Paper 276-25

Mixed Models Analysis Using JMP® Software 4.0

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ABSTRACT

The analysis of most designed experiments and observational studies require mixed models. Version 4.0 of JMP Software has greatly expanded its capabilities for analyzing mixed models by including restricted maximum likelihood (REML) methods. This paper will demonstrate the process of analyzing several mixed models using the 4.0 version of JMP. Models examined include randomized complete block designs, incomplete block designs, split plot designs, strip plot designs, and designs with random covariates, where examples are drawn from engineering, medicine and agriculture. Version 4.0 of JMP can fit many of the standard mixed models and the analysis provides estimation of the variance components, estimates of the fixed effect parameters, tests of hypothesis about the fixed effects parameters, appropriate estimated standard errors, confidence intervals about variance components using REML, and least squares means and comparisons. The functionality of JMP is contrasted with that of PROC MIXED of the SAS® System. The mixed model capability of JMP provides the data analyst with the tools to enable appropriate analysis of many mixed models. This presentation is geared toward the practicing statistician.

JMP BACKGROUND

JMP was first released in 1989 on the Mac only. In April of 1995, JMP was released for Windows 3.1, Windows 95, and WindowsNT.

COMMON JMP NOTATION

The interface of JMP is a point and click process. The data are in a spread sheet format where the variables can be designated as continuous, nominal or ordinal. The modeling process consists of selecting the data variable, the treatment variables and the blocking variables. Main effects and interactions can be inserted into the model and effects are designated either as random or fixed. Many types of analyses can be computed by menu selections.

FUNCTIONALITY OF MIXED MODELS IN JMP

A linear model is called a mixed model if there is more than one variance component in the model. The modeling process of JMP uses the designation of variables to construct an appropriate model. When an effect or interaction of effects is declared as random, a variance component is inserted in the model and REML estimates of the variance components are by default computed. Traditional Method of Moments is an alternative method to REML where a table of expected mean squares is provided for each source of variation along with a table of the Test Denominator Synthesis. Both methods construct the appropriate F-statistics to test hypotheses about the fixed effects and random effects in the model. Estimates of contrasts of the fixed effects can be evaluated as well as the least squares means. JMP does not offer options for alternative denominators or degrees of freedom. For split-plot and repeated measure designs, only error structures that can be constructed from combining independent random effects can be considered. More complex correlation structures cannot be evaluated. Thus only correlation structures that are equivalent to compound symmetry are possible.

The following sections present the analysis of a collection of examples taken from Milliken and Johnson (1992) and Littel, et. al. (1996) by using the functionality of JMP. The results are compared to the analyses of the identical models using PROC MIXED of the SAS® system.

RANDOMIZED COMPLETE BLOCK DESIGNS

The simplest mixed model is for describing data from a one-way treatment structure in a randomized complete block design structure. (See Chapter 4 of Milliken and Johnson for a discussion of treatment and design structures). The blocks are random effects, thus there are two variance components in the model. A model used to describe data from this design is

$y_{ij} = \mu + \tau_i + b_j + \varepsilon_{ij}$, i=1,2,...,t, j=1,2,...,b
where $b_j \sim$ iid $N(0, \sigma_b^2)$ and $\varepsilon_{ij} \sim$ iid $N(0, \sigma_\varepsilon^2)$.

An appropriate analysis for this model will provide estimates of the variance components, F_b^2 and F_ε^2, and estimates and comparisons of the treatment means. The data set in section 1.3.4 of Littell, et al, is used to demonstrate the use of JMP.

To run this in JMP, you can either operate from the menus or run a script. To run this model from the menus,

open the rcb.jmp datatable,
select Fit Model from the Analyze menu,
select *Pressure* as the Y variable,
select *metal* and *ingot*, then click Add
while selecting ingot in the model section, select Random Effect from the Attributes popup selection,
click Run Model

To run this model from a script, open the rcb.jmp datatable and submit the script:

```
Fit Model(  Y(pressure),
     Effects(metal, ingot & Random),
     Personality(Standard Least Squares),
     Run Model( ));
```

The equivalent SAS statements used to generate this output are:

```
Proc varcomp method=reml data=rcb;
     Class ingot metal;
     Model pres=metal ingot/fixed=1;
Run;
```

JMP results:

Analysis of Variance

Source	DF	SS	Mean Square	F Ratio
Model	8	337.96095	42.2451	4.0732
Error	12	124.45905	10.3716	Prob > F
C. Total	20	524.64952		0.0146

REML Variance Component Estimates

Random Effect	Var Ratio	Var Component	Std Err
ingot&R	1.10376	11.447778	10.5394
Residual		10.371587	
Total		21.819365	

REML Variance Component Estimates (continued)

Random Effect	95% Lower	95% Upper	% of Total
ingot&R	3.3289	280.0102	52.466
Residual			47.534
Total			100.000

-2 LogLikelihood = 109.98743

Effect Tests

Source	DF	DFDen	SS	F Ratio	Prob > F
metal	2	12	131.90095	6.3588	0.0131
ingot&R	6	12	206.06000	3.3113	0.0368S

Tests on Random effects refer to shrunken predictors rather than traditional estimates.

Least Squares Means Table

Level	Least Sq Mean	Std Error	Mean
c	70.185714	1.7655175	70.1857
i	75.900000	1.7655175	75.9000
n	71.100000	1.7655175	71.1000

LSMeans Differences Student's t

LSMean[i] By LSMean[j]   Alpha= 0.050   Q=2.17881

Mean[i]-Mean[j] Std Err Dif Lower CL Dif Upper CL Dif	c	i	n
c	0 0 0 0	-5.7143 1.72143 -9.465 -1.9636	-0.9143 1.72143 -4.665 2.83638
i	5.71429 1.72143 1.96362 9.46495	0 0 0 0	4.8 1.72143 1.04933 8.55067
n	0.91429 1.72143 -2.8364 4.66495	-4.8 1.72143 -8.5507 -1.0493	0 0 0 0

INCOMPLETE BLOCK DESIGN EXAMPLE

Incomplete block designs are very useful efficient designs. The model is similar to the RCB model, except not all possible block-treatment combinations are observed. There are several types of incomplete block designs from balanced incomplete blocks where each pair of treatments occur together within a block the same number of times, partially balanced incomplete block designs and just unbalanced incomplete block designs. As with the RCB design structure, the blocks are considered to be random effects. Thus the incomplete block design model involves two variance components and is a mixed model. The main advantage of using a mixed models approach to analyzing incomplete block data is that the process combines the intra and inter block information about the treatments in to common estimates. A model that can be used to describe data from a one-way treatment structure in an incomplete block design structure is

$y_{ij} = \mu + \tau_i + b_j + \varepsilon_{ij}$, $(i,j) \in$ {observed block-treatment combinations}
where $b_j \sim$ iid $N(0, \sigma_b^2)$ and $\varepsilon_{ij} \sim$ iid $N(0, \sigma_\varepsilon^2)$.

The example in Section 1.5.2 of Littell, et al, is used to demonstrate the use of JMP.

To run this in JMP, open the pbib.JMP data table and run the following script:

```
Fit Model(  Y( Y),
     Effects( block&Random, treatment),
     Personality(Standard Least Squares),
     Run Model( ));
```

The equivalent SAS Statements used to generate this output are:

```
Proc mixed data=pbib;
     class blk treat;
     model response=treat;
     random blk;
     lsmeans treat / pdiff;
```

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	28	5.1491711	0.183899	2.1494
Error	31	2.6523340	0.085559	Prob > F
C. Total	59	8.9993333		0.0200

Effect Tests

Source	DF	DFDen	SS	F Ratio	Prob > F
block&R	14	31	2.154838	1.7990	0.0851S
treatment	14	31	1.834055	1.5312	0.1576

Tests on Random effects refer to shrunken predictors rather than traditional estimates.

REML Variance Component Estimates

Random Effect	Var Ratio	Var Comp	Std Error
block&R	0.5437407	0.046522	0.03261
Residual		0.085559	
Total		0.132081	

REML Variance Component Estimates (continued)

Random Effect	95% Lower	95% Upper	% of Total
block&R	0.01680	0.37393	35.222
Residual			64.778
Total			100.000

