



RESEARCH ARTICLE

Application of machine learning tools for eco-strategising Fusarium wilt management of tomato caused by *Fusarium oxysporum* f. sp. *lycopersici*

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Abstract

Fusarium wilt of tomato, caused by *Fusarium oxysporum* f. sp. *lycopersici* (FOL), severely impacts global tomato production. A field experiment evaluated 25 treatments, categorised as compost-based [Farmyard manure (FYM) + de-oiled sweet basil compost], biological control (FYM + bio-agents) and chemical fungicides under field conditions. A random forest machine learning (ML) model predicted treatment effects, validated through biological assays and statistical tests. The treatment combining FYM + de-oiled sweet basil compost (25 t/ha) with *Trichoderma viride* (5 kg/ha) and *Pseudomonas fluorescens* (5 kg/ha) demonstrated the highest efficacy. It reduced disease incidence while maintaining soil health. The model revealed antagonism between bio-agents and fungicides. This study highlights ML's potential in optimising integrated disease management (IDM), reducing resource use and expediting decision-making. The validated model provides a reliable decision-support tool for precise and sustainable management of Fusarium wilt in tomato.

Keywords: biological disease management; Fusarium wilt; machine learning; random forest algorithm; tomato

Introduction

Global agricultural productivity is increasingly challenged by biotic and abiotic stresses, with plant diseases being among the major constraints on yield and quality. Fungal, bacterial and viral diseases cause substantial economic losses worldwide, affecting both staple and high-value crops. Among these, Fusarium wilt has been particularly devastating, necessitating effective management strategies to mitigate its impact (1). The global dependency on chemical fungicides and pesticides for disease control has led to concerns regarding their long-term sustainability due to their adverse effects on human health, the environment and the ecosystem, necessitating eco-friendly and sustainable management strategies to mitigate their impact (2). Excessive and indiscriminate reliance on chemical fungicides has raised serious ecological and health concerns. Residues in food products pose risks to consumers, potentially leading to chronic diseases, including endocrine disorders, neurological impairments and carcinogenic effects (3). Additionally, the continuous application of chemical fungicides has led to soil degradation, reduced microbial diversity and the emergence of resistant pathogen strains, further complicating disease management (4, 5). Recognising these risks, several countries have implemented strict regulations and bans on hazardous fungicides. These regulatory restrictions, while essential for safeguarding health and the environment, underscore the urgent need for sustainable and effective alternatives in disease management.

Biological disease management represents one of the most promising eco-friendly alternatives to chemical-based control, relying on natural mechanisms to suppress pathogens. The use of biocontrol agents, such as beneficial microorganisms, has gained significant attention due to their ability to inhibit pathogen growth through competitive exclusion, antibiosis and induced systemic resistance in plants (6). Similarly, organic amendments like compost enhance soil health and provide a conducive environment for beneficial microbes, thereby improving plant resistance against soil-borne diseases. Compost from medicinal plants, such as sweet basil (*Ocimum basilicum*), is particularly valuable due to antimicrobial secondary metabolites that directly suppress pathogens while promoting plant growth (7).

Humic acid, a natural organic substance, has attracted considerable attention due to its proven role in crop disease management. It has been reported to directly inhibit pathogen growth and synergise with biocontrol agents and Plant Growth-Promoting Rhizobacteria (PGPR) strains and also works in synergism with the biocontrol agents and PGPR strains of beneficial microorganisms (8). In addition, it also improves the plant growth and yield (9). Research has demonstrated the efficiency of humic acid and its associated substance, fulvic acid, in controlling the Fusarium wilt in crops (10). Jasmonic acid and salicylic acid are the plant hormones with vital roles in plant growth regulation and plant

defence. These phytohormones trigger systemic acquired resistance (SAR), thereby enhancing plants' defence mechanisms (11).

Tomato (*Solanum lycopersicum* L.), one of the most widely cultivated and nutritionally important crops, is highly vulnerable to soil-borne pathogens (12). As an essential source of vitamins A, C and lycopene, tomato plays a crucial role in global food security and human nutrition, which contribute to antioxidant activity and human health benefits. India, one of the leading tomato producers, is particularly vulnerable to Fusarium wilt outbreaks. However, tomato cultivation is frequently threatened by *Fusarium oxysporum* f. sp. *lycopersici* (FOL), the causative agent of Fusarium wilt (13). Symptoms include yellowing, wilting and vascular browning, which collectively result in significant yield losses, especially in tropical and subtropical regions (14). Conventional management relies primarily on chemical fungicides and resistant cultivars, but these measures have limitations, including resistance breakdown and environmental hazards (15).

Although several studies have individually demonstrated the effectiveness of Farmyard manure (FYM), composts, *Trichoderma viride*, *Pseudomonas fluorescens* and humic acids in reducing Fusarium wilt, their combined and interactive effects are poorly understood. Existing research generally evaluates these components in isolation or in limited pairwise combinations, ignoring the complex synergistic or antagonistic interactions that can occur when multiple inputs are applied together. Moreover, there is limited information on how varying concentration levels of amendments influence disease suppression and plant growth when integrated into multi-component management strategies. In light of these challenges, biological control represents a sustainable and environmentally friendly option for managing Fusarium wilt in tomato. Integrated disease management (IDM) strategies, combining biocontrol agents, organic amendments and cultural practices, have demonstrated promising synergistic effects in reducing disease incidence. However, the design and evaluation of effective IDM strategies demand considerable resources, including land, labour, water and time. Consequently, large-scale experimental validation is both expensive and time-intensive (16).

In recent years, machine learning (ML) has emerged as a powerful tool in agriculture, offering innovative solutions for disease prediction, monitoring and management. Machine learning models have been applied to analyse disease outbreaks, forecast progression and optimise control strategies under varying environmental and agronomic conditions (17). In Fusarium wilt management, ML can simulate and predict the outcomes of different strategies, supporting more precise decision-making and efficient resource allocation.

This study employs a ML-based approach, utilising the Random Forest algorithm, to evaluate and predict the effectiveness of biological and chemical treatments against Fusarium wilt in tomato. Random forest, recognised for its robustness and efficiency in handling complex datasets, has been widely used in agricultural research for disease classification and risk assessment (18). By integrating empirical disease control data with ML predictions, our study aims to identify the most effective treatment combinations for Fusarium wilt management. The objectives of this study are threefold: (i) to evaluate different biological and chemical treatments for managing Fusarium wilt in tomato, (ii) to apply ML techniques, specifically the Random Forest algorithm, to predict the efficacy of treatment combinations and (iii) to identify the most effective disease management strategy through ML predictions and experimental validation. This research integrates conventional plant disease

management approaches with cutting-edge computational techniques to enhance decision-making in crop protection. The outcomes will offer actionable insights for farmers, researchers and policymakers, supporting the adoption of sustainable, cost-effective and resource-efficient strategies for Fusarium wilt management in tomato.

Materials and Methods

The experimental materials, methodologies and workflow of the investigation are illustrated in Fig. 1.

Experimental site

The experiment was conducted in the Department of Plant Pathology at the Pathology laboratory and field of Jawaharlal Nehru Krishi Vishwa Vidyalaya (JNKV), Jabalpur, during the rabi season of 2020-22.

Experimental setup

The experimental design included 3 different groups of treatments: organic amendments, biological treatments and chemical control measures. Group A consisted of 8 treatments based on FYM and pre-composted de-oiled sweet basil leaves were applied to the soil before transplanting tomato seedlings. The experiment for each group was laid out in randomized block design (RBD) with 3 replications, where plot size was $2.5 \times 2 \text{ m}^2$ and spacing was $60 \times 45 \text{ cm}^2$. This treatment aimed to improve soil health, stimulate microbial activity and suppress *Fusarium oxysporum* f. sp. *lycopersici* (FOL). Twenty-one-day-old tomato seedlings were trimmed under aseptic conditions and dipped into a tray containing 50 mL spore suspension ($2 \times 10^6 \text{ CFU/mL}$) of FOL for 30 min. These pathogen-inoculated seedlings were used for transplanting.

Group B included 8 biological control treatments, evaluated individually and in combinations, for their efficacy against Fusarium wilt. The biocontrol agents, viz., *T. viride*, *P. fluorescens* and *Azotobacter chroococcum* were sourced from the Biofertilizer Producing Centre at JNKV, Jabalpur and applied to each plot after mixing with FYM before transplanting (Table 1). These treatments aimed to harness the potential of beneficial microbes to inhibit the pathogen through mechanisms such as competition, antibiosis and induced systemic resistance. Group C comprised 9 conventional chemical treatments for Fusarium wilt management. Tomato seedlings inoculated with the pathogen before transplanting were initially treated with 0.1 % Azoxystrobin. Following the onset of disease symptoms, foliar fungicide sprays were applied at recommended dosages. The treatment details are presented in Table 1.

