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Compound extremes in a changing climate - a Markov Chain approach

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Abstract. Studies using climate models and observed trends indicate that extreme weather has changed and may continue to change in the future. The potential impact of extreme events such as heat waves or droughts does not only depend on their number of occurrence but also on "how the extremes occur", i.e. the interplay and succession of the events. These quantities are quite unexplored, for past changes as well as for future changes and call for sophisticated methods of analysis. To address this issue, we use Markov chains for the analysis of the dynamics and succession of multivariate or compound extreme events. We apply the method to observational data (1951-2010) and an ensemble of regional climate simulations for Central Europe (1971-2000, 2021-2050) for two type of compound extremes, heavy precipitation and cold in winter and hot and dry days in summer. We identify three regions in Europe, which are probably susceptible to a future change in the succession or dynamics of heavy precipitation and cold in winter, which are a region south western France, northern Germany and in Russia around Moscow,. The change in the succession of hot and dry days in summer will probably affect regions in Spain and Bulgaria. The susceptibility to a dynamic change of hot and dry extremes in the Russian region will probably decrease.

1 Introduction

Multivariate extreme events (in this paper used in the sense of extremes of two or more climate variables occurring simultaneously) are likely to impact society greater than their univariate counterparts. For agriculture for example, the impact of a heat wave and a drought occurring at the same time is higher than for a univariate extreme where the other variable is in a normal state. These multivariate or so called compound events (IPCC, 2012) have received more and more attention in the scientific literature over the past years although still not to the extent of extremes of only one variable. Methods to analyze them include simple threshold analysis, multivariate distribution functions using copulas (e.g. Schoelzel et al., 2008; Durante and Salvadori, 2010), Bayesian approaches (e.g. Tebaldi and Sansó, 2009) or indices which are derived from multiple variables (e.g. the wildfire index KBDI (e.g. Keetch et al., 1968) or the revised CEI Gallant et al. (2014)). All these methods focus

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mostly on the linear climate change signal - the absolute change in the number of occurrence or the calculation of return periods. The succession, i.e. the temporal ordering of the compound events is in most cases mostly not the main objective. For instance, the IPCC (IPCC, 2012) states : "*A changing climate leads to changes in the frequency, intensity, spatial extent, duration, and timing of extreme weather and climate events, and can result in unprecedented extreme weather and climate events.*" What is implicitly addressed with "duration and timing", but not explicitly stated is the succession of extreme events, which is quite unknown for past as well as future extremes.

The method proposed here, which is based on Markov chains, concentrates on the dynamical behavior or succession of these compound extreme events and studies an aspect of climate change which has not received much attention up to now, but is nevertheless important. We investigate a behavior of extremes which cannot be determined by simply analyzing the change of the number of extremes. We can, for example, reveal changes in the entropy of the succession of compound extremes which is connected to the chaotic behavior of the climate variable. Thus an observed increase of this measure could be connected with an increase in the chaotic, intermittent or irregular nature of the system. On the other hand, a decrease of entropy corresponds to a slow-down of these dynamics. Knowledge about such developments for future climate, which rarely exists, could be important for many sectors e.g. agriculture, economy and society.

Previous studies on model dynamics have concentrated more on overall dynamical behavior such as Steinhaeuser and Tsonis (2014) who have conducted a model intercomparison study focusing on dynamical aspects based on a climate networks framework. The method introduced in this paper is modified from a work by Mieruch et al. (2010). The idea is to understand climate time series as trajectories on a complex, possibly strange attractor (Lorenz, 1963). We partition the time series or state space into a finite number of states. This yields a coarse-grained description of the system, which can then be analyzed in the framework of symbolic dynamics (Ebeling et al., 1998; Daw et al., 2003). We apply a Markov Chain analysis on these symbolic sequences representing compound extremes, and characterize their dynamical or successional behavior using a small set of descriptors.

In this paper we study two different kinds of compound extreme events which are likely to have an impact on society, namely cold and heavy precipitation in winter, and heat and drought in summer. The Markov method is applied to E-OBS observational data (1951-2010) (Haylock et al., 2008), and an ensemble of regional climate simulations with the regional climate model COSMO-CLM driven by different global climate model data and ERA-40 reanalysis (Uppala et al., 2005). The time periods considered are the recent past (1971-2000) and the near future (2021-2050).

We identify regions in Europe, where the dynamical behavior of the analyzed compound extremes is prone to change. These findings highlight that it is not only the (simple) linear increase of the occurrence of extremes (due to an increase in mean and variability), which is a challenge for adaption and mitigation. On top of these changes the regions also have to struggle with changes in the suc-

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cession of compound extremes (defined as relative to a new normal state with changed mean and variability).

