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Water Cycle

Heavy Vb-cyclone precipitation: a transfer entropy application showcase

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Abstract

Several past summer floods in Central Europe were associated with so-called Vb-cyclones propagating from the Mediterranean Sea north-eastward to Central Europe. This study illustrates the usefulness of the parametric transfer entropy measure TE-linear in investigating heavy Vb-cyclone precipitation events in the Odra catchment (Poland). With the application of the TE-linear approach, we confirm the impact of the Mediterranean Sea on precipitation intensification. Moreover, we also detect significant information exchange to Vb-cyclone precipitation from evaporation over the European continent along the typical Vb-cyclone pathway. Thus, the Mediterranean Sea could enhance the Vb-cyclone precipitation by pre-moistening continental moisture source regions that contribute to precipitation downstream in the investigated catchments. Overall, the transfer entropy approach with the measure TE-linear proved to be computationally effective and complementary to traditional methods such as Lagrangian and Eulerian diagnostics.

Keywords: Vb-cyclones, heavy precipitation events, transfer entropy, Odra, Poland, twentieth century reanalysis

1 Introduction

Vb-cyclones are defined by their pathway from the Gulf of Genoa along the eastern fringe of the Alps towards Central Europe (van Bebber, 1891). Especially during summer, this cyclone pathway is associated with a high flood potential in Central Europe (Petrow et al., 2007; Nissen et al., 2013; Nied et al., 2014) and caused, for example, the July 1954 and August 2002 floods (Blöschl et al., 2013). In previous studies, the origin of flood-triggering atmospheric moisture during Vb-cyclones has been investigated with Lagrangian moisture source diagnostics (e.g., Grams et al., 2014) or Eulerian moisture tagging (Sodemann et al., 2009; Winschall et al., 2014). In this study, we present a complementary and computationally less intensive approach using an information theory estimator.

Information theory estimators are based on the concept of Shannon entropy which was introduced by Shannon (1948) in the context of data compression and transmission. After the study of Shannon (1948), information theory methods have been applied to neurosciences (Dimitrov et al., 2011; Li et al., 2019, and references therein) and biology (Dancoff and Quastler, 1953), and later on also to other fields like economics (e.g., Maasoumi, 1993). In recent years, the role of information theory methods has grown also in earth system sciences in evaluating probabilistic forecasts (e.g., Ahrens and Walser, 2008; Weijs et al., 2010; Krakauer et al., 2013), in evaluating hydrological models (Bennett et al., 2019), and in studying interactions in the global climate systems (e.g., Das Sharma et al., 2012; Bhaskar et al., 2017; Gerken et al., 2019; Pothapakula et al., 2019; Yu et al., 2019; Pothapakula et al., 2020).

Previous studies on information theory methods applied in climate sciences focused mainly on large spatial and temporal scales. For example, Bhaskar et al. (2017) investigated the directional flow of information between various climate drivers and global mean temperature anomalies at monthly scales, and Pothapakula et al. (2019) examined (also with a monthly resolution) the information exchanged between the Pacific and the Indian Ocean. In this short contribution, however, we aim to motivate the application of information theory methods in studying the interactions also at regional climate scales and submonthly resolutions. Furthermore, we showcase the usefulness of information theory measures for studying extreme hydro-meteorological events. In particular, we demonstrate the usage of TE-linear for studying flood-causing Vb-cyclones in Central Europe. For this purpose, a transfer entropy (TE, Schreiber, 2000) measure is presented using the example of heavy Vb-cyclone precipitation in the Odra catchment region (Poland) in comparison to the climatological summer season (JJA) precipitation.

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2 Data and methods

2.1 Dynamically downscaled ERA-20C reanalysis

Even though Vb-cyclones occur about four to ten times per year, only a few cause flood-triggering rainfall (Messmer et al., 2015) and hence a long time series with high spatial resolution is required to analyse the most intense Vb-cyclone precipitation events. Therefore, we studied daily evaporation and precipitation sums in the dynamically downscaled ECMWF twentieth century reanalysis (ERA-20C; Poli et al., 2016). We used a regional atmosphere-ocean model setup for downscaling the reanalysis continuously from 1901 to 2010 over an extended EURO-CORDEX domain (Giorgi et al., 2009) to a horizontal resolution of about 12 km ($\Delta x = 0.11^{\circ}$; Krug et al., 2020). The regional climate model Consortium for Small-scale Modelling in Climate Mode (COSMO-CLM; Rockel et al., 2008) was interactively coupled with the regional ocean model NEMO (Nucleus for European Modeling of the Ocean; Madec, 2016) over the marginal seas (Mediterranean Sea, North Sea, and Baltic Sea) for an improved representation of the water cycle components. The model setup and its performance are discussed in Primo et al. (2019).

