Climate Dynamics (2019) 53:4217–4232
https://doi.org/10.1007/s00382-019-04783-4

On the weather types that shape the precipitation patterns across the U.S. Midwest

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Received: 4 December 2018 / Accepted: 17 April 2019 / Published online: 24 April 2019

Abstract

The U.S. Midwest is an area that has been plagued by heavy and persistent precipitation leading to frequent flood events. The improved understanding of the types of weather conditions and settings associated with heavy precipitation can provide basic information to improve our preparation for and response to these events. Here we identify five weather types from daily 500-hPa geopotential height using the k-means cluster analysis. Consistent with their distinct large-scale atmospheric patterns, these weather types exert different effects on precipitation in the Midwest. Weather type 1 (WT1) features a zonally-aligned wave train propagating from the North Pacific to North America. Overall, WT2 is characterized by a wave train pattern with high (low) pressure in the western (eastern) United States. WT3 features a unique pattern with a high pressure system over the continental United States except for the northwestern United States, similar to the La-Niña forced responses. WT4 is characterized by a wave train moving from the Pacific Northwest to the North Atlantic with a strong ridge over the western United States, while WT5 features a positive geopotential height anomaly originating from the Arctic, probably influenced by the Arctic Amplification. Because of the strong moisture transport, strengthened low-level jet stream and wavy upper-level polar jet stream located in the western United States, among the five weather types WT1 exerts the strongest impacts on precipitation, accounting for up to 40% of the total precipitation over the Midwest, followed by WT5. Moreover, we detect a significant upward trend in the number of WT1 and WT5 events for 1948–2017 and their persistency, suggesting a rising risk of heavy and long-lasting precipitation across the Midwest. Overall, the weather types during summer and winter are consistent with those obtained from the analysis of the entire year, although the weather types during winter have a larger magnitude in the geopotential height anomaly. WT1 accounts for the largest contribution to total precipitation in the Midwest during summer and winter.

Keywords Weather types · Precipitation pattern · U.S. Midwest

1 Introduction

The U.S. Midwest represents one of the most intensely cultivated areas in the world (e.g., Prince et al. 2001), but also a region that frequently experiences extreme flooding caused by heavy and long-lasting precipitation (e.g., Andresen et al. 2012; Dirmeyer and Kinter 2010; Groisman et al. 2001; Mallakpour and Villarini 2015; Mallakpour et al. 2017; Najibi et al. 2017; Nakamura et al. 2013). The floods in 1993 and 2008 are two examples of the catastrophic impacts that these events can exert on the people living in and on the economy of the Midwest (Bell and Janowiak 1995; Budikova et al. 2010; Guttman et al. 1994; Smith et al. 2013; West 2010). Therefore, it is of central importance for our improved preparation against these events to understand the climate drivers and physical mechanisms responsible for precipitation and extremes in the Midwest.

Major advances have been made to understand the variability of precipitation and climate modes underlying the precipitation changes in the Midwest (e.g., Angel and Huff 1997; Huff and Angel 1992; Mallakpour and Villarini 2016; Market et al. 2003; Najibi et al. 2017; Villarini et al. 2011, 2013). For example, heavy precipitation in the Midwest is closely related

Electronic supplementary material The online version of this article (https://doi.org/10.1007/s00382-019-04783-4) contains supplementary material, which is available to authorized users.

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to moisture transport (e.g., Gimeno et al. 2016) associated with the Great Plains low level jet stream (e.g., Cook et al. 2008; Feng et al. 2016; Higgins et al. 1997; Krishnamurthy et al. 2015) and atmospheric rivers (e.g., Lavers and Villarini 2013, 2015; Nakamura et al. 2013; Nayak and Villarini 2017). In addition, heavy precipitation in this region is modulated by pressure patterns associated with the Pacific–North American (PNA) teleconnection pattern (e.g., Harding and Snyder 2015), the North Atlantic subtropical high (e.g., Cook et al. 2008; Li et al. 2012) and mesoscale convective systems (e.g., Ashley et al. 2003; Feng et al. 2016; Fritsch et al. 1986; Schumacher and Johnson 2005) occasionally associated with atmospheric rivers (e.g., Moore et al. 2012). However, numerical weather prediction systems still exhibit limited skill in predicting extreme precipitation events several days ahead, representing a significant challenge when we try to extend the lead time up to 2 weeks (Cheruy et al. 2014; Lin et al. 2017). The lack of prediction skill for heavy precipitation may arise from our limited understanding of the small-scale, convective nature of intense precipitation and the large-scale circulation patterns determining the spatial patterns of precipitation. An approach to overcome this limitation is through the examination of weather types/regimes and their impacts on extreme precipitation.

Weather types/regimes are large-scale circulation patterns in atmospheric systems, playing important roles in affecting weather and climate (e.g., Coleman and Rogers 2007; Francis et al. 2018; Michelangeli et al. 1995; Muñoz et al. 2017; Raktham et al. 2015; Robertson and Ghil 1999; Sanchez-Gomez et al. 2009; Straus et al. 2007). More specifically, a typical weather regime is tied closely to unique temperature and precipitation patterns (e.g., Robertson and Ghil 1999; Santos et al. 2005; Yiou and Nogaj 2004). In North America, previous studies used reanalysis data and identified weather regimes in the North Pacific and North America (e.g., Amini and Straus 2019; Casola and Wallace 2007; Francis and Vavrus 2012; Vigaud et al. 2018), and the continental United States (e.g., Agel et al. 2018; Farnham et al. 2018; Loikith et al. 2017; Robertson et al. 2015; Roller et al. 2016). For example, Robertson et al. (2015) reported clear associations between large-scale circulation patterns and historical extreme flooding events on the Ohio River Basin associated with pronounced moisture flux during March–May. More recently, Farnham et al. (2018) found that the extreme precipitation in the Ohio River basin is related to geopotential height patterns in both observations and model simulations during March–May. However, there are still open questions related to whether, the extent to which and how weather regimes influence precipitation patterns across the Midwest more broadly and beyond the spring season. This study aims at providing a comprehensive examination of weather patterns and their impacts and tendencies from the second half of the 20th century to the present. More specifically, we want to unravel the weather/circulation regimes in the United States, to investigate the connections between weather regimes and precipitation patterns in the Midwest during the four seasons, and to assess their variability and underlying physical mechanisms during the 1948–2017 period.

