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The observed trend in unusual daily mean temperatures over Germany from 1949 to 2018 and their relationships to major climatic drivers

Yulizar Yulizar[1]

Abstract

Unusual events are detected by the statistical changes in 'extremes', when extreme anomalies persist through the temporal and spatial interactions of the variable of interest. To identify the occurrences of unusual daily mean temperature events in 3- and 5-day sequences, a statistical method based on an "outlyingness" function is proposed in this study. This function is based on the geometrical position of a point on the multivariate set. To illustrate the methodology, this study uses daily mean temperature records from 18 observation stations across Germany (1949–2018). The findings indicate discernible changes in the frequency of unusual events at the stations, mostly during the boreal winter months between the first and last 35 years of the study period. A wide range of temperature anomaly averages ($-12\ °C$ to $+12\ °C$) are produced by the interaction of series between warm and cold conditions, which affects the occurrence of disappearing days. While this is happening, the unusual warming is more pronounced on days that emerge from both the 3- and 5-day sequences, with temperature anomaly averages ranging from $+4$ to $+12\ °C$. The Atlantic Multi-Decadal Variability and the Arctic Oscillation/North Atlantic Oscillation, respectively, are both implicated in the unusual surface warming over Germany. The disappearance days of unusual events do not exhibit statistically significant correlations with climatic indices, suggesting a possible anthropogenic effect. The emphasis of this study is on the necessity of determining whether unusual events in daily temperature anomalies across Germany can be attributed to anthropogenic factors.

1 Introduction

Numerous detrimental effects of climate change affect not only human society but also the entire ecological community. Across all fields of study, climate change has been an important challenge for mitigation and adaptation policies. Understanding previous climate behavior contributes to our improved comprehension of how the current climate system may change in the future. Climate change scientific assessments have been conducted since the 1970s on a regular basis [20]. Moreover, several studies were carried out in various regions to comprehend the consequences of climate change (e.g., [6, 10, 34]). In addition, surface warming all around the world is a typical consequence of climate change (e.g., [1, 27, 28]). It often refers to global warming, resulting from the increases in greenhouse gases in the atmosphere due to human activities [37]. The Bulletin of the American Meteorological Society's special reports "Explaining Extreme Events

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from a Climate Perspective" and a number of Intergovernmental Panel on Climate Change assessment reports have both documented global warming [7, 11, 17, 18, 20, 23]. However, the extent of surface warming brought on by climate change is geographically variable [2], necessitating a more thorough analysis of surface warming detection and attribution.

The statistical properties of temperature can alter due to global warming, and record-breaking events can occur more frequently [29]. The compounding impact of a series of these breaking-record extreme events is expected to be more devastating. In Europe, for example, there has been an increase in severe heatwaves (e.g., [31, 33, 45]). Furthermore, the occurrences of extreme temperature would also have an impact on plant growth [13], bee species [21], and injury deaths [32].

Changes in the statistical characteristics of extreme temperatures have been extensively studied previously. At the ten stations in Europe and China with the longest daily temperature records, Yan et al. [40] looked at the trend behavior of severe temperatures. They found that western Europe had seen a greater increase in warm extremes since the 1960s. In contrast, the decrease in cold extremes was more evident in southern China. To examine the behavior of extremes in the daily temperature and precipitation records of selected observation stations in western Germany, Hundecha and Bárdossy [16] employed a number of extreme indices. In addition, Melillo et al. [30] studied climate change impacts in the U.S. and found that all regions have experienced warming in recent decades. According to Coupled Model Inter-comparison Project 5 (CMIP5) climate models, an increase in mean temperature throughout the twenty-first century is consistent over the globe [24].

An extreme event was defined by IPCC Working Group I as "an event that is rare at a particular place and time of year" [19]. In a univariate series, extreme events are frequently defined using a threshold value. However, any threshold value for detection of an extreme in one location may not be considered as an extreme in another location [16] and requires a normalized index for its own climate system [39]. This can be seen, for instance, where the Statistical and Regional Dynamical Downscaling of Extremes for European regions (STARDEX) Project introduced and used several indices (e.g., 90th percentile of rain day amounts, maximum number of consecutive dry days, 10th percentile of minimum tempera-ture) to analyze observed changes in extremes and expected changes in the future extremes over the European regions during 2071–2100 [36]. These indices are used only on a series at a single station or a univariate series.

However, a further difficulty is related to the extremes themselves due to their interaction on temporal and spatial scales. Some events may not be extreme from a univariate statistical perspective, but their impact may become extreme due to their simultaneous or sequential occurrence [9]. This condition can be exemplified by the fact that the daily mean temperature is often 30 °C or above. Particularly in tropical areas, it might be the usual temperature for 1 or 2 days. However, if it occurs for the next few days, then it exacerbates negative impacts on agriculture, health, and others. Fur-thermore, it is worse than the adverse effect of individual extreme events if seen as a multivariate interaction of joint occurrence with extremes from another variable (see [12, 44]. Although statistical changes in a series of extremes might not affect the means, variances, and extremes at an individual location or at a time step, the changes of extremes are detectable on multivariate spatiotemporal scales through their interaction in time and space [41]. In other words, to a certain extent, multiple spatial or temporal dimensions can identify the extremes, which is called unusual observations, in variables such as precipitation [42].

To determine the changes of unusual events and their potential causes, identification of the occurrence of unusual events and detection of their changes in the multivariate context are necessary. They provide critical information on how the field of interest (herein, the daily mean temperature) interacts along the temporal scale and how the characteristics of their unusual events change over time. From the multivariate perspective, unusual events are previously defined based on their geometrical position in a multivariate set of observations using the outlyingness function [41, 42]. This function enables the detection of 'outliers' located near or on the boundary of a multivariate set. However, the use of this function in multivariate studies for unusual event detection and attribution assessment remains limited.

This study aims to use a non-parametric statistical approach to identify the occurrence of unusual events and charac-terize the appearance and disappearance of unusual events across Germany. The impact of altitude on the identification of changes in unusual events is investigated in this study using the daily mean temperature record from 18 observation stations in Germany from 1949 to 2018. The analysis focuses on unusual events in 3- and 5-day sequences of the daily mean temperature time series. In addition, a bootstrap-based methodology is used to test the statistical significance of the occurrence of unusual days. The results of this study will not only help us understand the situation of unusual occur-rences from a multivariate perspective, but they will also contribute to strategies for minimizing the negative effects of unusual events in the future, such as unusual climate disaster risk.

