Research Methods Group

MIXED MODEL ANALYSIS USING R

Using Case Study 4 from the
BIOMETRICS & RESEARCH METHODS TEACHING RESOURCE

BY
Stephen Mbunzi & Sonal Nagda

www.ilri.org/rmg

www.worldagroforestrycentre.org/rmg

P. O. Box 30709 - 00100, Nairobi, Kenya
Phone + 254 2 422 3000
Fax +254 2 422 3001

P. O. Box 30677, Nairobi, Kenya
Phone + 254 20 722 4000
Fax + 254 2 722 4001

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1. INTRODUCTION

R is an open-source software which is free to use, distribute and modify under the open-source type license. The newest version of R and its documentation can be downloaded from http://www.R-project.org.

R can be defined as an environment within which many classical techniques are implemented. A few of these techniques are built into the base R environment, but many are added as packages. It is a language with many functions for statistical analyses and graphics.

There are 25 packages supplied with base R. Many more are available through the CRAN family of Internet site (http://CRAN.R-project.org). Only 7 packages are pre-loaded into memory when R is loaded.

To see the packages that are currently loaded into memory, one types in '**search()**'. Below are the 7 packages that are initially loaded.

```
> search()
[1] ".GlobalEnv"           "package:stats"      "package:graphics"
[4] "package:grDevices"    "package:utils"      "package:datasets"
[7] "package:methods"      "Autoloads"          "package:base"
```

Any function that belongs to one of the loaded packages is always available during an R session.

If a package is not among the 7 loaded packages, e.g. 'nlme', this can be loaded using the menus (Package -> Load packages..)

If the package in not amongst those already supplied with base R, it can be downloaded through the CRAN Internet site (http://CRAN.R-project.org) e.g. 'lme4'

We will illustrate the use of R for fitting a mixed model using Case study 4 from the Biometrics & Research Methods Teaching Resource. This data set has previously, on the CD been analysed using GENSTAT.

The data used in this example come from a study carried out at Diani Estate of Baobab farms, 20 Km south of Mombasa in sub-humid coastal region of Kenya between 1991 and 1996. The purpose of the experiment was to compare the genetic resistance to helminthiasis of two sheep breeds – Dorper and Red Maasai. For more background information, refer to the CD (Case Study 3 & 4).

Measurement of lamb weight was taken at the time of weaning. In addition, the age of weaning, the lamb's sex, the age of its dam and identity of both sire and dam were recorded. In this example we shall consider the weaning weight as the response variable and determine the effect of breed and other factors and covariates. An equivalent 'Fixed effects analysis' is shown in Case Study 3.

2. DESCRIPTION OF CONTENTS OF THE DATA

The data used in this example is stored in Excel file CS4Data.xls which is found on the Biometrics & Research Methods Teaching Resource CD.

The data set contains information on 882 lambs born and raised at Diani Farm on Kenya coast between 1991 and 1996. Records for weaning weights are missing in 182 of the lambs, mostly because of earlier death or because recording was missed. Missing data are indicated by blanks. A! at the end of the variable name implies that the variable is being considered as a factor.

Source: Isaac Kosgey

Field	**Description**
LAMB	Individual lamb identification
EWE-ID	Unique Identification of lamb's dam
EWE-BRD	Breed of ewe (D = Dorper and R = Red Maasai)
RAM-ID	Unique Identification of lamb's sire
RAM-BRD	Breed of ram (D = Dorper and R = Red Maasai)
BREED!	Breed of the lamb (DD = pure bred Dorper, DR = Dorper sire × Red Maasai dam, RD = Red Maasai sire × Dorper ewe, RR = pure bred Red Maasai)
YEAR!	The year of birth of the lamb (1991-1996)
SEX!	The sex of the lamb (M = male and F = female)
BIRTHWT	Weight(kg)of lamb at birth
AGEWEAN	Age in days of lamb at weaning
DAMAGE!	Age in years of dam
WEANWT	Weight (kg) of lamb at weaning
DAMAGE7!	Calculated from DAMAGE in order to represent DAMAGE in 7 categories (≤ 2,3,4,5,6,7, ,≥ 8)
DL	Duplicate of DAMAGE7 but considered as a variable (<=2yrs = 2 and >=8yrs = 8), not a factor.
DQ	Calculated as DL x DL
DAMAGE4!	Calculated from DAMAGE7 but collapsed into four categories (≤ 2,3-4,5-6,≥ 7)