2.2 Event selection

We tracked all cyclones with a 3-hourly resolution at mean sea level pressure in our dynamically downscaled ERA-20C reanalysis from 1901 to 2010 with the method of Wernli and Schwierz (2006) and refined in Sprenger et al. (2017). The cyclone centres were defined by the position of the deepest pressure within a closed isobar. The cyclone centre locations were then connected to cyclone tracks by a first guess approach. Like proposed in Blöschl (2019), we classified all cyclones crossing the 47° N latitude northwards between 12° E and 22° E as Vb-cyclones (available at Zenodo, Krug and Ahrens, 2020). In order to gain more insight in Vb-cyclone precipitation events, we compare these events with typical summer conditions since most of the heavy precipitation Vb-events occurred during the summer (Chimani, 2012; Messmer et al., 2015).Therefore, we analysed the information exchange from evaporation to precipitation during all summer months (JJA) from 1901 to 2010 and compared that with Vb-cyclone events. To focus on the most intense Vb-cyclone events, we selected only the 100 highest ranked Vb-cyclone precipitation events in the Odra catchment region (15.5° E, 19.5° E, 49.5° N, 53° N).

2.3 TE-linear

The Shannon entropy $H(X)$ of a random variable X is defined as the amount of information needed to describe the random variable X:

$$H(X) = -\sum_{x} p(x) \cdot \log p(x), \tag{2.1}$$

with the probability mass function $p(x)$ of the random variable X. If a natural logarithm is applied, the unit of the entropy is called [nats]. Alternatively, the entropy can be expressed in [bits] if the logarithm base is 2. The random variable X is deterministic if the entropy $H(X)$ is equal to 0 nats (i.e., no uncertainty lies in the prediction of the outcome of X).

In some cases, the uncertainty in the prediction of X can be reduced with the knowledge of another random variable Y. The reduced amount of uncertainty is called mutual information I. The mutual information is derived from the corresponding Shannon Entropy H as follows (e.g., Hlaváčová-Schindler et al., 2007; Bennett et al., 2019):

$$I(X;Y) = I(Y;X) = H(X) + H(Y) - H(X,Y), \tag{2.2}$$

where H(X,Y) represents the joint entropy, which is defined as

$$H(X,Y) = H(Y,X) = -\sum_{x}\sum_{y} p(x,y) \cdot \log p(x,y). \tag{2.3}$$

One disadvantage of the mutual information I is that it is a symmetric measure (like correlation). Thus, mutual information does not reveal the directional information transfer between X and Y. Moreover, if the systems X and Y are driven by a common driver Z, the mutual information fails to unravel the dependence between the systems X and Y.

In case of a common driver Z, conditioning on the random variable Z gives a realistic dependence of X and Y. The corresponding information metric is known as conditional mutual information and defined as follows (Hlaváčová-Schindler et al., 2007; Bennett et al., 2019):

$$I(Y;X|Z) = H(Y|Z) + H(X|Z) - H(Y,X|Z). \tag{2.4}$$

Based on this and by assuming a stationary Markov process, Schreiber (2000) introduced a measure known as transfer entropy (TE) which takes the dynamics of information transfer into account by conditioning the mutual information of X and Y to the past of Y. Thus, the TE is an asymmetric measure which quantifies not only the intensity but also the direction of information exchange from the source variable X to the target variable Y. The TE is often written in terms of conditioned mutual information (e.g., Hlaváčová-Schindler et al., 2007; Bennett et al., 2019):

$$TE_{X\rightarrow Y} = I(Y;X^{-}|Y^{-}), \tag{2.5}$$

where X^{-} and Y^{-} denote the whole (possibly infinite) history of X and Y. As a compromise for computational complexity, equation (2.5) is usually reduced to following (Schreiber, 2000; Bennett et al., 2019):

