



Spatial analysis of early-warning signals for a North Atlantic climate transition in a coupled GCM

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Abstract

The climate system can potentially switch from one stable state to another. The closer a system is to a bifurcation point (i.e., ‘tipping point’), the more likely it is that even small perturbations can force the system to experience a state shift, e.g., a collapsing Atlantic meridional overturning circulation (AMOC) and associated cooling in parts of the North Atlantic. Here, we present an abrupt state transition from a warm to a cold North Atlantic climate state with expanded sea ice during an orbitally forced transient Holocene simulation performed with the Community Climate System Model version 3. The state transition is associated with a weakening of the AMOC by about 33% in this simulation. The changing background climate induced by slow external orbital forcing plays an important role for the abrupt climate shift. The model allows the identification of regions and variables that play a key role for a potential climate transition and show early-warning signals. Increase in autocorrelation and standard deviation as well as trends in skewness especially for sea-surface salinity in the northern North Atlantic are identified as robust early-warning signals, whereas no early-warning signals are found in the time series of the AMOC stream function.

Keywords Early-warning signals · Climate transition · North Atlantic · AMOC

1 Introduction

Abrupt shifts in the Earth’s past, present and future climate which can be accompanied by extreme temperature anomalies have been discussed in numerous studies (e.g., Rahmstorf 2002; Clement and Peterson 2008; Lenton et al. 2008; Drijfhout et al. 2015; Kleppin et al. 2015; Jackson et al. 2016; Schulz et al. 2007; Zhang et al. 2014). The potential to switch between multiple stable states has been recognized in several parts of the Earth’s climate system (Alley et al. 2003, and references therein; Scheffer et al. 1993, 2001; Jongma et al. 2007). In particular, modeling

studies suggested that the Atlantic meridional overturning circulation (AMOC) has multiple equilibrium states with, with reduced or even without North Atlantic Deep Water (NADW) formation (e.g., Manabe and Stouffer 1999; Rahmstorf 1995; Prange et al. 2003). The risk of a collapsing AMOC after reaching a tipping point would affect the climate system on a regional or even larger scale (Kuhlbrodt et al. 2007; Srokosz et al. 2012; Sévellec and Fedorov 2013; Jackson et al. 2016). The cause of these shifts and the underlying mechanisms are topic of ongoing research (Bestmeyer et al. 2011; Kleppin et al. 2015) and have been discussed in several studies (e.g., Crowley 2000; Alley et al. 2005). External forcing such as solar forcing (Jiang et al. 2005; Steinhilber et al. 2009; Gray et al. 2010), volcanic activity (Sigl et al. 2015), and the input of freshwater (Broecker et al. 1990; Hawkins et al. 2011; Rahmstorf 1996) as well as internal variability (Hall and Stouffer 2001; Drijfhout et al. 2013; Kleppin et al. 2015), sea ice transport (Wanner et al. 2008, and references therein) and sea-ice-atmosphere interactions (Li et al. 2005; Li and Bitz 2010) could drive the climate system towards a tipping point, leading to an abrupt climate shift. Furthermore, the background climate influenced by

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slow external forcing may play an important role for the occurrence of an abrupt transition (Scheffer et al. 2001). In a system that is not close to a bifurcation point, perturbations will cause fluctuations around a mean state. The closer a system gets to a threshold (i.e., a ‘tipping point’), the more likely it is that even small perturbations, such as an increased input of freshwater into the ocean, can trigger a state transition (Rahmstorf 1995; Scheffer et al. 2009; Lenton et al. 2012a).

During the last decades various techniques have been developed and used to estimate the probability of a close state transition for a variety of applications (e.g., Lenton 2011). Approaching a critical threshold, ‘critical slowing down’ is often observed, that is, an increase in the system’s recovery time towards its equilibrium state after a disturbance (Wissel 1984; Held and Kleinen 2004; van Nes and Scheffer 2007). Exploring temporal and spatial variability of the surface temperature field is one suggested method to search for an associated change in variance or autocorrelation of a climate-system property (Lenton et al. 2017). Such properties are based on mathematical characteristics (Strogatz 1994; Scheffer et al. 2009) and can serve as potential early-warning signals for transitions (e.g., LeBaron 1992; Livina and Lenton 2007; Dakos et al. 2008, 2012; Scheffer et al. 2009; Drake and Griffen 2010; Veraart et al. 2012). To identify an approaching bifurcation of a non-linear (climate) system the mentioned early-warning signals can be helpful. To this end an underlying data set with sufficient length is needed. However, it is usually a priori not known which (measurable) variables play a key role for the instability of the system and if specific regions are more sensitive to an approaching bifurcation and therefore should be measured to get a reliable basis for the calculation of early-warning signals.

Here, we present an orbitally forced transient Holocene simulation performed with the Community Climate System Model version 3 (CCSM3) that experiences an abrupt and persistent mode transition from a warm to a cold North Atlantic climate state with enlarged sea-ice cover and weakened AMOC. By performing spatial analysis of potential early-warning signals in the model data we aim at analyzing which variables and regions of the North Atlantic climate system play a key role prior to the climate transition. This way we can identify which variables at which locations should be measured to get a reliable basis for the estimation of early-warning signals prior to a mode transition. We note that in the current study, we focus on temporal early-warning indicators and analyze the spatial distribution of the corresponding signals. We do not consider spatial early-warning indicators, which are based on, e.g., spatial correlation, variance or patch size (e.g., Dakos et al. 2010; Butitta et al. 2017). Mechanisms of spatial early-warning signals are diverse and beyond the scope of the current study.

Nevertheless, they might be an interesting subject for future work.

2 Methods

2.1 Model description and experimental setup

In the present study we used version 3 of the National Center for Atmospheric Research Community Climate System Model (CCSM3; <http://www.cesm.ucar.edu/models/ccsm3.0/>). The comprehensive global climate model is fully coupled and is composed of four components encompassing the atmosphere, ocean, land and sea ice (Collins et al. 2006a). A variable horizontal grid with a nominal resolution of 3° which gets finer (0.9°) close to the equator is used for the ocean (Parallel Ocean Program; Smith and Gent 2004) and sea ice component (Community Sea Ice Model version 5; Briegleb et al. 2004). In the vertical the ocean grid consists of 25 unevenly spaced levels. The atmospheric (Community Atmosphere Model version 3; Collins et al. 2006b) and land components (Community Land Model version 3, Yeager et al. 2006) share a horizontal grid (3.75° transform grid) with 26 levels in the atmosphere.

Starting from a 9 ka before present (BP) climate state a non-accelerated transient Holocene simulation was performed (Varma et al. 2016). While the original Holocene simulation by Varma et al. (2016) stops at 2000 years BP, the integration was continued towards the pre-industrial (240 years BP). Changes in the orbital parameters was the only external forcing in this simulation while all greenhouse gas concentrations as well as aerosol and ozone distributions were kept constant at pre-industrial values (i.e., CH₄ = 760 ppbv, CO₂ = 280 ppm, N₂O = 270 ppbv; Braconnot et al. 2007). The variability of continental ice-sheets as well as of the sun’s energy output was neglected. Hence, the simulation differs per se from the reconstructed evolution of climate during the Holocene. The model data were analyzed at annual resolution.

2.2 Determining early-warning signals

The R package early warnings has been used (Dakos et al. 2012; available at <http://www.early-warning-signals.org/resources/code/>) to determine early-warning signals in our Holocene simulation. Since trends can cause artificial signs of an approaching mode shift (Dakos et al. 2008) the data were detrended first. In this study we used a Gaussian filter. The choice of bandwidth is important to eliminate long-term trends without over-fitting the data. If not specifically marked otherwise we used a bandwidth of 6% of the data before the transition.

Since critical slowing down can lead to an increase in variability and autocorrelation as well as to an asymmetry in the data set, the standard deviation, skewness and autocorrelation were estimated. The skewness may increase or decrease prior to a mode transition as the new state can be left or right of the current one (e.g., cooler or warmer). To calculate the autocorrelation at lag-1 an autoregressive model of order 1 (AR(1)) has been used. The AR(1) model of $x_{i+1} = \alpha_1 x_i + \varepsilon_i$ with the autocorrelation coefficient α_1 and the Gaussian white noise ε_i has been fitted to the data points (Held and Kleinen 2004). For the analysis a sliding window has been used, which means values were calculated over a subset (“window”) of the total data. The window was shifted forward in an overlapping way through the data (in our study one data point forward). Standard deviation σ , skewness sk , and α_1 have been calculated within each sliding window (i.e., 50% of the data points before the transition if not marked otherwise). To verify the significance of the trends in α_1 , standard deviation, and skewness, Kendall’s τ (Mann 1945; Meals et al. 2011) has been calculated afterwards. A more detailed description of why the autocorrelation and standard deviation usually increase close to a bifurcation point and why they are not independent of each other is given in Ditlevsen and Johnson (2010).