The strategy of this study is first to show that the Markov method is able to extract different dynamics of compound extremes for different regions in Europe, based on observational data and model data. Thus, on the one hand we see that the method yields meaningful information and on the other hand we show that the climate models are able to reproduce these dynamics in the frame of acceptable uncertainties. Additionally, we extract temporal change signals of the dynamics of compound extremes based on observations between the periods 1951-1980 and 1981-2010. This information is new and if used as supplementary information to other analyses, could lead to a better understanding of changes of extremes in Europe. For this paper, the magnitude of the observed past changes have been assessed, because it is important for a better interpretation and classification of future changes which are calculated by using the simulated regional climate model data. A comparison of the change signals between 1971-2000 and 2021-2050 to the observed past changes shows that they are of the same order of magnitude.

The paper is divided into the following sections. In Sect. 2, data and method will be introduced, followed by a validation of the model ensemble in Sect. 3. The change signal is analyzed in Sect. 4. Summary and outlook will be given in Sect. 5 and some areas discussed where the application of this method might be of value.

2 Data and Methods

2.1 Regional Climate Ensemble

For our analysis, we use a 12-member ensemble of regional climate simulations for Central Europe at a resolution of 50 km. The ensemble has been generated by downscaling different global climate model outputs with the regional climate model COSMO-CLM (COnsortium for Small scale MOdelling model - in CLimate Mode, Doms and Schättler (2002); Rockel et al. (2008)), further referred to as CCLM. The CCLM is a non-hydrostatic climate model coupled to the soil vegetation model TERRA and is the climate version of the numerical weather model of the German weather service. Data from six different global climate models (GCMs) has been used as initial and boundary data. Two of the GCMs have used the emission scenario A1B (Nakicenovic and Swart, 2000) as external forcing : CCCma3 (Scinocca et al., 2008) and three realizations of ECHAM5 (Roeckner et al., 2003). The other four, ECHAM6 (Stevens et al., 2013), CNRM-CM5 (Voldoire et al., 2013), HadGM3 (Collins et al., 2011) and EC-EARTH (Hazeleger et al., 2010) have used the emission scenario RCP8.5 (Riahi et al., 2011; Van Vuuren et al., 2011). Additionally the Atmospheric Forcing Shifting method (Sasse and Schädler, 2014) was applied to the ECHAM6 data. For this method the global climate data interpolated to the 50 km grid is shifted by two grid points in all cardinal directions before being used as boundary data. This accounts for the uncertainty in positioning of

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synoptic systems when interpolating the GCM data to the required resolution for forcing the RCM simulations. As all five ECHAM6 driven simulations obtained this way exhibit a high correlation, they are all weighed with a factor of 1/5 when calculating the mean. All other models receive a factor of one which leads to an effective ensemble size of eight. Additionally we use a COSMO-CLM run driven by ERA-40 (Uppala et al., 2005) boundary conditions.

The simulation time periods are the recent past (1971-2000) and the near future (2021-2050). An analysis of the temperature trends of different ensemble members showed that the distribution of trend depends more strongly on the chosen global climate model than on the emission scenario. We therefore combine simulations with boundary data from GCMs with different emission scenarios to set up our ensemble.

We chose six regions, each comprising 6×6 grid points for our analysis. The regions were chosen based on the PRUDENCE regions (Christensen and Christensen, 2007) which could not be used because of the necessity of the same amount of grid points for each area, and due to test results which showed a different behavior for these regions. We investigate 30 year periods of daily data, thus each time series consists of $\approx 11,000$ data points, yielding $\approx 36 \times 11,000 \approx 400,000$ points in time for each region and ensemble member.

The model domain and the six investigation areas, which are located in Spain, France, Germany, Scandinavia, Bulgaria, and Russia are shown in Fig. 1. These roughly match the PRUDENCE regions which were not applicable for the analysis since equal sized areas are a requirement for comparison among regions.

2.2 Observational data

For the comparison of our regional climate ensemble with observations, we use temperature and precipitation data from the gridded E-OBS dataset (Haylock et al., 2008). This dataset was produced as part of the ENSEMBLES project by interpolating station data from the ECA&D station dataset (European Climate Assessment, Klok and Klein Tank, 2009) to a 25 km grid. The station density is highest in Switzerland, the Netherlands and Ireland and rather low in Spain and the Balkans which leads to an over-smoothing in these areas. This especially affects extremes and has to be taken into account when validating our ensemble against E-OBS data.

2.3 Compound extremes with Markov Chain descriptors

The method used in this paper consists of describing temperature and precipitation time series by a Markov Chain and subsequently calculating descriptors, which characterize the dynamical (successional) behavior of the compound extreme states. The method has been used in biology (Hill et al., 2004) to describe dynamics of succession of species in a rocky subtidal community. It has been introduced to atmospheric science by Mieruch et al. (2010) who used it for climate classification and a comparative study of two regions. In this section, a short introduction to Markov chains is given,

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followed by a step by step description of the method.