Assessment of antifungal activity of different treatments

Disease intensity was recorded for plants under different treatments by assessing the extent of symptom expression. The per cent disease index (PDI) was calculated following the formula provided (19). The efficacy of leaf extracts obtained from treated plants was evaluated against FOL using the poison food technique, as described in previous studies (20). The antifungal activity was assessed by measuring the radial growth inhibition of the pathogen in culture, expressed as a percentage reduction compared to the control.

Assessment of plant growth parameters

Observations were recorded at 120 days after sowing (DAS) to evaluate plant growth parameters, including shoot length, shoot weight, root length and root weight (21). Additionally, fruit yield was

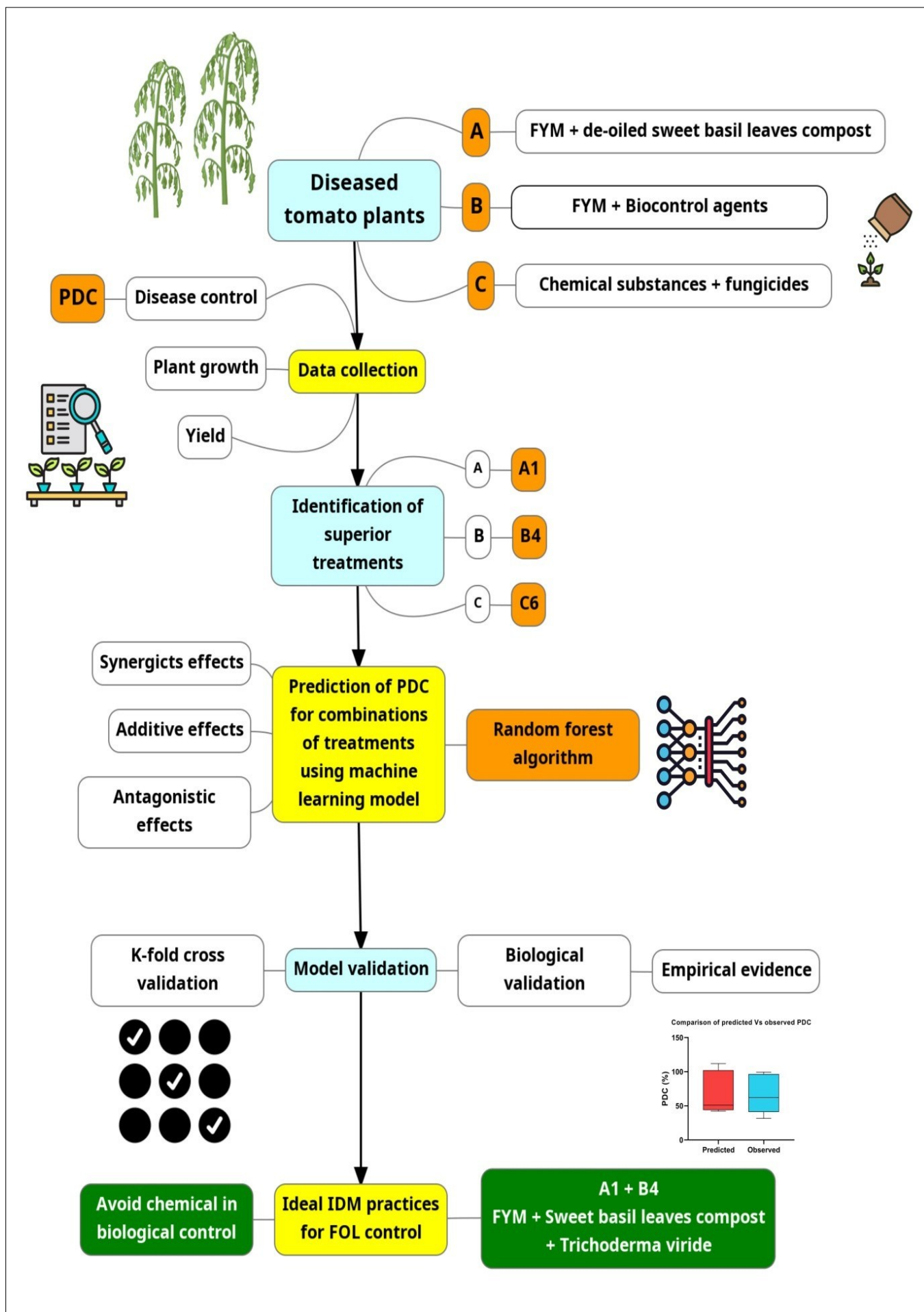


Fig. 1. Experimental outlay of the current investigation.

Table 1. Treatment details

Treatments	Details
Farmyard manure + deoiled sweet basil leaf compost (FYM + SBL)	
A ₁	FYM + SBL at 25 t/ha (100 %)
A ₂	FYM + SBL at 23.75 t/ha (95 %)
A ₃	FYM + SBL at 22.56 t/ha (90 %)
A ₄	FYM + SBL at 21.43 t/ha (85 %)
A ₅	FYM + SBL at 20.36 t/ha (81 %)
A ₆	FYM + SBL at 19.34 t/ha (77 %)
A ₇	FYM + SBL at 18.37 t/ha (73 %)
A ₈	FYM (Control)
Farmyard manure + Biocontrol agents	
B ₁	FYM + <i>T. viride</i> at 10 kg/ha
B ₂	FYM + <i>P. fluorescens</i> at 10 kg/ha
B ₃	FYM + <i>Azotobacter</i> at 10 kg/ha
B ₄	FYM + <i>T. viride</i> at 5 kg/ha + <i>P. fluorescens</i> at 5 kg/ha
B ₅	FYM + <i>T. viride</i> at 5 kg/ha + <i>Azotobacter</i> at 5 kg/ha
B ₆	FYM + <i>P. fluorescens</i> at 5 kg/ha + <i>Azotobacter</i> at 5 kg/ha
B ₇	FYM + <i>T. viride</i> at 3.33 kg/ha + <i>P. fluorescens</i> at 3.33 kg/ha + <i>Azotobacter</i> at 3.33 kg/ha
B ₈	FYM (Control)
Chemical substance and fungicides	
C ₁	Humic Acid (400 ppm)
C ₂	T ₁ + Salicylic acid (200 ppm)
C ₃	Humic acid 400 ppm + Azoxystrobin 1000 ppm
C ₄	Humic acid 400 ppm + Difenconazole 1000 ppm
C ₅	T ₁ + Tebuconazole (1000 ppm)
C ₆	Humic acid 400 ppm + (Pyraclostrobin + Epoxyconazole) 1000 ppm
C ₇	Humic acid 400 ppm + (Metiram+ Pyraclostrobin) 1000 ppm
C ₈	Azoxystrobin 0.1 % seedling treatment (Treated Control)
C ₉	Control

assessed to determine the impact of various treatments on productivity. Total phenol content was estimated using the standard Folin–Ciocalteu method to analyse plant defence responses against the pathogen (22).

Machine learning model for treatment effect prediction

A machine learning approach was employed to simulate and predict the effects of different treatment combinations on Fusarium wilt management. The study utilised the Random Forest algorithm, a widely used ensemble learning technique known for its robustness in handling complex datasets. The algorithm operates by constructing multiple decision trees during training and aggregating their outputs to enhance predictive accuracy while minimising overfitting (23). The experiment involved individual treatment assessments and the collected data were used to develop a predictive model that could estimate the combined effects of different treatments. The implementation was carried out in R Studio (version 2025.05.0, Mariposa Orchid) using the "randomForest" package (24). The model was trained using treatment data as input variables and the observed disease control as the response variable. The relationship between treatment factors and disease suppression was analysed through an interaction model, which allowed the exploration of synergistic, additive and antagonistic effects among treatments. To select variables for the Random Forest model, all treatment-related factors—such as type of organic amendment, quantity applied, presence of *T. viride*, *P. fluorescens*, humic acid concentration and fungicide dosage—were initially included as candidate predictors. Only variables with direct biological relevance to disease suppression were retained. A preliminary variable importance analysis was performed using the mean decrease in Gini metric and predictors contributing minimally to variance reduction were excluded to avoid noise and model inflation. To prevent overfitting, several safeguards were implemented: (i) the dataset was partitioned using 10-fold cross-validation; (ii) the number of trees (ntree) and the number of variables tried at each split (mtry)

were optimized through grid search to minimize prediction error; (iii) out-of-bag (OOB) error estimates were monitored as an internal validation measure; and (iv) diagnostic checks were performed to ensure that increasing model complexity did not improve accuracy disproportionately, which would indicate overfitting. These steps ensured that the final RF model was both biologically meaningful and statistically robust before prediction simulations were conducted. By utilising this predictive modelling approach, it was possible to assess the potential efficacy of different treatment combinations without the need for extensive field trials. The model provided insights into how various biological, chemical and organic treatments interact and influence disease progression in tomato plants.

