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# *Interactive comment on* "Bivariate return periods of temperature and precipitation explain a large fraction of European crop yields" *by* Jakob Zscheischler et al.

**Jakob Zscheischler et al.**

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Reviewer: This study seeks the linkage between multivariate climate conditions and crop yields. This paper is one of the first which employs bivariate return periods of temperature and precipitation as the indicator of climate variability to explain crop yield variability. It is clearly written and obtains the interesting finding that the combination of temperature and precipitation can explain more crop yield variability than models relying directly on temperature and precipitation as predictors on average in Europe. The result also reveals different sensitivities of crops to climate conditions. A need to incorporate the nonlinear impacts into the climate-crop yield assessment is highlighted. For



all these reasons, I recommend publication after addressing a few comments regarding the statistical examinations.

*Thank you for this positive evaluation.*

Reviewer: One comment is related to the calculation of return periods. As explained by the authors, a return period of RP, also known as a recurrence interval is an estimate of the likelihood of an event to occur, i.e., an occurrence probability of 1/RP every year. If the event of interest happens every year or the annual maximum/minimum data is in use, the mean interarrival time is 1 yr (i.e., the numerator in Eq. 1). If I understand correctly, the authors applied copulas to the seasonal and 2-month averaged climate variables for return period calculation. For such case, why the mean interarrival time is 1 yr? Instead, the mean interarrival time should be calculated as the length of data in years (L)/ the number of occurred events in the length of data (n), i.e., L/n.

*We used values averaged over two month periods but looked at only one value per year (e.g. only spring temperature and precipitation), similar to, e.g., the annual maximum. Hence the interarrival time is 1 yr. We will explain this more explicit in the revised manuscript to avoid confusion.*

Reviewer: The authors examined 6 types of copulas in order to represent different combined effects of temperature and precipitation, i.e. dry and hot, dry and cold, wet and hot, wet and cold. My understanding is that the impact of these combinations can be due to a single variable or both variables being in an extreme state. The examined copulas, however, do not include extreme-value copulas, which are usually considered more appropriate for reproducing the interrelationship/interdependence structure between rare events. Did the authors compare the result using extreme-value copulas?

*The t-copula and some of the Archimedean copulas allow tail dependence, i.e. dependence in the extremes, see e.g. Schoelzel and Friederichs (2008) Sections 4.1.2 and 4.2. The t-copula is symmetric such that if the upper tails are dependent, the lower tails are as well. In contrast, the Gumbel and Joe copulas can model only upper tail de-*

*pendence whereas the Clayton copula can model lower tail dependence (all three are asymmetric). Note that in this application we aim for modeling the whole distribution to capture also events with high return frequency and not only the extremes. Hence, only using extreme value copulas might not be appropriate. We will add a note in Section 2.4 to highlight that the copulas that we use are able to capture dependence in the extremes.*

*Schoelzel, C. and Friederichs, P.: Multivariate non-normally distributed random variables in climate research-introduction to the copula approach, Nonlin. Processes Geophys., 15, 761–772, 2008.*

Reviewer: Here the authors applied copulas to the seasonal and 2-month averaged climate variables. One of the prerequisites to apply copula is the assumption of temporal independence of variables, e.g. by examining the autocorrelation. Did the input variables meet this requirement?

*Thank you for this comment. We have now tested for autocorrelation in the yearly time series of temperature and precipitation averaged over the different time scales use in the study (66 years). Only 8.8% of the temperature time series and 4.4% of the precipitation time series are significantly autocorrelated for lag 1 at the 5% level. Since we look at bivariate distributions, we conclude that autocorrelation should not have a significant effect on the conclusions of the paper. We will add this information in the revised manuscript.*

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