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ANALYSIS OF COVARIANCE IN AUGMENTED RANDOMIZED BLOCK DESIGN WITH A SINGLE EXPLANATORY VARIABLE: AN EMPIRICAL EVIDENCE ON AGRONOMIC CROP

A.T. Momo[1] S. M. Sayem[1*] M.A. Islam[1]

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***Corresponding author:**
E-mail: sms.stat@bau.edu.bd (SM Sayem)

ABSTRACT

The augmented randomized block design is a robust and versatile framework that maximizes the use of treatments, not readily available in conjunction with treatments, making it a crucial tool for researchers looking to draw valid and significant findings from the experimental design. This study proposed an analysis of the covariance (ANCOVA) model in augmented randomized block design to incorporate the effect of a concomitant variable. The estimation procedure of the parameters in the covariance model (ANCOVA) has been developed using maximum likelihood estimation. The testing procedure for treatment effects has been proposed for the analysis of covariance (ANCOVA) in augmented randomized block design. Also, a field experiment for maize cultivation using augmented randomized block design has been performed to compare the proposed design (ANCOVA) with the results of the analysis of variance (ANOVA) in augmented randomized block design and simple linear regression. The comparison of AIC values among ANOVA, regression, and ANCOVA models reveals that the proposed analysis of covariance (ANCOVA) in augmented randomized block design is more efficient and informative, which is likely to provide a new horizon in agricultural research.

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[1]Department of Agricultural and Applied Statistics, Bangladesh Agricultural University, Mymensingh, Bangladesh.

I. INTRODUCTION

Analysis of covariance (ANCOVA) is a prominent statistical technique that is widely used in most agronomic and crop research. It is the process of analysis of variance on the observation of response variables after adjusting for the effects of uncontrolled concomitant variables (Pandey and Pandey, 2021). When analyzing data and conducting research, the analysis of covariance (ANCOVA) is crucial for adjusting the effect of uncontrolled concomitant variables (Silknitter et al., 1999). By addressing the impact of confounding variables, it enables researchers to improve the accuracy and validity of their conclusions. The control of external factors that can affect the dependent variable is made possible by the inclusion of a covariate in ANCOVA, improving the precision of predicted treatment effects (Yitayew et al., 2021). The true impact of independent variables is isolated using ANCOVA, which enables a more accurate interpretation of the data. By accounting for covariates, researchers can enhance the reliability and generalizability of their findings, providing a more robust basis for decision-making in various fields, including scientific research, agronomic studies, and beyond (Alemayehu et al., 2022). In agricultural experiments, plant breeders use variety screening experiments in which new varieties are developed in a plant breeding program and selected for further study on those producing the greatest yield. However, the supply of seed, land, and other resources may be limited, difficult to maintain homogeneous blocks when comparing so many genotypes. However, the seed is frequently the limiting element in a breeding program's early phases, making it impractical to sow more than one or two plots of the material being studied (new variety). Available seeds of the new variety may be sufficient only for one replication for a large number of breeding lines (Atlin et al., 2017). In such a situation check or control varieties (existing varieties) are arranged in a standard experimental design in which sufficient seeds allow several replications with new varieties, and new experimental units are augmented within each block and not replicated in the trial or have fewer replicates than the checks. This design is known as ‘augmented design’ introduced by Federer (1956) and later extended by him (Federer, 1961) and others (Federer and Raghavarao, 1975).

This study is about an augmented randomized complete block design where control or checks are included once in each block and replicated in the trial. In each replication number of available experimental plots may vary: the remaining plots are allocated to the new or test varieties not replicated in the experiment. The ability to evaluate multiple treatments within the given experimental design increases the study's efficiency and cost-effectiveness. Yields from the control varieties can be used to adjust the yields of the new varieties to make them comparable across replications and to provide an estimate of experimental error so that valid statistical tests can be performed (Boyle and Montgomery, 1996).

Maize (Zea mays L.) is a crop that is appropriate for experimental design because of its genetic variety, worldwide significance, and agronomic input responsiveness. One of the most extensively grown cereal crops, maize provides millions of people with a staple diet and is essential for industrial processes, including the manufacture of starch and biofuels as well as livestock feed (FAO, 2021). It is appropriate for assessing the effects of variables, including fertilizer administration, irrigation, and planting density, in controlled experiments due to its high production potential and sensitivity to environmental and management factors (Shiferaw et al., 2011). A division of a species that differs morphologically or physiologically is referred to as "variety." In general, it refers to inbred lines, hybrids, and open-pollinated populations (landraces and improved varieties). Plant breeders and agronomists also use the term "cultivar." (Badu-Apraku et al., 2012). Furthermore, maize has a high degree of genetic variability, which is advantageous for research on genotype-environment interactions and breeding (Xu et al., 2009). Its comparatively shorter growth cycle makes it possible to do several trials during a single growing season and collect data promptly. Worldwide maize production is facing several challenges to climatic change (Prasanna, 2012). Under this circumstance, the world needs to adopt more efficient varieties (Permana et al., 2021). Climate change is the defining issue of the twenty-first century. Shifting weather patterns threaten food production due to rising sea levels that increase the risk of catastrophic flooding (Raihan, 2023). Current varieties are still providing food for the people in that changing environment but to take on future challenges, agriculture sectors need to adopt more new varieties. Furthermore, the reliability and repeatability of experimental results are improved by the availability of established cultivation procedures and research methodologies for maize (Duvick, 2005). All of these arguments support the choice of maize as the focus of an experimental design that is both practically applicable and scientifically sound. In many research, the researcher uses ANOVA for augmented randomized block design for choosing new technology. Hence, the influence of the concomitant variable cannot be measured (Federer, 1956; Federer, 1961; Scott and Milliken, 1993; Agrawal and Sapra, 1995; Boyle and Montgomery, 1996; Federer et al., 2001; Burgueño et al., 2018). ANCOVA enables researchers to account for factors that may affect the outcome variable but are not the main focus of the study.