3 Results

3.1 Warm climate state, transition and cold climate state

Approximately between 1486 and 1371 BP a transition from a “warm” climate state (9000–1487 BP) to a “cold” climate state (1370–240 BP) occurs in the model. Some climate variables change within a couple of years (e.g., mixed-layer depth), whereas for other variables it takes more than 100 years to complete the transition. The climate transition is described in the following using variables from regions that include main areas of deep-water formation: the northern North Atlantic (NNA; between $\sim 54^\circ\text{N}$ – 62°N and $\sim 62^\circ\text{W}$ – 26°W) and the Nordic Seas (see Fig. 4 for the location of the regions).

During the warm state, the NNA and Nordic Seas are mostly ice-free year-round with a mean sea-ice concentration of 19.5 and 11%, respectively (Figs. 1a, 2a). In both the NNA and the Nordic Seas regions, mixed-layer depth is indicative of deep convection and hence deep-water formation (Fig. 1b). The sea-surface temperature (SST) of the NNA region shows a tendency towards lower values over time (annual area-mean of 2.8°C) while the SST in the Nordic Seas exhibits a mean of 2.8°C and shows no trend over time. The sea-surface salinity (SSS) in the NNA region (33.0 PSU) and the SSS in the Nordic Seas (33.6

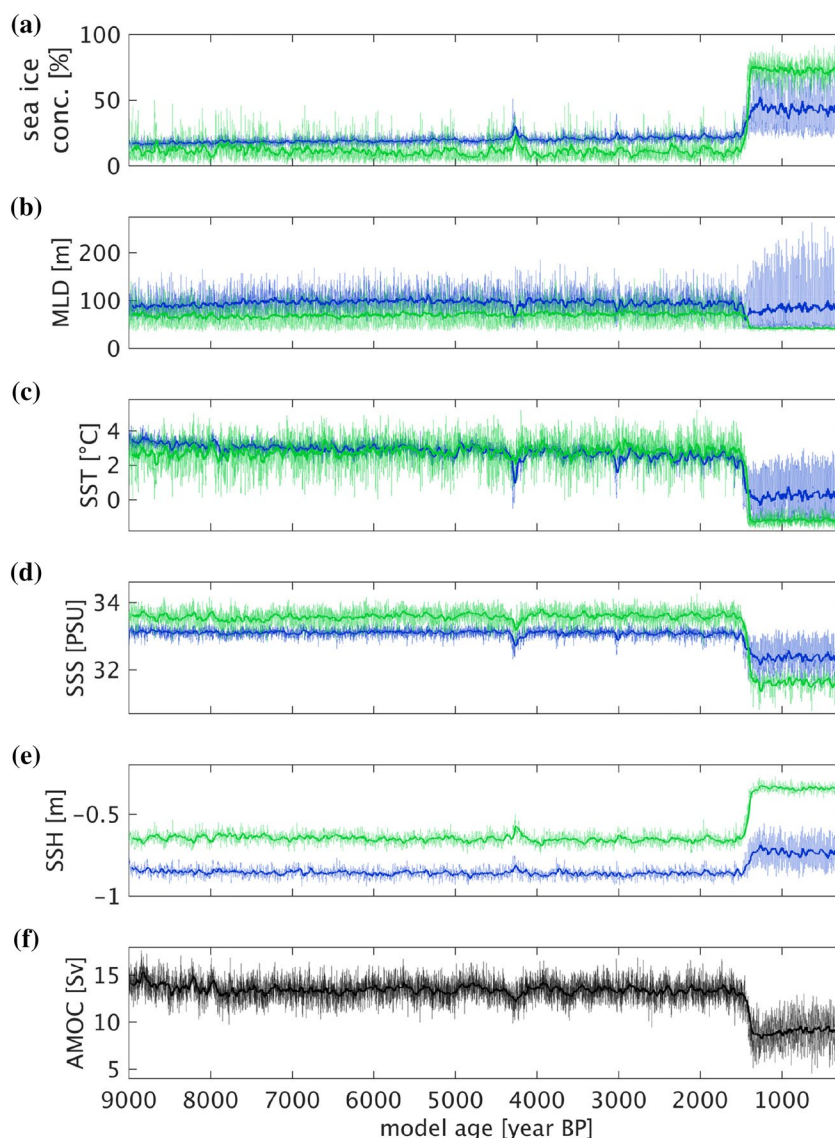
PSU) show no obvious trends (Fig. 1c–d). The annual mean sea-surface height (SSH) amounts to -0.85 m in the NNA and to -0.65 m in the Nordic Seas (Fig. 1e). The Atlantic meridional overturning circulation (AMOC, measured by the stream function maximum north of 30°N and below 500 m water depth) is in a strong state with an annual mean of 13.4 Sv and exhibits a negative trend during ~ 9 – 8 ka BP (Fig. 1f). During the warm state two multidecadal cold events occur in the North Atlantic: The first one between 4305 and 4267 BP and the second one between 3046 and 3018 BP. Both have been described in detail in Klus et al. (2018).

After the transition another climate state is observed between 1371 and 240 BP which is characterized by an increased sea-ice concentration in the NNA by 24% and in the Nordic Seas by 62% (Figs. 1a, 2c), as well as by an ice expansion towards the Iceland basin. Deep-water formation and the AMOC are strongly reduced indicated by a decrease in the mixed-layer depths in the NNA and the Nordic Seas (Fig. 1b, f). The AMOC has an average of 9.0 Sv, which implies a weakening of 4.4 Sv (Fig. 1f). An overall cooling and freshening of the NNA (anomalies between the warm climate state and the cold climate state of -2.6°C and -0.7 PSU) and the Nordic Seas (anomalies of -4.0°C and -2.0 PSU ; Figs. 1c–d, 2c–f) characterize the new climate state. The SSH in the NNA and the Nordic Seas rises to -0.73 m and -0.34 m , respectively (Fig. 1e). During the cold climate state quasi-decadal oscillations with a period of approximately 12.5 years are evident in several climate variables (i.e., SST, SSS, and AMOC). A wavelet power spectral analysis of the AMOC for the period 2000–1000 BP revealed that these oscillations first occur around 1400 BP (not shown).

3.2 Early-warning signals

Several variables were sampled for potential early-warning signals for the time interval starting immediately after the second multidecadal cold event and ending at the onset of the climate transition (3018–1486 BP). Since the cold events could increase autocorrelation, standard deviation and skewness of several North Atlantic climate variables, excluding them from the analysis ensures that early-warning signals are not misinterpreted or overestimated. After estimating the potential early-warning signals [α_1 , σ and sk for a sliding window of 50% and a filtering bandwidth of 6% (Dakos et al. 2012)] for sea-ice concentration, SST, SSS, and SSH, the associated τ has been calculated for each grid cell in the North Atlantic region (Fig. 3). Regions with a large τ for α_1 and σ as well as regions with large $|\tau|$ for the skewness (the skewness can be positive or negative) show a clear trend in the statistical quantities indicating early-warning signals. For each grid point we calculated the number of potential

Fig. 1 Time series of **a** sea-ice concentration [(%)], **b** mixed-layer depth [MLD (m)], **c** sea-surface temperature [SST ($^{\circ}\text{C}$)], **d** sea-surface salinity [SSS (PSU)], **e** sea-surface height [SSH (m)], and **f** the Atlantic meridional overturning circulation [AMOC (Sv)]. Data from NNA is colored in blue and from the Nordic Seas in green (see Fig. 4 for definition of the regions). The respective 40-year-running means are indicated by the bold lines and the transparent lines indicate the annual data. Created with Matlab



