Response of wheat yield in Spain to large-scale patterns

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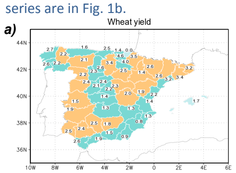
INTRODUCTION

- How can climate change affect wheat variability? In previous works [1], we obtained that wheat yield in the twenty-first century would experience a decrease due to a widespread drought and an increase of the diurnal temperature range over Spain.
- The uncertainty of this projection comes from the models imprecision to capture regional variables. Since large-scale patterns are best represented by GCMs, the aim here is at obtaining how large-scale patterns can contribute to explain wheat variability to project under climate change.
- Results indicate that wheat yield will suffer a downward trend that we claim as consequence of an increase in the surface solar radiation over Spain in the twenty-first-century, which agree with previous study.

DATA

- Wheat production is collected by the Spanish Agriculture, Food and Environment Department [2]. Wheat yield refers to the weight of production divided by the area of cultivation (T/ha). Data from different provinces (Fig. 1a) were classified by using K-mean clustering . The corresponding averaged time series are in Fig. 1b.

a)



b)

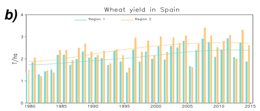
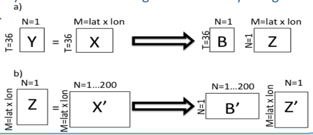


Figure 1a Spatial distribution of wheat yield over Spain. **Figure 1b** The evolution of spatially averaged wheat yield over the regions (R1 and R2) that gather similar behaviour (bars). Lines represent the corresponding nonlinear trend.

- Large-scale variables of monthly data for the period September 1979 to August 2014 are: Sea Surface Temperature (SST) from ERSST (v3b) [3]; Sea level pressure (MSL), zonal wind at 250 hPa (U), geopotential height at 500hPa (Z) and surface downward solar radiation (SSRD) from ECMWFs ERA-Interim reanalysis [4]. The same large-scale climate variables corresponding to CMIP5 models [5] for historical and RCP8.5 experiments.

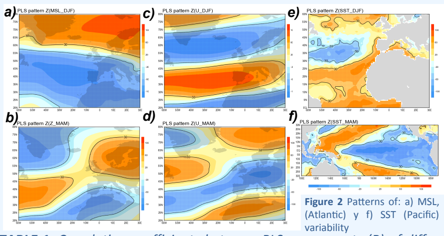
METHODS

- The influence and statistical modelling of the wheat yield is investigated through use of Partial Least Square (PLS) regression [6].
- PLS is applied in two different ways as scheme 1 shows: to assess the modes of the large-climate variables in conjunction with the observed wheat variability corresponding to the observational period (1980-2014) (temporal dimension); to derive the wheat variability under climate change conditions by using the CMIP5 data (spatial dimension).



RESULTS

Modes of climate variables associated to wheat yield



The modes of climate variables associated with wheat yield extract signal of teleconnection patterns (Table 1)

Figure 2 Patterns of: a) MSL, b) Z, c) and d) U, e) SST (Atlantic) y f) SST (Pacific) associated with wheat variability

***TABLE 1**: Correlation coefficients between PLS components (B) of different fields with wheat yield over Spain (W_S), region 1 (R1) and region 2 (R2) and teleconnection indices.*

	B_MSL (djf)	B_Z (mam)	B_U (djf)	B_U (mam)
W_S	0.41	0.49	0.42	0.55
W_R1	0.33	0.50	0.46	0.50
W_R2	0.46	0.46	0.46	0.53
NAO	-0.88	0.62	-0.73	0.55
SCAND	0.62	0.38	0.47	0.34

	B_SSTA (djf)	B_SSTP (mam)
W_S	0.56	0.48
W_R1	0.52	0.50
W_R2	0.55	0.49
AMO	0.42	
NIÑO3.4		-0.85

Modes of surface solar radiation associated to wheat yield

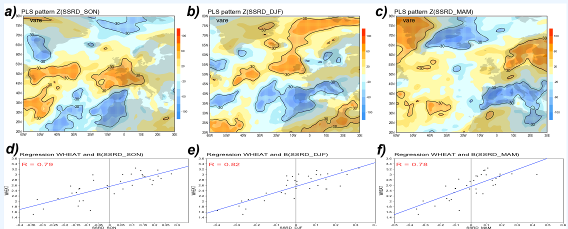


Figure 3 Patterns of surface downward solar radiation (SSRD) associated with wheat variability: a) autumn (son); b) winter (djf); c) spring (mam). Scatter plots of wheat yield against the PLS components (B) of the corresponding modes: d) autumn; e) winter and f) spring.

