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Efficiency of Balanced Incomplete Block Design in Assessing Wheat Productivity

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Keywords:
Randomization, Block design, Duncan test, and Variance analysis (ANOVA).

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Abstract: The present paper offers a procedure for constructing a solvable incomplete block design with claiming diversities t and blocks k, provided that t is a multiple of k. They incorporate relevant illustrations, exceptional examples, a portion grid, and a more concise cyclical design. Those designs are indicated as accessible with high-efficiency blocks for an inclusive range of observation values. This study includes data for comparing wheat varieties using balanced incomplete block design analysis techniques. The data are provided by the Directorate of Agricultural Research, Sulaymaniyah-Bakrjo. The study deals with 9 treatments and 12 blocks. By using the SPSS package version 27. This paper assesses the null hypothesis as:
Null hypothesis (H0): All nine wheat treatment means are equal to each other.
Alternative hypothesis (H1): At least one group mean differs significantly from the others.
The consequences demonstrate statistically significant differences among wheat types and blocks. On the other hand, the present paper suggests expanding the use of balanced, incomplete block design in agricultural experiments. Executives in the Central Office of Statistics should utilize advanced statistical methods to investigate the rise in the quality and quantity of agricultural products. Conducting uninterrupted studies on the agricultural products, especially with the occurrence of the economic and social crisis, by introducing more designs that affect the income of people.

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كفاءة تصميم الكتل غير المكتملة المتوازنة في تقييم إنتاجية اصناف القمح

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المستخلص

تقدم هذه الورقة خوارزمية لتصميم القطاعات غير المكتملة المتوازنة، القادرة على تحليل ودراسة عدة أنواع من محصول القمح (t) وعدد أصناف القمح في قطاع واحد (k)، بحيث يُضرب (t)في (k) وقد تم اعتماد تصميم دوري دقيق للغاية لتحقيق قطاع عالي الكفاءة والفعالية في الإنتاج من خلال استخدام قطاع غير متوازن، والذي يتميز بأن القطاعات في هذا التصميم لديها طاقة إنتاجية فائضة مقارنةً بمؤشراتها .يتضمن هذا البحث بيانات مقارنة لتسعة أصناف قمح مقسمة إلى اثني عشر قطاعًا مختلفًا، وقد تم الحصول على البيانات من مديرية البحوث الزراعية في السليمانية/ بكرجو، وتم تحليلها باستخدام برنامج الحزمة الإحصائية (SPSS) الإصدار 27 لاختبار فرضيتين إحصائيتين: الفرضية الصفرية التي يقول لا يوجد أي فرق بين متوسط أصناف القمح، والفرضية البديلة التي تنص على أن متوسط واحد منها على الأقل يختلف عن متوسط الأصناف الأخرى وقد أظهرت النتائج وجود فروق جوهرية بين أصناف محصول القمح والقطاعات ومن ناحية أخرى، وبناء على النتائج اقترحت الدراسة استخدام هذه الطريقة الإحصائية على نطاق واسع في البحوث الزراعية مع استخدام أساليب إحصائية أخرى مختلفة على المنتجات الزراعية الأخرى بهدف توضيحها والاستفادة منها أثناء الأزمات الاقتصادية والاجتماعية وتأثيرها على دخل الفرد.

الكلمات المفتاحية: العشوائية، تصميم الكتل، اختبار دنكن، وتحليل التباين(ANOVA).

Introduction

This module is an incomplete block design. Designs that depend upon ten treatments are accessible. To obtain exact estimations from comparisons of treatment means, uniform experimental conditions should have the opportunity to be administered when analyzing multiple treatments. This ensures that any observed contrasts between treatment groups can be directly attributed to their application. What's more, not start with an essential variable. To accomplish this, experimental trials often need aid gathered together under blocks. In such designs, conditions need to be held consistent within the blocks and permitted to fluctuate between the blocks (Kuehl, R.O.,2000: 330-339). The most common configurations of this type are a randomized block design. In this design, the greater part of the treatments would be applied within each block. Occasionally, the span for advantageous obstructs won't suit every one of the treatments for claiming premium. For example, suppose you need to test four types of car tires for wear. The obvious decision to select a car might be an opportunity to have ten cars. You could choose ten cars for the study. Assuming these tires were rotated in these four conditions, this analysis could control for variations in tire wear based on the type of car and the region each car traveled. But what would you do if you needed to test six types of tires? You could use an alternative design, or you could use a balanced incomplete block configuration. (Cotton, 2014: 2). When mounted side-by-side with an incomplete, balanced block design, the treatments would allocate the blocks so that each group of treatments, mounted side-by-side with block (A), would occur the same number of times. This achieves the balance described in the Methodology title. This alignment means that the sum of the differences between the treatments would be measured with high accuracy. The simulation will be an example of how four processors might be distributed using blocks for a shared volume of three experimental units. Four blocks are required for this modified, incomplete square plan. Note that each processor happens three times in this experimental Design.

