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Partial vs. Complete Confounding in Factorial Agricultural Designs: A Methodological Study Based on MSE Performance

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Abstract : This study examined the impact of full or partial confounding factorial treatment on the experiment's analytical outcomes. Three factors two kinds of herbicides B, two types of cotton C, and nitrogen fertilizer A are included in the mean amount of seeds of a cotton plant. The outcomes were comparable. After comparing the results using the experiment's mean square error (Mse), it was determined that employing partial confounding yields the best outcomes in every situation.

Keywords: Factorial Experiments, Randomized Complete Block Design, Confounding

INTRODUCTION: One of the most basic duties that needs rigorous scientific methodology is executing scientific experiments. In order to make the best use of the resources at hand, they attempt out the best treatments and the major factors that affect experimental units. so selecting appropriate and efficient experimental structures is vital for ensuring the validity and reliability of outcomes. per Montgomery (2020), a carefully planned design strengthens the interpretability of interactions among experimental factors in addition to the accuracy of the conclusions.

When full factorial designs are not practical, new developments in the theory of partial factorial designs have led to frameworks for optimizing experimental efficiency. For instance, researchers looked at current optimality criteria and proposed ways to construct based on the idea of Yates' ordering, making complex designs easier to implement in implementation. [9]. This approach becomes particularly useful when managing higher-order interactions. In a notable application, the complete confounding of a triple interaction effect with an incomplete block was employed to reduce the size of a full factorial layout from 27 experimental plots to just 9 plots thus significantly minimizing resource consumption [3]

To manage experimental units more effectively, these units are divided into blocks based on a theoretical model for constructing optimal blocked designs. Techniques such as doubling theory and second-order saturated designs are used in accordance with the general minimum degree of interference criterion to prevent overlapping or contamination among blocks [6]. This criterion ensures that the arrangement of treatments within blocks minimizes potential interference and maintains statistical validity.

Study Problem:

When studying experiments for more than one factor that requires many experimental units, which are difficult to provide, especially according to the conditions of the experiment, an approach was followed that depends on the number of blocks within the replicates through Confounding experiments and knowing the effect of the Confound significant and insignificant factors on the analytical results through the standard of the mean square error.

Study Objectives:

1. The research aims to address the problem of the large number of experimental units in factorial experiments using the concept of the block within the replicate through Confounding experiments by taking more than one case and comparing them with the Mse criterion.
2. The research aims to study the selection of Confounding factors and their effect on the analytical results of the experiment.
3. The research aims to apply more than one method to the experimental units

Study significance and contributions:

1. This research is important as it tackles the challenge of handling numerous experimental units in factorial experiments.

2. 2. It was suggested to Confound the non-significant and high-degree effects together.
3. Explain the importance of the combined significant and non-significant factors.

1-Factorial Experiments

If I want to know the effect of two or more factors on a phenomenon, the researcher can conduct a simple experiment for each factor. This procedure costs effort, time, money, and experimental materials. However, if the experimenter wants to collect independent and separate pieces of information, the factors used in the simple experiments must be independent. Therefore, it is necessary to conduct one experiment to demonstrate the independence of these factors. This situation can be overcome by conducting one experiment for all factors at once [5].

2-Randomized Complete Block Design

When applying a completely randomized block design with r blocks, the factorial treatments are randomly allocated to the experimental units within each block.

The formula of the mathematical model for the factorial experiment (A*B*C) implemented according to CRBD can be as follows [4][7]

$$y_{ijkl} = \mu + \alpha_i + \beta_j + (\alpha\beta)_{ij} + \gamma_k + (\alpha\gamma)_{ik} + (\beta\gamma)_{jk} + (\alpha\beta\gamma)_{ijk} + \rho_l + \varepsilon_{ijkl} \quad (1)$$

$i = 1,2..,a \quad ,j = 1,2,..,b \ ,k = 1,2,..,c \ ,l = 1,2,..,r$

Were

y_{ijkl} : The observation value that took level i of factor A, level j of factor B, and level K of factor c in block l, μ : Average value General of the experiment, α_i : Impact value of level (i) of factor A, β_j Impact value of level (j) of factor B, γ_k: Impact value of level (k) of factor C, $(\alpha\beta)_{ij}$ The value of the interference effect of level i of factor A with level j of factor B, $(\alpha\gamma)_{ik}$: The value of the interference effect of level i of factor A with level k of factor c, $(\beta\gamma)_{jk}$: The value of the interference effect of level j of factor A with level k of factor c, $(\alpha\beta\gamma)_{ijk}$ The value of the interference effect of level i of factor A with level j of factor B with level k of factor c, ρ_l : block impact value l, The value of the random error of the observation that took level (i) of factor A, level j of factor B, and level k of factor C, which is within block l.

