Published online August 1, 2005

Classification of Maize Environments Using Crop Simulation and Geographic Information Systems

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ABSTRACT

The effectiveness of a cultivar evaluation system largely depends on the genetic correlation between genotype performance in multi-environment trials (MET) and in the target population of environments (TPE). Previous classifications of maize (*Zea mays* L.) environments on the basis of climate and soil did not quantify their impact on the genetic correlations among environments. Consequently, plant breeders have favored classifications based on the similarity of cultivar discrimination in trials. However, these efforts frequently fail to provide adequate assessments of the TPE, since they require long-term performance data, which are not normally collected due to high cost. To describe the TPE, we performed crop simulations for each U.S. Corn Belt Township for the period 1952 through 2002, using standard CERES-Maize model inputs. To classify METs, input data were collected at or near the trial sites. Grain yield and biotic stress data for model confirmation were collected from 18 hybrids grown in replicated trials in 266 environments in 2000–2002. On the basis of prevailing conditions during key growth stages, and observed patterns of genotype × environment interactions (GEI), six major environment classes (EC) were identified. The relative frequency of each EC varied greatly from year to year and significant hybrid × EC interaction variance was observed. Our environmental classification system provided a useful description of some of the features of both the TPE and MET. Knowledge of the spatial (locations) and temporal (years) distributions of ECs that influence the incidence of GEI can be used to improve cultivar performance predictability in the U.S. Corn Belt TPE.

THE EFFECTIVENESS of a corn cultivar evaluation system largely depends on the degree to which the MET represents the TPE (Comstock, 1977). Using computer simulation, Cooper and Podlich (1999) and Podlich et al. (1999) demonstrated the value of using a weighted selection strategy when the environments sampled in the MET did not match the expectations in the TPE. The advantage of the weighted strategy increased as the amount of crossover GEI observed in the MET increased. Clearly, an adequate classification of the environments that compose the TPE constitutes a prerequisite for implementing a successful weighted selection strategy.

Previous efforts to classify maize environments relied mainly on climate and soils data (e.g., Runge, 1968; Pollak and Corbett, 1993; Hartkamp et al., 2000). While useful to describe environmental variables affecting crop productivity over long periods of time, these efforts did not attempt to identify the environmental variables that were most important in influencing GEI and thus the genetic correlations for genotype performance among testing sites, a key factor in determining the efficiency and efficacy of a cultivar evaluation system. Consequently, plant breeders have more extensively used classifications of environments based on similarity of cultivar discrimination using crop performance data collected from their cultivar evaluation or ad hoc trials, rather than basing the classification on environmental data.

Cooper et al. (1993) compared the relative merit of four strategies for classifying wheat (*Triticum aestivum* L.) environments and favored classifications based on the standardized and rank transformations. The value of these classifications for predicting cultivar performance is enhanced by knowledge of (i) the underlying causes of the observed GEI and (ii) whether the classification adequately depicts long-term patterns.

While requirement (i) can be met by collecting appropriate environmental information from the testing sites, these efforts normally fail to provide an adequate long-term description of the TPE, mainly because of the cost and impracticality of collecting empirical performance data for long-term studies.

More recent efforts to characterize environments for crop production have utilized crop models to integrate weather, soil, and management information and to produce categorical outputs that describe environments in terms of levels of stress that impact crop productivity. Using the Agricultural Production Systems sIMulator (APSIM) crop growth simulation model, Chapman et al. (2000) integrated soils and between 80 and 105 yr of weather data to classify sorghum [*Sorghum bicolor* (L.) Moench] environments in Queensland, Australia. For a subset of six testing locations, they found that three environment types, described in terms of the timing and intensity of water stress, had a consistent relationship with simulated yield.

Since the advent of crop simulation with the pioneering work from de Wit (1965), the CERES-Maize model was developed by the USDA-ARS primarily for assisting with crop management decisions, strategic planning, yield forecasting, and definition of research needs

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Published in Crop Sci. 45:1708–1716 (2005).
Crop Breeding, Genetics & Cytology
doi:10.2135/cropsci2004.0370

Abbreviations: APSIM, agricultural production systems simulator; AWC, available water capacity; CERES, crop environment resource synthesis; CRM, corn relative maturity; EC, environment class; ECB, European corn-borer (*Ostrinia nubilalis* H.); GEI, genotype by environment interactions; GGE, genotype main effects plus genotype by environment interaction effects; GIS, geographic information system; MET, multienvironment trials; NOAA, National Oceanic and Atmospheric Administration; RCB, randomized complete block design; STATSGO, state soil geographic database; TPE, target population of environments.

(Ritchie, 1986). In a study involving commercial maize hybrids, Wei et al. (2002) reported that 80% of the observed yield variation among 28 environments could be explained by the simulated yield. In a recent paper, White et al. (2002) discussed the need for spatial analyses at a "mesoscale" level in agricultural research. Specifically, they pointed out the need for promoting the use of simulation models to quantify crop responses to environmental factors.

The U.S. Corn Belt constitutes one of the most productive maize regions of the world. The spatial (locations) and temporal (years) dimensions of the environmental variation in this TPE are significant, though smaller than the variation observed in the sorghum TPE of northeastern Australia. Thus, the applicability of the environmental classification approach described by Chapman et al. (2000) for the characterization of the U.S. maize TPE and interpretation of GEI merits investigation.