Note also that every two treatments are performed twice. These requirements reinforce the fundamental characteristics of balanced, incomplete designs. (Patterson & Hunter, 1983: 1). Proposes that the accompanying decisions determine the point when utilizing such plans.

Blocks	Treatments
1	A B C
2	A B D
3	A C D
4	B C D

Note that each treatment is performed three times in this experimental design. Also note that every two treatments are performed twice. These requirements reinforce the fundamental characteristics of balanced imperfect designs. (Abeynayake & Jaggi, 2012: 3). Propose the accompanying point when utilizing such plans.

1. Randomly assign block numbers.
2. Randomly assign letter printouts to the processors.
3. Randomly assign processors to the blocks.
4. Randomly arrange the blocks, taking into account the repetitions of the demonstrations.

A repetition is a complete set of fixed processors (Kuehl, R.O.,2000: 335). Whether you take these steps, this plan could provide a chance to be

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utilized adequately on the individuals' particular circumstances, (Abdy & Sanusi, 2018: 3).

Research Problem: Researchers must compare numerous treatments in many experimental studies, particularly in agriculture (e.g., crop varieties, fertilizers, or management practices). All treatments, however, cannot be included in every block due to practical constraints, including land size, labor, cost, and the challenge of maintaining consistent experimental conditions. When there are many treatments, traditional designs like the random complete block design become impractical or ineffective, leading to erroneous comparisons and significant experimental error. This requires an experimental design that mitigates the impact of missing data or large, unwieldy datasets, while allowing accurate and reliable assessments. The balanced incomplete block design (BIBD) provides a solution by ensuring that each pair of treatments is associated with an equal number of blocks, even if not all treatments exist in each block.

Aim of the Study: The objectives of this study are as follows:

1. To enable the assessment of multiple treatments with reduced and practically manageable block sizes.
2. Maintaining equivalent pairwise evaluations throughout the planning stage to ensure fair and balanced comparisons between treatments.
3. Reducing experimental errors while maintaining the treatment accuracy.
4. Experimental research frequently employs incomplete block designs due to extensive constraints on labor, time, and land area.

Importance of this study.

1. This design allows the study of multiple treatments without needing enormous blocks, which are difficult to implement in real-world situations.
2. By ensuring that each pair of treatments is associated with as many repetitions as possible, the balanced structure decreases bias.
3. BIBD provides accurate estimations of treatment effects by reducing uncontrolled and unpredictable variation within blocks.
4. It is valuable in fields such as business, medicine, agriculture, and other sciences where researchers aim to compare multiple treatments but cannot test them all at once.
5. Maintaining the internal validity and reliability of the experiment while optimizing fiscal, temporal, and spatial resources.

Hypothesis: The primary hypothesis of this study examines whether the treatments investigated differ from one another.

- Null hypothesis (H_0): All nine wheat treatment means are equal to each other.
- Alternative hypothesis (H_1): At least one group mean differs significantly from the others.

Consequently, post-hoc pairwise comparisons were conducted following a significant omnibus test to identify specific differences among treatment means.

Incomplete Block Design: Depending on experiments based on random block designs, it may be impossible to apply all treatments within each block due to equipment or experimental space limitations. In such cases, designs that do not include all treatments in each block are used; these are known as incomplete randomized block designs. (Montgomery, 2017: 168).