2 Data and methods

We use daily atmospheric variables (e.g., 500-hPa geopotential height and 200-hPa wind fields) archived in the National Centers for Environmental Prediction and the National Center for Atmospheric Research (NCEP/NCAR) reanalysis data with a spatial resolution of $2.5° \times 2.5°$ for the period from 1948 to 2017 (Kalnay et al. 1996). We calculate the daily 500-hPa geopotential height anomaly by subtracting the climatology of the day of interest computed with respect to the base period 1981–2010, following the guidance by the World Meteorological Organization (WMO) on the calculation of standard climatological normals which recommends a rolling 30-year period updated every 10 years (WMO 2017) with the most-recent period being 1981–2010. Daily precipitation for the continental United States is obtained from the National Oceanic and Atmospheric Administration (NOAA)'s Climate Prediction Center (CPC) at a spatial resolution of $0.25° \times 0.25°$ available from 1948 to 2017 (Chen et al. 2008).

To identify the weather regimes, we apply the k-means clustering algorithm (Hartigan and Wong 1979; MacQueen 1967) to the daily 500-hPa geopotential height anomalies for the spatial domain from 140 to 60°W and from 10 to 50°N, which covers the continental United States. The k-means clustering algorithm has been widely used to identify weather types/regimes (Michelangeli et al. 1995; Robertson and Ghil 1999; Christiansen, 2007; Vrac and Yiou 2010; Robertson et al. 2015; Amini and Straus 2019); although Self Organizing Maps (SOMs) and empirical orthogonal function (EOFs) have been used to derive weather types/regimes (e.g., Cheng and Wallace 1993; Kimoto and Ghil 1993; Francis et al. 2018; Hempelmann et al. 2018), the k-means method is used in this study because of its good separability, and temporal and spatial stability (Huth 1996; Huth et al. 2008). We define as persistent weather types those events for which the same weather type lasts for at least four consecutive days (Francis et al. 2018). The k-means clustering algorithm is an unsupervised learning algorithm using distance as measurement (e.g., Han and Kamber 2001; Steinbach et al.2000). The fundamental idea is to define k centroids for k clusters. Each object is assigned to the nearest centroid. At each step we need to recalculate the centroids after the previous object has been assigned, and assign the next object to the updated centroids. This is performed until each object has been assign to one of the k clusters. The objective function to be minimized during clustering is:

$$O = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| x_i^j - c_j^2 \right\|, \tag{1}$$

where O is the objective function, $\left\| x_i^j - c_j^2 \right\|$ is a measure of distance between the data point x_i^j and the center of a cluster c_j which represents the distance of n points from their corresponding cluster centers. In this study, the n time steps of the reanalysis data are considered as n data points, each of which is a spatial map of the 500-hPa geopotential height anomaly. Euclidean distance is used to determine the nearest centroid. The k-means cluster analysis assigns each data point to one of the k clusters.

The number of clusters are selected based on the current understanding of weather types in the United States and North America, and deciding whether additional clusters bring enough additional information to grant their inclusion. To decide the number of clusters, we start by considering that the number of commonly-used weather types in the United States ranges from four to seven using k-means cluster analysis (e.g., Agel et al. 2018; Robertson et al. 2015; Roller et al. 2016); moreover, any new additional cluster should not be similar to any of the other identified ones. Here we have performed a sensitivity analysis by considering between four and seven clusters; we have selected five clusters because our analyses indicate that four clusters are too few while six or seven clusters bring redundant information in terms of patterns (Figures S1–4).

We use Poisson regression to calculate the trends in the frequencies of weather types in each year or season. The slope of Poisson regression (β) represents the trend in the frequency of weather types.

Moisture flux is an important ingredient for precipitation (e.g., Gimeno et al. 2016). We therefore diagnose the precipitation pattern using moisture flux. The moisture flux is defined as:

$$\vec{Q} = \int_{1000}^{300} q\vec{v}dp \tag{2}$$

where $\vec{Q}$ represents the horizontal moisture flux, q is specific humidity, $\vec{v}$ represents wind vector with the zonal (u) and meridional (v) components, and p the pressure level. We integrate $q\vec{v}$ from the 1000 hPa–300 hPa level to obtain the moisture flux ($\vec{Q}$). The moisture flux is calculated based on three-dimensional specific humidity, and zonal and meridional winds at daily scale using NCEP/NCAR reanalysis data.

Overall, the strong moisture flux lifted by the cold air mass associated with the polar jet stream is conducive to heavy rainfall. In addition to the moisture flux, we analyze upper-level winds (200-hPa) to represent the polar jet stream which is associated with cold temperature from the polar region. Heavy precipitation events are defined as those exceeding a threshold equal to the 95th percentile of the precipitation distribution at each spatial grid.

3 Results

3.1 Weather types and precipitation

We have identified five weather types from the 500-hPa geopotential height anomalies (Fig. 1; left panels). The WT1 features a zonal wave train propagating from the North Pacific to the eastern United States. The positive 500-hPa geopotential height anomaly of this weather type represents a high pressure system extending to the eastern Unites States, accompanied by a low pressure system over the western United States associated with the intrusion of polar cold air (Fig. 1a). This zonal wave train pattern is similar to the pattern of geopotential height anomaly associated with heavy precipitation in the central United States (e.g., Mallakpour et al. 2017). Moreover, the 200-hPa geopotential height outlines a low-pressure in the upper level over the western United States, suggesting a wavy upper-level jet stream (Fig. 1f). The upper-level jet stream separates the cold air in the polar region and warm and humid air in the tropics and subtropics (Fig. 1f). Therefore, the lifting associated with cold air from the Arctic caused by a wavy upper-level jet stream is an important factor for causing heavy precipitation (Schultz 2004). The weather setting in WT1 leads to strong low level jet stream over the Midwest, revealed as strong moisture flux transport from the Gulf of Mexico to the Midwest lifted by cold air from the Arctic (Fig. 1f), favorable for heavy frontal precipitation and the development of mesoscale convective systems over the area. The moisture transport associated with WT1 is similar to "The Great Plains Jet" and "The Maya Express" (Dirmeyer and Kinter 2009; Knippertz and Wernli 2010; Lavers and Villarini 2013; Nakamura et al. 2013). In addition to moisture transport and 200-hPa geopotential height, we also examine the spatial pattern of sea level pressure which has been used to diagnose heavy precipitation in the Midwest (e.g., Gutowski et al. 2010; Holman and Vavrus 2012; Kawazoe and Gutowski 2013). The pattern of sea level pressure also exhibits a strong potential for heavy precipitation in the Midwest with anomalously low sea level pressure (Figure S5).