This paper is structured as follows: Information on selected observation stations for the daily mean tempera-ture in Germany is described briefly in Sect. 2. The general concept of the depth function and the methodology of

appearance and disappearance used in this study are described in Sect. 3. Furthermore, Sect. 4 provides a discussion of the results.

2 Study region

In this study, 18 observational stations for daily mean temperature series are selected across Germany due to the period of available records (Fig. 1a). These stations have continuous records of the daily mean temperature series without any missing values over 1949–2018. The elevations of the 18 stations range from 4 m above sea level (m.a.s.l.) to about 3000 m.a.s.l. (Table 1). The observational records of daily mean temperatures from the selected station are available from the European Climate Assessment and Dataset [22]. 70-year daily records of daily mean temperatures anomalies are sufficient to explore the behavior that is driven by their interaction on temporal scales. It is worth noting that the observational data before the 1950s has significant uncertainties [14].

Fig. 1 Locations of the 18 selected temperature stations across Germany (**a**), correlation coefficients of daily average temperature among 18 stations (**b**), and the seasonality of the daily average temperature for each stations over the period of 1949–2018 (**c**)

	ID	Station	Altitude (m.a.s.l)
Table 1 Selected mean temperature observation stations in Germany	1	Schleswig	43
	2	Schwerin	59
	3	Bremen	4
	4	Potsdam	81
	5	Magdeburg	76
	6	Brocken	1142
	7	Cottbus	69
	8	Gorlitz	238
	9	Jena Sternwarte	155
	10	Chemnitz	418
	11	Fichtelberg	1213
	12	Geisenheim	110
	13	Bamberg	240
	14	Heinersreuth-Vollhof	350
	15	Weissenburg	422
	16	Regensburg	365
	17	Hohenpeissenberg	977
	18	Zugspitze	2964

3 Methodology

3.1 Depth function

This study uses the concept of depth function to identify the occurrence of unusual events. Tukey [38] first introduced it as a tool for the picturing of multivariate data. It is a robust and conservative tool because it is a non-parametric method without the assumption that the data is fitted to a probability distribution. The concept of a depth function is to measure the centrality of a point with respect to a data set (*center-outward*). It is like a linear ranking in univariate series [26], where the rank goes from the smallest to the largest or from the largest to the smallest. In the depth function, a point that is located at the center of the multivariate data set (e.g., close to the median, see Fig. 2a) has the highest depth value, and points that are far away from the center have lower depth values (see Fig. 2b). In addition, zero is the lowest depth value. This enables us to rank each data point even in the third or more *Nth*-dimensions based on the depth values of the dataset. Furthermore, these points with a low depth value are classified as unusual events (Fig. 2c). This illustrates that unusual events are caused by interactions between points as well as by extremes.

In this study, the half-space depth function is used among many other depth functions because it possesses all the properties of a depth function. Other depth functions are lacking in some properties (e.g., maximality, monotonicity, etc.). For further details about the depth function, please refer to Liu [25], Zuo and Serfling [46], and Zuo [47]. The mathematical formula of the half-space depth function is shown in Eq. (1).

$$D_{X(p)} = \min \left(\min_{nh} \left(\left| \{ x \in X \langle n_h, x - p \rangle > 0 \} \right| \right), \left(\left| \{ x \in X \langle n_h, x - p \rangle < 0 \} \right| \right) \right), \tag{1}$$

where D is a depth value of a point p (point of interest) in the dataset X, n_h is the hyperplane and x is the series within X dataset.

It shows that the half-space depth of a point p with respect to the finite set X in d dimensional space is defined as the minimum number of points of the set X lying on both sides of a n_h through the point p. The minimum number of points is calculated for all possible hyperplanes (n_h). The scalar product ‹x,y› represents the normal vector of a selected hyperplane in the d dimensional vectors. Figure 2 illustrates the calculation of a half-space depth function in the two dimensions (e.g., 2-day sequence), which is an example of how to calculate the depth value of a *rectangular point* (point of interest) with respect to the dataset. In Fig. 2a, b, the hyperplane (n_h) was drawn through a *rectangular point* and moved clockwise in 360°. The minimum number of points lying on both sides is counted for each hyperplane.
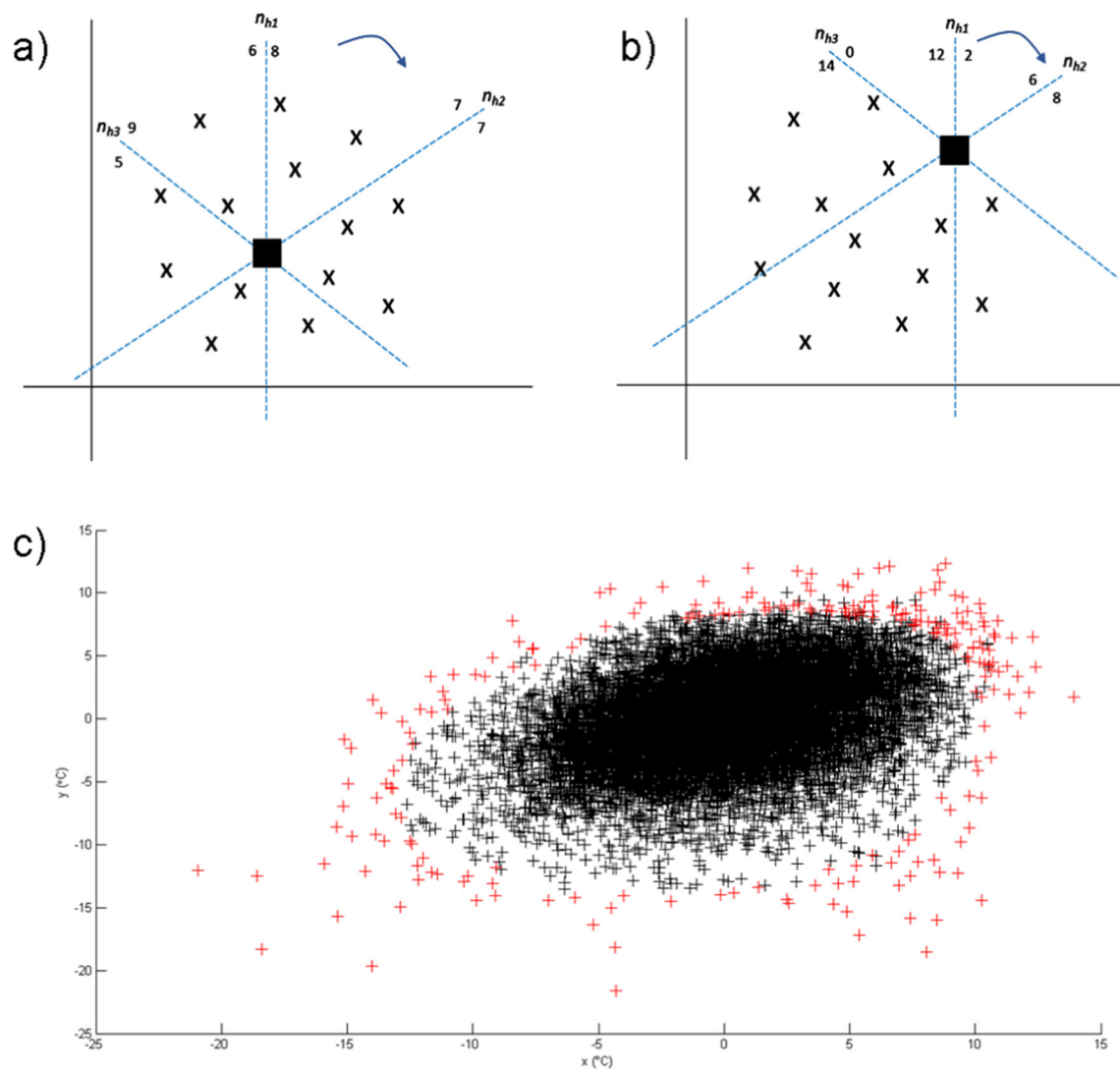
Fig. 2 Schematic calculation of depth value in two dimensions for a rectangle point: **a** depth value is 5; **b** depth value is 0; **c** two dimensions of the temperature series between 'x' and 'y' on the temporal scale. Unusual events (red '+') located at the periphery of the dataset. It has the lowest depth value as it decreases monotonically from the center (a highest depth value)

