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RESEARCH ARTICLE

A Bayesian inference for treatment effects in randomized block design

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Abstract

This paper presents a Bayesian analysis of the effect of organic spray treatment on the yield of *Amaranthus dubius,* a leafy vegetable of significant nutrition value. Given the increasing demand for sustainable agricultural practices, this research aims to provide a Bayesian perspective for the analysis of variance (ANOVA) of organic interventions. The Bayesian approach facilitated the incorporation of prior knowledge and the quantification of uncertainty in yield predictions. In the place of frequentist ANOVA including the Bayesian may include the prior knowledge by the given data and result in precise conclusions. A randomized controlled trial involving four replications was conducted to compare yields from plots subjected to 6 different organic spray treatments and one non- organic spray treatment (urea - for reference) against control plots with no treatment. Modelling was conducted using the R programming language, employing packages such as brms and rstan to fit hierarchical models that account for variability across treatments and environmental conditions. Findings revealed a statistically significant increase in yield associated with the organic spray treatment, with credible intervals indicating substantial effect sizes. Model diagnostics, including posterior predictive checks, confirmed the adequacy of the model fit. The application of Bayesian methods provides a comprehensive statistical approach to assess the impact of organic treatments, offering valuable insights for future agricultural research-like advanced factorial, balanced designs and practice.

Keywords: *Amaranthus*; ANOVA; Bayesian analysis; experimental design; organic sprays; R programming; statistical modelling

Introduction

In agricultural research, the Design of Experiments (DoE) plays a crucial role in accurately assessing the effects of various treatments on crop performance (1,2). Traditional analysis methods, such as Analysis of Variance (ANOVA)**,** are widely used across different experimental designs, typically under the assumption that the underlying data follow a normal distribution. However, in practical scenarios, agricultural data may often deviate from normality, either due to natural variability or external influences. In such cases, relying solely on classical methods may compromise inference quality. To address this, the Bayesian approach has emerged as a robust alternative, offering greater flexibility and improved precision in modelling both normal and non-normal data distributions (3).

This study applies the Bayesian framework to evaluate the effect of six organic spray treatments and one non-organic spray treatment on the fresh weight yield of *Amaranthus dubius* under a Randomized Block Design (RBD) with four replications (4). The primary objective is to implement and assess the effectiveness of Bayesian data analysis techniques in comparing treatment efficacies.

For this purpose, models were developed using R, particularly leveraging the brms package for Bayesian regression modelling. The analysis explores distributional assumptions, model diagnostics, prior and posterior checks and ultimately provides statistically sound conclusions regarding the treatment effects.

Materials and Methods

The objective of this study is to evaluate the effects of various foliar treatments on the yield of *Amaranthus dubius,* incorporating multiple organic sprays and a single non-organic treatment (T_8- urea) with control plot for comparative analysis. To achieve this, data were analysed using a Bayesian statistical framework (5) alongside a traditional frequentist ANOVA approach (6).

Experimental design and dataset

The experiment was conducted using Randomized Block Design (RBD) with eight treatments (T_1–T_8) and four replications. Treatment T_8 is used as Urea (non-organic) for the purpose of comparison. The data set was structured into three variables:

- **Replication**: Captures variability across experimental blocks

- **Treatment**: Indicates the specific foliar spray or control condition applied
- **Response**: Represents the recorded fresh weight yield of *Amaranthus dubius* (g)

This structure makes the dataset appropriate for analysing treatment effects while accounting for block-level variability.

Treatment details

T_1 - Control (No spray)

T_2 - Foliar spray of vermiwash (5 %)

T_3 - Liquid manure of the composite manure of ground nut cake + neem cake + poultry manure (1:0.5:0.5)

T_4 - Foliar spray of egg amino acid (0.2 %)

T_5 - Foliar spray of fish amino acid (0.1 %)

T_6 - Foliar spray of cowpea sprouted extract (2 %)

T_7 - Foliar spray of PPFM (2 %)

T_8 - Foliar spray of urea (2 %) – Non-organic treatment

Initially a classical ANOVA model was fitted using aov() function (7), where the response variable was modelled as a function of treatment and replication was treated as a blocking factor. Model diagnostics were conducted to validate assumptions of normality and homogeneity of variances using Shapiro-Wilk test, Levene's test and residual plots (8).

Bayesian analysis

To complement the frequentist approach, a Bayesian hierarchical model was developed using the brms package (9). The model specifications include the following:

- A likelihood function assuming a Weibull distribution (as per fit diagnostics)
- Treatment as a fixed effect
- Replication as a random effect

Prior distributions were defined based on prior predictive simulations and theoretical considerations. Posterior predictive checks, trace plots and R-hat statistics were used to assess model convergence and fit.

