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Detecting Climate Change Effects on Vb Cyclones in a 50-Member Single-Model Ensemble Using Machine Learning

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Key Points:
- Machine learning is employed to filter a single-model ensemble for cutoff low related Vb cyclones with high accuracy
- The seasonality of Vb cyclones changes considerably under the RCP8.5 scenario with a peak shift from summer to spring
- The daily precipitation intensity of Vb cyclones significantly increases in all seasons

Supporting Information:
- Supporting Information S1

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Abstract

Vb cyclones are major drivers of extreme precipitation and floods in the study area of hydrological Bavaria (Germany). When assessing climate change impacts on Vb cyclones, internal variability of the climate system is an important underlying uncertainty. Here, we employ a 50-member single-model initial-condition large ensemble of a regional climate model to study climate variability and forced change on Vb cyclones. An artificial neural network detects cutoff lows over central Europe, which are associated with extreme precipitation Vb cyclones. Thus, machine learning filters the large ensemble prior to cyclone tracking. Our results show a striking change in Vb seasonality with a strong decrease of Vb cyclones in summer (−52%) and a large increase in spring (+73%) under the Representative Concentration Pathway 8.5. This change exceeds the noise of internal variability and leads to a peak shift from summer to spring. Additionally, we show significant increases in the daily precipitation intensity during Vb cyclones in all seasons.

Plain Language Summary

Bavaria, a state in the southeast of Germany, has been hit by several devastating floods in recent decades triggered by a storm type called Vb. For future flood risk in Bavaria it is crucial to understand how climate change affects Vb storms. This study uses high-resolution climate simulations over Europe to study changes in the frequency of Vb storms, their seasonal occurrence, and their rainfall intensity under a high greenhouse gas concentration scenario. However, Vb storms are rare events and a single simulation may not provide enough events to distinguish between climate change and random, natural variations. Therefore, we employ a large database of 50 climate simulations with the same settings and greenhouse gas concentration scenario, but slightly different starting conditions, in order to robustly estimate climate change effects on Vb storms. The drawback of using 50 simulations is the high amount of data. Therefore, we apply machine learning for pattern recognition to detect the low-pressure systems related to extreme precipitation Vb storms in the climate simulations. Our results show that climate change considerably affects the seasonal occurrence of Vb storms with a shift from summer to spring. Furthermore, the daily rainfall intensity in Bavaria increases during Vb storms significantly with climate change.

1. Introduction

Climate projections indicate changes in precipitation patterns and an increase in river flood risk in many parts of the world with progressing climate change (Dore, 2005; IPCC, 2012; Willner et al., 2018). Floods count as one of the most devastating natural hazards with a high impact on society (IPCC, 2012; Willner et al., 2018). Midlatitude extreme precipitation and floods are often triggered by certain weather patterns and extratropical cyclones that act as large-scale drivers of intense rainfall (Hofstätter et al., 2016; Messmer et al., 2015). In central Europe, one specific cyclone type, known as *Vb*-cyclone (Van Bebber, 1891), is especially associated with extreme precipitation and a high risk of river flooding (Kundzewicz et al., 2005; Nissen et al., 2013). Vb cyclones develop in the Mediterranean Basin (Gulf of Genoa or northern Adriatic Sea; Muskulus & Jacob, 2005) and propagate to the northeast around the Eastern Alps, leading to orographic precipitation in the northern alpine foreland (Hofstätter et al., 2016; Messmer et al., 2015). One of the regions especially hit by Vb cyclones is the study area of *hydrological Bavaria* in the southeast of Germany (see Figure 1). Although Vb cyclones occur rarely with 2.3 (Messmer et al., 2015) to 4.8 (Hofstätter et al., 2018) events per

