Published July, 2001

STATISTICS

Interpreting Treatment × Environment Interaction in Agronomy Trials

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ABSTRACT

Multienvironment trials are important in agronomy because the effects of agronomic treatments can change differentially in relation to environmental changes, producing a treatment × environment interaction (T × E). The aim of this study was to find a parsimonious description of the T × E existing in the 24 agronomic treatments evaluated during 10 consecutive years by (i) investigating the factorial structure of the treatments to reduce the number of treatment terms in the interaction and (ii) using quantitative year covariables to replace the qualitative variable year. Multiple factorial regression (MFR) for specific T × E terms was performed using standard forward selection procedures for finding year covariables that could replace the factor year in those T × E terms. Subsequently, we compared the results of the final MFR with those of a partial least squares based analysis to achieve extra insight in both the T × E and final MFR model. The MFR model with a stepwise procedure used in this study for describing the T × E showed that the most important interaction with year was that due to different N fertilizer levels and the most important environmental variables that explained year × N interaction were minimum temperatures in January, February, and March and maximum temperature in April. Evaporation in December and April were important covariables for describing year × tillage and year × summer crop interactions, whereas precipitation in December and sun hours in February were important for explaining the year × manure interaction. We also discuss the parallels with extended additive main effect and multiplicative interaction analysis. Biological interpretation of the results are provided.

Multienvironment trials are important in plant breeding and agronomy for studying yield stability and predicting yield performance of genotypes and agronomic treatments across environments. The differential response of genotypes to environmental changes is a genotype × environment interaction (G × E). Like the effects of genotypes, the effects of agronomic treatments (or any other management practices) can change differentially in relation to environmental changes, producing a treatment × environment interaction (T × E). Statistical models for G × E (Crossa, 1990) are equally useful for T × E. Agronomist use multienvironment trials to compare combinations of agricultural production alternatives (treatments) such as N, plant density, organic fertilizers, and cropping systems and make recommendations to farmers about the superior treatments and their stability across environments.

The presence of T × E complicates the interpretation of the results and confounds the observed average performance of the agronomic treatments with their true values. Thus, significant resources in agronomy research are devoted to studying and interpreting T × E through replicated (or unreplicated) multienvironment trials. The standard analysis of variance for multienvironment trial data does not explore any underlying structure within the observed T × E and fails to determine patterns of response for agronomic treatments and environments. The simple regression of agronomic treatment means on the environment means (Yates and Cochran, 1938; Finlay and Wilkinson, 1963; Eberhart and Russel, 1966) models the T × E in one dimension by estimating a set of straight lines (one for each treatment over the environments). The heterogeneity of slopes accounts for the T × E; however, it usually explains only a small proportion of it and leaves a great deal of the T × E variability unexplained. The additive main effect and multiplicative interaction (AMMI) model (Kempton, 1984; Gauch, 1988) partitions the T × E in multiplicative components by means of the principal component analysis. The AMMI model describes the T × E in more than one dimension, and it offers better opportunities for studying and interpreting T × E than analysis of variance and regression on the mean.

Recently, statistical models that incorporate large number of external variables (environmental and genotypic variables) into the analysis of multienvironment trials have been used for studying and explaining G × E (Vargas et al., 1998; Vargas, et al., 1999; Crossa et al., 1999). Two of these models are the factorial regression (FR) model (Denis, 1988; van Eeuwijk et al., 1996) and the partial least squares (PLS) regression method (Aastveit and Martens, 1986). Multiplicative models for describing interaction, such as FR or AMMI, are useful because they usually use fewer degrees of freedom than the analysis of variance and they express the T × E as a string of product and (bilinear) terms. The results of the multiplicative decomposition obtained from PLS can be presented graphically in the form of a biplot with treatments, environments, and covariables represented

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Published in Agron. J. 93:949–960 (2001).

Abbreviations: A, April; AMMI, additive main effect and multiplicative interaction; D, December; EV, total monthly evaporation; F, February; FR, factorial regression; G × E, genotype × environment interaction; J, January; M, March; MFR, multiple factorial regression; mT, mean minimum temperature sheltered; MT, mean maximum temperature sheltered; mTU, mean minimum temperature unsheltered; N_L, linear N effects; N_Q, quadratic N effects; PLS, partial least squares; PR, total monthly precipitation; SH, mean sun hours per day; T × E, treatment × environment interaction.

as vectors in a two-dimensional space. Results from the AMMI analysis can also be represented in a biplot that can be enriched with some covariables so that a similar biplot as that obtained with the PLS can be obtained (Vargas et al., 1999).

Factorial regression models have two main advantages. One is that hypotheses related to the significance of the effects for the available external covariables can be tested. A second advantage is that standard selection procedures for variable subsets, like stepwise regression, can be used for model construction. Vargas et al. (1999) found, for two data sets, that FR combined with a stepwise forward selection procedure identified the same covariables as a PLS-based search procedure. One data set used by the authors consisted of several combinations of agronomic cultural practices: two levels of tillage, summer crop, and manure and three rates of N fertilization. The resulting 24 treatments were evaluated during 10 consecutive years, and the effect of several climatic covariables on the T × E were studied. However, this study did not investigate the interaction of the agronomic factors with years.

The aim of this study was to find a parsimonious description of the T × E existing in the 24 agronomic treatments evaluated during 10 consecutive years by (i) investigating the factorial structure of the treatments to reduce the number of treatment terms in the interaction and (ii) using quantitative year covariables to replace the qualitative variable year. We first retained only the most relevant factorial T × E terms by conventional *F* tests and by looking at the size of the interaction sum of squares that was explained by individual T × E terms. Next, we performed multiple factorial regression (MFR) for specific T × E terms using standard forward selection procedures for finding year covariables that could replace the factor year in those T × E terms. Subsequently, we compared the results of the final MFR with those of a PLS-based analysis to achieve extra insight in both the T × E and final MFR model. We also discuss the parallels with extended AMMI analyses.

MATERIALS AND METHODS

Statistical Models

A full description of the FR models and their applications for interpreting G × E using environmental and/or cultivar covariables are given in van Eeuwijk (1996). Vargas et al. (1998, 1999) described the theory of PLS in the context of G × E and gave details of its univariate and multivariate algorithm. Here, FR, PLS, and AMMI models are briefly described using, for simplicity, the same notation as Vargas et al. (1999).

A basic model for the analysis of the two-way table of treatment yield by environment data is the analysis of variance model that, in matrix notation, is given by

$$E(\mathbf{Y}) = \mu\mathbf{1_I}\mathbf{1_J}' + \tau\mathbf{1_J}' + \mathbf{1_I}\beta' + \tau\beta \qquad [1]$$

where E stands for expectation, $\mathbf{Y} = (y_{ij})$ is the data matrix of size I × J of the response variable (i.e., grain yield) of I treatments in J environments, μ is a scalar representing the grand mean, $\tau = (\tau_i)$ is a I × 1 vector of main effects of treatments, $\beta = (\beta_j)$ is a J × 1 vector of main effects of environments, and $\tau\beta = (\tau\beta)_{ij}$ is the I × J interaction matrix (not a vector product) where each element of the matrix specifies the interaction effect for the ith treatment in the jth environment. $\mathbf{1_I}$ and $\mathbf{1_J}$ are unit vectors of size I × 1 and J × 1, respectively. The common constraints are $\mathbf{1_I}'\tau = \mathbf{1_J}'\beta = 0$ and $\mathbf{1_I}'\tau\beta\mathbf{1_J}' = 0$.