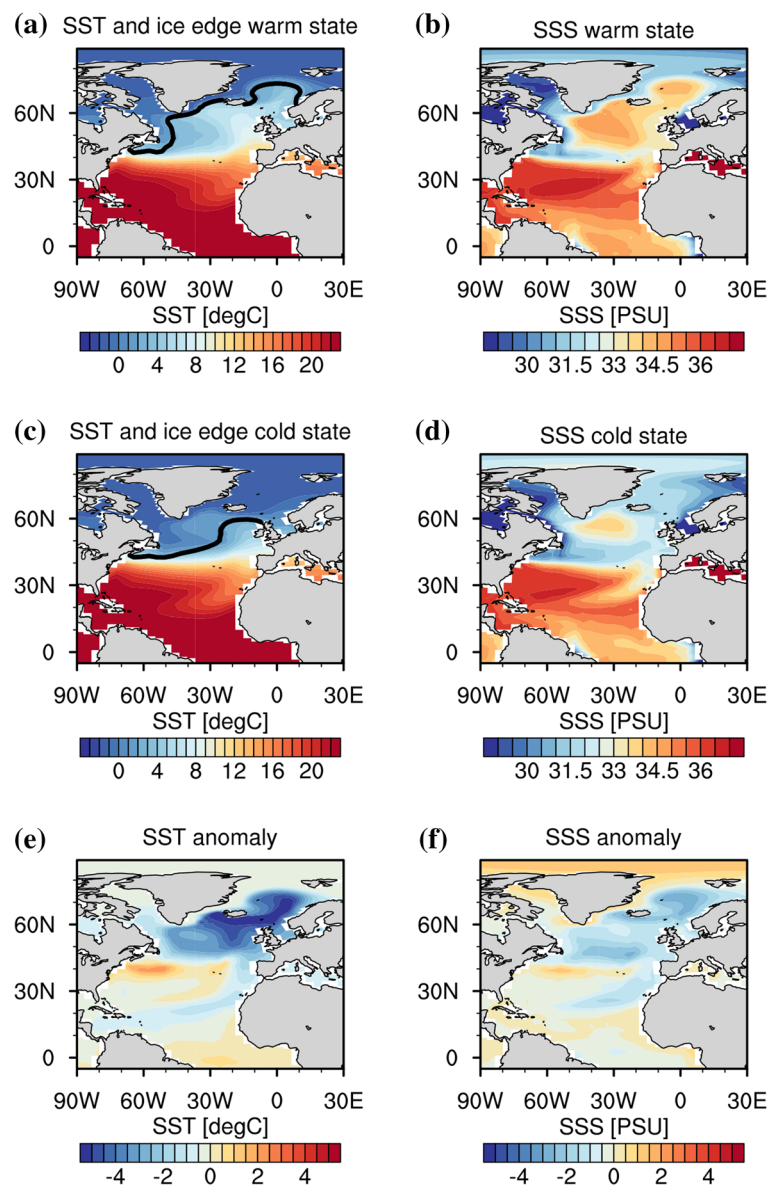
early-warning signals, i.e., the co-occurrence of $\tau > 0.5$ for α_1 and for σ , and for $|\tau| > 0.5$ for skewness (Fig. 4). Regions with two or even three parameters fulfilling the condition have a higher potential to serve as basis for early-warning signals. Furthermore, as already mentioned, α_1 and σ should increase together. The northernmost Nordic Seas and for SST and SSS the region close to Newfoundland, and for SSS and SSH regions in the western tropical Atlantic contain grid cells with two or more parameters that fulfill the condition. The region with all four climate variables (sea-ice concentration, SST, SSS, and SSH) showing a clear signal is the NNA (albeit in SST for a few grid points only; see black box in Fig. 4c), which also includes sites of deep-water formation. Comparing the temporal analysis of α_1 , σ and sk of the NNA with the Nordic Seas (the other important area for deep-water formation) and the AMOC (Figs. 5, 6) reveals that except for α_1 and mixed-layer depth all variables in the

NNA show a significant trend indicating an approach to a bifurcation (τ between 0.518 and 0.868). For SST and SSS for the skewness, τ is between -0.638 and -0.868 , respectively, while the AMOC and the variables in the Nordic Seas mostly do not show a clear early-warning signal (τ between -0.761 and 0.577).

3.3 Sensitivity analysis and significance testing for bandwidth and sliding window

Since the results of α_1 , σ and sk may depend on the choice of bandwidth and sliding window, we tested the robustness of our results with respect to these parameters. The potential early-warning signals were calculated for sliding windows ranging from 10 to 90% of the dataset and the bandwidth for the Gaussian filter ranged from 1 to 35% of the dataset, both with an increment of 15.31 points (Fig. 7a,

Fig. 2 Maps of **a, c** annual mean sea-surface temperature [SST (°C); colors] and annual mean ice-edge (10% sea-ice concentration; black line) and of **b, d** annual mean sea-surface salinity [SSS (PSU)] for the warm (9000–1487 BP) and cold (1371–240 BP) climate states. The anomaly between cold and warm climate state is shown for **e** SST and for **f** SSS. Created with ncl

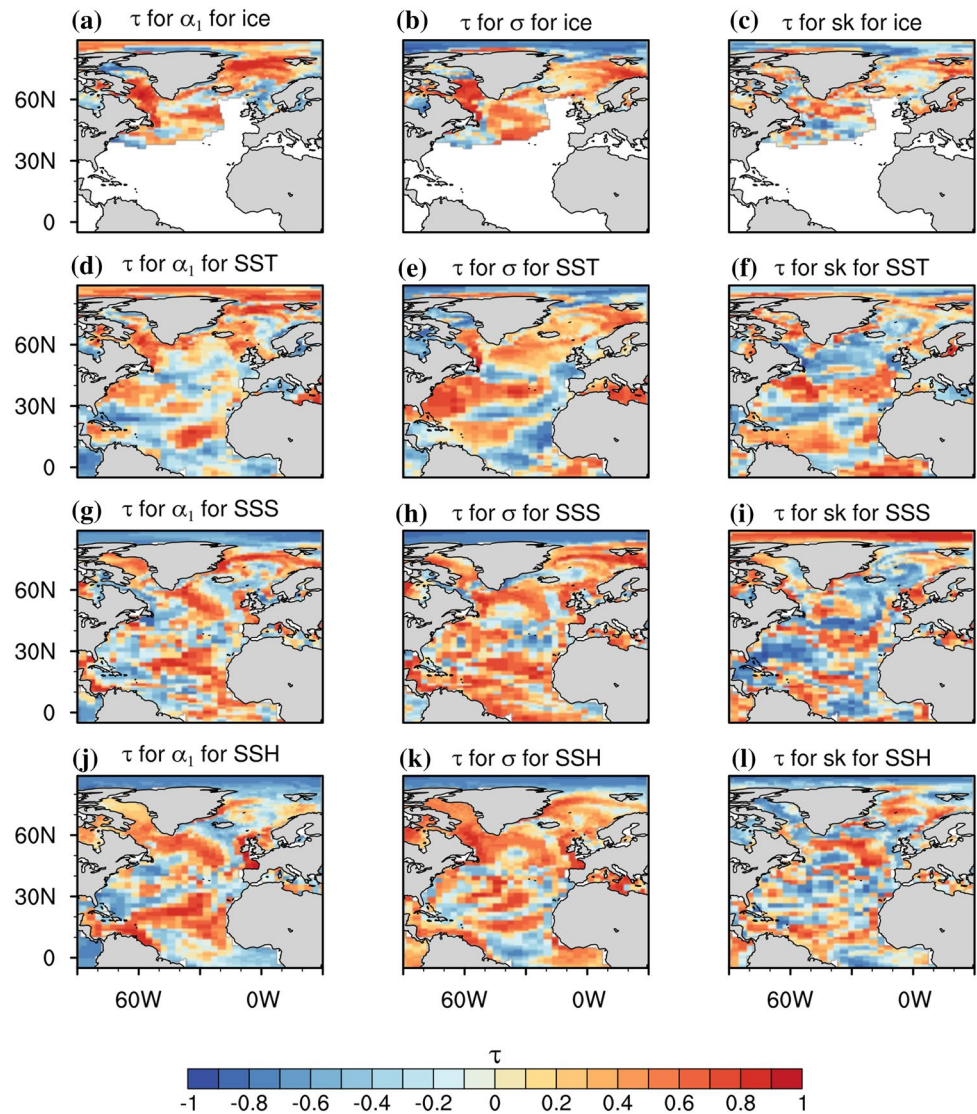


c, e). Afterwards, Kendall's τ was calculated for all combinations of the parameters. The analysis was performed for the NNA, exemplified for SST and SSS. For all tested combinations of bandwidth and size of the sliding window (Figs. 7a–d, 8a–d) the trends for α_1 range between -0.321 and 0.640 for SST and between -0.653 for a small number of combinations and 0.845 for SSS, respectively, and for the standard deviation between -0.219 and 0.843 for SST and between 0.109 and 0.908 for SSS. Lowest trends were obtained from a sliding window of approximately 72%, while for a sliding window of approximately 40–50% highest trends were obtained. Trends in the skewness are lower for most choices of bandwidth and sliding window (Figs. 7e, 8e) with values ranging between -0.878 and 0.210 for SST and between -0.896 and -0.387 for SSS.