A first order, m state (m= number of discrete states of the Markov Chain), homogeneous Markov Chain is a time discrete, state discrete stochastic process which fulfills the Markov property:

$$P(x_t|x_{t-1}, x_{t-2}, ..., x_{t-n}) = P(x_t|x_{t-1}) \tag{1}$$

meaning that the present state x_t is only dependent on the preceding state x_{t-1}. From the Markov chain, a transition probability matrix $\mathbf{P}$ of the order $m \times m$ can be calculated which consists of all possible conditional probabilities $P(x_t|x_{t-1})$ between the m different states of the Markov chain. For a homogeneous ($\equiv$ stationary) Markov chain, the transition probability matrix is time independent. A stationary distribution $\boldsymbol{\pi}$ is a vector that fulfills the following equation

$$\boldsymbol{\pi} = \mathbf{P}\boldsymbol{\pi}. \tag{2}$$

To test for homogeneity one must solve the eigenvalue problem of equation 2 to calculate the stationary distribution $\boldsymbol{\pi}$. If this is identical to the empirical distribution

$$\hat{\pi}_j = \frac{n_j}{\sum_j n_j}. \tag{3}$$

, the time series is considered stationary. The entries (transition probabilities) of the transition matrix $\mathbf{P}$ are estimated by

$$\hat{p}_{ij} = \frac{n_{ij}}{\sum_i n_{ij}}. \tag{4}$$

In the following, the main steps of the Markov analysis are explained:

a) **Partitioning and combining of univariate time series to a multivariate symbolic sequence**
To represent the univariate time series (here daily mean temperature anomalies and daily precipitation anomalies) by a Markov chain, each time series is partitioned into a symbolic sequence of extreme and non-extreme regimes. These univariate symbolic sequences are then combined into a multivariate symbolic sequence of $m = 2^v$ different states (v number of variables). In this paper, $v = 2$, thus there are four possible states.

b) **Calculation of the transition probability matrix**
From the 2^v-state Markov chain, a transition probability matrix $\mathbf{P}$ of dimension $2^v \times 2^v$ can be calculated. Two conditions have to be met when calculating the descriptors. No entry of the transition probability matrix should be equal to zero and the time series needs to be stationary for the transition probability matrix to be time independent (see equations 2, 3).

c) **Calculation of the descriptors**
Following Mieruch et al. (2010), we focus on only three of the descriptors mentioned in Hill

et al. (2004): persistence, recurrence time and entropy. These descriptors can be estimated for single states of the symbolic sequence or for the whole system. As the focus of this work lies on the compound extreme state, only the single-state definition of the descriptors is considered.

Persistence:

$$P_j = \hat{p}_{jj} \tag{5}$$

The persistence gives the probability that the system will stay in an extreme state in the following time step if it resides in an extreme state at the current time step. The limits are 0 (the system will never stay in the extreme state) and 1 (the system will always stay in the extreme state). Regarding the succession of the compound extremes, the persistence tells us how long the extremes last.

Recurrence time:

$$R_j = \frac{1-\hat{\pi}_j}{(1-\hat{p}_{jj})\,\hat{\pi}_j} \tag{6}$$

The recurrence time describes the number of days the system needs to get back to the extreme state. The limits are 0 (the system never leaves the state, corresponding to a persistence of 1) and ∞ (the system never comes back to the extreme state). The recurrence time is connected to the persistence. If the persistence increases, the recurrence time will also increase and vice versa, except if a change in the number of states $\hat{\pi}_j$ occurs. Thus, it is important to include the absolute numbers of the states for the interpretation of the results.

Entropy:

$$H(p_j) = -\sum_i \hat{p}_{ij} \log \hat{p}_{ij} / log\left(\frac{1}{m}\right) \tag{7}$$

According to Shannon (1948), the entropy is an inverse measure of the predictability of the Markov Chain. Its limits are 0 (deterministic system) and 1 (random system). The dynamics of complex chaotic systems lie in between these limits, thus the entropy can be used to identify and characterize complex dynamics like deterministic chaos, which is not possible with standard linear methods. Thus, in the sense of the succession of compound extremes a change in entropy tells us if the succession of extreme states gets more chaotic or more regular.

d) **Data pre-processing**

In order to extract the information on the succession of compound extremes, we have to remove linearities (e.g. trends) and cycles, which would bias the results. Thus, we remove the external solar forcing by subtracting the mean annual cycle. A long-term trend is removed by

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a linear regression. Although, e.g. the temperature trend due to the anthropogenic CO_2 emissions is removed from the data, we hypothesize that all changes in the succession of extremes are linked to the CO_2 increase. The reason for this is that the CO_2 forcing is the only difference between the model runs for the periods 1971-2001 and 2021-2050. We use percentiles to partition our datasets, and keep the number of univariate extreme events the same for different time periods and regions as well as for all ensemble members. By this, the results can be compared among each other, differences are only due to different dynamical behavior. For partitioning dry days, we did not use precipitation anomalies but the effective drought index (EDI). The EDI (see Sect. 2.4) is related to soil moisture and is therefore a much better measure for describing dry extremes than precipitation itself, since all percentiles below the percentage of dry days will lead to the same partitions.