Furthermore, the depth value of this point is the minimum value among the minimums of the number of points lying on both sides of each hyperplane. In Fig. 2a, for instance, the depth value of a point of interest is 6 for n_{h1}, and then it moves to n_{h2} with a depth value of 7 and continues with n_{h3} with a depth value of 5. Then, the depth value of this *rectangular point* is 5, as shown by *min* (6, 7, 5), which is equal to 5. The same things applied for Fig. 2b, where the depth value of a point of interest is zero.

3.2 Unusual mean temperature events

3.2.1 Cross depth

In this study, unusual events on the multi-dimension temporal scale are defined at a single site as the series of observations that are independent among different sequence sizes or subsets of the data [41, 42]. In this study, 3- and 5-day sequences of daily mean temperature anomalies are used from the selected stations because it is more computationally efficient to characterize unusual events from shorter than longer sequences of days. Meanwhile, choosing a longer sequence of days (e.g., 30 days) is more likely to be engulfed because it reduces the occurrence of unusual events. Furthermore, choosing these different days will give an understanding of how the unusual events extend due to their interaction.

Fig. 3 Illustration of unusual events (red colors) in a time series of temperature between 3-day (**a**) and 5-day sequences (**b**)
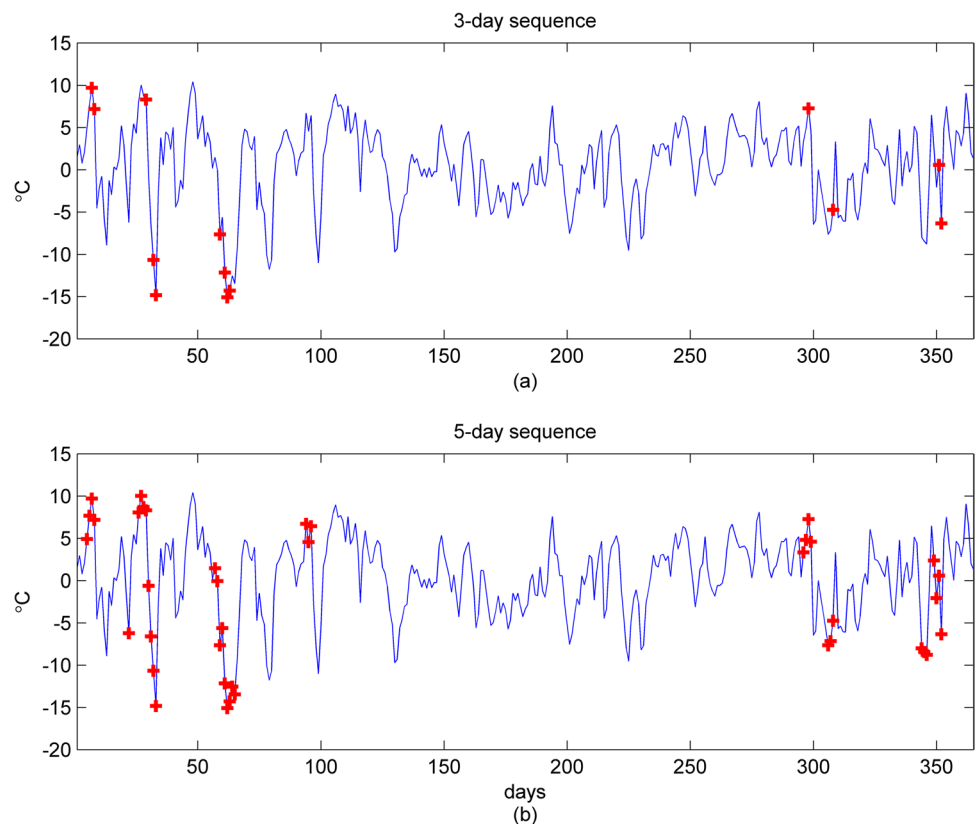

Using a depth function calculation, Fig. 3 illustrates the occurrence of unusual events in 3- and 5-day sequences from a single observation station. There is a lower frequency of unusual events in the 3-day sequences (Fig. 3a) than in the 5-day sequences (Fig. 3b). This example demonstrates that this function may identify not just extremes but also series where the individual temperature observations are not classified as extreme. Figure 3b suggests that many of these 'non-extreme' unusual events are cases in which temperature changes unusually rapidly with time. In other words, extreme events are part of unusual events. Moreover, this situation could only be recognized in the higher dimensions (two or more dimensions).