-2 LogLikelihood = 57.400994

Least Squares Means Table

Level	Least Sq Mean	Std Error	Mean
1	2.4479522	0.13151175	2.37500
2	2.6351082	0.13151175	2.65000
3	2.7357744	0.13151175	2.55000
4	2.7849291	0.13151175	2.72500
5	3.1232422	0.13151175	3.40000
6	2.9577418	0.13151175	3.10000
7	2.6536110	0.13151175	2.67500
8	2.5719419	0.13151175	2.42500
9	2.7517696	0.13151175	2.67500
10	2.6557732	0.13151175	2.65000
11	2.6122811	0.13151175	2.47500
12	2.6529338	0.13151175	2.62500
13	2.9682550	0.13151175	3.25000
14	2.7200949	0.13151175	2.67500
15	2.7785914	0.13151175	2.80000

SPLIT PLOT DESIGN EXAMPLE

The split-plot design is an incomplete block design involving at least a two-way treatment structure where more than one size of experimental unit is constructed because of the method of assigning the treatment combinations to the blocks. Generally, the treatment combinations within an incomplete block all have the same level of one of the factors (say factor A) with all levels of the other factor (say factor b). This assignment process generates the two sizes of experimental units where the incomplete blocks are the experimental units for the levels of factor A and the units within each block are the experimental units for the levels of factor B. These designs have models that involve at least two variance components, and most applications of split-plot designs have models with more than two variance components. A model to describe data from a two-way treatment structure in a split-plot design structure with randomized complete blocks in the whole-plot part of the model is

$y_{ij} = \mu + \tau_i + b_j + a_{ij} + \theta_k + (\tau\theta)_{ik} + \varepsilon_{ijk}$, $i=1,2,\ldots,t$, $j=1,2,\ldots,b$, $k=1,2,..,p$
where $b_j \sim$ iid $N(0, \sigma_b^2)$, $a_{ij} \sim$ iid $N(0, \sigma_a^2)$ and $\varepsilon_{ijk} \sim$ iid $N(0, \sigma_\varepsilon^2)$.

This model involves three variance components (σ_b^2, σ_a^2, and σ_ε^2) and the main effects and interactions of the levels of two factors. The examples in Chapter 24 of Milliken and Johnson, and in Chapter 2 of Littell, et al are used to demonstrate the functionality of JMP for providing the analysis of split-plot type designs.

To run this model in JMP, open the Variety Trials datatable and submit the following script:

```
Fit Model(Y(dry wt),
     Effects(cultivar, inoculation,
     cultivar*inoculation,  block & Random,
     block * cultivar & Random),
     Personality(Standard Least Squares),
     Run Model);
```

The equivalent SAS statements used to generate this output are:

```
Proc mixed data=a;
     class block cult inoc;
     model drywt = cult inoc cult*inoc/
     ddfm=satterth;
     Random block block*cult;
     Lsmeans cult;
```

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	11	152.97583	13.9069	19.7144
Error	12	8.46500	0.7054	Prob > F
C. Total	23	165.67333		<.0001

REML Variance Component Estimates

Random Effect	Var Ratio	Var Comp	Std Err
block&R	1.2474897	0.88	1.27794
block*cult&R	1.159874	0.818194	0.96156
Residual		0.705417	
Total		2.403611	

REML Variance Component Estimates (continued)

Random Effect	95% Lower	95% Upper	% of Total
block&R	0.17098	1288.5513	36.612
block*cult&R	0.19251	109.20548	34.040
Residual			29.348
Total			100.000

-2 LogLikelihood = 73.615949

Effect Tests

Source	Nparm	DF	DFDen	SS	F Ratio	Prob > F
cultivar	1	1	3	0.53725	0.7616	0.4471
inoculation	2	2	12	118.17583	83.7631	<.0001
cultivar*inoc	2	2	12	1.82583	1.2942	0.3098
block&R	4	3	3	3.53601	1.6709	0.3418S
block*cult&R	8	3	12	8.23161	3.8897	0.0374S

Tests on Random effects refer to shrunken predictors rather than traditional estimates.