Balanced, Incomplete Block Design: When treatments are of equal importance, they must be distributed within blocks in a balanced manner so that each pair is repeated the same number of times. BIBD is an example of an incomplete block design that achieves this balance. If there are t treatments and each block can only accommodate k of them, a BIBD design can be created by forming several C_k^t blocks and distributing processor configurations among them according to the rules of balance. (Montgomery, 2017: 169).

Statistical Analysis: The parameters of design are:

t = number of treatments.

b = number of blocks.

k = number of treatments per block ($k < t$).

r = number of times that each treatment occurs ($r < b$).

N = t.r = k.b is the total number of observations. (Montgomery, 2017: 168-169).

This number indicates the frequency at which any two treatments meet in a single block across the design.

$\boldsymbol{\lambda = \frac{r(k-1)}{t-1}}$ It must be an integer.

If t = b and r = k, the design is called symmetric.

$$\boldsymbol{Y_{ij} = \mu + \tau_i + \beta_j + e_{ij}} \quad ; \quad \boldsymbol{i = 1, 2, \dots, t} \quad ; \quad \boldsymbol{j = 1, 2, \dots, b} \quad \textbf{...(1)}$$

Where Y_{ij} is the i^{th} treatment in the j^{th} block.

μ = overall mean.

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τ_i = impact of the i^th^ treatment.
β_j = impact of the j^th^ block.
$e_{ij} \sim NID(0, \sigma^2)$ Is the random error component?

$$\boldsymbol{SS_T = \sum_{i=1}^{t}\sum_{j=1}^{b} Y_{ij}^2 - \frac{Y_{..}^2}{N}} \quad ; \quad \textbf{...(2)}$$

$$\boldsymbol{SS_{tr.adj.} = \frac{k\sum_{i=1}^{t} Q_i^2}{\lambda t}} \quad ...\,\mathbf{(3)}$$

Q_i = adjusted total treatment i^th^, and computed as follows:

$$\boldsymbol{Q_i = Y_{i.} - \frac{1}{k}\sum_{j=1}^{b} n_{ij} Y_{.j}} \quad ; \quad \boldsymbol{i = 1, 2, \dots, t} \quad \textbf{...(4)}$$ (Montgomery, 2017: 169).

By $n_{ij} = 1$ if the i-th treatment appears in the j-th block.
$n_{ij} = 0$

Note that: $\boldsymbol{\sum_{i=1}^{t} Q_i = 0}$

$$\boldsymbol{SS_{bl} = \frac{1}{k}\sum_{j=1}^{b} Y_{.j}^2 - \frac{Y_{..}^2}{N}} \quad \boldsymbol{then} \quad \boldsymbol{SS_E = SS_T - \left(SS_{tr.adj.} + SS_{bl}\right)} \quad \textbf{...(5)}$$

The table of ANOVA is:

S. O. V	d.f	S. S	M.S	F_0
Treatments	t - 1	$SS_{tr.\ adj.}$	$MS_{tr.\ Adj.}$	$MS_{tr.\ adj.} / MS_E$
Blocks	b - 1	SS_{bl}	MS_{bl}	
Error	N - t- b - 1	SS_E	MS_E	
Total	N - 1	SS_T		

If the factor under study is fixed, it may be useful to conduct tests on the means of individual treatment means; however, if orthogonal contrasts are used, the variance analysis should be performed on the adjusted treatment totals, i.e., on Q_i and not Y_i. The sum of the squares of the variance is: (Montgomery, 2017: 170).

$$\boldsymbol{SS_{C_m} = \frac{k\left[\sum_{i=1}^{t} c_{m_i} Q_i\right]^2}{\lambda t \sum_{i=1}^{t} c_{m_i}^2}} \quad \textbf{...(6)}$$

Recovering information between blocks in BIBD: BIBD analysis is commonly called inter-block analysis because it eliminates block effects, and all variations in treatment effects can be expressed as comparisons among observations within the same block. This analysis is suitable regardless of whether the blocks are fixed or random. Yates noted that if the block effects are random variables unrelated to treatment means. Then one can obtain additional information about the treatment effects τ_i.

