

# Module 3: Heritability and Reliability Estimations in R

## Fundamentals of Genomic Prediction and Data-Drive Crop Breeding

(November 24-28, 2025)



### **Waseem Hussain**

Senior Scientist-I

International Rice Research Institute  
Rice Breeding Innovations Platform

[waseem.hussain@cgiar.org](mailto:waseem.hussain@cgiar.org)

[whussain2.github.io](https://whussain2.github.io)

### **Mahender Anumalla**

Scientist-I

International Rice Research Institute  
South-Asian Hub, Hyderabad

[m.anumalla@cgiar.org](mailto:m.anumalla@cgiar.org)

### **Margaret Catolos**

Associate Scientist

International Rice Research Institute  
South-Asian Hub, Hyderabad

[m.catolos@cgiar.org](mailto:m.catolos@cgiar.org)

November 20, 2025

## Contents

<b>Load the Libraries</b>	<b>1</b>
<b>Upload the Phenotypic Data Sets</b>	<b>1</b>
<b>Run the Model to Estimate Heritability</b>	<b>2</b>
Heritability Based on Single Environment . . . . .	2
Run the mixed model . . . . .	2
Extract Results and Variance Components . . . . .	3
Extract variance components . . . . .	3
ANOVA for fixed effects . . . . .	4
Extract the Fixed effects . . . . .	4
Extract the Random effects . . . . .	4
Heritability . . . . .	4
Heritability Based on Variance Components . . . . .	4
Reliability based on Cullis et al. . . . .	5
Heritability Based on MET Analysis . . . . .	5
Combined ANOVA . . . . .	5
Combined Analysis in lme4 . . . . .	6
Summary of MET results . . . . .	6
Plot of model . . . . .	7
Reliability Using Mean Difference . . . . .	7
<b>Additional Resources</b>	<b>8</b>

## Load the Libraries

```
> # Load the Required Libraries
> rm(list=ls()) # Remove previous work
> library(easypackages)
> libraries("dplyr", "reshape2", "readxl", "lme4", "arm")
```

## Upload the Phenotypic Data Sets

Here we will use the Rainfed Rice Breeding Trial data of IRRI which has 192 entries, 2 replications and 5 blocks and experimental design is Alpha lattice.

```
> # Read the saved csv file, if working directly
> demo.data.filtered<-read.csv(file="demo.data.filtered2.csv",
+                             header = TRUE)
> str(demo.data.filtered)
```

```
'data.frame': 1600 obs. of 11 variables:
 $ Environment: chr "Env1" "Env1" "Env1" "Env1" ...
 $ Plot : int 59 19 27 127 132 92 106 82 199 57 ...
 $ Genotype : int 1 2 3 4 5 6 7 8 9 10 ...
 $ Rep : int 1 1 1 1 1 1 1 1 1 1 ...
 $ Block : int 2 1 1 4 4 3 3 3 5 2 ...
 $ Row : int 2 1 1 4 4 3 3 3 5 2 ...
 $ Column : int 19 19 27 7 12 12 26 2 39 17 ...
 $ Line.type : chr "Entry" "Entry" "Entry" "Entry" ...
 $ DTF : int 94 78 87 87 94 94 82 87 82 85 ...
```

```
$ HT      : num  118 116 108 116 134 ...
$ Yield   : num  5873 5844 5777 6284 5703 ...
```

```
> # factor conversion if below are not in factors
> columns<-c("Environment", "Genotype", "Rep", "Block",
+           "Row", "Column", "Line.type")
> demo.data.filtered[, columns]<-lapply(columns, function(x) as.factor(demo.data.filtered[[x]]))
> demo.data.filtered$Yield<-as.numeric(demo.data.filtered$Yield)
> demo.data.filtered$HT<-as.numeric(demo.data.filtered$HT)
> demo.data.filtered$DTF<-as.numeric(demo.data.filtered$DTF)
> # Subset the required columns
> demo.data.filtered<-demo.data.filtered[, c("Environment", "Genotype",
+           "Rep", "Block", "Row", "Column",
+           "Line.type", "Yield", "HT", "DTF")]
> # First we will arrange the rows and columns for spatial analysis.
> # Now we will subset the environments and Yields for analysis
> demo.data.filtered<-data.frame(demo.data.filtered%>% group_by(Environment)%>% arrange(Row, Column))
> demo.data.filtered<-data.frame(demo.data.filtered%>% arrange(Environment)) # Arrange by environment
```

## Run the Model to Estimate Heritability

- Here in this section we will use open source R package called **lme4** to run the mixed-model and extract variance components
- More on this R package can be found here [lme4 Tutorial 1](#), and [lme4 Tutorial 2](#).