In order to get a better feeling for the descriptors and understand how they relate with each other, we will do a small thought experiment. We take a Markov chain consisting of a time series of 1000 symbols of which 10% are extreme, the rest are normal. In this case a persistence of 0.5 would mean that in half of the 100 extreme cases, the next case is also extreme, there are 50 transitions from the extreme state to the extreme state. The maximum episode length in this case is thus 51 extreme states in a row (with all others randomly distributed).The recurrence time and entropy are inversely related to how these 50 extreme transitions are ordered. Recurrence time depends on the number of episodes (fewer episodes lead to a larger recurrence time, more episodes to a shorter recurrence time) and entropy additionally on the mean episode length. In this paper, we also look at changes in the descriptors. A change in persistence of 0.05 in the above case would mean 5 more extreme-extreme transitions per 1000 days, and an increase from 50/100 to 55/100 (extreme-extreme transitions/extreme-normal transitions) is surely a noticeable change. The range of actually probable values of the descriptors is smaller than the whole possible range. A persistence of 0.99 for example, would mean that there is only one extreme episode in the whole time period, all 100 extreme states occur after each other. In a climate system, this is unlikely to happen. Thus, for climate one cannot expect to observe a change of the daily persistence from e.g. 0.5 to 0.8, because such a change would be catastrophic.

2.4 Effective drought index: EDI

The effective drought index (EDI) is an index for detecting drought conditions by calculating daily deviations of precipitation from a climatological mean state. It was proposed by Byun and Wilhite (1999) and is calculated by the following formula for a given day d:

$$EDI_d = \frac{EP_d - \overline{EP_{d,rm}}}{\sigma\left(EP - \overline{EP}\right)_d} \tag{8}$$

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An important concept of the EDI is the use of effective precipitation EP, rather than precipitation P itself. EP describes the depletion of water sources by a weighted summation over the 365 days preceding a given day d:

$$EP_d = \sum_{n=1}^{365} \left(\frac{\sum_{m=1}^{n} P_{d-m}}{n} \right) \tag{9}$$

By this, the memory effect of the soil is taken into account. EP therefore strongly correlates with soil moisture and the EDI is thus a good measure when considering droughts.

3 Markovian descriptors for the reference period 1971-2000

We calculate the Markovian descriptors for two types of extremes, cold and heavy precipitation (temperature anomaly (Ta) < 10th percentile and precipitation anomaly (Pa) > 75th percentile) in winter (DJF) and heat and drought (Ta >95th percentile and EDI < 25th percentile) in summer (JJA), for the six regions shown in Fig. 1.

Fig. 2 shows the descriptors for cold extremes and heavy precipitation in winter from 1971-2000. The boxes show the 25th and 75th quantile of the ensemble, the whiskers the minimum and maximum. The colored line marks the ensemble median and the gray line the ensemble mean. Crosses mark the descriptors of the observations. The observed persistence for the different regions lies between 0.06 and 0.37. This means that the system does not stay in this extreme state for a very long time, the lowest observed persistence is in region 4 (Scandinavia) where extreme-extreme transitions are extremely rare. The recurrence times vary strongly between the regions, the values are between 64 and 314 days. Regions 1 and 6 (Spain and Bulgaria) show the lowest recurrence times. In region 6 (Bulgaria) the compound cold and wet episodes have the longest duration and occur with the highest frequency. The entropy of the observations lies between 0.23 in region 3 (Germany) and 0.25 in region 1 (Spain) and between 0.19 in region 3 (Germany) and 0.26 in region 5 (Russia) for the CCLM ensemble. Thus, the deduced entropy (both, observations and model) covers a rather small portion of the range of theoretically possible values from 0 to 1. As mentioned in Sect. 2.3 the range in which we actually expect the values of the descriptors is smaller. Therefore, when comparing the descriptors, the values have to be interpreted relative to the regions. One must be careful, however, because the descriptors do not permit to draw any conclusions about the absolute predictability of the states as long as the total numbers of states are not considered.

Focusing on the descriptors for the CCLM ensemble (box plots and gray bars in Fig. 2), we can see that with this method we are able to detect significant differences in dynamical behavior between some of the regions. In comparison to the descriptors of the observations (crosses in Fig. 2), the ensemble is able to capture the differences between the regions fairly well except for the persistence in region 5 where the ensemble shows a much lower persistence and the recurrence time of region 4

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(Scandinavia) which is lower for the observations. However, these are regions where the the density of station data underlying the E-OBS dataset is not very high and the E-OBS results may not be as reliable. The highest persistence is again in region 6 (Bulgaria) which also shows the lowest recurrence time and therefore has comparatively long events which occur more frequently than in other areas. The triangles mark the descriptors of the reanalysis driven simulations. They fit well for some regions, for others they are farther away from the observations than the CCLM-ensemble.