Factorial Regression Models

The T × E is modeled directly in relation to environmental covariables (with the regression coefficient depending on the treatment) or in relation to treatment covariables (with the regression coefficient depending on the environment). A FR model for the mean of the ith treatment in the jth environment, for which the interaction includes G (centered) treatment covariables x_{i1} to x_{iG}, can be written in matrix notation as

$$E(\mathbf{Y}) = \mu\mathbf{1_I}\mathbf{1_J}' + \tau\mathbf{1_J}' + \mathbf{1_I}\beta' + \mathbf{X}\Gamma' \qquad [2]$$

where the fourth term on the right side of the equation (T × E) consists of the product of the known treatment covariables, x_{i1} to x_{iG} ($G \leq I - 1$), represented by the I × G matrix $\mathbf{X} = (x_{ig})$ and multiplied by the unknown environmental effects (or environmental potentialities), γ_{j1} to γ_{jG}, denoted by the J × G matrix $\mathbf{\Gamma} = (\gamma_{jg})$. Convenient constraints on the parameters are sum to zero over i for the parameters τ_i and over j for β_j and γ_{jg}. The treatment covariables are known, but the environmental potentialities should be estimated.

A FR model in which the T × E term contains H (centered) environmental covariables, z_{j1} to z_{jH}, can be written as

$$E(\mathbf{Y}) = \mu\mathbf{1_I}\mathbf{1_J}' + \tau\mathbf{1_J}' + \mathbf{1_I}\beta' + \boldsymbol{\zeta}\mathbf{Z}' \qquad [3]$$

where the fourth term on the right side of the equation (T × E) consists of the product of treatments having differential effects (sensitivity), ζ_{i1} to ζ_{iH} ($H \leq J - 1$), collected in the I × H matrix $\boldsymbol{\zeta} = (\zeta_{ih})$ and multiplied by the values of the environmental covariables that are collected in the J × H matrix $\mathbf{Z} = (z_{jh})$. The values of the environmental variables are known, but the treatment sensitivities need to be estimated.

Partial Least Squares Regression

The main objective of the PLS method is to identify a linear combination of the explanatory variables that gives latent vectors that optimally predict the response variable using an iterative procedure. The number of PLS factors to be retained is determined by a cross-validation procedure (Stone, 1974) and an *F* test proposed by Osten (1988). For the multivariate PLS, the response variable is represented by the matrix **Y** of treatment performance on environments, and the matrix $\mathbf{Z} = (\mathbf{z}_1,..., \mathbf{z}_S)$ represents *S* environmental explanatory variables, such as temperature and precipitation. These matrices can be expressed in a bilinear form as

$$\mathbf{Z} = \mathbf{TP}' + \mathbf{E} \qquad [4]$$

and

$$\mathbf{Y} = \mathbf{TQ}' + \mathbf{F} \qquad [5]$$

where Matrix **T** contains the Z scores, Matrix **P** has the Z loadings, Matrix **Q** contains the Y loadings, and **E** and **F** are the residual matrices. It is clear from Eq. [4] and [5] that the relationship between **Z** and **Y** is transmitted through the latent variables of Matrix **T**.

Therefore, when T × E is explained using *S* environmental covariables (**Z**), Vargas et al. (1999) described the above equations using the transpose of **Y** such that, for $\mathbf{T} = \mathbf{ZW}$ and $\boldsymbol{\zeta} = \mathbf{QW}'$, $E(\mathbf{Y}') = (\mathbf{TQ}')' = \mathbf{QW}'\mathbf{Z}' = \zeta\mathbf{Z}'$ (the same as the last term of Eq. [3]). The rows of Matrix **T** contain the Z scores indexed by environments; the rows of Matrix **W** have the Z weights indexed by the environmental covariables; the rows of the Matrix **Q** include the Y loadings indexed by treatments; and Matrix ζ has the PLS approximation to the regression coefficients of **Y** to the explanatory covariables **Z**.

Results of the bilinear decomposition obtained from PLS can be summarized in a graphical form that includes representation of treatments, environments, and covariables, i.e., Matrices **T**, **W**, and **Q** are shown in the same biplot. The PLS biplot approximates interactions of treatments on environments (projections of rows of **T** on the rows of **Q** or vice versa), and it also approximates regression coefficients of treatment (environments) on environmental (treatments) covariables (projection of rows of **W** on the rows of **Q** or vice versa). A perpendicular projection of the treatments on one environment vector, extended in either direction, gives the relative values of the treatments for the G × E.

Additive Main Effect and Multiplicative Interaction

The AMMI model (Gollob, 1968; Mandel, 1971; Kempton, 1984; Gauch, 1988), or biadditive model (Denis and Gower, 1994), written in matrix notation is

$$E(\mathbf{Y}) = \mu\mathbf{1}_I\mathbf{1}_J' + \tau\mathbf{1}_J' + \mathbf{1}_I\beta' + \mathbf{\Theta\Lambda\Gamma}' \quad [6]$$

where the fourth term on the right side of the equation represents the T × E and $\mathbf{\Theta} = (\theta_{ik})$ is an I × K matrix, $\mathbf{\Gamma} = (\gamma_{jk})$ is a J × K matrix, and K is the number of multiplicative (bilinear) terms in the model. θ_{ik} is a treatment interaction parameter (or score) that measures treatment sensitivity to a hypothetical environmental factor denoted by environmental interaction parameter (or score) γ_{jk}. $\mathbf{\Lambda} = (\lambda_{kk})$ is a K × K diagonal matrix where λ_{kk} is a scaling constant obtained from the singular value decomposition of the residual matrix consisting of the two-way table of means corrected for treatment and environment main effects (residual from additivity)—$(T \times E)_{ij} = \bar{y}_{ij} - \bar{y}_{i.} - \bar{y}_{.j} + \bar{y}_{..}$ (where $\bar{y}_{ij}$ is the mean of the ith treatment on the jth environment and $\bar{y}_{i.}$, $\bar{y}_{.j}$, and $\bar{y}_{..}$ are the mean of the ith treatment, the mean of the jth environment, and the overall mean, respectively) (Gabriel, 1978)—and are ordered such that $\lambda_k \geq \lambda_{k+1}$. The kth bilinear term of $\mathbf{\Theta\Lambda\Gamma}'$—k = 1,..., K—is formed by a score θ_{ik} specific to Treatment i, a scale constant factor λ_{kk}, and a score γ_{jk} specific to Environment j. The normalization and orthogonality constraints are $\mathbf{1}_I'\tau = \mathbf{1}_J'\beta = 0$ and $\mathbf{1}_I'\mathbf{\Theta} = \mathbf{1}_J'\mathbf{\Gamma} = \mathbf{0}$ where **0** is a vector of zeros of size 1 × K and $\mathbf{\Theta}'\mathbf{\Theta} = \mathbf{\Gamma}'\mathbf{\Gamma} = \mathbf{I}_K$.

Biplots derived by plotting the cultivar and site markers (scores) of the first two multiplicative terms of the AMMI model are also useful for summarizing T × E patterns.

Experimental Data

The CIMMYT experimental station located in the Yaqui Valley near Ciudad Obregon, Sonora, Mexico is the main location in Mexico used by the CIMMYT wheat (*Triticum aestivum* L.) breeders to both screen and select segregating material and yield test advanced lines under conditions of high yield potential and irrigation. Therefore, it is imperative that the management of the station, in terms of cultural and production practices, is appropriate to allow for expression of full yield potential for those breeding nurseries and yield trials that are used by the breeders to assess yielding ability.

In the mid-1980s, there was concern that soil-related issues—including low organic matter levels, soil compaction, and inadequate N inputs—may have been constraining yields. The experiment reported in this study was initiated to investigate several feasible cultural and/or management practices—including deep subsoiling, use of summer legumes (including a legume green manure crop) in rotation with wheat, and comparing the use of chemical N fertilizers alone or in combination with chicken (*Gallus gallus domesticus*) manure—that could likely lead to expression of high yield potential in the wheat crop. Deep knifing was practiced to break up compacted soil layers, which often form just below the depth of the normal cultivation horizon (usually 30 cm), permitting better penetration of roots to nutrients and water available at deeper soil levels. Organic animal manure was applied because of its unique nutritional properties, which a number of studies show are not as easily supplied in inorganic form. The leguminous green-manure crop sesbania (*Sesbania* sp.) was grown in the summer and incorporated before land preparation to provide an extra source of N as well as crop residues, which can contribute positively to soil organic matter. The trial was developed with a long-term perspective to evaluate the effect of year on performance for various treatments.

