Environmental Variables for Modeling Wheat Yields in the Southwest Pampa Region of Argentina

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ABSTRACT

Two types of time scales (ten-day and phenological phases) for environmental variables were employed in the development of statistical regression models for the southwest Pampa, Argentina. Models were built to detect the effects of weather in wheat yields for the period 1977-1999. The parameters were grouped as meteorological, processed and indices. Total soil-water availability (Att) and the ratio of actual evapotranspiration to potential evapotranspiration (α), conform the processed variables and were obtained from a water balance model where moist anomaly index (Z) and Palmer drought severity index (ISP) are the indices calculated according to Palmer's model. For these parameters it was possible to detect the decades of the year and the phenological phases best related to grain yields. The regression equation for meteorological variables in decadal scale is the best fitted and skill-predictive. Using mixed parameters, both decadal and phenological stage models perform standard errors of estimate around 200 kg ha^{-1}. Truncated models on a phenological scale behave better than in decadal scale. The use of physiological stages improved yields estimation, in particular, for those years with extreme meteorological conditions. The optimal models were tested and a mean square root error (RMSE) of about 400 kg ha^{-1} was obtained.

Key Words: wheat modeling, multivariate regression, environmental variables, pampa region.

1. INTRODUCTION

The southwest border of the pampa region is characterized by its sub-humid climate, with high inter-annual rain variability and a negative soil moisture balance. Wheat is the most important regional cereal production. Variable weather conditions have a direct impact on crop yields. The environmental major components that affect wheat development are temperature, photoperiod and vernalization (Miralles and Slafer 2001). Other factors that have incidence on growth and productivity are water availability and radiation. Several authors pointed out that winter cereals in the region suffer from water stress during the late spring season. The largest correlation between monthly precipitation and yearly wheat yields is observed in November, March and April (Paoloni and Vazquez 1984). Other authors recognize the incidence in yield reduction of the initial soil moisture content, high air temperature in the filling stage and water deficiency during anthesis (Travasso et al. 1994). Average yields for the SW pampa region are 2000 kg ha^{-1} with maximum values of 3500-3600 kg ha^{-1}, provided that early and abundant rainfall occurs together with no late frosts and moderate temperatures during grain filling (Gallo Candolo 2001).

Regression-type models have been proposed and applied to estimate weather effects on yields since the beginning of the XX century and they have been criticized too, because of their empirical nature that restricts the use to the range of values from which they were developed. But their use is still adequate for regions where simulation or deterministic growth models are not available because, among others, the proper model parameters cannot be correctly determined. Lately, three crop simulation models used to test the accuracy of grain yield predictions under UK climatic conditions failed to predict wheat yield. Mis-specified parameters and errors in weather variables or sowing date, among others, (Landau et al. 1998), may have caused inaccuracy. The same authors were able to improve their results when they developed a parsimonious, multiple-regression model, using a minimum number of parameters without losing predictive power, (Landau et al. 2000). There is also a renewed interest in this type of models as tools to estimate the impact of climatic fluctuation on the crop productions over wide spread areas. Early investigations were performed for Bordenave, by Scian and Donnari (1995), using the monthly Palmer drought severity index (ISP) and the moisture anomaly index (Z) to estimate wheat yield.

In the present study we used weather data to study the availability of a multivariate model of wheat yield estimation, employing a time scale of ten days (decadal scale) as well as periods related to the physiological stages.

2. MATERIALS AND METHODS

Wheat yield and meteorological data from an experimental field in Bordenave (Latitude: 37° 51′ S, Longitude: 63° 01′ W, height: 212 m), province of Buenos Aires, were employed (Source: Ing. Venanzi 2001). Estimated grain yield for other counties was also used (Source: J.L. Ibaldi 2000). Palmer's model (Palmer 1965) was applied in a decadal time scale, from 1977 to 2000. Besides accumulated rainfall (pp), and minimum and maximum mean temperature (Tmi and Tx), other parameters were used. Total soil water storage (Att) and the ratio between Penman potential and actual evapotranspiration (ETP/ETR or α) were obtained for a water balance model (Palmer 1965) as well as the moisture anomaly index (Z) and the Palmer drought severity index (ISP).

The soil of the experimental station is a thermic, loamy sand Entic Haplustoll that is frequently observed in the study region. It owns medium to low fertility levels and is highly prone to eolian erosion. Effective depth varies between 0.8 and 1.8 m limited by the petrocalcic horizon (or tosca layer). `Tosca` is a local word used to define a soil layer strongly cemented by calcium carbonate.

Classical Pearson correlation formulas were applied with a 5% significance level. For the multivariate regression statistic analysis the step-wise method was used, with an F to-enter value between 1 and 3.5, except for truncated models, and a minimum tolerance between 0.01 and 0.20, depending on the restriction limit set to select the variables to enter (Draper and Smith 1981).