Biological validation

To ensure the reliability of the model's predictions, the top 10 treatment combinations identified under synergistic [predicted per cent disease control (PDC) ≥ 100 %], additive (predicted PDC = 50 %), or antagonistic (predicted PDC < 50 %) conditions were biologically validated through field trials. These treatments were applied following standard recommended practices and the observed outcomes were compared with the model's predictions to confirm its practical applicability.

Statistical analysis and model validation

Statistical analysis was performed to evaluate the significance of treatment effects and validate the performance of the ML model. The analysis of variance (ANOVA) was conducted to determine the mean performance differences among treatments within the three experimental groups (25). Pearson correlation analysis was used to assess the collinearity between predicted and observed PDC values, establishing the reliability of the model predictions (26). A paired t-test was performed to evaluate whether the predicted PDC values significantly differed from the observed values (27).

To further validate the predictive accuracy of the model, k-fold cross-validation (k = 10) was implemented. Performance metrics,

including R-squared (R^2), mean absolute error (MAE) and root mean squared error (RMSE), were calculated to assess the model's reliability and generalisation capability (28–30). Finally, a Bland-Altman plot was generated to compare the predicted and observed PDC values, demonstrating the degree of agreement between the two datasets (31).

Results and Discussion

Mean performance and analysis of variance

The performance of the plants under different treatments under groups A, B and C was subjected to analysis of variance (ANOVA) to test the significance of the treatment effects on the parameters studied. The variance partitioning from ANOVA is presented in Fig. 2. The analysis of variance for the treatments under group A, involving FYM + sweet basil leaves compost, showed significance for all the parameters, except for the mycelial growth and PDC. The Fig. 2A shows the effect of the treatments on the parameters studied. The Fig. 2B shows that all the parameters under treatments under group B, comprising FYM + biocontrol agents, are significant and the variation is largely due to the treatment effects. The ANOVA for Group C (chemical substances and fungicides) showed a significant treatment effect for all the traits, but not for total phenol content and root dry weight. The variation in other parameters is substantially affected by the treatment effects (Fig. 2C).

The mean performance of the tomato plants influenced by different treatments under three groups of disease control agents is presented in Fig. 3. The best treatments based on the highest PDC among the three groups are highlighted below. The per cent disease incidence was lowest for A₁: FYM + SBL at 25 t/ha (60.40 %), B₄: FYM + *T. viride* at 5 kg/ha + *P. fluorescens* at 5 kg/ha (39.81 %) and C₆ (34.79 %). Research indicates that disease reduction upto 70 % in tomato plants using the combination of *T. viride* and *P. fluorescens* (32). The PDC was the highest for A₁: FYM + SBL at 25 t/ha (22.58 %), B₄: FYM + *T. viride* at 5 kg/ha + *P. fluorescens* at 5 kg/ha (38.65 %) and C₆: Humic acid 400 ppm+ (Pyraclostrobin +

Epoxyconazole) 1000 ppm (52.92 %). The de-oiled sweet basil leaves compost is rich in bioactive compounds, including phenolics and essential oils, which possess antifungal properties (33, 34). Additionally, composting enhances microbial diversity, leading to increased populations of beneficial microbes that compete with pathogens and promote plant health (35). The combined effect of FYM and de-oiled sweet basil leaves compost likely improved soil fertility, microbial activity and plant resistance against disease (32). The efficacy of *T. viride* and *P. fluorescens* is well-documented, with *T. viride* producing hydrolytic enzymes (e.g., chitinases and glucanases) that degrade fungal cell walls, while *P. fluorescens* secretes siderophores and antibiotics that inhibit pathogen growth (36, 37). Additionally, the presence of FYM in this treatment may have further enhanced microbial activity and induced plant systemic resistance, contributing to improved disease suppression (38–40). Humic acid is known to enhance nutrient uptake, stimulate root growth and improve plant immunity, which may have contributed to disease suppression (41). Furthermore, Pyraclostrobin and Epoxyconazole are broad-spectrum fungicides that act by inhibiting fungal respiration and sterol biosynthesis, respectively, providing both protective and curative effects (42, 43).

The treatments under group A (FYM + sweet basil leaves compost) showed non-significant effects on the mycelial growth. The highest mycelial inhibition was observed in C₆ (72.69 %), followed by B₄ (58.57 %) and A₁ (29.59 %). Corresponding mycelial growth values were 1.91 cm, 2.83 cm and 4.5 cm, respectively. The inhibition of the mycelial growth under laboratory conditions was the highest under A₁ (29.59 %), B₄ (58.57 %) and C₆ (72.69 %). The chemical treatments showed superior inhibition of the mycelial growth compared to the treatments under groups A and B. Among all treatments, the highest inhibition of mycelial growth (72.69 %) was observed in C₆, with a minimum mycelial growth of 1.91 cm. The superior performance of this treatment can be attributed to the combined effect of humic acid and chemical fungicides (44, 45).

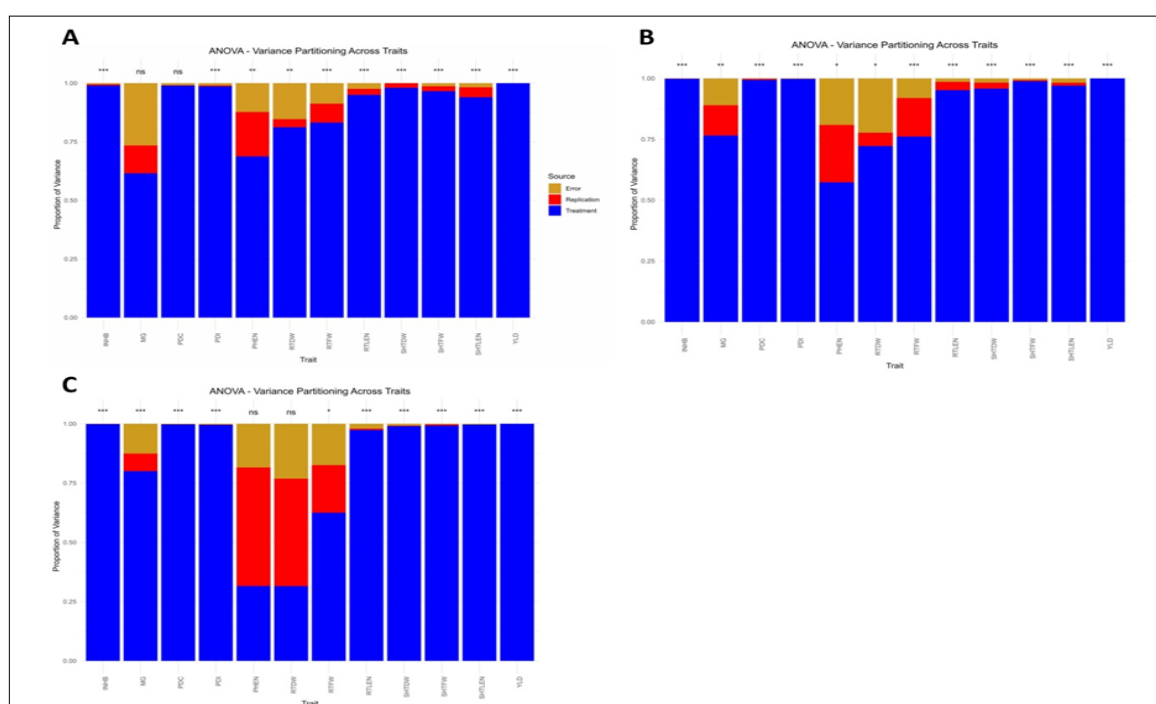


Fig. 2. Variance partitioning across traits from analysis of variance.