$$TE_{X\to Y} = I(Y; X_{t-\tau}|Y_{t-\omega})$$
$$TE_{X\to Y} = \sum_x \sum_y p(y_t, y_{t-\omega}, x_{t-\tau}) \cdot \log \frac{p(y_t|y_{t-\omega}, x_{t-\tau})}{p(y_t|y_{t-\omega})}, \tag{2.6}$$

with the time lag τ of the source variable X and the lag ω of the target variable Y. The values of τ and ω in equation (2.6) are chosen depending on the system dynamics (e.g., Vicente et al., 2011; Bennett et al., 2019).

In this study, we defined as target variable Y the daily precipitation amount averaged over the selected Odra catchment region and standardised with the multi-year (1901–2010) daily mean and standard deviation for the respective day of the year. Moreover, we defined as source variable X the standardised evaporation anomalies over land and oceanic grid boxes. During Vb-cyclone events, moisture uptake contributing to precipitation in the selected Odra/Poland region can occur already within the same day. This is, in particular, the case for continental source regions close to the selected river catchment and along the Vb-cyclone pathway, as well as the marginal seas for oceanic source regions. Thus, to keep the presented showcase brief and focused, we applied the TE-linear measure to daily data only with the time lags $\omega = 24$ hours (i.e., one time step) and $\tau = 0$. In other words, we quantified the reduction in uncertainty about the present state of precipitation in the Odra catchment when knowing the state of evaporation during the same day and the precipitation in the Odra region of the day before (i.e., the persistence in precipitation). We refer to this in the following as a zero-day time lag between the source and target variables.

For calculating the TE, we applied a parametric estimation of TE, called TE-linear, which is based on a multivariate Gaussian assuming linear interactions (applicable as the standardised anomalies of precipitation averaged over the selected region of interest and evaporation at individual grid cells were approximately Gaussian distributed). Unlike non-parametric estimations of TE, the parametric estimation of TE (i.e., TE-linear) is relatively straightforward and robust, because it is less sensitive to the length of the time series and free of tuning parameters (Pothapakula et al., 2019). We performed a significance test for the TE-linear measure with a significance level of 0.05 by considering 100 permuted surrogates of X and Y to test our hypothesis. In the following, we set the information exchange to zero in case it was not significant. For more details on the significance test, we refer to Lizier (2014). Note that a TE of 0 nats refers to no information exchange, while any significant value above zero is considered as information exchanged in the following (cf. Lizier, 2014; Pothapakula et al., 2019; Pothapakula et al., 2020). The applied source code is available at Zenodo under doi: 10.5281/zenodo.4568218.

3 Results

Figure 1 shows the information exchange from local oceanic evaporation anomalies to precipitation in the Odra catchment during the whole summer season (JJA, left panel) and during the 100 highest ranked Vb-cyclone precipitation events (right panel). During the summer season, we detected high information exchange of more than $1.0 \cdot 10^{-2}$ nats (cf. range of values in Pothapakula et al., 2019; Pothapakula et al., 2020) from the evaporation over the North Sea, Bay of Biscay, and Gulf of Lion. During the heavy precipitation Vb-cyclones, the western basin of the Mediterranean Sea and the Adriatic Sea show the highest information exchange to the event precipitation. Besides, the information exchange is above $2.0 \cdot 10^{-2}$ nats for evaporation over the North Atlantic, east of Greenland, where sometimes strong large-scale ocean evaporation occurs (Aemisegger, 2018).

The information exchange of evaporation anomalies over land during the summer season is highest (TE-linear $> 2.0 \cdot 10^{-2}$ nats, Figure 2) within the selected region in the Odra catchment and surrounding surfaces, in particular, north of the Alps and westwards of the Odra catchment, which corresponds to westerlies. For the selected Vb-events, several regions with high information exchange were detected, especially the southern Alpine region, the Carpathian mountains, and the eastern part of the selected catchment region (Figure 2).