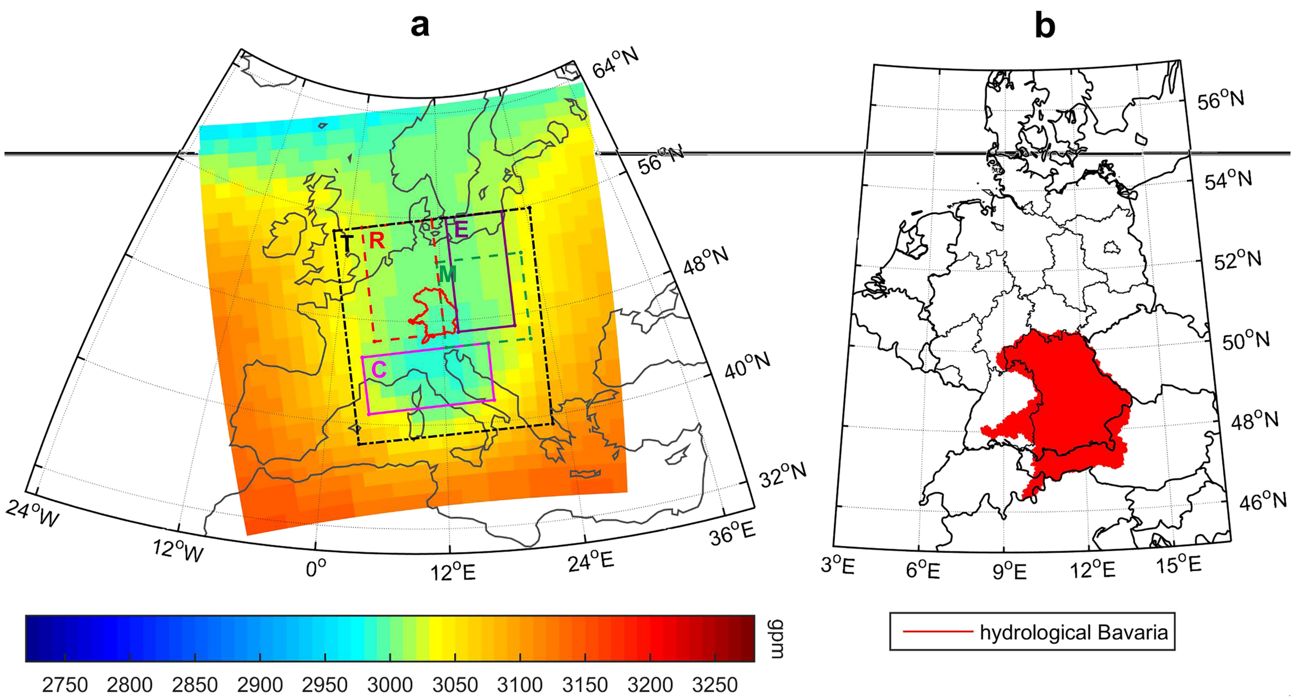

Figure 1. (a) Synoptic pattern at 700 hPa averaged over the 265 Class 1 training examples containing absolute JRA-55 values. A cutoff low over central Europe is visible. The study area of hydrological Bavaria is outlined in red. Additionally, the boxes for the Vb pathway definition are delineated: the tracking zone (T), the cyclogenesis region (C), the end area (E), the mandatory area (M), and the restrictive box (R). (b) State borders (black), federal states of Germany (gray) and position of hydrological Bavaria (red).

year, at least 30% of all summer floods in Bavaria have been related to Vb cyclones (Stahl & Hofstätter, 2018). Vb cyclones that trigger extreme precipitation account for 23% (Messmer et al., 2015) to 41% (Nissen et al., 2013) of all cyclones on a Vb track. Messmer et al. (2015) found the main difference between heavy and weak precipitation Vb cyclones in the corresponding geopotential height field and identified the existence of a cutoff low during heavy precipitation Vb cyclones. Hofstätter et al. (2018) furthermore show that strong Vb cyclones (cyclone intensity >85th percentile) are related to a cutoff low located over central Europe. Climate change is expected to alter the dynamic (e.g., frequency) and thermodynamic factors (moisture transport and related precipitation) of Vb cyclones (Volosciuk et al., 2016). The studies of Volosciuk et al. (2016), Nissen et al. (2013) and Kundzewicz et al. (2005) suggest more intense summer precipitation related to Vb cyclones in a warmer climate. Nissen et al. (2013) further identify a decrease in Vb frequency in summer.

Scientific knowledge on the role of internal variability on changes in Vb cyclone activity is still limited. Internal variability is one of the three major sources of uncertainty in climate change projections, besides model response and external forcing (Deser et al., 2012). It is tied to the intrinsic chaotic character of the climate system due to nonlinear dynamical processes in atmosphere and ocean (Deser et al., 2012). Internal variability affects climate projections, particularly at the regional scale and regarding extremes (Kay et al., 2015; Perkins & Fischer, 2013). This is why the range of internal variability for regional projections regarding rare Vb cyclones is an important open research question. In order to study internal variability, single-model ensembles are employed, which consist of several simulations of the same climate model using slightly different initial conditions (Deser et al., 2012). This paper examines cutoff low-related Vb cyclones using a large single-model ensemble with 50 members of high-resolution climate simulations, the Canadian Regional Climate Model Large Ensemble (CRCM5-LE; Leduc et al., 2019; von Trentini et al., 2019). The drawback of such a large single-model ensemble, however, is the concomitant data amount, which is overall 400 TB for the CRCM5-LE, with several terabytes per variable (Leduc et al., 2018).