Fig. 3 shows the descriptors for hot and dry extremes in summer. Crosses again mark the descriptors of the observations. All descriptors are higher than for cold and wet extremes in winter, this also holds when partitioning the data such that the number of univariate extremes is the same for hot and dry extremes and cold and wet extremes (not shown). This might partly be due to the lower variability of EDI compared to precipitation anomalies but one would also expect the dynamical behavior of these extremes to be different. By our definition, hot and dry episodes in summer are longer and not as frequent as cold and wet extremes in winter. The highest persistences are in regions 2,4 and 5 (France, Scandinavia and Russia), the lowest in region 3 (Germany). The entropy lies between 0.24 and 0.25 and is fairly similar for all regions considered. This is a higher value than for the cold and wet extremes, so this state probably exhibits more complex dynamics and is harder to predict (caution: this is also influenced by the total number of extremes). The CCLM ensemble (box plots) again captures the tendencies of the observed descriptors fairly well but shows a large spread and differences between the regions are not significant. The ERA-40 driven CCLM simulations (triangles in Fig. 3) fit well to the observations for most regions.

For both types of compound extremes the ensemble mean and median seem to be able to capture the differences between regions shown by observations although not always in absolute numbers. An interesting result is that reanalysis driven CCLM data is sometimes farther away from the observational descriptors than the model data, especially for the cold and wet extremes in winter. This leads to the question whether the dynamical behavior of the driving GCM is greatly altered by the RCM downscaling and errors in both models compensate during the downscaling process. A follow up study comparing dynamical behavior of both RCM and GCM is planned for the future.

4 Climate change signal of the Markovian descriptors

4.1 Change signal within the reference period

In order to get an idea about the order of magnitude of the change signal, the observational E-OBS dataset was split into two equal parts of 30 years, 1951-1980 and 1981-2010. The descriptors were calculated for both time periods and a change signal derived.

For cold and wet extremes (see Fig. 4) all regions except Bulgaria show a decrease in persistence, region 5 and 6 (Russia and Balkan) show the strongest absolute decrease (≈ 0.15) and Germany the highest relative decrease of -72 % (relative changes are shown above the respective bars). The recurrence time does not change much for all regions except region 5 (Russia) where it decreases by 150 days. In this region, compound cold and wet extremes occurred more frequently but were of shorter duration in 1981-2010. The entropy only shows changes greater than 5 % in Scandinavia where it decreases and the system becomes more regular.

Changes for hot and dry extremes in summer (see Fig. 5) show a decrease in all descriptors for most regions, region 5 (Russia) is the only one with an increase in persistence and recurrence time. The order of magnitude of the change signal is slightly lower than for cold and wet extremes in winter (maximum change persistence: -0.07, recurrence time -7 days) and here, regions 3 (Germany) and 4 (Scandinavia) are the ones with the largest changes.

4.2 Projected changes in the near future

In a second step we calculate the change signal between 1971-2000 and 2021-2050 for all members of the CCLM-ensemble. An additional information of interest for the interpretation of the results is the change in the number of compound extreme days. The number of univariate extreme days are kept constant when partitioning the data (see Sect. 2.3) but the combination can change.

The number of compound cold and wet extreme days increases in all regions except region 5 (Russia) between the two time periods 1971-2000 and 2021-2050 and the number of compound extreme days differs between the regions. Regions 1 and 6 (Spain and Bulgaria) show the highest number of compound extreme events. (see Fig. 6). The ensemble mean values of the descriptors for cold and wet extremes in winter are shown in Fig. 8,whiskers give the interquartile range. The significance of the change signal was calculated using the nonparametric Mann–Whitney–Wilcoxon test, the p-values are shown below the bars in the respective figures. Most of results of this chapter are not significant at the 5% significance level, region 5 (Russia) however shows a significant change signal for the persistence and some changes are significant at the 10 % or 20% significance level (P-value ≤ 0.1 or ≤ 0.2). Following von Storch and Zwiers (2013), who propose to use "*a simple descriptive approach for characterizing the information in an ensemble of scenarios*" instead of the ensemble significance, we also look at the ensemble spread in form of the interquartile range to assess the robustness of the results. In many cases, the majority of ensemble members show a change signal in the same direction and the change signal is of a similar order of magnitude as the observed past changes in the preceding section (Figs. 4 and 5). Therefore we conclude that these results do show that there might be possible changes in some regions and in the following we will discuss the changes of the ensemble mean values.

Fig. 8 reveals three regions which seem to be particularly susceptible to changes of the dynamics / succession, namely regions 2 (France), 3 (Germany) and 5 (Russia). The persistence changes for all regions and cold and wet episodes are likely to be of longer duration in the future. In regions 2 and 3 (France and Germany) the recurrence time decreases. The consequences of these changes are that these regions will probably experience more and longer cold and wet events in winter. Furthermore,

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these are less predictable (increase of entropy). The situation is different for region 5 (Russia), here the duration of cold and wet periods probably increases but the events will be fewer (decrease in recurrence time) but more predictable (decrease of entropy).