The corresponding histograms for the skewness show a clear maximum for negative τ (Figs. 7f, 8f).

In addition to the sensitivity analysis, the results were tested for significance to identify true or false positive early-warning signals, whereas false positive means that the indicators show a trend due to randomness. Here, we test the null hypothesis that the trends calculated for the indicators occur by chance. Therefore, 500 surrogate datasets were generated by linear stationary processes (Dakos et al. 2008, 2012) that have an identical correlation structure as well as probability distribution as the original dataset (here SST and SSS time series in the NNA; further information about the method can be found in e.g., Dakos et al. 2008, 2012; Theiler et al. 1992; Halley and Kugiumtzis 2011). Associated trends were calculated for all combinations of bandwidth and size of

Fig. 3 Maps for Kendall's τ for the autocorrelation coefficient α_1 , standard deviation (σ) and skewness (sk) calculated with a sliding window size of 50% and a filter bandwidth of 6% for sea-ice concentration [ice; (a–c)], sea-surface temperature [SST; (d–f)], sea-surface salinity [SSS; (g–i)] and sea-surface height [SSH; (j–l)]. Created with ncl

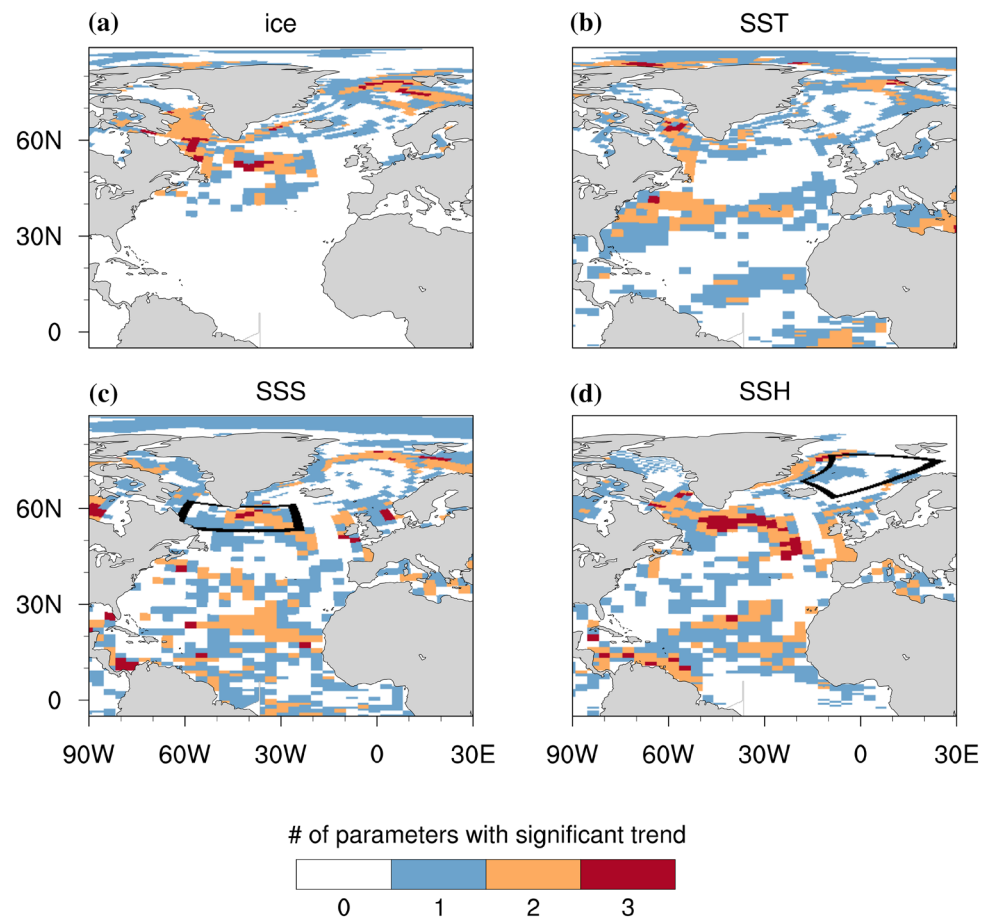


the sliding window. Kendall's τ from the original dataset was evaluated subject to the number of cases in which its (absolute) value was equal to or smaller than the (absolute) value of the estimates of the surrogates (probability $P(\tau \leq \tau_{\text{surr}})$ for α_1 and σ , and $P(|\tau| \leq |\tau_{\text{surr}}|)$ for sk) for all combinations of bandwidth and the size of the sliding window for SST (Fig. 9) and SSS (Fig. 10) including the distribution calculated for the combination used in this study (bandwidth = 6%; sliding window = 50%; Figs. 9b, d, f, 10b, d, f).

For SST and SSS in the NNA the rising trends are significant for some calculated combinations of sliding window and bandwidth for the autocorrelation at lag-1 (Figs. 9a, 10a) and the standard deviation (Figs. 9c, 10c). The p -value is between 0.240 and 0.868 for the autocorrelation for SST and between 0.002 and 0.578 for SSS. The p -value for the standard deviation lies between 0.076 and 0.780 for SST and 0.002 and 0.478 for SSS. For a sliding window of approximately 72% the trends are not significant while for approximately 40–50% sliding

window p -values of 0.1 and lower can be obtained for SST and SSS (Figs. 9a–d, 10a–d). The trend is highly significant for the skewness for most combinations (Figs. 9e, 10e). Due to the sensitivity and significance testing we have chosen 50% for the sliding window and 6% for the filtering bandwidth to get robust results, without filtering out trends. The corresponding p -values for autocorrelation at lag-1, standard deviation and skewness are 0.408, 0.294, and 0.080 for SST and 0.078, 0.038, and 0.006 for SSS, while the closer the p -value is to zero the more significant is the trend. Hence, statistical significance at the 0.05 level is only obtained for SSS early-warning indicators.

Fig. 4 Maps for number of parameters (potential early-warning signals calculated in this study), which fulfill for α_1 and standard deviation Kendall's τ greater than 0.5 and for the skewness $|\tau|$ is greater than 0.5 for **a** sea-ice concentration (ice), **b** sea-surface temperature (SST), **c** sea-surface salinity (SSS) and **d** sea-surface height (SSH). The black box in **c** indicates the region of the northern North Atlantic (NNA) and the black box in **d** indicates the location of the Nordic Seas (NS). Created with ncl



4 Discussion

Considering the previous analysis our results show that using a model run and spatial analysis of early-warning indicators, variables and regions can be detected that react sensitively prior to an approaching bifurcation. This can be used to perform temporal early-warning analysis by means of autocorrelation lag-1, standard deviation and skewness. The choice of the analyzed variable (i.e., SST, SSS), region and size of bandwidth as well as sliding window is important to obtain robust results. This can be ensured by performing a sensitivity analysis and significance testing. In our study SSS in the NNA with a sliding window of approximately 50% and a filtering bandwidth of 6% has been shown to be a promising choice to provide a reliable early-warning signal, while other regions (e.g., the Nordic Seas) and variables (e.g., AMOC volume flux) do not show clear early-warning signals.

4.1 Abrupt climate transition

The climate transition evident in our simulation causes SST anomalies of up to -4 °C averaged over the Nordic Seas and of -2.6 °C averaged over the NNA (Fig. 2e). In the

cold climate state sea ice covers the entire Nordic Seas and large areas of the NNA (Fig. 2c). Despite the low resolution of the CCSM3 used in this study we found a warming of the ocean surface close to Newfoundland (Fig. 2e) associated with AMOC weakening similar to the warming described by Saba et al. (2016) in simulations with much higher ocean-grid resolution. Quasi-decadal oscillations during the cold state may indicate that the transition happens at a bifurcation point from one stable mode to an oscillatory mode (Scheffer et al. 2009). This cold oscillatory mode has been described in detail by Yoshimori et al. (2010). A closer inspection of the transition phase indicates that the mode switch is triggered through an SSS reduction in the NNA which leads to a reduction in deep-water formation and hence regional cooling and sea-ice expansion.