Different models were proposed for three meteorological variables, two processed variables and two indices, in a single way or as mixed parameters. Variables such as management, genetics and technology were not included. The selection of the optimal variables conforms the total model. The truncated model is generated when restriction is imposed on the number of decades to include. The time period goes from previous to seeding variables (April and May) to harvest time (December). Variables are pre-selected using a forward step-wise method followed by a backward mode. Finally, between five to six optimal variables are selected, according to the determination coefficient (R^2) and the standard estimation error (SEE). Care was taken to avoid redundancy. The first 16 years of crop yields were used to obtain the models and the rest to test them, employing the root mean square error (RMSE) because of its sensibility to larger errors than the mean absolute error (MAE).

Wheat yields from the experimental field correspond to full season wheat cultivars; annual cropping and a fixed sowing date. Taking into account the growth patterns of wheat and suitable periods for ten-day agroclimatic data the following phenological stages and decades were used:

1) Seedling: jn3 to jl1;
2) Emergence: jl2 to ag3;

3) Tillaje: se1 to se3;

4) Stem elongation: oc1 to oc2;

5) Heading : oc3;

6) Anthesis or flowering: no1;

7) Grain filling: no2 to no3;

8) Maturity: de1 to de2;

9) Harvest: de3.

The ten-day period is identified by numbers 1, 2 or 3, indicating first, second or third ten-day period for the month.

3. RESULTS

3.1 Data analysis

Measured wheat yields from Bordenave as well as estimations from three neighboring counties (Espartillar, Puan, Pigue) were analyzed, year-by-year. Grain yields are shown in Figure 1. The average yield of the period 1979-2000 amounts to 1600 kg ha^{-1}. Two maxima are distinguished for years 1984/85 and 1997/98 respectively.

Figure 1.

The correlation coefficients between wheat yields from Bordenave and the other locations are highly significative. Maximum and minimum values range from 0.76 to 0.89. According to this, it might be possible to expand the application of the model obtained, based on regression equations for Bordenave data, to the regional area with a 60%-80% of explanation of yield variability.

Mean values of the meteorological variables (Tx, Tmi and pp) at Bordenave, for the 36 decades of the period 1971-2000 are represented in Figure 2, together with the crop cycle (June to November). The annual mean and standard deviation for rainfall is 790 ±

183 mm. Ten-day mean maximum temperature do not exceed 30 C and decadic minimum values are positive.

Figure 2.

The incidence of rainfall during wheat cycle is documented in Figure 3. Accumulated precipitation maxima for the crop cycle are coincident with years 1984-1985 and 1994, major yield years. The study region was affected during the ´70s with increasing rainfalls whose effect was reflected in larger yields (Sierra and Brynsztein 1990, Castañeda and Barros 1994, Roberto et al. 1994, Hoffmann et al. 1997). In contrast, during the analyzed period there is not a clear positive tendency, so assumption should be made that yield variability in this period would mainly be the expression of a climatic variability.

Figure 3.

3.2 a) Decadal scale models

Linear regression analysis was applied previous to the determination of the multivariate method to each one of the meteorological parameters (pp, Tx and Tmi), to the surface water balance variables (Att and α) and to Z and ISP indices. The total 36 decadal variables were considered as a first trial and then, only the decades of the crop season.

Table I.

Table I presents the selected variables for the exploratory regression models: MP01 (starting at decade ten) and MP02 (27 ten-day periods coincident with crop season). The best-related variables are enhanced, crossed for MP01 or shaded for MP02. Results for the seven linear regression variables show that the ordered parameters (ranked with decreasing R^2) are: α, Z, Tmi, Att, pp, ISP, Tx for MP01, and Z, α, ISP, Att, Tx, pp, Tmi for MP02. In consequence, it is deduced that α and Z are the two bests parameters for a statistical model in the region. The decades of the crop cycle with the largest number of significative variables are the first ten-days in August, the second decade in October and the first decade in November. This statistical analysis gives evidence that crop development during these particular decades is highly affected by thermal and hydric anomalies.

The best fitting equation for meteorological variables include: Tmi(jl2), Tmi(ag3), Tmi(no3), Tx(oc2) and pp(ag2), pp(no2), (model 1D). Minimum temperature during November and maximum in October affect yields with negative sign. The R^2 coefficient is 0.9813 and the SEE amounts 90.5 kg ha^{-1}, (here and following: see Table III for modeling summary results).

When processed parameters are used in a regression model, the selected variables are: α(oc1), α(no2), α(se2), α(ag2), Att(oc1), α(no1), (model 2D). The value of the coefficient R^2 is 0.9203, with SEE of 186.8 kg/ha. Taking account of the variables included in the model (up to the second decade of November), this selection should define a naturally truncated predictor model. The inclusion of the variable Att(oc1) shows the importance of soil moisture during stem elongation. Variable α denotes the relation of water availability and plant requirements and it is important during almost the whole crop cycle. According to RMSE obtained in the predictability test, this selection does not make a good predictor model.