Covariates in enhanced randomized block designs could be things in agricultural research like seed weights or plant height measures. This study will analyze ANCOVA of augmented randomized block design with a single explanatory variable (plant height at 87 days) for maize crops.

The study is to propose a methodology for the analysis of covariance of augmented randomized block design. The objectives are to – (i) document the systematic review of ANCOVA for augmented randomized block design; (ii) propose the estimation procedure of the covariance model for augmented randomized block design; (iii) determine the testing procedure for the treatment effects of analysis of covariance for augmented randomized block design; and (iv) set up a real-life experiment for maize cultivation to compare the proposed approach.

By adding covariate, the methodology provides a more accurate evaluation of treatment effects and helps to improve the validity and reliability of agronomic research findings. By lowering variability and raising estimate accuracy, augmented randomized block designs are frequently employed to boost statistical power and precision (AlAita and Talebi, 2023). This design is enhanced by ANCOVA, which increases statistical power, and also model section criterion of AIC gives the best model under comparison of ANOVA for augmented randomized block design model, linear regression, and proposed analysis of covariance model for augmented randomized block design.

II. LITERATURE REVIEW

2.1 Search Strategy of Systematic Literature Review

A systematic review of the literature is a rigorous and comprehensive method of gathering, evaluating, and synthesizing existing research studies on a specific topic or research question (Higgins and Green, 2011). To respond to the articulated question, a systematic literature review (SLR) identifies, picks, and critically evaluates research (Dewey and Drahota, 2016).

In May-June-July 2023, we conducted a thorough literature search using SCOPUS and Google Scholar to find any English-language publications on conducting this analysis of covariance of augmented randomized complete block design. Keywords used in this study are analysis of covariance in randomized block design, covariance analysis in augmented design, maximum likelihood estimation in experimental designs, augmented randomized block design, and augmented design. Source type characterized by journal articles in the years 1950-2023. Limiting all of these objects to specific keywords. In Google Scholar, searching was done with all the words in the article simultaneously using the advanced search. Document type used any type and review articles in 1950-2023 years of publication.

2.2 Inclusion Criteria

The inclusion criteria for a systematic review of the analysis of covariance (ANCOVA) in augmented randomized block design was thoroughly outlined to guarantee the selection of relevant and high-quality studies in agricultural research. Studies that used an enhanced randomized block design, augmented design of analysis of variance, or analysis of covariance in which other treatments or factors were added to the typical randomized block design setup were included in the criteria. Peer-reviewed journal articles that fulfill the required standards in the English language are included in the review.

2.3 Exclusion Criteria

Exclusion criteria included studies that do not specifically employ an analysis of variance or analysis of covariance analysis, as the review aims to concentrate on this specific design. Publications that did not provide sufficient information or details about the ANOVA or ANCOVA or augmented setup, covariates, or statistical analysis methods were excluded to ensure the reliability of the review findings. Studies published in languages rather than English were also excluded. Moreover, systematic review excluded studies with inadequate sample sizes, poor reporting quality, or those lacking relevant agricultural context, such as studies conducted in non-agricultural settings or unrelated to the agricultural field.

2.4 Study Selection

The flow diagram of the included studies is shown in Figure 1. The initial database search yielded 370 studies, of which 32 were duplicates and 286 studies were excluded reasons for inappropriate research design, improper and unclear statistical analysis, and imprecise table and graph. Of the remaining 52 articles were eligible criteria but among them, 18 studies were excluded because of did not give precise and relevant information about this study. Finally, 34 studies were included in this literature review study.

From 34 studies this paper included only five studies. In Table 1, a total of five studies is included for the keyword-augmented randomized block design. In these studies, they used an augmented randomized block design for their experiment to achieve their objectives. Two studies are used for the analysis of variance (ANOVA) (SL-1, 5). In the SL-1 study; by using the augmented complete randomized block design for missing observation, they proposed a new unique method termed the neutrosophic augmented randomized complete block design (NARCBD) and this performs better than other methods in this field. We also get the study for getting new variety or association with different attributes that are used in different screening programs in agricultural research (SL-2, 3, 4) but there is a missing ANOVA table. They used correlation analysis or path analysis or generalized linear model or principal component analysis. Studies used different sample sizes which is convenient for their research.

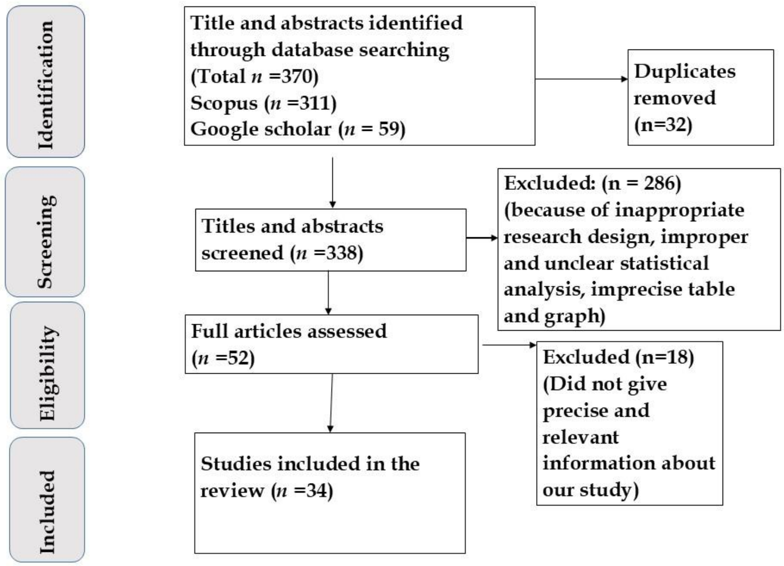

Figure 1: Study flow diagram; Scopus: A Multidisciplinary Database, Google Scholar: Scholarly search engine for books, journals, articles, documents, and literature