TREATMENTS	PDI	PDC	MG	INHb	RTLIN	SHTLEN	RTFW	RTDW	SHTFW	SHTDW	PHEN	YLD
A1	60.4g	22.58 ^{ns}	4.5 ^{ns}	29.59 ^a	22.97 ^a	77.90 ^a	6.35 ^a	3.32 ^a	37.78 ^a	18.34 ^a	6.39 ^a	673.09 ^e
A2	63.73 ^f	17.91 ^{ns}	4.43 ^{ns}	27.74 ^b	20.9 ^b	76.23 ^b	4.49 ^a	2.26 ^{bc}	36.29 ^{ab}	16.92 ^{ab}	6.07 ^a	462.01 ^e
A3	66.81 ^e	13.68 ^{ns}	4.62 ^{ns}	23.12 ^c	19.53 ^{bc}	75.46 ^{bc}	4.49 ^a	1.93 ^{ab}	34.62 ^{bc}	15.7 ^{bc}	5.35 ^{bc}	380.21 ^g
A4	68.35 ^{de}	11.24 ^{ns}	4.69 ^{ns}	22.62 ^c	17.67 ^c	74.67 ^c	3.85 ^b	1.62 ^{bc}	33.25 ^c	15.07 ^{cd}	5.84 ^a	397.76 ^f
A5	70.26 ^{de}	9.66 ^{ns}	5.15 ^{ns}	19.26 ^d	15.29 ^d	73.16 ^d	2.8 ^{bc}	1.09 ^{cd}	31.73 ^d	13.06 ^d	6.02 ^a	774.35 ^a
A6	72.28 ^e	5.84 ^{ns}	5.23 ^{ns}	18.38 ^{de}	12.88 ^{de}	70.61 ^e	1.98 ^{bc}	0.71 ^{bc}	29.65 ^{de}	11.05 ^e	5.45 ^{ab}	588.94 ^d
A7	74.33 ^b	3.94 ^{ns}	5.31 ^{ns}	17.71 ^e	11.52 ^e	67.82 ^f	0.89 ^{bc}	0.34 ^d	28.19 ^e	10.18 ^e	4.34 ^c	696.05 ^b
A8	78.25 ^a	0 ^{ns}	6.27 ^{ns}	0 ^f	9.7 ^f	69.82 ^e	0.77 ^c	0.29 ^{bc}	24.48 ^f	8.62 ^f	3.77 ^c	347.20 ^h
Mean	69.25	10.74	5.15	19.61	16.22	73.45	3.15	1.58	32.19	13.69	5.48	540.19
SE(m)	1.13	1.60	1.30	1.25	1.71	0.74	1.11	0.49	0.87	1.33	0.89	0.53
CV	1.53	11.79	22.15	5.71	2.14	1.17	33.45	44.33	2.90	8.43	2.14	0.14
LSD	1.86	2.22	1.99	1.96	2.29	1.51	1.85	1.23	1.64	2.02	1.66	1.31
B1	62.97 ^e	9.39 ^e	4.71 ^a	27.12 ^e	18.29 ^e	78.74 ^e	5.07 ^a	2.67 ^{abc}	46.00 ^a	22.90 ^{bc}	5.89 ^a	686.10 ^e
B2	57.21 ^f	15.59 ^b	4.32 ^a	31.89 ^b	21.03 ^b	80.61 ^b	5.52 ^a	2.88 ^{ab}	45.7 ^a	24.52 ^{ab}	5.25 ^{abcd}	406.77 ^f
B3	77.51 ^b	0.44 ^e	6.48 ^{ab}	2.01 ^f	12.51 ^f	75.11 ^d	2.257 ^{bc}	0.89 ^{cd}	44.49 ^a	17.48 ^e	4.21 ^{bcd}	785.29 ^a
B4	39.81 ^g	38.65 ^a	2.83 ^{abc}	58.57 ^a	22.96 ^a	82.58 ^a	6.70 ^a	3.66 ^a	46.37 ^a	25.09 ^a	6.4 ^{ab}	640.65 ^d
B5	72.93 ^d	2.55 ^d	5.87 ^{bc}	7.69 ^d	15.29 ^d	76.45 ^d	3.76 ^a	2.02 ^{abcd}	45.68 ^a	20.13 ^{de}	4.98 ^{abc}	387.56 ^h
B6	72.21 ^d	3.43 ^d	5.69 ^{bc}	9.67 ^d	15.29 ^{de}	76.99 ^d	3.94 ^a	2.31 ^{ab}	45.45 ^a	20.71 ^{cd}	4.26 ^{abcd}	698.46 ^b
B7	74.66 ^c	0.86 ^e	5.94 ^c	6.51 ^e	14.07 ^e	75.67 ^d	2.98 ^b	1.49 ^{bcd}	43.9 ^a	19.74 ^{de}	3.88 ^{cd}	496.05 ^e
B8	78.01 ^a	0 ^e	6.33 ^d	0 ^g	11.22 ^f	71.76 ^e	1.02 ^c	0.41 ^d	26.59 ^b	11.03 ^f	3.82 ^d	325.876 ^h
Mean	67.03	8.79	5.02	17.91	15.89	77.27	4.08	2.02	42.79	19.84	4.73	553.68
SE(m)	0.79	0.90	0.47	1.25	0.79	0.64	1.08	1.37	0.93	1.02	0.81	0.75
CV	1.33	10.79	13.63	6.23	5.63	1.04	25.55	57.87	2.25	5.09	2.14	0.16
LSD	1.56	1.66	1.19	1.95	1.57	1.40	1.83	2.05	1.69	1.77	1.58	1.51
C1	53.73 ^b	31.35 ^f	4.17 ^{bc}	35.85 ^g	19.39 ^f	91.67 ^e	4.17 ^{ab}	1.59 ^{ns}	44.02 ^e	19.51 ^d	5.35 ^{ns}	706.21 ^b
C2	50.03 ^c	34.92 ^e	3.5 ^{bc}	46.72 ^f	20.37 ^e	94.95 ^d	4.31 ^b	1.72 ^{ns}	40.63 ^f	19.02 ^d	3.35 ^{ns}	437.52 ^f
C3	38.45 ^f	52.92 ^b	2.42 ^{bcd}	65.06 ^b	24.49 ^{bc}	102.66 ^b	4.49 ^{ab}	2.62 ^{ns}	50.06 ^e	26.86 ^a	3.5 ^{ns}	379.90 ^h
C4	44.47 ^e	41.11 ^d	2.89 ^{bcd}	56.99 ^d	22.39 ^{cd}	98.12 ^c	4.28 ^{ab}	2.03 ^{ns}	46.82 ^d	23.29 ^{bc}	3.51 ^{ns}	813.86 ^a
C5	53.40 ^b	32.09 ^f	3.36 ^{bcd}	49.00 ^e	20.74 ^{de}	96.61 ^d	4.13 ^{ab}	1.96 ^{ns}	30.54 ^g	22.75 ^c	3.43 ^{ns}	687.31 ^c
C6	34.79 ^g	57.64 ^a	1.91 ^{cd}	72.69 ^a	25.76 ^a	107.64 ^a	4.94 ^{ab}	2.68 ^{ns}	52.4 ^a	29.21 ^a	3.5 ^{ns}	658.20 ^d
C7	38.53 ^f	50.82 ^c	2.37 ^d	65.73 ^b	24.83 ^{ab}	104.51 ^b	4.48 ^{ab}	2.34 ^{ns}	51.82 ^b	28.57 ^a	3.42 ^{ns}	516.15 ^e
C8	46.09 ^d	42.61 ^d	2.83 ^{bcd}	58.53 ^c	23.72 ^{bcd}	99.27 ^c	4.35 ^a	2.09 ^{ns}	47.85 ^d	24.61 ^b	3.74 ^{ns}	388.20 ^g
C9	75.49 ^a	0 ^g	6.46 ^a	0 ^h	11.38 ^g	68.43 ^f	0.74 ^c	0.36 ^{ns}	24.52 ^h	9.20 ^e	3.64 ^{ns}	305.66 ⁱ
Mean	48.22	38.16	3.22	49.63	21.43	95.84	4.24	1.84	43.59	22.70	3.67	543.44
SE(m)	1.55	1.72	0.95	1.16	1.21	1.26	1.08	0.91	0.78	1.00	0.56	0.89
CV	2.58	3.43	30.19	2.17	5.14	1.17	24.47	2.11	2.03	4.41	20.34	0.17
LSD	2.12	2.27	1.68	1.87	1.91	1.94	1.79	1.65	1.53	1.73	1.29	1.63

ns: non-significant

Fig. 3. Mean performance of plants under different treatments of three different groups A, B and C.

Root length was maximum under A₁ (22.97 cm), B₄ (22.96 cm) and C₆ (25.76 cm). Similarly, the highest shoot length was observed in A₁ (77.90 cm), B₄ (82.50 cm) and C₆ (107.64 cm). These results indicate that while chemical treatments promoted greater root elongation, the biocontrol and organic treatments contributed substantially to overall plant vigour and biomass accumulation. Despite the longer root length under chemical treatments (C₆), the highest root fresh and dry weights were observed in FYM + biocontrol agent treatments (A₁ and B₄). Specifically, B₄ recorded the highest root fresh weight (6.70 g) and dry weight (3.66 g), followed by A₁ (6.35 and 3.32 g), whereas C₆ exhibited lower root biomass (4.94 g and 2.68 g). This suggests that while chemical treatments may enhance root elongation, organic amendments and biocontrol agents contribute more effectively to root biomass accumulation, likely due to improved soil structure, microbial activity and nutrient availability. The role of FYM and biocontrol agents in enhancing root proliferation has been well documented, as they improve soil aeration, increase microbial interactions and promote hormone production such as auxins and cytokinins, which stimulate root growth (46).