Posterior predictive checks (10) compare data simulated from the model to observed data, assessing the model fit. Trace plots show parameter samples over iterations (11). Stable, well-mixed traces mean good sampling convergence. R-hat (12) measures if multiple chains have converged to the same distributions; values near 1 indicate good convergence.

Model performance was evaluated using AIC values and treatment comparisons were made based on the posterior distributions and credible intervals (13).

Results and Discussion

Frequentist approach

The frequentist ANOVA results provided F-statistics and corresponding p-values to evaluate the influence of different treatments (Table 1).

Statistically significant p-values suggest that at least one treatment group exhibited a yield response distinct from the others. To further investigate pairwise differences among treatments, Tukey's Honestly Significant Difference (HSD) test was employed without any correction (14). This post hoc analysis identified specific treatment combinations that significantly differed in their effects on yield.

Bayesian analysis

A histogram (Fig. 1 & 2) revealed deviations from normality in the yield data.

Trying to fit different distributions like normal, log normal, gamma and Weibull and compared the fitness using AIC values (Table 2).

Fitted plots of different distribution normal (Fig. 3), log normal (Fig. 4), gamma (Fig. 5) and Weibull (Fig. 6) using the packages brms and rstan has been shown below (15,16).

The AIC value found to be low for Weibull distribution when compared to other distributions (17). Weibull distribution found to be a better fit for the given dataset. Using Weibull distribution as likelihood conducted a Bayesian ANOVA using brms package in r. From the summary of the Bayesian ANOVA the credible intervals do not contain zero which infer that there is a significant difference between groups which is like rejecting the null hypothesis in frequentist ANOVA (Table 3) .

The Rhat values equal to one, which implies the better convergence. From The posterior predictive check plots (Fig. 7), the simulated data overlaps well with observed data, suggesting that the model is a good fit. For better visualization of the results the estimated marginal means of the Bayesian anova results is plotted (Fig. 8). From this plot it is clear that the treatment 4 performs well when compared to other treatments, having the difference of 0.43 than the null effect.

Conclusion

To compare the treatment effects and find the significant difference between treatments estimated the marginal means of the treatments and compared each pair of treatments.

The significant plot (Fig. 9), shows that most of the treatments found to be significant except the treatment pairs T_2-T_5 and T_3-T_5. Treatment 2 found to be less effective than treatment 3 and treatment 4. Treatment 3 is less effective than treatment 4. Treatment means arranged in their ascending order (Table 4). Treatment 4 found to be the superior with the mean value of 7.79 which is egg amino acid.

Table 1. Frequentist ANOVA results

	df	SS	MSS	F value	Pr (>F)
Treatment	7	2002077	286011	167.293	<2e-16 ***
Replication	3	31	10	0.999	
Residuals	21	35901	1710		

Table 2. AIC values of different distributions

Distribution	AIC
Normal	448.7880
Log Normal	452.5146
Gamma	455.1305
Weibull	444.0330

Table 3. Bayesian ANOVA results

	Estimate	Estimated error	l to 95% CI	U to 95% CI	R_hat	Bulk_ ESS	Tail_ ESS
Regression coefficients:							
Intercept	7.36	0.01	7.34	7.38	1.00	903	1362
Treatment 2	0.34	0.01	0.31	0.36	1.00	1491	1805
Treatment 3	0.38	0.01	0.36	0.41	1.00	1230	1857
Treatment 4	0.43	0.01	0.41	0.46	1.00	1336	1838
Treatment 5	0.36	0.01	0.33	0.39	1.00	1327	1740
Treatment 6	0.30	0.01	0.27	0.32	1.00	1189	1860
Treatment 7	0.24	0.01	0.21	0.26	1.00	1326	1456
Treatment 8	0.21	0.01	0.18	0.24	1.00	1226	1893
Distribution parameters:							
Shape	59.58	9.53	42.17	79.73	1.00	1726	2447