The data set consisted of one experiment, including 24 treatments for cultural practices, conducted over 10 yr (1988–1997) in Ciudad Obregón, México (Vargas et al., 1999). Each year the experiment was arranged in a randomized complete block design with three replicates. Treatments resulted from the combination of four factors: tillage at two levels (T = with deep knife, t = without deep knife), summer crop at two levels (S = sesbania, s = soybean), manure at two levels (M = with chicken manure, m = without chicken manure), and N fertilization rate at three levels (0 = 0 kg N ha^{-1}, n = 100 kg N ha^{-1}, and N = 200 kg N ha^{-1}), resulting in 2 × 2 × 2 × 3 = 24 treatments. Treatment 1 is TSM0, Treatment 2 is tSM0, Treatment 3 is TsM0, and so on, so that Treatment 23 is TsmN and Treatment 24 is tsmN. Three levels of applied inorganic N were used representing a zero baseline, a moderate level of application (100 kg ha^{-1}), and a relatively high level of application (200 kg ha^{-1}).

The elements of the data matrix **Y** of size 10 × 24 were the grain yield interaction residuals $\bar{y}_{ij} - \bar{y}_{i.} - \bar{y}_{.j} + \bar{y}_{..}$ where $\bar{y}_{ij}$ is the response of the ith treatment in the jth environment, $\bar{y}_{i.}$ is the mean of the ith treatment, $\bar{y}_{.j}$ is the mean of the jth environment, and $\bar{y}_{..}$ is the grand mean. There were 27 explanatory covariables in the **Z** matrix of size 10 × 27 (years × environmental variables): mean minimum temperature sheltered [°C] (mT), mean minimum temperature unsheltered [°C] (mTU), mean maximum temperature sheltered [°C] (MT), total monthly precipitation [mm] (PR), mean sun hours per day (SH), and total monthly evaporation [mm] (EV). All were measured during the growth cycle in December (D), January (J), February (F), March (M), and April (A).

All covariables were centered before analysis. Moreover, for PLS and for reasons of consistency with earlier analyses (Vargas et al., 1999), the columns of the **Y** matrix were standardized.

RESULTS AND DISCUSSION

Analysis of Variance with the Agronomic Factorial Structure for the Treatments

The main effect of treatments explained 50% of the total sum of squares, whereas differences between year means contributed 24% and the interaction term contributed 18% (Table 1).

All four main effects—tillage, summer crop, manure, and N—were highly significant ($P < 0.001$) as would be expected given their agronomically beneficial effect on plant nutrition. The two-factor interactions of summer crop × N and manure × N were highly significant ($P < 0.001$) while the two-factor interaction of tillage × manure was significant ($P < 0.05$) and the remaining three two-factor interactions (tillage × summer crop,

Table 1. Analysis of variance including the factorial structure for the treatments.

Source	df	Sum of squares ($\times 10^6$)	Mean squares ($\times 10^5$)	*F*	*P*
Year	9	373.260	414.733	172.07	0.0001
Treatment	23	773.970	336.508	139.62	0.0001
Tillage	1	16.160	161.600	67.03	0.0001
Summer crop	1	18.770	187.700	77.88	0.0001
Manure	1	98.630	986.300	409.19	0.0001
N	2	536.000	2680.000	1111.90	0.0001
Tillage × summer crop	1	0.206	2.069	0.86	0.3542
Tillage × manure	1	1.197	11.970	4.97	0.0262
Summer crop × manure	1	0.446	4.466	1.85	0.1744
Tillage × N	2	0.968	4.841	2.01	0.1351
Summer crop × N	2	17.780	88.920	36.89	0.0001
Manure × N	2	78.000	390.000	161.80	0.0001
Tillage × summer crop × manure	1	0.156	1.566	0.65	0.4205
Tillage × summer crop × N	2	2.135	10.680	4.43	0.0124
Tillage × manure × N	2	1.838	9.191	3.81	0.0228
Summer crop × manure × N	2	0.186	0.931	0.39	0.6772
Tillage × summer crop × manure × N	2	1.513	7.564	3.14	0.0442
Year × treatment	207	279.520	13.503	5.60	0.0001
Year × tillage	9	21.070	23.410	9.71	0.0001
Year × summer crop	9	8.729	9.699	4.02	0.0001
Year × manure	9	37.550	41.730	17.31	0.0001
Year × N	18	126.900	70.500	29.25	0.0001
Year × tillage × summer crop	9	2.860	3.178	1.32	0.2237
Year × tillage × manure	9	2.267	2.519	1.05	0.3989
Year × summer crop × manure	9	1.121	1.246	0.52	0.8603
Year × tillage × N	18	4.947	2.748	1.14	0.3095
Year × summer crop × N	18	18.330	10.180	4.22	0.0001
Year × manure × N	18	31.370	17.430	7.23	0.0001
Year × tillage × summer crop × manure	9	3.253	3.615	1.50	0.1450
Year × tillage × summer crop × N	18	5.841	3.245	1.35	0.1521
Year × tillage × manure × N	18	4.432	2.462	1.02	0.4351
Year × summer crop × manure × N	18	6.971	3.873	1.61	0.0536
Year × tillage × summer crop × manure × N	18	3.882	2.157	0.89	0.5911
Error	460	110.870	2.410		
	AMMI analysis of the T × E				
Year × treatment	207	279.520	13.503	5.60	0.0001
Bilinear term 1	31	151.130	48.751	20.23	0.0001
Bilinear term 2	29	39.112	13.486	5.59	0.0001
Bilinear term 3	27	36.781	13.622	5.65	0.0001
Deviations	120	52.497	4.374	1.81	0.0001

summer crop × manure, and tillage × N) were not significant ($P > 0.05$). The significant interactions are expected and reflect the fact that both the green manure and chicken manure treatments are introducing more N into the system, which would be of greater benefit at zero applied N than at the higher treatment levels and can be seen clearly from inspection of the treatment means. Two three-factor interactions and one four-factor interaction were significant ($P < 0.05$): tillage × summer crop × N, tillage × manure × N, and tillage × summer crop × manure × N. For similar reasons as those stated for the two-way interactions, the three-way interactions including tillage as a factor are expected. Tillage permits greater penetration of roots to deeper soil horizons where nutrients are available. This source of nutrition would be less important when ample N is applied to surface soil layers in the form of inorganic N or organic fertilizers such as manure or green manure.

Only six treatment × year interaction (T × E) terms were highly significant ($P < 0.001$): year × tillage, year × summer crop, year × manure, year × N, year × summer crop × N, and year × manure × N. The four-factor interaction of year × summer crop × manure × N was marginally significant ($P \simeq 0.05$), whereas the rest of the interaction terms were nonsignificant.

The analysis of variance including only the six highly significant interaction terms and partitioning the N effects into linear (N_L) and quadratic (N_Q) is shown in Table 2. Note that only 81 of the 207 df for interaction are used and that 87% of the sum of squares is explained, leaving a nonsignificant deviation. In terms of degrees of freedom and proportion of the year × treatment explained, these results were similar to those obtained by the AMMI model (Table 1). The AMMI with three bilinear interaction terms (87 df) explained 81% of the T × E, whereas in Table 2, 81 df described 87% of the interaction. However, the AMMI model still left a significant variation on the residuals, whereas this analysis did not. The year × N term contributes the most (45%) to the T × E sum of squares with only 18 df. The terms year × N_L, year × summer crop × N_L, and year × manure × N_L explained at least 75% of the interaction. On the contrary, the corresponding N_Q (year × N_Q, year × summer crop × N_Q, and year × manure × N_Q) described, at the most, only 25% of the T × E.

Multiple Factorial Regression for Each Year × Factor Interaction

The analyses of variance of Tables 1 and 2 indicated that 87% of the T × E can be described with 81 df

Table 2. Analysis of variance including only the six highly significant interaction terms and partitioning the linear (N_L) and quadratic (N_Q) effects for N.

