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Repeatable genotype × location interaction and its exploitation by conventional and GIS-based cultivar recommendation for durum wheat in Algeria

Paolo Annicchiarico[a,*], Fadila Bellah[b], Tiberio Chiari[c]

[a] *Istituto Sperimentale per le Colture Foraggere, viale Piacenza 29, 26900 Lodi, Italy*
[b] *Institut Technique des Grandes Cultures, BP 16, El-Harrach, Alger, Algeria*
[c] *Istituto Agronomico per l'Oltremare, via A. Cocchi 4, 50131 Florence, Italy*

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Abstract

Repeatable genotype × location (GL) interaction revealed by multi-locational trials may be exploited by site-specific cultivar recommendations. There is uncertainty, however, on methods for defining recommendations and extending results to non-test locations. With reference to durum wheat in Algeria, our main objective was the comparison of methods for defining the best pair of cultivars for local recommendation based on: (i) observed data; (ii) joint regression-modeled data; (iii) additive main effects and multiplicative interaction (AMMI)-modeled data; (iv) factorial regression-modeled data; (v) AMMI modeling interfaced with a geographic information system (GIS); (vi) factorial regression modeling interfaced with a GIS. The last two methods extended the recommendations to all sites in a GIS as a function of long-term climatic data. Concurrently, we aimed at assessing: (i) the repeatability over time of joint regression and AMMI parameters of adaptation; (ii) the consistency between predicted and actual yield gains derived from growing recommended cultivars in place of locally most-grown cultivars; (iii) the effect of different numbers of recommended cultivars. Modeling was based on grain yield of 24 genotypes evaluated across 2 years in a total of 31 environments. Cultivar responses at 16 sites in a third year were used for comparing methods according to average yields of recommended materials at individual sites and across sites, and for assessing repeatabilities. The selected AMMI model included one GL interaction principal component (PC 1). Winter mean temperature and rainfall over the cropping season were selected as covariates for factorial regression and as variables in a multiple regression for predicting the PC 1 score of sites in the GIS. Genotypic parameters, especially mean yield and PC 1 score, were highly repeatable ($r > 0.90$). Site parameters (PC 1 score, mean yield) showed moderate to fairly low repeatability mainly due to within-site variation in annual rainfall. Recommendations based on modeled data implied less subregions (i.e. sets of locations with same top-yielding material) and provided, on the average, 4–5% higher yields and much better predictions of actual yield gains from recommendation compared with those based on observed data. GIS-based recommendations implied a slight yield decrease relative to those based on conventional modeling. However, they allowed for about 9% higher yields than those of most-grown cultivars, while enlarging the scope for site-specific recommendations and assisting national seed production and distribution systems. Factorial regression showed a slight advantage over the other models. On the average, recommending two top-yielding cultivars (reference criterion) or the top-yielding cultivar provided similar yields, somewhat higher yields than three top-yielding cultivars, and 8–10% higher yields than larger sets of statistically ($P < 0.20$) not different cultivars.

Keywords: Adaptation; Cultivar recommendation; Geographic information system; Genotype × environment interaction; Modeling; *Triticum durum*

1. Introduction

Maximizing the yield potential of cropping environments by breeding and growing specifically adapted germplasm, instead of altering the environment (possibly with costly or environment-unfriendly inputs, such as pesticides, fertilizers and irrigation) to grow widely adapted cultivars, can be a major element of a research policy enforcing sustainable agriculture (Bramel-Cox et al., 1991; Ceccarelli, 1996). Specifically adapted cultivars may raise crop yields by exploiting genotype × location (GL) interaction effects (as determined by climatic, soil, biotic and crop management factors of locations), provided that these

* Corresponding author. Tel.: +39 0371 404751; fax: +39 0371 31853.
E-mail address: bred@iscf.it (P. Annicchiarico).

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effects are sufficiently repeatable over time and determine different top-ranking cultivars depending on the site (Gauch and Zobel, 1997; Annicchiarico, 2002). If this is the case, sets of locations that share the same top-yielding cultivars (i.e. the same recommendation domain) may be grouped to form a subregion or megaenvironment for recommendation. The same recommendation applies to the whole target region when, on the contrary, top-yielding genotypes remain the same across locations. For instance, specific recommendations for different subregions may allow for yield gains up to 7% for lucerne in northern Italy (Annicchiarico, 1998).

Several different models, such as joint linear regression (Finlay and Wilkinson, 1963), additive main effects and multiplicative interaction (AMMI) (Gauch, 1992) and factorial regression (Hardwick and Wood, 1972; Piepho et al., 1998), are available for assessing and predicting the cultivar responses to locations. Defining cultivar recommendations at each site based on modeled yields of cultivars rather than observed yields (i.e. mean yields of cultivars across observations at the site) may reduce the noise, i.e. the random error, that affects the estimates of genotype by location cell means, thereby: (i) improving the prediction of future responses of genotypes at each site and (ii) simplifying the recommendation through a reduction in the number of subregions (Gauch, 1992; Gauch and Zobel, 1997). Repetition in time of variety trials is warranted in annual species for estimation of non-repeatable GL interaction effects, i.e. the genotype × location × year (GLY) interaction, which largely contribute to the noise and represent the error term for testing GL effects in the analysis of adaptation (Annicchiarico, 1997). The predictive ability of each model also depends on the repeatability over time of its genotypic and environmental parameters.

In general, the definition of cultivar recommendations tends to be limited to individual test sites and their surrounding areas to which results can be extended. Even in the presence of many test sites, uncertainty may arise on recommendations for locations that are relatively distant from any test site or are intermediate between two or more test sites. Modeling of adaptive responses may facilitate the extension of results to all sites within a target region (Annicchiarico, 2002, pp. 57–60). At first, cultivar responses are modeled as a function of values at test sites of environmental variables that are associated with the occurrence of GL interaction (using test-year values for climatic variables). Then, the model is exploited for predicting responses at new sites or test sites as a function of site values of the selected environmental variables (using long-term means for climatic variables). While being straightforward for factorial regression, the extension of results for AMMI modeling requires that site scores on significant GL interaction PC axes could be predicted by environmental variables in a multiple regression equation with enough accuracy. Although subjected to this limitation, AMMI modeling has the advantage of being applicable even if environmental data were not available for the complete set of test environments, since locations with missing data could be excluded from analyses for predicting site PC scores while being used for modeling variety responses (thereby improving the estimation of genotypic parameters). Interfacing genotype modeling with a geographic information system (GIS) that includes the information on relevant environmental variables across the target region can simplify and make extremely fine-tuned the spatial up-scaling of results (Annicchiarico et al., 2002a). The re-assignment of test locations to subregions as a function of long-term values of climatic variables may also allow for a temporal up-scaling of results, possibly compensating for the effect of unusual values of climatic variables at test sites during test years. However, up-scaling procedures may also introduce a bias due to neglecting some important environmental variable or inaccurately estimating its effect. It is not known to which extent this bias may affect the prediction of yield responses and, ultimately, the reliability of these procedures for defining cultivar recommendations.

While focusing on the top-ranking, “winning” genotype at each site is essential for targeting novel genotypes by seed companies (Gauch and Zobel, 1997), recommending more than one cultivar per site may be envisaged for: (i) limiting the risk of disasters arising from the unforeseen susceptibility to a biotic or abiotic stress of the only cultivar recommended in a wide area (particularly for varieties that are genetically homogeneous, such as pure lines of wheat); (ii) possibly taking account of genotype differences that are not statistically significant. There is limited information, however, on the effect that the number of recommended cultivars may have on crop yields across a region.

