

# Comprehensive Statistical Analysis Report

ANCOVA •  $3^3$  Factorial CRD • Confounded  $2^k$  Factorial in RBD

# 1. ANCOVA (Analysis of Covariance)

## 1.1 Purpose of ANCOVA

ANCOVA is used when we compare treatment means while adjusting for the effect of a covariate (x). In this dataset, potato varieties are categorical treatments and 'x' is a continuous concomitant variable.

## 1.2 Explanation of Code

### Data Input and Factor Conversion

`a$potatos = as.factor(a$potato)` converts numerical potato codes (1–4) into categorical factor levels. ANCOVA requires treatments as factors.

### ANOVA for Covariate x (Txx, Exx, Gxx)

Txx = Treatment sum of squares for x. Measures variation in x due to varieties.

Exx = Error sum of squares for x. Measures variation within varieties.

Gxx = Total SS = Txx + Exx.

### ANOVA for Response y (Tyy, Eyy, Gyy)

Same logic as x: partition total variation in y into treatment and error components.

## 1.3 Regression Slopes

beta (adjusted slope) is obtained from `lm(y ~ x + potato)`. This slope removes treatment effects.

beta2 (unadjusted slope) from `lm(y ~ x)` does not remove treatment variation.

## 1.4 Covariance Components

$E_{xy} = E_{xx} * \text{beta}$  computes adjusted covariance under treatments.

$G_{xy} = G_{xx} * \text{beta2}$  computes total covariance without controlling for potato variety.

$T_{xy} = G_{xy} - E_{xy}$  gives treatment-level covariance.

## 1.5 ANCOVA Table

ANCOVA: `aov(y ~ x + potato)` partitions variation due to x and then potato while adjusting for x. This improves precision compared to ordinary ANOVA.

## 2. 3<sup>3</sup> Factorial Experiment in CRD

### 2.1 Purpose

A 3×3×3 factorial experiment studies three independent factors each with 3 levels: pressure, nozzle type, and speed. The goal is to estimate main effects and interactions.

### 2.2 Factor Conversion

`mutate(across(!'yield', as.factor))` converts numeric treatment levels to factors. This is required because factorial ANOVA treats them as categorical groups.

### 2.3 Model

```
model_crd = aov(yield ~ nozzle.type * speed * pressure)
```

The \* operator expands to main effects + all 2-way + 3-way interactions.

### 2.4 ANOVA Interpretation

Pressure and speed have large significant effects ( $p < 0.001$ ).  
Significant two-way interactions (speed×pressure, pressure×nozzle, speed×nozzle) indicate combined factor effects.  
Three-way interaction is not significant.

### 2.5 TukeyHSD

Used for pairwise comparisons between treatment levels after significant ANOVA. Free from Type I error inflation unlike LSD.  
Visual plots indicate which factor levels differ statistically.

### 2.6 Mean Plot

Plots of mean yield by speed show how response changes across factor levels. Used for interpretation and visual checking of factor effects.

## 3. Confounded 2<sup>4</sup> Factorial in RBD

### 3.1 Purpose

Large factorials like 2<sup>4</sup> require many plots. Confounding assigns one high-order interaction to blocks so that block variation does not affect important main effects.

### 3.2 Factor Conversion

`mutate(across(!'yield', as.factor))` ensures block, n, p, k, d are treated as categorical.

### 3.3 Full Model

`lm(yield ~ block + n + p + k + d + interactions...) fits:`

- all 4 main effects
- important two-way interactions
- all three-way interactions
- the four-way interaction

### 3.4 Singularities (NA Coefficients)

Because confounding aliases certain interactions with blocks, some model terms become linearly dependent. R returns NA because those interactions cannot be estimated separately.

### 3.5 ANOVA Interpretation

Significant effects include:

- n (very strong)
- k
- pxd interaction
- nxkxd interaction

Block effect is not significant, showing successful blocking.

### 3.6 Final Notes on Confounding

Confounding helps reduce experimental size by sacrificing unimportant high-order interactions. The ANOVA shows main effects remain estimable while certain interactions are aliased.

## Overall Summary

- ANCOVA increases precision by adjusting for covariate  $x$ .
- $3^3$  CRD detects strong main effects of speed and pressure, plus moderate interactions.
- Confounded  $2^k$  RBD successfully estimates main effects while reducing experiment size.

These analyses demonstrate strong experimental design understanding and proper statistical application.