***TABLE 2:** Correlation coefficients between PLS components (B) of surface solar radiation (SSRD) with wheat yield and teleconnection indices.*

	W_S	W_R1	W_R2	NAO	EA	SCAND	AMO	NIÑO3.4
B_SSRD (son)	0.79	0.75	0.77			0.27		
B_SSRD (djf)	0.82	0.64	0.80	-0.47	0.57	0.25		
B_SSRD (mam)	0.78	0.74	0.77	0.35	-0.33	0.40	-0.25	-0.29

The modes configuration show a negative influence of SSRD on the wheat yield over the Iberian peninsula. The PLS components of SSRD (B) show very significant association with the wheat yield. They account for signals of the influence of teleconnection patterns on the wheat yield.

Statistical model

The statistical model derived from the PLS components of SSRD fit quite well the wheat observed, describing 87% of the wheat yield variability.

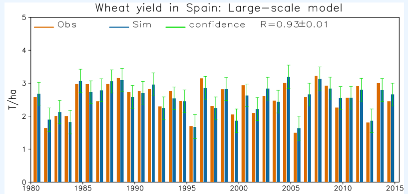


Figure 4 Simulation of the wheat yield by using the components of SSRD.

Wheat projection

Wheat yield projections are obtained by using CMIP5 models on the basis of PLS regression. Figure 5a shows the time evolution for the ensemble and the spread of the simulation corresponding to the 12 models used.

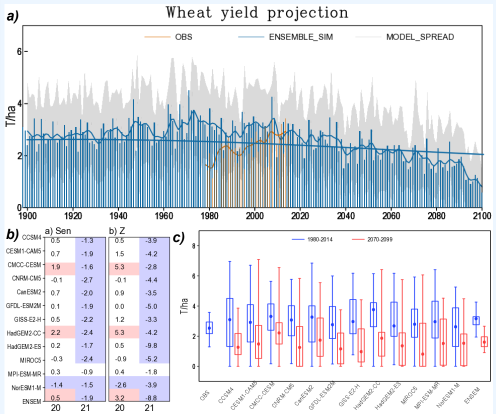


Figure 5a Projection of wheat yield simulation of the wheat yield by using the components of SSRD; **b** Trend of the different models using Sen´s test and significance (Z test); **c** Changes of wheat yield given by different models for two periods.

The trend of wheat for different models in the 20th and 21st century is shown in Figure 5b. Most models give a significant decreasing trend. The changes for two periods are shown in the box-whisker representation (Figure 5c).

CONCLUSIONS

- Wheat yield variability is driven by large-scale variables. The modes of large-scale extract signals of teleconnection patterns (Figure 2 and Table 1.)
- Surface solar radiation (SSRD) is the factor best connected to wheat variability incorporating the effects of different teleconnection patterns.
- Wheat variability is statistical simulated using the PLS components of SSRD. The model account for 87% of wheat variability.
- CMIP5 models project a decrease of the wheat yield under climate change, which is due to the increase of SSRD over the Iberian peninsula.
- Regarding the results show here, they are in agreement with [1]. However the statistical model derived from SSRD is more accurate than the one derived from drought and diurnal temperature range. In addition it easier to compute projection by using only the SSRD variable.

Acknowledgements

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Developers of Grads, CDO and R.

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References

[1] Hernandez-Barrera, S. et al 2016: Effects of diurnal temperature range and drought on wheat yield in Spain. Theoretical and Applied Climatology. DOI: 10.1007/ s00704-016-1779-9.

[2] MAGRAMA: http://www.magrama.gob.es/es/estadistica/temas/estadisticasagrarias/agricultura/avances-superficies-producciones-agricolas.

[3] Smith, T.M. et al., 2008. Historical reconstruction of monthly oceanic precipitation. Journal of Geophysical Research-Atmospheres, 113 (D17).

[4] Dee DP. et al, 2011. The ERA-Interim reanalysis: configuration and performance of the data assimilation system. *Q. J. R. Meteorol. Soc.* **137**: 553–597. DOI: 10.1002/qj.828

[5] Taylor et al. 2012: An overview of CMIP5 and the experiment design. DOI: 10.1175/bams-d-11-00094.1.

[6] Wold 2001: PLS-regression: a basic tool of chemometrics. DOI: 10.1016/ s0169-7439(01)00155-1.