3-Confounding

This design method is used without a block that accommodates all the factorial treatments. The primary goal of working with the design idea is to reduce the size of the block to obtain a good estimate of the experimental error. [11]

3-1 Complete Confounding

This type of Confounding means that the effect is combined with the differences between blocks in all repetitions of the experiment, as no information can be obtained about it at all and therefore it is not calculated in the analysis of variance [1][8].

Figure (1) shows a factorial experiment of type 2^3 that contains a complete Confounding of the effect of ABC

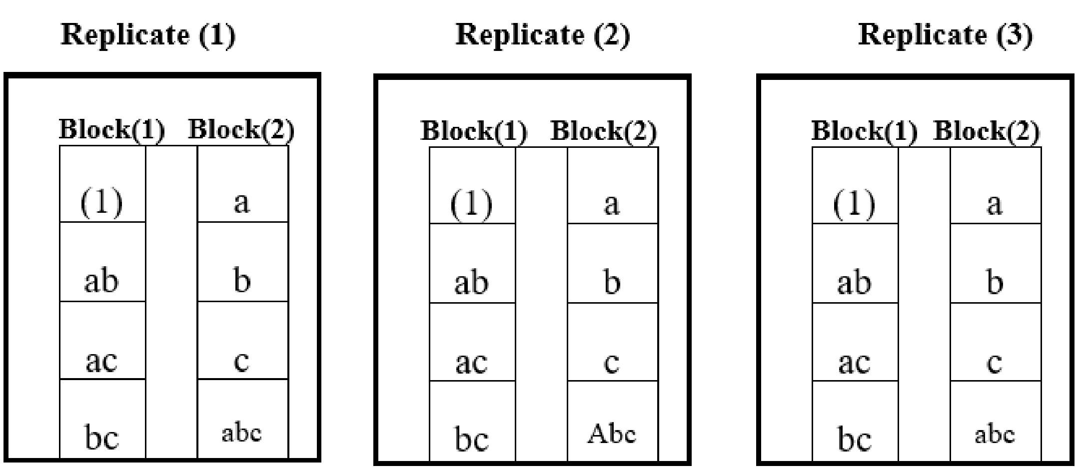

Figure 1: Complete Confounding

We note from the Figure above that the ABC effect is Confound into the difference between the two blocks in each of the three iterations, and therefore it is completely Confound and is not calculated in the analysis.

3-2 Partial Confounding

This type of Confounding means that the effect is Confound with the differences between the blocks in one or some of the repetitions of the experiment and not in all of them. Therefore, it is calculated in the analysis of the variance experiment, as information about it can be obtained from the repetitions in which it was not confounded. And General scheme of research [2][10]

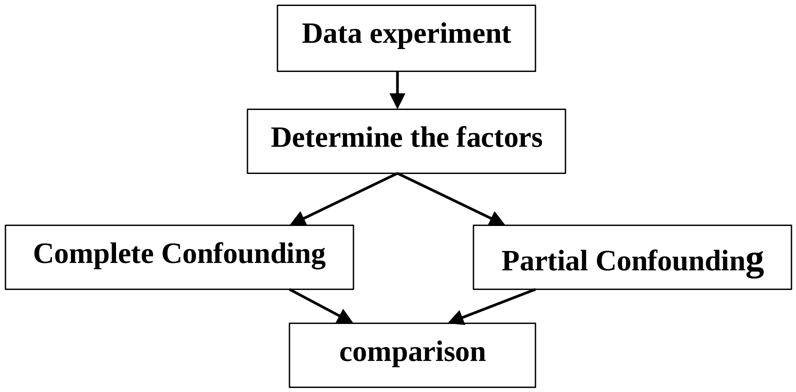

Figure 2: General Scheme for Research

4-Application

In this aspect, the data of a factorial experiment of 2^3 were analyzed through two axes:
the first was a Randomized Complete Block Design to determine the non-significant effects to benefit from in the confounding process, and the second was the confounding of its two types, complete and partial, which was applied in two blocks and then in four blocks for one replicate, and the confounding of the moral and non-moral effects and observing their effect on the results of the experiment.
The study was carried out in Nineveh Governorate, Iraq. Table (1) presents the mean number of roots per plant from a 2^3 factorial experiment arranged in a Randomized Complete Block Design (RCBD). The experiment investigated the effects of:

1. Two nitrogen fertilizer levels (Factor A).
2. Two herbicide types (Factor B).
3. Two cotton varieties (Factor C).

Table (1): Experiment data Average number of roots in cotton

Factor A	Factor B	Factor C	Block (1)	Block (2)	Block (3)	Block (4)	Block (5)	Σ
a_0	b_0	C_0	11	10	7	12	13	53
		C_1	12	9	23	15	15	74
	b_1	C_0	10	11	9	20	11	61
		C_1	12	13	13	17	10	65
a_1	b_0	C_0	13	13	11	9	16	62
		C_1	14	15	14	11	15	69
	b_1	C_0	19	20	17	14	21	91
		C_1	20	24	23	12	23	102

The following table shows the results that were reached in a Randomized Complete Block Design for an experiment, which is considered the basis for implementing confounding

Table (2): Analysis of variance for a (RCBD) of
a factorial experiment 2^3

S.O.V	d.f	S.S	M.S	F
Replicate	**4**	**15.65**	**3.9125**	**0.28**
Treatment Com.	**7**	**380.975**	**54.425**	***3.956**
A	**1**	**126.025**	**126.025**	***9.161**
B	**1**	**93.025**	**93.025**	***6.762**
C	**1**	**46.225**	**46.225**	**3.360**
AB	**1**	**99.225**	**99.225**	***7.213**
AC	**1**	**99.225**	**99.225**	**0.089**
BC	**1**	**1.225**	**1.225**	**0.307**
ABC	**1**	**4.225**	**4.225**	**0.801**
Error	**28**	**385.15**	**13.755**	
Total	**39**	**781.775**		

Table (2) reveals statistically significant differences ($p \leq 0.05$) among the main effects of factor A (nitrogen levels) and factor B (herbicide types), as well as their interaction effect (A×B).
In addition, there is no significant effect of factor C and its interaction with other factors, as well as the lack of significance of the triple interaction.

Complete confounding

Depending on the results of table (1) the effect of ABC will be confounding and the table below displays the analysis outcomes.

Table (3): Analysis of variance for a factorial experiment with 2^3 Complete
confounding, where the ABC effect was the confound

S.O.V	d.f	S.S	M.S	F
Replicates	**4**	**15.65**	**3.91**	**0.258**
Block/Replicates	**5**	**33.375**	**6.67**	**0.441**
Treatment Com.	**6**	**369.95**	**61.65**	***4.078**
A	**1**	**126.025**	**126.025**	***8.336**
B	**1**	**93.025**	**93.025**	***6.153**
C	**1**	**46.225**	**46.225**	**3.057**
AB	**1**	**99.225**	**99.225**	***6.563**
AC	**1**	**1.225**	**1.225**	**0.081**
BC	**1**	**4.225**	**4.225**	**0.279**
Error	**24**	**362.8**	**15.116**	
Total	**39**	**781.775**		

Results in Table (3) show significant effects ($p < 0.05$) of factors A, B, and their interaction, along with a slight MSE increase to 1.361.
Depending on the table (1) results, the effect of AC and AB will be confounding, and the following table shows the comparison results for all cases.

Table (4) Complete confounding: comparing the results of
Two blocks in the repeater

	Comparative experiment	Complete confounding		
	One block	Two blocks in one repeater ABC	Two blocks in one repeater AC	Two blocks in one repeater AB
Cal. F	**3.956**	**4.078**	**4.127**	**3.415**
Mse	**13.755**	**15.116**	**15.333**	**13.75**

Table (4) indicates a noticeable increase in the MSE value in the case of combining non-significant interference effects with a significant interference effect, corresponding to a noticeable decrease in the MSE value in the case of combining non-significant interference effects with a significant main interaction effect.