4 Discussion

The enhanced information exchange over the Mediterranean Sea during heavy precipitation Vb-cyclones is in line with previous studies that conclude a sensitivity of precipitation in Central Europe to Mediterranean Sea surface temperatures (Volosciuk et al., 2016; Messmer et al., 2017), even though the Mediterranean moisture contribution to Vb-cyclone precipitation was only minor compared to other oceanic source regions during several past Vb-flood events (e.g., Winschall, 2013; Winschall et al., 2014; Grams et al., 2014; Kelemen et al., 2016; Krug et al., submitted). A possible reason for this might be an intensification of the Vb-cyclones during their early stages by the short-range transport of Mediterranean moisture and associated latent-heat release. Moreover, Mediterranean moisture may be relevant for pre-moistening some continental moisture uptake regions. The latter hypothesis is supported by the enhanced information exchange of continental evaporation along the typical Vb-cyclone pathway from northern Italy along the eastern fringe of the Alps towards northern and eastern Central Europe. Note that the TE in that area is more homogenous for soil moisture (not shown here). Thus, the TE approach applied to evaporation does not quantify the overall moisture uptake of precipitation like with Lagrangian diagnostics, but it detects the source regions associated with a precipitation intensification.

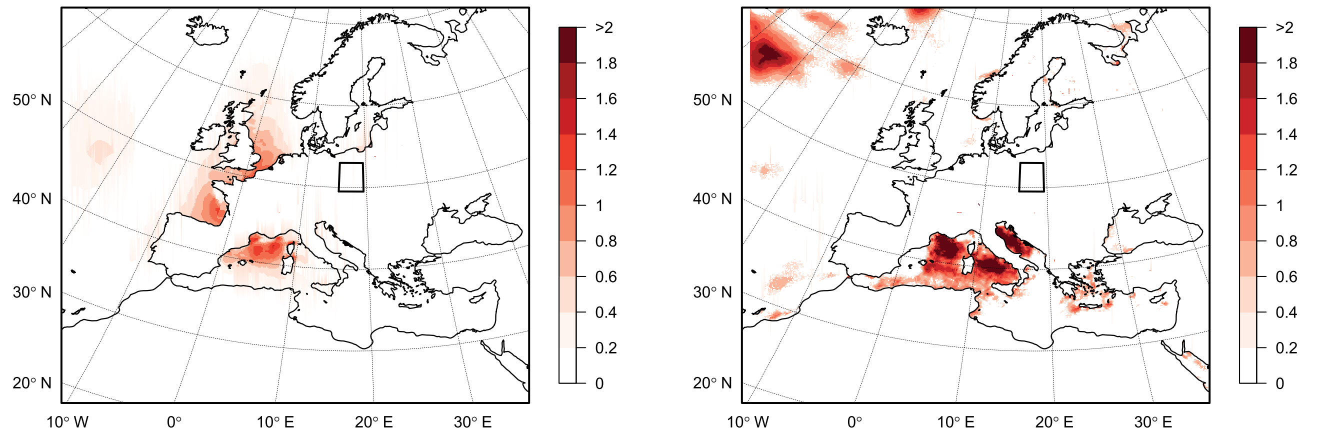

Figure 1: Significant information exchange (TE-linear, in 10^{-2} nats, bootstrapping with 0.05 significance level) from evaporation over the marginal seas (source) to total precipitation in the Odra catchment (target, black rectangle) during the summer season (JJA, left) and during the corresponding 100 highest ranked Vb-events (right) from 1901 to 2010.