Several other potential triggers of climate transitions and their underlying mechanism are the topic of ongoing research (Kleppin et al. 2015; Bestelmeyer et al. 2011; Crowley 2000; Alley et al. 2005). While volcanic activity (Sigl et al. 2015), solar forcing (Jiang et al. 2005; Steinhilber et al. 2009; Gray et al. 2010), and the external input of freshwater (Broecker et al. 1990; Hawkins et al. 2011; Rahmstorf 1996) are not relevant in the context of our study, sea-ice transport and sea-ice-atmosphere interactions (Wanner et al. 2008, and



Fig. 5 Autocorrelation (lag-1) coefficient α_1 calculated using the earlywarning toolbox of Dakos et al. (2012) for the northern North Atlantic (NNA) and the Nordic Seas (NS) with a sliding window size of 50% and a filter bandwidth of 6% for **a, b** sea-ice concentration (ice); **c, d** mixed-layer depth (MLD); **e, f** sea-surface temperature

(SST), **g, h** sea-surface salinity (SSS), **i, j** sea-surface height (SSH), and **k** the Atlantic meridional overturning circulation (AMOC). The associated Kendall's τ is a measure for the respective trend. Note the different y-axis-scalings. Created with Matlab

references therein; Li et al. 2005; Li and Bitz 2010) can play a potential role. Broecker et al. (1990) argued that millennial-scale North Atlantic climate oscillations during glacial periods were characterized by an air-temperature change of

$\sim 5^\circ\text{C}$. They proposed that these oscillations were driven by salinity variations in the Atlantic Ocean which modulate the strength of the overturning circulation. Although we agree with the important role of salinity in forcing the strength of

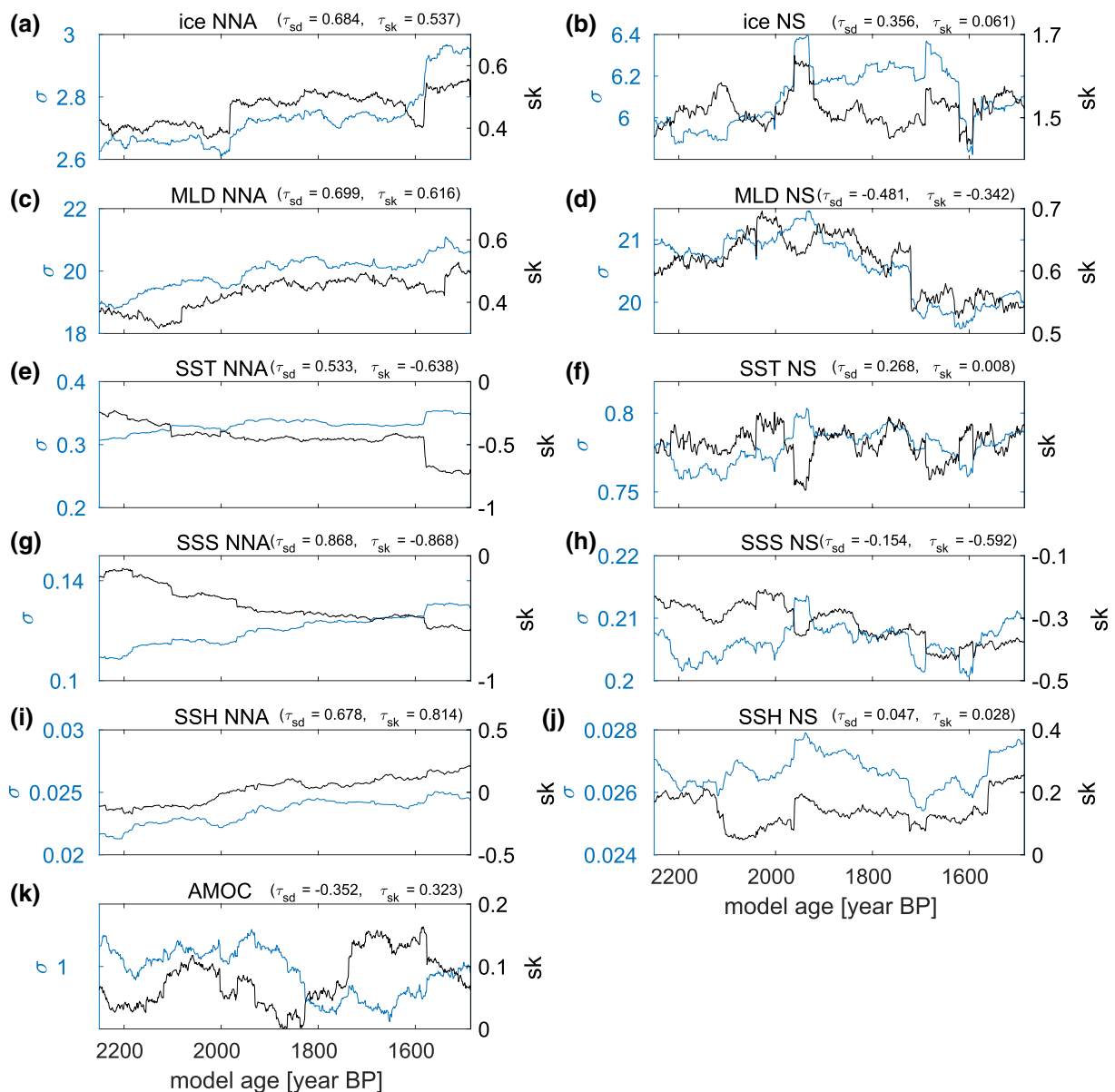


Fig. 6 Same as Fig. 5 for standard deviation (σ ; blue) and skewness (sk ; black)

the AMOC and possible state transitions, the origin of salinity changes is different in our simulation.

Prior to climate transitions, trends in the background climate may be important for a possible switch to another climate state (Scheffer et al. 2001; Ditlevsen and Johnson 2010). Due to the change in orbital forcing a trend in SST and other climate variables is generated over time in our simulation (Fig. 1), which brings the climate closer to a bifurcation point making a climate transition more likely. In particular, the model simulates a high-latitude cooling trend from the mid to the late Holocene accompanied by an increase in sea-ice extent (Varma et al. 2016) - in qualitative agreement with proxy records, see e.g., de Vernal and

Hillaire-Marcel (2000), Clement and Peterson (2008), Warner et al. (2008), and Müller et al. (2009). We can rule out the possibility that this is an erroneous model drift since Varma et al. (2016) showed that accelerating (by a factor of 10) the transient Holocene simulation has hardly any effect on the spatiotemporal evolution of the Holocene surface climate before the state transition. Therefore, we are confident that the climate trends in our study (e.g. in SST) are not an artifact of the model, but physically driven by the orbital forcing.

The final trigger for the state transition is related to internally generated climate noise. In our study the climate moves closer towards a bifurcation point due to slow orbital