3. IMPORTING DATA INTO R

Data may be stored in a variety of software programs (eg. Access, Excel, Genstat etc). The data are then exported as an ASCII file which can be used in R.

From Excel, a commonly used spreadsheet program, the data can be saved as '.csv' (comma separated values) format.

Open the Excel file **CS4data.xls**. The first row should be reading the variable names and then the data. Any extra rows before the row indicating variable names, should be deleted and then saved as '**CS4data.csv**'.

To read in the dataset, the following commands can be used.

```
> data4<-read.table("c://CS4data.csv", header=TRUE, sep=",")
> data4
```

or

```
> data4<-read.csv("c://CS4data.csv", header=TRUE, sep=",")
> data4
```

To display the names of variables in column order of the data frame, type in "**names(data4)**"

```
> names(data4)
 [1] "LAMB"     "EWE_ID."  "EWE_BRD." "RAM_ID."  "RAM_BRD." "BREED."
 [7] "YEAR."    "SEX."     "BIRTHWT"  "AGEWEAN"  "DAMAGE."  "WEANWT"
[13] "DAMAGE7." "DL"       "DQ"       "DAMAGE4."
>
```

The variables that were reading "**!**" at the end, R converts and puts a "**.**".

To display the variables existing in data4 and their characteristics, type in "**str(data4)**"

```
> str(data4)
'data.frame':   882 obs. of  16 variables:
 $ LAMB     :   int     627 629 635 636 638 639 640 642 643 644 ...
 $ EWE_ID.  :   int     1682 1082 1520 1450 5183 1471 1116 5138 1169 1595 ...
 $ EWE_BRD. :   Factor w/ 2 levels "D","R": 1 1 1 1 1 1 1 1 1 1 ...
 $ RAM_ID.  :   int     1980 4908 1974 4911 4909 1973 1981 4909 1973 4910 ...
 $ RAM_BRD. :   Factor w/ 2 levels "D","R": 1 1 1 1 1 1 2 1 1 1 ...
 $ BREED.   :   Factor w/ 4 levels "DD","DR","RD",..: 1 1 1 1 1 1 3 1 1 1 ...
 $ YEAR.    :   int     91 91 91 91 91 91 91 91 91 91 ...
 $ SEX.     :   Factor w/ 2 levels "F","M": 2 1 2 2 1 1 2 2 2 1 ...
 $ BIRTHWT  :   num      2.7 2.9 2.5 2.7 3 2.4 3.4 2.5 3.8 2.5 ...
 $ AGEWEAN  :   int     125 112 109 108 NA 107 107 NA 107 107 ...
 $ DAMAGE.  :   int   2 5 2 5 3 2 4 3 5 2 ...
 $ WEANWT   :   num      16.3 18.4 14.7 15.6 NA 10.8 15.5 NA 19.1 11.4 ...
 $ DAMAGE7. :   Factor w/ 7 levels "<=2",">=8","3",..: 1 5 1 5 3 1 4 3 5 1 ...
 $ DL       :   int  2 5 2 5 3 2 4 3 5 2 ...
 $ DQ       :   int  4 25 4 25 9 4 16 9 25 4 ...
 $ DAMAGE4. :   Factor w/ 4 levels ">=2",">=7","4-Mar",..: 1 4 1 4 3 1 3 3 4 1 ...
```

Usually if the variable is not numeric, then R considers it as a factor.