The purposes of this study were to characterize maize production environments in the U.S. Corn Belt using a modified CERES-Maize simulation model in combination with GIS and to test its usefulness to explain GEI in commercial hybrids.

MATERIALS AND METHODS

CERES-Maize Model Inputs

To describe the TPE, we performed crop simulations for each township in the U.S. Corn Belt for the period 1952–2002, using a modified CERES-Maize Version 3.5 model and standard model inputs (Ritchie, 1986). Weather data (daily maximum and minimum temperature and precipitation) from 8000 U.S. stations with consistent data over a 50-yr period (1952–2002) were acquired from the National Oceanic and Atmospheric Administration (NOAA). Daily solar radiation values were estimated from the temperature records using the equation provided by Bristow and Campbell (1984). The State Soil Geographic (STATSGO) database (U.S. Department of Agriculture, 1994) was used to characterize soils. Only the major soil series in each polygon were used and reclassified into 15 possible soil types on the basis of the available water capacity (AWC) and drainage rate in the STATSGO database. The AWC levels were grouped into three categories, and drainage rates were classified into five categories (Table 1). Soil physical properties such as percentage of sand, silt and clay, bulk density, and organic matter were calculated for each soil type. Finally, soil water properties were calculated by the method developed by Rawls et al. (1982). The resulting dominant soil type based on percentage of total crop area was assigned to each township for the TPE characterization. Average pH in the soil profile was mapped on the basis of the values from STATSGO. The U.S. Geological Survey hydrological unit map (Steeves and Nebert, 1994) was used to identify irrigated areas. The tiled crop area was mapped according to Donahue (1990). Planting dates were estimated each year on the basis of temperature and precipitation data, assuming that the crop would be planted immediately after the average date of last frost and when average temperatures stayed above 10°C, and the total precipitation for four consecutive days was below 30 mm. The following genetic coefficients (Ritchie et al., 1986) were calculated for a group of commercial hybrids of corn relative maturity (CRM, Lauer, 1998) 110.

- P1. Thermal time (degree days above 8°C) from seedling emergence to the end of the juvenile phase.
- P2. Extent to which development (expressed as days) is delayed for each hour increase in photoperiod above 12.5 h.
- P5. Thermal time (degree days above 8°C) from silking to physiological maturity.
- G2. Maximum number of kernels per plant.
- G3. Kernel filling rate (mg d^{-1}) during the linear phase of grain filling under optimum conditions.

The input values were 268, 0.3, 806, 780, and 8 for P1, P2, P5, G2, and G5, respectively. Plant population was set at 8 plants m^{-2}.

Data were preprocessed by MapInfo Professional (MapInfo Corporation, 2003), so that all CERES-Maize model inputs described before were stored as GIS data layers.

A similar procedure was used to classify METs, except that model inputs such as weather and soil data were collected at or near the trial sites. Doppler radar precipitation data at 2 × 2 km grid cell size (Hoblit and Curtis, 2000) was used as input for the 2000–2002 METs. Planting dates and populations were actual records from field trials.

Simulation Output

Historical Analysis

Simulations were run for each township in the CRM 110 Maize zone for the period 1952 to 2002. The study included only the geographical region where CRM 110 hybrids can be grown, regardless of the area devoted to this maturity group.

Table 1. Classification of U.S. Corn Belt soils based on available water capacity and drainage level.

Soil type	Available water capacity	Drainage level	Description
LE	low	excessive	water capacity 0–152 mm and excessively drained
LG	low	good	water capacity 0–152 mm and well drained
LM	low	moderate	water capacity 0–152 mm and moderately well drained
LL	low	limited	water capacity 0–152 mm and somewhat poorly drained
LP	low	poor	water capacity 0–152 mm and poorly or very poorly drained
ME	medium	excessive	water capacity 153–229 mm and excessively drained
MG	medium	good	water capacity 153–229 mm and well drained
MM	medium	moderate	water capacity 153–229 mm and moderately well drained
ML	medium	limited	water capacity 153–229 mm and somewhat poorly drained
MP	medium	poor	water capacity 153–229 mm and poorly or very poorly drained
HE	high	excessive	water capacity >229 mm and excessively drained
HG	high	good	water capacity >229 mm and well drained
HM	high	moderate	water capacity >229 mm and moderately well drained
HL	high	limited	water capacity >229 mm and somewhat poorly drained
HP	high	poor	water capacity >229 mm and poorly or very poorly drained

The CRM 110 maturity was chosen because of the breadth of environments normally planted with hybrids of this maturity group. Average maximum and minimum temperatures, average temperature, photoperiod, and solar radiation were calculated for the following four developmental periods simulated by CERES-Maize: (i) Planting−V7 (seven leaf collars visible); (ii) V7–R1 (silks visible outside the husks); (iii) R1– R3 (kernels inner fluid milky white due to development of starch); and (iv) R3– R6 (physiological maturity).