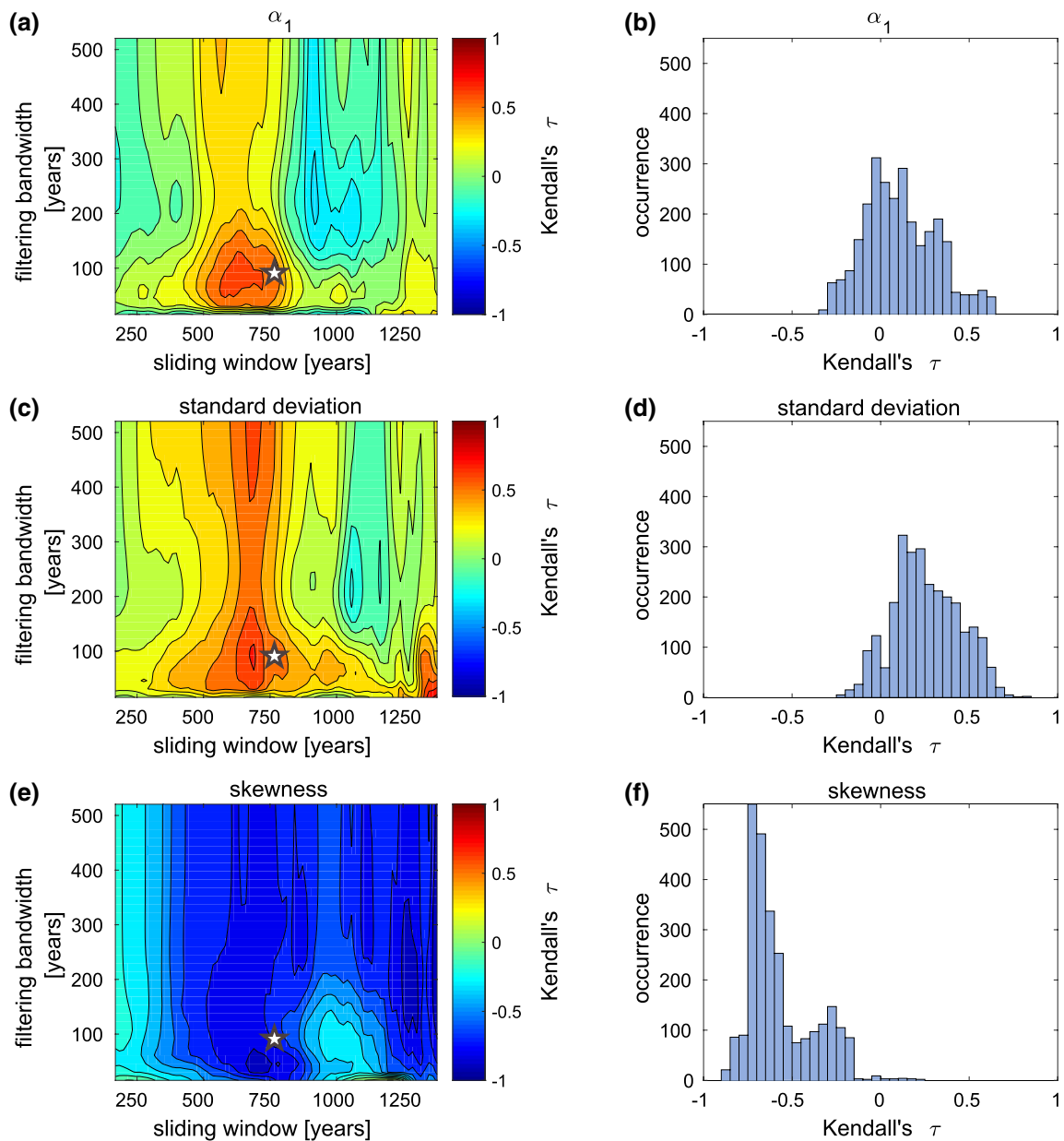


Fig. 7 Sensitivity analysis for the autocorrelation (lag-1) coefficient α_1 , standard deviation, and skewness for sea-surface temperature (SST) in the northern North Atlantic (NNA). The contour plots show the dependence of the trend (indicated by Kendall's τ) on the size of

the sliding window and on the bandwidth for the Gaussian filter (**a**, **c**, **e**). The star in each panel **a**, **c**, **e** indicates the parameter choice used in this study. The histograms **b**, **d**, **f** give the frequency distribution of the statistics. Created with Matlab

forcing. This (deterministic) movement towards the bifurcation point is clearly indicated by early-warning signals. A noise-induced transition becomes more likely to occur the closer the system is to the bifurcation point. As such, the state transition can be attributed to a mixture of deterministic (orbitally forced) climate change and a noise-induced transition as the “final kick”, as described by Lenton (2012). As a final trigger we identify an anomalous atmospheric circulation state characterized by a positive anomaly in sea-level pressure (SLP) over the mid-latitude North Atlantic in

the decade near the beginning of the state transition phase (Fig. S1), likely related to the occurrence of the “Atlantic ridge” weather regime (Madonna et al. 2017). The associated surface-wind anomaly induces, via Sverdrup balance, an anti-cyclonic oceanic circulation anomaly (Fig. S1), which reduces the transport of salty subtropical waters towards the sub-polar North Atlantic and the southward export of relatively fresh water from the sub-polar gyre. As a consequence, the northern North Atlantic starts to freshen (Fig. S1). During the next decades, a positive North Atlantic

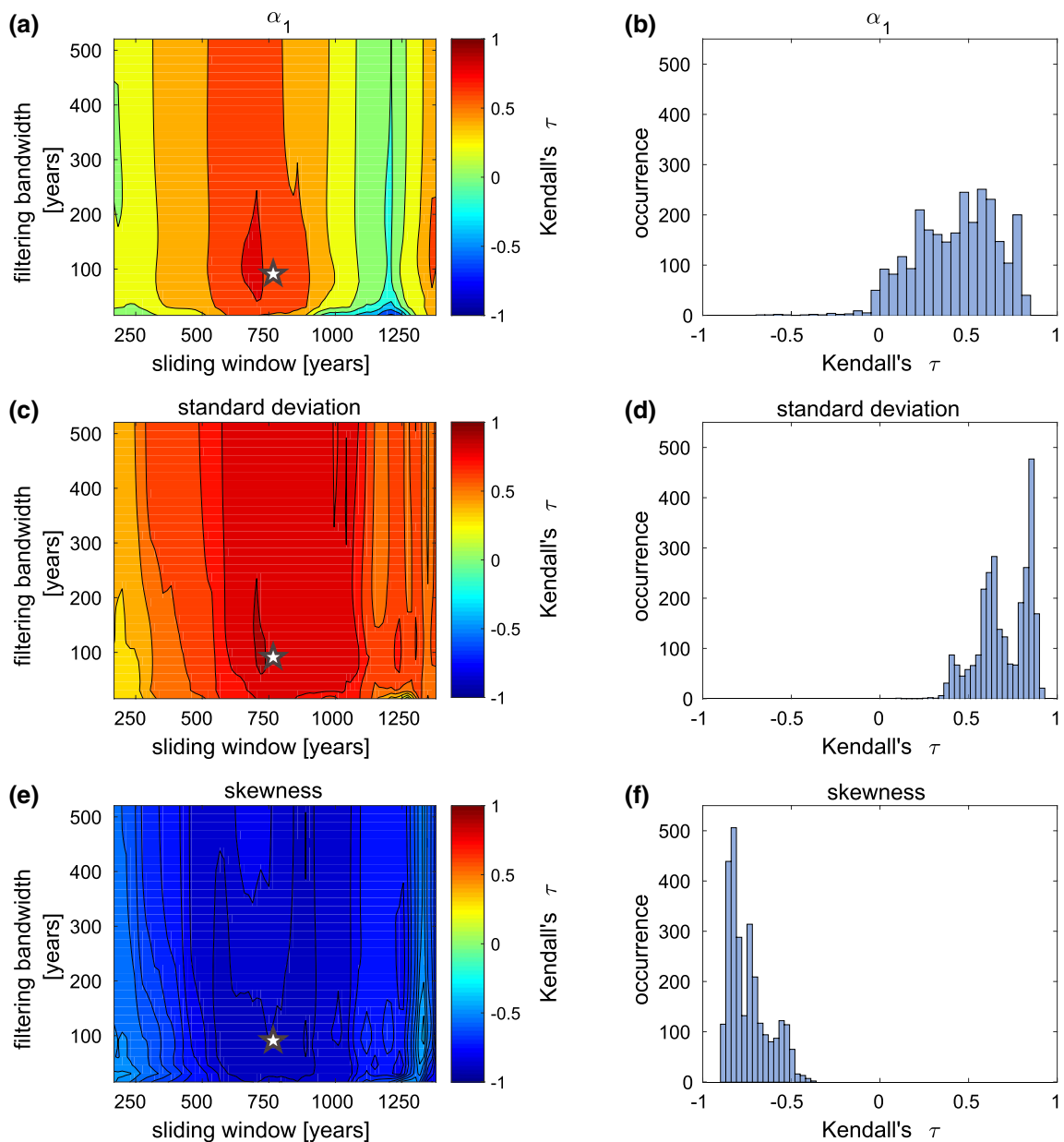


Fig. 8 Same as in Fig. 7 but for sea-surface salinity (SSS)