To transform numerical variable "YEAR." into factor type:

```
➢ data4$YEAR.<- as.factor(data4$YEAR.)
```

Check if again with "**str(data4)**" if it has converted to a factor.

4. DATA EXPLORATION

Before undertaking any statistical analysis, it is useful to explore the data.

To summarize the variables in data4 type in "**summary(data4)**"

```
> summary(data4)

     LAMB          EWE_ID.        EWE_BRD.     RAM_ID.          RAM_BRD.     BREED.
 Min.   : 627     Min.   : 1004   D:544       Min.   :1971      D:433        DD:310
 1st Qu.:1136     1st Qu.: 1463   R:338       1st Qu.:4906      R:449        DR:123
 Median :1628     Median : 4828               Median :5002      RD:234
 Mean   :1618     Mean   : 3778               Mean   :4594      RR:215
 3rd Qu.:2115     3rd Qu.: 5134               3rd Qu.:5073
 Max.   :2537     Max.   :12682               Max.   :5338

    YEAR.        SEX.        BIRTHWT          AGEWEAN          DAMAGE.
 Min.   :91.00   F:404     Min.   :0.800    Min.   : 56.0    Min.   : 1.000
 1st Qu.:92.00   M:478     1st Qu.:2.225    1st Qu.: 86.0    1st Qu.: 3.000
 Median :93.00             Median :2.700    Median : 93.0    Median : 4.000
 Mean   :93.34             Mean   :2.659    Mean   : 92.6    Mean   : 4.374
 3rd Qu.:95.00             3rd Qu.:3.100    3rd Qu.:100.0    3rd Qu.: 5.000
 Max.   :96.00             Max.   :4.900    Max.   :125.0    Max.   :10.000
                                            NA's   :175.0
    WEANWT          DAMAGE7.        DL               DQ               DAMAGE4.
 Min.    :  3.80    <=2: 89       Min.    :2.000   Min.    : 4.00    >=2  : 89
 1st Qu. :  9.40    >=8: 27       1st Qu.:3.000    1st Qu.: 9.00     >=7  : 79
 Median  : 11.00      3  :197     Median :4.000    Median :16.00     4-Mar:388
 Mean    : 11.10      4  :191     Mean   :4.373    Mean   :21.39     6-May:326
 3rd Qu. : 12.82      5  :212     3rd Qu.:5.000    3rd Qu.:25.00
 Max.    : 19.10      6  :114     Max.   :8.000    Max.    :64.00
 NA's    :182.00   7  : 52
>
```

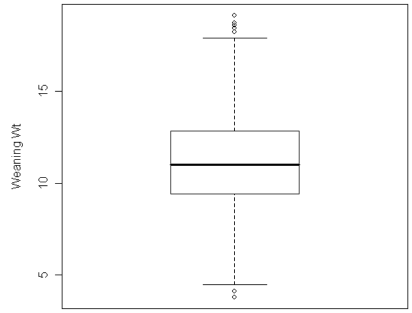
For variables that are continuous, the summary statistics are shown else for factors a frequency tabulation is displayed.

Each time you are calling a variable you need to attach it to data4. i.e. have to type in "boxplot(data4$WEANWT)". If one runs the "**attach(data4)**" command, then any time one is specifying the variable, do not need to type in data4$ i.e. can type in "WEANWT" instead of "data4$WEANWT".

```
> attach(data4)
```

First to check the distribution of the dependent variable WEANWT. Type in

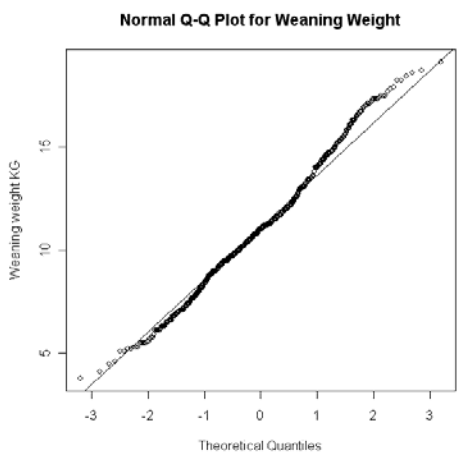
```
> boxplot(WEANWT,ylab = "Weaning Wt")
```



The weight at weaning appears normally distributed, as indicated by the relative position of the median within the box that contains half the data. However, there are some ‘outliers’ as shown in the above figure.