Source	df	Sum of squares (×10⁶)	Mean squares (×10⁵)	*F*	*P*
Year	9	373.260	414.733	172.07	0.0001
Treatment	23	773.970	336.508	139.62	0.0001
Year × treatment	207	279.520	13.503	5.60	0.0001
Year × tillage	9	21.070	23.410	9.71	0.0001
Year × summer crop	9	8.729	9.699	4.02	0.0001
Year × manure	9	37.550	41.730	17.31	0.0001
Year × N	18	126.900	70.500	29.25	0.0001
Year × N_L	9	111.100	123.400	51.21	0.0001
Year × N_Q	9	15.800	17.570	7.29	0.0001
Year × summer crop × N	18	18.330	10.180	4.22	0.0001
Year × summer crop × N_L	9	13.840	15.380	6.38	0.0001
Year × summer crop × N_Q	9	4.490	4.985	2.07	0.0307
Year × manure × N	18	31.370	17.430	7.23	0.0001
Year × manure × N_L	9	26.760	29.730	12.14	0.0001
Year × manure × N_Q	9	4.610	5.119	5.12	0.0266
Deviations	126	35.571	2.823	1.17	0.1258
Error	460	110.870	2.410		

and leaving a nonsignificant deviation. The idea in this section is to show how to use the MFR, and therefore substitute the qualitative variable years for the quantitative environmental covariables with the purpose of finding a more parsimonious model with the most relevant environmental covariables. This was done using only the six most important components of the T × E term.

The first strategy for selecting the best covariables is to perform a MFR with the stepwise selection procedure for each of the 27 environmental covariables × factorial effect interactions; for example, compute a MFR for the environmental covariables × tillage interaction and select the environmental covariable that accounts for most of the variability. Similarly, this is done for the other five interaction terms (summer crop, manure, N, summer crop × N, and manure × N) that were significant. Then, with the environmental covariables selected in this manner, a MFR model is fitted.

Results for the MFR of the 27 environmental covariables × tillage interactions showed five significant covariables in the following order of importance: EVD, EVM, PRM, MTA, and mTM. However, only the EVD × tillage sum of squares was relevant, accounting for 68% of the whole year × tillage sum of squares (Table 3). (The contribution of the other four covariables to the year × tillage sum of squares was negligible.) The interaction between tillage and the environmental variable EVD may be explained by the fact that, in years when EV was higher in December, mild soil water deficit before scheduled irrigations might have been avoided in treatments where tillage had permitted roots to penetrate deeper into the soil profile. Alternatively, because yield was, on average, 0.5 Mg higher in years showing a response to tillage, high EVD (which is a function of higher radiation) may have been associated with better early stand establishment and more tillering. This in turn would provide a basis for higher yield potential in favorable years, especially where tillage permitted greater access to nutrients and water with depth.

For summer crop interaction with the 27 environmental covariables, the following were significant (Table 3): EVA, SHF, EVD, PRD, and mTUM. However, only the first covariable (EVA) accounted for a sizeable portion (36%) of the year × summer crop sum of squares. The interaction between summer crop and year is apparently associated with a buffering of the effect of low EVA where green manure was grown. One explanation may be that low EV was associated with lower radiation, which was compensated for by higher leaf N levels in plots receiving green manure. Higher leaf N is often associated with delayed senescence and could effectively extend the period of grain filling.

For manure, covariables PRD, SHF, MTD, MTM, and MTA were found to be significant, but only the first two were important, contributing to 56% of the year × manure sum of squares. This interaction may

Table 3. Factorial regression (FR) model including the variables found by stepwise for each factorial effect.

Source†	df	Sum of squares (×10⁶)	Mean squares (×10⁵)	*P*
Treatment	23	773.970	336.508	0.0001
Year	9	373.260	414.733	0.0001
Year × treatment	207	279.520	13.503	0.0001
Year × tillage	9	21.070	23.410	0.0001
EVD × tillage	1	14.290	142.900	0.0001
Deviations	8	6.780	8.480	0.0001
Year × summer crop	9	8.729	9.699	0.0001
EVA × summer crop	1	3.152	31.500	0.0001
Deviations	8	5.577	6.971	0.0001
Year × manure	9	37.556	41.730	0.0001
PRD × manure	1	16.170	161.700	0.0001
SHF × manure	1	4.756	47.560	0.0001
Deviations	7	16.630	23.750	0.0001
Year × N	18	126.900	70.500	0.0001
mTF × N	2	61.360	306.800	0.0001
mTJ × N	2	20.840	104.200	0.0001
MTA × N	2	25.580	127.900	0.0001
mTM × N	2	11.790	58.950	0.0001
Deviations	10	7.330	7.330	0.0009
Year × summer crop × N	18	18.325	10.180	0.0001
MTF × summer crop × N	2	8.487	42.430	0.0001
Deviations	16	9.838	6.149	0.0008
Year × manure × N	18	31.366	17.430	0.0001
mTUM × manure × N	2	19.050	95.250	0.0001
SHJ × manure × N	2	5.457	27.290	0.0001
Deviations	14	6.859	4.899	0.0141
Error	460	110.870	2.410	

† EV, total monthly evaporation; PR, total monthly precipitation; SH, sun hours per day; mT, mean minimum temperature sheltered; MT, mean maximum temperature sheltered; mTU, mean minimum temperature unsheltered; D, December; J, January; F, February; M, March; A, April.

be explained by the ability of manure to buffer the detrimental effects of (i) mild water deficit (low PRD), which could otherwise reduce tillering and by (ii) low radiation during the critical spike growth stage (SHF). Both factors are important in determining yield potential. Both factors could also be related to improved nutritional status associated with manure application due to better nutrient availability in dryer soil for the first factor and higher leaf N levels permitting better canopy development and light interception for the second.

Nitrogen was the best contributor to the year × treatment interaction sum of squares where seven covariables were found to be significant: mTF, mTJ, MTA, mTM, PRM, EVM, and mTA. Only the first four were considered for further analyses, accounting for the 94% of the year × N sum of squares. No systematic trend in yield was apparent to explain the interaction between N levels and minimum temperatures. However, there was an interaction between lower maximum temperatures in April and N level. Cooler temperatures during the final stages of grain filling may delay senescence, and thus permit those lines with higher leaf N to prolong grain filling.

For year × summer crop × N interaction, the order of significant covariables was: MTF, mTJ, mTA, EVA, and EVM; however, the proportion of sum of squares accounted for by each covariable was relatively low, so only MTF was selected because it explained 46% of the year × summer crop × N sum of squares. Response to N was lower when maximum temperatures in February were higher where the summer crop was soybean. (Soybean treatment would be associated with reduced N availability compared with the green-manure summer crop.) This could be explained by the fact that a higher capacity for photosynthesis (associated with higher leaf N) is best realized under cooler conditions. Therefore, higher temperatures during the critical spike growth stage (i.e., in February) would reduce the potential benefit of higher leaf N.

Finally, for year × manure × N interaction, the significant covariables were: mTUM,nSHJ, MTM, PRJ, and MTF. Only the first two (mTUM and SHJ) were selected because they contributed to 78% of the year × manure × N sum of squares. In years with a high minimum temperature in March, higher N levels had less effect on yield when manure was present while in years with cooler minimum temperatures in March, the response to N was similar with or without manure. Warmer night temperatures during grain filling (i.e., March) would accelerate the cycle, and it is possible that the higher leaf N made available by higher levels of organic and inorganic N was not subsequently taken advantage of. No systematic trend was observed between the interaction of N level with manure and the environmental variable SHJ.

Table 4. Factorial regression (FR) model including the variables found by stepwise for each factorial effect and partitioning the linear and quadratic effects for N.