Effect Details:
Least Squares Means Tables

cultivar

Level	Least Sq Mean	Std Error	Mean
a	30.100000	0.69522179	30.1000
b	30.733333	0.69522179	30.7333

inoculation

Level	Least Sq Mean	Std Error	Mean
con	27.962500	0.64066480	27.9625
dea	29.950000	0.64066480	29.9500
liv	33.337500	0.64066480	33.3375

cultivar*inoculation

Level	Least Sq Mean	Std Error
a,con	27.900000	0.77517919
a,dea	29.250000	0.77517919
a,liv	33.150000	0.77517919
b,con	28.025000	0.77517919
b,dea	30.650000	0.77517919
b,liv	33.525000	0.77517919

block&Random

Level	Least Sq Mean	Std Error	Mean
1	30.979700	0.61544754	31.3167
2	31.042259	0.61544754	31.4167
3	30.166430	0.61544754	30.0167
4	29.478278	0.61544754	28.9167

block*cultivar&Random

Level	Least Sq Mean	Std Error
1,a	30.562287	0.45616333
1,b	31.920602	0.45616333
2,a	30.420899	0.45616333
2,b	32.245274	0.45616333
3,a	30.277169	0.45616333
3,b	29.823029	0.45616333
4,a	29.139646	0.45616333
4,b	28.944428	0.45616333

If you select EMS (traditional) rather than REML (recommended), you will also see the EMS table in the output:

Expected Mean Squares
The Mean Square per row by the Variance Component per column

EMS	Intercept	cult	inoc	cult*inoc	block&R	block* cultivar&R
Intercept	0	0	0	0	0	0
cultivar	0	12	0	4	0	3
inoculation	0	0	8	4	0	0
cultivar*inoc	0	0	0	4	0	0
block&R	0	0	0	0	6	3
block*cult&R	0	0	0	0	0	3

plus 1.0 times Residual Error Variance

STRIP PLOT DESIGN EXAMPLE

The strip-plot design has some of the features of a split-plot design and some features of a Latin square design. The experimental units are arranged into a rectangle and the levels of one factor are assigned to the rows of the rectangle and the levels of the other factor are assigned to the columns of the rectangle. Thus there are three sizes of experimental units, the row, the column and the cell of the rectangle. Generally these designs are conducted such that there are several rectangles and each rectangle forms a block. The resulting model consists of at least four variance components. A model to describe a two-way treatment structure in a strip-plot design structure conducted in several blocks (rectangles) is

$y_{ij} = \mu + b_k + \tau_i + r_{ik} + \theta_j + c_{jk} + (\tau\theta)_{ij} + \varepsilon_{ijk}$, i=1,2,...,t, j=1,2,...,b, k=1,2,..,p
where $b_k \sim$ iid $N(0, \sigma_b^2)$, $r_{ik} \sim$ iid $N(0, \sigma_r^2)$, $c_{jk} \sim$ iid $N(0, \sigma_c^2)$ and $\varepsilon_{ijk} \sim$ iid $N(0, \sigma_\varepsilon^2)$.

The r_{ik} denotes the random effect associated with the rows of a rectangle, c_{jk} denotes the random effect associated with the columns of a rectangle, and ε_{ijk} denotes the random effect associated with the cells of a rectangle. The example of Chapter 25 of Milliken and Johnson is used to demonstrate the analysis of a strip-plot design using the mixed model capabilities of JMP.

To run this model in JMP, open the Field.JMP data table and submit the following script:

```
Fit Model(Y( Y),
     Effects(Nitrogen, Irrigation,
     Nitrogen*Irrigation, Rep &Random,
     Rep*Nitrogen &Random, Rep*Irrigation
     &Random),
     Personality(Standard Least Squares),
     Run Model);
```

The equivalent SAS statements used to generate this output are:

```
Proc mixed cdl covtest method=reml data=ex25;
   class rep n irr;
   model y = n|irr/ddfm=satterth;
   random rep re*n irr*rep;
   lsmeans n|irr;
```

JMP results:

Effect Tests

Source	DF	DFDen	SS	F Ratio	Prob > F
Nitrogen	2	6	172.04721	60.1330	0.0001
Irrigation	1	3	74.64882	52.1817	0.0055
Nitrogen*Irrigation	2	6	94.75000	33.1165	0.0006
Rep&R	3	3	10.04453	2.3405	0.2516S
Rep*Nitrogen&R	6	6	8.48323	0.9883	0.5055S
Rep*Irrigation&R	3	6	29.78806	6.9409	0.0223S

Tests on Random effects refer to shrunken predictors rather than traditional estimates.