Normality of the weight at weaning could also be checked by use of a QQplot.

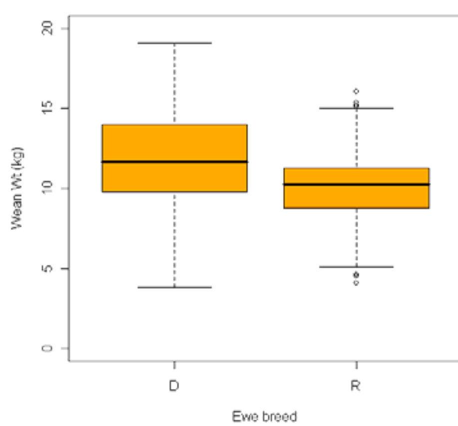
```
> qqnorm(WEANWT, main = "Normal Q-Q Plot for Weaning Weight", ylab="Weaning weight  KG")
> qqline(WEANWT)
```



“qqnorm” produces a QQplot and qqline adds a line to a normal qqplot. The plot shows that weaning weight is normally distributed as the points fall close to the line.

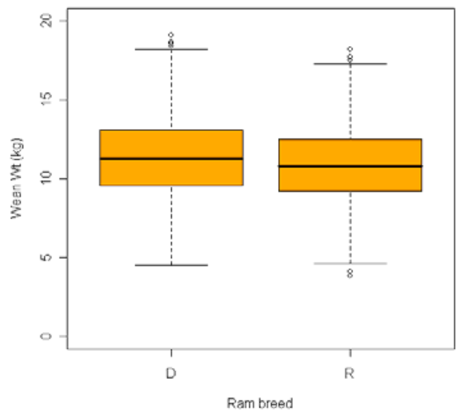
Now, produce a boxplot of weaning weight against ewe breed to check the weaning weight distribution for individual ewe breeds.

```
> boxplot(WEANWT ~ EWE_BRD., data=data4,
          col="orange", xlab="Ewe breed", ylab="Wean Wt (kg)", ylim=c(0,20))
```



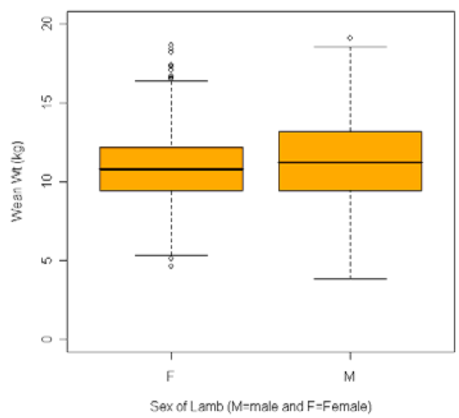
The previous boxplot reveals that offspring from the Dorper ewe breed generally have higher weaning weights than those from Red Maasai breed.

Similar programming was done for the other following additional plots and changed accordingly to the variable of interest.



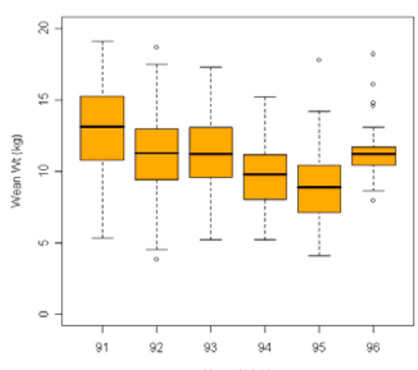
Effect of ram breed on the weight at weaning

The above boxplot shows that two ram breeds have almost the same distribution of offspring weaning weights.