Consider the block totals $Y_{.j}$ as: (Montgomery, 2017: 174)

$$Y_{.j} = k\mu + \sum_{i=1}^{t} n_{ij}\tau_i + \left(k\beta_j + \sum_{i=1}^{t} e_{ij}\right) \quad ...(7)$$

The term in parentheses may be considered incorrect. Estimates between blocks using least squares for:

$$L = \sum_{j=1}^{b}\left(Y_{.j} - k\mu - \sum_{i=1}^{t} n_{ij}\tau_i\right)^2$$ Are:

$$\mu = \bar{Y}_{..} \qquad and \qquad \tilde{\tau}_i = \frac{\sum_{j=1}^{b} n_{ij}Y_{.j} - kr\bar{Y}_{..}}{r-\lambda} \quad ...(8)$$

It is probable that the inter-block estimators. $\tilde{\tau}_i$ and the inter-block estimators $\hat{\tau}_i$ are uncorrelated.

The least combined estimator with Unbiased Minimum Variance Estimates UMVE of each τ_i is:

$$\tau_i^* = \frac{kQ_i\left(\hat{\sigma}^2 + k\hat{\sigma}_\beta^2\right) + \left(\sum_{j=1}^{b} n_{ij}Y_{.j} - kr\bar{Y}_{..}\right)\hat{\sigma}^2}{(r-\lambda)\hat{\sigma}^2 + \lambda t\left(\hat{\sigma}^2 + k\hat{\sigma}_\beta^2\right)} \qquad when\ \hat{\sigma}_\beta^2 > 0$$

$$\tau_i^* = \frac{Y_{i.} - \frac{Y_{..}}{t}}{r} \qquad when\ \hat{\sigma}_\beta^2 = 0 \quad ...(9)$$

Where:

$$\hat{\sigma}^2 = MS_E \qquad and \qquad \hat{\sigma}_\beta^2 = \frac{\left(MS_{bl.adj.} - MS_E\right)(b-1)}{t(r-1)}$$

If the design is not symmetric, then:

$$MS_{bl.adj.} = \frac{1}{b-1}\left[\frac{k\sum_{i=1}^{t} Q_i^2}{\lambda t} + \sum_{j=1}^{b}\frac{Y_{.j}^2}{k} - \sum_{i=1}^{t}\frac{Y_{i.}^2}{r}\right] \quad ...(10)$$ (Montgomery, 2017: 175)

Duncan multi-range test: The treatments are ranked in ascending order in Duncan's test for equal samples, and the standard error is calculated for each average.

$$S_{\bar{Y}_{i.}} = \sqrt{\frac{MS_E}{n}}$$

The values of $r_\alpha(p,f)$ are extracted from Duncan's table and then transformed into less significant ranges (t−1) R_p according to the specified formula.

$$R_p = r_\alpha(p,f)S_{\bar{Y}_{i.}} \quad for\ p = 2,3,\dots,t.$$ (Montgomery, 2017: 173-174)

Comparisons among means are made starting with the largest and the smallest mean. By comparing the observed range with the least significant range, R_p, the critical threshold is used to determine if the difference between two treatment means is statistically significant. The ranges of the next largest, second, and smallest means are then calculated and compared with the range R_{t-1}. This process continues until all pairs of means $(t(t-1))/2$ are covered. If the observed range exceeds the least significant range, the pair is considered significantly different. To maintain logical consistency, any subset of a non-significant range is inherently classified as non-significant, preventing contradictory inferences within the multiple comparison procedure. This method is used to compare the adjusted mean of all pairs.

$$\hat{\tau}_i = \frac{kQ_i}{\lambda t}.$$

Appropriate standard error $= \sqrt{\frac{k * MS_E}{\lambda t}}.$

Sometimes we want to evaluate the effects of a block. To do this, we need an alternative partition for SS_T, which is:

$$SS_T = SS_{tr} + SS_{bl.adj.} + SS_E$$

Now, SS_{tr} is unmodified. If the design is symmetric, i.e., if t = b, a simple formulation for $SS_{bl.adj}$ can be obtained. The total adjusted blocks are:

$$Q'_j = Y_{.j} - \frac{1}{r}\sum_{i=1}^{t} n_{ij} Y_{i.} \quad ; \quad j = 1, 2, \dots, b$$

And $$SS_{bl.adj.} = \frac{r\sum_{j=1}^{b}(Q'_j)^2}{\lambda b}$$ (Montgomery, 2017: 173-174)