This study addresses challenges in identifying Vb cyclones in large climate ensembles by employing machine learning as an efficient data-handling technique. Machine learning proves to be a powerful tool for pattern recognition and seems promising for high-performance analysis of spatiotemporal climate data sets (Grotjahn et al., 2016). Here, a supervised machine learning algorithm for pattern recognition, an artificial neural network (ANN), is employed. Using the ANN, it is possible to scan the CRCM5-LE for the synoptic pattern of a cutoff low over central Europe, which is associated with the initial state of extreme precipitation Vb cyclones (Hofstätter et al., 2018; Messmer et al., 2015). Thus, the large ensemble is specifically filtered for potential cutoff low-related Vb cyclones, before a detailed tracking of their cyclone centers and an analysis of their pathways is conducted. First, cyclones following the Vb pathway are identified, then climate change effects on their occurrence and precipitation intensity over the study area of hydrological Bavaria are studied.

This study addresses the following research question: How does climate change under the Representative Concentration Pathway 8.5 (RCP8.5; Meinshausen et al., 2011) affect the frequency and seasonality of cutoff low-related Vb cyclones and their precipitation intensity while considering the noise of internal variability?

2. Methods

To address this research question on how climate change and internal variability affect cutoff low-related Vb cyclones, a large single-model ensemble with 50 members, the CRCM5-LE, is examined. The CRCM5-LE was created as part of the ClimEx project (Climate Change and hydrological Extremes; Leduc et al., 2019; www.climex-project.org; von Trentini et al., 2019). The CRCM5-LE was generated by dynamically downscaling the 50-member initial-condition ensemble of the Canadian Earth System Model version 2 (CanESM2-LE; Fyfe et al., 2017) using the Canadian Regional Climate Model version 5 (CRCM5; Martynov et al., 2013; Separovic et al., 2013). The dynamical downscaling was performed for two domains (Europe and northeastern North America) to a high spatial resolution of 0.11°. The time series cover the period from 1950 to 2099. Up to the year 2005 the model is forced with historic greenhouse gas and aerosol emissions, while from 2006 on the RCP 8.5 forcing scenario is used (Leduc et al., 2019). The variables examined here are geopotential height at 700 hPa (z700; 3-hourly) and precipitation (pr; hourly; for hydrological Bavaria only). One CRCM5 run was driven by the boundary conditions of the ERA-Interim (Dee et al., 2011) reanalysis (ERA-Interim-CRCM5) and covers the period of 1979 to 2013. It is used to validate the model's capability of reproducing historic Vb cyclones.

The training set for the machine learning algorithm is based on reanalysis data of historic cutoff lows over central Europe and their related Vb cyclones. The Japanese 55-year Reanalysis (JRA-55; Harada et al., 2016; Kobayashi et al., 2015) is used. Dates of historic Vb cyclones are derived from a JRA-55 based catalog of historic cyclone tracks over central Europe from Hofstätter et al. (2018). The catalog identifies 296 Vb cyclones in the period from 1959 to 2015. In the catalog 23% of Vb cyclones occur with associated cutoff lows at 700 hPa, but these account for 75% of extreme precipitation events over hydrological Bavaria associated with Vb cyclones (minimum distance to other cyclones: 500 km). The 69 Vb cyclones with a distinct cutoff low, which consist in total of 265 time steps (training examples), are manually extracted. The JRA-55 reanalysis has a temporal resolution of 6 hr and a spatial resolution of 1.25° on a uniform latitude-longitude grid. The variable used to identify Vb cyclones is z700.

Cutoff low related Vb cyclones in the CRCM5-LE are identified as follows:

1. training an ANN on the detection of historic synoptic patterns of cutoff lows over central Europe with JRA-55 data,
2. applying the trained ANN on the entire ensemble to extract the beginning stage of potential Vb cyclones from the CRCM5-LE,
3. tracking the cyclone centers of potential Vb cyclones, and
4. testing the tracked pathways for fulfilling the definition of Vb.

The following methodology is graphically illustrated in the supporting information (see Figure S2).