Durum wheat is the main food product in Algeria. The national production has only accounted for 34% of the country consumption in the last decade and the consumption–production gap has progressively increased, making of Algeria the world’s leading durum wheat importer (Belaid, 2002). Previous work issued from 2-year multi-locational testing predicted an average yield increase between 10% and 12% on Algerian test sites by adopting specifically recommended cultivars in place of locally most-grown ones, based on modeled data (Annicchiarico et al., 2002b). It also produced recommendations for the potential durum wheat cropping area by interfacing a GIS with AMMI modeling on one hand and factorial regression modeling on the other (Annicchiarico et al., 2002a). Subregions included locations with same pair of expected top-yielding cultivars, as reported in Fig. 1 for factorial regression. For individual cultivars, the recommendations issued by the two techniques were coincident for about 77% of the region.

The present work exploits an independent data set issued from further testing of the same set of durum wheat genotypes across Algerian locations. Our main objective was to assess the merit of various methods for cultivar recommendation that are based either on observed data or data modeled by different techniques and, in the latter case, interfaced or not with a GIS. As additional objectives, we aimed at assessing: (i) the repeatability over time of the estimates of some adaptation parameters; (ii) the consistency between predicted and actual yield gains derived from growing recommended cultivars in place of locally most-grown entries; (iii) the effect on crop yields of different numbers of recommended cultivars.

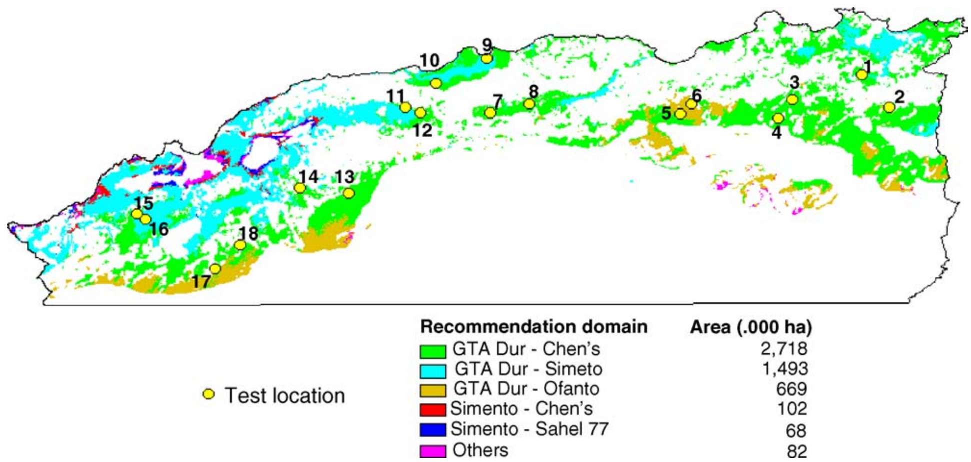

Fig. 1. Geographical position of test sites, and pair of top-yielding cultivars for grain yield in the potential durum wheat cropping area of Algeria predicted by interfacing factorial regression modeling of Data set 1 with long-term rainfall from October to June and winter mean temperature across January and February in a geographic information system (each colour corresponds to a pair defining a recommendation domain; from: Annicchiarico et al., 2002a).

2. Materials and methods

2.1. Experimental data

Twenty-four durum wheat (*Triticum durum* Desf.) cultivars of different origin, chosen among the most-grown or the best-performing from previous testing in Algeria, were evaluated for grain yield during the cropping seasons 1998–1999 through 2000–2001. They comprised four traditional cultivars derived from Algerian landraces (‘Hedba 3’, ‘Bidi 17’, ‘Oued Zenati 368’, ‘M. Ben Bachir’), two old varieties (‘Polonicum’, ‘T. Polonicum/Z.B.’), and 18 improved varieties of which 10 were released from international research centres, three from Italy, two from Algeria, one from France, one from Spain and the last from Tunisia (Table 1). Name and altitude of the test sites are reported in Table 2, whereas the site geographic position is given in Fig. 1. The data from the first two seasons, referred hereafter as Data set 1, were used for prior modeling and definition of recommendations. Those from the third season (Data set 2) acted as a validation data set for assessing the merit of recommendation methods, the repeatability of adaptation parameters, the consistency between predicted and actual yield gains, and the effect of different numbers of recommended cultivars. Data set 1 included 17 locations of which three had only 1 year’s data, whereas Data set 2 included 16 sites (Table 2). Missing trials were caused by crop failure or other reasons. One location (site 17 in Fig. 1) experienced repeated crop failures and was never considered for analyses.

Each trial was sown in autumn according to a randomized complete block design with four replications, with plots 10 m long × 1.2 m wide (6 rows, 20 cm apart). The adopted management of experiments, which was the common one for the crop at each site, is reported in ITCF-IAO (2002) together with additional information on test environments. In all cases the crop was rainfed, was preceded by fallow or a grain legume crop, and received nitrogen and phosphate mineral fertilization.

2.2. Prior modeling, and definition of cultivar recommendations in Data set 1

GL interaction effects were modeled by joint regression (Finlay and Wilkinson, 1963), AMMI (Gauch, 1992) and factorial regression as a function of environmental covariates (Hardwick and Wood, 1972), for a balanced subset of Data set 1 that included 2-year data for 14 sites. Sites with 1-year data were excluded at this stage to improve the assessment of repeatable GL effects, but their information was exploited at a later stage. The F_R test of GL interaction principal component (PC) axes, recommended by Piepho (1995) because of its greater robustness to non-normality and heteroscedasticity of errors compared with alternative tests, supported the selection of the AMMI model with one PC axis. The test adopted the GLY interaction as an error term, as appropriate under the assumption of year as random factor (Annicchiarico, 1997). The uni-dimensional AMMI model allowed for the graphical expression of genotype responses as nominal yields (i.e. expected responses from which the site main effect, that has no influence on genotype ranking, has been eliminated) as a function of the scaled PC 1 score of locations (Gauch and Zobel, 1997). Site mean values across test years of six environmental variables were used for factorial regression analysis. They were: rainfall (from October to June); winter mean and minimum temperatures (across daily values in January and February); spring mean and maximum temperatures (across daily values from April 11 to May 10); altitude. All of these variables were also available in the GIS (as long-term values, for climatic variables). The analysis was carried out as suggested by Denis (1988) and described for a multi-year data set by Annicchiarico (2002, p. 45). The best one-covariate model was identified, and then additional covariates were added if significant ($P < 0.05$), according to a stepwise forward selection strategy. Mean squares of covariates (derived, for second and higher order covariates, from partial regression sums of squares) and of the residual GL interaction were tested on the GLY interaction

Table 1
Code, name, origin, estimate of mean grain yield, slope of regression on site mean yield (b) and scaled score on the first genotype × location (GL) interaction principal component (PC 1) in two data sets, and estimate of intercept value (α) and partial regression coefficients for winter mean temperature (β_{T_i}) and rainfall (β_{R_i}) in a factorial regression equation of GL effects in one data set, for durum wheat cultivars in Algeria