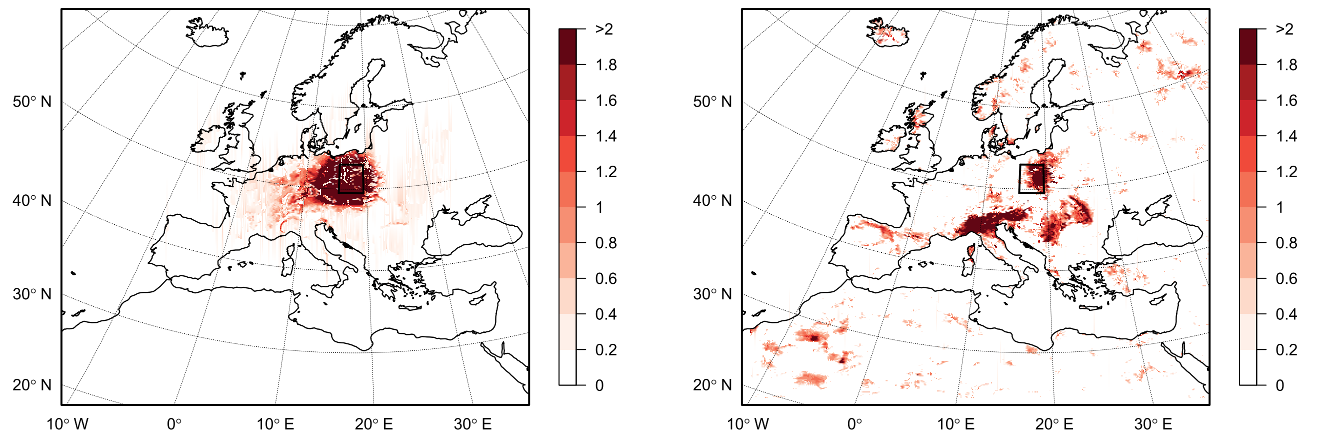

Figure 2: Same as Figure 1 but for evaporation anomalies over the land.

However, one has to be cautious with the interpretation of detected regions with high information exchange because information theory methods and other statistical approaches like correlation analyses give only indications of causative processes but no clear evidence. Moreover, detected information exchange which is distant to the Odra region does not necessarily imply a direct link of evaporation in these remote regions and precipitation in the Odra catchment via atmospheric moisture transport, especially if short time lags are used in equation (2.6). Examples of remote regions with high information exchange are the enhanced information exchange from the south-east of Greenland in Figure 1 (right panel) or from areas in eastern Europe and northern Africa in Figure 2 (right panel). These areas might be linked with contributing moisture uptake regions via common drivers, for example, an atmospheric blocking high.

Furthermore, the information theory approach reveals no information about the sign of the anomalies of interest. For example, the information exchange from the Mediterranean Sea surface temperatures (SST, not shown here) shows a similar pattern like evaporation (Figure 1, right). One might deduce that high SSTs in the western basin enhance the moisture uptake there. However, Krug et al. (submitted) showed that the opposite is the case: evaporation was intensified by high wind speeds and thus associated with lower SST anomalies for the highest precipitation impact Vb-cyclones, as selected in our study.

Our results with TE-linear are complementary to previous studies using Lagrangian moisture diagnostics or Eulerian moisture tagging. In contrast to these approaches, an advantage of the TE-linear method is that already a limited number of variables (i.e., total precipitation and evaporation) on a daily time scale provides the required information. For example, the TE-linear calculation without bootstrapping lasts for the 100 selected Vb-cyclone events and all source grid points less than one minute on a standard personal computer. For a moisture tagging analysis, however, tracer particles have to be implemented directly in the simulation. For Lagrangian analysis, temporally and spatially high-resolved 4D variables like atmospheric pressure, specific humidity, or wind fields are needed. The computational effort regarding only the input data is increased in comparison with TE-linear by a factor of the number of additionally used variables, times the number of vertical levels, times a factor of 8 if 3-hourly data is used instead of daily aggregations. Thus, TE-linear is significantly less computationally intensive with robust results.

5 Conclusions

The asymmetric information exchange measure TE-linear proofed as a useful tool for detecting the drivers of precipitation intensification in the Odra catchment. Our results show an enhanced information exchange to heavy Vb-cyclone precipitation from evaporation over the Mediterranean Sea and the European continent along the Vb-cyclone pathway. These findings are in accordance with previous studies which conclude a particular role of the Mediterranean Sea in precipitation intensification (Volosciuk et al., 2016; Messmer et al., 2017) and moisture uptake over the continental surfaces (e.g., Winschall et al., 2014; Kelemen et al., 2016). Future studies might use the TE-linear approach to investigate potential hydro-climatic drivers and teleconnections of other flood types, such as rain-on-snow floods (Merz et al., 2020; Krug et al., 2020). In particular, large data amounts and long time series can be analysed robustly and computationally efficiently, for example, to filter out relevant variables, and regions. The associated processes can then be studied in further detail with other, more computationally intensive methods like Lagrangian backward trajectories.