The change in number of compound hot and dry extreme days is depicted in Fig. 7. Here, the number of compound extreme days varies with the region (although the number of univariate extremes are kept the same). Region 1 (Spain) shows a relatively low number of compound hot and dry days (note: all extremes in this paper are relative), regions 5 and 6 (Russia and Bulgaria) have a high number and also the highest decrease between the two time periods. Except for region 3 (Germany), which shows a slight increase, the number of compound extremes decreases in all regions. However, the change is generally small, $< 10\,\%$. Thus, the observed changes of the descriptors can mostly be attributed to the change in the dynamics and not to a change in the numbers of events, except maybe for regions 4 and 5 (Russia and Bulgaria).

The change signal of the descriptors is pictured in Fig. 9. Two regions are probably susceptible to changes in the dynamics of the hot and dry state, namely regions 1 (Spain) and 6 (Bulgaria). Region 1 shows a quite strong increase in persistence and recurrence time of the hot and dry state and a corresponding decrease in entropy. The hot and dry periods get longer and the system gets more regular, as indicated by the entropy decrease. The situation for region 6 is similar to that of region 1, with an increase in persistence and recurrence time and a decrease in entropy.

5 Conclusions and Outlook

The changing climate leads to a change in extreme weather, which comprises several aspects like frequency, duration, intensity etc. On top of these rather linear changes, modifications of the complex succession of extremes can be expected. However, information on the succession or dynamical behavior of climate extremes is rare. Therefore, to extract such information from climate time series we applied a Markov chain analysis on compound extremes, namely cold and wet in winter and hot and dry in summer. We have shown that our climate model ensemble is able to reproduce past dynamics of compound extremes fairly well within acceptable uncertainties. Thus, we have reasonable confidence in the future simulations of this model ensemble. We identified three regions in Europe, which are probably susceptible to a future change in the succession and dynamical behavior of cold and wet extremes in winter. In region 5 (Russia) we detected an increase of the persistence and recurrence time, which means that the probability of staying in the cold and wet state from one day to the next will increase, but the system will take longer to approach this state again. In regions 2 (France) and 3 (Germany), cold and wet episodes become both longer and more frequent. The entropy in these regions also decreases in the future, which is counterintuitive, because one would expect that an increase in persistence is related to a decrease in entropy (cf. Eqs. 5 and 7). However, since the entropy (Eqs. 7) does not only consider the compound extreme state but also transitions from this

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state to the normal state and univariate extreme states, complex interactions can be extracted with the entropy. The impacts of these calculated changes are beyond the scope of this study, and it can only be speculated about possible effects. One could imagine that longer and less predictable cold and wet periods could lead to larger snow chaos regarding traffic and other human life, especially in regions which already experience extreme cold temperatures in winter. Again, these findings suggest that a reordering of the succession of compound extremes could be happening on top of the observed linear changes, as e.g. the temperature increase.

For hot and dry states in summer, the Markov method identified two regions where changes are probable, Spain and Bulgaria. The persistence and recurrence time in regions 1 and 6 (Spain and Bulgaria) both increase in the future, which means that the system resides longer in the extreme state. The entropy decreases, which is expected, because it is easier to predict that an extreme state will follow an extreme state. In this light, the systems are getting more regular. However, any re-ordering of the succession of extremes has an impact. For instance such changes could be harmful for the local agriculture, because, as explained above, these dynamic changes would occur on top of the known linear increase of e.g. temperatures. Interestingly, in region 6 (Bulgaria) the absolute number of compound hot and dry extremes (Fig.7) decreases in the future, but the extreme periods become longer. The changes for region 5 (Russia) are small for persistence and entropy but larger for recurrence time, which increases. This is probably connected with the decrease of the number of compound events in the future. Thus, it seems that the region in Russia near Moscow will be less susceptible to dynamical changes of the succession of compound extremes and will additionally experience less compound extremes in the near future.

Areas to apply this method are manifold. Besides the analysis of different dynamical behavior varying on the region and extreme considered, it can be used as a model validation tool. As extremes and especially compound extremes are an important quantity that we want to assess with climate model data, it is necessary for the models to capture the dynamical behavior of these extreme events. As shown in this paper, the models can also project changes of the future dynamical behavior which is are an interesting supplementary information to changes in mean and variability. An example where this could be useful is the decision whether to apply simple or more sophisticated bias correction techniques.

Follow up studies using simulations of other regional climate models and regional climate ensembles for time periods further in the future (e.g. ENSEMBLES, http://ensembles-eu.metoffice.com/, or CORDEX, http://www.euro-cordex.net/, data for the end of the century) would be interesting. For one, this would allow an analysis of whether or not there are significant differences depending on the regional climate model used. In addition, data for the end of the 21st century is available where changes in the descriptors could possibly be larger because the influence of the CO2 forcing plays a more important role. In this sense, the Markov chain analysis could be useful to identify possible future regime shifts (Scheffer and Carpenter, 2003; Scheffer et al., 2009). Of further interest is an analysis of the dynamical behavior of the driving GCMs as well as the ERA-40 reanalysis dataset since for parts the ERA-40 driven CCLM model runs performed worse in comparison to observations than the CCLM ensemble. This leads to the question whether or not the CCLM model runs compensate for errors in the driving GCMs and are right for the wrong reasons. Comparison of the E-OBS dataset to other regionally defined datasets would also be helpful to evaluate the observational data.