The index variable integrates in only one value the effect of meteorological and available soil water parameters. The selected variables for such a model includes ISP during planting (model 3D). Other variables are: Z(se3), Z(no2), Z(ag2), Z(no3) and Z(ag1), and this model has a SEE of 318 kg/ha.

3.2 b) All-variables decadal model

The forward step-wise method was used in order to perform a general selection of variables. According to the results obtained in the above paragraph, ten variables were included in the model: α(oc1), Z(no2), Z(no3), Z(oc2), Tx(ag2), Z(no1), pp(se3), pp(jl2), pp(jl3), Tmi(se3). Then, using the backward mode, the selected variables obtained were, in increasing order: pp(jl2), pp(se3), pp(no1), pp(no3), Tmi(ag2), Tx(ag2), Z(oc2), Z(no1), Z(no2), α(oc1). Consequently, the common variables obtained from one and the other method were established and they are: α(oc1), Z(no2), Z(oc2), Tx(ag2) and pp(jl2). This result reinforces the importance of Z and α as predictors of wheat yield, while the ISP index and the Att were not included as valid variables.

The condition of ´up to 6 variables´ was added to simplify their future application in crop estimation equations and the possibility of having more degrees of freedom so as to obtain better statistical significance. From the different combinations employed, the best result for the multiple regression equation was expressed by α(oc1), Z(no1), Tmi(se3), Att(oc1) and pp(jl2) variables, (model 4D) and it is characterized by an SEE of 178.96 kg ha^{-1} and R^2 coefficient of 0.9187.

Figure 4.

The relation between predicted and observed values, residuals, and predicted SEE for this model is shown in Figure 4. When verifying it against 1995 to 1998 observed yields, a RMSE of 470 kg ha^{-1} was obtained.

3.2 c) Truncated model

It was possible to select an equation with four variables: α(oc1), Z(oc3), α(ag1) and pp(oc3), in order to obtain an ´early estimation model´ truncated by the end of October (model 5D). The fitting values were: SEE equal to 287 kg ha^{-1}, R^2 equal to 72.0 %, F to enter: 4.85 and minimum tolerance: 0.200. With the introduction of more severe conditions only two variables were included: Tx(oc1) y Z(oc2). In such case the estimated SEE increases to 410 kg ha^{-1}, in spite of an R^2 value of 76 %. For both cases, as was expected for truncated models, the testing procedure gives RMSE values greater than 670 kg ha^{-1}.

3.3 a) Phenological phase models

For the phenological phase scale the same steps as for decadal time scale were followed. The result of linear regression analysis, when wheat phases are employed is condensed in Table II.

Table II.

Statistical results establish that grain yields are strongly related to rainfall amounts during emergence, stem elongation and flowering stages. Low temperature in the maturity stage impacts negatively on wheat yields, and so do high temperatures during stem elongation. Total water storage (Att) is increasingly important during almost all stages. α and Z indices are detected as variables closely related to grain yields during stem elongation and grain filling stages. Stem elongation is by far the phenological stage with more parameters statistically related to yield.

The selection of variables according to crop phases (model 1F) are: pp(7), Tx(7), Tx(2), Tx(1), Tmi(4), with R^2 of 87.3% and SEE of 235.5 kg ha^{-1}. Model 2F is composed of: α(4), α(7), Att(4), Att(6) and α(5), with a fitted regression explained by R^2 value of 84.1% and 250.2 kg ha^{-1} as estimated SE. Finally, model 3F is formed with Z(7), ISP(1) and Z(6) variables, with R^2 of 75.8% and SEE equal to 297.3 kg ha^{-1}.

3.3 b) All-variables phenological model

The best model equation obtained to express wheat yield estimation, $\hat{\mathbf{Y}}$**,** is:

$$\hat{\mathbf{Y}} = 2628.0 + 2273.3\,\alpha\,\mathbf{(4)} + 6.1\,\mathbf{Z(7)} - 17.8\,\mathbf{Att(4)} + 11.9\,\mathbf{Att(6)} - 101.7\,\mathbf{Tx(4)},$$

with R^2 of 88.87% and SEE value of 209.5 kg ha^{-1}, (model 4F, in Table III).

Figure 5.

Figure 5 shows the relation between predicted and observed values, residuals, and predicted SE for phenological scale and mixed parameters (model 4F). Residual errors as function of observed yields are presented in Figure 6.

Figure 6.

A tendency to under-estimate yields for low and medium crop-yield values is apparent. Control test estimation for this model was measured. The RMSE accounts for 440.0 kg ha^{-1} , being the best of all the cases presented.

3.3 c) Truncated phenological model

The first six phenological stages including anthesis, were considered in an early yield estimated model. The best result was obtained for a model which include parameters α, pp, Att and Tx with a R^2 coefficient of 0.8727 and a SEE of 224.0 kg ha^{-1}. Variable selection for this truncated model is in accordance with the general model. Slight differences are due to the elimination of variable Z in phase 7 and the inclusion of precipitation during anthesis. In contrast with the results for the decadal scale, truncated models for the phenological case did not result in good estimations and the RMSE obtained was above 500 kg ha^{-1}.