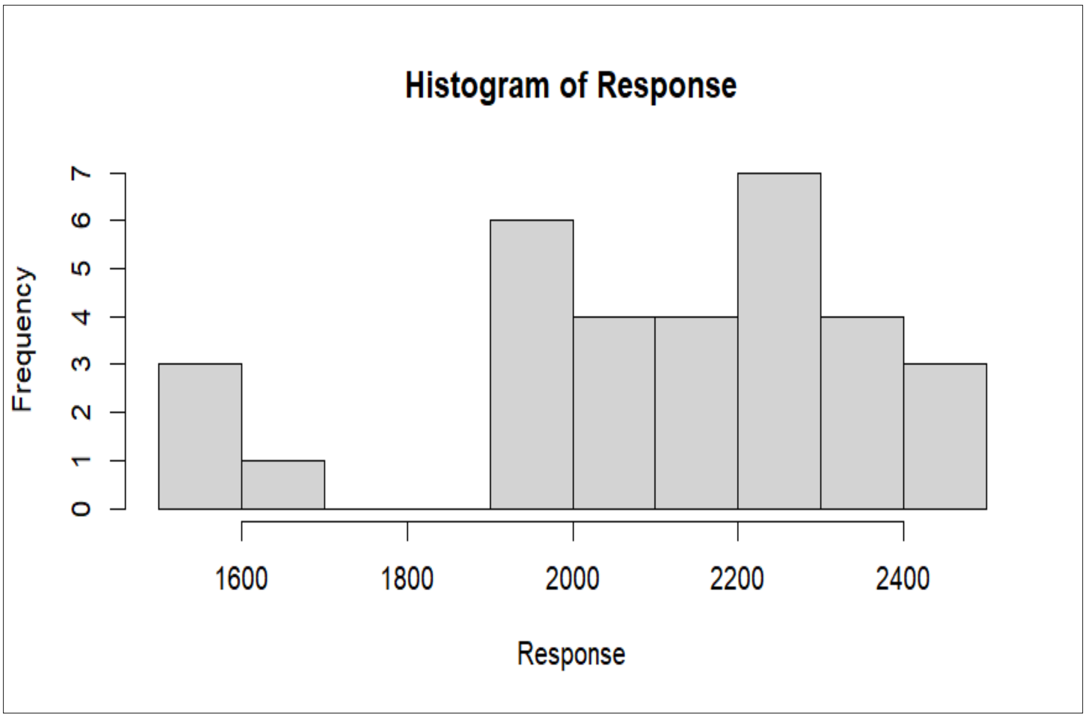

Fig. 1. Histogram of response.

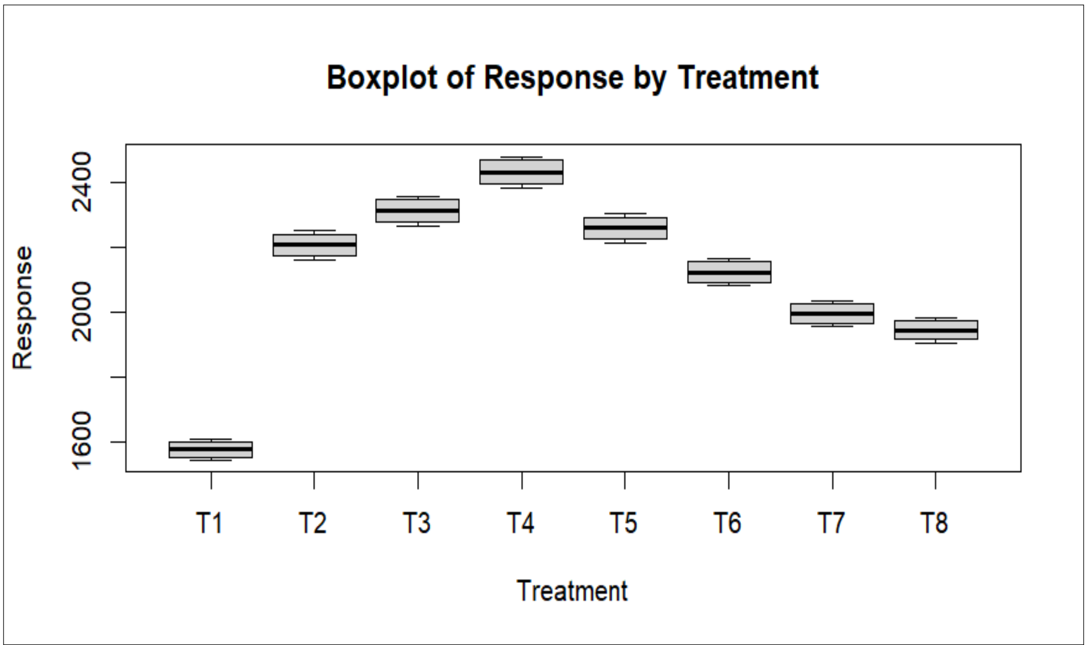

Fig. 2. Boxplot of response.