The number of unusual mean temperature days is identified based on the depth value of five or lower ($d \leq 5$). It is assumed that there will be around 10% of unusual days in a given month, which is why this amount was selected. In general, the detection of unusual events between the first and last 35 years of the study period is conducted through the following steps: Firstly, a daily time series for the period 1949–2018 is divided into two equal periods: 1949–1983 (series set 1) and 1984–2018 (series set 2), respectively. Secondly, a cross-depth analysis is conducted between these periods, and the total number of unusual days (β) is counted based on series having $d \leq 5$. The cross-depth analysis provides information about unusual behaviors such as appearing and disappearing. In Yulizar and Bárdossy [42], the definition of appearing is a new situation that occurred in 'series set 2' (*recent time*) that never occurred before in 'series set 1' (*preceding time*). The definition of disappearing is a situation that did not occur in 'series set 2', but only occurred in 'series set 1'. In terms of unusual events behavior, these two situations are called shrinking (more disappearing) and growing (more appearing). Another behavior is called "translation", when the number of appearing and disappearing is equal in the different periods [42]. The concepts of "disappearing" and "appearing" are illustrated in Fig. 4.

3.2.2 Significance testing

To evaluate whether the total numbers of "appearing" and "disappearing" days from the observational records are statistically significant or happen by chance (randomly), a significance test is performed. In the significance test, the number (a_i) of unusual days was calculated from 100 bootstrap samples (N) of 3- and 5-day sequences. The number (a_i) of unusual days for each of the bootstrap samples (herein, $i = 1, 2, \ldots, 100$) is defined based on the same depth value ($d \leq 5$). For each bootstrapping sample, significance information (S) is computed from Eq. (2), and the sum of the S values is reported for the

Fig. 4 Schematic cross-depth calculation in two dimensions: depth values of the points in *preceding time* are calculated with respect to the points in *recent time*. The disappearing is points that not occurred in *recent time* (**a**–**b**); depth values of the points in *recent time* are calculated with respect to the points in *preceding time*. The appearing is points that not occurred in *preceding time* (**c**–**d**)
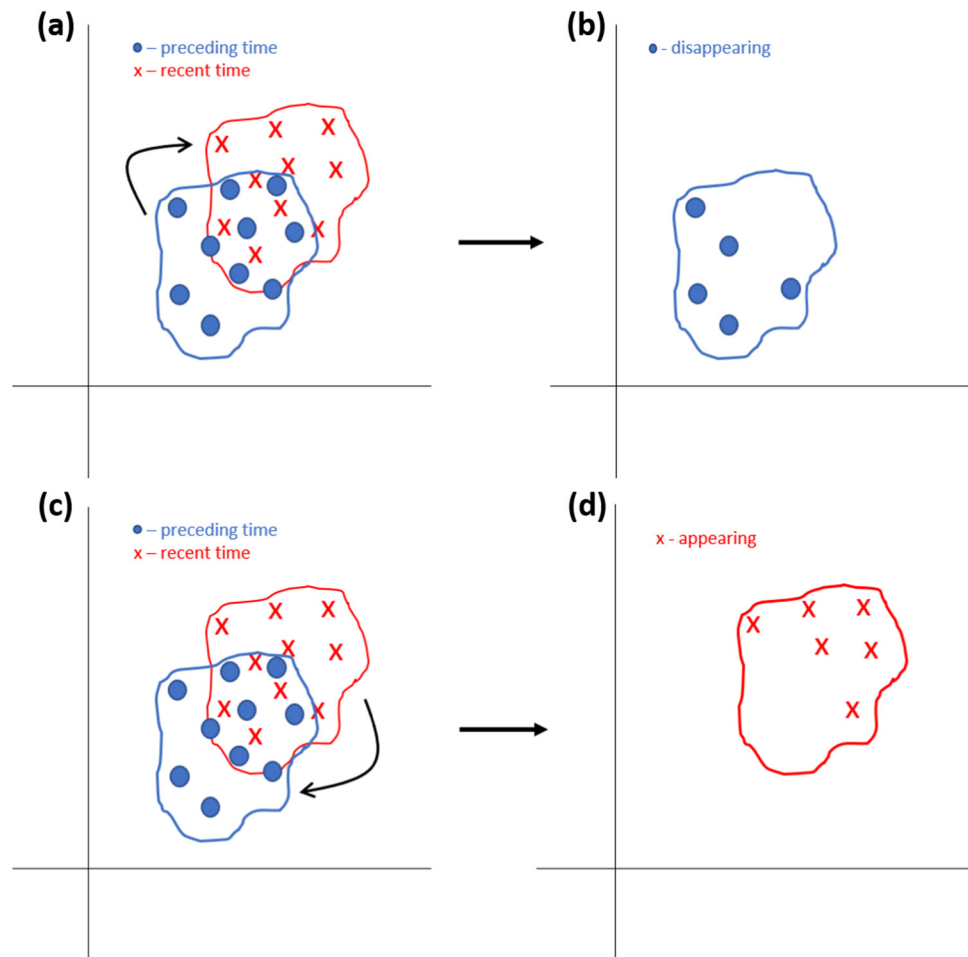
significance test. In this study, *S* is significant and very significant when 90 and 95 bootstrapping samples show less than or equal *β*, respectively.

$$S = \begin{cases} 1, & \alpha_i \leq \beta \\ 0, & \alpha_i > \beta \end{cases} \tag{2}$$

3.3 Associations with large-scale climate indices

The temporal correlations of the temperature anomaly averages of appearance and disappearance days with four climatic indices are computed to look into possible causes of detectable changes in unusual events. The Arctic Oscillation (AO), North Atlantic Oscillation (NAO), Pacific Decadal Oscillation (PDO), and Atlantic Multi-Decadal Oscillation (AMO) indicators are the four climate indices used. Strong winds that round the North Pole are weaker and more distorted during negative AO phases, which makes it easier for colder arctic air masses to penetrate southward and increases storminess across the mid-latitudes [15]. Warm temperatures across northern Europe typically accompany NAO-positive phases, particularly in winter [3]. According to Zampieri et al. [43], the AMO impacts air temperatures over Europe and North America. In addition, the PDO is associated with mid-latitude atmospheric circulation via the modulation of Arctic sea-ice loss [35]. While typical weather patterns are well known given a certain phase of the climate indices, understanding of the impact of this large-scale climatic variability on changes in extreme weather remains limited.