On the basis of the above outputs, an algorithm was built into the model, so that five possible abiotic environment types, which corresponded with major macroenvironments previously determined by analyses of performance data (Pioneer Hi-Bred International, Inc. unpublished results) resulted from the simulation:

- Subtropical: if average photoperiod in developmental period 1 was below 13.4 h d^{-1}.
- High latitude: if average maximum temperature at all developmental periods were below 28°C.
- Temperate Dry: if maximum temperature in developmental periods 3 and 4 were equal to or greater than 30°C, and average solar radiation in developmental periods 2 and 4 was greater than 24 and 21 MJ $d^{-1}m^{-2}$, respectively.
- Temperate Humid: if maximum temperatures in developmental periods 3 and 4 were less than 30°C, and average solar radiation in developmental period 2 and 4 was equal to or less than 24 and 21 MJ $d^{-1}m^{-2}$, respectively.
- Temperate: if conditions described for any of the previous four classes were not met.

To describe the TPE in terms of long-term environment class frequencies, simulations were run on a township basis for each year for the period 1952 to 2002. To describe the MET, simulations were run for each cultivar testing site for the period 1952 to 2002.

To create maps of both the TPE and MET simulation results, a custom automated GIS application was built on the basis of MapInfo Professional (MapInfo Corporation, 2003). The process brought together all of the input data for the CERES maize model, geo-referenced them to a township level and created input files for the model. Once the simulation was run for each township, the results were fed back into the GIS for map generation. For a multiyear map, the GIS calculated which environment class was dominant on the basis of the number of years it occurred.

Experimental Data

Eighteen maize commercial hybrids adapted to the central U.S. Corn Belt, released by Pioneer Hi-Bred International, Inc., were planted in two row by 5-m-long plots arranged in two to six randomized complete blocks at 90 sites, representing 13 research stations, in 2000, 2001, and 2002 using standard agronomic practices at each site.

Standard data collection protocols used for cultivar advancement trials were applied to this experiment. The following traits were analyzed.

European Corn Borer (ECB, *Ostrinia nubilalis* H.) infestation. Sites where the damage caused by ECB infestation was severe enough to cause at least a 10% yield loss in susceptible cultivars were characterized as "ECB." Yield in kg/m^2 on a 150 g kg^{-1} moisture basis.

Analysis of variance of the 2000–2002 hybrid yield data was performed by the ASREML software (Gilmour et al., 2002) for the computation of variance components, using the following model:

$$X_{ijkl} = \mu + (\mathrm{EC})_j + (E/\mathrm{EC})_{jk} + (r/E/\mathrm{EC})_{jkl} + H_i + [H(\mathrm{EC})]_{ij} + [H(E/EC)]_{ijkl} + \varepsilon_{ijk} \quad [1]$$

where X_{ijkl} is the observation (yield) in replicate l on hybrid i in environment (location-station-year combination) k within environment-class j, μ is the grand mean, $(\mathrm{EC})_j$ is the fixed effect of environment-class j, $(E/\mathrm{EC})_{jk} \sim N(0,\sigma^2_{L/C})$ is the random effect of location k within environment-class j, $(r/E/\mathrm{EC})_{jkl} \sim N(0,\sigma^2_r)$ is the random effect of replicate l within location k within environment-class j, $H_i \sim \mathrm{N}(0,\sigma^2_H)$ is the random effect of hybrid i, $[H(\mathrm{EC})]_{ij} \sim N(0,\sigma^2_{HC})$ is the interaction effect between hybrid i and environment-class j, $[H(E/EC)]_{ijk} \sim N(0,\sigma^2_{HL/C})$ is the random interaction effect between hybrid i and location k within environment-class j, and $\varepsilon_{ijkl} \sim \mathbf{N}(0,\sigma^2_\varepsilon)$ is the random residual effect of observation l on hybrid i in environment k within environment-class j.

Genetic correlations were computed for all possible pairs of environments using the procedure developed by Burdon (1977). The estimates were summarized and plotted as relative frequencies using average density shifted histograms (Venables and Ripley, 1999) to examine the distribution of the genetic correlation coefficients within and between environment classes. Pioneer proprietary software was used to generate GGE biplots following the procedures described by Cooper and DeLacy (1994) for Hybrid × Environment (location-station-year combinations) and Hybrid × EC means, using the model:

$$y_{ij} = \bar{y}_{.j} + s_j \sum_{k=1}^{K} \lambda_k u_{ik} v_{jk} + e_{ij}$$

where y_{ij} is the hybrid mean predicted performance (BLUP: Best Linear Unbiased Predictor) for environment j, $\bar{y}_{.j}$ is the mean performance of the hybrids in environment j, s_j is the standard deviation of the hybrid performance values in environment j, λ_k, u_{ik}, and v_{jk} are the singular values, the hybrid scores, and environment scores obtained from the singular value decomposition of the matrix with standardized performance scores computed as $\frac{y_{ij} - \bar{y}_{.j}}{s_j}$. For further details see DeLacy et al. (1996).

RESULTS AND DISCUSSION

The five abiotic environment classes defined by the classification algorithm occurred in some areas of the U.S. Corn Belt almost every year, but the relative frequency of each environment class varied greatly from year to year (Fig. 1). This was due primarily to the different temperature regimes prevailing during developmental stages simulated by the crop model. Temperate environments historically occurred in over half of the total maize hectares. However, even within the region where "temperate" constituted the dominant environment class, other environment classes occurred in up to 75% of the years.