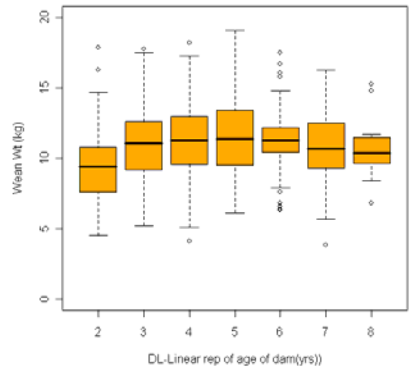
Effect of sex of lamb on the weight at weaning

The above boxplot shows male lambs show a higher variation in weights than females.



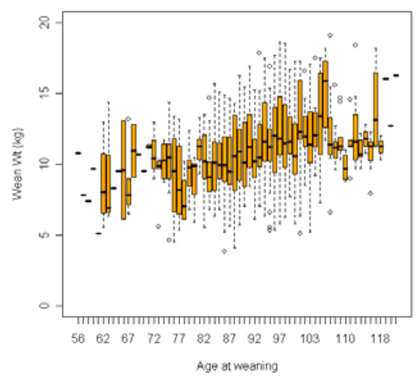
Effect of year of birth on the weight at weaning

The previous boxplot shows that generally the weaning weight of lambs decreased gradually over time, with an increase in the final year.



Effect of age of dam on the weight at weaning

The above boxplot illustrates the association between weaning weight and age of lamb's dam. The boxplot shows that the offsprings weaning weight appears to gradually increase as a dam increases in age from 2 to 5 years and decreases from 6 years onwards.



Effect of age at weaning on the weight at weaning

The above figure demonstrates a possible linear relationship between age of the lamb at weaning and the weaning weight. Hence, suggesting we should include the age at weaning as a continuous covariate in order to correct for its effect on weaning weight.

5. DATA ANALYSIS

Source Issac Kosgey

Following the exploratory analysis a mixed model analysis with ram and ewe as random effects on weaning weight was undertaken to investigate the influence of each of the fixed effects.

Before undertaking the mixed model, first a generalised linear model (fixed effects model) was fitted to check the significance of each of the fixed effects that is: [Year; Sex; Agewean; DL-linear term for dam age; DQ-quadratic term for dam age; Ewe breed; Ram breed.]

To run a generalised linear model to fit

Response variable: WEANWT
Fixed effects: YEAR., SEX., AGEWEAN, DL, DQ, EWE_BRD., RAM_BRD.

the following command could be used:

```
> fit1<-
lm(WEANWT~YEAR.+SEX.+AGEWEAN+DL+DQ+EWE_BRD.+RAM_BRD.,data4)
> summary(fit1)
> anova(fit1)
```

Or

```
> print(fit1<-
lm(WEANWT~YEAR.+SEX.+AGEWEAN+DL+DQ+EWE_BRD.+RAM_BRD.,data4))
>anova(fit1)
```