The root fresh and dry weights were the maximum for A₁ (6.35 g and 3.32 g), B₄ (6.70 g and 3.66 g) and C₆ (4.94 g and 2.68 g). Despite higher root length under the chemical treatments, the root weight was higher in the treatments comprising FYM + biocontrol agents. This indicates the role of FYM + biocontrol agents in boosting plant growth. The root development is considered to be a crucial component in the resistance to disease. The shoot fresh and dry weights were the highest for A₁: FYM + SBL at 25 t/ha (37.78 g; 18.34 g), B₄: FYM + *T. viride* at 5 kg/ha + *P. fluorescens* at 5 kg/ha (46.37 g; 25.09 g) and C₆: Humic acid 400 ppm + (Pyraclostrobin + Epoxyconazole) 1000 ppm (52.40 g and 29.21 g). This indicates that chemical fungicides, biocontrol agents and organic amendments all contribute to plant biomass production, albeit through different mechanisms. While chemical fungicides provide immediate disease suppression, biocontrol agents and organic amendments enhance soil microbial interactions and plant metabolic activity, leading to better nutrient uptake and overall plant health (6, 47). Root architecture plays a crucial role in nutrient uptake, plant stability and resistance to soil-borne pathogens. The higher root biomass under organic and biocontrol treatments suggests that these amendments may contribute to enhanced plant resilience against diseases. A well-developed root system facilitates better water and nutrient absorption, which strengthens plant immunity and reduces vulnerability to pathogen invasion (48–50). These findings align with previous studies emphasising the importance of root biomass in conferring resistance against soil-borne diseases (51).

The total phenol content in the leaf tissues was the highest in A₁ (6.39 mg/100 g), B₄ (6.40 mg/100 g) and C₁ (5.35 mg/100 g). The effect of chemical substances and fungicides on the total phenol content is insignificant from the analysis of variance (Fig. 2C), indicating their lack of role in inducing the plant resistance. On the other hand, the treatments including FYM + sweet basil leaves compost and FYM + biocontrol agents showed higher phenol contents. Interestingly, the chemical treatments did not significantly influence total phenol content, as evidenced by the non-significant effect in ANOVA (Fig. 2C). This suggests that fungicides primarily act through direct pathogen inhibition rather than by inducing plant defence responses. On the other hand, FYM + de-oiled sweet basil leaves compost and FYM + biocontrol

agents exhibited higher phenol accumulation, indicating their role in inducing systemic resistance in plants. Previous studies have shown that organic amendments and beneficial microbes can activate plant defence pathways, leading to the production of phenolic compounds that contribute to disease resistance (52–54).

The fruit yield per plant was maximum under A₆ (774.35 g), B₃ (785.29 g) and C₄ (813.86 g), revealing that the superior growth parameters do not necessarily manifest in superior yield. This also indicates that greater shoot and root growth does not always translate into higher yield, highlighting the importance of nutrient-use efficiency and reproductive development in determining final yield outcomes (55, 56). The superior fruit yield observed in organic and microbial treatments (A₆ and B₃) suggests that balanced nutrient availability, improved soil microbiome and plant-microbe interactions play a crucial role in enhancing fruit production (57). The role of *Azotobacter* in nitrogen fixation, hormone production and root development may have contributed to the increased yield under B₃ (58, 59). Similarly, the addition of sweet basil leaves compost in A₆ may have provided slow-release nutrients and bioactive compounds that stimulated reproductive growth.

The overall performance of different treatments under groups A, B and C is presented in Fig. 4. For traits, namely per cent disease incidence, per cent disease control, mycelial growth and its inhibition, length of root and shoot, weights of root and shoot, the chemical substances and fungicides showed superior effects. Despite this superiority in the above growth and disease control parameters, the chemical substances and fungicides could not manifest higher yields than the FYM + sweet basil leaves compost and FYM + biocontrol agent treatments. The findings of this study indicate that while chemical substances and fungicides demonstrated superior efficacy in disease control, mycelial growth inhibition and vegetative growth parameters (root length, shoot length and biomass accumulation), they did not translate into higher fruit yields. This suggests that disease suppression and vegetative vigour alone are not the sole determinants of productivity, highlighting the importance of soil health, microbial interactions and nutrient efficiency in maximising crop yield (60). This is due to the insignificant correlation among the above traits and the fruit yield (Fig. 5). In the present investigation, the fruit yield per plant was insignificantly correlated with growth and disease control parameters, but is strongly associated with the phenol content in the plant tissues. This highlights the complexity of yield determination, where multiple physiological and biochemical factors interplay. However, the strong association between fruit yield and phenol content in plant tissues indicates a potential role of phenolic compounds in enhancing yield, possibly through improved stress tolerance or metabolic efficiency. However, similar results are hard to find. Despite the mediocre performance in FYM + sweet basil leaves compost and FYM + biocontrol agent treatments, yield was not compromised, which was attributed to the plant-resistance-inducing properties of these materials. This property was expressed as a boost in the phenol biosynthesis and its accumulation in plant tissues that helped the plants fight the pathogen without a cutback in the fruit yield (Fig. 5). There are reports available wherein the composts outperformed the chemical fungicides (35). The ultimate purpose of crop protection is to safeguard the yield. However, measures aimed at defending the yield loss should not be a concern and a threat to the environment, ecosystem and

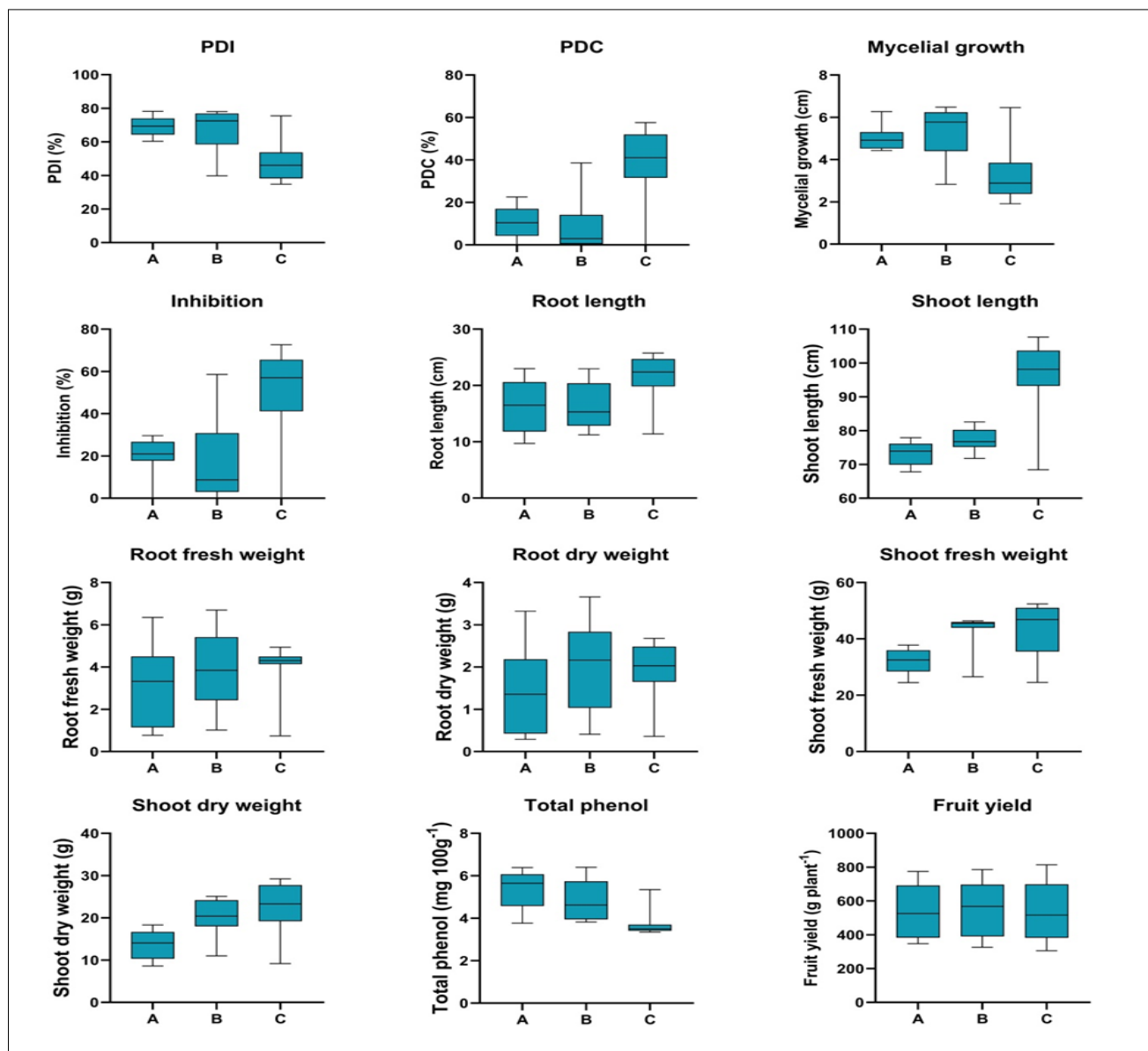


Fig. 4. Boxplots explaining the performance and variation in the treatment effects. A: FYM + sweet basil leaves; B: FYM + biocontrol agents; C: Chemical substances and fungicides.