Among the biotic environmental challenges observed in the field experiments, only the incidence of ECB was considered of enough significance to merit its addition as a classification criterion. Figure 2 displays the frequency of each of the five abiotic environment classes for the 50-yr period of study, the results of the TPE or regional classification for 2002, and the MET or site-

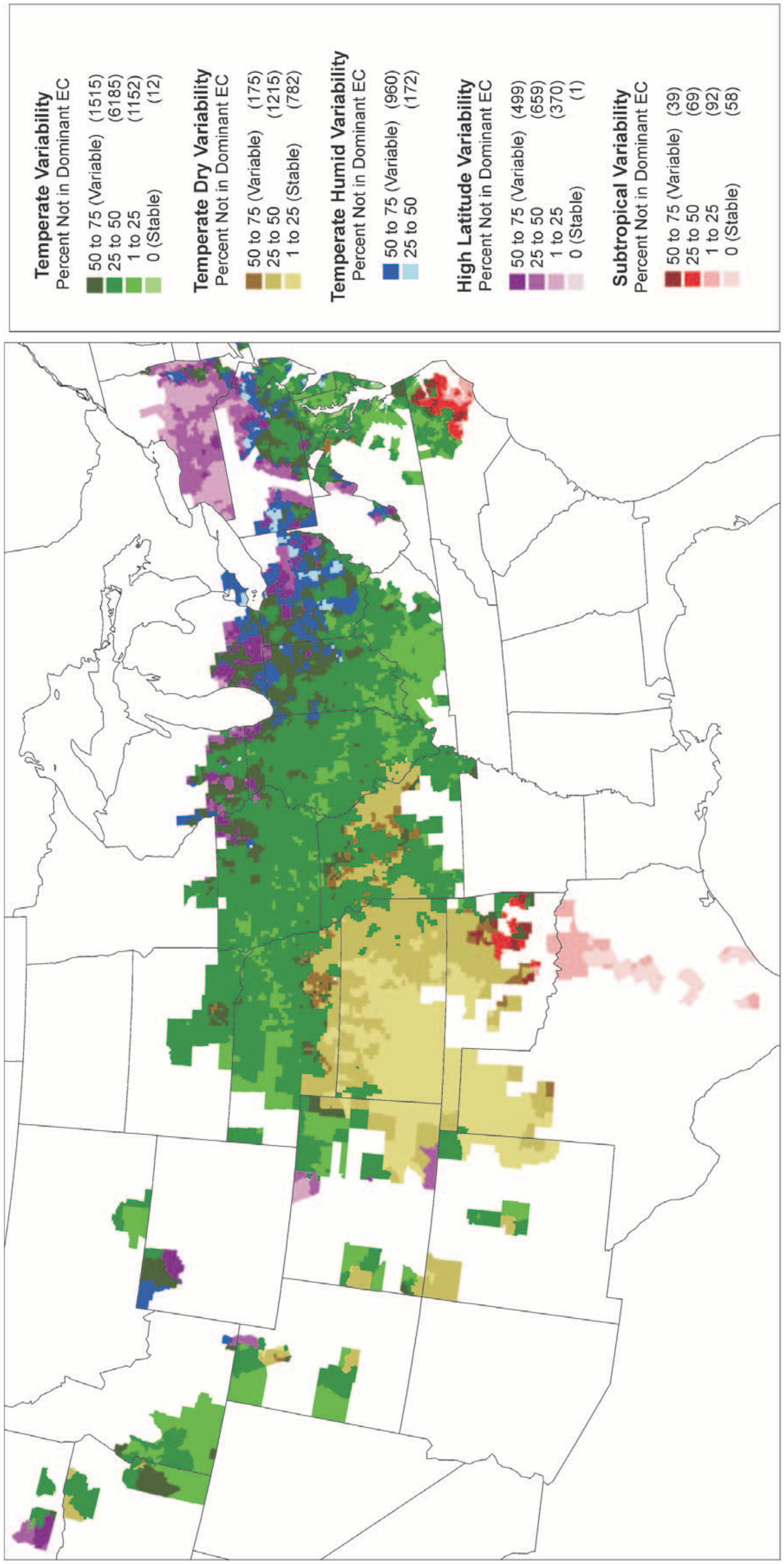

Fig. 1. Geographic distribution and variability of five abiotic environment classes (EC) in the United States for CRM 110 maize in 1952–2002. Number of townships under each variability class indicated in parentheses. Percent Not in Dominant EC: percent of years in which a township classified overall as a given class (e.g., EC = Temperate) fell into a different class (e.g., EC = Temperate Dry, Temperate Humid, High Latitude or Subtropical).