Cultivar			Mean yield[a] (t/ha)		b[b]		PC 1		α[c]	β_{T_i}[c,d]	β_{R_i}[c,d]
Code	Name	Origin	Data set 1[c]	Data set 2[e]	Data set 1[c]	Data set 2[e]	Data set 1[c]	Data set 2[e]			
1	Hedba/Gerardo	Algeria	1.73	2.29	1.11	1.02	0.15	0.05	−0.285	0.00070*	0.0010
2	Bidi/Waha/Bidi	Algeria	2.06 a	2.81 a	1.17**	1.01	0.25	0.17	−0.565	0.00035	0.0519**
3	GTA Dur	CIMMYT	2.19 a	2.97 a	1.25**	1.15*	0.34	0.28	−0.642	0.00103*	0.0283
4	Eider	CIMMYT	1.98 a	2.92 a	1.13	1.19	0.31	0.39	−0.593	0.00031	0.0573*
5	Chen's	CIMMYT	2.14 a	2.92 a	1.20**	1.15	0.33	0.56	−0.655	0.00079*	0.0418*
6	Sahel 77	CIMMYT	2.08 a	2.79 a	1.17*	0.97	0.28	0.22	−0.553	0.00024	0.0556*
7	T.Polonicum/Z.B.	Algeria	1.59	2.36	0.71**	0.77	−0.54	−0.81	1.066	−0.00084*	−0.0888**
8	Hedba 3	Algeria	1.48	2.31	0.59**	0.75	−0.66	−0.94	1.295	−0.00153**	−0.0835*
9	Mexicali 75	CIMMYT	1.98 a	2.88 a	1.20*	1.24	0.34	0.54	−0.598	−0.00008	0.0765*
10	Kebir	ICARDA	1.82	2.46	0.97	0.97	−0.05	0.01	−0.008	0.00036	−0.0165
11	Om Rabi 9	ICARDA	1.90	2.72 a	0.95	1.24	−0.09	0.41	0.172	−0.00024	−0.0095
12	Belikh 2	ICARDA	1.97 a	2.58	1.12	1.12	0.19	0.31	−0.451	0.00072	0.0202
13	Bidi 17	Algeria	1.60	2.15	0.63**	0.71*	−0.65	−0.71	1.291	−0.00101*	−0.1082**
14	Waha	ICARDA	2.01 a	2.78 a	1.20**	0.95	0.33	−0.06	−0.636	0.00029	0.0629**
15	Oued Zenati 368	Algeria	1.49	2.17	0.57**	0.75	−0.74	−0.83	1.577	−0.00145**	−0.1216**
16	M. Ben Bachir	Algeria	1.51	2.18	0.58**	0.75*	−0.79	−0.66	1.643	−0.00125*	−0.1392**
17	INRAT 69	Tunisia	1.70	2.31	1.05	0.98	0.07	0.13	−0.213	−0.00028	0.0390
18	Ardente	France	1.75	2.69	1.04	1.12	0.00	0.05	0.120	0.00011	−0.0199
19	Vitron	Spain	1.94	2.57	1.15	1.08	0.32	0.37	−0.695	0.00015	0.0769**
20	B. Dur 1.94	CIMMYT	2.06 a	2.87 a	1.21**	0.99	0.30	0.12	−0.582	0.00072	0.0358
21	Ofanto	Italy	2.06 a	2.86 a	1.02	1.00	0.20	0.05	−0.279	0.00074	−0.0016
22	Simeto	Italy	2.08 a	2.76 a	1.23*	1.06	0.43	0.46	−0.941	0.00028	0.1008**
23	Duilio	Italy	1.99 a	2.64	1.19*	1.23	0.37	0.49	−0.837	0.00122**	0.0429**
24	Polonicum	France	1.58	2.42	0.56**	0.82	−0.68	−0.65	1.370	−0.00133*	−0.1023**

[a] Genotypes with letter 'a' do not differ from the top-ranking one according to Dunnett's one-tailed test at $P < 0.20$.
[b] Different from unity at $P < 0.05$ (*) and $P < 0.01$ (**), respectively.
[c] Modeling data set: 14 sites in the seasons 1998–1999 and 1999–2000 (mean yield = 1.86 t/ha); from Annicchiarico et al. (2002b).
[d] Different from zero at $P < 0.05$ (*) and $P < 0.01$ (**), respectively, in Data set 1 (modeling data set); rainfall from October to June in mm, temperature across January and February in °C.
[e] Validation data set: 16 sites in the season 2000–2001 (mean yield = 2.60 t/ha).

mean square. The analysis selected two covariates, namely winter mean temperature and rainfall. The proportion of GL interaction variation accounted for by joint regression, AMMI and factorial regression models was 45%, 70% and 61%, respectively. Indications on top-yielding cultivars for each of the three sites with 1 year's data were derived from the expected yield responses for the most similar location among those included in the analysis of adaptation. The degree of similarity was assessed in terms of genetic correlation coefficient for genotype yields, estimated for all relevant pairs of locations using each time only data of the same cropping season (Annicchiarico et al., 2002b).

Genotypic parameters of adaptation estimated in Data set 1 for the different models are reported in Table 1. Conventional cultivar recommendations were based on modeled yields at test sites, which implicitly depended on genotype responses to test-year values of the climatic variables associated with GL interaction. Delli et al. (2002) described the currently available GIS and its exploitation for defining the potential durum wheat cropping region of Algeria (which excluded steepy-sloping and mountain areas, saline or rocky soils, and sites with annual rainfall <350 mm). GIS-based recommendations were produced for factorial regression and AMMI modeling. They were based on genotype yields at the site predicted as a function of long-term values of the selected climatic variables, as proposed by Annicchiarico (2002, pp. 57–60) and described earlier for this data set (Annicchiarico et al., 2002a). For factorial regression, the nominal yield N_{ij} of genotype i at location j in the GIS (including test sites) was estimated as a function of long-term values on the site of the two covariates by the formula:

$$N_{ij} = m_i + \alpha_i + \beta_{T_i} T_j + \beta_{R_i} R_j \quad (1)$$

where m_i is the mean value (as estimated by analysis of variance), β_{T_i} and β_{R_i} the coefficients of partial regression on winter mean temperature (T_j, in °C) and rainfall over the crop cycle (R_j, in mm), respectively, and α_i is the intercept value in the factorial regression equation, for genotype i. Interfacing the AMMI modeling with the GIS is less straightforward. In general, the AMMI-modeled nominal yield N_{ij} for genotype i at location j is (Gauch and Zobel, 1997; Annicchiarico, 2002, p. 39):

$$N_{ij} = m_i + \sum (u_{in}\sqrt{l_n})(v_{jn}\sqrt{l_n}) = m_i + \sum (u'_{in} v'_{jn}) \quad (2)$$

Table 2
Site code, name, altitude, mean grain yield and scaled score on the first genotype × location interaction principal component (PC 1) in two data sets, and PC 1 predicted from long-term values of rainfall over the crop cycle and winter mean temperature in a geographic information system (GIS), for Algerian durum wheat test locations

