to be considered at each split of a node[20-22]. To achieve the best performance, low values of minimum node size and high values of the number of randomly selected inputs hyperparameters were used. To reach the optimal settings of the tuning parameters, the dataset was divided into random 80% training and 20% test sets[23]. However, to overcome overfitting RF, 30% of the training dataset was used for the validation. A combination of tuning hyper parameters was selected using a grid search in combination with 5 to 10-fold cross-validation to produce the best prediction performance based on the testing dataset explained by Kuhn[23]. After training and testing RF, the importance of input variables was estimated using the optimal run.

Data analyses were performed using R software ver. 4.2.3. (R Core Team, 2023)[19]. The RF was run using the random Forest package[23], while the caret package was used to tune the RF parameters, with consideration to multicollinearity[24,25] and the iml(An R package for random forest model) package was used to produce the ALE (accumulated local effect) plots[26].

RESULTS

Plant growth evaluation: Means of the growth parameters of olive trees (cvs. Manzanilla and Picual) over the two successive seasons, in response to application of different fertilizers were presented in Table 1 and 2. For both olive cultivars, results obtained from the field experiment showed that mostly all the applied treatments enhanced, at varying degrees, the number of shoots per branch, shoot length, number of leaves per shoot, leaf dry weight and leaf area when compared with the untreated control trees. For both seasons, the triple treatment (FA+EM+MCT) recorded the highest values for all evaluated growth parameters, compared with the control treatment. In this regard, the dual treatment (EM+MCT) ranked the second-best fertilizing treatment, followed by the dual treatment (FA+MCT), while the single treatment (FA) recorded the lowest values with regard to all evaluated growth parameters, compared with the untreated control.

Effect on contents of N, P, K and water: Means of the mineral nutrient and water contents in leaves of olive trees (cvs. Manzanilla and Picual) over the two seasons, in response to the application of different fertilizers, were presented in Table 3 and 4. Over both growing seasons, data obtained revealed that all the tested fertilizing treatments significantly improved the N, P and K contents, as well as the water content in olive leaves of both cultivars, when compared with the untreated control treatment. In this regard, the triple treatment (FA+EM+MCT) recorded the highest values for all nutrient and water contents, when compared with the untreated control treatment. The dual treatment (EM+MCT) came second in this regard, followed by the dual treatment (FA+MCT), while the fertilizing treatment (FA) was the lowest one, compared with the untreated control.

Table 1: Effects of application of different fertilizers on growth parameters of olive trees cv. Manzanilla*

	Number of shoots/branch		Shoot length (cm)		Number of leaves/shoot		Leaf dry weight (g)		Leaf area (cm^2)	
Treatment**	2020	2021	2020	2021	2020	2021	2020	2021	2020	2021
Control	17.7±0.5[f]	18.6±0.6[e]	16.9±0.5[f]	19.7±1.2[e]	18.3±0.6[e]	20.0±1.0[f]	0.07±0.01[f]	0.08±0.01[f]	3.6±0.4[e]	3.8±0.1[d]
FA	23.3±1.5[e]	26.0±1.8[d]	18.1±0.3[e]	20.9±1.0[de]	20.3±0.9[d]	21.7±0.6[e]	0.09±0.01[e]	0.10±0.01[e]	3.8±0.5[d]	3.9±0.1[d]
EM	25.3±1.2[d]	26.7±1.5[d]	19.3±0.6[d]	22.3±1.1[d]	21.7±1.1[c]	23.0±1.2[d]	0.10±0.02[d]	0.12±0.02[d]	4.0±0.2[c]	4.3±0.2[c]
FA+MCT	27.7±1.1[c]	29.3±1.1[c]	21.8±0.3[c]	26.0±1.0[c]	22.0±1.0[c]	24.7±1.8[c]	0.13±0.01[c]	0.14±0.01[c]	4.2±0.3[c]	4.4±0.2[c]
EM+MCT	31.7±0.6[b]	34.0±2.0[b]	25.0±1.1[b]	28.7±0.9[b]	24.0±0.9[b]	27.3±2.0[b]	0.16±0.01[b]	0.17±0.02[b]	4.5±0.3[b]	4.7±0.1[b]
FA+EM+MCT	33.3±0.5[a]	37.0±1.9[a]	26.7±0.8[a]	31.0±1.9[a]	26.3±1.2[a]	29.0±1.8[a]	0.19±0.02[a]	0.20±0.01[a]	5.0±0.4[a]	5.3±0.3[a]

*Values are the means of ten replicates ±SD, FA: Fulvic acid, EM: Effective microorganisms®, MCT: Micro carbon technology® and **Values of each column followed by the same letter(s) are not significantly different according to Tukey's HSD test ($p \leq 0.05$)

Table 2: Effects of application of different fertilizers on growth parameters of olive trees cv. Picual*