First, the training set for the ANN is built based on JRA-55 and the catalog by Hofstätter et al. (2018). The ANN is trained to separate two classes: Class 1 showing a cutoff low over central Europe (positives), and Class 0 showing no cutoff low over central Europe (negatives). For Class 1, the 265 time steps are used that contain a historic cutoff low over central Europe in combination with a Vb cyclone. Figure 1 shows the synoptic pattern at z700 averaged over all positive training examples in JRA-55 reanalysis data. For Class 0 (negatives) 62,955 counterexamples without Vb cyclones are employed. The training data set suffers of a skewed class distribution as historic situations with Vb related cutoff lows over central Europe (positives) are much scarcer than counterexamples (negatives). To account for inaccuracies resulting from such an imbalanced data set, error-weighting, respectively, cost-sensitive learning (Zhou et al., 2018) is applied during training with a weighting factor of 0.025 on Class 0. Preprocessing of JRA-55 data consists of extracting the CRCM5-LE-domain and interpolating the data to the rotated latitude-longitude CRCM5-LE grid (see Figure 1). The original, fine RCM resolution of 0.11° is not necessary for the detection and tracking of large-scale synoptic patterns, thereby data is aggregated to 1.1°.

Second, a two-layered ANN for pattern recognition is employed (input layer: 784 nodes, hidden layer: 25 nodes, output layer: 2 nodes) using MATLAB's Neural Network Toolbox (nntool). The settings of the ANN are the hyperbolic tangent sigmoid function as activation function in the hidden layer (LeCun et al., 2015) and the softmax function in the output layer (Zhou et al., 2018). Cross-entropy (Kline & Berardi, 2005) serves as cost function and is minimized by scaled conjugate gradient backpropagation (Møller et al., 1993). In order to evaluate the performance of the training setup a k fold stratified cross validation is conducted with a number of 10 subsamples ($k = 10$) and a setup division of 90% for training and 5% each for validation and independent test set. As performance indices a confusion matrix with precision and recall is calculated (see Table S1 and Text S1).

Third, the detected events of possible Vb cyclones undergo a tracking procedure. The cyclone centers are tracked based on Murray & Simmonds (1991) without consideration of splitting and merging of tracks. The position of a cyclone center is defined as local minimum in z700 and is tracked during the consecutive time steps of the cyclone's lifetime. For each time step the current cyclone position is identified by first calculating the absolute minimum within a defined distance and, second, comparing this value to its eight neighbor pixels. The distance measure is a constant value of 3 pixels. The tracking ends as soon as the cyclone leaves the tracking area (T) in Figure 1. With this approach, open cyclones that have no clear local pressure minimum and are rather identifiable by local vorticity maxima (Hofstätter et al., 2018) are not detectable. As tracking results also depend on the chosen method (Neu et al., 2013), related uncertainties cannot be resolved in this study.

As the fourth step, the tracked pathways are tested for a set of criteria, which define the characteristics of Vb pathways using four boxes (see Figure 1 Hofstätter et al., 2016; Messmer et al., 2015). Cyclones are classified as Vb if all of the following statements apply: (1) the cyclone track is within the cyclogenesis region (C) for at least one time step, (2) at any later time step the track appears in the end area (E), (3) the cyclone appears within the mandatory area (M) between C and E, (4) the track moves from west to east between C and E, (5) the cyclone does not appear in the restrictive zone (R) any time before it has moved to E and 6. the track lasts for at least 24 hr.

To analyze climate change effects the frequency of Vb cyclones is compared between three 30-year periods: the reference period 1961–1990 (past), 2021–2050 (near future), and 2070–2099 (far future). Significance is tested with a ks test, which is applied to the distribution of the pooled members using a 5% significance level. Additionally, the signal-to-noise ratio (SNR) is calculated according to Aalbers et al. (2018). It describes the ratio between climate change signal and internal variability by dividing the averaged difference between far future and reference (past) by the standard deviation of the CRCM5-LE. $|SNR| > 1$ indicates that the signal has emerged from internal variability and confidence on the sign of change is very high. However, even given a SNR of 1, single members may yield largely deviating changes. At the same time, for an ensemble as large as the one used here, the forced climate response can be robustly estimated even for a SNR smaller than 1.

In order to assess the capability of the CRCM5 to capture the characteristics of Vb cyclones, the CRCM5-LE is compared to the ERA-Interim driven CRCM5 run and ERA-5 reanalysis. ERA-5, the fifth generation of ECMWF atmospheric reanalysis products, is chosen in place of ERA-Interim, because it is available in 3-hourly temporal resolution. The lower temporal resolution of ERA-Interim (6 hr) leads to a noticeably lower accuracy during tracking. The fact that ERA-Interim-CRCM5 is not directly compared to its driving data might, however, be a potential source of inaccuracies in the evaluation.