Opposite to WT1, WT2 features a negative 500-hPa geopotential height anomaly over the eastern United States and a positive anomaly over the western United States (Fig. 1b). Because the wavy jet stream with low 200-hPa geopotential height is shifted to the eastern United States,

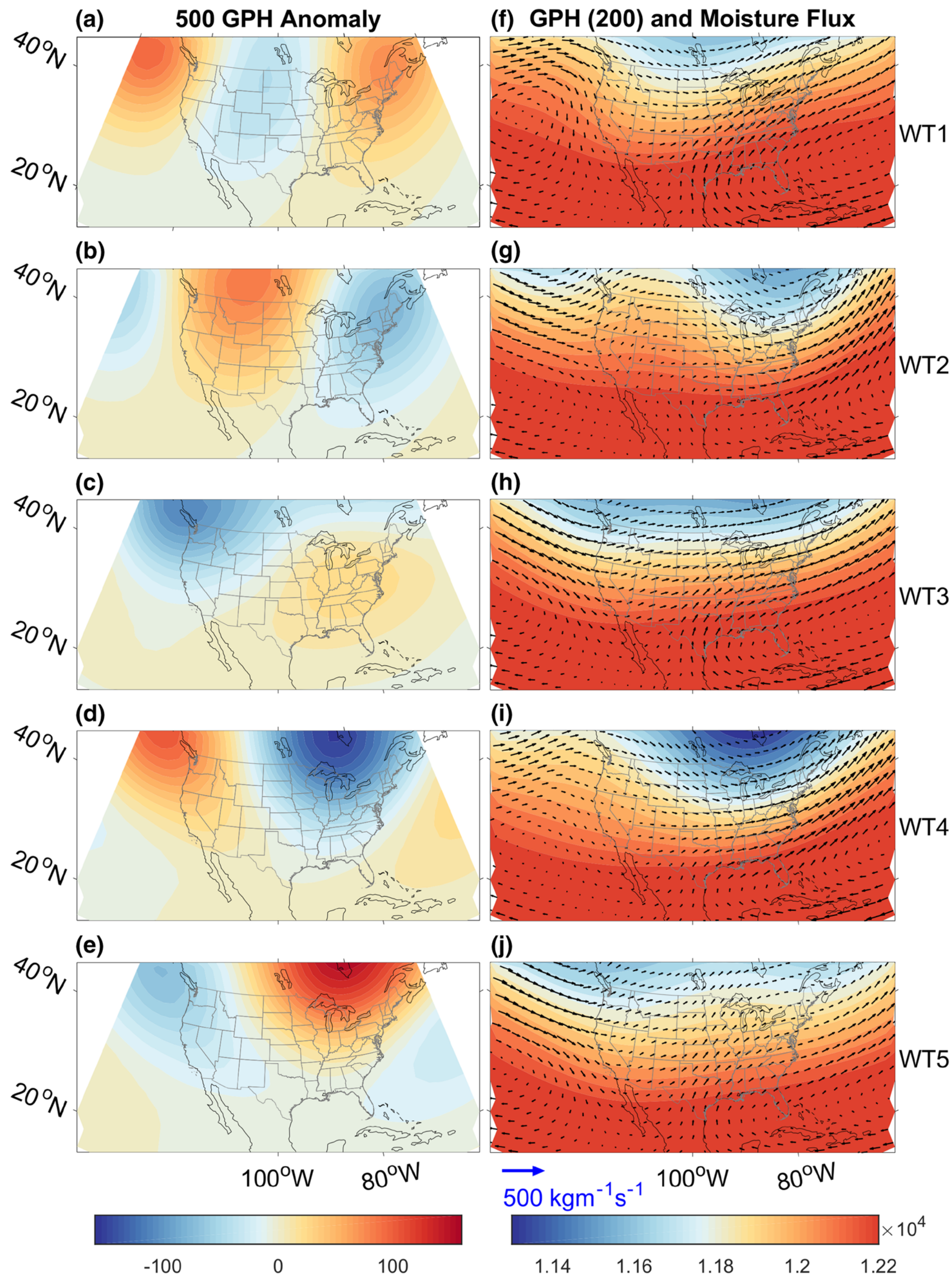

Fig. 1 Left panel: maps with the five weather types/regimes (WT1-5) derived from the 500-hPa geopotential height (unit: gpm) and k-means cluster analysis. Right panels: moisture flux (vector) and 200-hPa geopotential height (shading, unit: gpm) for the five weather types. The numbers of days assigned to WT1-5 are 5503, 5836, 5782, 4115, and 4613 respectively

the moisture transport to the Midwest for WT2 is suppressed compared with to WT1 (Fig. 1, panels b and g). WT3 features a high pressure system over the continental United States with the exception of the northwestern United States (Fig. 1c), similar to the La-Niña forced responses (Straus and Shukla 2002). In addition, WT3 enhances moisture transported to the southeastern United States (Figs. 1, panels c and h). However, the polar jet stream is located more poleward compared to WT1, indicating that less cold air mass can move equatorward to the western United States, critical for the development of frontal systems (Fig. 1h). WT4 features a high pressure system over Florida, favorable for moisture transport to the southeastern United States, together with the polar jet stream located north of the southeastern United States (Fig. 1d), leading to favorable conditions for precipitation in the southeastern United States. WT4 is similar to the 'Ω block' weather type (Robertson and Ghil 1999) which focused on the Pacific Coast. WT5 features a wave train moving from the Pacific Northwest to the North Atlantic, with a ridge elongated in upper-level geopotential heights (Fig. 1e), likely caused by enhanced warming in Arctic known as the Arctic Amplification (Francis et al. 2018; Francis and Vavrus 2012; Overland et al. 2015). The