	Number of shoots/branch		Shoot length (cm)		Number of leaves/shoot		Leaf dry weight (g)		Leaf area (cm^2)	
Treatment**	2020	2021	2020	2021	2020	2021	2020	2021	2020	2021
Control	16.3±0.6[f]	18.7±0.5[f]	15.8±0.3[e]	17.0±0.8[e]	15.3±0.6[e]	16.7±0.6[f]	0.04±0.01[f]	0.05±0.01[f]	3.2±0.1[e]	3.3±0.2[e]
FA	18.7±0.5[e]	21.3±0.7[e]	17.1±0.5[d]	18.0±0.6[e]	16.7±0.5[de]	18.3±0.5[e]	0.06±0.01[e]	0.07±0.01[e]	3.4±0.6[d]	3.6±0.1[d]
EM	21.7±0.8[d]	23.7±1.1[d]	18.0±0.6[cd]	19.7±1.2[d]	17.7±0.8[d]	20.0±0.5[d]	0.09±0.01[d]	0.08±0.01[d]	3.7±0.3[c]	3.9±0.1[c]
FA+MCT	26.0±1.0[c]	28.3±1.2[c]	19.2±0.8[c]	22.3±0.6[c]	20.3±1.5[c]	22.7±1.0[c]	0.12±0.01[c]	0.13±0.01[c]	3.8±0.2[c]	4.0±0.1[bc]
EM+MCT	27.7±0.9[b]	30.7±1.5[b]	21.2±1.3[b]	24.3±0.5[b]	22.3±1.2[b]	25.0±1.4[b]	0.14±0.02[b]	0.16±0.01[b]	4.0±0.2[b]	4.1±0.2[b]
FA+EM+MCT	29.0±1.1[a]	33.7±1.1[a]	24.0±1.1[a]	27.0±1.1[a]	24.0±1.3[a]	27.0±1.1[a]	0.17±0.01[a]	0.18±0.01[a]	4.5±0.2[a]	4.7±0.2[a]

*Values are the means of ten replicates ±SD, FA: Fulvic acid, EM: Effective microorganisms®, MCT: Micro carbon technology® and **Values of each column followed by the same letter(s) are not significantly different according to Tukey's HSD test ($p \leq 0.05$)

Table 3: Mineral nutrient and water contents in leaves of olive tree cv. Manzanilla in response to application of different fertilizers*

	Nitrogen (%)		Phosphorus (%)		Potassium (%)		Leaf water content (%)	
Treatment**	2020	2021	2020	2021	2020	2021	2020	2021
Control	2.03±0.03[f]	2.05±0.06[f]	0.13±0.01[f]	0.14±0.02[f]	1.99±0.01[e]	2.09±0.02[d]	50.8±0.87[f]	52.0±1.36[e]
FA	2.11±0.04[e]	2.17±0.04[e]	0.17±0.01[e]	0.19±0.01[e]	2.05±0.01[d]	2.13±0.04[d]	52.0±1.13[e]	53.3±0.71[d]
EM	2.21±0.02[d]	2.24±0.07[d]	0.19±0.01[d]	0.20±0.03[d]	2.08±0.02[cd]	2.19±0.02[c]	53.4±0.94[d]	55.0±0.95[c]
FA+MCT	2.33±0.03[c]	2.36±0.09[c]	0.25±0.03[c]	0.25±0.02[c]	2.10±0.03[c]	2.21±0.03[c]	54.3±0.87[c]	56.7±0.98[b]
EM+MCT	2.50±0.05[b]	2.53±0.02[b]	0.28±0.02[b]	0.29±0.04[b]	2.23±0.03[b]	2.31±0.02[b]	56.2±1.11[b]	58.8±1.02[a]
FA+EM+MCT	2.58±0.06[a]	2.60±0.09[a]	0.31±0.03[a]	0.33±0.03[a]	2.48±0.02[a]	2.55±0.04[a]	58.6±1.02[a]	59.3±1.01[a]

*Values are the means of ten replicates ±SD, FA: Fulvic acid, EM: Effective microorganisms®, MCT: Micro carbon technology® and **Values of each column followed by the same letter(s) are not significantly different according to Tukey's HSD test ($p \leq 0.05$)

Table 4: Mineral nutrient and water contents in leaves of olive tree cv. Picual in response to application of different fertilizers*

	Nitrogen (%)		Phosphorus (%)		Potassium (%)		Water content (%)	
Treatment**	2020	2021	2020	2021	2020	2021	2020	2021
Control	1.98±0.04[f]	2.00±0.02[f]	0.11±0.01[e]	0.12±0.01[f]	1.98±0.01[e]	2.00±0.02[e]	50.1±0.65[f]	50.0±0.36[f]
FA	2.03±0.03[e]	2.07±0.04[e]	0.12±0.01[d]	0.14±0.02[e]	1.99±0.03[e]	2.05±0.03[d]	51.6±1.09[e]	52.7±0.39[e]
EM	2.12±0.03[d]	2.18±0.05[d]	0.14±0.02[d]	0.15±0.02[d]	2.04±0.02[d]	2.06±0.05[d]	53.0±1.10[d]	54.7±0.74[d]
FA+MCT	2.20±0.02[c]	2.26±0.09[c]	0.19±0.02[c]	0.24±0.03[c]	2.07±0.02[c]	2.09±0.04[c]	54.5±1.08[c]	56.3±0.78[c]
EM+MCT	2.38±0.05[b]	2.39±0.08[b]	0.24±0.04[b]	0.27±0.04[b]	2.11±0.03[b]	2.41±0.05[b]	56.0±1.01[b]	58.0±1.01[b]
FA+EM+MCT	2.43±0.07[a]	2.50±0.09[a]	0.28±0.03[a]	0.29±0.07[a]	2.37±0.05[a]	2.76±0.04[a]	58.0±1.02[a]	59.7±1.02[a]

*Values are the means of ten replicates ±SD, FA: Fulvic acid, EM: Effective microorganisms®, MCT: Micro carbon technology® and **Values of each column followed by the same letter(s) are not significantly different according to Tukey's HSD test ($p \leq 0.05$)

Effect on contents of the photosynthetic pigments: Effect of application of different fertilizing treatments on the contents of the photosynthetic pigments (Chl a, b and carotenoids) in olives leaves (cvs. Manzanilla and Picual) over the two growing seasons were illustrated in Fig. 1a and b. For season 2020, data obtained revealed that application of all the tested fertilizing treatments led to a significant elevation in the contents of the studied photosynthetic pigments in olive trees cv. Manzanilla. While in season 2021, application of the fertilizing treatments enhanced the contents of photosynthetic pigments, except for the single treatments (FA) and (EM) for the carotenoids content, when compared with the untreated control treatment. The triple treatment (FA+EM+MCT) was the best one in this regard, while the single treatment (FA) was the lowest one (Fig. 1a). For olive trees cv. Picual, data indicated that all applied treatments considerably enhanced all studied photosynthetic pigments in season 2020, except for the FA treatment on the Chl b