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Abbreviation List

COSMO-CLM	**Co**nsortium for **S**mall-scale **Mo**delling in **Cl**imate **M**ode
NEMO	**N**ucleus for **E**uropean **M**odeling of the **O**cean
SST	**S**ea **S**urface **T**emperatures
TE	**T**ransfer **E**ntropy
TRIP	**T**otal **R**unoff **I**ntegrating **P**athways

References

Aemisegger, F., 2018: On the link between the North Atlantic storm track and precipitation deuterium excess in Reykjavik. – Atmos. Sci. Lett. **19**, e865, DOI: 10.1002/asl.865.

Ahrens, B., A. Walser, 2008: Information-Based Skill Scores for Probabilistic Forecasts. – Mon. Wea. Rev. **136**, 352–363, DOI: 10.1175/2007MWR1931.1.

Bennett, A., B. Nijssen, G. Ou, M. Clark, G. Nearing, 2019: Quantifying Process Connectivity With Transfer Entropy in Hydrologic Models. – Water Resour. Res. 2018WR024555, DOI: 10.1029/2018WR024555.

Bhaskar, A., D.S. Ramesh, G. Vichare, T. Koganti, S. Gurubaran, 2017: Quantitative assessment of drivers of recent global temperature variability: an information theoretic approach. – Climate Dyn. **49**, 3877–3886, DOI: 10.1007/s00382-017-3549-5.

Blöschl, G., T. Nester, J. Komma, J. Parajka, R.A. Perdigão, 2013: The June 2013 flood in the Upper Danube Basin, and comparisons with the 2002, 1954 and 1899 floods. – Hydrol. Earth Syst. Sci. **17**, 5197–5212, DOI: 10.5194/hess-17-5197-2013.

Dancoff, S.M., H. Quastler, 1953: The Information Content and Error Rate of Living Things. – University of Illinois Press.

Das Sharma, S., D.S. Ramesh, C. Bapanayya, P.A. Raju, 2012: Sea surface temperatures in cooler climate stages bear more similarity with atmospheric CO2 forcing. – J. Geophys. Res. Atmos. **117**, D13110, DOI: 10.1029/2012JD017725.

Dimitrov, A.G., A.A. Lazar, J.D. Victor, 2011: Information theory in neuroscience. – J. Comput. Neurosci. **30**, 1–5, DOI: 10.1007/s10827-011-0314-3.

Gerken, T., B.L. Ruddell, R. Yu, P.C. Stoy, D.T. Drewry, 2019: Robust observations of land-to-atmosphere feedbacks using the information flows of FLUXNET. – NPJ Clim. Atmos. Sci. **2**, 37, DOI: 10.1038/s41612-019-0094-4.

Giorgi, F., C. Jones, G. Asrar, 2009: Addressing climate information needs at the regional level: the CORDEX framework. – WMO Bulletin **58**, 175–183.

Grams, C.M., H. Binder, S. Pfahl, N. Piaget, H. Wernli, 2014: Atmospheric processes triggering the central European floods in June 2013. – Nat. Hazards Earth Syst. Sci. **14**, 1691–1702, DOI: 10.5194/nhess-14-1691-2014.

Hlaváčová-Schindler, K., M. Paluš, Milanand Vejmelka, J. Bhattacharya, 2007: Causality detection based on information-theoretic approaches in time series analysis. – Phys. Reports **441**, 1–46, DOI: 10.1016/j.physrep.2006.12.004.

Hofstätter, M., G. Blöschl, 2019: Vb Cyclones Synchronized With the Arctic-/North Atlantic Oscillation. – J. Geophys. Res. Atmos. **124**, 3259–3278, DOI: 10.1029/2018JD029420.

Hofstätter, M., B. Chimani, 2012: Van Bebber's cyclone tracks at 700 hPa in the Eastern Alps for 1961–2002 and their comparison to Circulation Type Classifications. – Meteorol. Z. **21**, 459–473, DOI: 10.1127/0941-2948/2012/0473.

Kelemen, F.D., P. Ludwig, M. Reyers, S. Ulbrich, J.G. Pinto, 2016: Evaluation of moisture sources for the Central European summer flood of May/June 2013 based on regional climate model simulations. – Tellus, Series A: Dynamic Meteorology and Oceanography **68**, 29288. DOI: 10.3402/tellusa.v68.29288.