Location		Altitude (m a.s.l.)	Mean yield (t/ha)		PC 1		
Code	Name		Data set 1[a]	Data set 2[b]	Data set 1[a]	Data set 2[b]	GIS
1	Guelma	272	2.94	2.87	0.72	−0.25	0.74
2	Souk Ahras	963	1.74	2.70	−0.23	−0.34	0.01
3	El Khroub	713	(3.24)	3.20	–	0.17	0.15
4	Oum El Bouaghi	869	1.58	0.76	−0.28	−0.34	−0.11
5	Sétif	1023	1.42	1.36	−0.32	−0.27	−0.26
6	EAC Dahal	1318	1.24	3.11	−0.56	−0.32	−0.35
7	Beni Slimane	743	0.88	1.18	−0.25	−0.30	−0.01
8	Ain Bessam	707	0.80	2.92	−0.42	−0.30	0.14
9	Oued Smar	34	3.45	3.70	1.63	1.70	1.07
10	Tipaza	114	1.90	1.23	0.18	−0.21	1.06
11	Khemis Miliana	344	1.80	2.32	−0.03	−0.37	0.51
12	Djendel	366	2.48	3.78	−0.01	−0.10	0.64
13	Tiaret Sebaine	1003	(0.84)	2.52	–	−0.79	−0.20
14	Rahouia	773	2.71	3.59	−0.28	0.36	0.19
15	Tessala	594	(1.60)	–	–	–	0.37
16	Sidi Bel Abbes	554	1.51	3.30	0.01	0.78	0.26
18	Abdelkader	992	1.65	3.10	−0.17	0.59	−0.16

[a] Modeling data set: seasons 1998–1999 and 1999–2000. Sites with 1-year data (with mean yield into parentheses) were not used for modeling. From: Annicchiarico et al. (2002b).
[b] Validation data set: season 2000–2001.

where m_i is the genotype mean value, and u'_{in} and v'_{jn} the scores on the PC axis n for genotype i and location j, respectively, that are scaled through multiplication of the respective eigenvectors u_{in} and v_{jn} by the square root of the singular value l_n for the PC axis. The extension of results to new sites requires that for each PC axis in the selected AMMI model a large portion of the variation in v'_{jn} values (e.g. $R^2 > 60\%$) could be explained by the environmental variables in a multiple regression equation, using test-year values for climatic data (Annicchiarico, 2002, p. 57). In this case, the following equation was selected by a stepwise multiple regression analysis aimed at describing the variation for v'_j values of PC 1 (the only PC axis in the selected AMMI model), holding a $P < 0.10$ level for selection among the six environmental variables:

$$v'_j = -2.025 + 0.1612T_j + 0.00176R_j \quad (3)$$

indicating that the scaled PC 1 score increased with the winter mean temperature (T_j, in °C) and the rainfall over the crop cycle (R_j, in mm) of location j. This model, which was sufficiently reliable ($R^2 = 0.81$), was exploited for predicting the v'_j value of location j in the GIS as a function of long-term values of the two climatic variables. The predicted v'_j values were inserted in formula (2), computing for each site the nominal yield of each cultivar. Joint regression modeling was not interfaced with the GIS because of the rather poor ability to predict the site mean yield as a function of the available environmental variables in a multiple regression equation ($R^2 = 0.63$) (Annicchiarico et al., 2002c). For AMMI-modeled and factorial regression-modeled data, the geographical display of GIS-based recommendations for subregions that grouped the sites with same pair of top-yielding cultivars was produced using IDRISI 32.11 software and adopting 1 km^2 as the mapping resolution.

Recommending the pair of top-yielding cultivars was adopted as the reference criterion for comparing the following methods for defining site-specific recommendations: (i) observed data (i.e. no modeling); (ii) joint regression-modeled data; (iii) additive main effects and multiplicative interaction (AMMI)-modeled data; (iv) factorial regression-modeled data; (v) AMMI modeling interfaced with a GIS; (vi) factorial regression modeling interfaced with a GIS.

The yield gain derived from growing recommended cultivars was predicted at each site as the difference between the mean yield of the pair of top-yielding cultivars and the mean yield of the pair of currently most-grown cultivars at the site, for data of each recommendation method. Most-grown material was defined according to indications provided by local extension services.

The effect of different numbers of recommended cultivars was assessed for factorial regression-modeled data, which showed a posteriori a slight advantage for recommendation over joint regression- and AMMI-modeled data. The following site-specific recommendations were compared: (i) the top-yielding cultivar; (ii) the two top-yielding cultivars; (iii) the three top-yielding cultivars; (iv) a variable set of top-yielding cultivars that did not differ at $P < 0.20$ from the top-yielding one. This rather liberal Type 1 error rate was adopted to achieve a better balance with Type 2 error rates (Kang, 1998). Statistically inferior cultivars were those that differed from the top-yielding cultivar according to Dunnett's one-tailed test, also known as Gupta's test, as recommended by Dagnelie (1975, p. 253). The least significant (or critical) difference d for the comparison, assuming the year factor as random, held the within-site genotype × year (GY) interaction mean square (M_{GY}) as an error term and was computed as

$$d = t' \sqrt{\left(\frac{2M_{\mathrm{GY}}}{N}\right)} \qquad (4)$$

where N is the total number of observations for each genotype (N = no. years × no. experiment replications = 8). Reference t' values for $P < 0.20$ (different from Student's t values) are reported in Annicchiarico (2002, p. 26). Two possible estimates of M_{GY} were considered. The former was its average value across sites, obtained from a combined analysis of variance (ANOVA) by pooling the variation and the degrees of freedom of GY and GLY interactions (Annicchiarico, 2002, pp. 34 and 46). The latter was site-specific, and was provided by the GY interaction in a separate ANOVA for each site that held genotype and year (besides block) as factors.

2.3. Reliability of modeled data, and merit of cultivar recommendations using Data set 2

The relative extent of genotype main effects and GL interaction effects in Data set 2 was preliminarily assessed by estimating these variance components from mean squares of a combined ANOVA holding genotype and location as random factors, as described for Model 1 in Table 4.1 of Annicchiarico (2002). A second ANOVA holding genotype as fixed factor compared the cultivars for mean yield across locations. The repeatability in the third year of joint regression and AMMI parameters of genotype adaptation estimated in the modeling data set was assessed by simple correlation between estimates provided by the two data sets. The consistency between estimates of parameters for test sites was also verified, considering also the scaled PC 1 score predicted from long-term values of climatic variables in the GIS besides those estimated from each of the two data sets. The assessment was not extended to genotypic parameters of factorial regression, because these parameters could not be estimated in Data set 2 due to the limited number of test sites with available climatic information.

The value of each method for defining the best pair of recommended cultivars was provided by the mean yield at each site of the recommended material in the validation data set (Data set 2). The actual yield gain derived from growing the recommended cultivars was estimated at each site as the difference between the mean yield of the recommended material and the mean yield of the two most-grown cultivars, and then compared with its predicted value. The comparison of methods was based on original data as well as on data adjusted by AMMI analysis. The purpose of AMMI modeling in this case was to increase the estimation accuracy of genotype by location cell means by reducing the noise due to experimental error (Gauch, 1990; Piepho, 1994). Therefore, the error term adopted in the F_{R} test of GL interaction PC axes was the pooled experimental error.

The merit of different numbers of recommended cultivars defined according to factorial regression-modeled data was provided by the mean yield at each site of the recommended material in the validation data set, considering both original and AMMI-adjusted data.