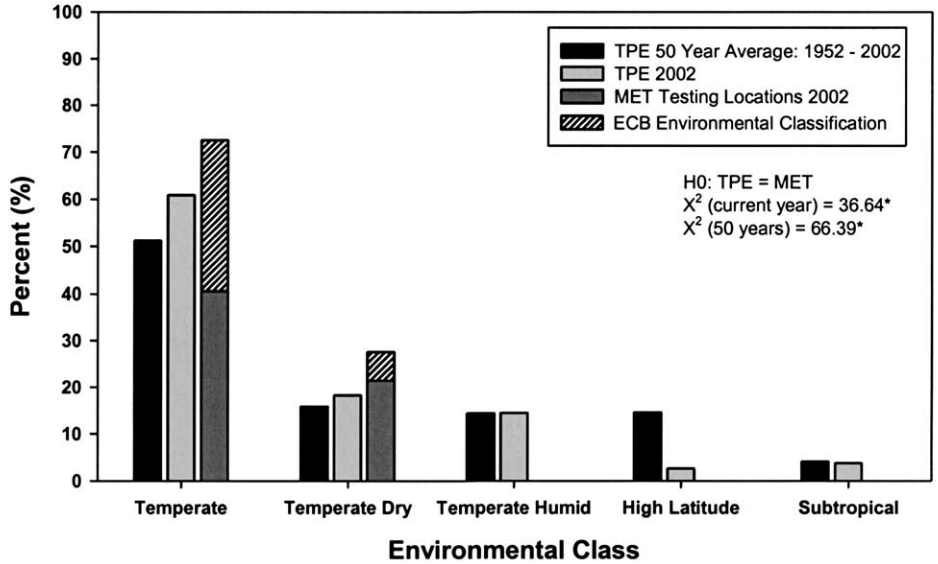

Fig. 2. **Frequency in percent of total hectares of CRM 110 maize environments in the USA in 1952–2002, compared to frequencies in 2002, both at the regional (TPE) and site-specific (MET) levels, $*p < 0.05$.**

specific classification for 2002. Significant ECB pressure was observed at 38% of these locations and thus classified as "ECB." This comparison of single-year versus long-term frequencies of environment classes is useful for assessing the value of the single-year performance data for cultivar advancement and placement decisions. Figure 2 also illustrates how the environmental classification scheme can be used to assess the relevance to the TPE of current year performance data. The Chi-Squared test indicated that the sample of 2002 trial locations failed to represent the regional distribution of ECs for 2002 and for the 50-yr period, mainly because of excessive sampling of the temperate environments to the detriment of sampling the temperate humid, high latitude, and subtropical ECs.

Grain yield data were collected for a total of 266 environments in 2000–2002. The variance component for hybrids was more than twice the size of the standard error of the estimate, and hence it can be considered statistically significant. (Table 2). This result can be considered typical for grain yield in this type of MET. The hybrid by environment-class interaction variance component was also significant (4.6 times the size of its standard error). Therefore, grouping of locations based on similarity of environmental conditions considered to affect cultivar discrimination, as defined by the environmental classification scheme, was found to be a useful way to increase the repeatability of yield for the set of hybrids and environments used in this study. However, the variance component for hybrid by environment within environment class interaction was also significant, which indicates that a significant portion of the GEI variance remained unexplained by the environmental classification. The impact of the environmental classification can be visualized by the distribution of the genetic correlations within and across environment classes. Genetic correlations between environments grouped within each of five environment classes were generally higher than those between environments across classes, particularly for the two environment classes defined as ECB and Temperate Humid (Fig. 3). The between-class genetic correlations were also generally lower than the within-class genetic correlations (Fig. 3 and 4). Estimating the genetic correlation coefficients between environments by the equation given by Burdon (1977) identified some questionable estimates that were outside of the expected range of –1 and +1. These questionable estimates were usually associated with environments with low estimates of line mean heritability. For demonstration purposes, we constrained the distribution of genetic correlation coefficients to those values within the fifth and 95th quantiles.

Table 2. **Estimates of variance components and the ratio of the variance component to the standard error of the variance component from analysis of variance of grain yield by Residual Maximum Likelihood based on the model given in Eq. [1] for 18 maize hybrids in 266 environments in the USA.**

Source of variation	Number of observations	Variance component	Component/SE
Environments (E)/ environment class (EC)	266	641	10.6
Rep/E/EC	621	77.7	13
Environment class (EC)	5	84	1.1
Hybrid (H)	18	147.1	2.7
H × EC	90	40.3	4.6
H × E/EC	4 788	84.9	21.4
Residual	7 005	227	62.9
Total	12 798	1302	

An advantage of stratifying environments by EC rather than the traditional stratification by region is also illustrated by the GGE biplots in Fig. 5 and 6. Each vector in Fig. 5 represents the average position in the plane of all the trial locations within a given state, represented with the same color and symbol. The generally small angle observed between any two vectors underscores the challenge of making cultivar recommendations for specific geographies without an understanding