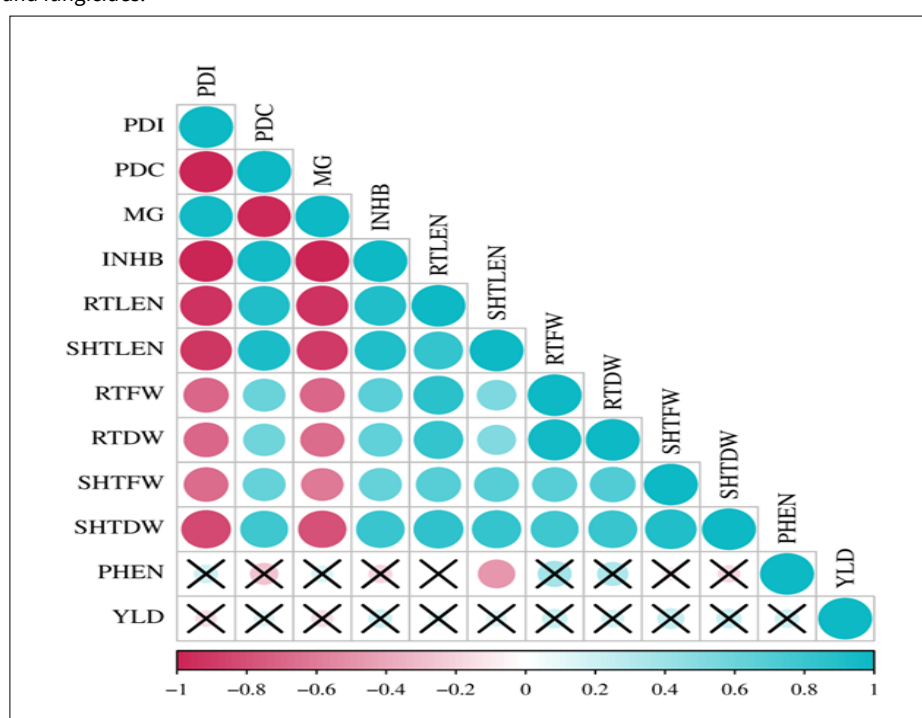


Fig. 5. Correlation among the parameters.

consumer health. Recent bans on certain fungicides have been implemented due to their detrimental health and environmental effects. In August 2024, the U.S. Environmental Protection Agency issued an emergency suspension of dimethyl tetrachloroterephthalate (DCPA or Dacthal) after identifying significant health risks, including embryo-fetal toxicity. Similarly, chlorothalonil, a widely used fungicide, was banned in the European Union in 2019 due to concerns over its high toxicity to aquatic life and potential to cause DNA damage (61, 62). Given that a yield parallel to that attained with chemical substances is also attainable and as evident with the biological agents, the chemical substances and fungicides could be eliminated, ultimately intercepting yield loss as well as damage to the environment and consumer health. For instance, a recent review highlights that biological control agents (BCAs) not only control diseases but also enhance fruit quality and productivity without the negative impacts associated with chemical pesticides (63). A similar research emphasises that BCAs offer a sustainable alternative to chemical pesticides, reducing environmental pollution and health hazards (64). These findings support the potential of BCAs to replace chemical fungicides, thereby preventing yield loss and safeguarding both environmental and consumer health. Furthermore, the usage of chemicals in biological agriculture increases the production costs as well as suppresses the efficiency of the biological materials employed for disease control (65).

The boxplot also provides a comparison between the FYM + sweet basil leaves compost and FYM + biocontrol agent treatments. For most of the traits, FYM + biocontrol agent treatments showed superiority. Nevertheless, the total phenol content was the highest in the FYM + sweet basil leaves compost treatments. This shows that the biocontrol agents not only offer resistance but also promote plant growth. The sweet basil leaves compost didn't show any influence on the growth, but has a key role in enhancing the phenol biosynthesis and accumulation in the plants, thereby preventing the yield loss due to the pathogen attack. Therefore, the usage of FYM + sweet basil leaves compost + biocontrol agents, in combination, provides beneficial effects, given their additive and synergistic effects evident through the prediction with an ML model and empirical evidence.

Prediction of per cent disease control for treatment combinations using a machine learning model

The predicted PDC through ML using the random forest model is presented in the Fig. 6. The model predicted the PDC for a total of 576 treatment combinations for 8 treatments each in groups A and B and 9 treatments in group C (Supplementary Table 1). The top 14 treatment combinations showing synergistic effects (>100 %); top 5 treatment combinations with < 100 %, top 5 treatment combinations showing additive effects (~50 %) and bottom 10 combinations showing antagonistic effects (< 50 %) are plotted in Fig. 5. The top 7 combinations showing synergistic effect involved the treatment B₄: FYM + *T. viride* at 5 kg/ha + *P. fluorescens* at 5 kg/ha and C₅: control. Similarly, the top 18 combinations with synergistic and additive effects included B₄, indicating a strong role of B₄ in controlling the pathogen. *Trichoderma* spp. suppress the pathogen through mycoparasitism, enzyme production and induced plant resistance. *Pseudomonas* spp. inhibits fungal growth via antimicrobial compounds and competition for nutrients. Their combined application enhances disease suppression, promoting healthier root systems and improved yield (66, 67). From this, it is also learnt that the FYM + sweet basil leaves compost and B₄,

particularly without any chemical control measure has been predicted to be synergistic and beneficial for controlling the Fusarium wilt in tomato plants. Biological control methods thrive without chemical intervention, preserving beneficial microbes and maintaining ecological balance (68). Eliminating chemicals reduces environmental pollution, safeguards soil health and prevents pesticide resistance in pathogens. Additionally, it enhances crop resilience in the long term by promoting natural plant defence mechanisms (69).

In contrast, the treatment combinations with antagonistic effects were those combinations involving the biocontrol agents and chemical fungicides, particularly B₃: FYM + Azotobacter at 10 kg/ha, B₅: FYM + *T. viride* at 5 kg/ha + Azotobacter at 5 kg/ha, B₇: FYM + *T. viride* at 3.33 kg/ha + *P. fluorescens* at 3.33 kg/ha + Azotobacter at 3.33 kg/ha; and C₃: Humic acid 400 ppm + Azoxystrobin 1000 ppm, C₆: Humic acid 400 ppm + (Pyraclostrobin + Epoxiconazole) 1000 ppm, C₇: Humic acid 400 ppm + (Metiram + Pyraclostrobin) 1000 ppm, respectively. The chemical fungicides disrupt microbial communities by directly inhibiting beneficial fungi and bacteria through toxic effects (70). Fungicides can also interfere with the production of antimicrobial compounds and enzymes essential for biocontrol activity. Additionally, they reduce microbial competition by altering soil microbiota, favouring pathogen resurgence (71, 72). These effects weaken the efficacy of biological control, making chemical fungicides unsuitable for organic disease management.

The treatment combinations with additive effects (i.e., predicted PDC around 50 %) mostly involved the chemical treatments viz., C₄: Humic acid 400 ppm + Difenconazole 1000 ppm, C₆: Humic acid 400 ppm + (Pyraclostrobin + Epoxiconazole) 1000 ppm, C₇: Humic acid 400 ppm + (Metiram + Pyraclostrobin) 1000 ppm and C₈: Azoxystrobin 0.1 % seedling treatment, indicating their harmless combinational usage. However, the elimination of chemical fungicides in biological management is mostly recommended by previous reports and current investigation results. Similarly, research discusses the overuse of chemical fungicides leading to unsafe produce due to residual effects, advocating for sustainable disease control methods (73). Research notes the decreasing use of synthetic fungicides due to global concerns about residues in the environment and foods, promoting the adoption of biocontrol agents (1).