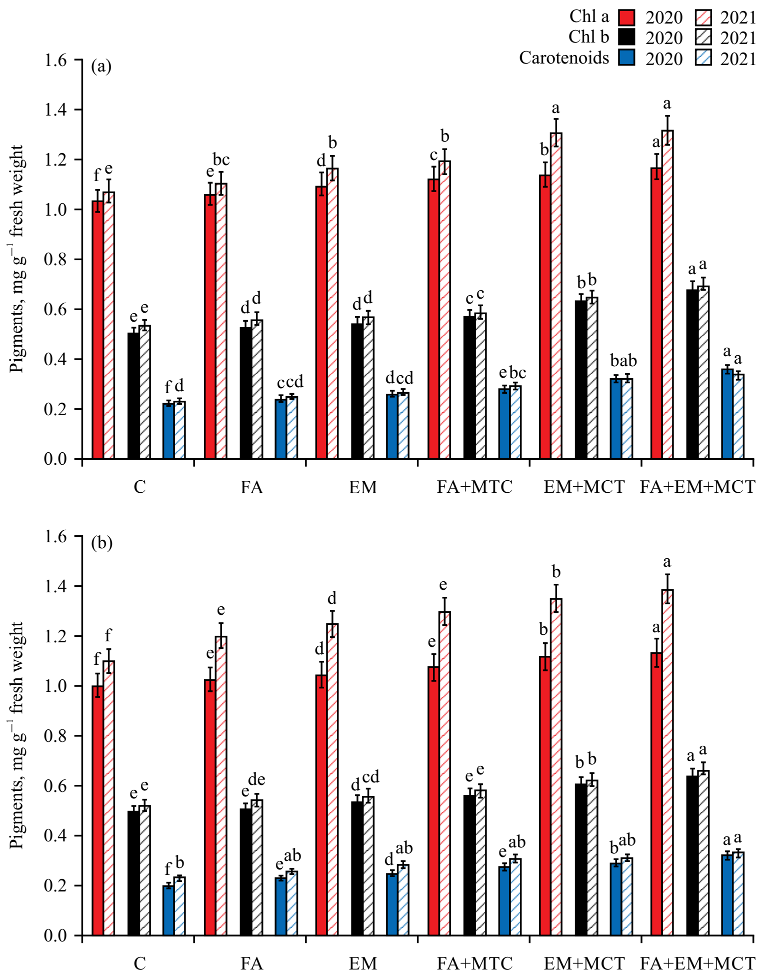

Fig. 1(a-b): Barchart showing effects of application of different fertilizers on the photosynthetic pigments (chlorophyll a and b and carotenoids) in leaves of two olive cultivars, (a) Manzanillo and (b) Picual

C: Untreated control, FA: Treated with fulvic acid, EM1: Treated with effective microorganisms® and MCT: Treated with Micro Carbon Technology®. For each year, columns of the same parameter superscripted with the same letter(s) were not significantly different according to Duncan's Multiple Range Test ($p \leq 0.05$). Each value represents the mean of three replicates. Error bars represent standard errors

content. In season 2021, all fertilizing treatments improved the Chl a and b contents, except for FA treatment on the Chl b, while the carotenoids content was only enhanced by the treatment (FA+EM+MCT). The triple treatment (FA+EM+MCT) recorded the highest photosynthetic pigments contents, while the single treatment (FA) was the lowest one (Fig. 1b).

Effect on the yield and its components: Mean yield and its components of olive trees (cvs. Manzanilla and Picual) in response to application of different fertilizers during 2020 and 2021 were presented in Table 5 and 6. Compared to the untreated control trees, all evaluated yield parameters of Manzanilla olive trees, during both seasons, were enhanced when treated with the all applied treatments, except for initial fruit sitting and fruit oil of olive trees treated with FA treatment, during both seasons. However, dual treatments were more effective than the single ones. The highest values of all evaluated yield parameters, during the two seasons, were recorded for the triple treatment (FA+EM+MCT), when compared to the untreated control trees. For olive trees (cv. Picual), all tested treatments led to an increment in all evaluated yield parameters during both seasons, except for initial fruit sitting of olive trees treated with FA treatment in season 2021 and their fruit oil in 2020, when compared to the untreated control treatment. However, the dual treatments enhanced all evaluated yield parameters more than the single ones. The triple treatment (FA+EM+MCT) achieved the highest values regarding the studied yield parameters, compared to the control treatment.