4 Results and discussion

The correlation coefficients of daily mean temperatures across the 18 stations show a clear regionalization among the stations with high correlation coefficients (0.85–1), which consists of four groups: Group 1 (ID 1–ID 5), Group 2 (ID 7–ID 10), Group 3 (ID 12–ID 17), and Group 4 (ID 6, ID 11, ID 18) (Fig. 1b). The majority of stations exhibit comparable seasonality in their daily mean temperatures, with the warm season lasting from May to October (Fig. 1c). Meanwhile, Brocken (ID 6), Fichtelberg (ID 11), Hohenpeissenberg (ID 17), and Zugspitze (ID 18) are high-altitude stations that exhibit a cooler seasonality than the majority of low-altitude stations, demonstrating the orographic effect of altitude on the climatology of daily mean temperatures.

Tables 2 and 3 show the number of unusual 3- and 5-day sequences, respectively, from the 18 stations. Results show that the number of unusual days increased as the number of sequence days increased. Even when a shorter (3-day) sequence is not classified as an extreme event, extending the sequence (in this case, to 5 days) may make it extreme [42]. As a consequence of this, changes in unusual events (appearing or disappearing) are detectable in the 5-day sequences but not in the 3-day sequences between the first and last 35-year periods. Additionally, the chance of having unusual events for 3- and 5-day sequences was 1.35% (4.44%) in the period 1949–1983 and 1.48% (4.47%) in the period 1984–2018.

It is important to note that not all simultaneous occurrences will lead to unusual events due to their interaction in different sequences. This condition may be driven by the interaction of the local scale with the global atmospheric patterns for a particular duration of time or by the dominant role of internal variability. As one illustration, Auer et al. [2] found that the faster temperature rise is frequently associated with an increase in average atmospheric pressure, which may be caused by a movement of the subtropical high-pressure zone to the north. Due to the attribution of an anthropogenic effect, further research is required to fully understand this occurrence, which is beyond the scope of this study.

The results in Tables 2 and 3 show clearly the variety of unusual events behavior (appearing and disappearing) in both sequence days. From the 18 stations in this study, 13 stations (72%) have growing in 3-day sequences and 11

Table 2 Numbers of 3-day sequences with the occurrence of unusual events

No	Station	3-day sequence			
		Disappearance (days)	Average temperature (°C)	Appearance (days)	Average temperature (°C)
1	Schleswig	**185****	− 2.27	167	2.62
2	Schwerin	165	− 2.67	**195****	3.50
3	Bremen	**198****	− 2.24	151	3.48
4	Potsdam	157	− 2.67	**185***	2.94
5	Magdeburg	152	− 4.39	**257****	4.42
6	Brocken	156	− 0.30	**160**	2.63
7	Cottbus	134	− 4.67	**221****	4.63
8	Gorlitz	125	− 4.61	**233****	3.96
9	Jena Sternwarte	187	− 4.24	**196****	4.36
10	Chemnitz	172	− 3.86	**201****	4.53
11	Fichtelberg	160	− 2.09	**185**	4.21
12	Geisenheim	**219****	− 1.78	157	3.95
13	Bamberg	**192****	− 4.90	159	4.93
14	Heinersreuth-Vollhof	182	− 4.18	**188***	3.94
15	Weissenburg	**211****	− 4.47	175	5.63
16	Regensburg	159*	− 4.05	**168****	4.29
17	Hohenpeissenberg	170	− 3.43	**182**	5.43
18	Zugspitze	187	− 4.33	**217****	3.42

Bold value indicates the bigger values between disappear and appear for each sequence days

*High significance

**Very high significance

**Table 3** Numbers of 5-day sequences with the occurrence of unusual events

No	Station	5-day sequence			
		Disappearance (days)	Average temperature (°C)	Appearance (days)	Average temperature (°C)
1	Schleswig	**559****	− 1.25	484	2.02
2	Schwerin	585	− 1.17	**598***	2.12
3	Bremen	**615***	− 1.00	587	2.29
4	Potsdam	**535**	− 1.63	549	2.37
5	Magdeburg	490	− 2.68	**679****	3.16
6	Brocken	**565**	0.27	541	2.22
7	Cottbus	426	− 2.41	**641****	3.01
8	Gorlitz	423	− 2.31	**631****	2.87
9	Jena Sternwarte	**613****	− 2.29	558	3.03
10	Chemnitz	553	− 2.06	**649****	3.11
11	Fichtelberg	548	− 0.68	**649****	2.54
12	Geisenheim	**679****	− 0.86	457	2.41
13	Bamberg	**603****	− 2.29	481	3.16
14	Heinersreuth-Vollhof	**573****	− 2.30	557*	2.84
15	Weissenburg	**663****	− 2.19	477	3.67
16	Regensburg	**529****	− 2.20	475*	3.08
17	Hohenpeissenberg	**629****	− 1.11	562	3.65
18	Zugspitze	613	− 2.71	**703****	1.80

Bold value indicates the bigger values between disappear and appear for each sequence days

*High significance

**Very high significance

stations (61%) have shrinking in 5-day sequences. These results indicate that changes in the occurrence of unusual events might have a different sign depending on the temporal scale of interest. Furthermore, the different behavior patterns of 3- and 5-day sequences unusual events are found from stations Bremen (ID 3; 4 m.a.s.l.) and Zugspitze (ID 18; 2964 m.a.s.l.), indicating there is no influence of altitude on the statistical occurrence of appearing and disappearing for these stations. For a station in Bremen, the occurrences of disappearing are very significant in 3-day sequences and significant in 5-day sequences. Meanwhile, Zugspitze shows the appearing days are very significant in both sequences.