Table 1: Review results for augmented randomized block design keyword with methodology and major findings

SL	Author	Research Objective	Experimental Design	Sample Size	Data Analysis	Findings
1	AlAlta and Talebi (2023)	To address the issues with enhanced randomized complete block design (ARCBD), which is utilized in plant breeding programs, missing observations of control treatments. To handle missing data in an uncertain environment, the study suggests a unique method termed the neutrosophic augmented	They introduce the idea of a neutrosophic model and suggest a neutrosophic analytical approach for the Augmented Randomised Block design. To account for missing values, the proposed NARCBD technique	99 cultivars of safflower (an oil and medicinal plant) genotypes were planted using a NARCBD with three blocks. Each block contains 8 control (check) treatments and 25 genotypes (new treatments)	ANOVA	According to the study's findings, the proposed neutrosophic precise method performs better than the conventional method at handling missing values and data uncertainties. When there are no records of control treatments or when dealing with ambiguous and imprecise data, researchers can obtain more

SL	Author	Research Objective	Experimental Design	Sample Size	Data Analysis	Findings
		randomized complete block design (NARCBD).	takes an augmented incomplete block design into account inside the neutrosophic statistics framework.			accurate results by adopting the NARCBD technique.
2	Iqbal et al. (2021)	Find out which mung bean genotypes thrive in three different agroecological zones under normal and high-temperature stress conditions.	Augmented Randomized Block Design	80 mung bean genotypes and 3 check varieties	Pearson correlation analysis, principal component analysis (PCA)	The genotypes G14, G38, and G51 were shown to be consistent and heat-tolerant in the majority of conditions, offering important information for the future creation of heat-tolerant mung bean breeding resources.
3	Galvão et al. (2017)	To develop new F1 hybrid strawberry cultivars with greater environmental tolerance and potential yields than current varieties.	Augmented Randomized Block Design	A total of 504 F1 hybrid strawberry plants were generated from twelve hybrid populations.	General linear model (GLM) procedures in SAS.	In comparison to certain existing cultivars, the study successfully created new F1 hybrid strawberry plants with better prospective yields.
4	de Oliveira et al. (2010)	The goal of the study was to determine the association between 16 morphological and agronomical parameters of papaya (Carica papaya L.) and the number of commercial fruits per plant (CFrP).	Augmented Randomized Block Design	A total of 22 genotypes (19 germplasm accessions and 3 common genotypes) and each genotype was evaluated with ten repetitions.	Correlation and Path Analysis	This study advances our knowledge of the variables affecting papaya commercial fruit yield per plant and offers insightful information for breeding programs aiming to increase fruit yield in this crop.
5	Boyle and Montgomery (1996)	to address the difficulties presented by researchers studying avian health while assessing a variety of potential infectious factors	Augmented Randomized Block Design	13 trials were performed and 27 combinations of agents were tested.	ANOVA	The use of augmented experimental designs in avian health research can shorten the amount of time and experimental units

SL	Author	Research Objective	Experimental Design	Sample Size	Data Analysis	Findings
		while having restricted facilities, a desire to use animals as little as possible, and financial restrictions. The paper also seeks to suggest the use of augmented experimental designs in poultry research to effectively select interesting candidates for additional in-depth investigation. These designs are frequently utilized in plant breeding variety screening.				needed to find the disease agents or poultry kinds that have the best chance of developing a disease. Similar to its demonstrated efficacy in plant breeding variety screening, the augmented design technique offers a useful tool for efficient screening trials in avian health research.

III. MATERIALS AND METHODS

The augmented randomized block design is a popular experimental design in most agricultural and biological science research. It has significant demand to develop a new variety of genotypes all over the world.

3.1 Analysis of Covariance (ANCOVA) for Augmented Randomized Block Design

Model Specification

The linear model of analysis of covariance in augmented randomized complete block design $y_{ijk} = \mu + \beta_i + C_j + \tau_{k(i)} + \gamma X_{ijk} + \varepsilon_{ijk}$;i = 1, 2, …, r ; j = 1, 2, …, p ; k = 1, 2, …, q

where, μ is the general mean;β_i is the effect of the ith block; C_j is the effect of the jth check variety;$\tau_{k(i)}$ is the effect of the kth new variety in the ith block; γ is the coefficient of covariate for ith check variety and kth new variety;X_{ijk} is the covariate for all treatments in the ith block;y_{ijk} is the response of the variety assigned to the ith block;ε_{ijk} is the random error which is assumed to be normally and independently distributed (NID) with mean zero and constant variance σ^2.

Assumptions

The analysis of covariance in enhanced randomized block design is based on several assumptions. The covariate(s) are fixed, measured without error, and independent of the treatments and block effects; The ANOVA model is linear; Effects in the model are additive; Homogeneity of variance for treatment and block effect; Independence of variance estimates; The random component follows normal distributions with zero mean and a constant variance; There is no interaction between blocks and treatments.

3.1 Proposed Estimation Procedure for Analysis of Covariance in Randomized Block Design

Parameter Estimation

The maximum likelihood estimation (MLE) procedure is used to estimate the parameter of the statistical model by maximizing the likelihood function. Hence, MLE is used to estimate the parameters in the analysis of the covariance (ANCOVA) model for augmented randomized block design.