Validation of the random forest model - biological validation

The treatment combinations to be top-performing in the category of synergistic, additive and antagonistic effects were selected and applied to the plants in the following season. The results and their statistical results are presented in Fig. 7. The results of the paired t-test done to find the significance of the differences between the predicted and observed PDC values are presented in Fig. 7A. A high t-value ($t = 6.953$) reveals a significant difference between the predicted and observed PDC values, indicating that the model made slightly more accurate predictions that couldn't exactly match the practical outcomes under dynamic biological and environmental factors. An extremely small p -value ($p = 2.85e^{-08}$) signifies the same. It is observed that the predicted PDC is 6.01 % higher than the observed evidence, suggesting that the model has slightly amplified the disease control power of the treatment combinations to a small extent of 6.01 %. However, the slight overestimation might not be predominantly due to the model bias, given the volatile nature of plant trials implicated by biological variability and dynamic environmental factors.

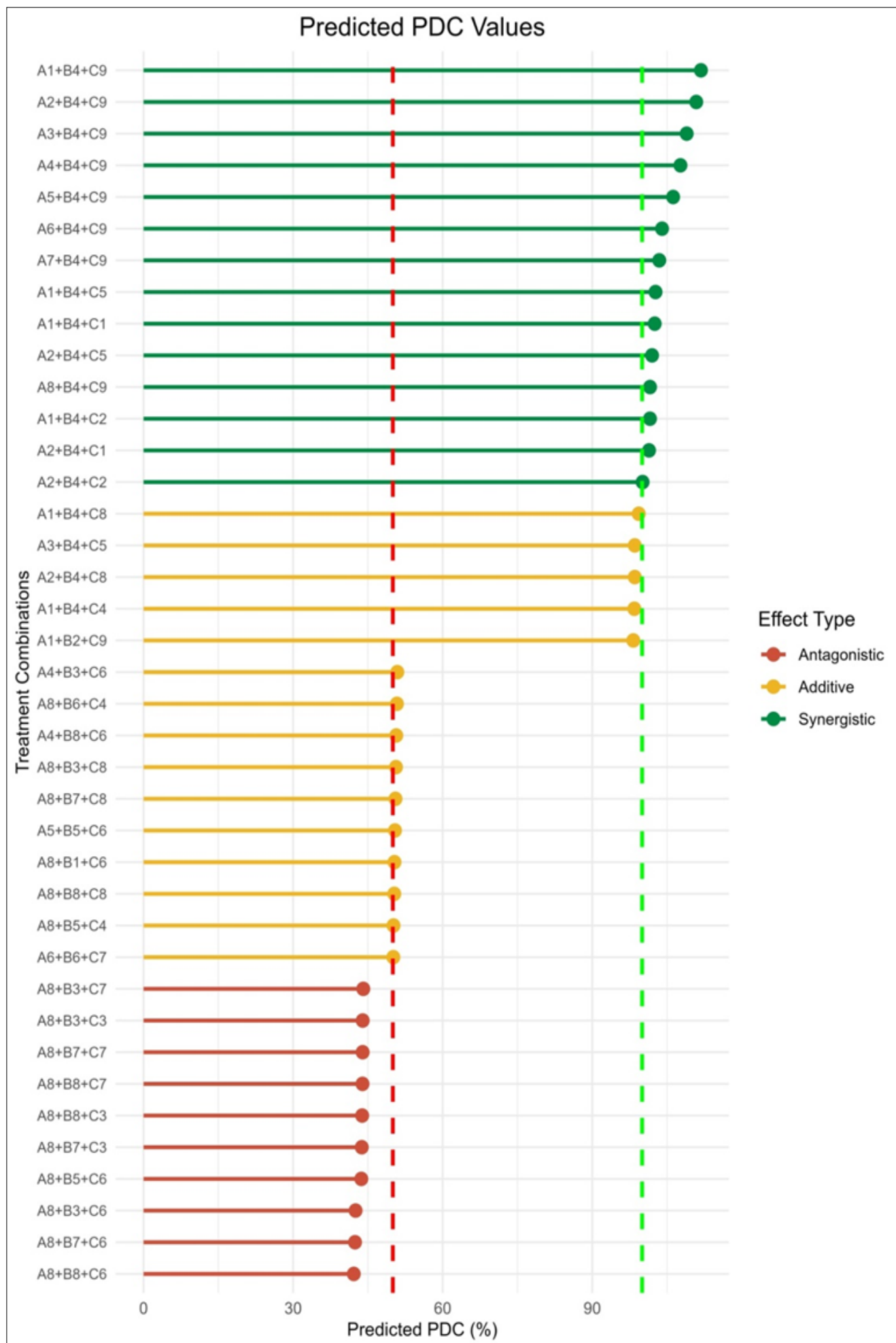


Fig. 6. PDC predicted with random forest algorithm.

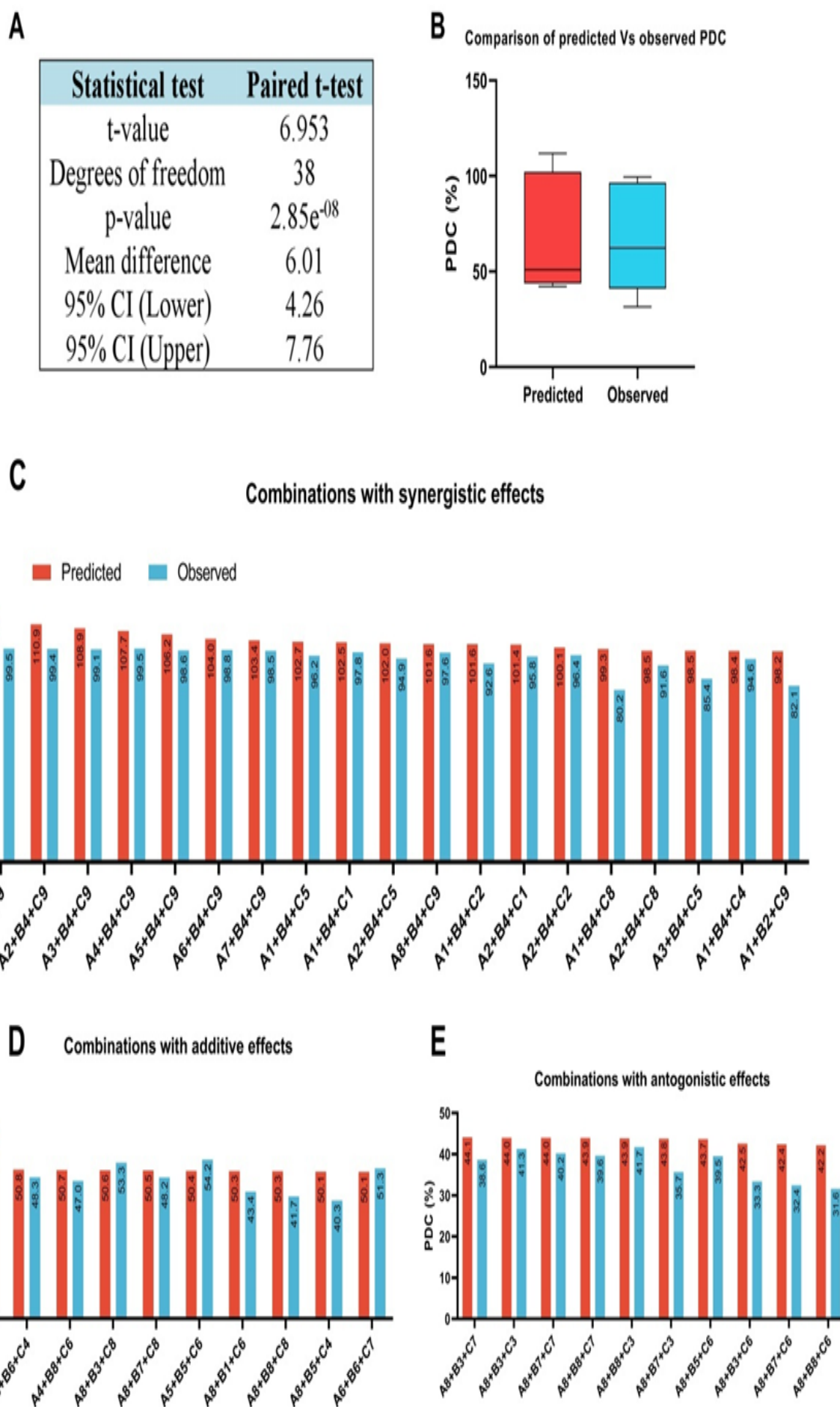


Fig. 7. Biological validation of the model. A: Statistics of paired t-test; B: Boxplot showing the range and similitude of predicted and observed PDC; C: Predicted and observed PDC values for synergistic; D: Additive; E: Antagonistic effects.

Research indicates the limitations of ML models in accurately predicting crop yields and disease prevalence, emphasising the influence of environmental factors and biological variability on model performance (74). Research discussed how climate variability and environmental unpredictability can lead to overestimations in ML models applied to agricultural management, underscoring the need for models that account for such dynamics (75).