## Heritability Based on Single Environment

- First let us subset the data for on environment to show how to perform the analysis for one trial or environment in lme4 R package
- We will run models which are feasible in lme4 R package.
- We will use basic models and show how to extract the results
- Subset the data for one environment first.

```
> # Subset the environment 1
> sub.data<-subset(demo.data.filtered, Environment=="Env1")
> sub.data<-droplevels.data.frame(sub.data)
```

## Run the mixed model

### Model 1.lme4

- The model described below is:

$$y_{ijk} = \mu + g_i + r_j + b_{jk} + \epsilon_{ijk}$$

$y_{ijk}$  = is the effect of  $i$ th genotype in  $j$ th replication and  $k$ th block within the  $j$ th replication

$\mu$  = overall mean

$g_i$  = random effect of the  $i$ th genotype

$r_j$  = fixed effect of the  $j$ th replication

$b_{jk}$  = random effect of  $k$ th block nested within  $j$  replication

$\varepsilon_{ijk}$  = residual error

here we assume errors are independent and identically distributed  $\epsilon \sim iidN(0, \sigma_\epsilon^2)$

```
> # Now apply model
> model1<-lmer(Yield~Rep+(1|Genotype)+(1|Rep:Block), data =sub.data)
```

## Extract Results and Variance Components

- Here we will summarize the results using *summary()* function.
- The first few lines of output indicate that the model was fitted by REML as well as the value of the REML criterion.
- The second piece of the summary output provides information regarding the random-effects and residual variation.
- The third piece of the summary output provides information regarding the fixed-effects and the fourth piece of summary output provides information regarding the correlation of fixed effects.

```
> # Summarise the results
> summary(model1)
```

```
Linear mixed model fit by REML ['lmerMod']
Formula: Yield ~ Rep + (1 | Genotype) + (1 | Rep:Block)
Data: sub.data
```

REML criterion at convergence: 6239.3

Scaled residuals:

Min	1Q	Median	3Q	Max
-1.90048	-0.59387	0.03899	0.60311	1.71001

Random effects:

Groups	Name	Variance	Std.Dev.
Genotype	(Intercept)	431861	657.2
Rep:Block	(Intercept)	28499	168.8
Residual		193255	439.6

Number of obs: 394, groups: Genotype, 197; Rep:Block, 10

Fixed effects:

	Estimate	Std. Error	t value
(Intercept)	5233.19	94.20	55.552
Rep2	60.38	115.60	0.522

Correlation of Fixed Effects:

	(Intr)
Rep2	-0.614

## Extract variance components

- Here we will extract variance components

```
> Ve<- VarCorr(model1)
> Ve
```

Groups	Name	Std.Dev.
Genotype	(Intercept)	657.16

```
Rep:Block (Intercept) 168.82
Residual              439.61
```

## ANOVA for fixed effects

```
> # ANOVA
> anova(model1)
```

	npar	Sum Sq	Mean Sq	F value
Rep	1	52724.26	52724.26	0.2728223

## Extract the Fixed effects

- Here will show how to extract the BLUEs.

```
> BLUEs<-fixef(model1)
> BLUEs
```

```
(Intercept)      Rep2
5233.1856      60.3794
```

## Extract the Random effects

- Here will show how to extract the BLUPs.

```
> # Extract the Random effects
> BLUPs<-data.frame(Blups.yield=ranef(model1)$Genotype)
> GV<-data.frame(BLUPs.GY=coef(model1)$Genotype[,1]) #Genotype values (Blups +Intercept)
```

## Heritability

- Here will show how to calculate the heritability. Two approaches will be show how to estimate heritability: 1) Based on Variance components and 2) Based on Cullis et al. 2006 is also  $1 - \frac{\bar{V}_{BLUP}}{2\sigma^2_g}$ . Where  $\bar{V}_{BLUP}$  is mean variance difference of two genotypes based on BLUPs and  $\sigma^2_g$  is variance of genotypes.