Using the first five phenological phases which includes as selected variables $\alpha(4)$, Tx(4), pp(1), Att(4) and Att(5) resulted in an R^2 equal to 0.8406 and estimated SE of 250.6 kg ha^{-1} (model 5F). In spite of a larger SE, the RMSE was rather smaller than for the above model, (491.3 kg ha^{-1}).

4. DISCUSSION

It is possible to establish many different associations between variables with statistical significance which may have a good fitting to the data, but a criterion for predictability should conform to the agronomic adequacy of the selected variables to crop developing stages.

Multiple regression models are valuable tools as long as they can stand for easy-to-obtain variables. In this study variables were kept as linear, no attempt was made to include crossed variables, exponential or potential functions. The use of a very elaborated variable like the ISP shows an inadequate fitting to data; on the other hand, raw meteorological variables and those from a simple soil water balance give better results (Table III).

Table III

However, other authors have found that the mean monthly ISP index has good correlation with wheat yields (Akinremi and McGinn, 1995). There is no statistical evidence for the inclusion of pre-season variables into the models selected. The multiple regression equations for some of the models presented are summarized in Table 1.A of the Appendix.

In testing the predictive ability of the regression models, unsatisfactory results were obtained for those years in which meteorological extremes occurred. The high-risk meteorological extremes such as late frost damage (as in 1998), and heavy rains during physiological maturity (as in 1996), might be included in future models.

The investigations with complex simulation models as CERES-wheat, for the pampa region proved that the differences between observed and predicted yields do not exceed a standard deviation (660 kg ha^{-1}), (Magrin et al., 1991). It is then possible to assess that simple regression models, as some of those presented in this study, might be considered practical as predictive models and a tool to estimate the impact of climate change.

Among the limitations and restrictions of this study it is possible to mention: 1) small number of crop years, 2) no application of the models outside the region and 3) fixed starting and ending dates of physiological phases.

5. CONCLUSIONS

For both scale analysis, decadal and phenological models, the following results were obtained: D1 and D3 are the best fitted and skill-predictive models while D1 has the smallest mean square root error. Models 4 (D and F) are both good and it is thought that the inclusion of the grain filling phase in 4F performs a better yield fitting, with a RMSE of 440 kg ha^{-1}. Models 1F, 2F and 3F fail to express yields predictions. Truncated models on a phenological scale (5F) behave better than in a ten-day scale (5D). In fact, the best models would be those for which SEE and RMSE amount to similar values, such as in 3D, but with a cost expressed in a smaller determination coefficient, 76.9%.

In summary, this investigation shows that environmental variables for decadal and phenological scale can be employed in the design of multiple regression crops modeling for wheat yields at Bordenave. In the step-wise regression the decadal models have higher R^2 than the phase models. Models with simple averages and totals of temperature and precipitation, respectively, (model 1D, Table III), provide more meaningful representation of crop conditions than models with indices as variables. Those variables related to processed parameters confirm the effect of soil water availability in planting stage and thermal factors included indirectly in α, (models 2D and 2F, Table III). A predictive equation with indices evidences the preference of Z variable over ISP (models 3D and 3F, Table III). Between decadal and phenological scales for truncated models, the best predictive equations were obtained for phenological stages (models 5D and 5F, Table III). But, when selecting the variables using all parameters at decadal scales the step-wise method provides the best results (models 4D and 4F, Table III).

According to RMSE values, the use of physiological stages improved yields estimation, in particular, for those years with extremes meteorological conditions. A possible explanation is that phenological phases include several ten-day periods, moderating the effect of extreme events that have small probability of occurrence. When extreme values are present just in a decade not included in the decadal model, estimations may fail. These models can be improved including new terms with the incidence of late frost and intense rainfall events.

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NOTE: This research was carried out according to and within current laws of Argentina.

Appendix

Table I-A. Interception, variables and coefficients for the best multivariate regression models as mentioned in the text.

MODEL	**1D(met.)**	**4D(tot.)**	**4F(tot.)**	**5F(trun.)**
Intercep. (kg ha^{-1})	9079.4	249.3	2843.5	2628.5
Variables Coefficients	Tmin(jl2) 23.9	Pp(jl2) 13.8	α(4) 2532.3	α(4) 2532.3
Variables Coefficients	Pp(ag2) 21.24	Tmi(se3) 108.1	Att(4) -18.0	Att(4) -17.9
Variables Coefficients	Tmi(ag3) -134.9	Att(oc1) -8.1	Tx(4) -101.8	Tx(4) -130.4
Variables Coefficients	Tmx(oc2) -215.2	α(oc1) 1714.6	Att(6) 11.9	Att(5) 10.0
Variables Coefficients	Pp(no2) 5.6	Z(no1) 8.1	Z(7) 6.1	Pp(6) 11.0
Variables Coefficients	Tmi(no3) -203.0	-	-	-
Adj R^2	0.9688	0.8781	0.8330	0.8090
R^2	0.9813	0.9187	0.8886	0.8727