The linear model of analysis of covariance in augmented randomized complete block design is
$y_{ijk} = \mu + \beta_i + C_j + \tau_{k(i)} + \gamma(x_{ijk} - \bar{x}_{...}) + \varepsilon_{ijk}$; where, $X_{ijk} = x_{ijk} - \bar{x}_{...}$

The assumptions of the target model are

i) $\varepsilon_{ijk} \sim NID(0, \sigma^2_{ijk})$; ii) $\sum_{i=1}^{r} \beta_i = 0$; iii) $\sum_{j=1}^{p} C_j = 0$; iv) $\sum_{k=1}^{q} \tau_{k(i)} = 0$ and v) μ, β_i, C_j, $\tau_{k(i)}$ and γ are unknown parameters.

The log-likelihood function for the response variable comes from augmented randomized complete block design with covariate,

$$\log L = -rpq \log(\sigma\sqrt{2\pi}) - \frac{1}{2}\sum_{i=1}^{r}\sum_{j=1}^{p}\sum_{k=1}^{q}\left[\frac{y_{ijk} - \mu - \beta_i - C_j - \tau_{k(i)} - \gamma(x_{ijk} - \bar{x}_{...})}{\sigma}\right]^2$$

where $y_{ijk} | x_{ijk} \sim N(\mu + \beta_i + C_j + \tau_{k(i)} + \gamma(x_{ijk} - \bar{x}_{...});\ \sigma^2)$. For formulating the normalized equation, differentiate the log-likelihood function to maximize the likelihood function concerning μ, β_i, C_j, $\tau_{k(i)}$, and γ and equating zero; then the normalized equations are-

$$\frac{1}{\sigma^2} \times \sum_{i=1}^{r}\sum_{j=1}^{p}\sum_{k=1}^{q}\left[y_{ijk} - \mu - \beta_i - C_j - \tau_{k(i)} - \gamma(x_{ijk} - \bar{x}_{...})\right] = 0$$

$$\frac{1}{\sigma^2}\sum_{j=1}^{p}\sum_{k=1}^{q}\left[y_{ijk} - \mu - \beta_i - C_j - \tau_{k(i)} - \gamma(x_{ijk} - \bar{x}_{...})\right] = 0$$

$$\frac{1}{\sigma^2} \times \sum_{i=1}^{r}\sum_{k=1}^{q}\left[y_{ijk} - \mu - \beta_i - C_j - \tau_{k(i)} - \gamma(x_{ijk} - \bar{x}_{...})\right] = 0$$

$$\frac{1}{\sigma^2} \times \sum_{i=1}^{r}\sum_{j=1}^{p}\left[y_{ijk} - \mu - \beta_i - C_j - \tau_{k(i)} - \gamma(x_{ijk} - \bar{x}_{...})\right] = 0$$

$$\frac{1}{\sigma^2} \times \sum_{i=1}^{r}\sum_{j=1}^{p}\sum_{k=1}^{q}\left[y_{ijk} - \mu - \beta_i - C_j - \tau_{k(i)} - \gamma\left(x_{ijk} - \bar{x}_{...}\right)\right]\left[\left(x_{ijk} - \bar{x}_{...}\right)\right] = 0$$

Hence, the maximum likelihood estimate (MLE) of the parameters is $\hat{\mu}$, $\hat{\beta}_i$, $\hat{C}_j$, $\hat{\tau}_{k(i)}$ and $\hat{\gamma}$.

$\hat{\mu} = \bar{y}_{...}$

$\hat{\beta}_i = \bar{y}_{i..} - \bar{y}_{...} - \gamma(\bar{x}_{i..} - \bar{x}_{...})$

$\hat{C}_j = \bar{y}_{.i.} - \bar{y}_{...} - \gamma(\bar{x}_{.j.} - \bar{x}_{...})$

$\hat{\tau}_{k(i)} = \bar{y}_{..k} - \bar{y}_{...} - \gamma(\bar{x}_{..k} - \bar{x}_{...})$

and $\hat{\gamma} = \frac{1}{N\sigma_x^2}\left[\sum_{i=1}^{r}\sum_{j=1}^{p}\sum_{k=1}^{q} y_{ijk}\left(x_{ijk} - \bar{x}_{...}\right) - pq\sum_{i=1}^{r}\beta_i\left(x_{ijk} - \bar{x}_{...}\right) - rq\sum_{j=1}^{p} C_j\left(x_{ijk} - \bar{x}_{...}\right) - p\sum_{i=1}^{r}\sum_{k=1}^{q}\tau_{k(i)}\left(x_{ijk} - \bar{x}_{...}\right)\right]$

Also, any hypothesis regarding the regression parameters may be tested as standard error can be calculated.

3.3 Proposed Testing Procedure for Analysis of Covariance in Augmented Randomized Block Design

The results of the Analysis of covariance are summarized in the following table.