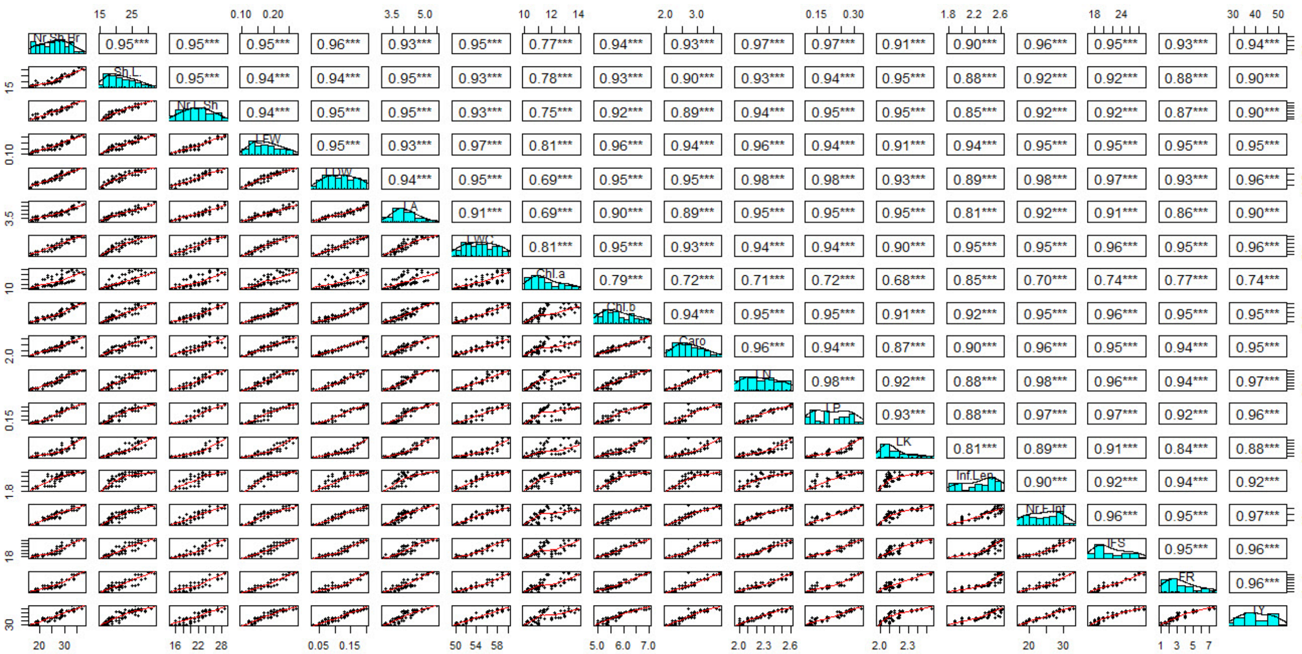

Fig. 2: Spearman correlation among the studied parameters

Nr.Sh.Br.: Number of shoots per branch, Sh.L.: Shoot length, Nr.L.Sh.: Number of leaves per shoot, LDW: Leaf dry weight, LA: Leaf area, Chl a: Chlorophyll a, Chl b: Chlorophyll b, Caro: Carotenoids, LN: Leaf nitrogen content, LP: Leaf phosphorus content, LK: Leaf potassium content, Inf.Len: Length of inflorescence, Nr.F.Inf: Number of flowers per inflorescence, IFS: Initial fruit sitting and FR: Fruit retention

Table 5: Effects of application of different fertilizers on yield and its components of olive trees cv. Manzanilla*

	Length of inflorescence (cm)		Number of flowers/inflorescence		Initial fruit sitting		Fruit retention (%)		Yield/tree (kg)		Fruit oil (%)	
Treatment**	2020	2021	2020	2021	2020	2021	2020	2021	2020	2021	2020	2021
Control	1.9±0.01^e	2.0±0.01^f	18±1.1^f	19±1.2^f	18.5±0.5^e	19.0±1.1^e	1.2±0.1^f	1.6±0.2^f	30.7±3.4^e	32.0±1.9^f	19.7±1.6^d	20.3±1.8^d
FA	2.0±0.01^d	2.2±0.01^e	21±1.3^e	22±1.3^e	19.0±0.7^e	19.7±1.2^de	2.0±0.2^e	2.4±0.3^e	35.3±2.7^d	35.7±1.7^e	21.0±2.1^d	22.0±2.6^d
EM	2.0±0.02^d	2.3±0.02^d	24±1.0^d	24±1.1^d	19.9±0.8^d	20.3±1.1^d	2.5±0.2^d	2.8±0.2^d	38.8±2.2^c	39.0±2.2^d	24.7±2.2^c	25.3±1.2^c
FA+MCT	2.4±0.01^c	2.4±0.01^c	27±1.3^c	27±1.0^c	22.0±1.0^c	22.3±1.2^c	3.0±0.1^c	3.2±0.1^c	41.7±3.1^c	42.7±2.4^c	26.7±2.3^bc	27.7±1.4^b
EM+MCT	2.5±0.01^b	2.4±0.02^b	29±1.1^b	30±1.1^b	25.0±1.1^b	25.3±1.2^b	5.0±0.2^b	5.4±0.2^b	46.3±2.7^b	46.7±2.6^b	28.7±3.1^ab	29.7±2.3^ab
FA+EM+MCT	2.6±0.03^a	2.6±0.01^a	31±1.2^a	32±1.3^a	27.3±1.2^a	28.3±1.0^a	7.0±0.3^a	7.5±0.3^a	50.7±2.9^a	52.0±3.3^a	30.6±2.5^a	31.3±2.1^a

*Values are the means of ten replicates ±SD, FA: Fulvic acid, EM: Effective microorganisms®, MCT: Micro carbon technology® and **Values of each column followed by the same letter(s) are not significantly different according to Tukey's HSD test ($p \leq 0.05$)

Modeling the mode of action of treatments on tree yield via machine learning: The function that used to estimate variable importance in RF provided information about the additive predictive value of a certain input, which enabled the model to rank the most important inputs using the mean decrease in accuracy that triggered when a certain input was permuted randomly. The mean decrease in accuracy was an indication of how much accuracy was loosed in the prediction when an input was removed from the model. The variables that have large values of mean decrease in accuracy were considered as the strongest independent inputs to the output.

The Spearman correlation among the studied parameters was illustrated in Fig. 2. The Spearman correlation demonstrated that there was a highly significant correlation among the studied parameters. However, due to the multi collinearity among the studied parameters, the effect of each parameter on the tree yield could not be tested. Therefore, ALE plots were used to demonstrate the effect of each parameter on the tree yield.