Practical Consequences: According to data from the Sulaymaniyah-Bakrjo Agricultural Research Directorate, a 2021 trial comparing nine wheat varieties was conducted using a balanced incomplete block design. Table -1 below illustrates afield trial design, which also shows the raw quantity data in kilograms per experimental unit. After data processing, a BIBD is applied to the collective data. The F-test was used to determine whether the treatment differences were significant at the 0.05 level. Least Significant Difference (LSD) mean comparisons or Duncan's multiscale test (DMRT) were used to identify superior varieties when statistically significant differences existed. SPSS Software, which has built-in processes for analysing incomplete block designs, was used for all statistical analyses.

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Table (1): Data Set Table

Treatments	Balanced Incomplete Blocks											
t_i	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	b_9	b_{10}	b_{11}	b_{12}
t_1	0.30			0.31			0.32			0.33		
t_2		0.34			0.35			0.36		0.37		
t_3			0.38			0.39			0.40	0.41		
t_4	0.44					0.45		0.46			0.47	
t_5		0.48		0.49					0.51		0.50	
t_6			0.53		0.55		0.58				0.60	
t_7	0.64				0.66				0.68			0.69
t_8		0.70				0.72	0.71					0.73
t_9			0.74	0.75				0.76				0.77

Table (2): Tests of Between-Subjects Effects

Dependent Variable: Responses					
Source	**Type III Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
Corrected Model	0.812	19	0.043	363.608	0.000
Intercept	9.828	1	9.828	83578.606	0.000
Treatments	0.596	8	0.075	633.811	0.000
Blocks	0.008	11	0.001	6.257	0.001
Error	0.002	16	0.000		
Total	10.643	36			
Corrected Total	0.814	35			
R Squared = 0.998 (Adjusted R Squared = 0.995)					

Table 2, with an adjusted R^2 value of 0.995, the variance analysis illustrates that the fitted model is highly significant, F (19,16) = 363.61, p <.001, meaning that the experimental factors accounted for 99.5% of the response variability. Different wheat varieties had a significant effect on the measured response, as evidenced by the highly significant treatment effect, F (8,16) = 633.81, p < 0.001, and wheat mass is also statistically significant, F test of (11,16) is 6.26, p is 0.001, signifying that experimental or environmental situations across the mass influence the variance in response. The small error variance confirmed the great accuracy and reliability of the experimental design. Considering all factors, these results provide conclusive evidence that the performance of the wheat varieties varied greatly. and that the block design effectively measured for inessential variation.

Table (3): Grand Mean

Dependent Variable: Responses			
Mean	**Std. Error**	**95% Confidence Interval**	
		Lower Bound	**Upper Bound**
0.523	0.002	0.519	0.526

In Table 3 responses, the dependent variable had a grand mean of 0.523 (SE = 0.002). The estimate is extremely accurate, as evidenced by the mean's 95% Confidence Interval, which varied from 0.519 to 0.526. According to this result, the sample's overall average level of responses was marginally higher than the 0.50 midpoint value, and the population means are most likely to fall within this small range.

Table (4): Types of wheat

Dependent Variable: Responses				
Types of wheat	**Mean**	**Std. Error**	**95% Confidence Interval**	
			Lower Bound	**Upper Bound**
t_1	0.315	0.006	0.302	0.328
t_2	0.355	0.006	0.342	0.368
t_3	0.399	0.006	0.386	0.412
t_4	0.459	0.006	0.446	0.472
t_5	0.490	0.006	0.477	0.503
t_6	0.566	0.006	0.553	0.579
t_7	0.666	0.006	0.653	0.679
t_8	0.698	0.006	0.685	0.711
t_9	0.755	0.006	0.742	0.768

Table 4: The wheat varieties were divided into different subsets according to a post-hoc mean comparison. In contrast to the other wheat varieties, varieties t_1 and t_2 had the lowest mean responses. A second group,

consisting of varieties t_3 and t_4, displayed responses that were moderate but still below those of the middle and higher categories. varieties t_5 and t_6 occupied the mid-range, whereas t_7 and t_8 showed higher responses. Finally, treatment group t_9 exhibited the maximum mean response, significantly outperforming all other experimental groups ($p < 0.05$). These data reveal statistically significant variance among the wheat varieties, characterized by a progressive incremental trend in responses from t_1 through t_9.