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TABLES

Table I. **a)** Agroclimatic ten-day variables best related to wheat yields at Bordenave for MP01 model, (shown as X cells) and MP02 model, (pre-season and crop-cycle months, shown as shaded cells), corresponding to (i) meteorological, (ii) processed and (iii) index parameters. Enhanced decades (boldface) indicate largest and simultaneous number of significative parameters. **b)** Correlation coefficients for both models and each parameter, (Roman numbers indicate parameters order with decreasing R^2 values).

a)	pp(i)	Tmi(i)	Tx(i)	Att(ii)	α (ii)	Z(iii)	ISP (iii)
ap1						X	
ap2							
ap3						X	
my1				X			
my2						X	
my3			X				
jn1				X	X		
jn2							
jn3		X					
jl1							
jl2							
jl3		X					
ag1	X		X	X	X		X
ag2						X	X
ag3							X
se1		X					
se2		X					
se3		X					
oc1	X		X	X	X		
oc2	X		X	X	X	X	
oc3			X		X		
no1	X		X	X		X	X
no2	X			X			
no3							X
de1							
de2							
de3							

b)	pp (i)	Tmi(i)	Tx(i)	Att(ii)	α (ii)	Z(iii)	ISP (iii)
Adj R^2	0.8211	0.8932	0.6643	0.9066	0.9696	0.9463	0.7498
R^2	0.8964	0.9497	0.7566	0.9417	0.9826	0.9718	0.8420
MP01	V	III	VII	IV	I	II	VI
Adj R^2	0.7220	0.7424	0.7648	0.8498	0.9138	0.9235	0.8602
R^2	0.8538	0.8485	0.8893	0.9028	0.9594	0.9640	0.9178
MP02	VI	VII	V	IV	II	I	III

Table II. Correlation coefficients between grain yields and agroclimatic variables using phenological stages. Enhanced values (boldface) indicate significance level of 5%.

Period	pp	Tmi	Tx	α	Att	Z	ISP
Previous Mr1_Jn2	-0.1210	**-0.4359**	-0.1658	0.0162	0.0488	-0.1559	0.0919
Planting Jn3_Jl1	0.0661	0.3584	0.1438	-0.1193	-0.1157	-0.0745	-0.1367
Emergence Jl2_Ag3	**0.3677**	0.2168	-0.2975	0.1627	0.1503	0.3119	0.0558
Tillering Sp1_Sp3	0.2737	0.2317	-0.2844	0.3526	0.2600	0.3429	0.1249
Stem elong. Oc1_Oc2	**0.5412**	-0.0371	**-0.5480**	**0.6990**	**0.4833**	**0.5870**	0.3702
Heading Oc3	0.2528	-0.0742	-0.2554	**0.4484**	**0.5081**	0.3185	**0.4363**
Flowering No1	**0.4493**	-0.2292	-0.3083	0.3576	**0.5311**	**0.4452**	**0.4743**
Grain fill. No2_No3	0.0400	-0.0936	-0.2499	**0.5964**	**0.5961**	**0.6125**	**0.5342**
Maturity De1_De2	-0.2865	**-0.4058**	-0.0910	0.0650	0.1072	-0.2612	0.2162
Harvest De3	0.2570	-0.2490	-0.0156	-0.2280	0.2620	0.2249	0.2562

Table III. Selected variables for decadal (D) and phenological (F) models, its determination coefficient, R^2 (%), estimated standard error, SEE (kg ha^{-1}) and root mean square error, RMSE (kg ha^{-1}). The best fitted models are enhanced (boldface).

Models	**Variables**						**R^2**	**SEE**	**RMSE**
1D(met)	Tmi(jl2)	Tmi(ag3)	Tx(oc2)	Tmi(no3)	pp(ag2)	pp(no2)	**98.1**	**90.5**	**345.7**
2D(pro)	α(oc1)	α(oc2)	α(se2)	α(ag2)	Att(oc1)	α(no1)	92.0	186.8	501.8
3D(ind)	Z(se3)	Z(no2)	ISP(jn3)	Z(ag2)	Z(no3)	Z(ag1)	76.9	318.2	365.8
4D(tot)	α(oc1)	Z(no1)	Tmi(se3)	Att(oc1)	Pp(jl2)	-	**91.9**	**178.9**	**470.0**
5D(tru)	α(oc1)	pp(ag3)	pp(se3)	pp(oc2)	α(oc2)	pp(se1)	82.5	276.7	668.6
1F(met)	pp(7)	Tx(7)	pp(6)	pp(1)	Tmi(3)	-	87.2	224.2	791.3
2F(pro)	α(4)	α(7)	Att(4)	Att(6)	α(5)	-	84.1	250.2	740.0
3F(ind)	Z(7)	ISP(1)	Z(3)	Z(1)	-	-	61.8	373.5	>1000
4F(tot)	α(4)	Z(7)	Att(4)	Att(6)	Tx(4)	-	**88.9**	**209.5**	**440.0**
5F(tru)	α(4)	Tx(4)	pp(1)	Att(4)	Att(5)	-	**84.0**	**250.6**	**491.3**

Figure Legends

Figure 1. Estimated (for three counties of the Southwest Pampa) and measured (Bordenave) wheat yields (kg ha^{-1}) during 1979-2000 crop years.