Importance of the studied parameters using nine different loss functions was presented in Fig. 3. The ALE plots demonstrated that the number of flowers per inflorescence and the leaf nitrogen content were the most important parameters to the tree yield. While, the least important parameters were the number of leaves per shoot, shoot length, leaf area and Chl a.

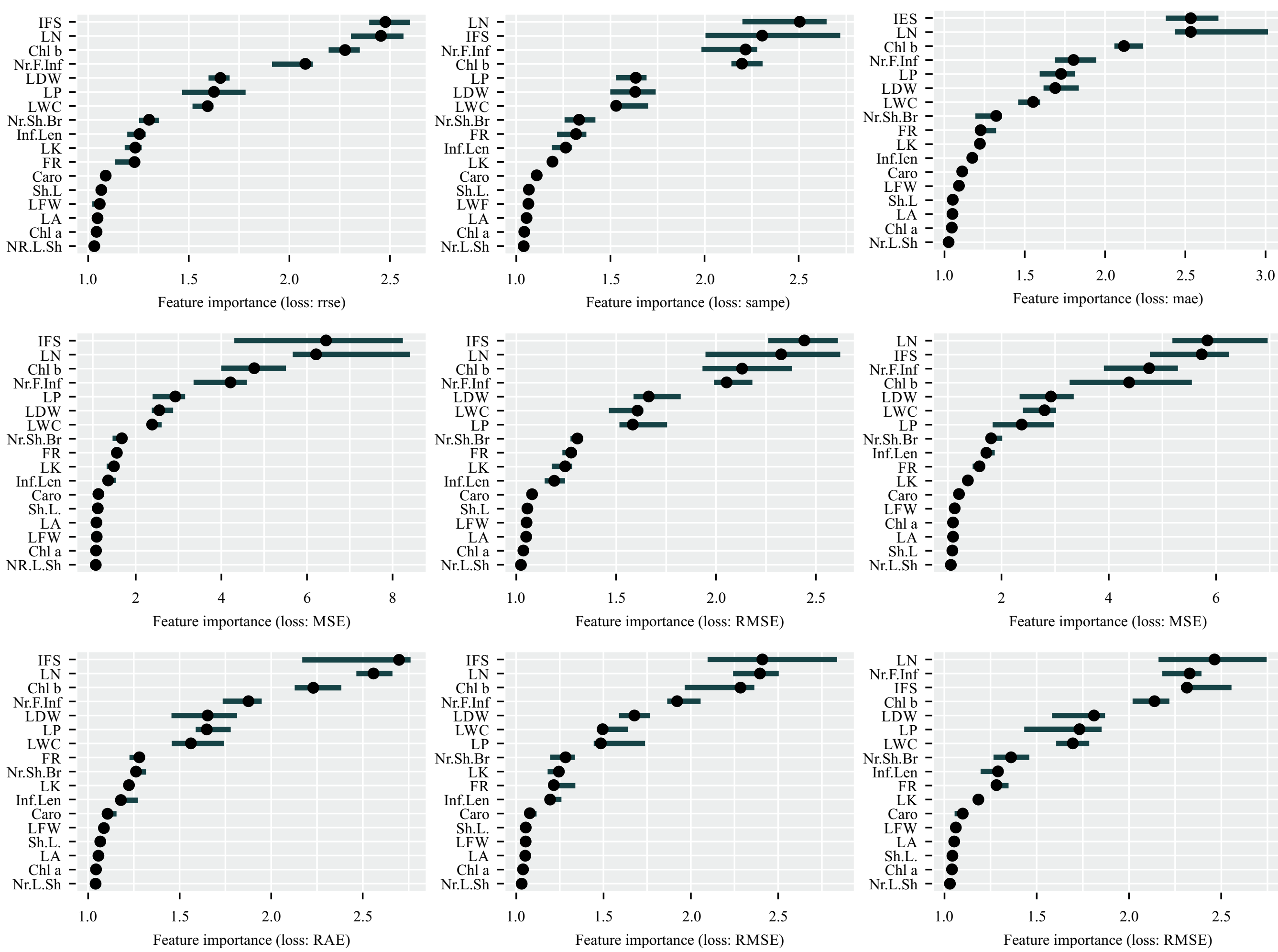

Fig. 3: Importance of parameters using nine different methods of loss functions

Nr.Sh.Br.: Number of shoots per branch, Sh.L.: Shoot length, Nr.L.Sh.: Number of leaves per shoot, LDW: Leaf dry weight, LA: Leaf area, Chl a: Chlorophyll a, Chl b: Chlorophyll b, Caro: Carotenoids, LN: Leaf nitrogen content, LP: Leaf phosphorus content, LK: Leaf potassium content, Inf.Len: Length of inflorescence, Nr.F.Inf: Number of flowers per inflorescence, IFS: Initial fruit sitting and FR: Fruit retention

Table 6: Effects of application of different fertilizers on yield and its components of olive trees cv. Picual*