## Heritability Based on Varaince Components

```
> # Extract the variance components
> Ve<- data.frame (VarCorr(model1))
> Ve
```

grp	var1	var2	vcov	sdcor
Genotype	(Intercept)	NA	431860.94	657.1613
Rep:Block	(Intercept)	NA	28498.55	168.8151
Residual	NA	NA	193254.94	439.6077

```
> # Now calculate heritability using variance components
> genotype.var=Ve[1,4]
> error.var=Ve[2,4]
> # Now heritability
> h2=genotype.var/(genotype.var+error.var)*100
> h2
```

```
[1] 93.8095
```

## Reliability based on Cullis et al.

```
> # Reliability
> std.err<-se.ranef(model1)$Genotype
> v_BLUP<- mean(std.err)
> # Heritability/Reliability
> h2<- (1-((v_BLUP)^2/(Ve[1,4]*2)))*100
> h2
```

```
[1] 90.55036
```

## Heritability Based on MET Analysis

### Model 2.lme4

- Here we will analyze all the environments jointly and extract the single BLUPs for each genotype.
- We will use mixed model analysis in lme4 r package model.
- We will treat genotypes as random and environment as fixed effect.

## Combined ANOVA

- Here ANOVA will be generated for all the factor levels.
- Replications are nested with environments and Blocks are within Replications which are nested within environment.

```
> # Linear model to get ANOVA
> demo.data.filtered$Environment<-as.factor(demo.data.filtered$Environment)
> model.anova<-lm(formula = Yield~Genotype+Environment+Genotype*Environment+Environment:Rep+ Environment:Block,
+ data=demo.data.filtered)
> # Get ANOVA
> anova(model.anova)
```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Genotype	199	547177221	2749634	5.577295	0.00e+00
Environment	3	2081940510	693980170	1407.653397	0.00e+00
Genotype:Environment	588	1002589262	1705084	3.458553	0.00e+00
Environment:Rep	4	22794162	5698541	11.558788	0.00e+00
Environment:Rep:Block	32	37568681	1174021	2.381358	3.54e-05
Residuals	754	371725774	493005	NA	NA

Significant differences are observed for all factors and genotype by environment interactions are significant

## Combined Analysis in lme4

- The model we will use is give below:

$$y_{ijkl} = \mu + g_i + e_j + (ge)_{ij} + r_{jk} + b_{jkl} + \epsilon_{ijklm}$$

$\mu$  = overall mean

$g_i$  = random effect of the  $i$ th genotype

$e_j$  = random effect of the  $j$ th environment

$(ge)_{ij}$  = is the interaction effect of  $i$ th genotypes with the  $j$ th environment

$r_{jk}$  = fixed effect of the  $k$ th replication nested within  $j$ th environment

$b_{jkl}$  = random effect of  $l$ th block nested with  $j$  environment and  $k$ th replication

$\epsilon_{ijkl}$  = residual error

here we assume residuals are independent and identically distributed

- Mixed models are powerful tools to handle assumptions of linear model Read this one
- We will extract variance components and also calculate heritability.

```
> demo.data.filtered$Environment<-as.factor(demo.data.filtered$Environment)
> Model3.lme4<-lmer(Yield~Rep+(1|Genotype)+(1|Environment)+
+ (1|Block), data=demo.data.filtered)
```

### Summary of MET results

- In summary we will get following summarized results: 1) Description of model we used, 2) Random effects and variances, 3) Fixed effects, 4) Correlation of fixed effects

```
> summary(Model3.lme4)
```

Linear mixed model fit by REML ['lmerMod']

Formula: Yield ~ Rep + (1 | Genotype) + (1 | Environment) + (1 | Block)

Data: demo.data.filtered

REML criterion at convergence: 26571.7

Scaled residuals:

	Min	1Q	Median	3Q	Max
	-3.7537	-0.5702	-0.0115	0.4669	5.3187

Random effects:

Groups	Name	Variance	Std.Dev.
Genotype	(Intercept)	205131	452.9
Block	(Intercept)	7224	85.0
Environment	(Intercept)	1789049	1337.6
Residual		1033082	1016.4

Number of obs: 1581, groups: Genotype, 200; Block, 5; Environment, 4

Fixed effects:

	Estimate	Std. Error	t value
(Intercept)	4740.65	671.60	7.059

```
Rep2          -151.88      51.13  -2.971
```

Correlation of Fixed Effects:

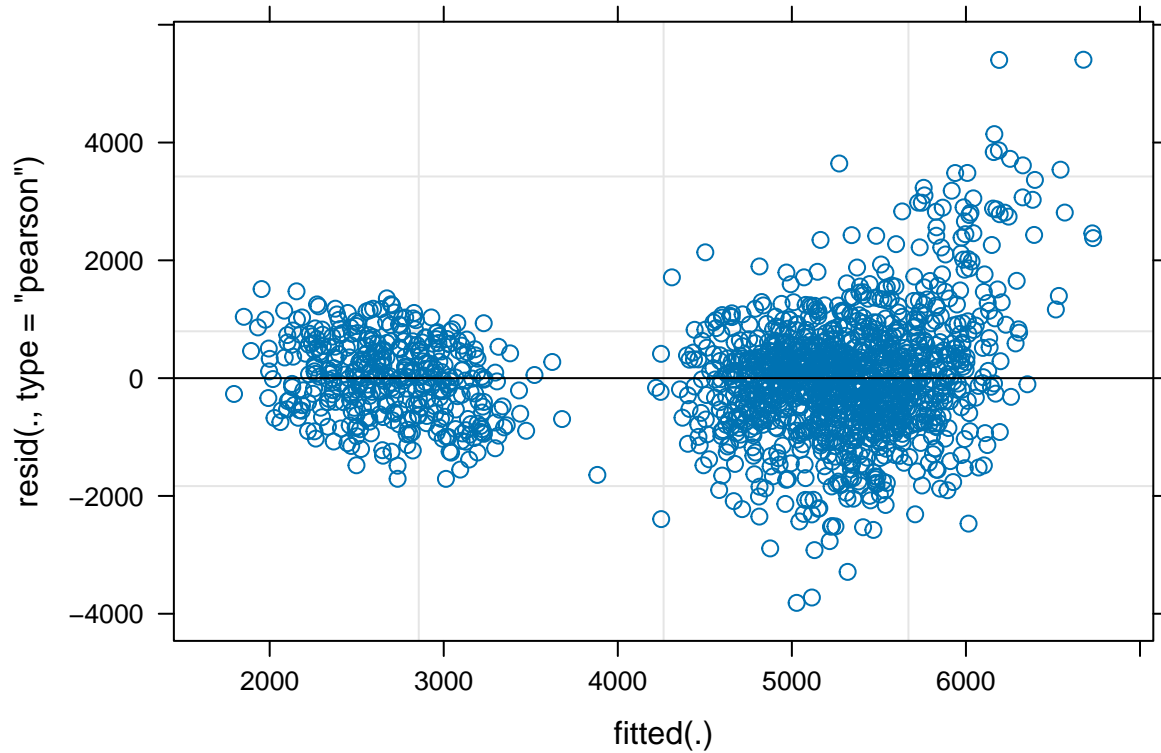
(Intr)

```
Rep2 -0.038
```

### Plot of model

- With the plot function model we will get the residuals vs fitted values

```
> plot(Model13.lme4)
```



## Reliability Using Mean Difference

- Based on Cullis et al.2006

```
> # Extract the variance components
> Ve<- data.frame (VarCorr(Model13.lme4))
> Ve
```

grp	var1	var2	vcov	sdcov
Genotype	(Intercept)	NA	205131.050	452.91395
Block	(Intercept)	NA	7224.397	84.99645
Environment	(Intercept)	NA	1789048.808	1337.55329
Residual	NA	NA	1033082.471	1016.40665

```
> std.err<-se.ranef(Model13.lme4)$Genotype
> v_BLUP<- mean(std.err)
> # Heritability/Reliability
```



```
> h2<- (1-((v_BLUP)^2/(Ve[1,4]*2)))*100  
> h2
```

```
[1] 80.29987
```

## Additional Resources

- Here In this section we have provided additional R resources where similar analysis and mixed models can be run:
- Fitting linear mixed-effects models using lme4
- Linear Mixed-Effects Models Using R
- sommer: Solving Mixed Model Equations in R
- robustlmm
- Introduction to Linear Mixed Models
- Computing Heritability and Selection Response From Unbalanced Plant Breeding Trials
- Estimating Broad-Sense Heritability with Unbalanced Data from Agricultural Cultivar Trials

---

For any suggestions or comments, please feel to reach at [waseem.hussain@cgiar.org](mailto:waseem.hussain@cgiar.org); [m.anumalla@cgiar.org](mailto:m.anumalla@cgiar.org); [m.catolos@cgiar.org](mailto:m.catolos@cgiar.org)

---

*If your experiment needs a statistician, you need a better experiment - Ernest Rutherford*