The number of unusual events from January through December is depicted in Fig. 5. Regardless of the length of sequences, the results indicate that the winter season (DJF) is a dominant season for disappearing and appearing across all the stations. The occurrences of disappearing days are more prominently identified in December and January, while the appearance of unusual days occurred in January.

While disappearing unusual events have predominantly negative daily mean temperature anomalies, the anomalies on appearing days are predominantly positive (Table 2 and Fig. 6). The number of occurrences of appearing days across all stations is mostly driven by the interaction of positive value series. Further, the results showed that longer sequences (e.g., 5 days) have a higher total number of appearing days than shorter sequences (e.g., 3 days). In all stations, the number of disappearing days is largely driven by the interaction of series between negative and positive values. These results imply that positive (warmer) series interactions are more likely to result in hotter days and fewer cold days. This is consistent with a shifting average temperature with more hot days as a result of climate change. However, the variability of changes in the temperature series that contribute to the disappearing days is clearly identified due to the interaction of warm and cold series.

Additionally, it is well known that Europe is experiencing an increase in high temperatures (e.g., [4, 5]). In line with the results of earlier research, these findings suggest that more unusual days are expected to happen across Germany in the future. Due to several factors (such as local natural variability in the temporal variation), a local station's response to global warming may differ from the global pattern [8]. Furthermore, it is important to note that the trend in a short period of time is not reflecting the trend in a long period of time.

Fig. 5 Frequency of the number of appearing and disappearing days from January to December
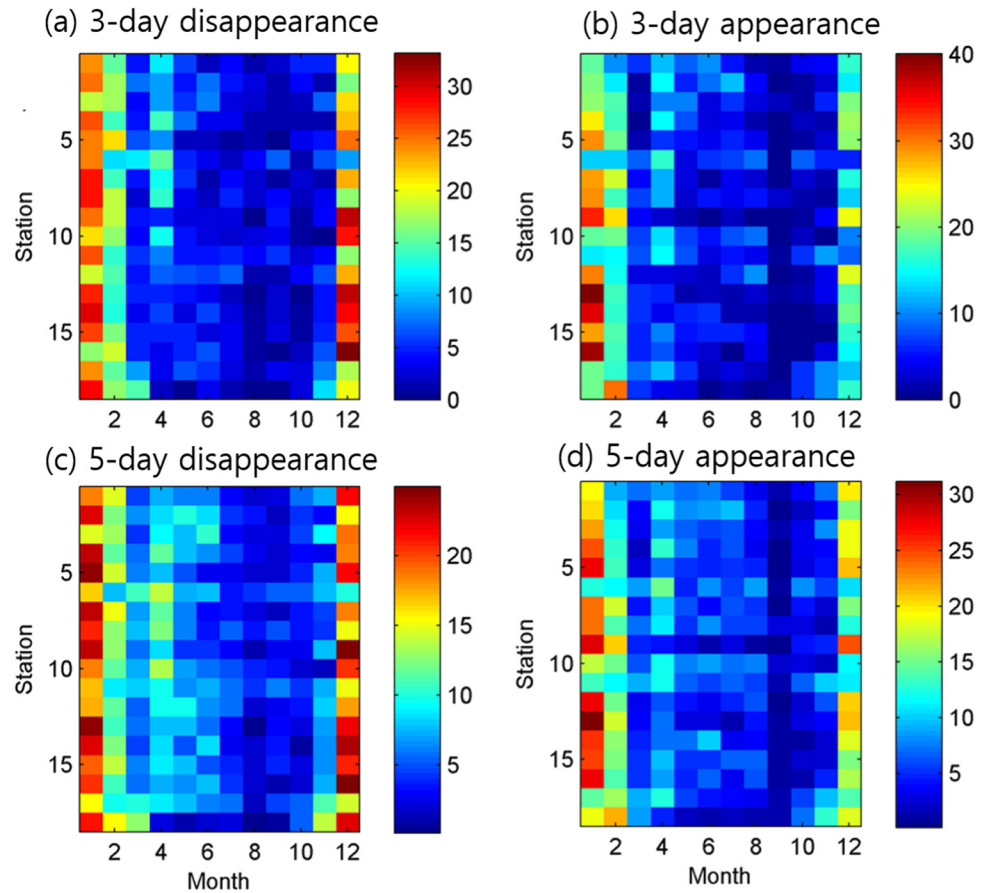
Using 10-year moving windows, a temporal correlation analysis with a number of climate indices and the average temperatures from days with the occurrence of appearing and disappearing days is carried out to investigate probable drivers of changes in unusual events over recent decades (Fig. 7). Over the stations in northern Germany, there is a strong link with AMO index in the disappearing conditions from both sequences, while there is a weak correlation over the other stations. Other climate indices show weak correlations with the average temperatures of disappearing and appearing days (see Fig. 8a, c).

NAO shows a strong correlation with the average temperatures in appearing behaviors (Fig. 8b, d). In addition, the AO index shows a relatively stronger correlation with the average temperature of 3- and 5-day appearances from the stations over southern Germany (ID 12–15). While stations at around 1000 m above sea level (ID 6, 11, and 17) show a high correlation with AMO, Zugspitze (ID 18) at 2964 m.a.s.l. shows a strong correlation with AO, PDO, and NAO, indicating that there is no dominant climate driver among them. Particularly in a 5-day sequence, the majority of stations have a weak correlation with PDO.