REML Variance Component Estimates

Random Effect	Var Ratio	Var Comp	Std Error
Rep&R	3.3592232	4.8055555	6.371898
Rep*Nitro&R	0.4854369	0.6944444	1.151033
Rep*Irrig&R	2.2135922	3.1666667	3.643519
Residual		1.4305556	
Total		10.097222	

REML Variance Component Estimates (continued)

Random Effect	95% L	95% U	% of Total
Rep&R	1.01428	2195.968	47.593
Rep*Nitro&R	0.11962	8775.817	6.878
Rep*Irrig&R	0.75928	351.3305	31.362
Residual			14.168
Total			100.000

-2 LogLikelihood = 94.647063

Effect Details:
Least Squares Means Tables

Nitrogen

Level	Least Sq Mean	Std Error	Mean
1	68.250000	1.3962997	68.2500
2	71.750000	1.3962997	71.7500
3	77.375000	1.3962997	77.3750

Irrigation

Level	Least Sq Mean	Std Error	Mean
1	67.583333	1.4731391	67.5833
2	77.333333	1.4731391	77.3333

Nitrogen*Irrigation

Level	Least Sq Mean	Std Error
1,1	61.500000	1.5888063
1,2	75.000000	1.5888063
2,1	66.000000	1.5888063
2,2	77.500000	1.5888063
3,1	75.250000	1.5888063
3,2	79.500000	1.5888063

Rep&Random

Level	Least Sq Mean	Std Error	Mean
1	69.801735	1.2618435	68.6667
2	73.888809	1.2618435	74.5000
3	73.421715	1.2618435	73.8333
4	72.721074	1.2618435	72.8333

Rep*Nitrogen&Random

Level	Least Sq Mean	Std Error
1,1	64.747044	1.3244780
1,2	69.724877	1.3244780
1,3	74.549384	1.3244780
2,1	69.605703	1.3244780
2,2	73.352009	1.3244780
2,3	78.915432	1.3244780
3,1	69.444516	1.3244780
3,2	72.451906	1.3244780
3,3	78.507940	1.3244780
4,1	69.202736	1.3244780
4,2	71.471209	1.3244780
4,3	77.527244	1.3244780

Rep*Irrigation&Random

Level	Least Sq Mean	Std Error
1,1	62.494261	0.81288648
1,2	75.358619	0.81288648
2,1	70.390459	0.81288648
2,2	78.329785	0.81288648
3,1	68.610636	0.81288648
3,2	78.867624	0.81288648
4,1	68.837978	0.81288648
4,2	76.777305	0.81288648

PURE RANDOM EFFECTS MODEL (GAGE R&R)

Gage R&R studies are very important to the development of a measurement system of a process or instrument. Such models involve selecting a random sample of units to measure and then measuring the unit at several randomly selected places, generally more than once. The resulting data can be analyzed using a random effects model where there are two or more variance components. A model to describe data from a three level nested sampling process is

$y_{ij} = \mu + b_i + r_{j(i)} + \varepsilon_{k(ij)}$, i=1,2,...,t, j=1,2,...,b, k=1,2,..,p
where b_j ~ iid $N(0, \sigma_b^2)$, $r_{j(i)}$ ~ iid $N(0, \sigma_r^2)$, and $\varepsilon_{k(ij)}$ ~ iid $N(0, \sigma_\varepsilon^2)$.

The estimation of the variance components and functions of the variance components are of main interest. A data set from a gage R&R study is used to demonstrate the process of analyzing the data set using JMP.

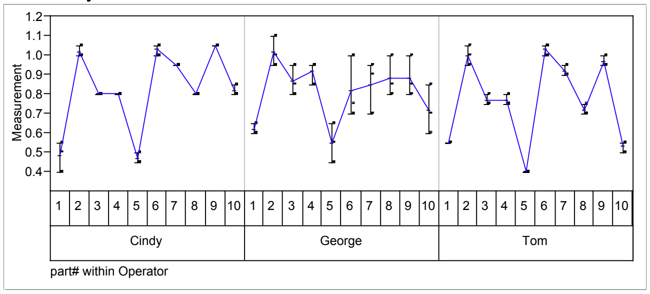
Open the data table, *2 factors crossed,* and either submit the following script or choose Variability Chart from the Graph menu and select Measurement as the Y and Operator and Part as Grouping variables.