The software IRRISTAT, released by the International Rice Research Institute (IRRI) of Manila, was used for all analyses. Its use for analyses of adaptation has been exemplified by Annicchiarico (2002, pp. 89–103) with reference to Data set 1.

3. Results

3.1. Repeatability of parameters of adaptation

The estimated GL interaction variance component for Data set 2 was about thrice as large as the genotypic one, 0.182 and 0.058 $(\mathrm{t/ha})^2$ respectively, confirming the possible interest of exploiting GL interaction effects by site-specific cultivar recommendations. Both variance components differed significantly from zero ($P < 0.001$).

The differences in mean yield between cultivars estimated in the modeling data set (Data set 1) were highly repeatable in the third year (Data set 2), as shown by the high correlation between the data sets for entry mean value ($r = 0.91$, $P < 0.01$). 'GTA Dur' and 'Chen's' ranked consistently first and second, respectively, and the germplasm from CIMMYT confirmed its good performance in the region (Table 1).

Heterogeneity of genotype regressions in the joint regression analysis, and the first GL interaction PC axis in the AMMI analysis, were both significant in Data set 2 ($P < 0.01$). The former, however, explained only 12% of the GL interaction sum of squares in comparison with 39% of the latter, and the deviations from regression term was significant ($P < 0.01$). The slope of regression on site mean yield (b value) differed from unity at $P < 0.05$ (indicating interaction with site mean) for only three cultivars in this data set due to the large deviation from regression of individual cultivars, in contrast with the large genotype variation for b that emerged in Data set 1 (Table 1). However, the estimates of regression slopes were largely consistent between data sets ($r = 0.81$, $P < 0.01$). PC 1 scores for the two data sets are reported for cultivars in Table 1 and for locations in Table 2. Cultivar scores were highly consistent between data sets ($r = 0.92$, $P < 0.01$). The consistency was moderate for PC 1 score ($r = 0.68$, $P < 0.01$) and fairly low for mean yield ($r = 0.49$, $P < 0.10$) of locations. For site yield there was, in addition, a marked difference in mean value over sites between Data set 1 (1.86 t/ha, with means of 1.85 t/ha for the first year and 1.87 t/ha for the second) and Data set 2 (2.60 t/ha). The site PC 1 score in Data set 2 showed modest consistency ($r = 0.43$, $P < 0.10$) also with its value predicted from long-term values of rainfall and winter mean temperature in the GIS, which is also reported in Table 2.

In both data sets the two genotype adaptation parameters (b and PC 1) were closely associated positively ($r \geq 0.94$), suggesting the interpretation of PC 1 as a measure of cultivar adaptation to favourable growing conditions at the site. This indication agreed well with the correlations of site PC 1 score with mean yield ($r = 0.79$, $P < 0.01$), rainfall ($r = 0.62$, $P < 0.05$) and winter mean temperature ($r = 0.79$, $P < 0.01$) of locations in Data set 1. The meaning of site PC 1 score was more elusive in Data set 2. Its positive association with mean yield was only moderate ($r = 0.52$, $P < 0.05$), whereas the available information on environmental variables (Table 3) revealed just a trend ($P > 0.10$)

Table 3
Rainfall over the crop cycle and winter mean temperature of some Algerian durum wheat test sites across the seasons 1998–1999 and 1999–2000 (Data set 1), in the season 2000–2001 (Data set 2) and in the long term

Location		Rainfall[a] (mm)			Winter mean temperature[b] (°C)		
Code	Name	Data set 1	Data set 2	Long term	Data set 1	Data set 2	Long term
1	Guelma	631	362	593	9.4	–	10.7
5	Sétif	368	328	396	6.1	6.8	6.6
6	EAC Dahal	397	462	487	4.5	4.4	5.1
7	Beni Slimane	306	348	424	8.1	4.9	7.9
9	Oued Smar	625	484	671	12.8	13.1	11.9
10	Tipaza	374	453	691	12.7	16.8	11.6
12	Djendel	582	467	553	7.4	7.3	10.5
16	Sidi Bel Abbes	261	377	381	9.3	10.4	10.0
18	Abdelkader	236	386	418	8.2	6.6	7.0

[a] From October to June.
[b] Daily values across January and February.

towards correlation with site rainfall ($r = 0.34$) and winter mean temperature ($r = 0.41$).

The substantial repeatability of AMMI-modeled genotype responses as a function of site PC 1 score is graphically displayed in Fig. 2 for a subset of best-performing entries. The extent of genotype variation at sites with extreme PC 1 scores was somewhat smaller in Data set 1, probably due to the buffering effect at individual sites provided by averaging the genotype responses across 2 years. As a result, the possible advantage in extremely harsh environments of landrace or old cultivar material (‘Bidi 17’, ‘Polonicum’, ‘Hedba 3’) clearly emerged only in Data set 2. The chief difficulty for performing reliable recommendations concerned the prediction of the site PC 1 score (whose value influences the indications on top-yielding entries at the site: see formula (2)), as already indicated by its only moderate repeatability. Recalling that the site score on PC 1 increased with the rainfall and winter temperature of the site in the modeling data set (see formula (3)), the difference between values of these variables recorded at individual sites across modeling years, the third year and the long-term period could partly explain the inconsistencies for site PC 1 score estimated in Data set 1, Data set 2 and in the GIS. In particular, the markedly low PC 1 score estimated in Data set 2 for site 1 (Table 2) was relative to a cropping year with unusually low rainfall at the site (Table 3). The estimate of PC 1 for site 6 in Data set 2 was closer to that predicted in the GIS than its estimate in Data set 1 (Table 2), because rainfall in the third year was closer to its long-term value (Table 3). The difference between data sets for site PC 1 score in western locations (sites 16 and 18) could be related to higher rainfall in the third year (Tables 2 and 3). The markedly low PC 1 score of site 10 in the two data sets relative to its predicted value in the GIS may partly be accounted by lower rainfall across test years than in the long term (Tables 2 and 3), although the terminal heat stress indicated by particularly high spring temperatures at this site (data not reported) may have contributed to the large difference between the values of PC 1 estimated in the two data sets and the predicted one (Table 2). Correlations between data sets for the environmental variables indicated that the dif-