Table (5): Blocks

Dependent Variable: Responses				
Blocks	**Mean**	**Std. Error**	**95% Confidence Interval**	
			Lower Bound	**Upper Bound**
b_1	0.503	0.007	0.488	0.517
b_2	0.515	0.007	0.500	0.529
b_3	0.499	0.007	0.485	0.514
b_4	0.519	0.007	0.505	0.534
b_5	0.514	0.007	0.499	0.528
b_6	0.504	0.007	0.489	0.518
b_7	0.533	0.007	0.518	0.548
b_8	0.526	0.007	0.512	0.541
b_9	0.534	0.007	0.519	0.549
b_{10}	0.536	0.007	0.522	0.551
b_{11}	0.541	0.007	0.526	0.555
b_{12}	0.546	0.007	0.532	0.561

Table 5 illustrates the classification of experimental blocks into three distinct cohorts based on cluster analysis of their respective 95% confidence intervals. The first cohort (b_1–b_6) exhibited low-magnitude responses, with mean values narrowly constrained between 0.52 and 0.53. The second cohort (b_7–b_{10}) represented a median response range. Finally, the third cohort, comprising blocks b_{11} and b_{12}, formed the uppermost set with mean responses exceeding 0.54. These results indicate a discernible upward trend, where terminal blocks (b_{11} and b_{12}) demonstrated a statistically superior response relative to preceding blocks, although the overall effect size across all blocks remained relatively modest.

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Table (6): Responses

Duncan test										
Types of wheat	N	Subset								
		1	2	3	4	5	6	7	8	9
t_1	4	0.315								
t_2	4		0.355							
t_3	4			0.395						
t_4	4				0.455					
t_5	4					0.495				
t_6	4						0.565			
t_7	4							0.667		
t_8	4								0.700	
t_9	4									0.755
Sig.		1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Table 6 illustrates that each of the nine wheat types fits a dissimilar subsection; Duncan's test reveals significant differences among wheat types in terms of the responses. t_9 (0.755) is the greatest acting, while t_1 is the wickedest acting with the value (0.315). This requires a strong parting between the diversities, suggesting that the wheat variety has a great and important impact on the answer variable.

Table (7): Responses

Duncan Test								
Blocks	N	Subset						
		1	2	3	4	5	6	7
b_{10}	3	0.370						
b_1	3		0.460					
b_6	3			0.500				
b_2	3			0.506	0.506			
b_4	3			0.516	0.516	0.516		
b_5	3			0.520	0.520	0.520		
b_{11}	3				0.523	0.523		
b_8	3				0.526	0.526		
b_9	3					0.530		
b_7	3					0.536	0.536	
b_3	3						0.550	
b_{12}	3							0.730
Sig.		1.000	1.000	.053	.057	.060	.152	1.000

Table 7 illustrates that many assessment tests, likewise recognized as Duncan's test, for the responses, compare the 12 blocks. (b_1 to b_{12}). Compared to most others, b_{10} had the lowest response. The highest response, b_{12}, differed significantly from the others. The responses of the middle groups (b_2–b_9, b_{11}) do not differ significantly from one another because their subsets overlap. The lowest (b_{10}), mid-level (b_1–b_9, b_{11}), and highest (b_{12}) are clearly separated. b_{10} is the lowest group. b_1, b_6, b_2, b_4, b_5, b_{11}, b_8, b_9, b_7, and b_3 are the middle homogeneous group. b_{12} is the highest group.