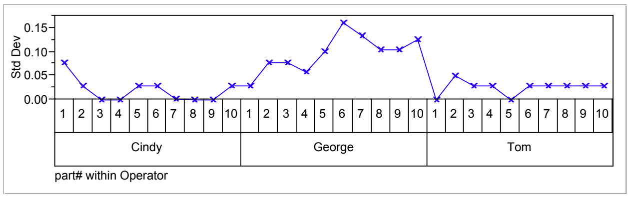
```
Variability Chart(Y(Measurement),
     X(Operator, part#), Show Points(1),
     Std Dev Chart(1), Gage R R(5.15, .),
     Variance Components(Crossed));
```

To replicate the results in SAS, please refer to page 1565 (Appendix 1) in the SAS/QC Usage & Reference 2 for a description on running the Gage application in SAS.

JMP results:

Variability Chart for Measurement





Analysis of Variance

Source	DF	SS	MS	F Ratio	Prob > F
Operator	2	0.054889	0.02744	1.3150	0.29306
part#	9	2.633583	0.29262	14.0209	0.00000
Operator*part#	18	0.375667	0.02087	5.0425	0.00000
Within	60	0.248333	0.00414		

Variance Components

Component	Var Comp	% of Total	Sqrt(Var Comp)
Operator	0.00021914	0.55	0.01480
part#	0.03019444	75.24	0.17377
Operator*part#	0.00557716	13.90	0.07468
Within	0.00413889	10.31	0.06433

Gage R&R

Measurement			= k*sqrt()
Repeatability (EV)	0.3313211	Equipment Variation	V(W)
Reproducibility (AV)	0.0762367	Appraiser Variation	V(Operator)
Operator * Part (IV)	0.3846040	Interaction Variation	V(Oper*Part)
Gage R&R (RR)	0.5133283	Measurement Variation	V(W)+V(Oper)+ V(Oper*Part)
Part Variation (PV)	0.8948923	Part Variation	V(Part)
Total Variation (TV)	1.0316676	Total Variation	V(W)+V(Oper)+ V(Oper*Part)+V (Part)

5.15	k
0.24758	% Gage R&R = 100*(RR/TV)^2
0.57362	Precision to Process Width Ratio = (RR/PV)^2

Using column 'Operator' for Operator, and column 'part#' for Part.

COMPLEX DESIGN (SPLIT-STRIP W/RANDOM COVARIATE)

The final example uses a complex strip-split plot involving a three-way treatment structure where there is a covariate measured on the cell of the rectangle of the strip-plot part of the design. The analysis of this complex design demonstrates the complexity of models that can be analyzed by using JMP. A model used to describe a three-way treatment structure in a strip-split-plot design structure where the levels of A are assigned to the rows of each rectangle, the levels of B are assigned to the columns of each rectangle, and the levels of C are assigned to the sub-plots within each cell of each rectangle and a covariate is measured on each cell is

$y_{ij} = \mu + b_k + \tau_i + r_{ik} + \theta_j + c_{jk} + (\tau\theta)_{ij} + e_{ijk} + \beta x_{ijk} + \rho_m + (\tau\rho)_{im} + (\theta\rho)_{jm} + (\tau\theta\rho)_{ijm} + \varepsilon ijm$, i=1,2,...,t, j=1,2,...,b, k=1,2,..,p

where $b_j \sim$ iid $N(0, \sigma_b^2)$, $r_{ik} \sim$ iid $N(0, \sigma_r^2)$, $c_{jk} \sim$ iid $N(0, \sigma_c^2)$, $e_{ijk} \sim$ iid $N(0, \sigma_e^2)$ and $\varepsilon_{ijk} \sim$ iid $N(0, \sigma_\varepsilon^2)$.

This complex model involves five variance components and the analysis encompasses investigating the main effects and interactions among the levels of the three factors. Since there are several error terms, it is imperative that appropriate combinations of the variance components be used in evaluating the fixed effects. The data set from Example 10.5 of Littell, et al is analyzed.