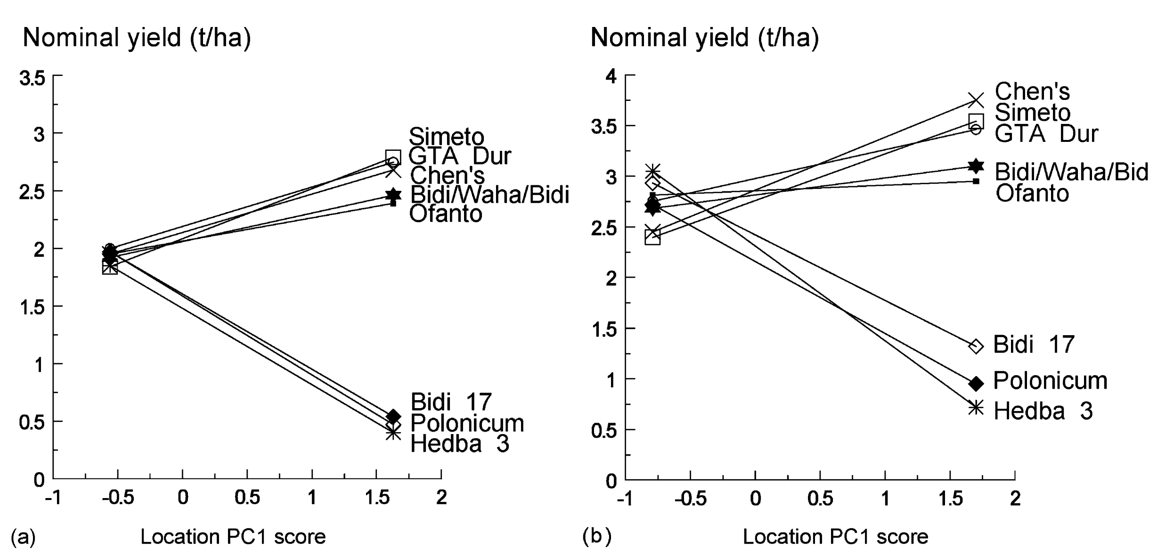

Fig. 2. Nominal grain yield of best-performing durum wheat cultivars as a function of the scaled score of locations on the first genotype × location interaction principal component (PC 1) in Data set 1 (a) and Data set 2 (b). Data set 1: modeling data set, seasons 1998–1999 and 1999–2000; Data set 2: validation data set, season 2000–2001 (see Table 2 for PC 1 scores of sites).

ferences among sites were much less repeatable for rainfall amount ($r = 0.44$) than winter temperature ($r = 0.90$). The wide year-to-year variability for environmental variables, especially rainfall, also affected the factorial regression-based prediction of locally top-yielding material (see formula (1)) and, most likely, also joint-regression-based predictions in an indirect manner, by affecting the site mean yield.

3.2. Comparison of methods for cultivar recommendation

The pair of cultivars recommended at each site based on the different methods applied to Data set 1 is reported in Table 4. Most-grown cultivars usually differed from those recommended at each site according to each method. Compared with the method based on observed yields, which implied a specific pair of recommended cultivars for almost every site (15 different pairs for 17 sites), modeling allowed in all cases for a noticeable reduction in the number of site groups characterized by specific recommendations (four for factorial regression-modeled data; two for AMMI modeling interfaced with the GIS; three in the remaining cases). The reassignment of test locations to subregions as a consequence of the up-scaling procedure implied a change of the pair of recommended cultivars at four locations (sites 6, 10, 12 and 15) for AMMI modeling and six locations (sites 5, 10, 13, 14, 16 and 18) for factorial regression modeling (Table 4). GIS-based recommendations issued from factorial regression, reported in Fig. 1, implied more subregions compared with those from AMMI (reported in Annicchiarico et al., 2002a). In particular, they comprised an additional major subregion of climatically unfavourable sites that extended over 13% of the cropping area and in which ‘Ofanto’ could be recommended besides ‘GTA Dur’. For test sites, the consistency between recommendations of the two modeling techniques tended to increase as a consequence of the up-scaling procedure, passing from 41% for conventional modeling (i.e. 7 locations out of 17: sites 2–4, 7–9 and 12) to 65% for GIS-interfaced modeling (sites 2–5, 7–9, 13–15 and 18) (Table 4). As a matter of fact, inconsistencies were not so dramatic because they usually concerned only one of the two recommended cultivars at the site.

The AMMI model selected for adjusting data of individual locations in Data set 2 included three PC axes based on the F_R test at $P < 0.05$ for PC selection. The greater complexity of this model relative to that selected in Data set 1 (including only one PC) was due the smaller error term adopted in this context (i.e. the pooled experimental error instead of the GLY interaction). The mean yield over locations provided by the pair of cultivars recommended according to each method, and the yield gain relative to most-grown cultivars, are reported in Table 5 for observed and AMMI-adjusted yields of Data set 2. A second type of comparison was based on the gain relative to most-grown cultivars estimated at individual sites and then averaged across locations (Table 5). Since absolute differences between cultivars were much larger at high-yielding than low-yielding sites (as commonly observed in data sets including large variation in site mean yield: Yau, 1991), this latter comparison is nearer to the perception of yield differences at the farm level, whereas the former comparison may better reflect the impact of recommendation methods on yields at the country level. For data not subject to AMMI-adjustment, the two types of comparison provided similar results, showing that: (i) recommendations based on modeled data produced additional yield gains from around 3% to over 5% compared with those based on observed data; (ii) the extension of recommendations by spatial modeling through the GIS implied for test sites a modest yield decrease (1–2%) relative to recommendations based on conventional modeled data; (iii) the yield gains obtainable by GIS-based rec-

Table 4
Pair of most-grown cultivars, and pair of recommended cultivars according to: (i) observed experiment data, (ii) joint regression (JR) modeling, (iii) additive main effects and multiplicative interaction (AMMI) modeling, (iv) factorial regression (FR) modeling, (v) AMMI modeling interfaced with a geographic information system (GIS), and (vi) factorial regression modeling interfaced with a GIS, for durum wheat in 17 Algerian test sites (see cultivar code in Table 1)

Location		Most-grown	Observed data	JR	AMMI	FR	AMMI + GIS	FR + GIS
Code	Name							
1	Guelma	14, 19	3, 5	3, 5	3, 22	3, 5	3, 22	3, 5
2	Souk Ahras	14, 19	12, 21	3, 5	3, 5	3, 5	3, 5	3, 5
3	El Khroub	14, 19	9, 14	3, 5	3, 5	3, 5	3, 5	3, 5
4	Oum El Bouaghi	14, 19	3, 21	3, 5	3, 5	3, 5	3, 5	3, 5
5	Sétif	14, 16	5, 21	3, 21	3, 5	3, 21	3, 5	3, 5
6	EAC Dahal	14, 16	3, 12	3, 21	3, 13	3, 21	3, 5	3, 21
7	Beni Slimane	14, 19	5, 21	21, 24	3, 5	3, 5	3, 5	3, 5
8	Ain Bessam	14, 19	21, 22	21, 24	3, 5	3, 5	3, 5	3, 5
9	Oued Smar	14, 19	3, 22	3, 5	3, 22	3, 22	3, 22	3, 22
10	Tipaza	14, 19	3, 22	3, 5	3, 5	6, 22	3, 22	3, 5
11	Khemis Miliana	5, 19	9, 22	3, 5	3, 5	3, 22	3, 5	3, 22
12	Djendel	5, 19	2, 3	3, 5	3, 5	3, 5	3, 22	3, 5
13	Tiaret Sebaine	19, 22	21, 23	3, 21	3, 5	3, 21	3, 5	3, 5
14	Rahouia	14, 19	5, 20	3, 5	3, 5	3, 21	3, 5	3, 5
15	Tessala	14, 19	5, 6	3, 5	3, 22	3, 5	3, 5	3, 5
16	Sidi Bel Abbes	14, 19	9, 21	3, 5	3, 5	6, 22	3, 5	3, 22
18	Abdelkader	14, 19	6, 14	3, 5	3, 5	6, 22	3, 5	3, 5

Based on Data set 1 (modeling data set); from: Annicchiarico et al. (2002a, 2002b).

