The first DESIGN specification requests an analysis of variance for this experiment (Figure 1.26b).

Figure 1.26b

TESTS OF SIGNIFICANCE FOR DEP USING SEQUENTIAL SUMS OF SQUARES

SOURCE OF VARIATION	SUM OF SQUARES	DF	MEAN SQUARE	F	SIG. OF F
RESIDUAL	8909.36190	43	207.19446		
CONSTANT	461120.05556	1	461120.05556	2225.54237	0.0
REPLICS	3836.61111	3	1278.87037	6.17232	.001
BLOCKS WITHIN REPLICS	2836.33333	8	354.54167	1.71115	.123
A	1116.02778	2	558.01389	2.69319	.079
B	253.69444	2	126.84722	.61221	.547
C	868.05556	1	868.05556	4.18957	.047
A BY B	1129.34921	4	282.33730	1.36267	.263
A BY C	2995.02778	2	1497.51389	7.22758	.002
B BY C	423.52778	2	211.76389	1.02205	.368
A BY B BY C	1015.95556	4	253.98889	1.22585	.314

The second and third analyses give the AB and AC two-way means adjusted for the block effects (Figure 1.26c). For more information about the use of CONSPLUS to obtain marginal means and summary tables, see Section 1.50.

Figure 1.26c

CONSPLUS A AND B

PARAMETER	COEFF.	STD. ERR.	T-VALUE	SIG. OF T	LOWER .95 CL	UPPER .95 CL
12	72.1964285714	6.02764	11.97757	0.0	60.10109	84.29176
13	73.2261904762	6.02764	12.14841	0.0	61.13086	85.32152
14	79.7023809524	6.02764	13.22283	0.0	67.60705	91.79771
15	86.7738095238	6.02764	14.39600	0.0	74.67848	98.86914
16	87.8035714286	6.02764	14.56684	0.0	75.70824	99.89891
17	79.4226190476	6.02764	13.17641	0.0	67.32729	91.51795
18	89.0297619048	6.02764	14.77026	0.0	76.93443	101.12510
19	74.3452380952	6.02764	12.33406	0.0	62.24990	86.44057
20	77.7500000000	6.02764	12.89892	0.0	65.65467	89.84533

CONSPLUS A AND C

PARAMETER	COEFF.	STD. ERR.	T-VALUE	SIG. OF T	LOWER .95 CL	UPPER .95 CL
12	62.5833333333	4.21611	14.84385	0.0	54.13406	71.03261
13	87.5000000000	4.21611	20.75372	0.0	79.05073	95.94927
14	84.3333333333	4.21611	20.00264	0.0	75.88406	92.78261
15	85.0000000000	4.21611	20.16076	0.0	76.55073	93.44927
16	82.7500000000	4.21611	19.62709	0.0	74.30073	91.19927
17	78.0000000000	4.21611	18.50046	0.0	69.55073	86.44927

1.27 Split-plot Designs

In many factorial designs, it may not be possible to completely randomize the assignment of treatments to the experimental unit. Consider, for example, an experiment to compare three varieties of wheat (factor A) and two different types of fertilizer (factor B). Three locations are selected as blocks. Three levels of A are randomly assigned to plots of equal area within each block. After A is assigned, each plot is "split" into halves (called subplots) to receive the random assignment of B. What is the difference between a complete 3 × 2 factorial and the 3 × 2 split-plot design? In a 3 × 2 factorial, each block is divided into six subplots to receive the random assignment of treatment combinations of A and B. In the split-plot design, two treatment combinations that have the same level of A are always in the same plot. If the subplot is considered the experimental unit, the plot is a "small" block of size 2. The differences among these "small" blocks are the differences between levels of A, since the main effects of A are confounded. A split-plot design is a design in which certain main effects are confounded.

Intuitively, the variation of plots within A should be used as the error term to test for the main effects of A. The effects of plot within A can be partitioned into two parts. One is the block effects and another is the block and A interaction. Thus the model for a split-plot design is

$$Y_{ijk} = \mu + \alpha_i + \beta_k + (\alpha\beta)_{ik} + \gamma_j + (\alpha\gamma)_{ij} + \epsilon_{ijk}$$

where α_i is the A effect, β_k is the block effect, $(\alpha\beta)_{ik}$ is the interaction of A and block and is the error term for testing A, γ_j is the B effect, $(\alpha\gamma)_{ij}$ is the AB interaction, and ϵ_{ijk} is the residual used as the error term for testing B and AB.

Another model is

$$Y_{ijk} = \mu + \alpha_i + \beta_k + (\alpha\beta)_{ik} + \gamma_j + (\alpha\gamma)_{ij} + (\beta\gamma)_{jk} + (\alpha\beta\gamma)_{ijk} + \epsilon_{ijk}$$