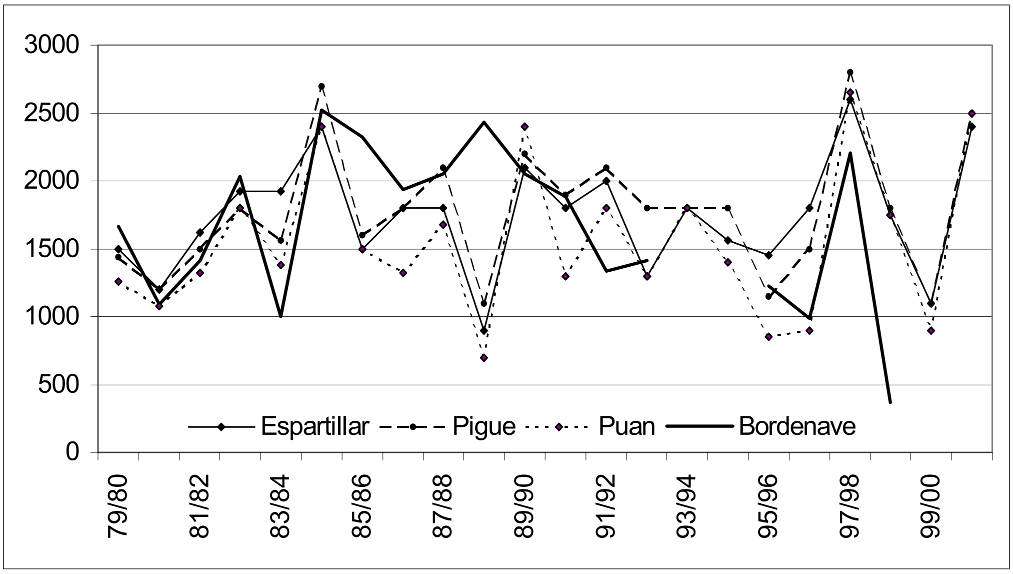
Figure 2. 30 years (1971-2000) ten-day mean for accumulated precipitation and mean maximum and minimum temperature at Bordenave. The growing season ranges from June to December.

Figure 3. Accumulated precipitation (mm), during the crop season period at Bordenave. The same, for two counties of Buenos Aires province. Period 1979-2000.

Figure 4. Predicted and observed grain yields, residuals, and predicted standard error (kg ha^{-1}), for decadal variables α(oc1), Z(no1), Tmi(se3), Att(oc1) and pp(jl2), (model 4D).

Figure 5. Predicted and observed grain yields, residuals, and predicted standard error (kg ha^{-1}), for phenological scale variables α(4), Z(7), Att(4), Att(7) and Tx(4), (model 4F).

Figure 6. Residual errors as a function of observed grain yields (kg ha^{-1}) for model 4F.



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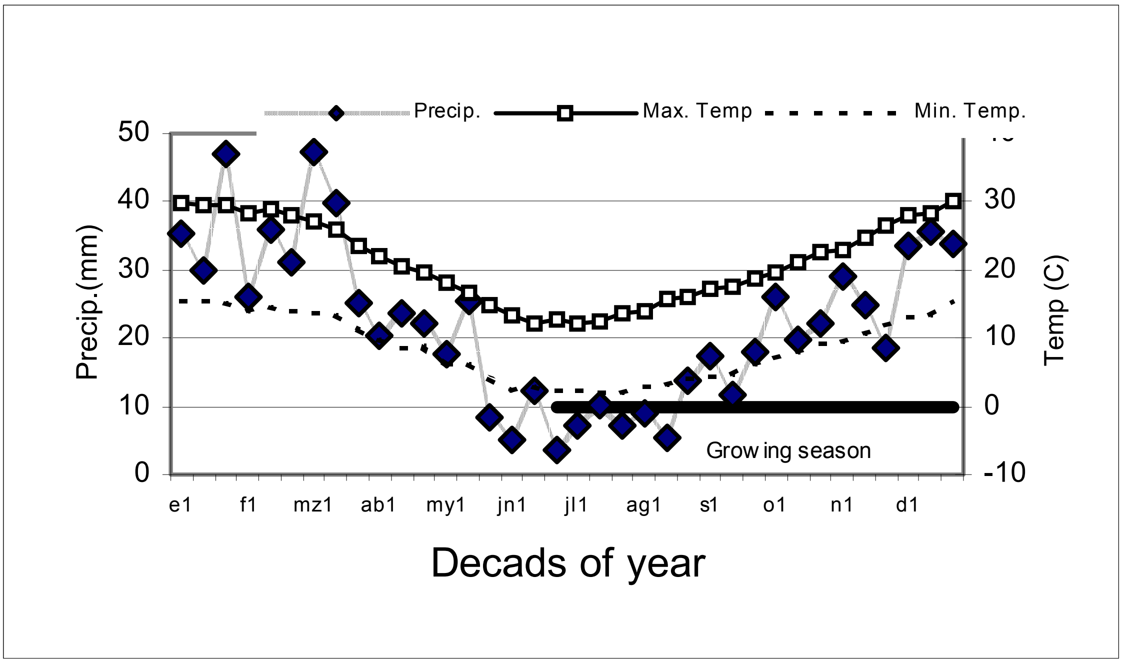