Table 5
Actual and predicted yield gain over the pair of most-grown cultivars of the pair of recommended cultivars according to: (i) observed experiment data, (ii) joint regression (JR) modeling, (iii) additive main effects and multiplicative interaction (AMMI) modeling, (iv) factorial regression (FR)-modeling, (v) AMMI modeling interfaced with a geographic information system (GIS), and (vi) factorial regression modeling interfaced with a GIS, for durum wheat in Algeria in a validation data set

Cultivars[a]	Observed data[b]			Adjusted data[b]			Predicted average gain[c] (%)
	Mean yield		Average gain (%)	Mean yield		Average gain (%)	
	Value (t/ha)	Gain (%)		Value (t/ha)	Gain (%)		
Most-grown	2.663	–	–	2.683	–	–	–
Observed data	2.829	6.2	6.9	2.786	4.2	6.2	24.4
JR	2.947	10.7	10.3	2.931	9.2	10.2	12.5
AMMI	2.937	10.3	9.7	2.921	8.9	10.0	10.7
FR	2.977	11.8	11.8	2.944	9.7	11.3	10.8
AMMI + GIS	2.902	9.0	8.6	2.914	8.6	9.5	9.4
FR + GIS	2.919	9.6	9.4	2.907	8.4	9.5	11.4

[a] Recommended cultivars are the pair of top-yielding ones at each site in Data set 1 (see Table 4).
[b] Mean grain yield and gain over 16 sites, and average gain in individual sites, in Data set 2.
[c] Average gain in 16 individual sites in Data set 1 (modeling data set).

ommendations remained remarkable, i.e. around 9%, relative to the adoption of most-grown cultivars (Table 5). AMMI-adjusted data determined some shrinkage of the yield gains relative to most-grown cultivars when comparing mean yields over locations. They confirmed, however, the substantial yield gain offered by modeled data over observed data for recommendations (4–5%), the modest yield decrease (<2%) derived from further interfacing the modeling with the GIS, and the noticeable advantage of GIS-recommended cultivars over most-grown cultivars (Table 5). Factorial regression tended to show a slight advantage for definition of recommendations compared with the other models with the exception of GIS-based recommendations assessed on adjusted data, for which it was as good as AMMI.

3.3. Consistency between predicted and actual yield gains from recommendation

The average yield gains from cultivar recommendation predicted according to factorial regression- and AMMI-modeled yields in Data set 1 were highly consistent with the actual yields (observed or AMMI-adjusted) in Data set 2, the difference never exceeding 1% (Table 5). Also predictions based on AMMI modeling interfaced with the GIS were highly consistent, whereas those based on joint regression modeling or on factorial regression modeling interfaced with the GIS were about 2% higher than the actual gains (Table 5). Predicted yield gains that were based on observed data were quite unreliable, since they largely overestimated the actual gains in Data set 2 (predicted >24%, actual between 6% and 7%; see Table 5).

3.4. Effect of different numbers of recommended cultivars

With reference to factorial regression-modeled data, recommending at each site the pair of top-yielding cultivars (reference criterion) or only the top-yielding cultivar provided similar yields at the site and across sites based on observed or AMMI-adjusted yields in Data set 2 (Table 6). Recommending the three top-yielding cultivars tended to imply a modest yield penalty (between 1% and 2%) relative to the reference criterion.

The two recommendation criteria based on statistically significant differences issued the same set of recommended cul-

Table 6
Grain yield response in a validation data set of different numbers of recommended durum wheat cultivars in Algeria: (i) pair of top-yielding cultivars (reference criterion), (ii) top-yielding cultivar, (iii) three top-yielding cultivars, and (iv) the set of statistically not different cultivars according to each of two testing procedures

Cultivars[a]	Observed data[b]			Adjusted data[b]		
	Mean yield		Average difference (%)	Mean yield		Average difference (%)
	Value (t/ha)	Difference (%)		Value (t/ha)	Difference (%)	
Top-yielding pair	2.977	–	–	2.944	–	–
Top-yielding one	2.966	−0.3	0.1	2.937	−0.2	0.0
Top-yielding three	2.915	−2.1	0.0	2.907	−1.3	−1.2
Non-different set A[c]	2.679	−10.0	−9.2	2.681	−8.9	−9.5
Non-different set B[d]	2.698	−9.4	−7.9	2.697	−8.4	−8.3

[a] Top-yielding entries defined according to factorial regression-modeled yields in Data set 1.
[b] Mean yield and yield difference relative to the reference criterion over 16 sites, and average difference in individual sites relative to the reference criterion, in Data set 2.
[c] According to Dunnett's one-tailed test at $P < 0.20$, holding the average within-site genotype × year interaction as an error term.
[d] According to Dunnett's one-tailed test at $P < 0.20$, holding the genotype × year interaction for the individual site as an error term.

tivars for all locations except the sites 5, 7, 8, 9 and 13. The criterion that held the specific GY interaction for these locations as an error term identified a smaller number of non-different, recommended entries in all cases except the high-yielding site 9, where the alternative criterion separated a smaller set of recommended entries. The GY interaction mean squares of individual sites differed widely and tended to increase as a function of site mean yield ($b = 1.67$, $P < 0.01$). For both criteria the recommended cultivars at individual sites were never less than eight, usually many more. Recommendations by the criterion based on site-specific errors for cultivar comparison showed somewhat higher mean yields in Data set 2 than those by the criterion holding the average within-site GY interaction as an error term (Table 6). Both criteria, however, provided mean yields of recommended material largely lower (8–10%) than the recommendation of the top-yielding one or two cultivars (Table 6).

4. Discussion

Earlier studies revealed the only moderate repeatability across years of joint regression and AMMI estimates of adaptation parameters for cereal or soybean cultivars in non-Mediterranean regions (Léon and Becker, 1988; Weber and Westermann, 1994; Sneller et al., 1997), indicating the need for estimating them in a multi-year data set. Accordingly, a 2-year data set was currently used for modeling. It is unlikely that modeling may be based on longer testing periods in most instances, given the high costs entailed by multi-environment testing and the turn-over of tested cultivars imposed by the release of novel germplasm. The present assessment of methods for cultivar evaluation and recommendation suffers from the limited time span (i.e. one cropping season) of the validation data. However, our results confirm and quantify the theoretical expectation (Gauch, 1992; Gauch and Zobel, 1997) that observed data, compared with modeled data, are less useful for cultivar recommendation because they provide worse predictions of future top-yielding cultivars, too optimistic predictions of yield gains derived from growing recommended cultivars, and unnecessarily complex recommendations caused by too many recommendation domains (subregions). While the present activity of testing and data collection produced an average yield gain of 6–7% at individual sites as a result of cultivar recommendation based on observed data, the additional modeling of data produced an extra yield gain of 4–5% as a result of more accurate recommendation (Table 5), proving to be a very cost-effective activity. This is remarkable also in consideration of the difference in mean yield between the two data sets, indicating that modeling was performed across two relatively unfavourable years while validation concerned a relatively favourable year.