Even though the paired t-test showed significance of differences, Fig. 7B-E shows the similarity of predicted and observed PDC. The treatment combination predicted to be synergistic, additive and antagonistic showed to be the same in reality too. The model's prediction power on the synergy, antagonism and additive effects is appreciable and should be further explored, is its uncovered potential in the arena of crop health management. Research sheds light on the potential of ML for making smart decisions in farming (76).

Validation of the random forest model - Statistical cross-validation

The cross-validation of the model using K-fold analysis is presented in Fig. 8. The Random Forest model demonstrated strong predictive performance, with an R^2 value of 0.981, indicating that 98.1 % of the

variation in observed PDC was explained by the model predictions. The RMSE was 4.85, suggesting that, on average, predicted PDC deviated by 4.85 % from observed values. The MAE was 3.70, showing a low overall prediction error. These results confirm that the model provides highly reliable estimates of disease control percentages (Fig. 8A). The correlation between the predicted and observed PDC showed a high positive correlation ($r = 0.98$), indicating a high level of parallelism for prediction and observation on PDC (Fig. 8B). The scatter plot (Fig. 8C) illustrates the relationship between predicted and observed PDC, revealing a strong correlation between model predictions and empirical observations. The regression line closely follows the 1:1 diagonal, indicating that the Random Forest model provides a reliable estimation of treatment efficacy. However, a slight overestimation is observed at higher PDC values, while some deviations appear in the lower PDC range.

To further prove the similarity between the predicted and observed PDC values, the Bland-Altman plot is employed (Fig. 8D). The red line represents the average bias and its positive placement above zero indicates a slight overestimation of the values, yet with an acceptable agreement. The blue line represents the limits of agreement within which 95 % of differences should fall. Since most of the data points are plotted within the limits of agreement, the slight deviation between the predicted and observed values is within

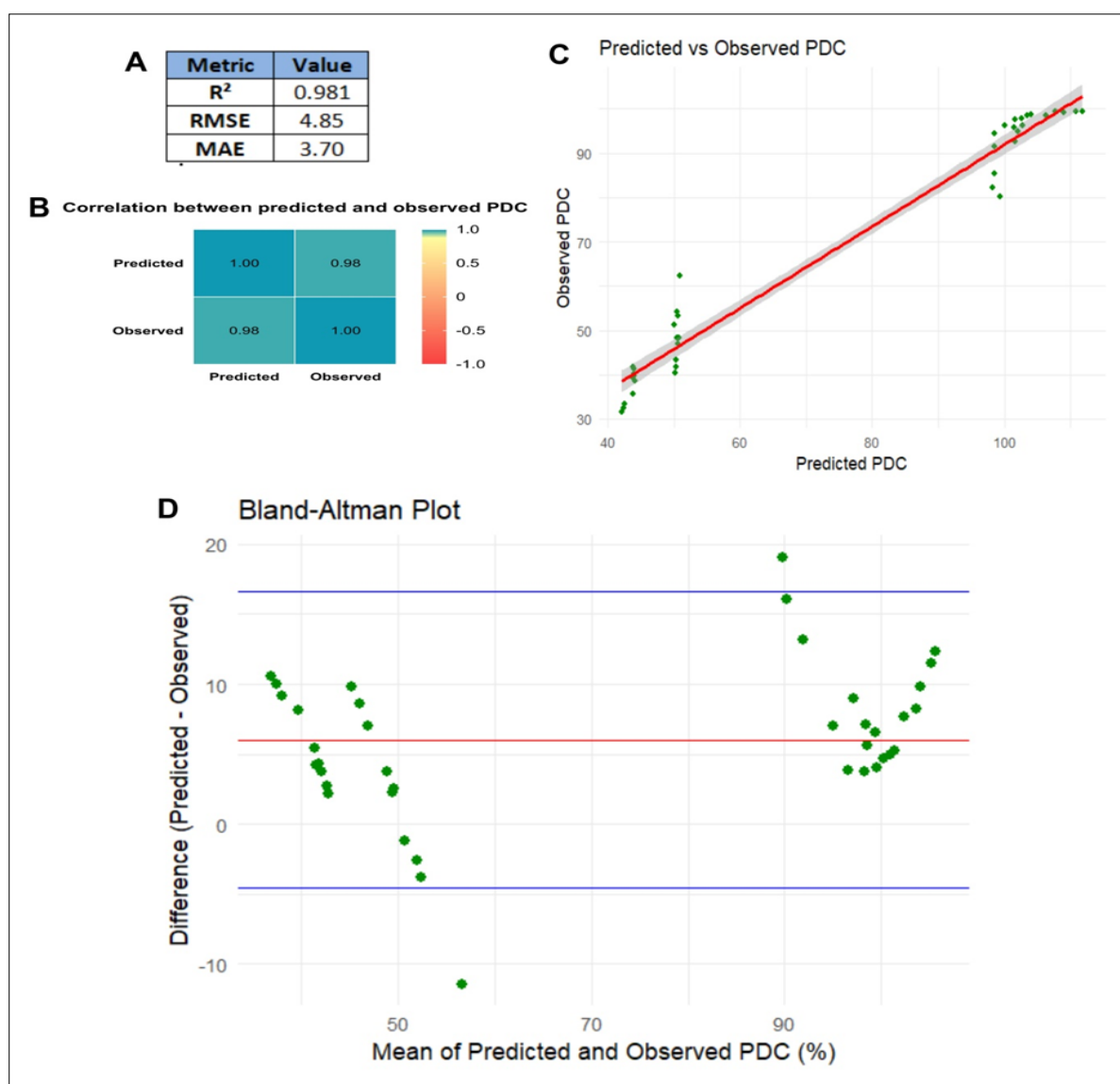


Fig. 8. Cross validation of the model. A: Performance metrics from K-fold cross validation; B: Correlation; C: Scatterplot for the predicted and observed PDC; D: Bland-Altman plot showing similitude between the predicted and observed PDC.

the expected and acceptable variability for a trial with volatile and dynamic biological and environmental factors (1, 30). Research employed the Bland-Altman plot to assess the agreement between predicted and observed phosphorus levels in soil, demonstrating the effectiveness of ML models in soil nutrient prediction (77).

Both the biological validation and the k-fold cross-validation established the reliability of the proposed model. However, a slight overestimation is observed at higher PDC values, while some deviations appear in the lower PDC range. This discrepancy can be attributed to biological variability and environmental dynamics inherent in field trials of plants. Unlike controlled laboratory conditions, field experiments introduce factors such as soil heterogeneity, microclimatic variations and plant physiological responses, all of which can influence disease progression and treatment effectiveness. Additionally, the interactions among multiple treatments may exhibit nonlinear and context-dependent effects, further contributing to the observed variability. Despite these natural fluctuations, the overall model performance remains strong, capturing key treatment trends while reflecting the inherent complexity of plant-pathogen interactions under field conditions. Future refinements, including integrating additional environmental parameters and leveraging ensemble modelling techniques, may further enhance predictive accuracy while accounting for field-based uncertainties.

Conclusion

The present study successfully integrates biological, organic and chemical approaches to manage *Fusarium* wilt in tomato, with the aid of a ML-based predictive model. The Random Forest algorithm proved highly reliable in predicting effective treatment combinations. It identified the optimal strategy as FYM + de-oiled sweet basil leaf compost (25 t/ha) + *T. viride* (5 kg/ha) + *P. fluorescens* (5 kg/ha), which together provided strong disease suppression. Additionally, the study highlights the suppressive effect of chemical fungicides on biological agents, reinforcing the importance of selecting compatible treatment combinations.

Looking ahead, the application of ML in plant pathology holds immense potential in refining disease management strategies with minimal resource investment. Future research can extend this approach to a broader spectrum of crops and pathogens, further improving predictive accuracy with larger datasets and advanced deep-learning techniques. Additionally, integrating environmental factors such as soil microbiome composition, temperature and humidity into the model could enhance disease prediction and control strategies. By leveraging artificial intelligence, this research paves the way for precise, resource-efficient and environmentally sustainable disease management solutions, demonstrating the transformative potential of AI in agriculture.

Authors' contributions

PV contributed to conceptualisation, resource inventories, formal analysis, writing and reviewing the manuscript. JJ contributed to conceptualisation, formal analysis, machine learning model development, writing and reviewing the manuscript. DJ contributed to machine learning model development and its validation, writing and reviewing the manuscript. MS contributed to methodology, formal analysis; PH contributed to methodology, formal analysis,

writing and reviewing the original manuscript. All authors read and approved the final manuscript.

Compliance with ethical standards

Conflict of interest: Authors do not have any conflict of interest to declare.

Ethical issues: None

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