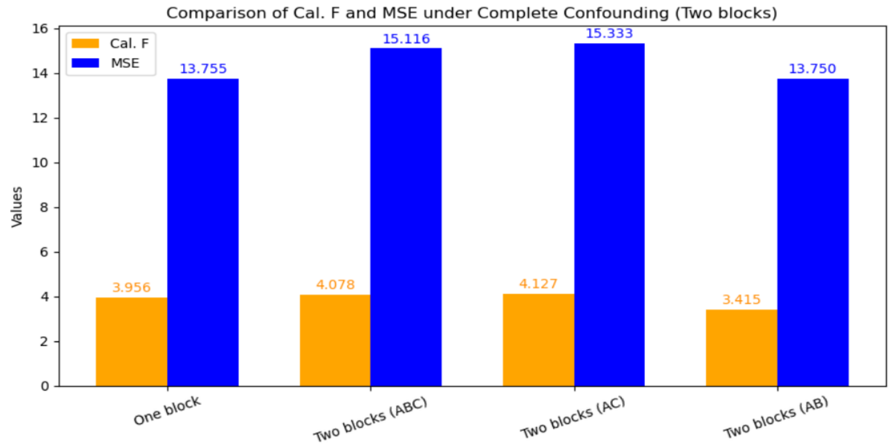

Figure 3: Comparison measures for Complete confounding 2 blocks

The figure shows that confounding in experimental designs is an effective tool for controlling variability, but it comes with statistical costs. The confounded effect must be carefully selected to avoid mixing with major effects. In this context, confounding the three-way interaction (ABC) is the least detrimental option, whereas confounding two-way interactions (AC or AB) leads to a significant increase in MSE and a reduction in test power (Cal. F). Therefore, the two-block design with confounding of (ABC) is considered the most balanced approach between controlling variability and maintaining statistical analysis efficiency.

confounding of AB.AC and BC (the repeater contains four blocks). These interactions were chosen based on table (2), one of which indicates their statistical significance.

Also, the effect of confounding the effect A, BC, and ABC (the repeater contains four blocks). These interactions were chosen based on table (1), one of which indicates their statistical significance. The data was analyzed based on Complete confounding, and the table (5) show the results of the comparison.

Table 5: Complete confounding: comparing the results of Four blocks in the repeater

	Comparative experiment	Complete confounding	
	One block	Four blocks in one repeater AB, AC, BC	Four blocks in one repeater A, BC, ABC
Cal. F	**3.956**	**3.695**	**5.962**
Mse	**13.755**	**18.2**	**10.05**

Table (5) indicates a noticeable increase in the MSE value in the case of confounding non-significant interference effects with a significant interference effect, corresponding to a noticeable decrease in the MSE value in the case of confounding non-significant interference effects with a significant main interaction effect.

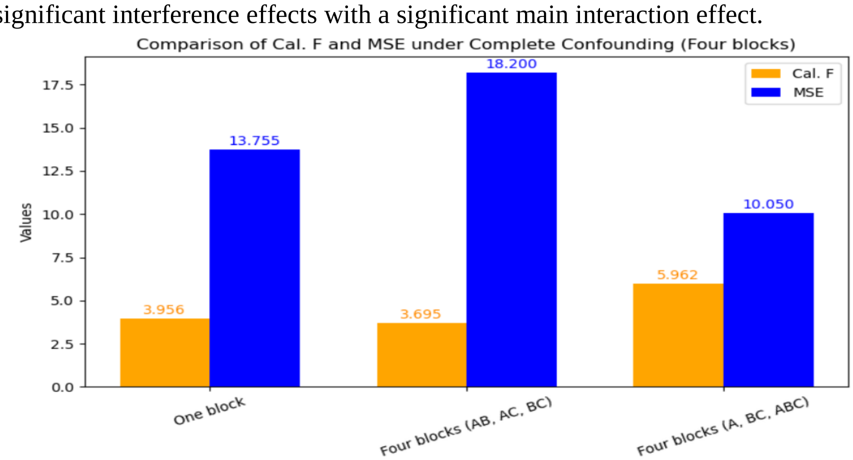

Figure 4: Comparison measures for Complete confounding 4 blocks

The results of table (5) and the figure (4) illustrate the effect of complete confounding when using four blocks as follows:

1. For the Cal. F values, there is a slight decrease from 3.956 in the one-block case to 3.695 when confounding occurs with (AB, AC, BC). However, a noticeable increase to 5.962 is observed when the confounding involves (A, BC, ABC).
2. Regarding the MSE values, the trend shows a sharp increase from 13.755 (one block) to 18.200 under confounding with (AB, AC, BC), followed by a substantial decrease to 10.050 when confounding occurs with (A, BC, ABC).

These findings suggest that complete confounding alters both Cal. F and MSE in opposite directions depending on the type of confounding applied. Specifically, while one type of confounding inflates the error variance (MSE), another reduces it considerably, which highlights the sensitivity of the model's reliability to the confounding structure.

Partial confounding

confounding the effect of ABC and AB (the repeat contains two blocks). These interactions were chosen based on the table (2), one of which indicates its statistical significance.

Also, the effect of confounding is the effect of ABC and AC (the repeat contains two blocks). These interactions were chosen based on the table (2) and they are non-significant interactions. The data was analyzed based on Partial confounding, and the countries (6) show the results of the comparison.