Factorial regression, which showed a slight advantage over the other two modeling techniques, allows for an explicit assessment of environmental factors associated with the GL interaction both overall and for the individual cultivars (as depicted from partial regression coefficients of genotypes: see Table 1). Besides, it can interface with a GIS in a straightforward manner. Its adoption may be limited, however, by its need for environmental data that affect the GL interaction and are available for the complete set of test environments. In various reports (van Eeuwijk and Elgersma, 1993; Vargas et al., 1999) and also here, factorial regression and AMMI identified the same environmental factors as those related to GL interaction and produced fairly similar results in terms of genotype adaptive responses and site similarity for GL effects (Annicchiarico et al., 2002a), despite the higher requirements in terms of input data of the former model. This study adds to previous findings by showing the modest advantage of factorial regression over AMMI for defining cultivar recommendations, indicating the latter model as a valuable option when the former could not be adopted. Joint regression modeling, despite its lower ability in describing the GL interaction variation in Data set 2 and in most comparative studies (Brancourt-Hulmel et al., 1997) and the lower repeatability of its estimated parameters (b values and site mean yield) compared with AMMI ones (PC 1 scores of genotypes and sites), proved as valuable as AMMI for definition of recommendations on the basis of mean values of recommended material in Data set 2. Its main disadvantage relative to the other models laid in the aforementioned difficulty of interfacing with the GIS, owing to the poor ability to predict site mean yields from the available environmental variables.

Some crop simulation models may offer an alternative to the current models for predicting cultivar adaptive responses, but their adoption is frequently limited by the difficulty of reliably representing the GL effects by coefficients that summarize the genetic make-up of individual cultivars (Hunt et al., 2003). Recent models that incorporate gene action are promising but may still lack a sufficient accuracy and/or require too large modeling data sets to be routinely available (White and Hoogenboom, 2003). So far such models are mainly targeted to breeders, to investigate the impact on adaptation patterns of single traits or combinations of traits (Chapman et al., 2002).

Our results highlight the difficulty of predicting cultivar responses at sites of a Mediterranean region, showing the implications of the well-known unpredictability of rainfall amount (Pinna, 1977, pp. 366–369) on the repeatability over time of relevant site parameters (environmental covariates, PC 1 score, mean yield). The reliable estimation of genotypic parameters of adaptation proved easier, probably because of the widely diversified environments that Algerian test locations could provide even in a single cropping season. Despite the wide year-to-year variation, the extent of consistent climatic differences and repeatable GL interaction effects between contrasting areas of Algeria are large enough to be exploited by growing specifically adapted germplasm, just like reported by Ceccarelli (1996) for another Mediterranean region (northern Syria).

There are many examples of interfacing a GIS with agronomic models, e.g. for optimizing crop management, or for predicting soil erosion, nitrate leaching, and pesticide or herbicide fate (Hartkamp et al., 1999). Conversely, interfacing a GIS with modeling of genotype responses has been rare and has usually meant to support the breeding activity by focusing on crucial adaptive traits of genotypes, such as flowering date (Chapman and Barreto, 1996). This study highlights the practical interest of interfacing the modeling of cultivar adaptive responses with a GIS to obtain a fine-tuned geographical definition of cultivar recommendations across a target region, thereby maximizing the information from regional variety trials. In fact, GIS-based recommendations are not always applicable, e.g. when a multiple regression equation could not describe a large portion of the variation in site scores on PC axes selected for AMMI modeling, or when the factorial regression analysis could not account for a large portion of the GL interaction variation. In any case their indications should not extend over the range of values of the environmental variables that are used in these regression analyses (those for the currently selected variables are reported in Annicchiarico et al., 2002a). The risk of multicollinearity in regression analyses may be eliminated by a careful selection of environmental variables prior to the analyses or, for factorial regression, by adopting a partial least squares regression model (Aastveit and Martens, 1986). However, the close agreement between results of this technique and of factorial regression reported by Vargas et al. (1999) for a data set including a very large number of environmental variables suggests that multicollinearity may be a minor problem in a wide range of situations. In this study, GIS-based recommendations implied just a slight yield penalty in comparison with recommendations based on modeled data, while offering a means for extending results to all sites within the region. While being adequate for this comparison, the assessment of yield gains from GIS-based recommendations performed on the same sites used for prior modeling may overestimate the actual gains obtainable across the country. GIS-based recommendations have the additional advantage of improving the efficiency of seed production and distribution systems, especially those in developing countries, by allowing for the estimation of seed amounts of elite varieties possibly needed by farmers from the size of each subregion and the proportion of it that is devoted to the crop. Efficient seed systems complement the site-specific recommendation by allowing for a timely introduction into cultivation of recommended material. Minor subregions, such as those around 100,000 ha or less in Fig. 1, may be merged with larger, relatively similar subregions when the additional costs of multiplying and marketing specifically adapted cultivars are likely to outweigh the expected benefits (Gauch, 1992, p. 220). The current GIS has also been exploited for a different purpose, i.e. the geographical definition of two subregions object of separate breeding by the national durum wheat improvement program, performed by a discriminant analysis-based procedure that up-scaled the initial classification of test sites based on similarity for GL effects (Annicchiarico et al., 2005). Given the differences in objective and in analytical procedures, these subregions differed from any of the current recommendation domains. They confirmed, however, the contrast between the low-elevation, mild-winter area nearer to the cost and the high-elevation, cold-prone area of inland Algeria that also emerged for cultivar recommendation (Fig. 1).

The present inconsistencies between models for attribution to subregions of test sites could be related to imprecisions in the estimation of model parameters rather than to the up-scaling procedures, since they tended to decrease for up-scaled data. Actually, some inconsistencies were the consequence of inversions between the second- and the third-ranking cultivars at the site due to very small differences in predicted yields (<0.02 t/ha) (data not reported).

Recommending two top-yielding cultivars allowed for: (i) maintaining a reasonable level of biodiversity of cultivated material without evident yield penalties, in comparison with one recommended genotype and (ii) obtaining somewhat higher yields, and a simpler definition and exploitation of recommendation domains, in comparison with three recommended cultivars. Indeed, for three cultivars the graphical display of subregions and the estimation of seed amounts that are possibly needed by farmers may be too complex to be managed. For site-specific recommendation of several cultivars, Annicchiarico (2002, p. 59) has suggested to develop a simple Decision-aid System that outputs the nominal yields of all cultivars as a function of inputed values of the selected environmental variables (possibly, together with a reference least-significant difference). Such approach, although more flexible and informative, may be less suited to the needs of extension services in less developed countries.

Taking account of statistical differences for cultivar recommendation, although more appealing in principle, may determine markedly lower yields over a region due to the introduction into cultivation of lower-yielding material. This danger is higher in a region such as Algeria, characterized by wide year-to-year climatic variability and, hence, large within-site GY interaction (which acts as the error term for cultivar comparison). The somewhat lower mean yield of sets of top-yielding genotypes separated according to the average within-site GY interaction mean square was due to the inadequacy of this error term when the GY interaction mean square of individual sites tends to increase as a function of site mean yield. In this situation, which is likely to occur only in the presence of wide variation in site mean yield (Annicchiarico, 2002, p. 54), the least-significant difference issued by the average within-site GY interaction tends to be too small for higher-yielding sites and too large for lower-yielding sites. When appropriate, this error term offers a simple means for computing a reference least-significant difference for comparison of cultivar yields that are modeled as a function of long-term values of environmental variables (as in the current GIS).

The average yield increase (around 9%) observed at Algerian locations by site-specific germplasm recommendation based on modeled data is remarkable, when considering that it may be obtained at virtually no cost (unlike other means aimed at improving the cropping environment). Improved targeting of cultivars is a necessary complement of plant breeding that may prove in itself a powerful and cost-efficient means of enhancing crop productivity, food security and farmers' incomes.

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