	Length of inflorescence (cm)		Number of flowers/inflorescence		Initial fruit sitting		Fruit retention (%)		Yield/tree (kg)		Fruit oil (%)	
Treatment**	2020	2021	2020	2021	2020	2021	2020	2021	2020	2021	2020	2021
Control	1.8±0.02[f]	1.9±0.01[d]	18±1.5[f]	17±1.0[f]	17.2±0.9[f]	18.0±1.0[e]	1.0±0.3[e]	1.3±0.3[e]	29.7±2.7[f]	31.0±1.7[f]	21.8±1.9[d]	23.3±1.5[d]
FA	1.9±0.01[e]	2.2±0.02[c]	19±1.7[e]	20±1.4[e]	18.0±0.8[e]	18.7±1.1[e]	2.1±0.2[d]	2.3±0.3[d]	34.0±1.3[e]	36.7±2.0[e]	23.3±2.2[cd]	25.3±2.2[c]
EM	2.2±0.03[d]	2.4±0.01[b]	22±1.6[d]	23±1.3[d]	18.9±1.1[d]	20.0±1.7[d]	2.8±0.5[c]	3.3±0.8[c]	37.1±2.5[d]	38.7±2.3[d]	25.3±2.5[c]	26.3±1.6[c]
FA+MCT	2.3±0.02[c]	2.6±0.02[a]	25±1.1[c]	25±1.4[c]	21.0±1.0[c]	22.3±1.6[c]	3.1±0.5[c]	4.0±1.0[c]	39.3±2.0[c]	41.3±2.5[c]	27.7±2.0[b]	28.9±1.2[b]
EM+MCT	2.4±0.02[b]	2.6±0.02[a]	27±1.5[b]	28±1.1[b]	24.0±1.2[b]	25.0±1.4[b]	4.9±0.6[b]	5.1±0.8[b]	45.7±2.1[b]	46.3±2.8[b]	29.3±2.7[b]	30.0±2.5[b]
FA+EM+MCT	2.5±0.02[a]	2.6±0.03[a]	29±1.8[a]	29±1.6[a]	27.0±1.0[a]	28.3±1.5[a]	6.8±0.7[a]	7.0±0.7[a]	48.3±2.6[a]	49.3±3.0[a]	32.7±2.9[a]	35.3±2.8[a]

*Values are the means of ten replicates ±SD, FA: Fulvic acid, EM: Effective microorganisms®, MCT: Micro carbon technology® and **Values of each column followed by the same letter(s) are not significantly different according to Tukey's HSD test ($p \leq 0.05$)

The accumulated local effect plots of the relation between the studied parameters and the tree yield were showed in Fig. 4. The plots revealed that the effect of the number of flowers per inflorescence, initial fruit setting, fruit retention and leaf nitrogen content on the prediction of tree yield was high, where their slopes were changed from the beginning of their values. While shoot length, Chl a, number of leaves per shoot and leaf area were almost had no effect on