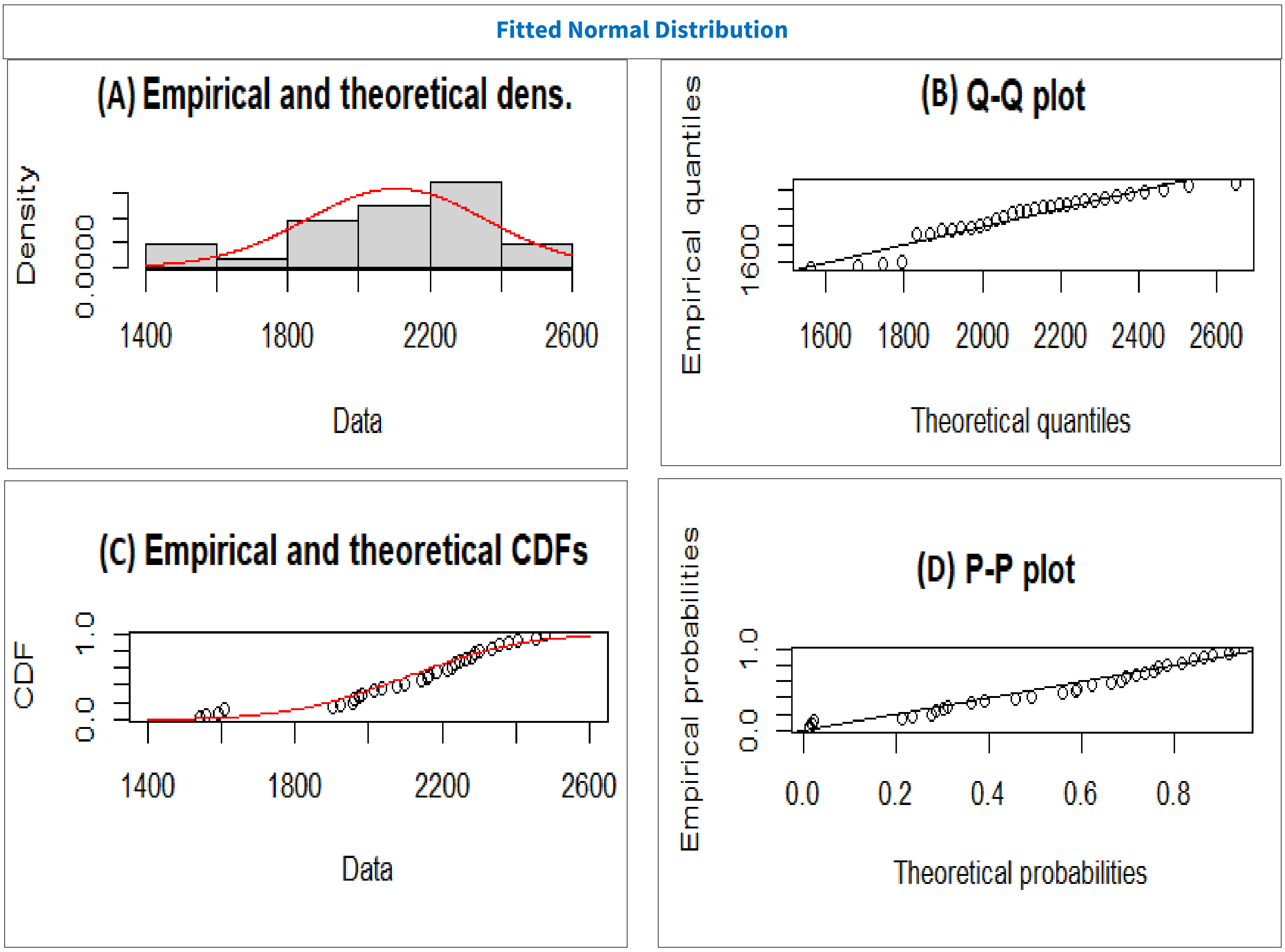

Fig. 3. Plots of normal distribution fitting.