Source†	df	Sum of squares ($\times 10^6$)	Mean squares ($\times 10^5$)	*P*
Year × treatment	207	279.520	13.503	0.0001
Year × tillage	9	21.070	23.410	0.0001
EVD × tillage	1	14.290	142.900	0.0001
Deviations	8	6.780	8.480	0.0001
Year × summer crop	9	8.729	9.699	0.0001
EVA × summer crop	1	3.152	31.500	0.0001
Deviations	8	5.577	6.971	0.0001
Year × manure	9	37.556	41.730	0.0001
PRD × manure	1	16.170	161.700	0.0001
SHF × manure	1	4.756	47.560	0.0001
Deviations	7	16.630	23.750	0.0001
Year × N	18	126.900	70.500	0.0001
mTF × N	2	61.360	306.800	0.0001
mTF × N_L	1	51.290	512.900	0.0001
mTF × N_Q	1	10.070	100.700	0.0001
mTJ × N	2	20.840	104.200	0.0001
mTJ × N_L	1	20.060	200.600	0.0001
MTA × N	2	25.580	127.900	0.0001
MTA × N_L	1	24.990	249.900	0.0001
mTM × N	2	11.790	58.950	0.0001
mTM × N_L	1	10.710	107.100	0.0001
mTM × N_Q	1	1.078	10.780	0.0350
Deviations	10	7.330	7.330	0.0009
Year × summer crop × N	18	18.325	10.180	0.0001
MTF × summer crop × N	2	8.487	42.430	0.0001
MTF × summer crop × N_L	1	6.710	67.100	0.0001
MTF × summer crop × N_Q	1	1.777	17.770	0.0068
Deviations	16	9.838	6.149	0.0008
Year × manure × N	18	31.366	17.430	0.0001
mTUM × manure × N	2	19.050	95.250	0.0001
mTUM × manure × N_L	1	17.330	173.300	0.0001
mTUM × manure × N_Q	1	1.722	17.220	0.0078
SHJ × manure × N	2	5.457	27.290	0.0001
SHJ × manure × N_L	1	4.935	49.35	0.0001
Deviations	14	6.859	4.899	0.0141
Error	460	110.870	2.410	

† EV, total monthly evaporation; PR, total monthly precipitation; SH, sun hours per day; mT, mean minimum temperature sheltered; MT, mean maximum temperature sheltered; mTU, mean minimum temperature unsheltered; D, December; J, January; F, February; M, March; A, April; N_L, N linear effect; N_Q, N quadratic effect.

It is interesting to note that, in almost all of the six significant year × treatment interaction terms, the environmental covariables selected left relatively low deviation sum of squares; however, they were still significant.

With the objective of finding a more parsimonious model, that is, a model that includes a small number of environmental covariables explaining as much of the T × E as possible, a MFR was fitted with the environmental covariables previously selected. This model (Table 3) accounted for 68% of the whole year × treatment interaction using only 18 df (out of 207 df). Notice that the most important variables contributing to the sum of squares are those related to the main effect of N, and four of them (mTF, mTJ, MTA, and mTM) accounted for 43% of the entire year × treatment interaction with only 8 df.

When the N effect is partitioned into linear and quadratic components, it is always found that the linear components are the most important (Table 4). The terms mTJ × N_Q, MTA × N_Q, and SHJ × manure × N_Q were not significant, and thus were deleted from the model. The new model explained 67.63% of the year × treatment sum of squares with only 15 df. If the N_Q are eliminated from the model, 62.39% of the year × treatment interaction is accounted for with 11 df.

It is interesting to note that the relevant environmental covariables of Table 3 (and Table 4) were also found to be the most important when a MFR with a stepwise procedure was applied to subsets of covariables based on type (Table 5). For maximum temperatures, the first two covariables selected were MTA and MTF (MTA × N_L, MTF × summer crop × N_L, and MTF × summer crop × N_Q; Table 4). For mT, three of the first four covariables were mTF, mTJ, and mTM (mTF × N_L, mTF × N_Q, mTJ × N_L, mTM × N_L, and mTM × N_Q; Table 4). For mTU, the fourth covariable selected was mTUM (mTUM × manure × N_L and mTUM × manure × N_Q; Table 4). For PR, the first month selected was December (PRD × manure; Table 4). For SH, the first variables were SHJ and SHF (SHJ × manure × N_L and SHF × manure; Table 4). Finally, for EV, the first two covariables selected were EVD and EVA (EVD × tillage and EVA × summer crop; Table 4).

Similarly, a MFR using all the covariables available per month was performed (data not shown). For the first month of the season, December, EVD was the most important variable; for January, the second variable selected was mTJ; in February, the first two variables were mTF and SHF; for March, the first variable selected was mTUM; and in April, the first two covariables were MTA and EVA. Note that all of these covariables are the same as those in Table 3 (and Table 4).

The last strategy tried selecting the most relevant environmental covariables for computing individual FR analyses by including in the model only the main effects of year and treatments and the interaction of each factor (tillage, manure, summer crop, and N) with each of the 27 environmental covariables. The covariables with the largest R^2 were selected. The best individual models (data not shown) were: EVD × tillage, EVA × summer crop, PRD × manure, mTF × N, MTA × N, MTF × summer crop × N, and mTUM × manure × N. Again, these covariables are the same as the final MFR model given in Table 3 (and Table 4).

Table 5. Multiple factorial regression (MFR) models for different type of covariables.

Source†	df	Sum of squares (×10^6)	Mean squares (×10^5)	*F*	*P*
Year × treatment	207	279.52	13.503	5.60	0.0001
MT					
Treat × MTA	23	58.02	25.23	10.47	0.0001
Treat × MTF	23	54.85	23.85	9.89	0.0001
Treat × MTJ	23	48.26	20.98	8.70	0.0001
Treat × MTM	23	19.30	8.391	3.48	0.0001
Deviations	115	99.09	8.616	3.57	0.0001
mT					
Treat × mTF	23	78.53	34.14	14.17	0.0001
Treat × mTJ	23	40.50	17.61	7.31	0.0001
Treat × mTD	23	33.87	14.73	6.11	0.0001
Treat × mTM	23	25.19	10.95	4.54	0.0001
Treat × mTA	23	25.34	11.02	4.57	0.0001
Deviations	92	76.09	8.271	3.43	0.0001
mTU					
Treat × mTUF	23	71.81	31.22	12.95	0.0001
Treat × mTUJ	23	48.65	21.15	8.78	0.0001
Treat × mTUD	23	27.52	11.96	4.96	0.0001
Treat × mTUM	23	24.25	10.55	4.38	0.0001
Deviations	115	107.30	9.329	3.87	0.0001
PR					
Treat × PRD	23	31.80	13.82	5.74	0.0001
Treat × PRM	23	23.44	10.19	4.23	0.0001
Treat × PRJ	23	27.18	11.82	4.90	0.0001
Treat × PRF	23	14.49	6.30	2.61	0.0001
Deviations	115	182.60	15.88	6.58	0.0001
SH					
Treat × SHJ	23	28.73	12.49	5.18	0.0001
Treat × SHF	23	15.33	6.66	2.76	0.0001
Treat × SHD	23	20.65	8.979	3.73	0.0001
Deviations	138	214.80	15.57	6.45	0.0001
EV					
Treat × EVD	23	60.60	26.35	10.93	0.0001
Treat × EVA	23	40.09	17.43	7.23	0.0001
Treat × EVF	23	19.59	8.518	3.53	0.0001
Treat × EVM	23	18.35	7.979	3.31	0.0001
Treat × EVJ	23	14.08	6.120	2.54	0.0001
Deviations	92	126.80	13.78	5.71	0.0001
Error	460	110.870	2.410		

† EV, total monthly evaporation; PR, total monthly precipitation; SH, sun hours per day; mT, mean minimum temperature sheltered; MT, mean maximum temperature sheltered; mTU, mean minimum temperature unsheltered; D, December; J, January; F, February; M, March; A, April.