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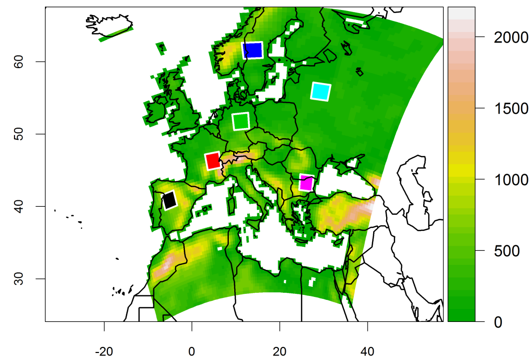

Figure 1. Elevation of the CCLM 50 km Model domain [m]. Boxes mark the six investigation areas, 1:Spain (black), 2:France (red), 3:Germany (green), 4:Scandinavia (blue), 5:Russia (cyan) and 6:Bulgaria (magenta).

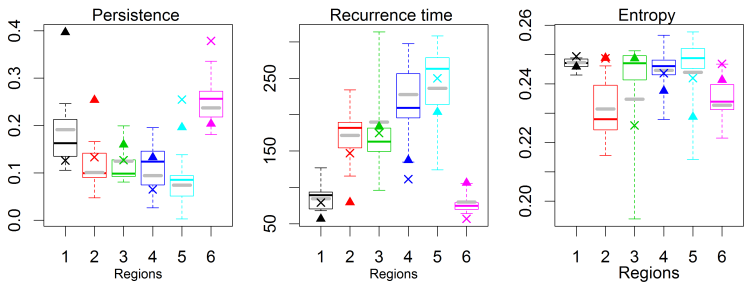

Figure 2. Descriptors for cold and wet extremes in winter (DJF) (Ta < 10th percentile and Pa > 75th percentile) in the reference period 1971-2000 for the 6 investigation areas. Box plots of the CCLM ensemble: box = ensemble median and interquartile range, whiskers = ensemble minimum/maximum, gray bars: ensemble mean, triangles :reanalysis driven CCLM runs, crosses: E-OBS observations. The coloring corresponds to the regions in Fig. 1.

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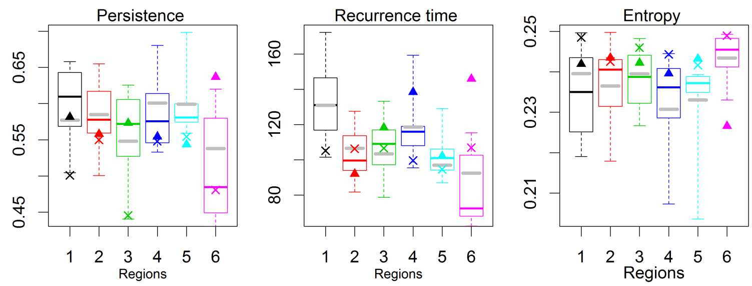

Figure 3. Descriptors for hot and dry extremes in Summer (JJA) (Ta > 95th percentile and EDI < 25th percentile) in the reference period 1971-2000 for the 6 investigation areas. Box plots of the CCLM ensemble: box = ensemble median and interquartile range, whiskers = ensemble minimum/maximum, gray bars: ensemble mean, triangles :reanalysis driven CCLM runs, crosses: E-OBS observations. The coloring corresponds to the regions in Fig. 1.

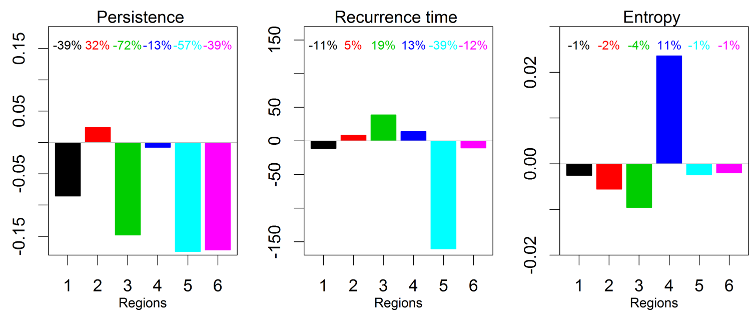

Figure 4. Change signal for of descriptors for E-OBS observations: Cold and wet extremes in winter (DJF) (Ta < 10th percentile and Pa > 75th percentile) ,1951-1980 vs 1981-2010. Percentages denote the relative change. The coloring corresponds to the regions in Fig. 1.