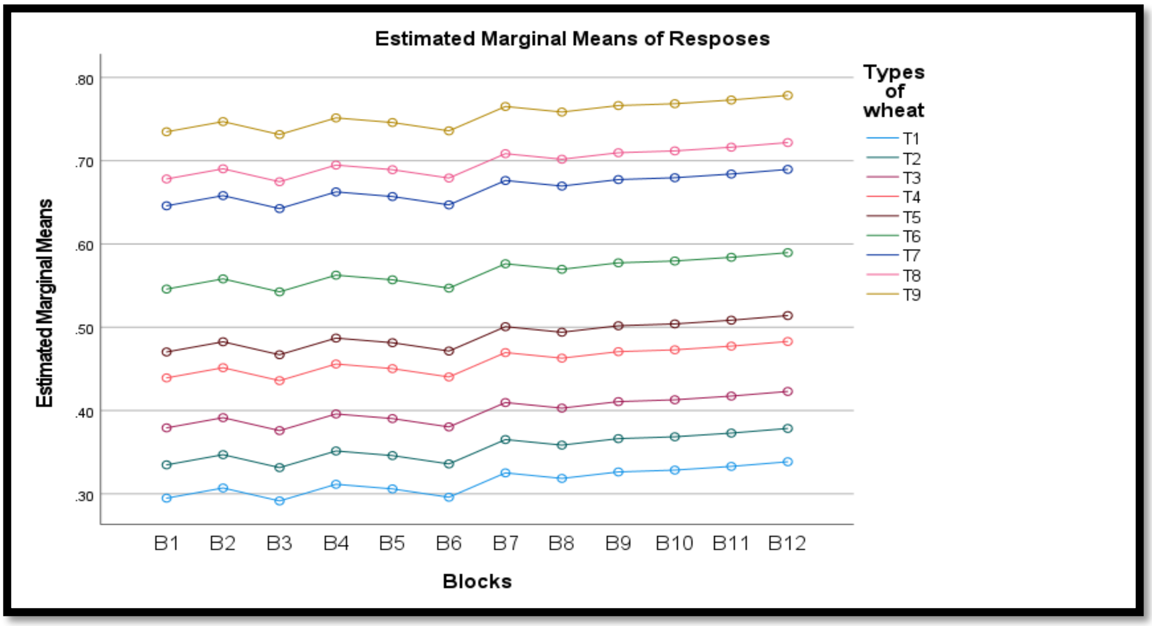

Figure (1)

(Figure1) shows how nine wheat varieties (t_1 to t_9) perform across 12 blocks (b_1 to b_{12}) in a (BIBD) experiment. Demonstration adjustments are dependable and obvious owing to the great impact of wheat varieties. The qualified grade of genetic constitution does not change greatly, despite slight variations, representing a negligible block effect. t_9 has the excessive performance wheat, revealing the maximum steady and great replies, and t_2 and t_8 had the lowest replies, which were low performance of wheat.

Results and Discussion: The treatment effects show the results of the analysis of variance (ANOVA). Adjusted R^2 is 0.995; the fitted model was extremely significant, F-test (19,16) is about 364, $p < 0.001$. That means treatments and groups described for 99.5 percent of the variance. This maximum coefficient of resolution appears to be correlated with the productivity of the experimental plan, which describes the greatest of the data variance. Concerning the response variable, the treatment impact is similarly very important; the F-test of (8,16) is about 634, $p < 0.001$, representing that the wheat variabilities achieved pretty inversely. This advises that production is importantly affected by the wheat diversity selected. Besides, block effect, which replicates variances in field or environmental situations between groups, is similarly significant statistically; the F-test of (11,16) is about 6 with $p = 0.001$. The importance of the group impact proves how actual the (BIBD) design is in minimizing needless bases of variance and refining experimental precision. The small residual error variance maintained the consistency of the consequences. The total responses of the mean, the dependent variable, were 0.523 with SE equal to 0.002. The precision of the evaluation was confirmed by the thin range of the 95 percent confidence interval, from about 0.52 to 0.53. The mean shows an overall tendency above the baseline level, which is a little above the centre of 0.50. The thin array similarly cares for the reliability of the results, signifying that the correct population mean is actually possible to fall inside this slight range. The test of Duncan's multiple-range in Table 6 is used to additionally identify treatment variances. The results showed that the nine wheat varieties were gathered into diverse classes. For instance, t_1, t_2, and t_3 wheat varieties steadily achieved the lowest and were located in the bottommost subcategories. Besides that, the t_7, t_8, and t_9 subcategories have the maximum performance, which displayed improved responses. The middle varieties (t_4, t_5, and t_6) displayed regular performance, which covered significantly across the subcategories. This different departure validates that, below the verified situations, some wheat varieties have important returns over the others. In applied rapports, these consequences provide a great indication that not all wheat varieties are similarly appropriate for agriculture in the Kurdistan Region. Specified their probable to rise yield and expand variation to regional climatic environments, the maximum performance diversities t_7, t_8, and t_9 can be recommended for extensive implementation. Additionally, the lower-yielding diversities t_1 to t_3 may not be appropriate for agriculture or may need different managing practices to be creative. Moreover, the prominent group impact highlights the rank of conservation changeability, signifying variety. Exact locations must also be considered in references. To enhance crop consistency and certify sustainable wheat production in the region, these consequences, engaged together, provide officials, academics, and agriculturalists with valuable direction for diversity