Below is the output:

```
>summary(fit1)
Call:
lm(formula = WEANWT ~ YEAR. + SEX. + AGEWEAN + DL + DQ + EWE_BRD. +
   RAM_BRD., data = data4)

Residuals:
     Min       1Q         Median     3Q        Max
-7.40371  -1.32744   -0.01093   1.44031   7.70632

Coefficients:
              Estimate    Std. Error   t value     Pr(>|t|)
(Intercept)   0.274005    1.065133      0.257      0.79706
YEAR.92      -1.565831    0.292949     -5.345 1    .23e-07 ***
YEAR.93      -1.095781    0.275268     -3.981      7.60e-05 ***
YEAR.94      -2.832501    0.357504     -7.923      9.34e-15 ***
YEAR.95      -3.228367    0.343630     -9.395      < 2e-16 ***
YEAR.96      -2.351101    0.389751     -6.032      2.64e-09 ***
SEX.M         0.477910    0.169498      2.820      0.00495 **
AGEWEAN       0.070217    0.008856      7.928      8.97e-15 ***
```

```
DL              2.726355      0.315012       8.655         < 2e-16 ***
DQ             -0.268882      0.034007      -7.907         1.05e-14 ***
EWE_BRD.R      -0.585536      0.236554      -2.475         0.01355 *
RAM_BRD.R      -0.442866      0.172768      -2.563         0.01058 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.221 on 688 degrees of freedom
  (182 observations deleted due to missingness)
Multiple R-Squared: 0.3835,     Adjusted R-squared: 0.3736
F-statistic:  38.9 on 11 and 688 DF,  p-value: < 2.2e-16
```

```
> anova(fit1)
Analysis of Variance Table

Response: WEANWT
            Df    Sum Sq     Mean Sq    F value     Pr(>F)
YEAR.       5     1208.1     241.6      48.9853     < 2.2e-16 ***
SEX.        1     56.0       56.0       11.3494      0.0007968 ***
AGEWEAN     1     344.2      344.2      69.7804      3.651e-16 ***
DL          1     151.5      151.5      30.7160      4.258e-08 ***
DQ          1     275.8      275.8      55.9115     2.316e-13 ***
EWE_BRD.    1     42.7       42.7       8.6548      0.0033717 **
RAM_BRD.    1     32.4       32.4       6.5708      0.0105780 *
Residuals   688   3393.7     4.9
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

"**lm**" is a generic function used to fit linear models. It can also be used to carry out regression, single stratum analysis and analysis of covariance.

The following can be summarised from the above output:

- Lambs born in the later years had lower weaning weights compared with those born in the earlier years. All the years showed significantly lower weaning weights than 1991.

- Male lambs had a significantly higher weaning weight by 0.48(±0.17) kg than females.

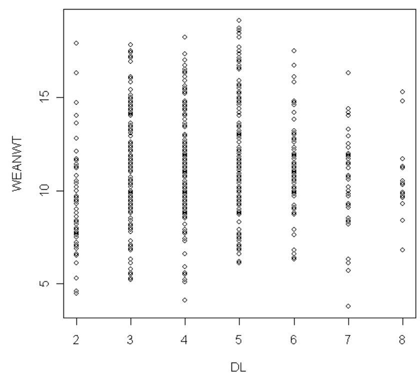
- The age at weaning was highly significant. With every increase in day at weaning, there would be an increase of 0.07(±0.01) kg.

- Age of ewe (DL & DQ), ewe breed and ram breed were also significant.

- DL and DQ are different representation of the effects of DAMAGE (age of dam). DL represents the linear relationship while DQ represents the quadratic relationship. A quadratic relationship was used because it gave a better fit.

To check the relationship between DL and WEANWT, type in

```
> plot(DL,WEANWT)
```



Mixed model "**lmer2**" function which is a development version of **"lmer"** was used to incorporate random effects Ram and Ewe to study the variation among the rams and ewes and their influence on lamb weaning weight.

When all the methods for the **"lmer"** have been duplicated for new representation of **"lmer2"**, will replace the old one and **"2"** will be dropped from the name.

The "**lmer2**" function is not amongst those packages supplied by R. The package to be downloaded from http://CRAN.R-project.org is "**lme4**" which has the function "**lmer2**"

To introduce random effects models, the three models were compared:

Model 1: with Ewe and Ram as random effects

Model 2: with only Ewe as random effect

Model 3: with only Ram as random effect

Model 1:

Response variable: WEANWT
Fixed effects: YEAR., SEX., AGEWEAN, DL, DQ, EWE_BRD., RAM_BRD.
Random effect RAM_ID+EWE_ID

The following command can be used. The vertical bar "|" indicates the variable to be considered as random.