Oscillation- (NAO-) like SLP pattern establishes, maintaining the anomalous anti-cyclonic gyre and associated freshwater transports. At the same time, a cyclonic gyre around Iceland leads to enhanced freshwater transport towards the NNA through Denmark Strait, further freshening the region. At some point, the NNA becomes too fresh such that convection stops, sea ice expands and the AMOC weakens. A weakened AMOC acts as a positive feedback due to reduced northward salt and heat transports. During the Holocene simulation similar phases with persistent positive NAO-like atmospheric states occurred before, but induced only multi-decadal North Atlantic cold events rather than a state

transition (Klus et al. 2018), probably because the system was too far from the bifurcation point. During the Holocene, the bifurcation point is approached through orbital forcing which leads to a slow cooling of the northern North Atlantic (Varma et al. 2016). This cooling not only reduces the thermal expansion coefficient of the water (hence increasing the effect of salinity on density), but also allows the sea ice to expand, isolating the ocean from the atmosphere, which acts as a positive feedback to reduced oceanic convection (Lohmann and Gerdes 1998). In order to verify that the state transition has a stochastic component, we repeated a short portion of the Holocene run over the time of the transition

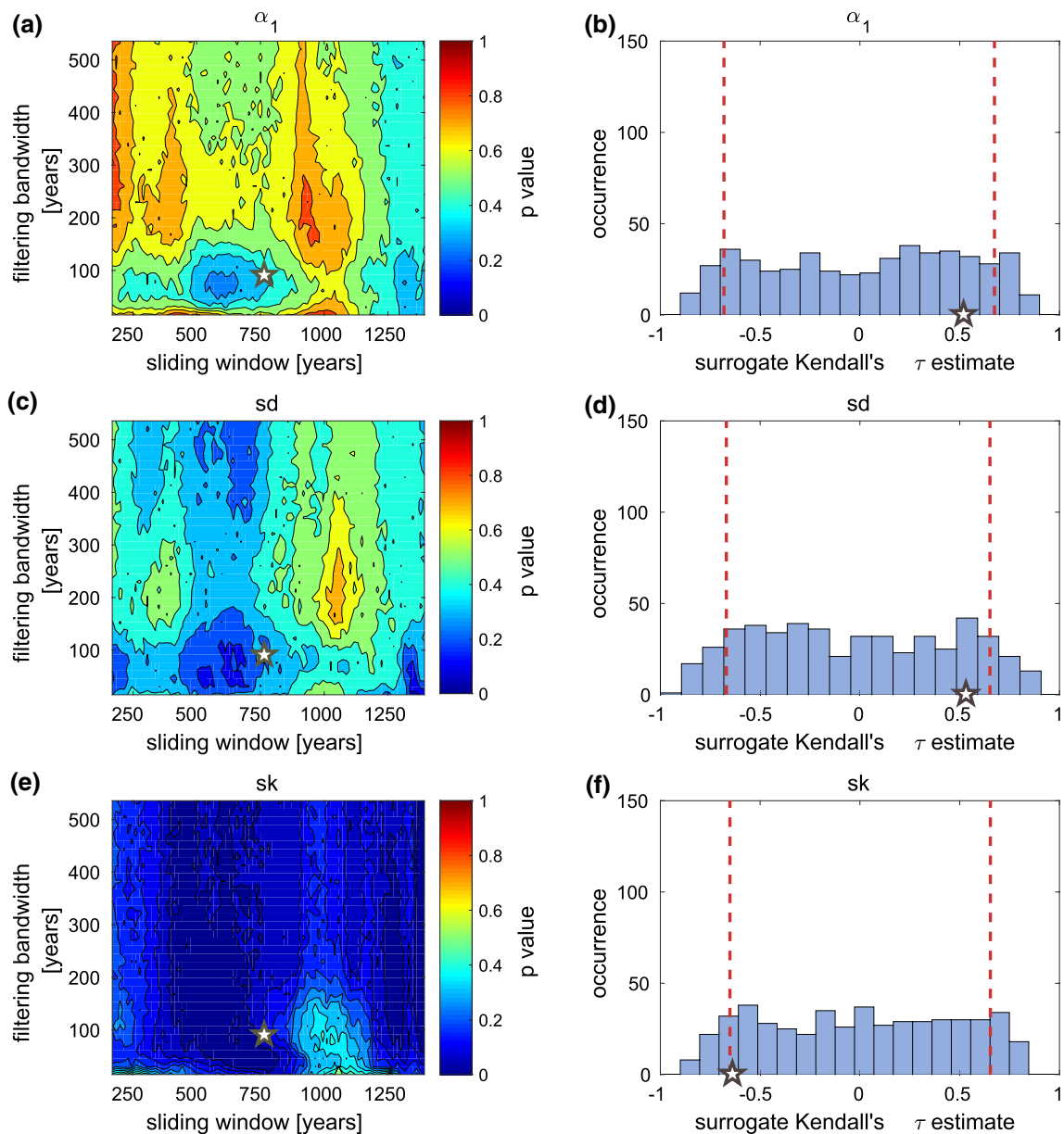


Fig. 9 Significance testing for the sea-surface temperature (SST) in the NNA with a sliding window of 10–90% and a filter bandwidth of 1–35% for 500 surrogates. The contour plots show the p -value for each combination for **a** the autocorrelation (lag-1) coefficient α_1 , **c** standard deviation, and **e** skewness. The star indicates the parameter

choice used in this study. The histograms **b**, **d**, **f** show the distribution of Kendall's τ for the combination used in this data set. The star shows the calculated τ in our study. The dashed red lines indicate a p -level of 0.1. Created with Matlab

(from year 1900 BP to 1350 BP) on another platform with a different compiler and found no transition to occur this time (not shown).

4.2 Interpretation of early-warning signals

Spatial analysis of early-warning signals reveals that it is important to choose the right region to obtain a significant early-warning signal (Figs. 3, 4). Some regions (e.g., NNA,

northern Nordic Seas, and the region close to Newfoundland) react more pronounced to the upcoming bifurcation than others. A strong signal in autocorrelation at lag-1 and standard deviation for several oceanic surface variables is found in the sub-polar North Atlantic (Fig. 3). This region has been extensively discussed during the last years in the literature (e.g., Rahmstorf et al. 2015; Hansen et al. 2016, and references therein), since this region has been cooling while global mean temperature is rising. It has been