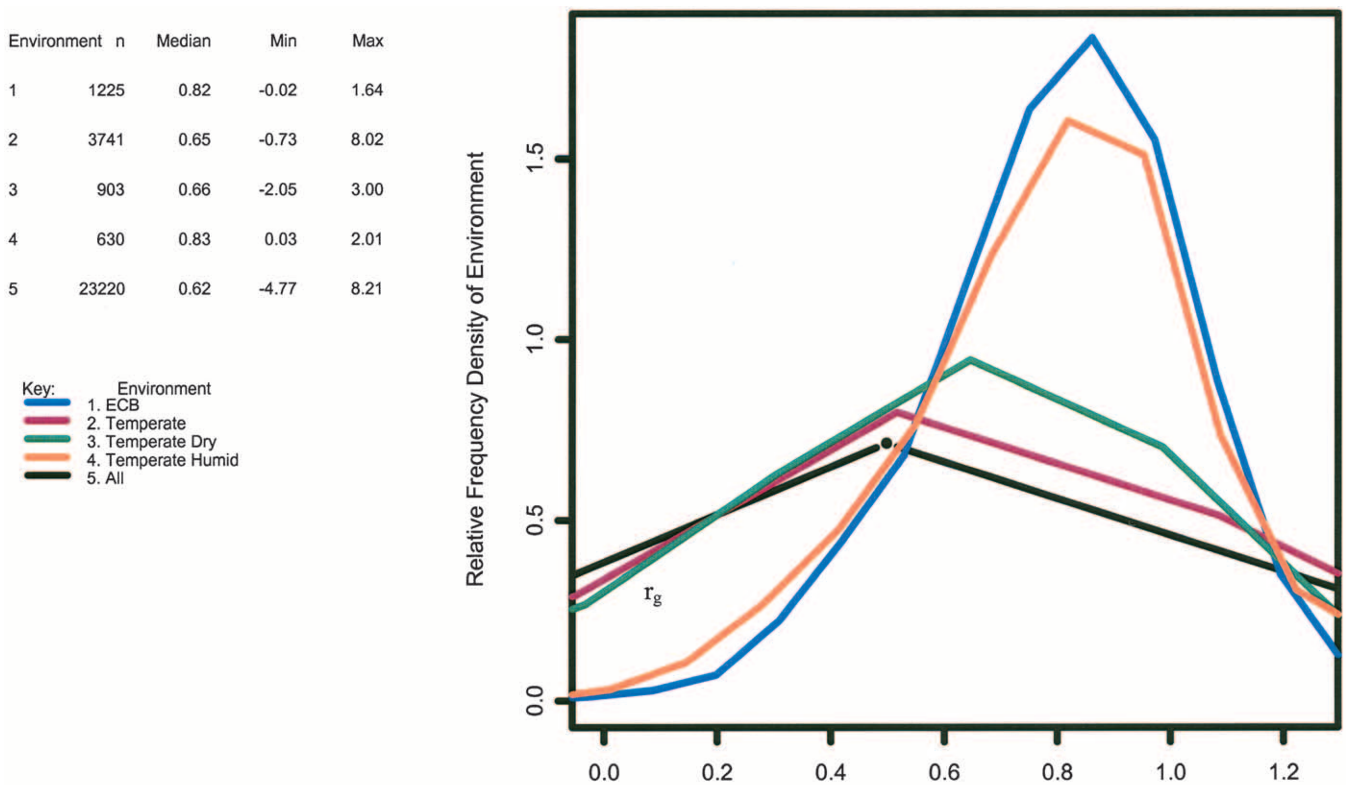

Fig. 3. Average density shifted histogram of distribution of genetic correlations (r_g) within temperate, temperate dry, temperate humid and ECB environment classes for CRM 110 maize in the USA in 2000–2002, compared to the genetic correlations distribution for unclassified environments (all).