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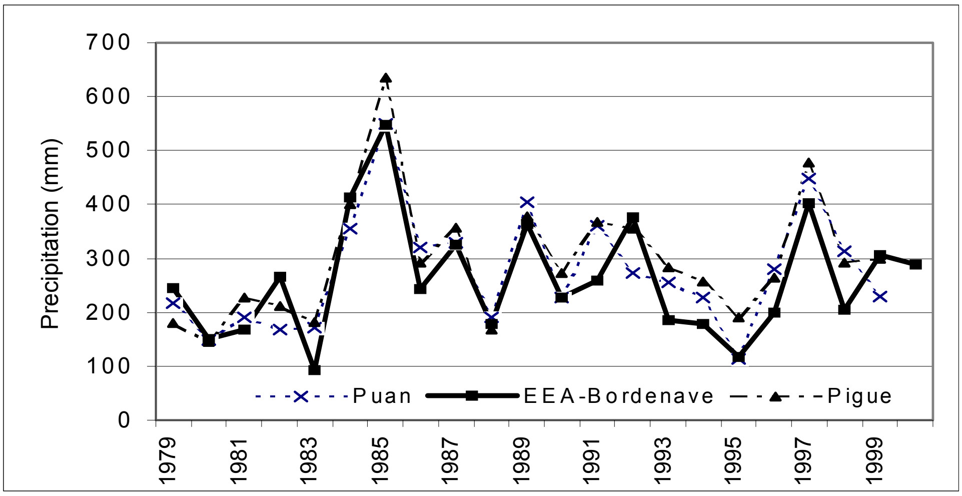

Figure 3. Accumulated precipitation (mm), during the period june to november at Bordenave. The same for 2 counties of Buenos Aires province. Period 1979-2000.

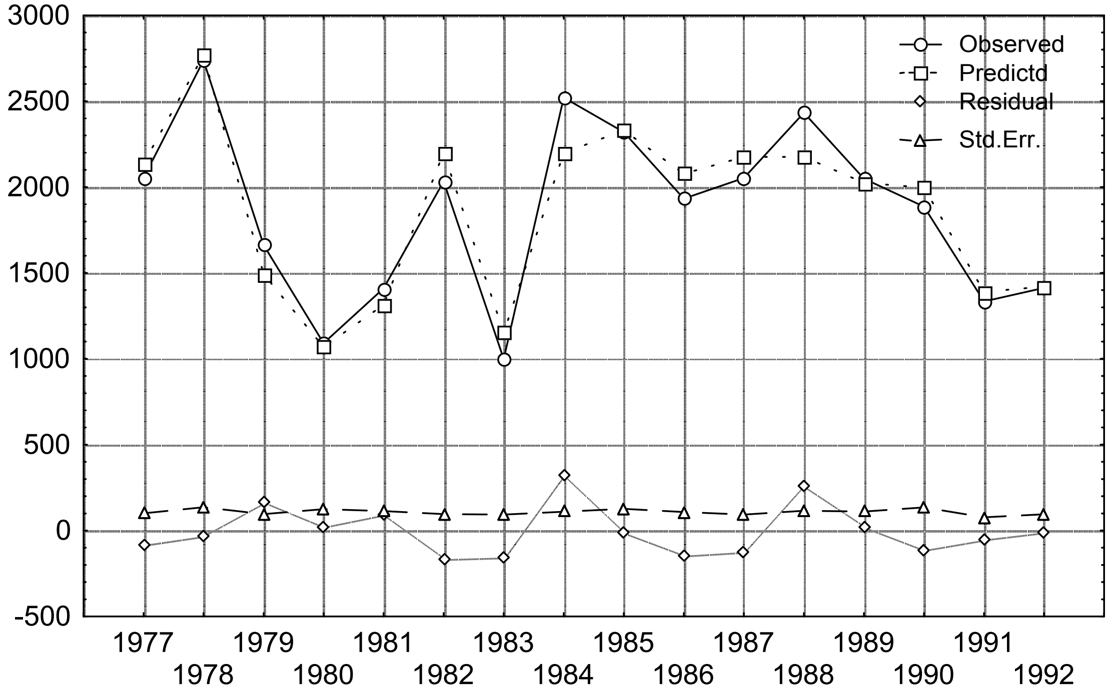

Figure 4. Predicted and observed grain yields, residuals, and predicted standard error (kg ha^{-1}), for decadal variables α(oc1), Z(no1), Tmi(se3), Att(oc1) and pp(jl2), (model 4D).

