Joint probability of droughts and wheat yield anomalies in Iberia

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1 Target

This work aims to develop a **multivariate probabilistic model using copulas** to contribute to agricultural drought risk management and consequently attempt to prevent crop losses. The main target is to estimate the **likelihood of drought risk** in rainfed cropping systems.

How is drought assessed?

- **Drought impacts** are assessed by wheat yield anomalies (t/ha) during 1986-2012, over two clusters of provinces in the Iberian Peninsula (IP) dominated by rainfed agricultural practices (Fig. 1).

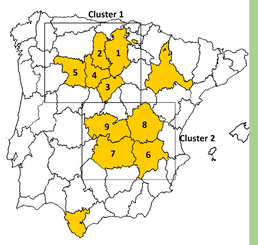

Fig. 1 – Provinces with more than 50% of agricultural areas and more than 50% of rainfed crops based on CLC2012.

- **Drought hazard** is evaluated using the drought index SPEI (Standardized Precipitation Evapotranspiration Index) and satellite-based indices VCI (Vegetation Condition Index), TCI (Temperature Condition Index) and VHI (Vegetation Health Index)

What are copulas?

Mathematically, a copula is the joint distribution of the univariate variables u and v (such as yield and drought indicator):

$$F(u,v) = C(F(u),F(v))$$ (Sklar, 1959)

This study adopts a bivariate modelling approach using Elliptical (t-copula) and Archimedean (Clayton, Frank and Gumbel) copulas.

Cluster	Drought indicator	Regression coefficient
1	TCI 23	0.76
2	SPEI 4-1	1.05

Table 1 – Variables used for copula application. In the second column, the numbers correspond to the selected weeks in the case of the remote sensing indices, and to the selected months and time-scales in the case of SPEI.

The most relevant drought indicator was selected for each cluster, based on the largest absolute value of the standardized regression coefficient (Table 1) from models developed based on stepwise regression.

2 Copula fits during 1986-2012

i) Transform data to the unit scale using the kernel density estimator of CDF

Fig. 2 - Pseudo-observations (scatter) of the margins.

ii) Estimate the dependence parameters and select the more adequate copula function based on AIC

Table 2 – Copula dependence parameter estimates (θ), 95% confidence interval (ci) and AIC values.

	t			Clayton		
	θ	ci 95%	AIC	θ	ci 95%	AIC
W1	0.75	(0.02,2.23)	-3.73	1.91	(1.14,2.68)	-11.07
W2	0.54	(-0.25,2.82)	-3.55	1.35	(0.56,2.13)	-7.95

	Frank			Gumbel		
	θ	ci 95%	AIC	θ	ci 95%	AIC
W1	6.45	(3.95,8.95)	-13.42	2.34	(1.72,2.96)	-16.7
W2	4.35	(1.83,6.88)	-6.69	1.81	(1.24,2.38)	-8.78

iii) Graphical visualization of copulas

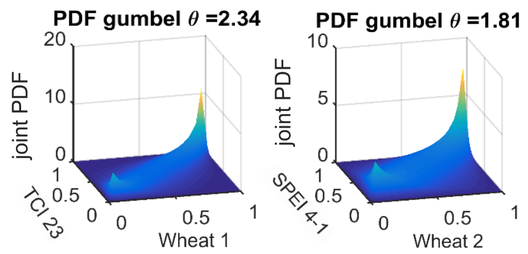

Fig. 3 –Joint PDFs.

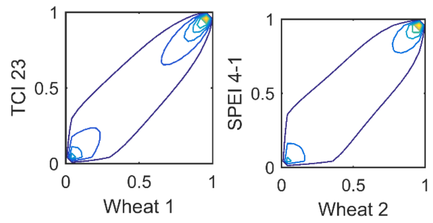

Fig. 4 – Contours of the joint PDFs.

Stronger dependence in the upper tail of the joint distributions based on Gumbel copulas

iv) Simulate random values using the copula fits

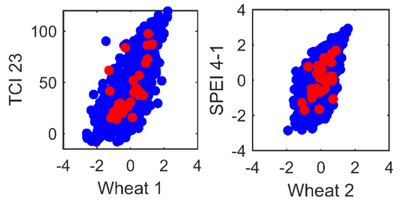

Fig. 5 – Observed (blue) and copula-based simulations (red) scatter plot of crop yield and drought indicators.