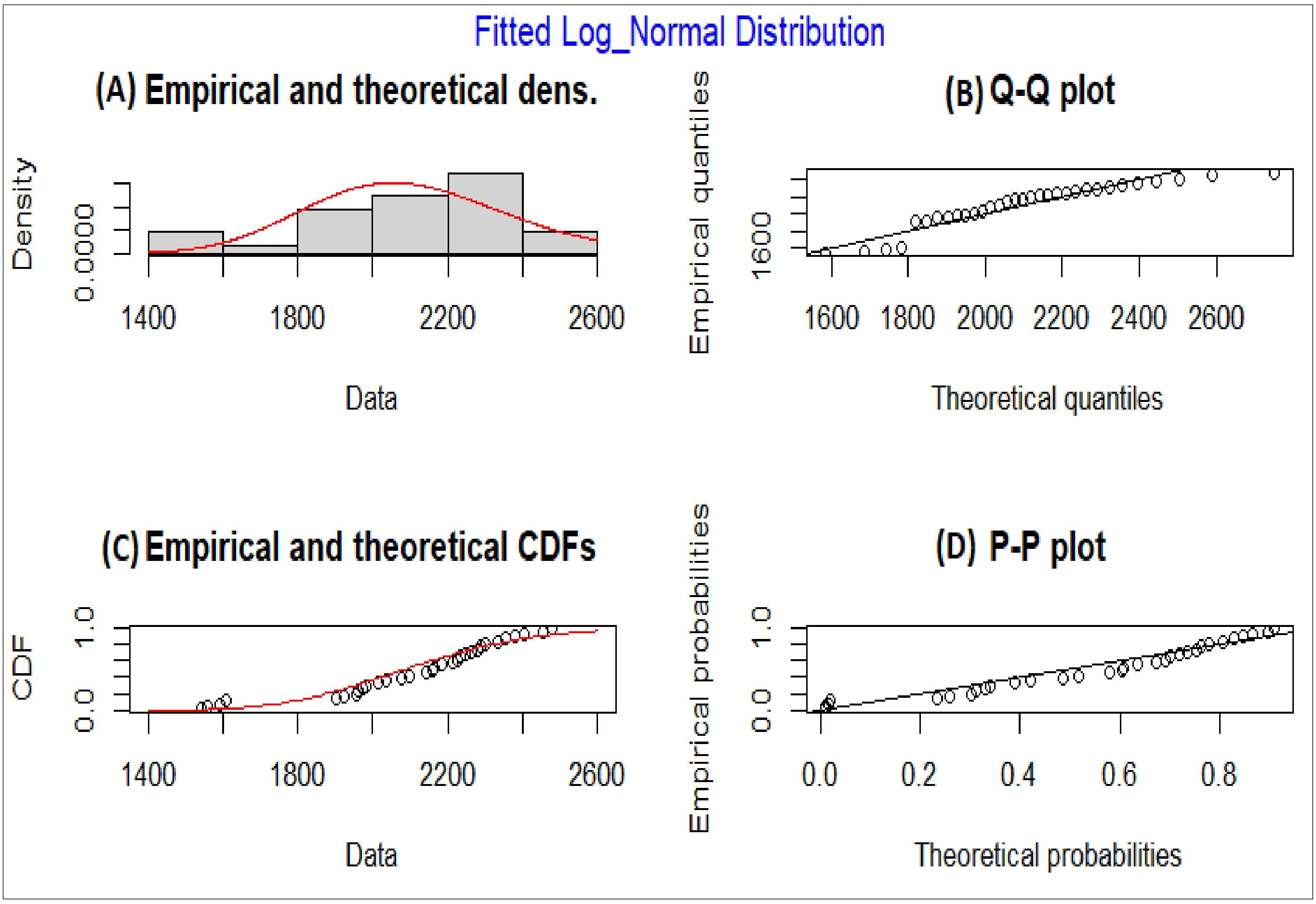

Fig. 4. Plots of lognormal distribution fitting.