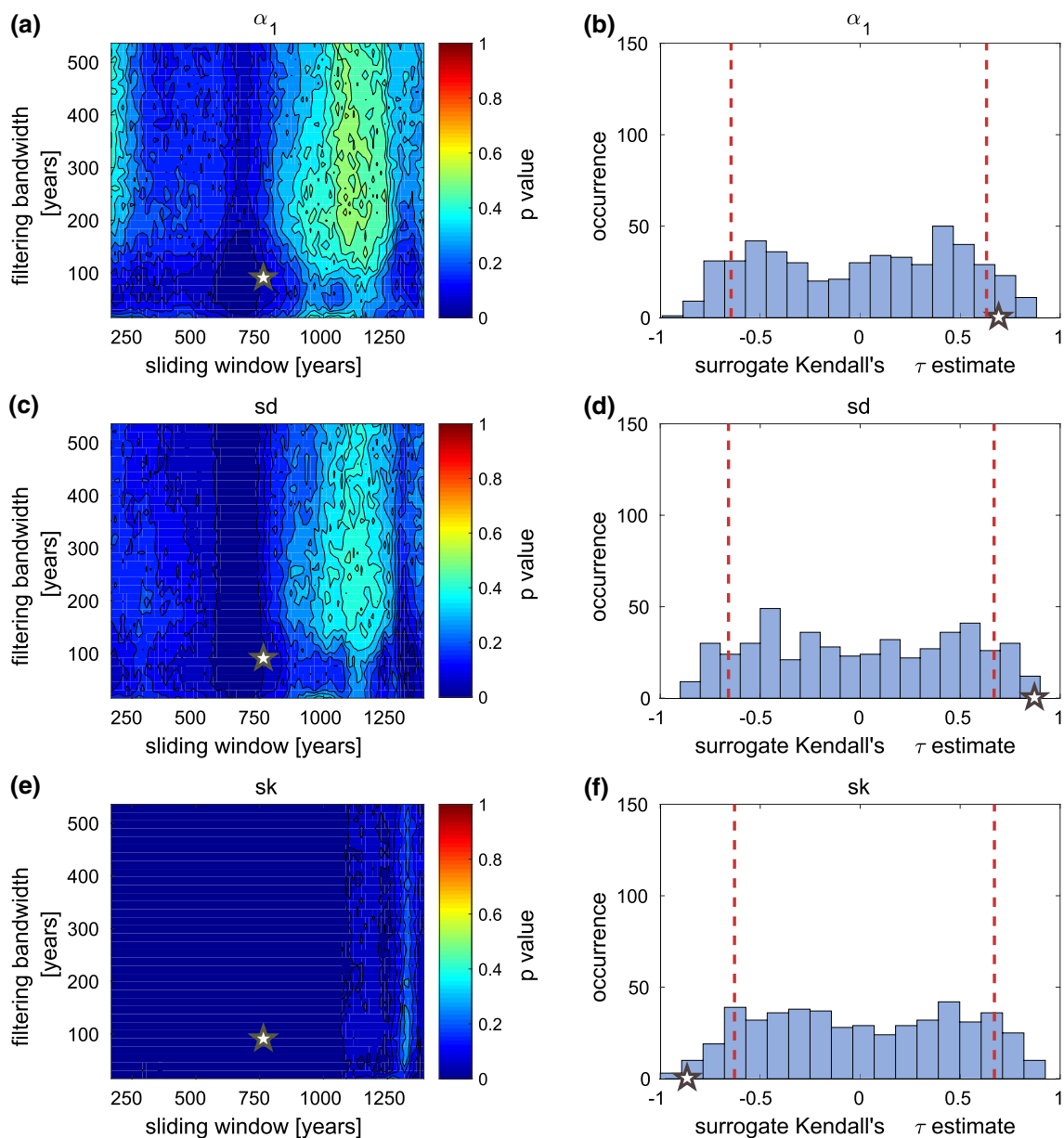


Fig. 10 Same as in Fig. 9 but for sea-surface salinity (SSS)

suggested that this cooling trend is possibly caused by a weakening of the northward heat transport and can be associated with a reduction in the AMOC strength (e.g., Driesshout et al. 2012; Rahmstorf et al. 2015) as well as with internal fluctuations (Ortega et al. 2017; Robson et al. 2016).

Using the temporal early-warning analysis for the NNA, it can be seen that it is also important to choose the right climate variable to obtain a significant trend (Figs. 5, 6). As discussed in Ditlevsen and Johnson (2010) the trends in autocorrelation at lag-1 and standard deviation can only be seen as sign of critical slowing down if they increase simultaneously, which is the case in our study. Dakos et al. (2008) showed that the trend for the autocorrelation at lag-1

for several reconstructed climatic shifts in Earth history with τ -values between 0.17 and 0.83 can be interpreted as a (weak) signal of slowing down. In addition to that, the skewness was also taken into account by Dakos et al. (2012). For most parameter choices a clear increase in autocorrelation at lag-1 and standard deviation was found, while the skewness became more negative. Not every climate variable of our Holocene simulation is influenced by the slow external forcing in the same way. Using a global climate model the sensitivity of several variables and regions can be tested to find measurable variables that show significant signals prior to an approaching bifurcation and, furthermore, choose the region of interest for further observations wisely. Although

the AMOC does not show an early-warning signal (Figs. 5k, 6k) it plays a key role during the climate transition. The skewness reveals a strong significant trend in the NNA as well, which is positive or negative depending on the size of the new mode (Fig. 6a, c, e, g). Furthermore, performing sensitivity analysis and significance testing helped to find a good combination of filter bandwidth and sliding window.

Although signals of critical slowing down might be evident in the studied data, one needs to be cautious and should bear in mind that these signals could also appear due to other reasons, e.g., due to inadequate detrending (Lenton et al. 2012b). As discussed in Dakos et al. (2008, 2012) the choice of bandwidth is important to obtain reasonable results. For both, a too narrow or a too wide choice, long-term trends can remain in the data set or an over-fitting of data can occur. This could lead to false-positives in early-warning signal analysis. A too short sliding window and therefore small number of data points in this window reduces the reliability of the calculation of early-warning signals (see supplement of Dakos et al. 2008). In contrast to that, a very long sliding window leads to a reliable result within a sliding window, while a trend over time cannot be resolved anymore.

Still, critical transitions can also occur without an early-warning signal as it was shown by an experiment with a rotifer population (Sommer et al. 2017), where true positive and false positive signals were found and the signal appeared when the population already started to decline. Boerlijst et al. (2013) showed that not all mode transitions are preceded by an increase in autocorrelation or other early-warning signals. If the dominant eigenvector of the analyzed system does not point in the direction of destabilization, the early-warning signal will not appear, even though fold bifurcations are always accompanied by critical slowing down.

Furthermore, state transitions can occur due to pure noise, which is not predictable using autocorrelation, standard deviation, or skewness. These noise-induced climate transitions can occur if a second climate state exists and the noise level is just strong enough to push the system towards a second potential well described as ‘noise-induced tipping’ (Timmermann et al. 2003; Franzke and O’Kane 2017). This can be checked for by a potential analysis (e.g., Livina et al. 2010). The potential analysis for our simulation reveals more than two climate states for most of the time series (Fig. S2), indicating a high degree of non-stationarity. Livina et al. (2010) and Dakos et al. (2012) found one or two states for most of their time series. However, for some sliding windows multiple states were identified, potentially indicating that the data did not have a distinct potential (Livina et al. 2010; Dakos et al. 2012).

Moreover, Bathiany et al. (2016) pointed out that an increase in autocorrelation and variance is no evidence of a catastrophic transition since they just reflect present changes in the timescale of a system. Only if the existence

of catastrophic transitions is proven, can they be used as early-warning signals. In our study, we do not only have multidecadal cold events indicating the existence of at least a second potential climate state, but already know that a catastrophic bifurcation will be approached. Another important factor is the number of data points to quantify significance of a change in autocorrelation and variance (Bathiany et al. 2016). It has been argued that a significant number of data points is needed to find meaningful changes (see supplement of Ditlevsen and Johnson (2010) for further explanation). Therefore, high-resolution quantitative observations are required to calculate significant potential early-warning signals, e.g. for a collapse of the AMOC. In contrast to the AMOC stream function that was used in other studies to check for potential early-warning signals (e.g., Boulton et al. 2014), studying surface fields, such as SST and SSS as in our study, is a more promising approach and observations are easier to access. Nevertheless, if translating model results to the real world one has to be cautious. As models can never perfectly replicate the real world, locations that show early-warning signals in the model might differ from reality. For instance, coarse-resolution models usually have problems in simulating sea-ice margins, convection sites, or ocean currents at their exact locations (e.g., Prange 2008). Early-warning signals associated with those features might therefore be spatially displaced in the model compared to reality. Our approach of taking wider area-averages of ocean surface variables for early-warning analysis partly overcomes this problem. We finally note that although our approach helps to identify potential key regions and key variables that offer an opportunity to search for an upcoming bifurcation, it would take substantial time until a significant signal could be observed and without the certainty that a transition will occur there is always the chance of false (or missed) alarm.

5 Summary and conclusions

If several factors (e.g., the sensitivity to the size of the sliding window and the bandwidth of the filter) are considered, autocorrelation, standard deviation, and skewness have been found to be reliable early-warning signals in our study for SSS in the NNA. Using a global climate model, it has been found that variables as well as regions can be identified that react most sensitively to an approaching bifurcation and allow for the detection of early-warning signals. While SSS, SSH, sea-ice concentration, and—to a lesser extent—SST in the NNA show a significant signal, variables in the Nordic Seas and the AMOC do not. The identified key variables (which are more easily accessible than, e.g., the AMOC) could therefore be measured in the mentioned region to obtain a robust base for calculating early-warning signals. One has to be cautious if only one indicator increases, since

autocorrelation at lag-1 and the standard deviation cannot be seen independently (Ditlevsen and Johnson 2010). Our results support the notion that many past climate transitions have been accompanied by crossing critical thresholds and that generic early-warning signals prior to climate shifts are often evident (Dakos et al. 2012). Yet, it is not possible to predict all drastic state transitions and false positive alarms can occur, therefore, significance testing should be performed simultaneously. Additionally, it should be kept in mind that in reality several control parameters are subject to permanent change, e.g., the orbital forcing, greenhouse gases or the input of meltwater into the ocean. This further complicates the bifurcation analysis. Nevertheless, if we have the facilities to check for early-warning signals, we should use them (although with caution) to examine, e.g., the temporal and spatial variability of a surface temperature field (Lenton et al. 2017) or the sea-surface salinity. Although noise-induced abrupt climate transitions may always be present, an upcoming bifurcation which might be associated with a change in climate variability possibly caused by anthropogenic activity, could be predicted by analyzing potential changes in autocorrelation, standard deviation, and skewness. Our results suggest that slow gradual cooling of the northern North Atlantic may give rise to a critical transition, which might be heralded by early-warning signals that can be found in ocean surface variables.

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