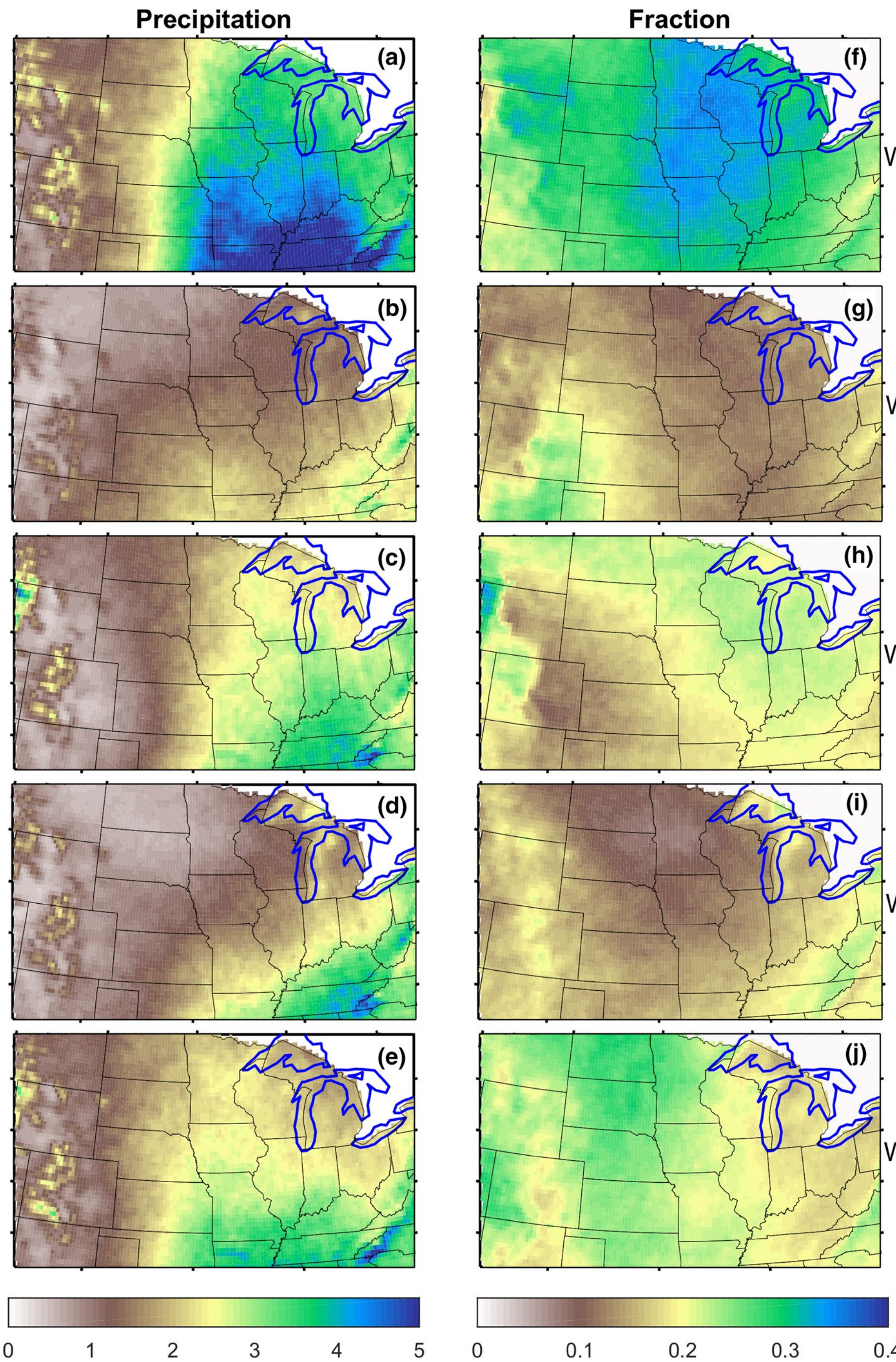

Fig. 2 Left panels: composite precipitation rate (unit: mm) across the Midwest for each weather type (WT1-5). Right panels: fractional contribution of precipitation by each weather type to the total precipitation

composite 200-hPa geopotential height for WT5 is higher than for the other weather types, while the moisture flux transport transported to the Midwest is weaker compared with WT1 and WT3 (Fig. 1j).

The identified weather types are associated with distinct precipitation patterns across the Midwest (Fig. 2; left panels). The composite rainfall is calculated by averaging the rainfall rate over the days associated with each weather type (e.g., WT1) on a grid basis. Meanwhile, the fractional contribution of precipitation for each weather type is computed by dividing the total rainfall in each weather type by that of all the weather types. WT1 is tied to very large precipitation over the study region (Fig. 2a), consistent with the moisture transport and low-level jet stream, and the polar cold air intrusion caused by the wavy polar jet stream in the western United States (Fig. 1, panels a and f). Because of its remarkable impacts on precipitation, we refer to WT1 as the 'Midwest Water Hose.' As expected, WT2 results in much smaller precipitation amounts over the Midwest compared to WT1 (Fig. 2b). WT3 produces higher precipitation than WT2, but lower precipitation than WT1, probably due to the fact that the North Atlantic subtropical high is so strong that it transports moisture westward instead of enhancing moisture transport in the Midwest (Fig. 1c, 2c), similar to what was discussed in Zhang and Villarini (2017). WT4 produces a precipitation pattern similar to WT2, albeit with a slight enhancement in the southeastern part of the Midwest because of the interactions between the polar jet stream and the moisture transport (Fig. 2d). The precipitation pattern of WT5 is similar to WT3, with rainfall shifted slightly towards the Rocky Mountain (Fig. 2e).