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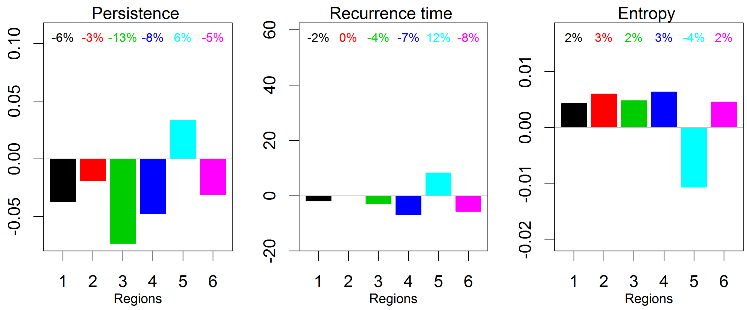

Figure 5. Change signal for of descriptors for E-OBS observations: Hot and dry extremes in Summer (JJA) (Ta > 95th percentile and EDI < 25th percentile),1951-1980 vs 1981-2010. Percentages denote the relative change. The coloring corresponds to the regions in Fig. 1.

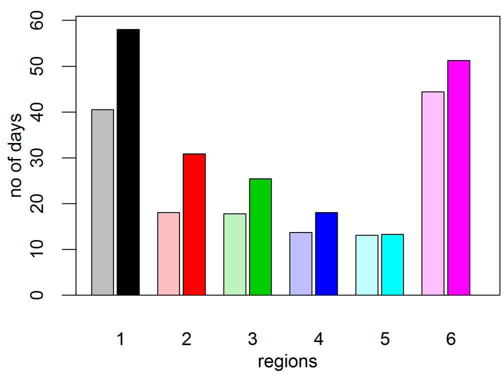

Figure 6. Number of compound cold and wet extremes in winter (DJF) (Ta < 10th percentile and Pa > 75th percentile) , 1971-2000 (light colors) and 2021-2050 (dark colors), ensemble mean. The coloring corresponds to the regions in Fig. 1.

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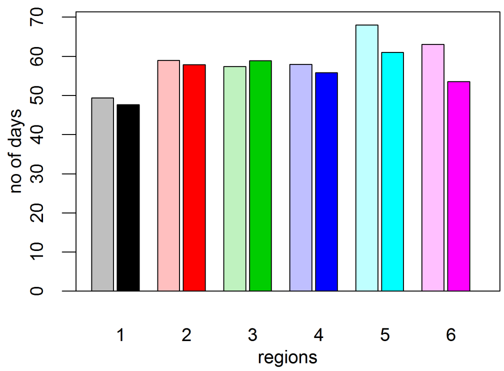

Figure 7. Number of compound hot and dry extremes in summer (JJA) (Ta > 95th percentile and EDI < 25th percentile), 1971-2000 (light colors) and 2021-2050 (dark colors), ensemble mean. The coloring corresponds to the regions in Fig. 1.

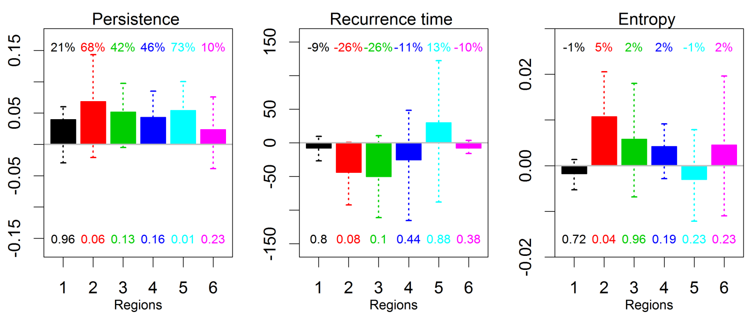

Figure 8. Ensemble mean climate change signal of descriptors for cold and wet extremes in winter (DJF) (Ta < 10th percentile and Pa > 75th percentile) ,1971-2000 vs 2021-2050. Points show the ensemble mean, whiskers the 75th and 25th quantile, respectively. Percentages above the bars denote the relative change of the ensemble mean, the numbers below the p-value. The coloring corresponds to the regions in Fig. 1.

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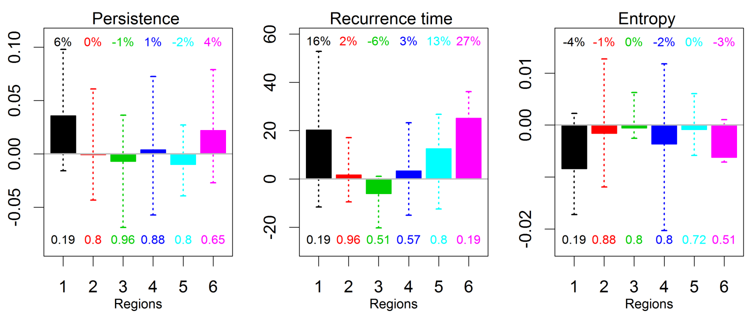

Figure 9. Ensemble mean change signal of descriptors for hot and dry extremes in Summer (JJA) (Ta > 95th percentile and EDI < 25th percentile),1971-2000 vs 2021-2050. Points show the ensemble mean, whiskers the 75th and 25th quantile, respectively. . Percentages above the bars denote the relative change of the ensemble mean, the numbers below the p-value. The coloring corresponds to the regions in Fig. 1.