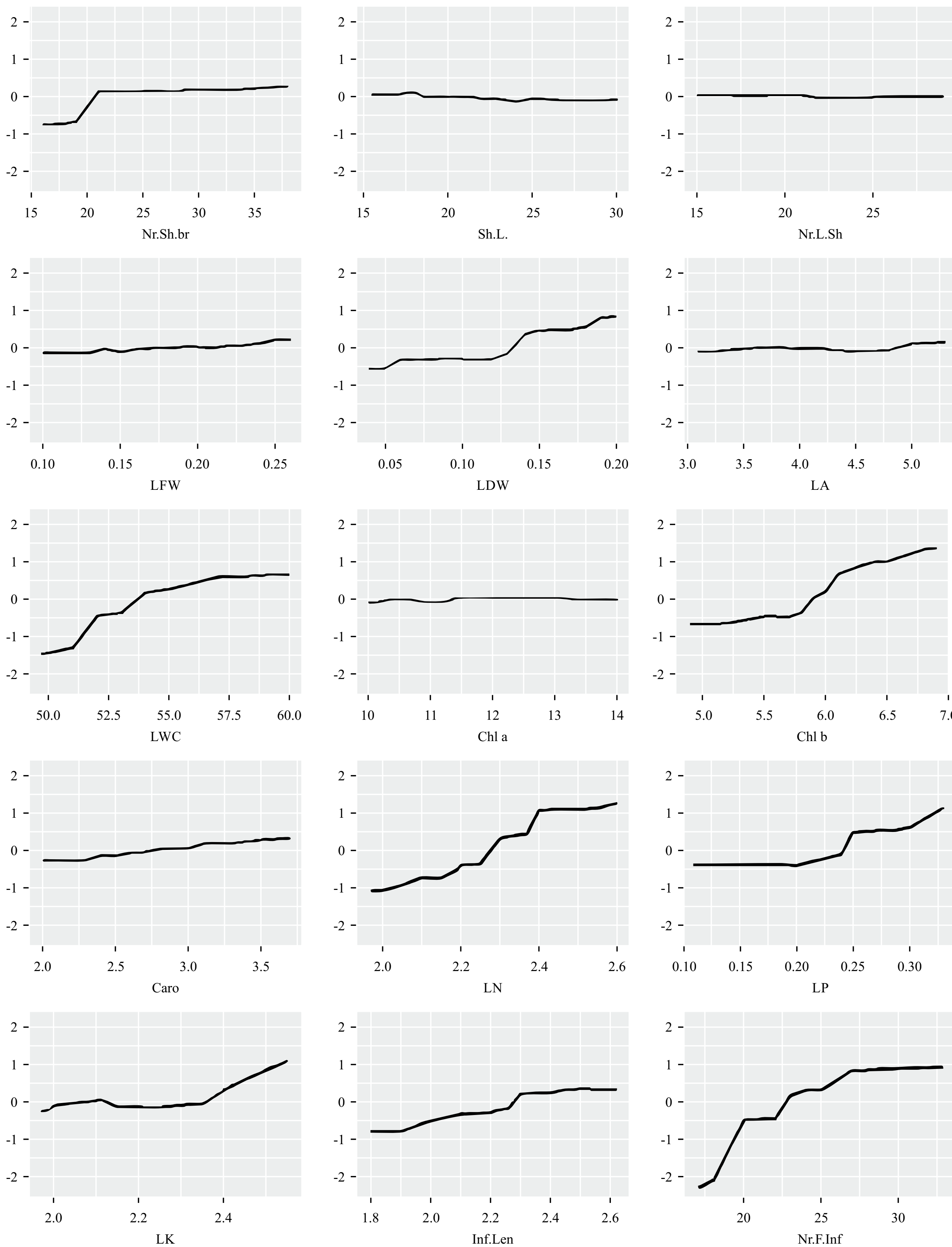

Fig. 4: Continue

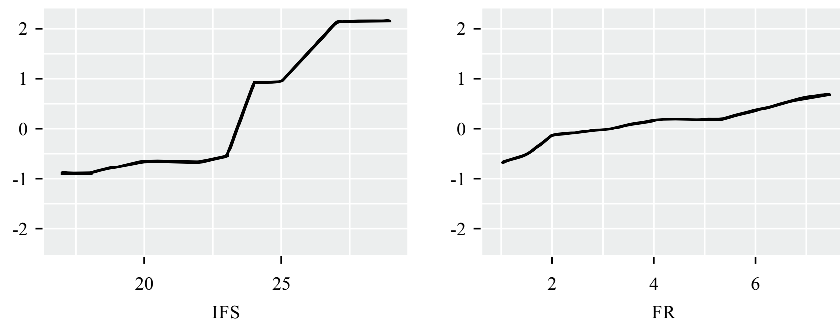

Fig. 4: Accumulated local effect plots showing the effect of the studied parameters on the prediction of the tree yield
Nr.Sh.Br.: Number of shoots per branch, Sh.L.: Shoot length, Nr.L.Sh.: Number of leaves per shoot, LDW: Leaf dry weight, LA: Leaf area, Chl a: Chlorophyll a, Chl b: Chlorophyll b, Caro: Carotenoids, LN: Leaf nitrogen content, LP: Leaf phosphorus content, LK: Leaf potassium content, Inf.Len: Length of inflorescence, Nr.F.Inf: Number of flowers per inflorescence, IFS: Initial fruit sitting and FR: Fruit retention

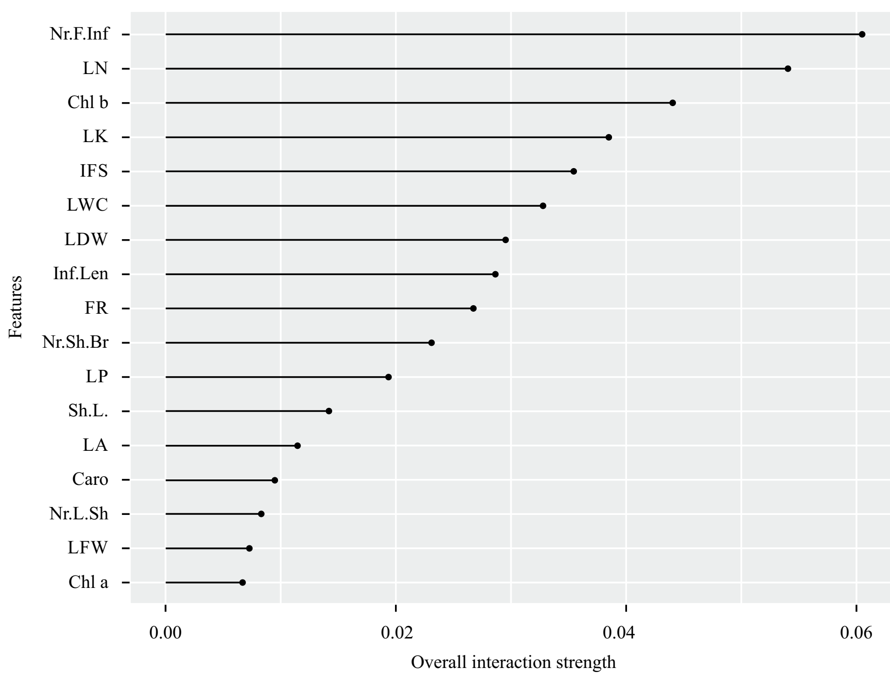

Fig. 5: Overall interaction strength of the studied parameters
Nr.Sh.Br.: Number of shoots per branch, Sh.L.: Shoot length, Nr.L.Sh.: Number of leaves per shoot, LDW: Leaf dry weight, LA: Leaf area, Chl a: Chlorophyll a, Chl b: Chlorophyll b, Caro: Carotenoids, LN: Leaf nitrogen content, LP: Leaf phosphorus content, LK: Leaf potassium content, Inf.Len: Length of inflorescence, Nr.F.Inf: Number of flowers per inflorescence, IFS: Initial fruit sitting, FR: Fruit retention, TY: Yield per tree and FO: Fruit oil

the prediction of the tree yield as their slopes did not change when their values were changed. Leaf dry weight, carotenoids content, Chl b and leaf phosphorus and potassium contents started to affect the prediction of the tree yield when their values reached their mid. Number of shoots per branch and length of inflorescence were medium in their effect on the tree yield.

The overall interaction strength of the studied parameters as well as the interaction between the most important parameter (number of flowers per inflorescence) and the rest of the studied parameters as shown in Fig. 5 and 6. The strength of the interaction was measured on a scale from 0 to 1. It was apparent from the Fig. 5 and 6 that number of flowers per inflorescence was the most parameter that interacted with the other parameters followed by leaf nitrogen content, while the length of inflorescence was the least important parameter.