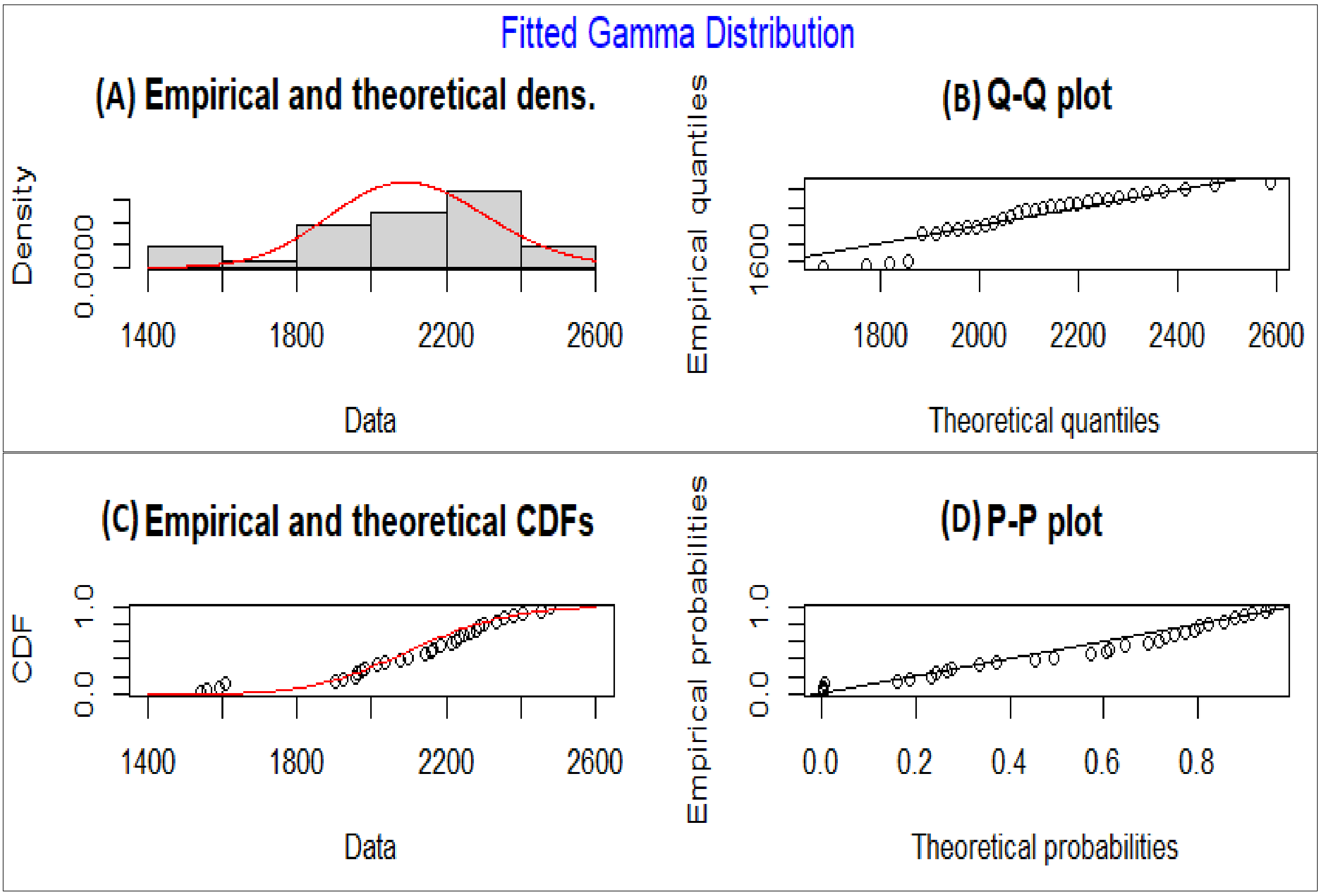

Fig. 5. Plots of gamma distribution fitting.