Because there are pronounced regional differences in the precipitation climatology across the Midwest, we also analyze the fractional contribution of each weather type to total precipitation (Fig. 2, right panels). WT1 accounts for ~ 35% of the total precipitation across the study region, higher than the other four weather types (Fig. 2f); the second highest contribution is represented by WT5 (Fig. 2j). The highest contribution by WT1 is located in Missouri, Iowa, Wisconsin and Michigan, highlighting the importance of this weather type in shaping the precipitation patterns across the Midwest (Fig. 2f). The pattern and magnitude of the precipitation associated with WT1 suggest that a better understanding of this weather type may provide better prediction for precipitation and flooding in this region. Indeed, Robertson et al. (2015) found that large-scale circulation patterns are responsible for historical extreme flooding events on the Ohio River Basin associated with pronounced moisture transport. Moreover, Farnham et al. (2018) also reported extreme precipitation in the Ohio River basin and relevant geopotential height patterns in observations and model results. Similarly, Nakamura et al. (2013) showed that the composites of synoptic fields for the flood events in the Ohio basin between 1901 and 2008 feature a similar pattern of low-level moisture transport and warm air from the tropical Atlantic Ocean and the Gulf of Mexico.

In addition to the examination of the spatial patterns of geopotential height and precipitation for the five weather types, we also examine their temporal changes. The persistent WT1 has a significant upward trend over the historical period, as does the persistent WT5 (Table 1 and Fig. 3a). The detected trend in WT5 may be associated with higher Rossby wave amplitude which slows down the eastward wave progression associated with the Arctic Amplification (Francis et al. 2018; Francis and Vavrus 2012). In addition, there is a significant downward trend for WT3 (significant at the 0.01 level based on *t* test; Table 1 and Fig. 3). Different from WT1, WT3 and WT5, the trends for persistent WT2 and WT4 are not statistically significant (Fig. 3). Overall, the trends for the frequencies of weather types are consistent with those for persistent weather types (Table 1 and Fig. 3). The spatial maps of total rainfall trend for each weather type at every spatial grid (Fig. 4) are consistent with the time series of the weather types (Fig. 3). For example, the spatial maps of trend in total rainfall for WT1 point to increasing trends, while the trend maps for WT3 are overall negative across the study region (Fig. 4). Because WT1 and WT5 account for a large fraction of the total precipitation in the Midwest, the upward trends of WT1 and WT5 suggest an on-going rising risk for extreme precipitation across the Midwest. This risk is further enhanced by the significant upward trends for the persistent WT1 and WT5. Therefore, the historical data point to an increased risk for a wetter Midwest in terms of weather patterns and their connections with precipitation. Previous studies have found that extreme precipitation in the Midwest exhibits a rising trend because of intensified low-level jet based on observations and this trend is expected to continue based on climate model simulations (Cook et al. 2008; Feng et al. 2016; Lopez et al. 2018).

Table 1 Magnitude and *p* value of the Poisson regression slope for each weather type and their persistence

Annual	Regression slope magnitude	P value
WT1/persistence	0.0075/0.0053	**0.001/0.000**
WT2/persistence	0.0011/0.0015	0.578/0.022
WT3/persistence	− 0.0117/− 0.0093	**0.000/0.000**
WT4/persistence	− 0.0023/− 0.0011	0.350/0.173
WT5/persistence	0.0042/0.0043	**0.010/0.000**

P values smaller than 0.01 are in bold face

3.2 Seasonal change

To complement the examination of the weather types at the annual scale, we examine the changes in their frequency at the seasonal level. WT1 exhibits the strongest upward trend during the summer among the upward trends for all seasons (Table 2 and Fig. 5). With respect to WT2, the upward trend is not significant at the annual scale, while the trend becomes significant for the summer. In contrast with WT1, WT3 shows a downward trend for all the seasons (Table 2 and Fig. 5). Similar to WT2, the trend of WT4 is not significant at the annual scale (Table 2 and Fig. 3) because of the combination of an upward trend during winter (Table 2 and Fig. 5d) and a downward trend during summer (Table 2 and Fig. 5b). The upward trend for WT5 is mostly a result of the trends during spring and autumn (Figs. 5, panels a and c), consistent with the Arctic Amplification (Francis et al. 2018). The spatial patterns of trends in total rainfall for the five weather types during summer and winter (Fig. 4) are in good agreement with the frequencies of the weather types (Fig. 5).