```
> fit2<- lmer2 (WEANWT~ YEAR. + SEX. + AGEWEAN + DL + DQ + EWE_BRD. + RAM_BRD.
+ (1|RAM_ID.) + (1|EWE_ID.), data4)
> print (fit2, digits = 6, corr = FALSE)
```

Output for Model 1:

```
Linear mixed-effects model fit by REML
Formula: WEANWT ~ YEAR. + SEX. + AGEWEAN + DL + DQ + EWE_BRD. + RAM_BRD. +      (1 |
RAM_ID.) + (1 | EWE_ID.)
   Data: data4
    AIC       BIC          logLik       MLdeviance      REMLdeviance
 3109.55    3173.27     -1540.78     3052.72          3081.55
Random effects:
 Groups      Name        Variance      Std.Dev.
 EWE_ID.     (Intercept) 1.456488      1.20685
 RAM_ID.     (Intercept) 0.066577      0.25803
 Residual                3.427208      1.85127
Number of obs: 700, groups: EWE_ID., 358; RAM_ID., 74

Fixed effects:
                    Estimate          Std. Error        t value
(Intercept)         0.18578683        1.02634025        0.18102
YEAR.92             -1.57090479       0.26778469        -5.86630
YEAR.93             -1.07663138       0.26429730        -4.07356
YEAR.94             -3.00250608       0.34456803        -8.71383
YEAR.95             -3.28831695       0.34521411        -9.52544
YEAR.96             -2.45008161       0.39463241        -6.20852
SEX.M                0.40381088       0.16231107         2.48788
AGEWEAN              0.06592851       0.00861291         7.65462
DL                   2.92231786       0.29454555         9.92145
DQ                  -0.28997335       0.03178411        -9.12322
EWE_BRD.R           -0.45429429       0.26644819        -1.70500
RAM_BRD.R           -0.41303768       0.17553472        -2.35303
```

Model 2:

Response variable: WEANWT
Fixed effects: YEAR., SEX., AGEWEAN, DL, DQ, EWE_BRD., RAM_BRD.
Random effect EWE_ID

The following command can be used

```
> fit3<- lmer2 (WEANWT~ YEAR. + SEX. + AGEWEAN + DL + DQ + EWE_BRD. +    RAM_BRD. +
(1|EWE_ID.), data4)
> print (fit3, digits = 6, corr = FALSE)
```

Output for Model 2:

```
Linear mixed-effects model fit by REML
Formula: WEANWT ~ YEAR. + SEX. + AGEWEAN + DL + DQ + EWE_BRD. + RAM_BRD. +      +(1 |
EWE_ID.)
   Data: data4
    AIC       BIC          logLik       MLdeviance      REMLdeviance
 3108.27    3167.44 -1541.14       3052.96          3082.27
Random effects:
 Groups           Name        Variance     Std.Dev.
 EWE_ID.          (Intercept) 1.4459       1.2025
 Residual                     3.4968       1.8700
Number of obs: 700, groups: EWE_ID., 358


Fixed effects:
                    Estimate              Std. Error            t value
(Intercept)         0.21857708            1.02529945             0.21318
YEAR.92             -1.59573821           0.26385732            -6.04773
YEAR.93             -1.09095617           0.25726325            -4.24062
```

```
YEAR.94      -3.00646582    0.33904721    -8.86740
YEAR.95      -3.29914481    0.33738317    -9.77863
YEAR.96      -2.43996697    0.38734058    -6.29928
SEX.M         0.40574300    0.16248633     2.49709
AGEWEAN       0.06586956    0.00859359     7.66497
DL            2.92107276    0.29561856     9.88122
DQ           -0.29023253    0.03190402    -9.09705
EWE_BRD.R    -0.46497519    0.26654803    -1.74443
RAM_BRD.R    -0.42009128    0.16357811    -2.56814
>
```

Model 3:

Response variable: WEANWT
Fixed effects: YEAR., SEX., AGEWEAN, DL, DQ, EWE_BRD., RAM_BRD.
Random effect RAM_ID

The following command can be used