Additionally, the maximum daily precipitation falling over hydrological Bavaria during a Vb event is analyzed. The maximum daily precipitation values of all Vb events in the ensemble are compared to the 95th percentile of all daily precipitation values (averaged over hydrological Bavaria) in the entire ensemble and the reference period 1980 to 2009 in order to identify the quantity and change of extreme events. The drizzle effect is eliminated by a threshold of <1 mm/day (Kjellström et al., 2010). The value of the 95th percentile is

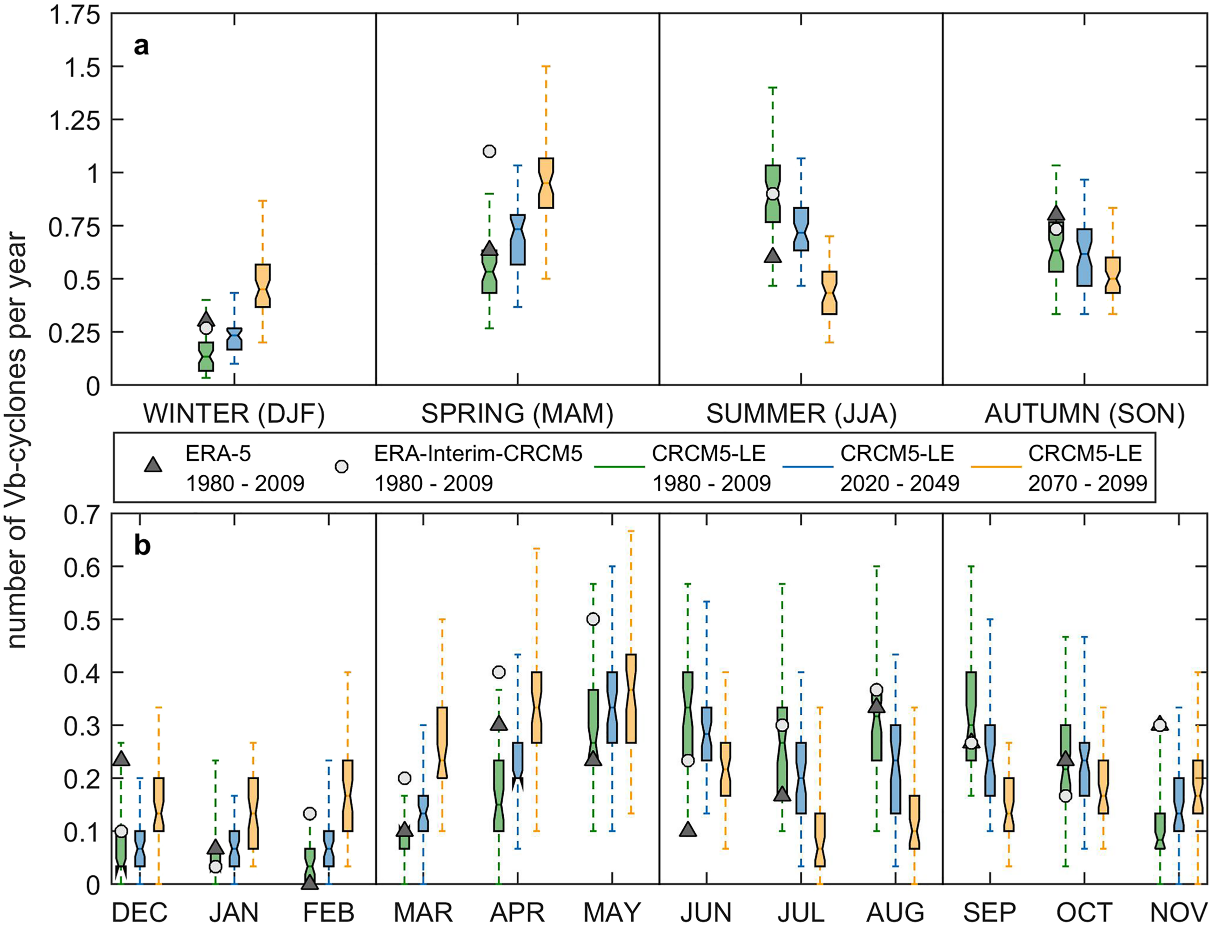

Figure 2. Number of identified cutoff low-related Vb cyclones per year and season (a) respectively per year and month (b) averaged over 30-year periods in the past (1980–2009; green), near future (2020–2049; blue), and far future (2070–2099; orange). The boxplots show the spread between the 50 members of the CRCM5-LE. The line indicates the median, the box stretches from the 25th to the 75th percentiles, and the whiskers extend to the minimum and maximum values. The dark gray triangle (light gray circle) depicts the identified Vb cyclones in ERA-5 reanalysis (ERA-Interim-CRCM5 simulation).