For testing the hypothesis, H_0: Checks are not significantly different for yield, the test statistics

$$F = \frac{S_{\tilde{C}}^{2}}{S_{\tilde{Er}}^{2}} = \frac{CSS_{\tilde{y}} / \mathrm{p}-1}{ErSS_{\tilde{y}} / [(\mathrm{p}-1)(\mathrm{r}-1)]-1} \text{ with } \mathrm{p}-1 \text{ and } [(\mathrm{p}-1)(\mathrm{r}-1)] - 1 \text{ d.f.}$$

To test the hypothesis, H_0: New varieties are not significantly different in yield, the test statistics

$$F = \frac{S_{\tilde{N}}^{2}}{S_{\tilde{Er}}^{2}} = \frac{NSS_{\tilde{y}} / \mathrm{q}-1}{ErSS_{\tilde{y}} / [(\mathrm{p}-1)(\mathrm{r}-1)]-1} \text{ with } \mathrm{q}-1 \text{ and } [(\mathrm{p}-1)(\mathrm{r}-1)] - 1 \text{ d.f.}$$

Table 2: ANCOVA for Augmented Randomized Block Design

S.V	d. f	SS(X)	SS(Y)	SP(XY)	Adjustment for Regression		
					d. f	SS	Mean Square(MS)
Total	N - 1	TSS_x	TSS_y	TSS_{xy}			
Blocks	r - 1	BSS_x	BSS_y	BSS_{xy}			
Entries(e)	e - 1		eSS_y				
Checks(c)	p – 1	CSS_x	CSS_Y	CSS_{xy}			
New Varieties(N)	q – 1	NSS_x	NSS_y	NSS_{xy}			
Check vs New	1		$CNSS_y$				
Error	(p – 1)(r – 1)	$ErSS_x$	$ErSS_y$	$ErSS_{xy}$	[(p – 1)(r – 1)] - 1	$ErSS_{\tilde{y}}$	$S_{\tilde{Er}}^{2}$
Checks + Error	r (p – 1)				[r (p – 1)] - 1	$(CSS_y + ErSS_y)^{\sim}$	
New Varieties + Error	r (p – 1) – p +q				[r (p – 1) – p +q] - 1	$(NSS_y + ErSS_y)^{\sim}$	
Adjusted Checks					p - 1	$CSS_{\tilde{y}}$	$S_{\tilde{C}}^{2}$
Adjusted New Varieties					q - 1	$NSS_{\tilde{y}}$	$S_{\tilde{N}}^{2}$

3.4 Validation of the proposed approach for maize cultivation in the field experiment

Location of the Experiment

The study was conducted to diagnosis the performance of proposed methods of ANCOVA for Augmented Randomized Block Design at the Bangladesh Agricultural University's Farm Management Section's experimental field in the Mymensingh district. There were 2.75 decimals of land in all. The study was carried out from November 2022 to April 2023, the planting season.

Plant Materials

A total of 8 different types, including three checks and five test varieties, made up the fundamental plant material. The test varieties were T1 (BHM-16), T2 (PIONOL-07), T3 (VASUDHA-1655), T4 (DALIA-4455) and T5 (DON-111). The checks were V1 (EUREKA), V2 (BHM-13), and V3 (BHM-9). The Bangladesh Agricultural Research Institute (BARI) provided four types (V1 (EUREKA), V2 (BHM-13), V3 (BHM-9), and BHM-16), and the other varieties were purchased from the local market.

Experimental Design

Augmented Block Design was used for the field evaluation (Federer, 1956). With 5 tests entries and 3 checks, the material was grown in 3 blocks. Each block had a total of 5 or 4 plots. Each block's checks were separately randomized. Each variety was represented by a plot size of 2m x 4m with 3 blocks. In the field, there were 14 plots.

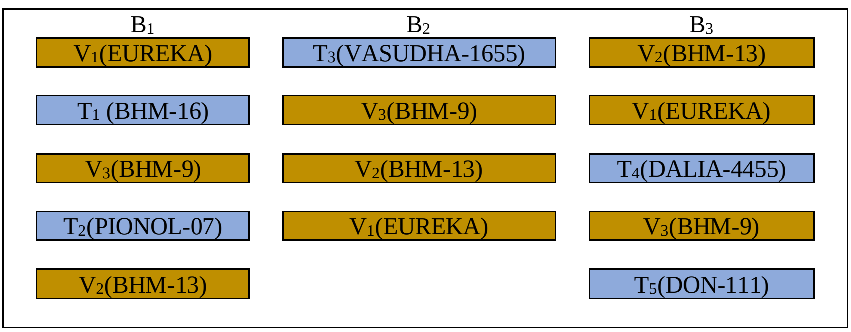

Figure 2: The field layout of the experimental design

Growing and Harvesting of the Final Yield

The experimental plots were each 8.0 m^2 (2 m × 4 m) in size, had three lines, and had a plant-to-plant spacing of 8–10 cm and a line-to-line distance of 25–30 cm. On November 27, 2022, maize seeds were planted after the soil had been prepared. The correct agronomic procedures, including fertilization and weeding, were followed (Jui et al., 2023).

Weeding was done three times. In the field, urea used was 2100 gm, muriate of potash (*MOP*) used was 1000 gm, triple superphosphate (TSP) used was 1000 gm, 1700 gm was used as gypsum, and 25 gm boron was used. Four irrigations were carried out. The first irrigation was carried out 15 days after the seed was sown; the second, at 35 days later; the third, at 60 days; and the fourth, 85 days later. After 137 days of the seeding date, the yields were harvested. The maize cobs were harvested on 5 April 2023. When the cobs were dried finally, we measured the yields by putting the maize grain in a zip lock bag.

Data Collection

At first, seed weights for every variety were measured before sowing the seed on 25 November 2022. After 30 days of seed sowing, plant heights were recorded by measuring tape. Plant heights vary from variety to variety. After 87 days of seed sowing, plant heights were measured. Measurements were done randomly for five plants per plot. The number of maize cobs was counted for the randomly selected plants on 15 March 2023. Finally, on 15 April 2023, the yield was harvested from the plant. Yield for five plants in every plot were recorded from the randomly selected plants.

Statistical Analysis

Based on an augmented randomized block design, study data were examined. The augmented-RCBD package was used to analyze variations in the R program (R Core Team, 2018) (Aravind et al., 2019).