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choice. Three extensive groups appeared from subsequent assessments of average groups. The minimum performing group, b_1 to b_6, had typical group replies around 0.5. Means extending from about 0.53 to 0.54, from b_7 to $b_{10,}$ were in the central. With replies above 0.54, b_{11} and b_{12} reached the maximum points. The experimental variances may be owing to environmental or progressive features, like soil differences, management practices, or climatic features, while the impact of the group is lower than that of the diversity. b10 had the minimum rate, whereas b_{12} had the maximum, according to Duncan's group reply test. The common groups from b_1 to b_9 and b_{11} were in the central group, which contained meeting subcategories that did not vary significantly from each other. The impact of a fairly slight but important group is confirmed by the arrangement, with future groups, particularly b_{11} and $b_{12,}$ experiencing slightly worse consequences.

The outcomes provide substantial indication supporting the theory that reply variance is powerfully influenced by the wheat diversity. The significance of genetic choice in wheat breeding programs is evident in the substantial treatment impact and high level of diversity. The greater presentation of t_9 recommends its potential for wider submission in breeding and agriculture, and its embracing by agriculturalists. Despite its statistical significance, the impact of the group is weakly associated with the differences in diversity. The slightly greater response design of the consequent groups b_{11} and b_{12} may show experimental situations or increasing environmental enhancements over the progression of the experiment. Though the BIBD effectively adjusted for these differences, confirming an exact valuation of the treatment impact, attractive all features into the explanation.

Conclusion: This research, using a balanced incomplete block design (BIBD), presented a definite and statistically significant indication of differences among the nine experienced wheat varieties. The fitting model is strongly significant, with an adjusted R^2 value of 0.99, signifying that experimental influences explained practically all variances in responses. A pair of treatment and block effects was experimental; however, the impact of diversity is significantly stronger. The small error variance confirmed that the experimental design was strongly correct and dependable. Performance status displayed that the wheat diversity t_9 executed the greatest, with the

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strongest typical response. On the other hand, t_1 and t_2 steadily performed the lowest. The progressive evolution from t_1 to t_9 exposed that the confirmed diversities had dissimilar genetic configurations. The block effects were present; however, they were not as strong as those of the variety variances. later blocks, particularly varieties b_{11} and b_{12}, showed slightly higher responses. In summary, wheat variety was found to be the most important factor influencing performance. The t_9 variety was the ideal choice for further cultivation, research, and potential use in the Kurdistan Region of Iraq.

Recommendation:

1. Adoption Better Varieties: Farmers and other agricultural stakeholders are urged to order the t9 wheat variety due to its reliably greater performance. Given its strong response, longer-term testing of the t7 and t8 varieties could also be considered. On the other hand, the t1 and t2 varieties are not suitable for large-scale cultivation under current experimental conditions.
2. Upbringing and Genetic Breeding: Breeders should use t9 as the parental line when producing crosses so that its desirable traits can be transferred to other varieties. The intermediate-performing varieties (t5-t6) could be good candidates for genetic improvement.
3. Environmental and Agricultural Considerations: Although the effects of the clusters were not very large, the high responses in subsequent blocks demonstrate the importance of monitoring environmental and management factors (such as soil fertility gradients and local climate variations) in future field trials.
4. To evaluate the reliability and flexibility of the t9 diversity and other high-performance diversities under various agroecological situations, it is recommended to repeat the experiment in several locations and growing seasons.
5. Local agriculturalists should be informed of these consequences by agricultural extension services, with an emphasis on signifying t9's probable to increase yield and quality in accurate field locations. Experiment design will help connect the gap between agriculturalists' implementation of variety and the experimental results.

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