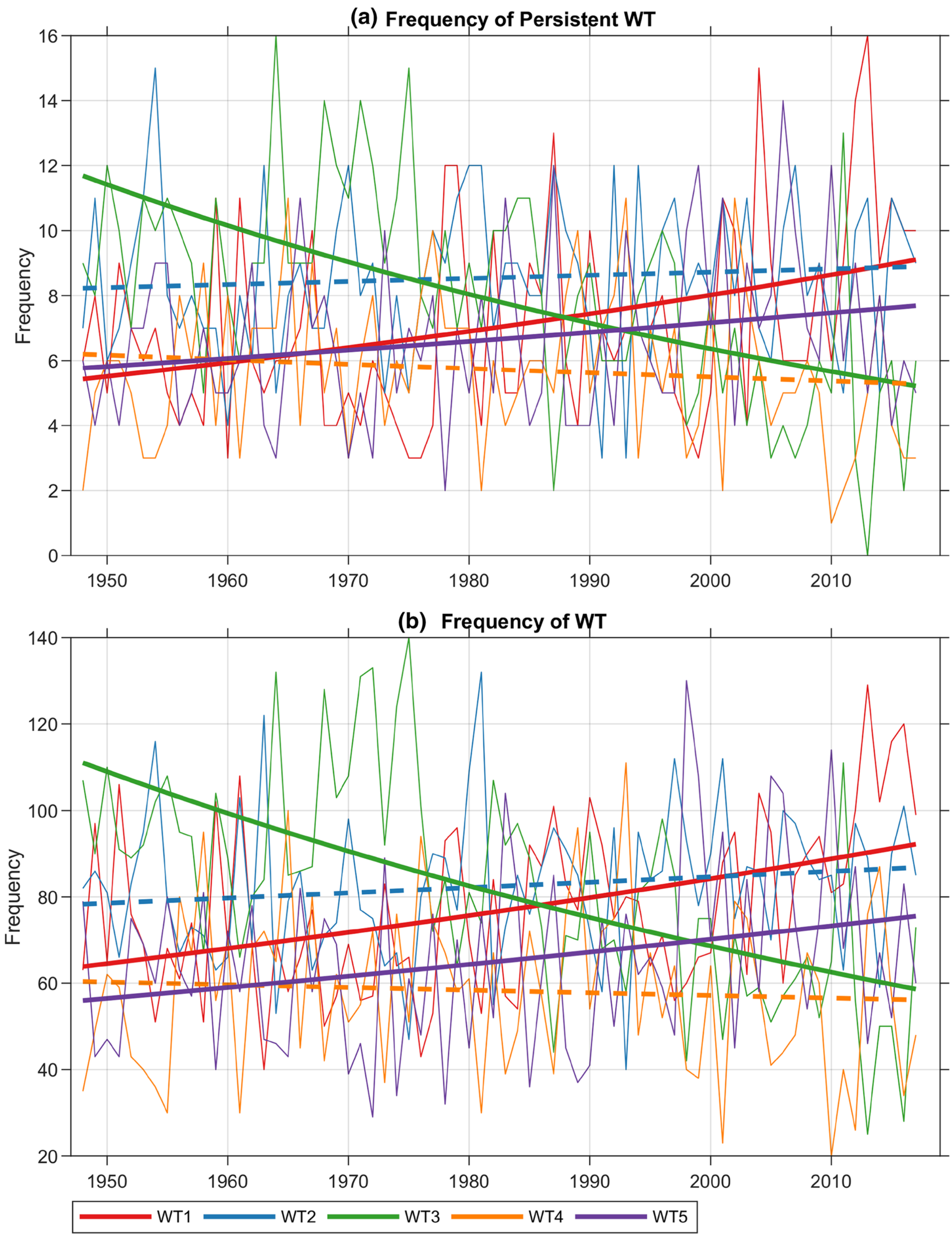

Fig. 3 Time series of the frequency (thin line) and the corresponding fitted line (thick line; based on Poisson regression) for (**a**) persistent weather types and (**b**) weather types. The solid regression lines indicate the trends are statistically significant at the 0.01 level

Overall, the spatial patterns of the weather types during the summer (Fig. 6; left panels) are in agreement with those for the entire year, albeit having a smaller magnitude in geopotential height anomaly during the summer (Fig. 1; left panels). WT1 during summer is responsible for heavy rainfall in the Midwest, suggesting that WT1 plays a crucial role in shaping precipitation over Iowa, Michigan and Wisconsin (Fig. 7a). In contrast, the other weather types produce less

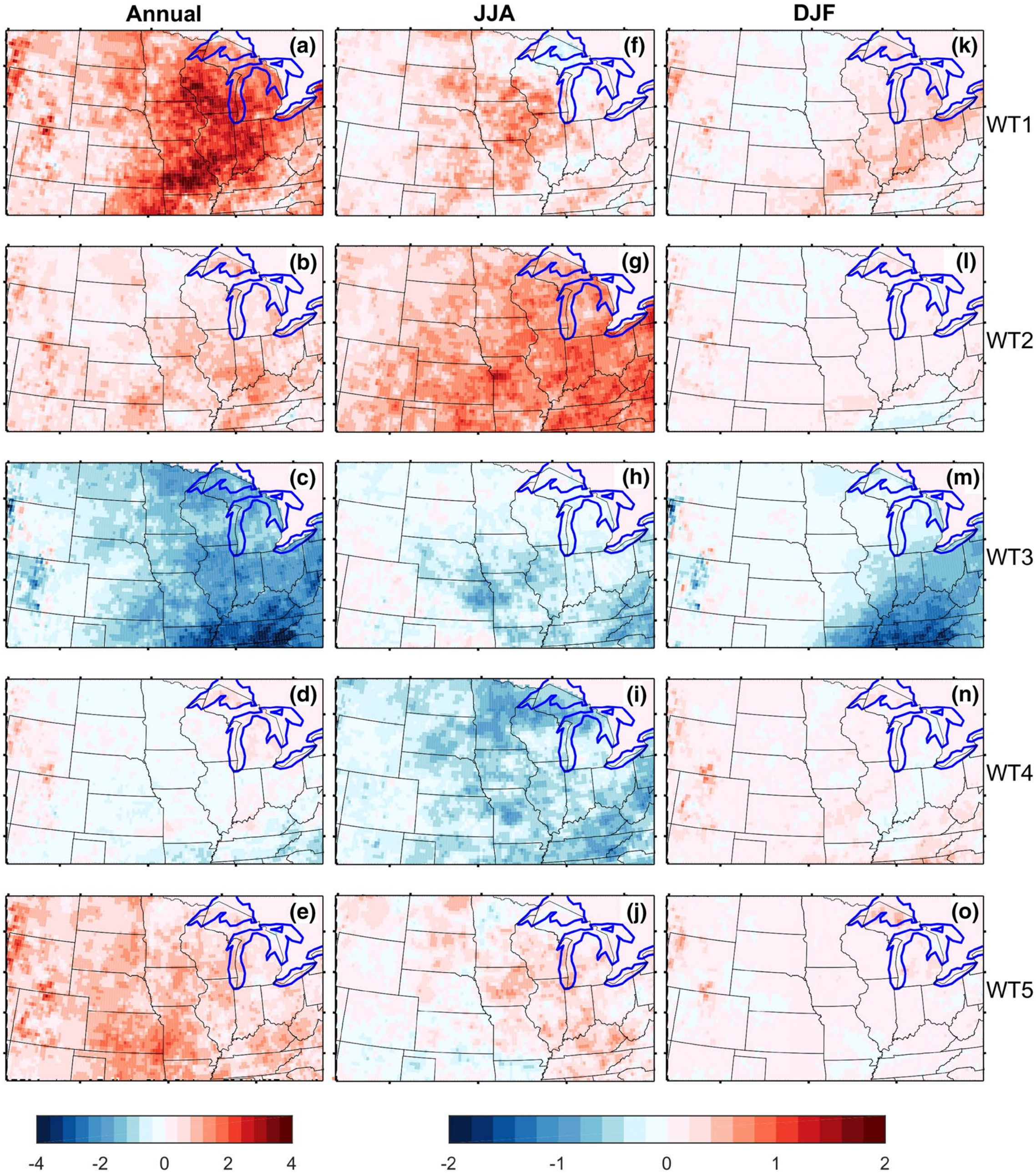

Fig. 4 Annual and seasonal (JJA and DJF) trends (unit: mm/year) of total precipitation in the Midwest for the five weather types (WT1-5)