IV. RESULTS AND DISCUSSIONS

4.1 Analysis of Variance

For analysis of variance, a demonstration of our field data is shown in Table 3. The table provides mean values for various variables measured under different treatments (T1, T2, T3, T4, and T5) for analysis of covariance in an augmented randomized block design experiment. Yield per cob, single seed weight (used in the experiment), plant heights at 30 days, plant heights at 87 days, and number of cobs per plant were the aspects or characteristics that were measured. The experiment appeared to have different treatment groups (T1, T2, T3, T4, T5, V1, V2, and V3). The numbers in the table represent the mean (average) values of each variable under each treatment condition. This yield per cob measured the average yield per corn cob. For example, under treatment T1, the mean yield per cob was 72.62 gm, under treatment T5, it was 113.26 gm. For V1, V2, and V3, it was 128.77 gm, 75.70gm, and 73.44 gm respectively.

Table 3: Mean value by treatments

	Treatments							
Variables	T1	T2	T3	T4	T5	V1	V2	V3
Yield per cob (gm)	72.62	102.75	99.18	82.60	113.26	128.77	75.70	73.44
Single Seed weight (mg)	0.43	0.35	0.33	0.36	0.26	0.24	0.29	0.21
Plant height at 30 days (cm)	29.40	23.60	20.20	29.00	22.00	32.47	20.20	25.13
Plant height at 87 days (cm)	72.6	66.2	68.8	78.2	65	86.17	63.3	75.17
Number of cobs per plant	2	2	2	2	1	1.67	1.33	1.67

Source: Experimental study

Single seed weights measured the average weight of a single seed. For example, under treatment T2, the mean single seed weight was 0.35 mg, under treatment T5, it was 0.26 mg, and for V1, V2, and V3 mean single seed weights were 0.24 mg, 0.29 mg, and 0.21 mg respectively.

The variable plant height at 30 days measured the average plant height at 30 days after planting. For treatment T1, the mean plant height at 30 days was 29.40 cm. The plant heights at 87 days measured the average plant height at 87 days after planting. The mean values for treatments (T1, T2, T3, T4, T5, V1, V2, and V3) were 72.6 cm, 66.2 cm, 68.8 cm, 78.2 cm, 65 cm, 86.17 cm, 63.3 cm, and 75.17 cm. The number of cobs per plant measured the average number of cobs produced per plant. For example, under treatment T1, the mean number of cobs per plant was 2; and under treatment T5, it was 1 (indicating that, on average, only one cob was produced per plant in treatment T5).

Analysis of variance results is shown in Table 4. The degree of freedom, sum of squares, mean sum of squares, and F ratio were presented for yield per cob in the table which was the ultimate targeted variable in this study. The Analysis of variance showed that there were statistically significant differences in treatment, check varieties, test varieties, test and test vs. check, and test vs. check for yield per cob.

Table 4: Results of analysis of variance for augmented randomized block design

Source of variation	Degree of freedom	Sum of Squares	Mean sum of squares	F - ratio
Block (ignoring Treatments)	2	36	18.20	0.575
Block (eliminating Treatments)	2	206	102.89	3.25
Treatment (eliminating Blocks)	7	7120	1017.19	32.130***
Treatment (ignoring Blocks)	7	6951	993.00	31.366***
Check varieties	2	5883	2941.6	92.918***
New Varieties	4	1061	265.2	8.378**
New and New vs. Check	5	1237	247.41	7.815**
New vs. Check	1	6.7	6.70	0.212
Error	4	127	31.7	

Source: Experimental study (***, and ** denote 1%, and 5% level of significance)

For the calculation of the AIC value, this study considered the analysis of variance in augmented randomized block design for yield per cob variable. The mean sum of squares of error was 31.7 and it was used for the calculation of the AIC value. This study found the AIC value for the ANOVA model is 45.015.

4.2 Linear Regression Analysis

To model the link between a dependent variable (in this case, the yield of maize per cob) and one independent variable (in this case, the height of the maize plants at 87 days), a statistical approach known as linear regression is used. In linear regression, the relationship between the independent variable(s) and the dependent variable is assumed to be linear.

Table 5: Regression Analysis

Coefficient	Estimate	Std. Error	t value	P value	AIC value
Intercept	-15.1401	48.1932	-0.314	0.7588	128.3186
Plant heights at 87 days	1.4796	0.6541	2.262	0.0431**	

Source: Statistical analysis (** represents 5% level of significance)

From Table 5, the estimated coefficient for the variable "Plant heights at 87 days" is 1.4796. This represents a 1.4796 gm change in the yield per cob for a 1 cm increase in plant heights at 87 days while holding other things constant. The standard error associated with this coefficient estimate is 0.6541 and the calculated t-value is 2.262. The p-value associated with this coefficient is 0.0431. It suggests that the coefficient for "Plant heights at 87 days" is statistically significant at the 0.05 significance level. This means that there is evidence to suggest that "Plant heights at 87 days" have a significant impact on the dependent variable. AIC is a model goodness-of-fit indicator that takes model complexity into account. It measures how well the model fits the data and restricts models with more predictors (parameters) than necessary. Lower AIC values suggest a better balance between model fit and complexity. In this model, the AIC value is 128.3186.

4.3 Analysis of Covariance of Augmented Randomized Block Design

Analysis of covariance of augmented randomized block design has been presented in Table 6. For computational validation, the analysis of covariance in augmented randomized block design has been done by the proposed R program by ANCOVA function.

The results of the Analysis of covariance are summarized in the following table (Table 6).