Biplots

The first bilinear interaction term of the AMMI analysis of the T × E accounted for 54% of the T × E sum of squares, the second accounted for 14%, and the third 13%, using 31, 29, and 27 df, respectively (Table 1). The first two bilinear terms accounted for 68% of the T × E sum of squares and used 60 of the total 207 df available in the interaction, whereas the first three bilinear terms explained 81% of the T × E with 87 df. These results are similar to those found in the factorial analyses of variance in Tables 1 and 2. However, the AMMI model does not allow decomposing of the whole T × E into its agronomic factorial components. It also does not allow partitioning of the year × treatment interaction into environmental variables × treatment interaction

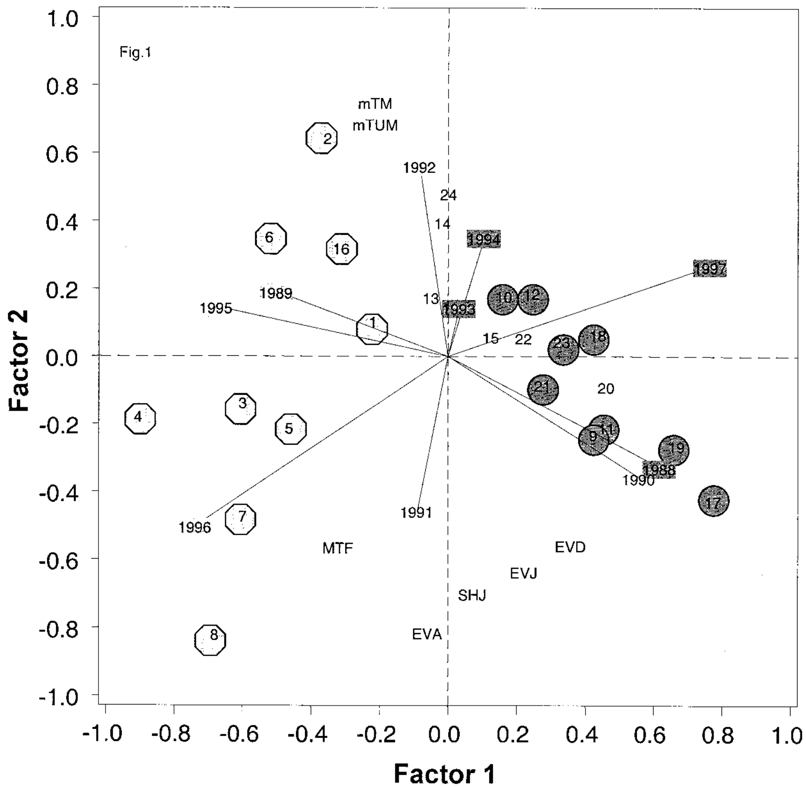

Fig. 1. Biplot of the first and second additive main effect and multiplicative interaction (AMMI) axes representing 24 cultural practice treatments (1–24) evaluated over 10 yr (1988–1997) and enriched with the following selected environmental covariables: mT, minimum temperature sheltered; mTU, minimum temperature unsheltered; EV, total monthly evaporation; MT, maximum temperature; D, December; J, January; F, February; M, March; and A, April (from Vargas et al., 1999).

using the FR model and the MFR with the stepwise variable selection procedure.

The AMMI biplot with the first two bilinear terms and enriched with the seven environmental covariables with $R^2 > 0.50$ values is shown in Fig. 1. The main results from the AMMI biplot were: (i) the four highest-yielding years (1994, 1988, 1997, and 1993) were separated from the four lowest-yielding years (1995, 1992, 1989, and 1996); (ii) the nine highest-yielding treatments (9, 19, 21, 17, 11, 12, 10, 23, and 18; five treatments had 200 kg N ha^{-1} and four had 100 kg N ha^{-1}) are separated from the nine treatments with the lowest grain yield (1, 2, 3, 4, 5, 6, 7, 8, and 16; all had 0 kg N ha^{-1}, except Treatment 16, which had 100 kg N ha^{-1}); (iii) years 1988, 1990, 1991, and 1997 were positively associated with the covariables EVD, EVJ, EVA, SHJ, and MTF and had below-average values for mTM and mTUM; and (iv) years 1989, 1992, 1993, 1994, and 1995 had above-average values for covariables mTM and mTUM and below-average values for the other environmental covariables.

The PLS biplot is depicted in Fig. 2. The first two PLS factors clearly separated the nine highest-yielding treatments (9, 19, 21, 17, 11, 12, 10, 23, and 18) from the nine lowest-yielding treatments (1, 2, 3, 4, 5, 6, 7, 8, and 16) (Table A1, see Appendix). However, the separation of years was not as clear as it was in the AMMI biplot. Only the third and fourth highest-yielding years (1988 and 1997, respectively) were clearly situated near the group of highest-yielding treatments. The ninth and tenth yielding years (1992 and 1995, respectively) were close to the group of lowest yielding treatments. The first and second highest-yielding years (1994 and 1991, respectively) as well as the seventh yielding year (1989) were located near the origin while the eighth yielding year (1990) was located with the highest-yielding years. The nine lowest-yielding treatments (1, 2, 3, 4, 5, 6, 7, 8 and 16) had a positive interaction with year 1995 (high and positive residuals; Table A2, Appendix) but a negative interaction with year 1988 (high and negative residuals; Table A2, see Appendix) located on the opposite quadrant of the biplot.

The low-yielding treatments—1, 2, 3, 4, 5, 6, 7, 8, and 16—had positive interactions in years with high mTF and mTUF and high MTF and MTA (Table A3, see Appendix). This positive interaction occurred especially in 1995 (Table A2). February is the month in which rapid spike growth occurs, a stage which is critical in determining grain number (Fischer, 1985). If conditions are warmer, development is accelerated; hence, assimilate availability during this phase is reduced, reducing grain number and, therefore, yield potential. Yield may further be reduced by high maximum temperatures in April, which again, accelerates plant development, truncating the period of grain filling. Moreover, 1995 can be further characterized as being low in mTUA, EVD, and MTD. This is to be expected because all of these variables are associated with low radiation, which limits productivity. Negative interactions occurred for the low-yielding treatments in 1988, 1990, and 1997. These years

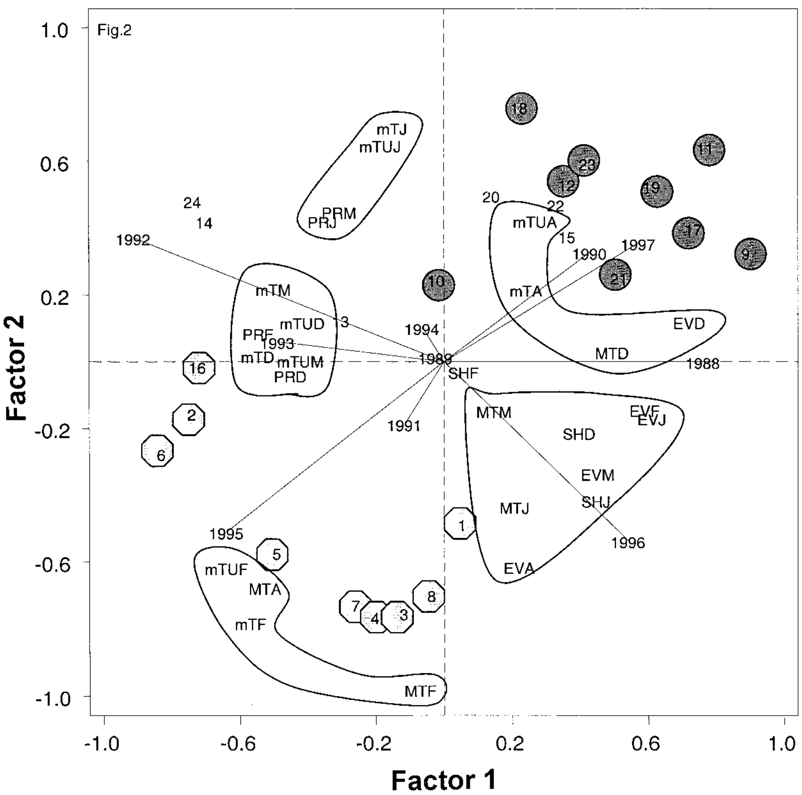

Fig. 2. Biplot of the first and second partial least squares (PLS) factors representing the Z scores of the 10 yr (1988–1997) and the Y loadings of the 24 practice treatments (1–24) enriched with the Z loadings of 27 environmental variables: EV, total monthly evaporation; PR, total monthly precipitation; SH, sun hours per day; mT, mean minimum temperature sheltered; MT, mean maximum temperature sheltered; mTU, mean minimum temperature unsheltered; D, December; J, January; F, February; M, March; A, April; and N (from Vargas et al., 1999).

scored just the opposite on the variables enumerated for 1995. In contrast, the nine highest-yielding treatments did relatively well in 1988, 1990, and 1997 and relatively poorly in 1995.