```
> fit4<- lmer2 (WEANWT~ YEAR. + SEX. + AGEWEAN + DL + DQ + EWE_BRD. +   RAM_BRD. +
(1|RAM_ID.), data4)
> print (fit4, digits = 6, corr = FALSE)
```

Output for Model 2:

```
Linear mixed-effects model fit by REML
Formula: WEANWT ~ YEAR. + SEX. + AGEWEAN + DL + DQ + EWE_BRD. + RAM_BRD. +    +(1
|RAM_ID.)
  Data: data4
   AIC      BIC          logLik        MLdeviance      REMLdeviance
 3146.26  3205.42    -1560.13        3091.53            3120.26
Random effects:
 Groups       Name          Variance         Std.Dev.
 RAM_ID.      (Intercept)   1.0629e-07       0.00032603
 Residual                   4.9327e+00       2.22096926

Number of obs: 700, groups: RAM_ID., 74

Fixed effects:
              Estimate       Std. Error       t value
(Intercept)   0.27400479     1.06513341       0.25725
YEAR.92      -1.56583097     0.29294938      -5.34506
YEAR.93      -1.09578091     0.27526834      -3.98077
YEAR.94      -2.83250132     0.35750389      -7.92299
YEAR.95      -3.22836683     0.34363048      -9.39488
YEAR.96      -2.35110107     0.38975131      -6.03231
SEX.M         0.47791031     0.16949755       2.81957
AGEWEAN       0.07021659     0.00885624       7.92849
DL            2.72635497     0.31501182       8.65477
DQ           -0.26888211     0.03400664      -7.90675
EWE_BRD.R  -0.58553622       0.23655431      -2.47527
RAM_BRD.R  -0.44286637       0.17276813      -2.56336
>
```

Now to test the 3 models to see which is the most appropriate, one can use the function "**anova**"

```
> anova(fit2,fit3,fit4)
```

```
Data: data4
Models:
fit3: WEANWT ~ YEAR. + SEX. + AGEWEAN + DL + DQ + EWE_BRD. + RAM_BRD. +
fit4:     (1 | EWE_ID.)
fit2: WEANWT ~ YEAR. + SEX. + AGEWEAN + DL + DQ + EWE_BRD. + RAM_BRD. +
fit3:     (1 | RAM_ID.)
fit4: WEANWT ~ YEAR. + SEX. + AGEWEAN + DL + DQ + EWE_BRD. + RAM_BRD. +
fit2:     (1 | RAM_ID.) + (1 | EWE_ID.)
         Df   AIC      BIC     logLik     Chisq    Chi Df   Pr(>Chisq)
fit3.p   13  3079.0   3138.1  -1526.5
fit4.p   13  3117.5   3176.7  -1545.8     0.000      0
fit2.p   14  3080.7   3144.4  -1526.4    38.814      1      4.661e-10 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Warning message:
NaNs produced in: pchisq(q, df, lower.tail, log.p)
```

Though ram contributes genetically to the variation in the lamb slightly, we may choose Model 3 (with only ewe as the random effect) on the basis of its low values of AIC and BIC.

Comparison of the Ram_ID and EWE_ID variance components in Model 1 indicates that the variance component for ewes (1.46), rams (0.07) and residual (3.43). With the random terms (ewe and ram) included in the model, the variance reduced from 4.90 to 3.43.

With only ewe as random term in the Model 2, the variance component for ewes is (1.45) and residual is (3.50).

The mixed model with ewe component alone included utilizes almost equivalent information as the mixed model with both ewe and ram component included.

But our main objective was to examine the incorporation of random effects to study variations among rams (sires) and ewes (dams) and their influence on lamb weaning weight. Thus to achieve this goal we may choose Model 1 since it contains both rams and ewes.