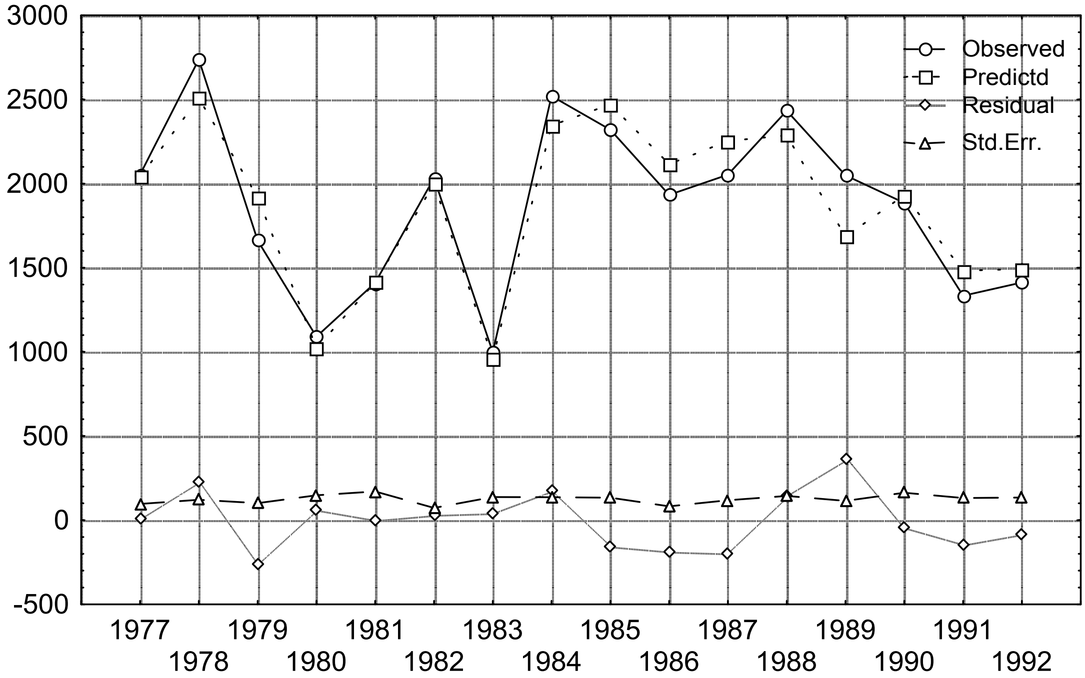

Figure 5. Predicted and observed grain yields, residuals, and predicted standard error (kg ha^{-1}), for phenological scale variables $\alpha(4)$, Z(7), Att(4), Att(7) and Tx(4), (model 4F).

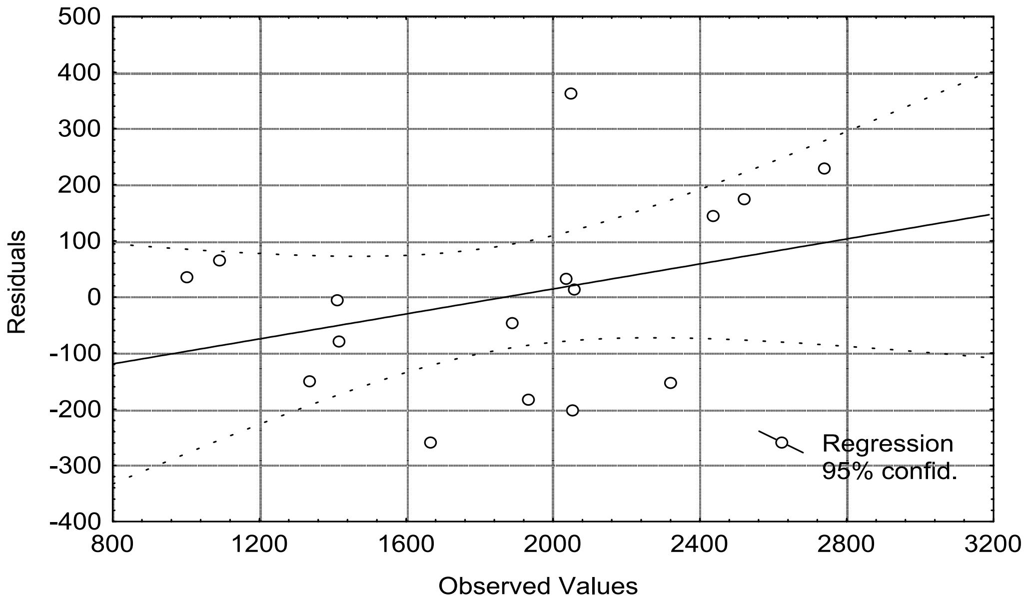

Figure 6. Residual errors as a function of observed grain yields (kg ha^{-1}) for model 4F.