The PLS biplot (Fig. 2) contains roughly five clusters of environmental covariables. The first cluster is in the lower left quadrant and includes correlated variables mTF, mTUF, MTA, and MTF. The second cluster is in the lower right quadrant and comprises correlated variables EVJ, EVF, EVM, EVA, MTJ, MTM, SHD, SHJ, and SHF. The third cluster involves mTA, mTUA, MTD, and EVD. The fourth group had mTJ, mTUJ, PRM, and PRJ. The fifth cluster includes mTM, mTUM, mTD, mTUD, PRD, and PRF.

In general, SH, EV, and MT are grouped in the right quadrants of the biplot, whereas PR, mT, and mTU are grouped in the left quadrant of the biplot. It is expected that with more sun hours, there will be higher maximum temperatures and more evaporation; also, with more precipitation, there will be fewer sun hours, and thus, lower temperature. This is clear for the lower right cluster of variables comprising MT, EV, and SH. The group of environmental variables located in the right upper quadrant indicates that minimum temperature in April with maximum temperature and evaporation in December had a similar effect on the T × E for the treatments located in that quadrant. The two groups of variables in the left upper quadrant indicate that minimum temperatures in December, January, and March are related to precipitation in December, January, and March.

From an agronomic perspective, if the crop was irrigated, variable precipitation should not be a limiting production factor. However, it was associated with treatments that had low average production (left quadrants of the biplot). Furthermore, the most highly productive treatments are associated with high N levels (100 and 200 kg ha^{-1}) and no precipitation. The explanation may be that precipitation is associated with leaching of N (especially if the texture of the soil is coarse). In addition, higher precipitation is also associated with clouds, which reduce radiation. While radiation is the major yield-limiting factor when N and water are nonlimiting, high radiation may also be associated with higher temperatures and excessive evaporative demand. These factors may be confounding because a crop is most productive with a combination of high radiation for photosynthesis and cooler temperatures, which permit slower developmental rates. As already outlined, accelerated development rate may be especially prejudicial to yield during spike growth (February) and to a lesser extent during grain filling (March–April). Excessive evaporative demand may reduce the ability of the plant to cool itself directly by not permitting sufficient evapotranspiration or indirectly by reducing soil moisture.

It is interesting to note that the order of inclusion of the environmental covariables in the stepwise selection procedure for each factor effect (tillage, summer crop, manure, N, summer crop × N, and manure × N) corresponds to selecting covariables for different cluster groups depicted in the PLS biplot of Fig. 2. For example, in the case of tillage, the stepwise procedure first selected EVD from the cluster in the upper right quadrant. Next, it selected EVM from cluster located in the lower right quadrant. Then, it selected covariable PRM in the upper left quadrant cluster followed by covariable MTA in the lower left quadrant. Finally, covariable mTM was selected in the center left quadrant. This makes sense for the environmental variable EV because deep tillage allows roots to access water at a depth in the soil profile permitting sustained growth in years with high evaporative demand when the upper soil profile may become relatively dry before scheduled irrigation. The other variables would also be expected to influence water availability to the crop, directly in the case of precipitation and indirectly in the case of temperatures, which influence evaporative demand.

For summer crop, the order of inclusion of environmental covariables was EVA and SHF from second cluster, EVD from third cluster, and PRD and mTUM from fifth cluster. In the case of manure, the sequence was PRD from the fifth cluster, SHF from second cluster, MTD from third cluster, MTM from second cluster, and MTA from the first cluster. The factors summer crop, manure, and N have a direct effect on the nutrition of the crop, may interact with environmental variables as discussed previously.

CONCLUSIONS

The MFR model with a stepwise procedure used in this study for finding a parsimonious description of the T × E showed that the most important interaction with year was due to different N fertilizer levels and that the most important environmental variables explaining year × N interaction were minimum temperatures in January, February, and March and maximum temperature in April. Evaporation in December and EVA were detected as important covariables for describing the interaction of year × tillage and year × summer crop, whereas PRD and SHF were important for explaining the year × manure interaction. Similar results were obtained for selecting the most relevant covariables using other procedures such as when the MFR with the stepwise procedure was applied to a subset of covariables based on type or on the month of the year.

The analyses of this study show a basis for the interaction of agronomic practices with weather variables. For example, the interaction of deep tillage with evaporative demand confirms the benefit of this treatment under conditions that can lead to rapid drying of the soil surface layers. Similarly, the use of manure, which has been associated with more vigorous crop establishment (Badaruddin et al., 1999), was shown to be more beneficial in years where precipitation was low during crop establishment (i.e., December). Such analyses could be used to permit a more strategic and economically sound deployment of management factors by enabling the prediction of yield responses in light of long-term weather patterns.

ACKNOWLEDGMENTS

The authors thank Dr. R.A. Fischer for his valuable comments and constructive suggestions on the manuscript.

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APPENDIX

Table A1. Mean grain yield (kg ha^{-1}) of 24 treatments (Treat) evaluated over 10 yr.

		Year										
Treat	Code†	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	Mean
1	TSM0	8132	7434	5243	7799	6085	7456	8435	5865	7564	7794	7181
2	tSM0	6691	7140	4861	7448	6767	7197	8750	5543	6639	6992	6803
3	TsM0	7163	7483	4724	7857	5645	6961	7377	5749	7877	6780	6761
4	tsM0	5632	7146	4181	6787	4559	6021	6830	5194	7477	5145	5897
5	TSm0	5942	5544	4717	6410	5396	5824	5650	4242	6316	4683	5472
6	tSm0	5164	5650	4437	6015	5693	5759	7200	4186	5740	4364	5421
7	Tsm0	4537	3913	4463	5964	4282	4425	5331	4210	6348	3969	4744
8	tsm0	4085	4657	4554	6320	3149	4129	4760	3507	6049	3304	4451
9	TSMn	9521	7560	8016	9017	6844	8054	9227	5998	7813	9469	8152
10	tSMn	8189	6922	7337	8320	6930	8116	9608	6165	7410	8503	7750
11	TsMn	8785	7440	8203	8658	7197	7579	8692	4867	7722	9101	7824
12	tsMn	8353	7526	7718	8082	7006	7561	9931	5600	7406	8490	7767
13	TSmn	7982	7406	7435	7686	7632	7405	8009	6432	7643	8204	7583
14	tSmn	7211	7158	7217	7878	7664	7217	8345	6093	7006	8131	7392
15	Tsmn	8132	7217	7431	7624	7006	6965	8186	5832	7187	8089	7367
16	tsmn	6150	7117	7067	7551	7331	7407	7852	5999	7474	7448	7139
17	TSMN	9852	6785	8517	8896	6507	7755	9355	4873	7035	8875	7845
18	tSMN	8639	6782	7690	8337	7433	8179	8679	5211	7101	8666	7672
19	TsMN	9597	6903	8204	8781	6876	8761	9028	4976	7380	9121	7963
20	tsMN	8536	6173	7478	8787	7094	8340	8426	5222	6910	8535	7550
21	TSmN	8940	7361	7989	8519	7059	7714	8447	6564	7362	8988	7894
22	tSmN	8203	7275	7314	8294	6730	7406	8354	5923	6880	8586	7496
23	TsmN	8686	7748	7706	8362	7196	7634	7939	5883	7025	9164	7734
24	tsmN	7384	7667	7289	7937	7610	7945	8424	6250	6940	8424	7587
Mean		7563	6833	6658	7805	6487	7159	8035	5433	7096	7534	7060

† T, with deep knife; t, without deep knife; S, sesbania; s, soybean; M, with chicken manure; m, without chicken manure; 0, 0 kg N ha^{-1}; n, 100 kg N ha^{-1}; N, 200 kg N ha^{-1}.