The simulations lead to results close to the real observations and more extreme values are generated using the joint distributions

v) Risk of crop loss - Probability of non-exceedance (PNE) function (%)

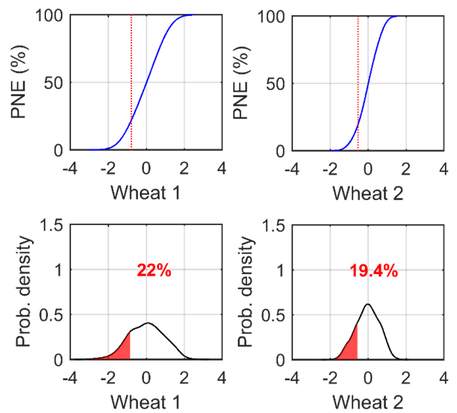

Fig. 6 – PNE function (%) of yield anomalies based on the derived simulations and respective probability density estimates indicating the probability of not exceeding -1 standard deviation (dotted line in the top PNE curves).

PNE left tail values (negative yield anomalies) are higher in cluster 1 and the PNE -1 standard deviation is 22% in the cluster 1 and 19.4% in the cluster 2

3 Copula fits differentiating drought (TCI <=40 or SPEI <=-0.84) and non-drought years (TCI > 40 or SPEI >-0.84)

Wheat yield anomalies during drought and non-drought years

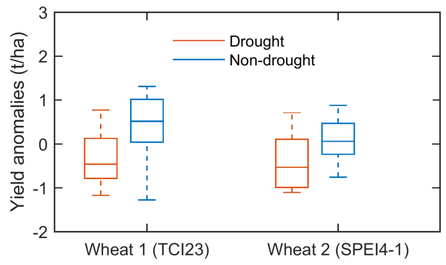

Fig. 7 – Wheat yields during drought years (red) and non-drought years (blue) according to the respective drought indicator.

- Lower values of yield anomalies during drought events in comparison with non-drought episodes

Simulations using the copula fits

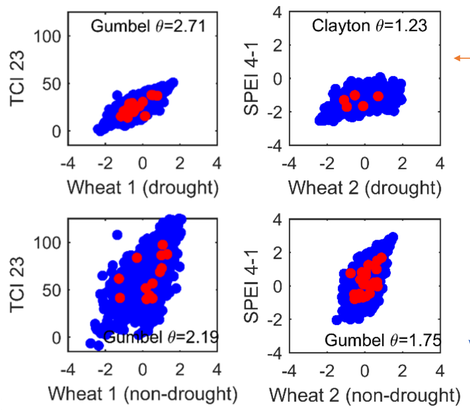

Fig. 8 – Observed (blue) and copula-based simulations (red) scatter plot of crop yield and drought indicators.

Drought years

Right tail dependence in the northern sector (Clayton copula) and a left tail dependence in the southern sector (Gumbel copula)

The crop loss (PNE -1 std) is substantial larger during drought years (36.9% and 37.7%)

Non-drought years

Upper tail dependence in both clusters (Gumbel copulas)

Risk of crop loss

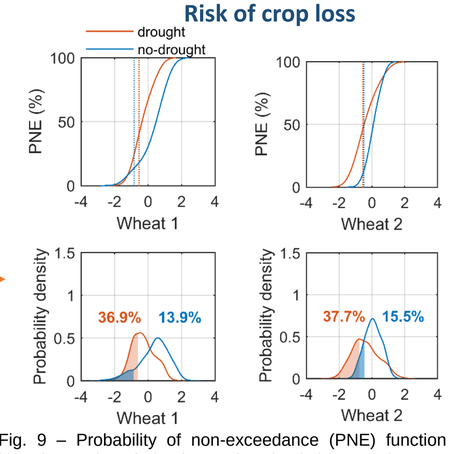

Fig. 9 – Probability of non-exceedance (PNE) function (%) based on the derived copula simulations and respective probability density estimates under drought (orange) and non-drought conditions (blue).

Conclusions

- The joint distributions were found to be better estimated based on Archimedean copulas, suggesting a dependence among extreme values of wheat yield anomalies and drought indicators.
- The established copula models suggest relevant drought risk levels of wheat in the major agricultural areas of the IP.

References

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Acknowledgments

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