12.7 mm daily precipitation over hydrological Bavaria. According to the seasonality, the precipitation results of the CRCM5-LE are compared to the time series of ERA-Interim-CRCM5 and ERA-5 reanalysis.

3. Results

Vb cyclones connected to a cutoff low over central Europe are identified in the CRCM5-LE with high accuracy indicated by the recall of 94.6% (test set). Table S2 shows the averaged confusion matrices over all cross-validation iterations (see Table S3 for the network used for inference). Due to the skewed class distribution between Class 0 and Class 1, the overall accuracy of 99.2% (test set, Figure S2) is not a reliable indicator for the performance of the ANN in respect of the minority class. The false positives lead to a low precision of 33.2%, but they are minimized in the subsequent step of tracking during which all possible Vb cyclones undergo further tests.

The analysis of cutoff low-related Vb cyclones in the CRCM5-LE under the RCP8.5 scenario indicates a slight, but nonsignificant increase in the absolute number of Vb cyclones per year using the ks test and a 5% significance level (see Figure S3). The mean values in events per year are 2.26 (past), 2.27 (near future), and 2.37 (far future). The spread between the 50 members, which represents internal variability, is considerable. The value of SNR between past and far future is 0.32, which indicates that internal variability is larger than the climate change signal.

Figure 2a shows the number of Vb cyclones per season and year (respectively, Figure 2b per month and year) for three periods of the 50 members of the CRCM5-LE (boxplots) and for the reference period of the single time series of ERA-Interim-CRCM5 and ERA-5 reanalysis (circles and triangles). For the reference