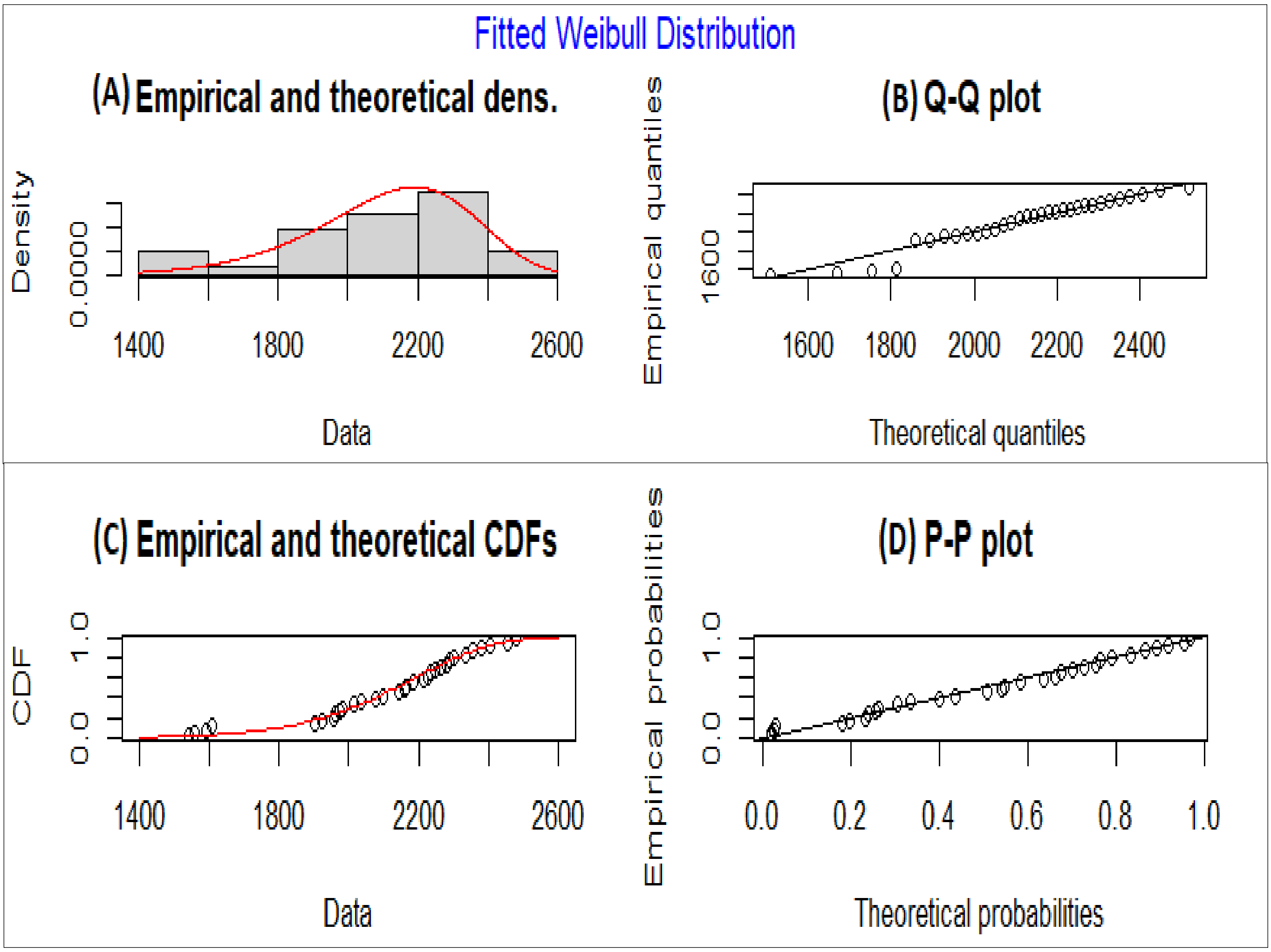

Fig. 6. Plots of Weibull distribution fitting.

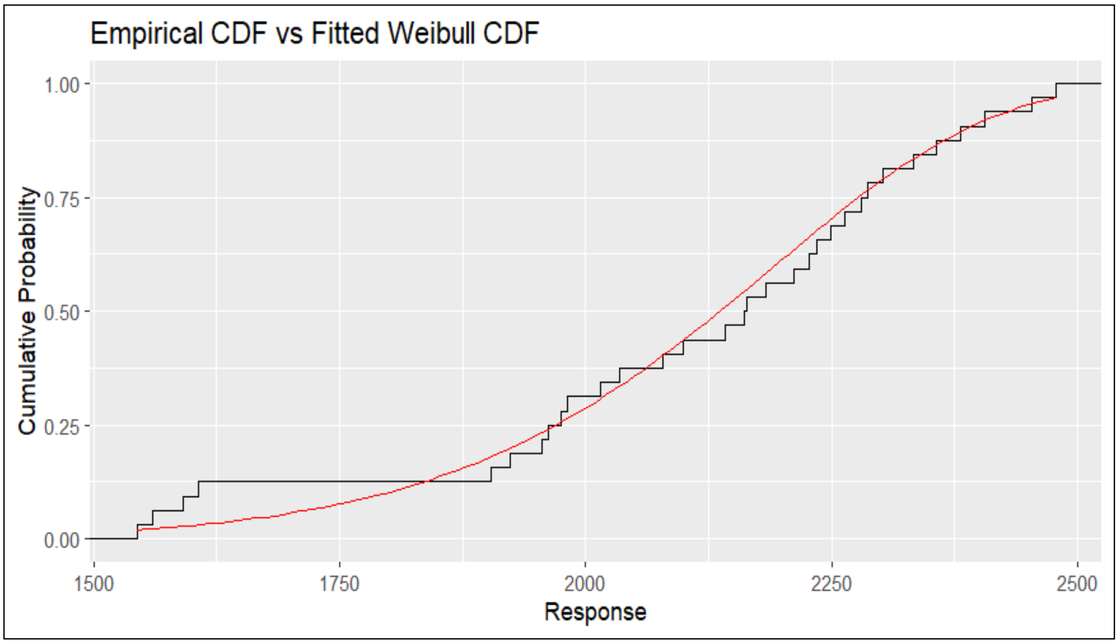

Fig. 7. Plot of empirical CDF vs Weibull CDF.