This Study considered the plant heights at 87 days as a covariate or explanatory variable and adjusted the effects of yield per cob for maize with plant heights at 87 days. Note that for ANCOVA of augmented randomized block design, the concomitant variable should be independent of treatments. We initially considered seed weight (test variety and check) as a potential concomitant variable. There has been significant measurement error in seed weight due to the scale used to measure weight which could only show two decimal points. Hence, we ignored using seed weight. Instead, we have used plant heights at 87 days as a concomitant variable despite in violation of assumptions. We consider this as a practice data set to evaluate the performance of the proposed approach. No interpretation will be made using the ANCOVA result.

Table 6: Results of R analysis of covariance for Augmented Randomized Block Design

Source of variation (S.V.)	Degrees of freedom (d.f)	The sum of squares (S.S.)	Mean sum of squares (M.S.S.)	F - statistics
Block	2	29	14.4	1.041
New	4	628	156.9	11.323**
Checks	3	4408	1469.4	106.037***
Plant heights at 87 days	1	2177.1	2177.1	157.106***
Error	3	42	13.9	
Total	13	7284.1		

Source: Experimental study (***, and ** denote 1% and 5% levels of significance)

The results for the analysis of covariance in augmented randomized block design showed that a statistically significant difference in new, checks, and plant height at 87 days.

For the calculation of the AIC value, this study took the value of the mean sum of squares error from Table 6. The AIC value for analysis of covariance in randomized block design is 42.002.

4.4 Comparison of the proposed approach with the AIC model selection criterion

The proposed approach is contrasted with the Akaike Information Criterion (AIC), the most widely used model selection technique. AIC is one of the most powerful and practical methods for model selection for choosing the best model. It is particularly good for predictive modelling rather than just explanatory modelling (Burnham, 1998). By reducing the parameters, AIC strikes a compromise between model fit and complexity, making it a powerful metric for assessing new approaches (Akaike, 1974). Because of its simplicity, computational ease, wide range of applications, and efficiency in identifying models that perform well when applied to new data, AIC is preferred over other criteria.

A real-life experimental setup for maize crops was considered to analyze the data for analysis of variance and analysis of covariance in augmented randomized block design. A simple linear regression model between yield per cob and plant heights at 87 days was conducted. Analysis of variance for this study focused on yield per cob, which is the ultimate response of the experiment. For analysis of variance, results showed statistically significant results in treatments or entries (eliminating block), new varieties, checks, and new and new vs. check varieties. The mean sum of squares for treatments (eliminating block), test varieties, checks, and test and test vs. check were 1017.19, 265.2, 2941.6, and 247.41, respectively. For analysis of covariance in augmented randomized block design this study considered the yield per cob as a response with plant height at 87 days as a concomitant variable. By adjusting for the effect of the concomitant variable, this study also investigated the significant results for new varieties and checks. This study also found that the AIC value is 42.002. A table is shown below for a comparison of the value of AIC for different models.

Table 7: AIC value for comparison models

Model	Formulation	AIC value
ANOVA	$y_{ijk} = \mu + \beta_i + C_j + \tau_{k(i)} + \varepsilon_{ijk}$	45.015
Regression	$Y = \alpha + \beta X + \epsilon$	130.069
ANCOVA	$y_{ijk} = \mu + \beta_i + C_j + \tau_{k(i)} + \gamma X_{ijk} + \varepsilon_{ijk}$	42.002

Source: Experimental study

From Table 7, the result showed that the AIC value is minimum for the ANCOVA model. In comparison to the ANOVA (Analysis of Variance) model and regression models, the ANCOVA (Analysis of Covariance) model exhibits a special significance considering the minimum value of the Akaike Information Criterion (AIC). AIC is a useful tool for model selection since it assesses a model's goodness of fit while compensating for complexity. Finding the minimal AIC is essential in ANCOVA because it creates a balance between the requirement to explain variance in the response variable (as in ANOVA) and the impact of covariates (as in regression). ANCOVA incorporates aspects of both ANOVA and regression by including covariates. In ANCOVA, where the inclusion of covariates can make model selection challenging, a lower AIC indicates a more parsimonious model that strikes a better balance between goodness of fit and model complexity, assisting researchers in choosing the best model for their data. Regression emphasizes prediction while ANOVA just considers group differences; as a result, ANCOVA modeling places a greater emphasis on the role of AIC in striking this delicate balance.

V. CONCLUSION

This study can conclude that ANCOVA in an augmented randomized block design model is a more efficient and robust estimate than ANOVA in an augmented randomized block design. This not only produces more reliable and trustworthy results but also maximizes the use of resources and statistical power. The proposed ANCOVA for augmented randomized block design will be essentially a potent tool for agricultural research that would help in the creation of sustainable and successful methods for crop management, soil enhancement, and pest control, ultimately advancing agricultural science and food production. Despite all of the positive steps taken to carry out this study correctly, there were some limitations. In this study, augmented randomized block design has been developed for a single observation per cell. If multiple observations are taken, there is no established method of adjusting this. Furthermore, this study assumes that there is no interaction between blocks and treatments so blocks and treatments are independent. However, interaction effects may be present in augmented randomized block design. This research is the first of its kind, hence, lacks comparison with the results of similar other studies. However, it may be claimed that this study marks the first step for many futuristic research.

REFERENCES

Agrawal, R. C., and Sapra, R. L. (1995). Augment 1: A microcomputer-based program to analyze augmented randomized complete block design. *Indian Journal of Plant Genetic Resources*, *8*(1): 61-69.