Table 2 Magnitude and p-value of the Poisson regression slope for each weather type during MAM, JJA, SON and DJF

Seasons	Regression slope magnitude (WT1-5)	P value (WT1-5)
MAM	0.0048/− 0.0002/− 0.0093/− 0.0013/0.0067	**0.000**/0.908/**0.000**/0.409/**0.000**
JJA	0.0070/0.0044/− 0.0089/− 0.0103/0.0019	**0.000/0.000/0.000/0.000**/0.277
SON	0.0045/− 0.0024/− 0.0074/− 0.0007/0.0078	**0.001**/0.065/**0.000**/0.620/**0.000**
DJF	0.0043/0.0039/− 0.0117/0.0038/0.0009	**0.006/0.005/0.000/0.006**/0.506

P-values smaller than 0.01 are in bold face

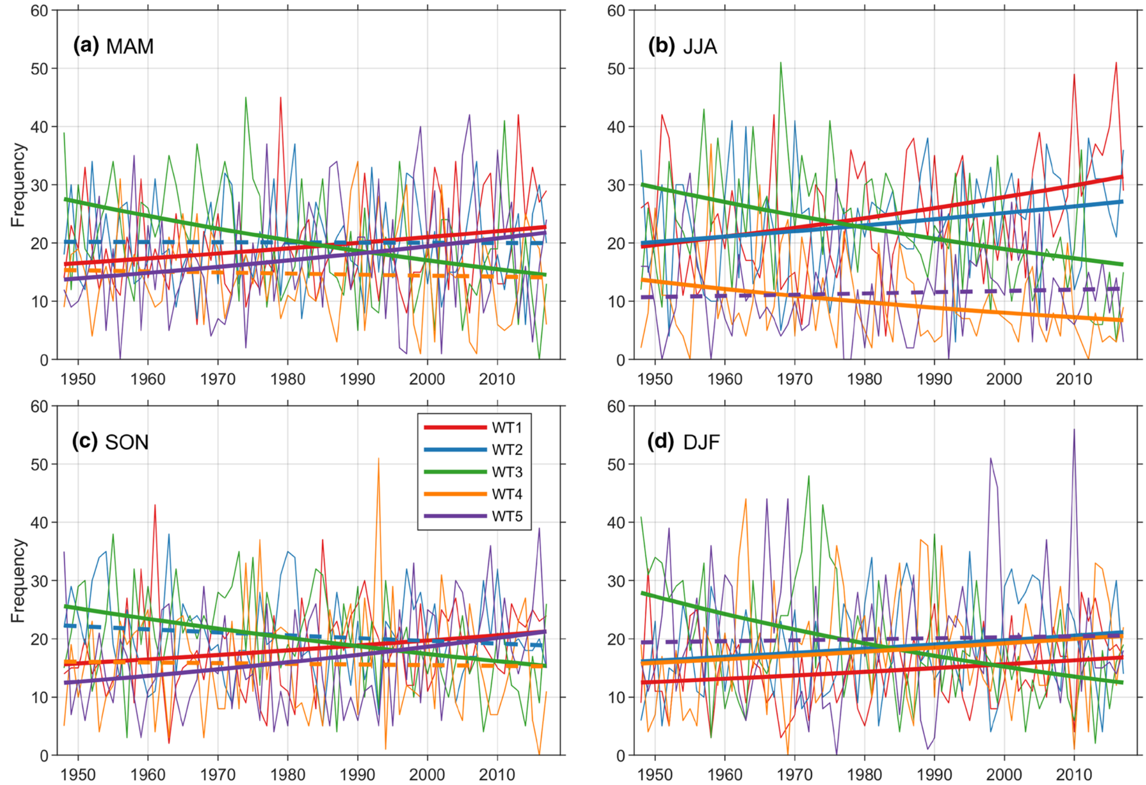

Fig. 5 Time series of the frequencies of weather types and their fitted lines during (**a**) March–April-May (MAM), (**b**) June-July–August (JJA), (**c**) September–October-November (SON), and (**d**) December-January–February (DJF). The solid regression lines indicate the trends are statistically significant at the 0.01 level

rainfall than WT1 during the summer (Fig. 7; left panels). Moreover, WT1 during the summer accounts for the largest fractional contribution to the total precipitation (Fig. 8a).

During winter, the weather types are overall consistent with those for the entire year and for the summer (Fig. 6; right panels). However, the geopotential height anomalies during winter are stronger than those during summer (Fig. 6). In addition, WT1 during summer features the strongest anomaly located more poleward than during the winter (Fig. 6), consistent with a more poleward shift in rainfall during the summer (Fig. 7). The precipitation patterns for the five weather types during the cold season (Fig. 7; right panels) are shifted more southeastward compared with those during the warm one (Fig. 7; left panels). Again, WT1 accounts for the highest contribution among the five weather types followed by WT5, confirming the key role of these two weather types (Fig. 8, panels f and j). There are some differences in the precipitation patterns associated with the weather types during summer and winter. For example, the fractional contribution of precipitation for WT1 during winter (Fig. 8f) is higher than that during summer over the Midwest (Fig. 8a). The striking contribution of WT1 to the total precipitation during winter is associated with the combination of strong moisture transport from the Gulf of Mexico and cold air masses from the Arctic. Moreover, the fractional contribution of precipitation in WT1 during summer and winter exhibits different spatial patterns, with the regions having high fractional contributions located in the northern (central) part of the Midwest during summer (winter) (Fig. 8, panels a and f). Moreover, WT1 and WT5 play more important roles in the precipitation patterns across the study area during winter (Fig. 8, panels f and j) than during summer (Fig. 8, panels a and e). In addition to the fractional contribution to total rainfall, the fractional contribution of WT1 to heavy precipitation events is the largest in the Midwest among the five weather types during JJA and DJF (Fig. 9). In particular, the fractional contribution of WT1 to heavy precipitation events during DJF is larger than 0.4 across the vast majority of the Midwest (Fig. 9). These analyses highlight the key role of WT1 in shaping precipitation patterns in the Midwest. A better prediction of WT1 will mark progress in predicting precipitation in the Midwest, especially during winter.