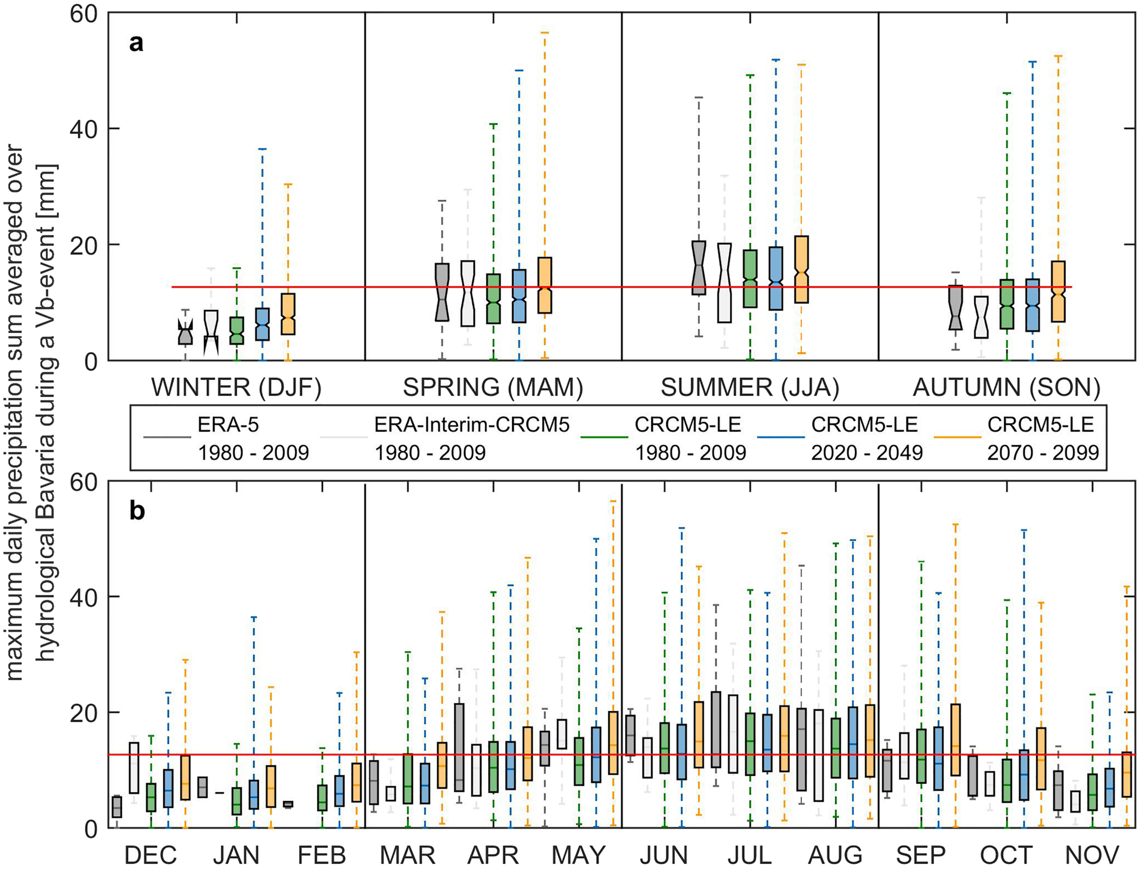

Figure 3. Maximum daily precipitation sum (mm) averaged over hydrological Bavaria during Vb events.The boxplots illustrate the spread of Vb events. For the reference period (1980–2009) ERA-Interim-CRCM5, ERA-5, and the CRCM5-LE are illustrated. The near (2020–2049) and far future (2070–2099) are only covered by the CRCM5-LE. For ERA-Interim-CRCM5 and ERA-5 the underlying database is only a single time series, whereas the CRCM5-LE provides 50 time series.

period the comparison of ERA-Interim-CRCM5 with ERA-5 shows that the frequency of Vb cyclones in the CRCM5 model run, which is driven by ERA-Interim boundary conditions, differs from the frequency of Vb cyclones in the ERA-5 reanalysis product for on-average 0.06 events per month and year. In most months, the frequency of Vb cyclones in the ERA-Interim-CRCM5 time series is higher than in the ERA-5 reanalysis. Here, the CRCM5 model might tend to overestimate the frequency of Vb cyclones. Distinct differences occur especially in spring (May). In two cases in spring, the number of Vb cyclones in the ERA-Interim-CRCM5 run furthermore lies outside of the distribution of the CRCM5-LE (March and April). In most cases, however, the CRCM5-LE covers the time series of both ERA-Interim-CRCM5 and ERA-5.

Looking at the climate change signal between the three 30-year periods of the CRCM5-LE a remarkable impact on the seasonal distribution of Vb cyclones is visible. Whereas in the past, the peak of Vb frequency used to be in summer (June), it transitions to spring (May) with progressing climate change. In the far future, the number of Vb cyclones in summer decreases strongly by −51.8% (mean: −0.47 events/year; changes are calculated between 2070–2099 and the reference period 1980–2009). In the past, one Vb cyclone occurred almost every summer, but in the far future a summer Vb cyclone appears only every 830 days. At the same time the number of Vb cyclones increases considerably in spring by +73.4% (mean: +0.40) to about one Vb cyclone every spring. The changes in spring and summer are significant on a 5% significance level. The SNR values for spring (1.25) and summer (2.86) are clearly larger than 1, consequently the climate change signal exceeds internal variability and confidence in the sign of change is high. The strongest increase happens in the months March and April, the strongest decrease in July and August. Furthermore, Vb frequency significantly increases in winter by +220.7% (mean: +0.32). The change is consistent throughout all winter months. In the far future, the number of winter Vb cyclones even exceeds the frequency in summer. The SNR is 0.82 and therefore noise is larger than the signal. For autumn, the signal is mixed, with a decrease in

September and October and an increase in November. Still, there is a slight but significant decrease in Vb frequency in autumn by −20.6% (mean: −0.14). The SNR has a value of 0.67 and thus, as in winter, internal variability is larger than the climate change signal.

Figure 3 shows the seasonality of the maximum daily precipitation averaged over hydrological Bavaria during Vb events. When comparing ERA-Interim-CRCM5 and ERA-5, some differences are clearly visible. For one thing, ERA-Interim-CRCM5 produces lower maximum daily precipitation sums in summer than ERA-5. This is true for both the median values (influence from June) and extreme values (influence from August) and might indicate that the CRCM5 underestimates the maximum precipitation related to Vb cyclones in summer. In autumn (September), however, the ERA-Interim-CRCM5 run contains more extreme values than ERA-5, which implies that the CRCM5 might slightly overestimate the maximum Vb related precipitation in autumn. However, when comparing the single time series of ERA-Interim-CRCM5 and ERA-5 to the reference period of the CRCM5-LE, both distributions are well covered by the large data base of Vb events resulting from the 50 members of the ensemble. The threshold considered for extreme precipitation over hydrological Bavaria (solid red line) is the 95th percentile of all days in the CRCM5-LE reference period. In the past as well as in the future, Vb cyclones mainly exceed this threshold in the warmer months of the summer half year (April to September). In summer the median of all data sets lies above the threshold. For the CRCM5-LE the peak of median values lies in July for both the reference period (15.0 mm) and the far future (15.9 mm). In combination with the results from Figure 2a, this means that the absolute number of Vb cyclones in the season of the highest daily precipitation values (summer) decreases with progressing climate change. At the same time climate change leads to a rise in the maximum daily precipitation sum over hydrological Bavaria in all seasons. Consequently, the percentage of Vb cyclones exceeding the threshold increases in all seasons. The strongest increase in median values between reference and far future occurs in winter with +2.8 mm (spring: +2.4 mm, summer: +1.2 mm, autumn: +2.0 mm). The changes in all seasons are statistically significant on a 5% significance level. It is worth noting that the spread between the Vb events is considerable. Especially on a monthly basis the single time series of ERA-Interim-CRCM5 and ERA-5 do not, in contrast to the CRCM5-LE, provide a statistically reliable distribution of Vb cyclones (e.g. January and February).