Table (6) Partial confounding: comparing the results of Two blocks in the repeater

	Comparative experiment	Partial confounding	
	One block	Two blocks in one repeater AB, ABC	Two blocks in one repeater AC, ABC
Cal. F	3.956	3.787	3.424
Mse	13.755	13.835	15.441

Table (6) indicates a noticeable increase in the value of MSE in the case of confounding non-significant interference effects with a significant interference effect, corresponding to a noticeable decrease in the value of MSE in the case of confounding non-significant interference effects with a significant main interaction effect.

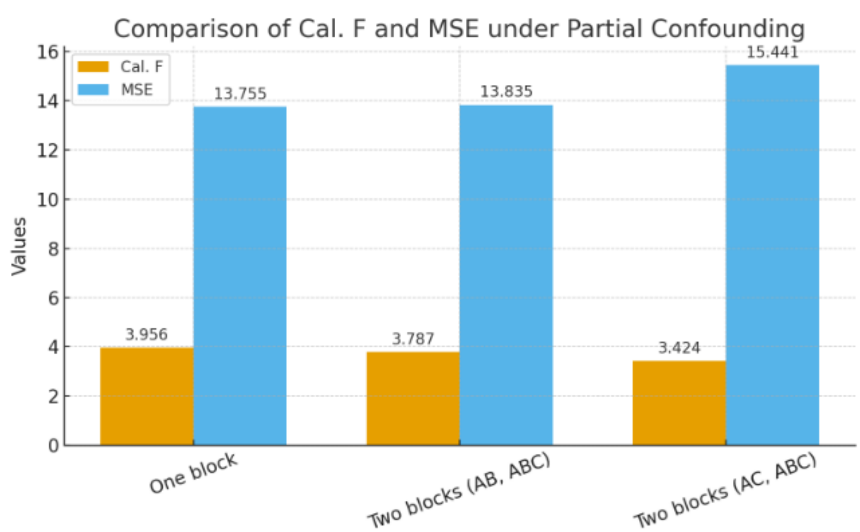

Figure 5: Comparison measures for Partial confounding 4 blocks

Accordingly, the graph provides a visual representation of the differences between the values, showing that partial confounding leads to a decrease in Cal. F values accompanied by a noticeable increase in MSE values.

5-Conclusion

1. Full and partial confounding techniques have proven their ability to control variance within an experiment, especially when used to partition treatments into blocks. However, these techniques come with statistical costs that depend on the appropriate selection of the effects to be confounded.
2. When fully confounding the non-significant three-way interaction (ABC) into two blocks, there was a slight increase in the Mean Squared Error (MSE), while the calculated F-value retained acceptable statistical power

confounding ABC thus becomes an ideal choice for reducing variance while still maintaining the value of the statistical analysis.

3. The test's statistical power vanished when significant interactive effects such as AB) were merged with non-significant effects (like AC or ABC). In the case of full confounding, four blocks of AB, AC, and BC exhibited a discernible rise in the MSE value along with a decrease in the calculated F-value.
4. The MSE significantly decreased and the calculated F-value rose when significant main effects (like A) were mistaken for with insignificant interactive effects (like BC and ABC). This improved the model's sensitivity and its capacity to identify significant variations.
5. The results of partial confounding, such as conflating ABC with AC or AB, were in between the results from full confounding and the basic experiment (RCBD), with the MSE rising and the measured F-value slightly falling. This indicates that when confounding only non-significant effects, partial confounding offers a better balance than full confounding.
6. Due to partial confounding reduces statistical risks when compared to full confounding, it's made a viable option when the researcher is uneasy of how important the effects to be confounded are.
7. Because it leads to a loss of vital information and an increase in random variance (MSE), confounding significant interactive effects (like AB in this experiment) should be avoided.
8. In order to preserve the statistical model's accuracy, confounding non-significant effects (ABC, AC, and BC) are preferred.
9. Further confounding flexibility can be gained by designing blocks with four sections; yet, the confounded effects have to be carefully chosen to prevent error or loss of statistical power.
10. All analyses proved that the main impacts of herbicides (B) and nitrogen (A), as well as their interaction (AB), were significant, showing their importance in raising the number of roots on cotton plants.
11. The variety decision had no major impact on the applied experimental conditions, as determined by the non-significance of the Variety effect (C) and its interactions with other factors.
12. A useful tool to boost the design of agricultural experiments, the confounding method specifically the full confounding of ABC helped control variance without altering the findings regarding the significant effects.

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