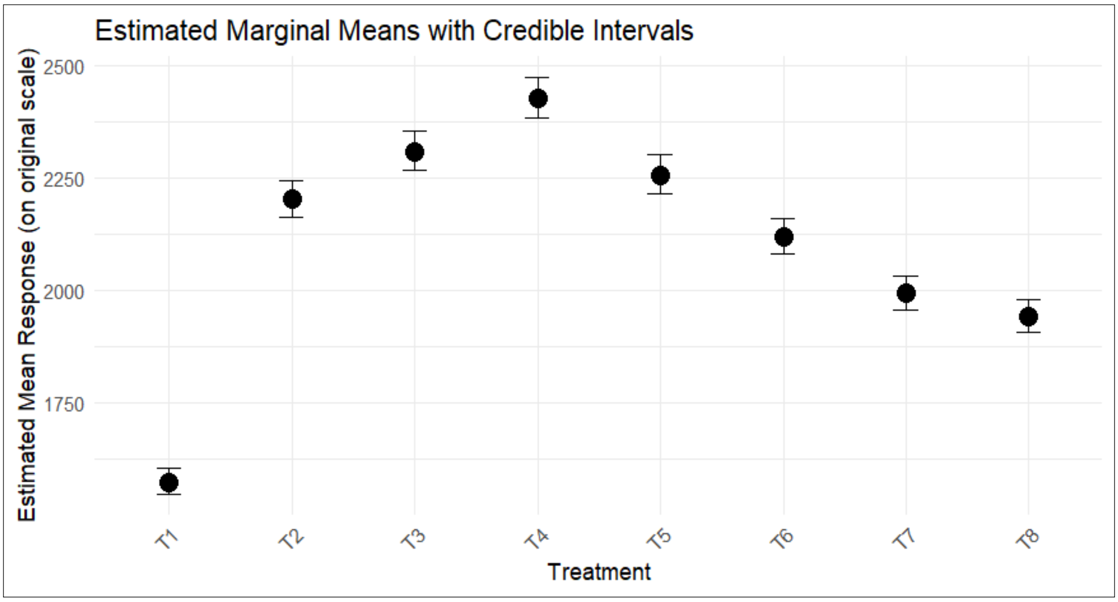

Fig. 8. Estimated marginal means with credible intervals.

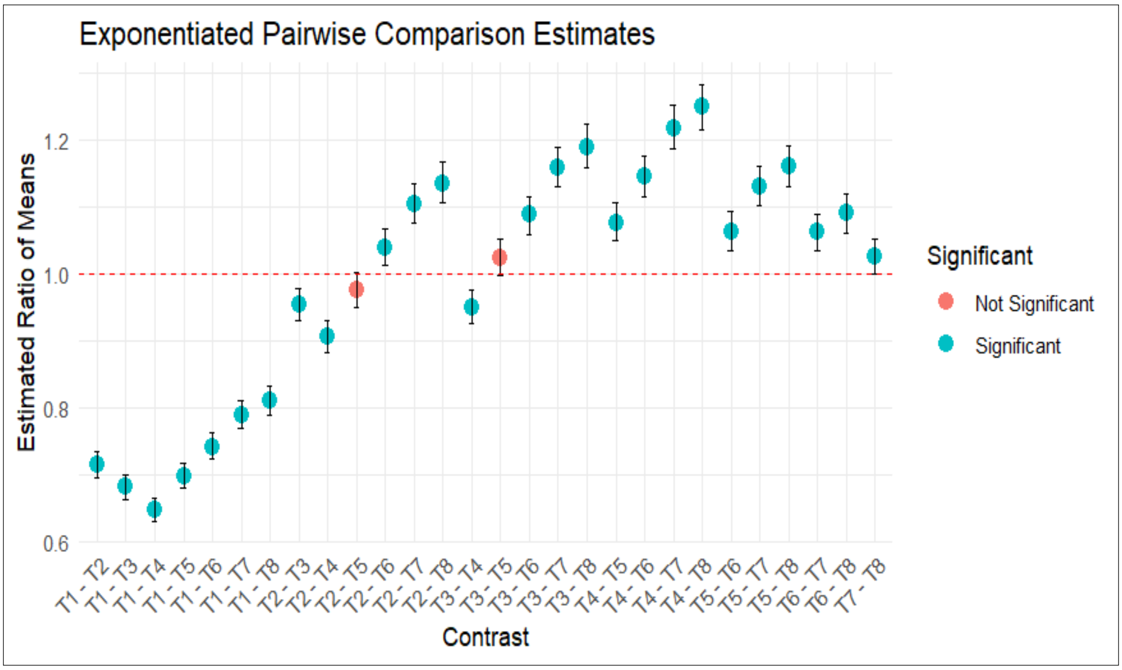

Fig. 9. Pairwise treatment comparison.

Table 4. Treatments means arranged in descending order

Treatment	Mean	Lower_HPD	Upper_HPD
T1	7.360710	7.343727	7.380109
T8	7.570675	7.552364	7.590912
T7	7.597198	7.578480	7.616699
T6	7.658572	7.640109	7.677983
T2	7.697112	7.678702	7.716188
T5	7.720920	7.702487	7.740807
T3	7.743907	7.725760	7.763377
T4	7.794320	7.775874	7.813520

Authors' contributions

NR carried out agricultural- statistic work. AV finalised of manuscript. All authors read and approved the final manuscript.

Compliance with ethical standards

Conflict of interest: Authors have no conflict of interest to declare.

Ethical issues: None

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