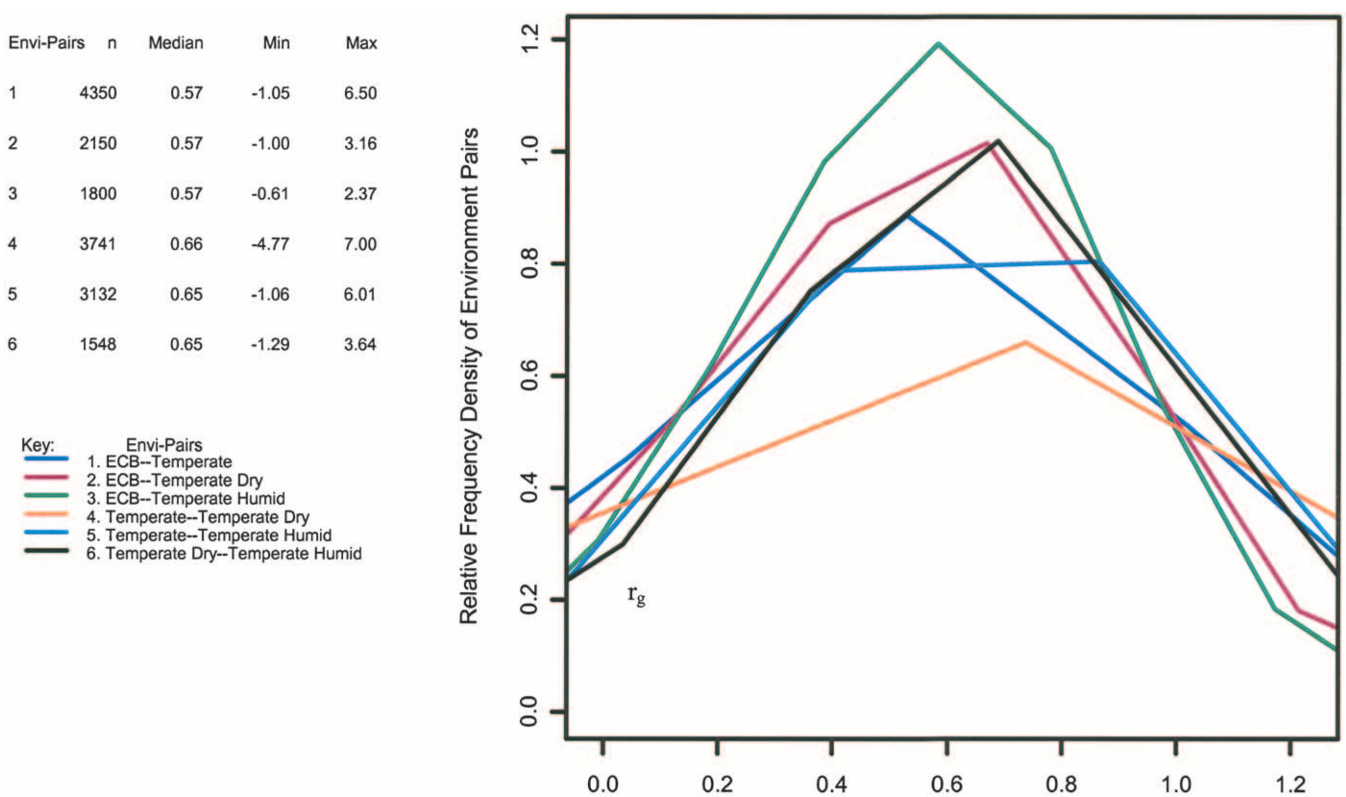

Fig. 4. Average density shifted histogram of distribution of genetic correlations (r_g) between temperate, temperate dry, temperate humid and ECB environment classes for CRM 110 maize in the USA in 2000–2002.

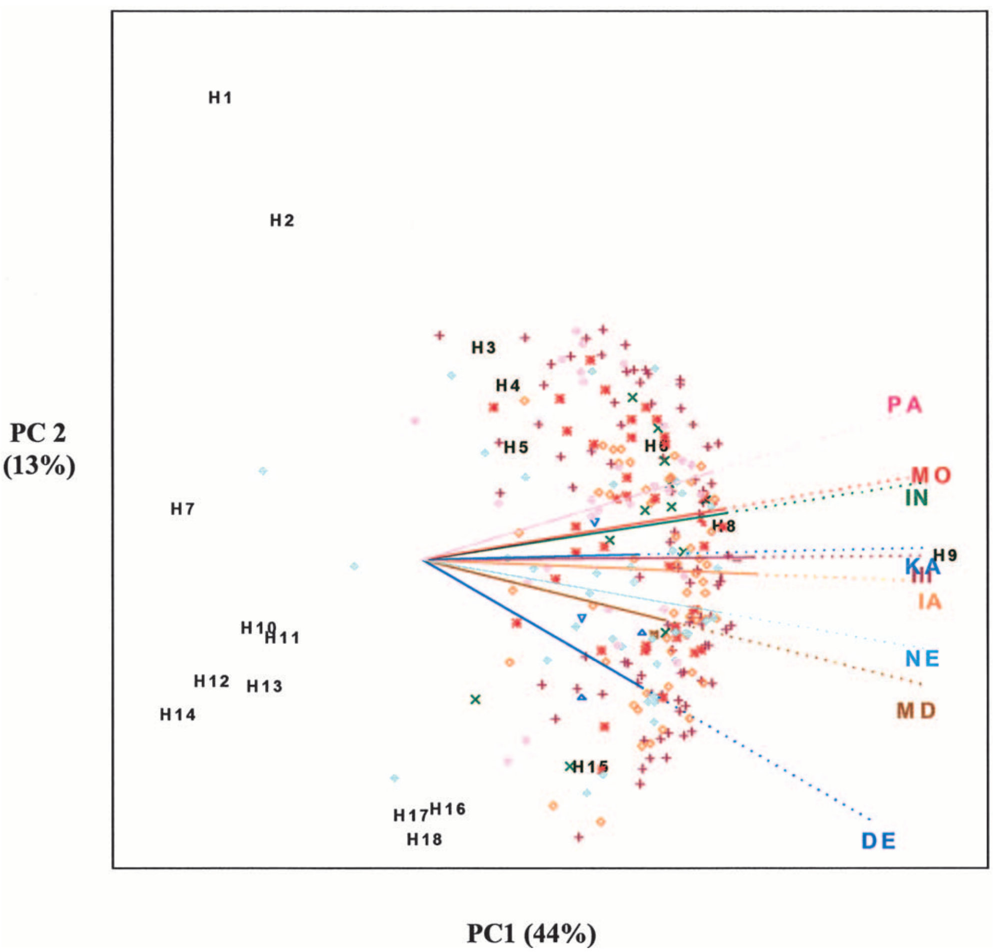

Fig. 5. Environment-standardized GGE biplot of grain yield of 18 maize hybrids (H1-H18) grown in 266 environments over three years, stratified by state. Percent of the total GGE variation explained by the main two principal components in parentheses. PA: Pennsylvania, MO: Missouri, IN: Indiana, KA: Kansas, IA: Iowa, NE: Nebraska, MD: Maryland, DE: Delaware.

of the underlying causes of the GEI contributing to differential cultivar discrimination in the various targets. Hybrid 9 is expected to perform well in all states and in almost all locations. However, it is unclear whether any of the other hybrids perform well relative to H9 in specific situations. It appears that hybrids H1 through H5 performed as well as or better than H9 at some locations. However, from this analysis based on states and year-location combinations there is little basis for predicting these situations. The stratification of locations by EC enabled interpretations of the hybrid responses in the MET that were not possible with the traditional stratification by geography (Fig. 6 cf. Fig. 5). Hybrid 9 outperformed all other hybrids included in this study in the temperate, temperate dry and ECB environments; these are the most frequent environments found in the central Corn Belt. H9 is an example of a hybrid with broad adaptation; the projection of the vector with coordinates (0, H9) onto any of these environments is greater than for any other hybrid. However, GEI is evident in this graph. When comparing H9 with the other five hybrids (H1–H5) in high latitude environments [project the vector (0, H9) onto the high latitude vector], the clear yield advantage of H9 vanished and its yield is comparable to any of the hybrids from H1 to H5 (Fig. 6).