Krakauer, N.Y., M.D. Grossberg, I. Gladkova, H. Aizenman, 2013: Information Content of Seasonal Forecasts in a Changing Climate. – Adv. Meteor. **2013**, 1–12, DOI: 10.1155/2013/480210.

Krug, A., B. Ahrens, 2020: Cyclone tracks from 1901 to 2010 in dynamically downscaled ERA-20C reanalysis

(COSMO-CLM+NEMO) [Data set]. – Zenodo, DOI: 10.5281/zenodo.4333258.

Krug, A., C. Primo, S. Fischer, A. Schumann, B. Ahrens, 2020: On the temporal variability of widespread rain-on-snow floods. – Meteorol. Z. **29**, 147–163, DOI: 10.1127/metz/2020/0989.

Krug, A., F. Aemisegger, M. Sprenger, B. Ahrens, submitted: What intensifies Vb-cyclone precipitation in Central Europe?. – Climate Dynamics.

Li, M., Y. Han, M.J. Aburn, M. Breakspear, R.A. Poldrack, J.M. Shine, J.T. Lizier, 2019: Transitions in information processing dynamics at the whole-brain network level are driven by alterations in neural gain. – PLOS Computational Biology **15**, e1006957, DOI: 10.1371/journal.pcbi.1006957.

Lizier, J.T., 2014: JIDT: An Information-Theoretic Toolkit for Studying the Dynamics of Complex Systems. – Front. Robot. AI **1**, DOI: 10.3389/frobt.2014.00011.

Maasoumi, E., 1993: A compendium to information theory in economics and econometrics. – Econom. Rev. **12**, 137–181, DOI: 10.1080/07474939308800260.

Madec, G., 2016: NEMO Ocean Engine. – Note du Pôle de modélisation de l'Institut Pierre-Simon Laplace No 27, Paris. ISSN No 1288-1619.

Merz, R., L. Tarasova, S. Basso, 2020: The flood cooking book: ingredients and regional flavors of floods across Germany. – Env. Res. Lett. **15**, 114024, DOI: 10.1088/1748-9326/abb9dd.

Messmer, M., J.J. Gómez-Navarro, C.C. Raible, 2015: Climatology of Vb cyclones, physical mechanisms and their impact on extreme precipitation over Central Europe. – Earth Syst. Dyn. **6**, 541–553, DOI: 10.5194/esd-6-541-2015.

Messmer, M., J.J. Gómez-Navarro, C.C. Raible, 2017: Sensitivity experiments on the response of Vb cyclones to sea surface temperature and soil moisture changes. – Earth Syst. Dyn. **8**, 477–493, DOI: 10.5194/esd-8-477-2017.

Nied, M., T. Pardowitz, K. Nissen, U. Ulbrich, Y. Hundecha, B. Merz, 2014: On the relationship between hydro-meteorological patterns and flood types. – J. Hydrol. **519**, 3249–3262, DOI: 10.1016/j.jhydrol.2014.09.089.

Nissen, K.M., U. Ulbrich, G.C. Leckebusch, 2013: Vb cyclones and associated rainfall extremes over Central Europe under present day and climate change conditions. – Meteorol. Z. **22**, 649–660, DOI: 10.1127/0941-2948/2013/0514.

Petrow, T., B. Merz, K.E. Lindenschmidt, A.H. Thieken, 2007: Aspects of seasonality and flood generating circulation patterns in a mountainous catchment in south-eastern Germany. – Hydrol. Earth Syst. Sci. **11**, 1455–1468, DOI: 10.5194/hess-11-1455-2007.

Poli, P., H. Hersbach, D.P. Dee, P. Berrisford, A.J. Simmons, F. Vitart, P. Laloyaux, D.G.H. Tan, C. Peubey, J.N. Thépaut, Y. Trémolet, E.V. Hólm, M. Bonavita, L. Isaksen, M. Fisher, 2016: ERA-20C: An Atmospheric Reanalysis of the Twentieth Century. – J. Climate **29**, 4083–4097, DOI: 10.1175/JCLI-D-15-0556.1.

Pothapakula, P.K., C. Primo, B. Ahrens, 2019: Quantification of Information Exchange in Idealized and Climate System Applications. – Entropy **21**, 1094, DOI: 10.3390/e21111094.