Table A2. Grain yield (kg ha^{-1}) of the treatment by environment interaction [T × E] (residuals) of 24 treatment (Treat) evaluated over 10 yr.

		Year									
Treat	Code†	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997
1	TSM0	448.9	480.2	−1535.3	−126.5	−522.2	177.0	279.6	311.5	347.9	138.7
2	tSM0	−613.9	563.6	−1539.2	−100.1	537.1	295.4	973.0	368.2	−199.6	−284.5
3	TsM0	−101.3	947.8	−1635.0	350.4	−543.6	100.7	−358.7	615.1	1079.9	−455.2
4	tsM0	−767.5	1475.0	−1313.5	144.9	−765.1	25.2	−41.5	924.6	1544.4	−1226.4
5	TSm0	−32.9	298.6	−353.2	192.8	497.1	253.1	−796.6	397.2	807.6	−1263.8
6	tSm0	−759.0	455.5	−581.6	−150.8	845.7	239.4	804.6	392.8	283.9	−1530.5
7	Tsm0	−709.6	−604.4	121.0	475.1	110.7	−417.2	−387.6	1093.5	1567.9	−1249.5
8	tsm0	−868.5	432.0	504.7	1123.6	−729.1	−420.4	−665.5	682.9	1561.7	−1621.4
9	TSMn	866.9	−365.1	266.6	120.1	−734.9	−196.6	100.6	−526.5	−374.1	843.0
10	tSMn	−63.8	−600.9	−10.8	−174.9	−246.7	267.6	883.5	43.0	−375.8	278.9
11	TsMn	458.1	−157.2	781.5	88.6	−54.0	−344.0	−107.1	−1329.9	−138.2	802.3
12	tsMn	83.4	−14.6	352.7	−430.0	−187.8	−304.4	1189.4	−539.7	−397.3	248.5
13	TSmn	−103.6	49.3	253.7	−642.4	621.7	−276.5	−548.6	476.2	23.6	146.5
14	tSmn	−683.2	−7.3	227.1	−259.0	845.5	−273.7	−21.5	328.9	−421.9	265.2
15	Tsmn	262.9	76.5	466.9	−487.8	212.0	−499.9	−155.0	92.4	−215.7	247.7
16	tsmn	−1492.3	204.5	330.3	−333.8	764.7	168.7	−262.3	486.8	298.9	−165.5
17	TSMN	1504.5	−833.2	1074.5	305.6	−764.4	−188.3	535.1	−1344.3	−845.8	556.3
18	tSMN	464.8	−663.2	420.4	−79.6	334.8	408.5	32.8	−832.6	−606.5	520.6
19	TsMN	1131.7	−832.9	643.7	72.9	−513.4	700.2	90.7	−1359.0	−617.9	683.9
20	tsMN	483.7	−1150.3	330.3	491.8	116.7	691.8	−98.9	−700.4	−676.0	511.1
21	TSmN	543.0	−306.3	497.0	−120.7	−262.1	−278.8	−421.5	297.6	−567.6	619.5
22	tSmN	204.3	4.9	219.6	52.8	−193.6	−188.9	−117.0	54.1	−651.7	615.4
23	TsmN	449.1	240.7	373.8	−117.6	34.5	−199.0	−769.4	−223.6	−744.5	955.9
24	tsmN	−705.9	306.6	104.7	−395.0	596.4	259.8	−137.9	290.9	−682.9	363.2

† T, with deep knife; t, without deep knife; S, sesbania; s, soybean; M, with chicken manure; m, without chicken manure; 0, 0 kg N ha^{-1}; n, 100 kg N ha^{-1}; N, 200 kg N ha^{-1}.

Table A3. Environmental variables (Var) collected during the 10 yr that 24 treatments were evaluated.

	Year									
Var	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997
MTD†	24.6	24.3	24.9	24.2	23.2	23.9	25.0	22.9	26.0	26.3
MTJ	25.2	21.4	24.2	24.1	22.2	24.3	25.9	24.5	27.2	24.3
MTF	27.0	25.2	24.0	27.1	24.4	23.9	25.1	27.2	28.3	25.2
MTM	28.5	27.6	27.5	26.1	26.3	28.9	27.8	29.3	29.2	30.0
MTA	31.1	31.8	32.1	31.5	32.2	32.9	32.3	31.7	33.1	30.3
mTD	8.3	8.4	9.2	10.1	10.9	10.9	11.0	11.3	8.6	8.0
mTJ	7.5	6.2	7.5	8.9	10.8	11.6	8.3	8.1	5.8	7.9
mTF	9.8	9.6	6.8	10.9	10.7	10.4	8.1	11.9	10.3	7.6
mTM	8.9	10.0	9.0	10.0	10.8	10.2	10.7	11.4	9.5	10.8
mTA	13.2	13.4	12.4	11.5	13.0	12.6	12.2	9.9	12.6	12.2
mTUD	4.5	4.0	5.2	6.9	7.8	8.0	9.3	9.1	3.7	3.7
mTUJ	3.8	2.9	4.1	5.9	8.4	9.2	6.3	5.2	0.3	3.6
mTUF	6.9	8.3	3.0	7.7	8.3	8.1	5.9	9.0	6.0	3.8
mTUM	5.8	9.4	5.4	6.5	7.4	7.4	7.3	7.8	5.2	7.2
mTUA	9.9	9.6	8.8	7.4	9.7	9.2	7.4	5.5	8.0	8.1
PRD	1.9	30.3	35.0	94.4	87.7	20.3	2.2	85.1	0.0	0.0
PRJ	2.4	12.0	1.6	2.6	152.3	26.9	0.0	0.7	0.0	11.1
PRF	0.2	61.6	15.2	11.6	59.1	41.3	0.0	14.0	0.0	4.3
PRM	0.2	0.0	3.0	0.0	20.4	0.0	0.0	0.0	0.0	0.0
SHD	8.1	8.1	7.3	7.0	6.4	5.8	5.7	5.8	8.4	8.2
SHJ	9.2	6.9	7.9	8.5	5.5	6.2	7.9	8.2	9.2	8.4
SHF	7.2	8.4	8.8	7.8	8.3	6.2	7.6	7.3	8.9	8.8
EVD	97.7	78.5	79.3	71.5	51.2	59.4	67.7	50.2	72.8	76.5
EVJ	104.5	73.9	84.6	77.0	42.8	59.9	84.7	71.4	84.2	78.2
EVF	107.6	85.7	86.3	93.0	69.8	62.3	84.3	75.1	98.1	98.2
EVM	172.7	134.6	140.5	134.0	102.3	153.2	131.6	146.1	165.0	156.2
EVA	209.4	202.6	210.2	204.6	188.1	211.2	194.1	195.7	218.6	195.5

† MT, mean maximum temperature sheltered; mT, mean minimum temperature sheltered; mTU, mean minimum temperature unsheltered; PR, total monthly precipitation; SH, sun hours per day; EV, total monthly evaporation; D, December; J, January; F, February; M, March; A, April.

New Books Received

Agriculture and Intellectual Property Rights: Economic, Institutional, and Implementation Issues in Biotechnology. *Edited by V. Santaniello, R.E. Evenson, D. Zilberman, and G.A. Carlson.* CABI Publishing, 10 E 40th St., Suite 3203, New York, NY 10016. 2000. ISBN 0-85199-457-1. $85.00.

Climate Change and Global Crop Productivity. *Edited by K.R. Reddy and H.F. Hodges.* CABI Publishing, 10 E 40th St., Suite 3203, New York, NY 10016. 2000. ISBN 0-85199-439-3. $140.00.

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