4. Discussion and Conclusion

The CRCM5-LE shows that climate change under the RCP8.5 scenario affects the seasonal distribution and rainfall intensity of cutoff low-related Vb cyclones. The absolute frequency of Vb cyclones does not change significantly, but summer Vb cyclones decrease strongly. With this, our results reinforce the findings by Nissen et al. (2013), although we use a large single-model ensemble and examine only one GCM-RCM combination and one scenario. Climate change projections using the CRCM5-LE do not account for uncertainties regarding model or scenario choice, but for the first time allow an in-depth analysis of internal variability regarding Vb cyclones. This shows that the climate change signal of a decrease in summer Vb cyclones exceeds the noise of internal variability. Furthermore, we detected a robust increase in Vb frequency in spring with a SNR larger than 1. In the light of a possible tendency of the CRCM5-LE to overestimate the number of Vb cyclones in certain months, the absolute numbers of Vb events might differ in other model ensembles. The climate change signal between the three periods of the CRCM5-LE, however, is unaffected by a potential model bias. Regarding precipitation intensity related to Vb cyclones, our study shows that climate change leads in all seasons to an increase in the maximum daily precipitation sums over hydrological Bavaria during Vb events. Vb cyclones occur less often in the warm season (summer), which is associated with the highest rainfall intensities. The 50 members of the CRCM5-LE beneficially support the analysis of precipitation related to Vb cyclones, because they provide a larger and thus more reliable database for the analysis of extreme events.

The decrease in summer Vb activity might be due to a shift in the cyclone pathway to the east as suggested by Nissen et al. (2013). Another explanation is a change in Rossby-waves and jet streams due to the Arctic Amplification, which is discussed in the general context of decreasing summer storm activity in the Northern Hemisphere (Mann et al., 2017). The increase in the percentage of Vb cyclones leading to extreme precipitation could be explained by an increased saturation vapor pressure of warmer air following the Clausius-Clapeyron rate and by increased sea surface temperatures of the Mediterranean Sea leading to an enhanced moisture transport by cyclones emerging there (Volosciuk et al., 2016).

With a recall of 94.6% Vb cyclones related to a cutoff low over central Europe are successfully detected in the CRCM5-LE using machine learning. Our approach is specifically designed for Vb cyclones that develop during the synoptic situation of a cutoff low over central Europe, because such a cutoff low is an indicator for extreme precipitation Vb cyclones (Hofstätter et al., 2018) and occurred during historic Vb related floods in hydrological Bavaria. With 2.3 Vb cyclones per year identified in the reference period in the CRCM5-LE, the number agrees with the number of Vb cyclones identified by Messmer et al. (2015), though methods and data differ. The number is about half of the Vb cyclones identified by Hofstätter et al. (2018) in JRA-55 data. Hofstätter et al. (2018) also considered open Vb cyclones, which make up to about 50% of all identified Vb cyclones. Limitations of the tracking procedure lie in the incapability of distinguishing splitting tracks or simultaneous cyclones. The choice of 700 hPa as tracking variable has the disadvantage that not all geopotential height minima on a Vb track necessarily extend to the surface or the other way round (Nissen et al., 2013). In contrast, the main advantage of 700 hPa lies in less disturbances due to orography, which leads to less ambiguous cases during tracking (Hofstätter et al., 2018).

Our study provides the novelty of accounting for internal variability in the context of analyzing cutoff low related Vb cyclones with a large single-model ensemble of 50 members. Furthermore, Vb cyclones are simulated by a RCM with 0.11° resolution. This ensures a better representation of orography, a finer delineation of atmospheric processes and of the land-sea contrast (Akhtar et al., 2019; Lucas-Picher et al., 2017), which is important in the development of Vb cyclones. By employing machine learning for cyclone identification an efficient data analysis strategy is ensured in addressing the Big Data scale of the CRCM5-LE.

Acknowledgments
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