AlAita, A., and Talebi, H. (2023). Exact neutrosophic analysis of missing value in augmented randomized complete block design. *Complex & Intelligent Systems*, 1-15. https://doi.org/10.1007/s40747-023-01182-5

Alemayehu, N., Keneni, G., Bediye, S., and Dechassa, N. (2022). Research Methods: A Handbook for Agricultural Researchers.

Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, 19(6): 716–723. https://doi.org/10.1109/TAC.1974.1100705

Aravind, J., Mukesh, S. S., Wankhede, D. P., and Kaur, V. (2019). *Augmented RCBD: Analysis of Augmented Randomised Complete Block Designs*. R package version 0.1.1.9000.

Atlin, G. N., Cairns, J. E., and Das, B. (2017). Rapid breeding and varietal replacement are critical to adaptation of cropping systems in the developing world to climate change. *Global food security*, *12*, 31-37.https://doi.org/10.1016/j.gfs.2017.01.008

Badu-Apraku, B., Fakorede, M. A. B., Menkir, A., and Sanogo, D. (2012). Conduct and management of maize field trials.

Boyle, C. R., and Montgomery, R. D. (1996). An application of the augmented randomized complete block design to poultry research. *Poultry Science*, 75(5): 601-607.

Burgueño, J., Crossa, J., Rodríguez, F., and Yeater, K. M. (2018). Augmented designs-experimental designs in which all treatments are not replicated. In. Applied statistics in agricultural, biological, and environmental sciences, 345-369.

Burnham, K. P. (1998). Model selection and multimodal inference. *A practical information-theoretic approach*. Springer

de Oliveira, E. J., de Lima, D. S., Lucena, R. S., Motta, T. B. N., and Dantas, J. L. L. (2010). Genetic correlation and path analysis for the number of commercial fruit per plant in papaya. *Pesquisa Agropecuária Brasileira*, 45(8): 855-862.

Dewey, A., and Drahota, A. (2016). Introduction to systematic reviews: online learning module. *Cochrane Training*.

Duvick, D. N. (2005). The contribution of breeding to yield advances in maize (Zea mays L.). *Advances in agronomy, 86*: 83-145.

FAOSTAT, F. (2021). *Statistical database*. Food and Agriculture Organization of the United Nations, Rome, Italy.

Federer, W. T. (1956). Augmented (or hoonuiaku) designs. *Hawaii Plant. Rec*., 55: 191-208.

Federer, W. T. (1961). Augmented designs with one-way elimination of heterogeneity. *Biometrics*, *17*(3): 447-473.

Federer, W. T., and Raghavarao, D. (1975). On augmented designs. *Biometrics*, 31: 29-35.

Federer, W. T., Reynolds, M., and Crossa, J. (2001). Combining results from augmented designs over sites. *Agronomy Journal*, *93*(2): 389-395.

Galvão, A. G., Resende, L. V., Maluf, W. R., Resende, J. T. V. D., Ferraz, A. K. L., and Marodin, J. C. (2017). Breeding new improved clones for strawberry production in Brazil. *Acta Scientiarum". Agronomy*, 39: 149-155.

Higgins, J. P. T., and Green, S. (Eds.). (2011). *Cochrane Handbook for Systematic Reviews of Interventions,* Version 5.1.0., The Cochrane Collaboration. https://doi.org/10.1007/s12038-012-9227-1

Iqbal, J., Shabbir, G., Shah, K. N., and Qayyum, A. (2021). Deciphering of genotype× environment interaction to identify stable heat-tolerant mung bean genotypes by GGE biplot analysis. *Journal of Soil Science and Plant Nutrition*, 21: 2551-2561.

Jui, S. A., Mukul, M., M., Rashid, M. H. O., Nur, I. J., Ghosh, R. K., Mostofa, M. G., Akter, N., and Sultan, M. T. (2021). Responses and screening of white jute (*Corchoruscapsularis* L.) genotypes against salinity stresses. *Plant Sci. Today,* 8(2): 416–424.

Pandey, P., and Pandey, M. M. (2021). *Research methodology tools and techniques*. Bridge Center.

Permana, A., Hanafiah, D.S., andHasanuddin (2021). Evaluation of maize hybrids resistance to northern corn leaf blight in KaroHighland.*Earth and Environmental Science*, 713: 012004.

Prasanna, B. M. (2012). Diversity in global maize germplasm: characterization and utilization. *Journal of biosciences*, *37*(5): 843-855.

Raihan, A. (2023). A review of the global climate change impacts, adaptation strategies, and mitigation options in the socio-economic and environmental sectors. *Journal of Environmental Science and Economics*, *2*(3): 36-58. https://doi.org/10.56556/jescae.v2i3.587

Scott, R. A., and Milliken, G. A. (1993). A SAS program for analyzing augmented randomized complete-block designs. *Crop Science*, *33*(4): 865-867.

Shiferaw, B., Prasanna, B. M., Hellin, J., and Bänziger, M. (2011). Crops that feed the world 6. Past successes and future challenges to the role played by maize in global food security. *Food security*, *3*:307-327.

Silknitter, K. O., Wisnowski, J. W., and Montgomery, D. C. (1999). The analysis of covariance: a useful technique for analysing quality improvement experiments. Quality and reliability engineering international, 15(4): 303-316.

Xu, Y., Li, P., Yang, Z., andXu, C. (2017). Genetic mapping of quantitative trait loci in crops. *The Crop Journal*, *5*(2): 175-184.

Yitayew, A., Abdulai, A., Yigezu, Y. A., Deneke, T. T., and Kassie, G. T. (2021). Impact of agricultural extension services on the adoption of improved wheat variety in Ethiopia: A cluster randomized controlled trial. *World Development*, *146,* 105605. https://doi.org/10.1016/j.worlddev.2021.10560.