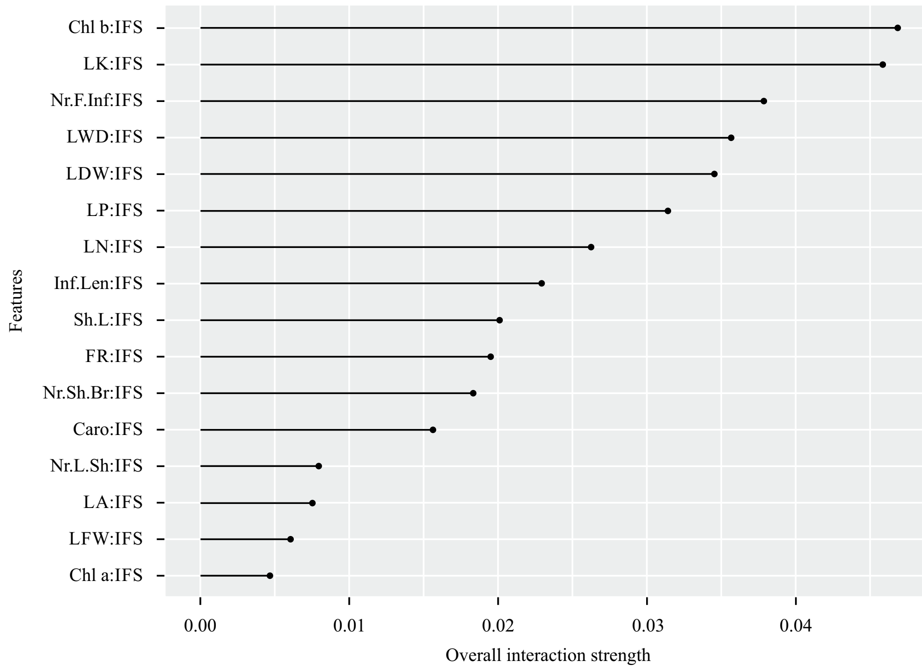

Fig. 6: Interaction between the most important parameter and the rest of the studied parameters

Nr.Sh.Br.: Number of shoots per branch, Sh.L.: Shoot length, Nr.L.Sh.: Number of leaves per shoot, LDW: Leaf dry weight, LA: Leaf area, Chl a: Chlorophyll a, Chl b: Chlorophyll b, Caro: Carotenoids, LN: Leaf nitrogen content, LP: Leaf phosphorus content, LK: Leaf potassium content, Inf.Len: Length of inflorescence, Nr.F.Inf: Number of flowers per inflorescence, IFS: Initial fruit sitting, FR: Fruit retention

DISCUSSION

The current study revealed that fulvic acid and effective micro-organisms as well as micro-carbon can be used to improve olive yield in semi-arid areas in Upper Egypt. Investigating how the tested fertilizers affect olive yield via the studied parameters was an important aim of the present study. However, when collinearity (high correlation) among inputs is existed, variable importance becomes less reliable and less interpretable[25]. In such case, the accumulated local effects plots (ALE) should be used to explore the shape of the relationship between the inputs and the output. On the other hand, when the collinearity is absent, estimation of the variable importance becomes reliable and the partial dependence (PD) plots can be used to provide information about the shape of the relation between each input and the output[27]. The ALE and PD plots indicate how the prediction of the output changes by changing the values of an input while keeping all other inputs at their original values. The PD plots show the average predicted output against each value of the input, while ALE plots look for the local effects of an input (certain range of the input). The ALE plots have an advantage avoiding extrapolation of the effect at values of the input that lie outside the range of this input, that do not occur in the dataset, which make a problem when multicollinearity among inputs existed[27].

Due to the obtained data had the problem of collinearity, ALE plots were used to explore the importance of each parameter on the olive yield. Spearman correlation coefficients revealed that all the studied parameters had a highly significant association with the olive yield, which means that all the studied parameters were contributing to olive yield. However, ALE plots after random forest optimum run revealed that not all the studied parameters were significant to olive yield because some parameters were driven by other parameters due to collinearity. For example, chlorophyll a, leaf area, shoot length and number of leaves per shoot showed a significant correlation with olive yield but ALE plots revealed that they had no effect on the yield, whereas ALE plots liberated them from their association with the other parameters and consequently their real effects appeared. On the other hand, other parameters such as leaf nitrogen content, number of flowers per inflorescence and initial fruit setting showed a significant correlation with olive yield, while ALE plots confirmed their high effect on olive yield even after they were liberated from their association with the other parameters.

A wide range of olive cultivars, with variable morphological, genetic, physiological and biochemical characteristics, is cultivated all over the world including traditional local, hybrid and introduced cultivars[28]. Each olive cultivar has a specific unique taste, phenotypic, resistance and product characteristics and is adapted to its natural environments[29]. However, agronomic practices and geographical characteristics have potential effects on the growth, yield and adaptation of the olive cultivar. Among these cultivars, the Spanish cultivars "Picual and Manzanilla" have emerged as two of the most frequently cultivated cultivars worldwide due to their high oil content[30]. From obtained data of Table 6 the triple treatment (FA+EM+MCT) were best treatment in all parameters this agreed with effect of fulvic acid on plants which It increases cell division rates and promotes greater root development and consequently causes the growth of stronger plants that are likely more resistant to plant diseases, also using both of fulvic acid and effective micro-organisms may enhance the microbial structures and physiochemical properties in farmland soils which help in improve growth of olive trees roots and uptake of nutrients from soils. Using of MCT enhance the growth and productivity of olive trees cause its roles to enhance physiological processes in plant and its rate.

CONCLUSION

The use of organic and bio-fertilizers such as fulvic acid and effective micro-organisms as well as micro-carbon proved to enhance olive yield in semi-arid areas in Upper Egypt and consequently make such marginal soils in such dry and semi-arid areas a source of horizontal extension and increasing the production of food in these regions. In additions, the use of advanced mathematical and statistical models can figure out how these fertilizers affect olive yield through the studied parameters.

SIGNIFICANCE STATEMENT

The purpose of the current study is to improve the yield as well as oil percent of olive trees under semi-arid conditions in upper Egypt. The addition of Fulvic acid with effective micro-organisms and micro carbon has proven to enhance both olive yield and oil content. The perspectives were to study the interactions among these treatments to figure out how they affect the yield of olive trees.

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