A further study can be conducted using climate models to investigate whether the behavior of simulated unusual events is consistent with the observed pattern and how it changes in different future scenarios. This will help us identify the trajectories of unusual events, eventually guiding adaptation and mitigation strategies practically in order to mitigate their impact in the future (unusual climate-related disaster risk).
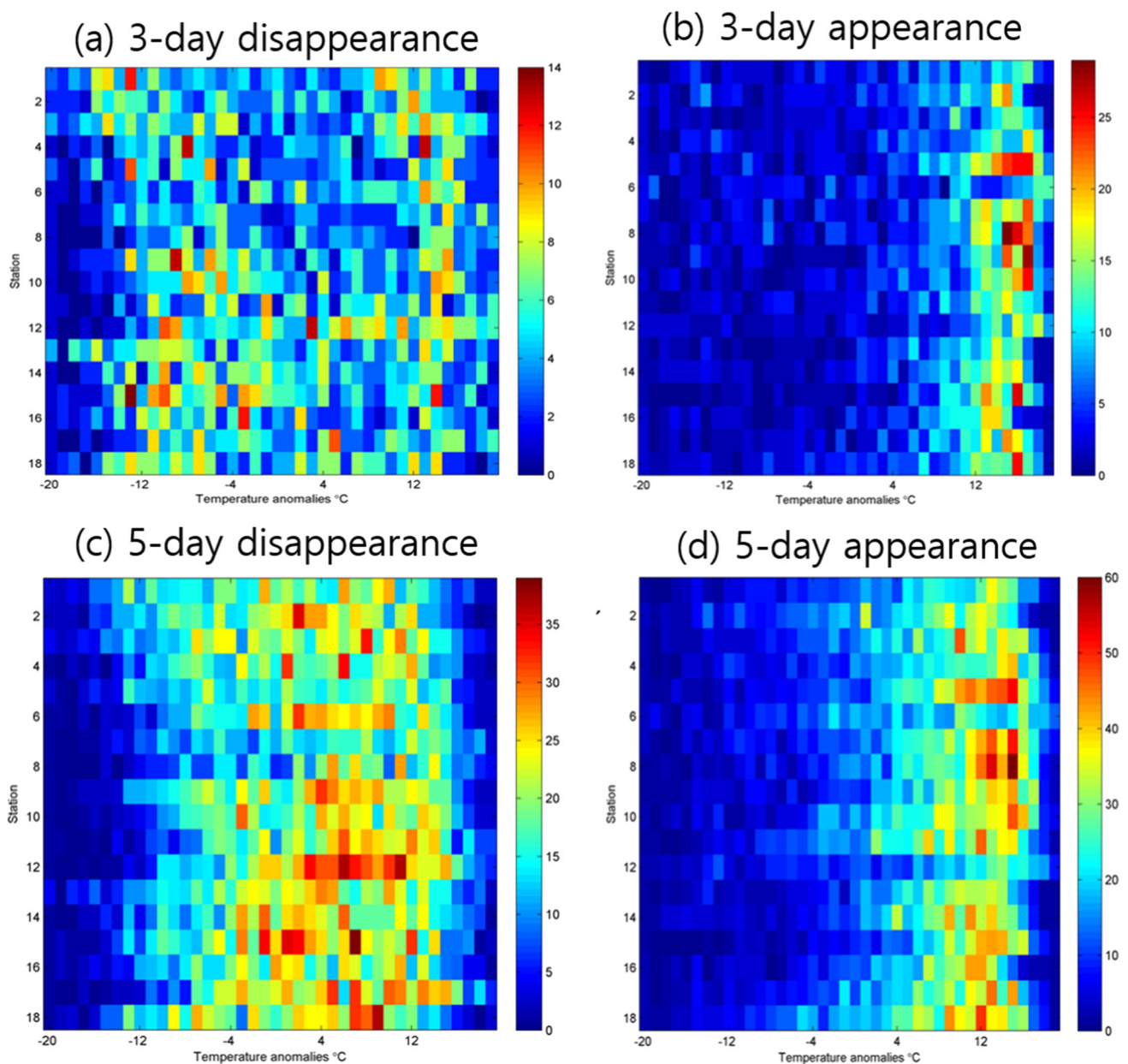
Fig. 6 Frequency of the temperature anomaly averages of disappearing and appearing days from the 3-day (**a** and **b**) and 5-day (**c** and **d**) sequences

5 Conclusions

In this study, the occurrence of unusual mean temperature events in multivariate data sets was defined through a cross-depth analysis using the outlyingness function. From a statistical point of view, unusual events were defined based on the interaction of series in a geometrical data set. Under this definition, combinations of extremes on a temporal scale
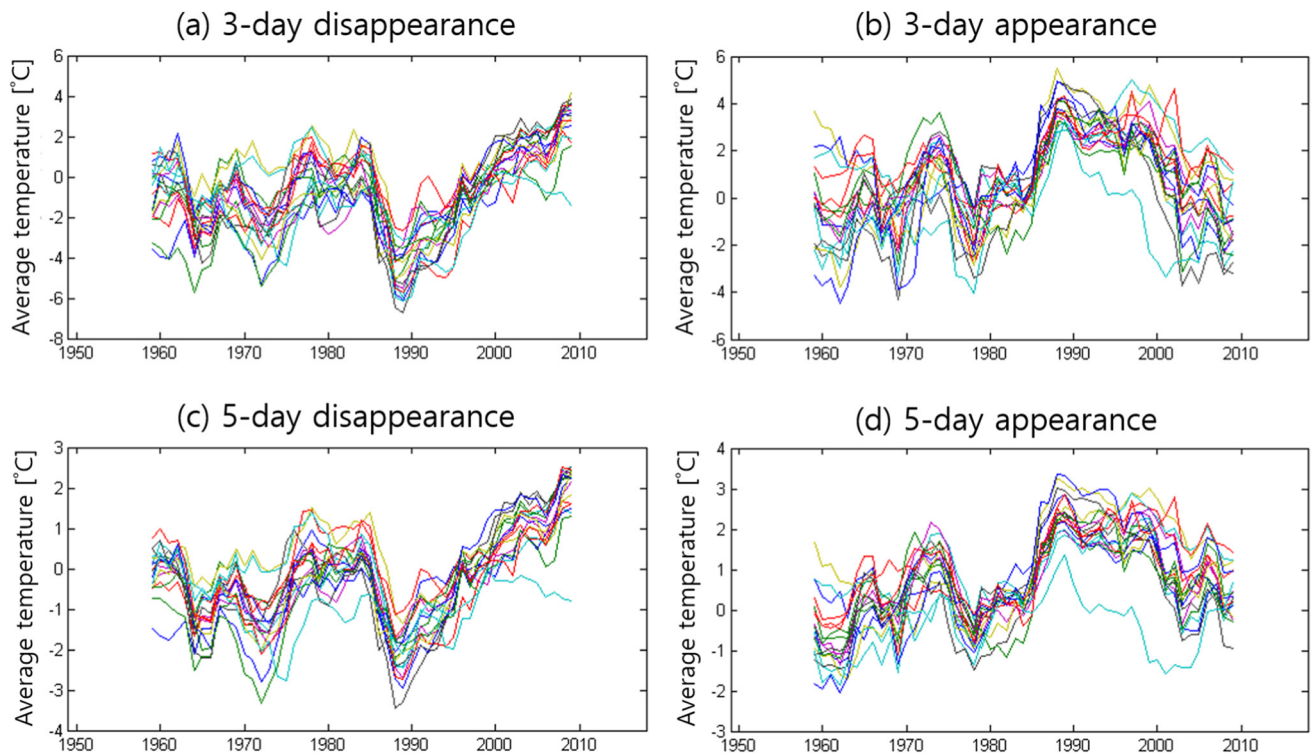
Fig. 7 10-year running means of the averaged temperatures of 3-day with the occurrence of disappearance (**a**) and appearance (**b**) and 5-day with the occurrence of disappearance (**c**) and appearance (**d**) at 18 stations over Germany