Pothapakula, P.K., C. Primo, S. Sørland, B. Ahrens, 2020: The synergistic impact of ENSO and IOD on Indian summer monsoon rainfall in observations and climate simulations – an information theory perspective. – Earth Syst. Dyn. **11**, 903–923, DOI: 10.5194/esd-11-903-2020.

Primo, C., F.D. Kelemen, H. Feldmann, N. Akhtar, B. Ahrens, 2019: A regional atmosphere-ocean climate system model (CCLMv5.0clm7-NEMOv3.3-NEMOv3.6) over Europe including three marginal seas: on its stability and performance. – Geosci. Model Dev. **12**, 5077–5095, DOI: 10.5194/gmd-12-5077-2019.

Rockel, B., A. Will, A. Hense, 2008: The Regional Climate Model COSMO-CLM (CCLM). – Meteorol. Z. **17**, 347–348, DOI: 10.1127/0941-2948/2008/0309.

Schreiber, T., 2000: Measuring Information Transfer. – Phys. Rev. Lett. **85**, 461–464, DOI: 10.1103/PhysRevLett.85.461.

Shannon, C.E., 1948: A mathematical theory of communication. – Bell Syst. Tech. J. **27**, 379–423, DOI: 10.1002/j.1538-7305.1948.tb01338.x.

Sodemann, H., H. Wernli, C. Schwierz, 2009: Sources of water vapour contributing to the Elbe flood in August 2002 – A tagging study in a mesoscale model. – Quart. J. Roy. Meteor. Soc. **135**, 205–223, DOI: 10.1002/qj.374.

Sprenger, M., G. Fragkoulidis, H. Binder, M. Croci-Maspoli, P. Graf, C.M. Grams, P. Knippertz, E. Madonna, S. Schemm, B. Škerlak, H. Wernli, 2017: Global climatologies of Eulerian and Lagrangian flow features based on ERA-Interim. – Bull. Amer. Meteor. Soc. **98**, 1739–1748 DOI: 10.1175/BAMS-D-15-00299.1.

van Bebber, W.J., 1891: Die Zugstrassen der barometrischen Minima nach den Bahnenkarten der deutschen Seewarte für den Zeitraum 1875–1890. – Meteorol. Z. **8**, 361–366.

Vicente, R., M. Wibral, M. Lindner, G. Pipa, 2011: Transfer entropy – a model-free measure of effective connectivity for the neurosciences. – J. Comput. Neurosci. **30**, 45–67, DOI: 10.1007/s10827-010-0262-3.

Volosciuk, C., D. Maraun, V.A. Semenov, N. Tilinina, S.K. Gulev, M. Latif, 2016: Rising Mediterranean Sea Surface Temperatures Amplify Extreme Summer Precipitation in Central Europe. – Sci. Rep. **6**, 32450, DOI: 10.1038/srep32450.

Weijs, S.V., G. Schoups, van de N. Giesen, 2010: Why hydrological predictions should be evaluated using information theory. – Hydrol. Earth Syst. Sci. **14**, 2545–2558, DOI: 10.5194/hess-14-2545-2010.

Wernli, H., C. Schwierz, 2006: Surface Cyclones in the ERA-40 Dataset (1958-2001). Part I: Novel Identification Method and Global Climatology. – J. Atmos. Sci. **63**, 2486–2507, DOI: 10.1175/JAS3766.1.

Winschall, A., 2013: Evaporative moisture sources for heavy precipitation events. – Ph.D. thesis, ETH Zurich, DOI: 10.3929/ethz-a-009755505.

Winschall, A., S. Pfahl, H. Sodemann, H. Wernli, 2014: Comparison of Eulerian and Lagrangian moisture source diagnostics – the flood event in eastern Europe in May 2010. – Atmos. Chem. Phys. **14**, 6605–6619, DOI: 10.5194/acp-14-6605-2014.

Yu, R., B.L. Ruddell, M. Kang, J. Kim, D. Childers, 2019: Anticipating global terrestrial ecosystem state change using FLUXNET. – Glob. Change Biol. **25**, 2352–2367, DOI: 10.1111/gcb.14602.