To run this model in JMP, open the Range data table and run the following script:

```
Fit Model(Y(Y),
     Effects(Erosion Control, Irrigation,
     Erosion Control*Irrigation, Variety,
     Erosion Control*Variety, Irrigation
     *Variety, Erosion Control*Irrigation
     *Variety, Location&Random, Location
     *Erosion Control&Random, Location*
     Irrigation&Random, Location*Irrigation*
     Erosion Control&Random),

     Personality(Standard Least Squares),
     Run Model);
```

The equivalent SAS code is:

```
proc mixed data=range;
     class loc ec ir v;
     model y = ec ir ec*ir v v*ec v*ir
     v*ec*ir/ddfm=satterth;
     random loc loc*ec loc*ir loc*ec*ir;
     lsmeans ic ir ec*ir v v*ec v*ir v*ec*ir;
```

Results:

REML Variance Component Estimates

Random Effect	Var Ratio	Var Comp	Std Error
Location&R	21.089167	77.898112	91.7976
Location*EC&R	0.4196277	1.55	6.11881
Location* Irrigation&R	1.3875916	5.1254167	9.5874
Location* Irrigation*EC&R	1.3659898	5.045625	7.7060
Residual		3.6937501	
Total		93.312904	

REML Variance Component Estimates (continued)

Random Effect	95% Lower	95% Upper	% of Total
Location&R	18.28419	10654.386	83.481
Location*EC&R	0.141594	1.5563e24	1.661
Location* Irrigation&R	0.791845	854876.41	5.493
Location* Irrigation*EC&R	0.936307	15648.721	5.407
Residual			3.958
Total			100.000

-2 LogLikelihood = 112.58582

Effect Tests

Source	DF	DFDen	SS	F Ratio	Prob > F
EC	1	2	157.03936	42.5149	0.0227
Irrigation	1	2	1.72442	0.4668	0.5650
EC*Irrigation	1	2	0.57878	0.1567	0.7305
Variety	1	8	167.48167	45.3419	0.0001
EC*Variety	1	8	9.88167	2.6752	0.1406
Irrigation*Variety	1	8	49.88167	13.5043	0.0063
EC*Irrigation *Variety	1	8	0.73500	0.1990	0.6674
Location&R	2	2	113.71100	15.3924	0.0610S
Location*EC &R	2	2	3.39230	0.4592	0.6853S
Location*Irrigation&R	2	2	11.22250	1.5191	0.3970S
Location*Irrigation*EC&R	2	8	30.91266	4.1845	0.0571S

Tests on Random effects refer to shrunken predictors rather than traditional estimates.

Effect Details:
Least Squares Means Tables

Erosion Control

Level	Least Sq Mean	Std Error	Mean
1	27.966667	5.3371987	27.9667
2	39.866667	5.3371987	39.8667

Irrigation

Level	Least Sq Mean	Std Error	Mean
1	33.100000	5.3927352	33.1000
2	34.733333	5.3927352	34.7333

Erosion Control*Irrigation

Level	Least Sq Mean	Std Error
1,1	27.450000	5.5216552
1,2	28.483333	5.5216552
2,1	38.750000	5.5216552
2,2	40.983333	5.5216552

Variety

Level	Least Sq Mean	Std Error	Mean
1	31.275000	5.2732237	31.2750
2	36.558333	5.2732237	36.5583

Erosion Control*Variety

Level	Least Sq Mean	Std Error
1,1	25.966667	5.3659578
1,2	29.966667	5.3659578
2,1	36.583333	5.3659578
2,2	43.150000	5.3659578

Irrigation*Variety

Level	Least Sq Mean	Std Error
1,1	29.016667	5.4211996
1,2	37.183333	5.4211996
2,1	33.533333	5.4211996
2,2	35.933333	5.4211996

Erosion Control*Irrigation*Variety

Level	Least Sq Mean	Std Error
1,1,1	23.833333	5.5771230
1,1,2	31.066667	5.5771230
1,2,1	28.100000	5.5771230
1,2,2	28.866667	5.5771230
2,1,1	34.200000	5.5771230
2,1,2	43.300000	5.5771230
2,2,1	38.966667	5.5771230
2,2,2	43.000000	5.5771230

CONCLUSION

Version 4.0 brings JMP more mature mixed models abilities. Many of the models and options available in proc mixed of SAS are now available in JMP. Available models include, but certainly are not limited to randomized complete block designs, incomplete block designs, split plot designs, strip plot designs, and designs with random covariates.

REFERENCES

Littell,, Ramon C., Milliken, George. A., Stroup, Walter W., and Wolfinger, Russell D., *SAS® System for Mixed Models*, Cary, NC: SAS Institute, Inc., 1996.

Milliken, George A. and Johnson, Dallas E., Analysis of Messy Data: Designed Experiments, Vol I., London: Chapman Hall, 1992.

TRADEMARKS

CONTACT INFORMATION

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