might also be considered unusual. Furthermore, the statistical significance of the results was tested by a bootstrap-based method.

A daily mean temperature series from 18 stations in Germany was investigated on a temporal scale over 1949–2018. It shows that changes in the occurrence of unusual events are detectable between the two equal periods, 1949–1983 and 1984–2018, respectively. Furthermore, most of the disappearing and appearing days occurred during the winter season. Additionally, the interaction of positive mean temperature series (extreme surface warming) is a major contributor to the number of appearing days. It's interesting to note that the Atlantic Multidecadal Variability and Arctic Oscillation/North Atlantic Oscillation indices are linked to these days of unusual warming winter temperature events at high and low altitudes. This information can also be taken into consideration for relevant policies in adaptation planning, such as in the agriculture sector and energy supply.
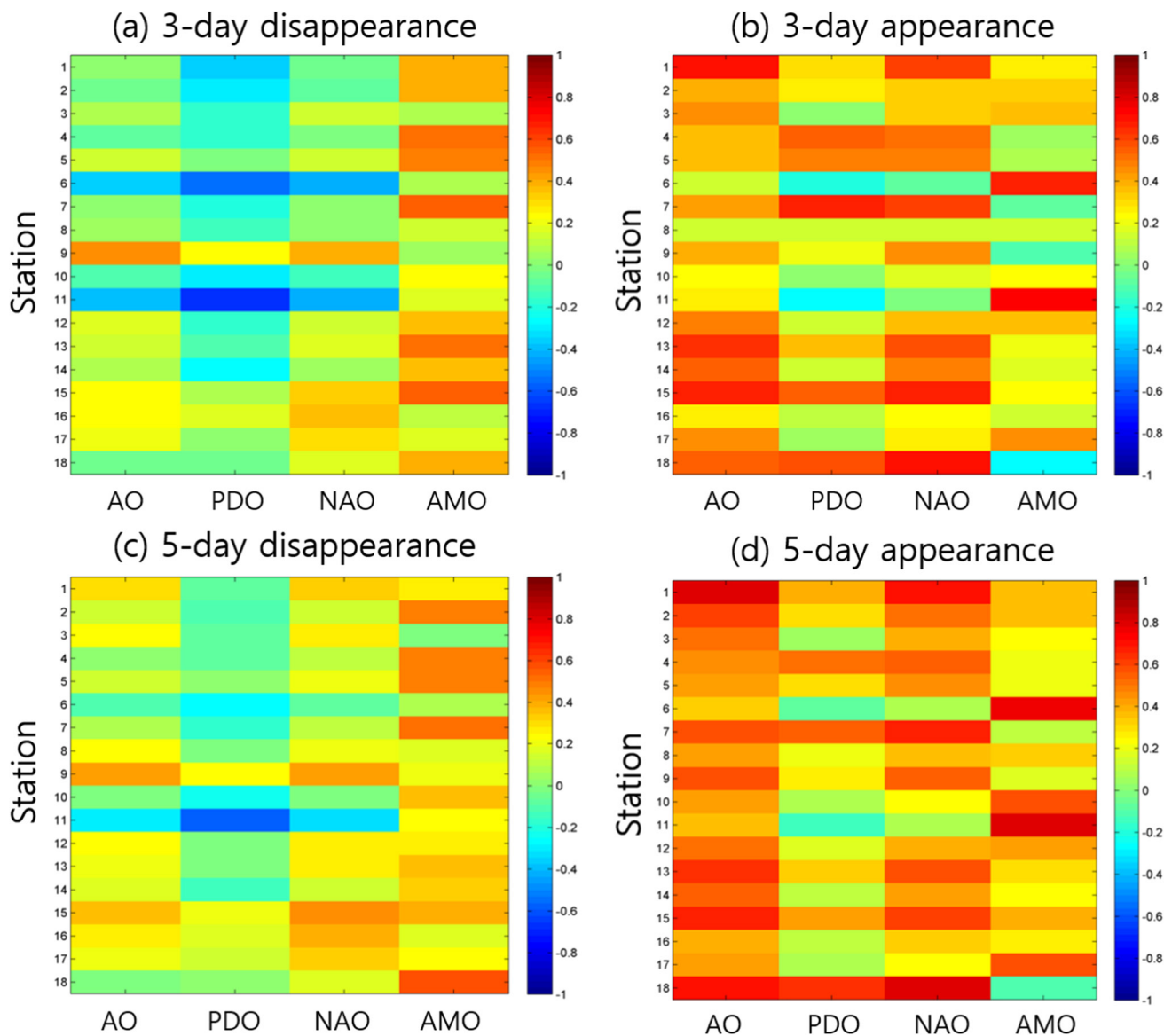
Fig. 8 Temporal correlation coefficients between the 10-year running of the average temperature anomalies of 3-day and 5-day sequences with the occurrence of disappearance (**a** and **c**, respectively) and appearance (**b** and **d**), respectively) and climate indices (AO, PDO, NAO, and AMO)

Declarations

Competing interests The author has no relevant financial or non-financial interests to disclose.

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