The environmental classification system described here provided a useful description of the distribution of conditions influencing GEI for yield in both the TPE and MET environments of the U.S. Corn Belt. The stratification of environments sampled in the MET by EC explained a significant portion of the hybrid × environment interactions for grain yield observed in field trials over a 3-yr period. Thus, appropriate classification of maize production environments can enable the identification of some of the repeatable causes of GEI for yield and agronomic traits, and this knowledge can in turn be used to improve predictability of cultivar performance in the TPE.

ACKNOWLEDGMENTS

The authors are grateful for the input received from the following Pioneer colleagues: D. Avey, P. Bax, G. Boulch, G. Edmeades, B. Guse, J. Hotchkiss, and B. Johnson. Ian DeLacy provided assistance with the ASREML analyses of the field data. Maggie Zhu wrote the S-Plus code used to compute genetic correlations. Special thanks to Scott Chapman for the

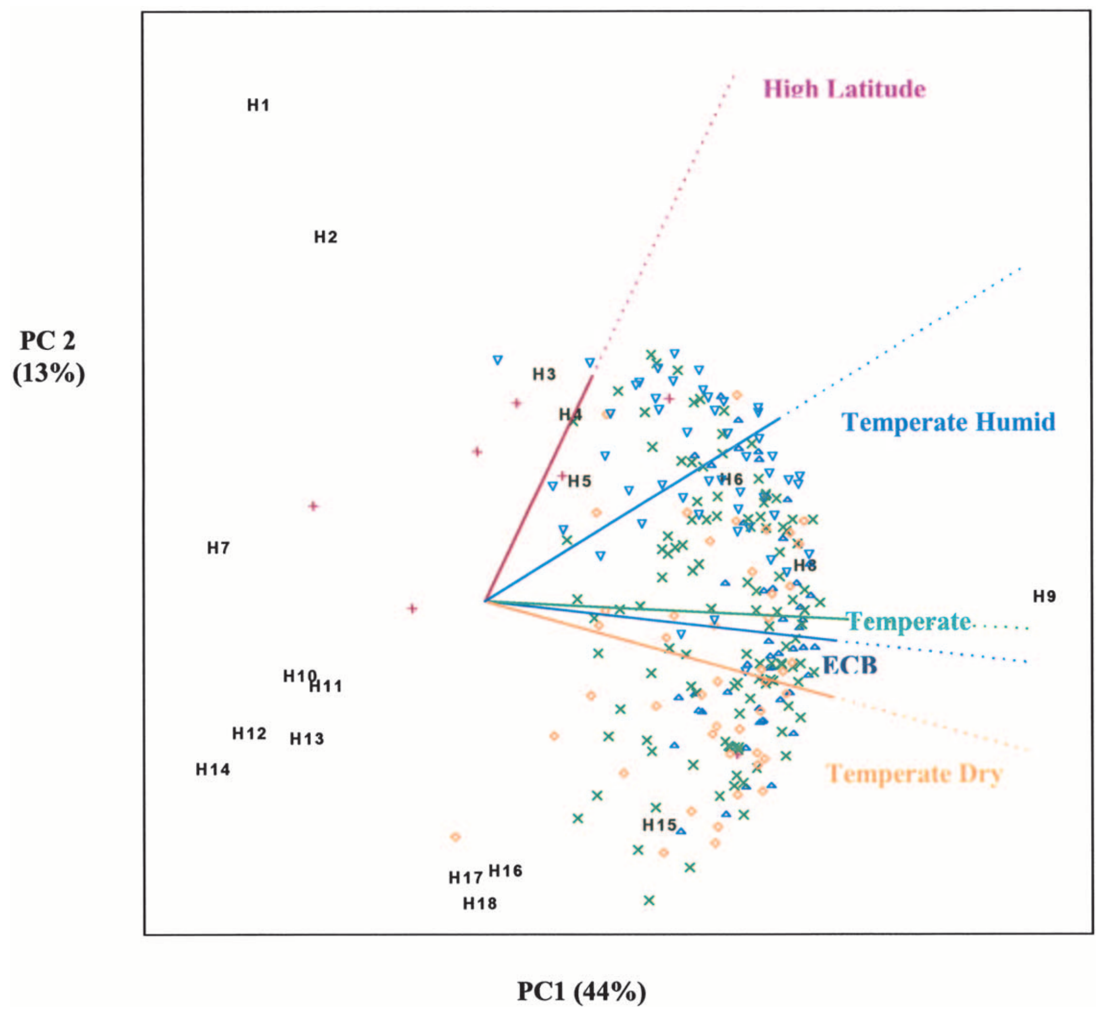

Fig. 6. Environment-standardized GGE biplot of grain yield of 18 maize hybrids (H1-H18) grown in 266 environments over three years, stratified by environment class. Percentage of the total GGE variation explained by the main two principal components in parentheses.

valuable scientific consultation provided during the initial phase of this study.

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