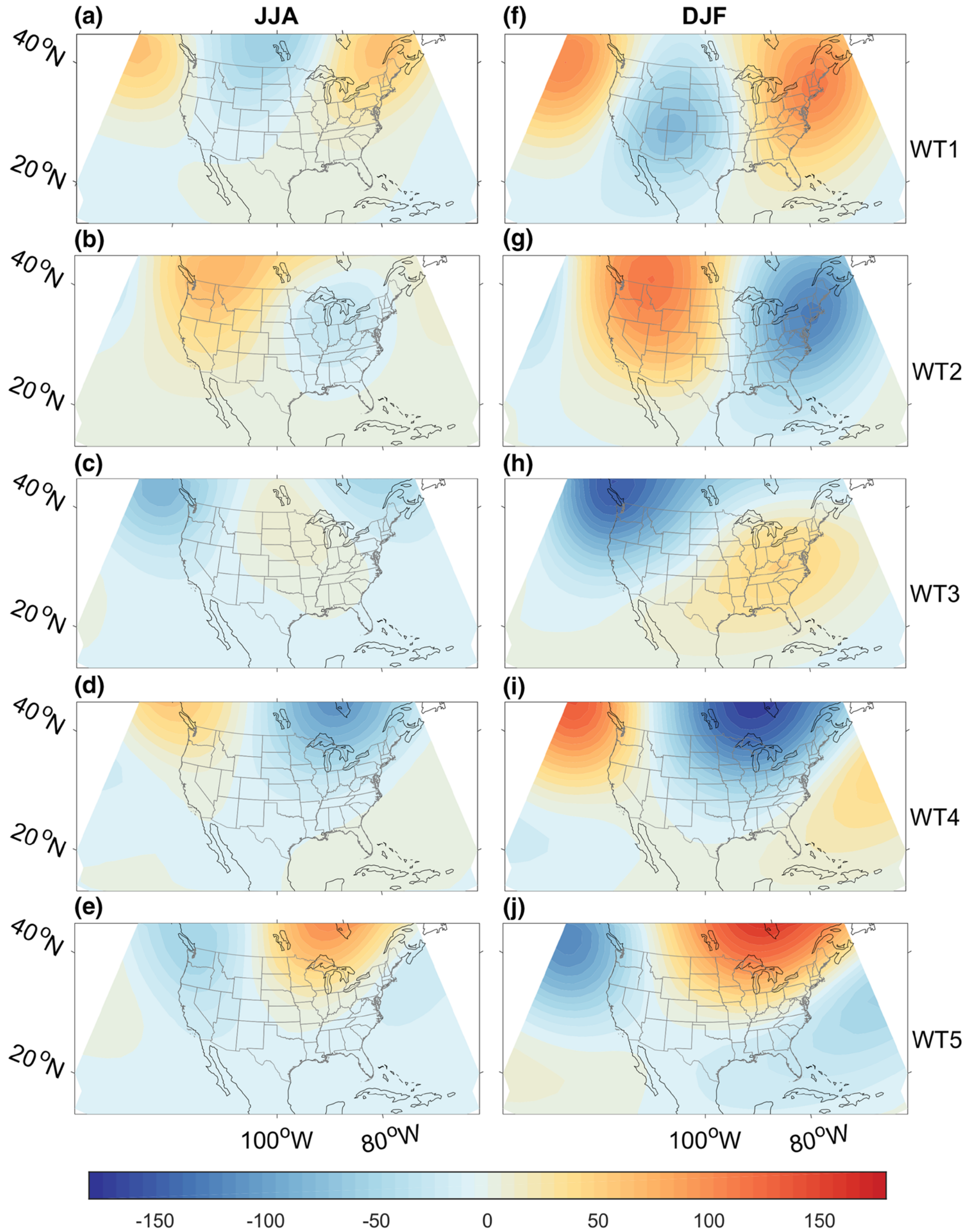

Fig. 6 Five weather types derived from 500-hPa geopotential height (unit: gpm) and k-means cluster analysis during (left panels) JJA and (right panels) DJF. The numbers of days assigned to WT1-5 during JJA are 1368,1162, 1171, 1220 and 1519 while those for DJF are 1138, 1114, 1335, 1337 and 1394

4 Discussion and conclusions

Weather types/regimes are important components of the weather and climate, shaping temperature and precipitation patterns. Extreme weather and climate events are mostly tied with persistent weather regimes. Here we focus on the weather regimes across the United States, with particular interest in the Midwest, which is an area of the country that is severely affected by flooding caused by heavy and long-lasting precipitation events.

We have identified five weather regimes in the spatial domain covering the continental United States using the k-means clustering algorithm. The five weather regimes feature distinct spatial patterns in geopotential height anomaly and moisture transport, leading to different precipitation patterns. WT1 is responsible for the largest precipitation in the Midwest among the five weather types, tied to strong moisture transport, strengthened low level jet stream and a wavy polar jet stream located in the western United States. We detected a significant upward trend in the annual frequency and persistence of WT1, suggesting that there has been a higher risk of heavy and long-lasting precipitation in the Midwest over the most recent decades. WT5 accounts for the second largest contribution to total precipitation in the Midwest, together with a statistically

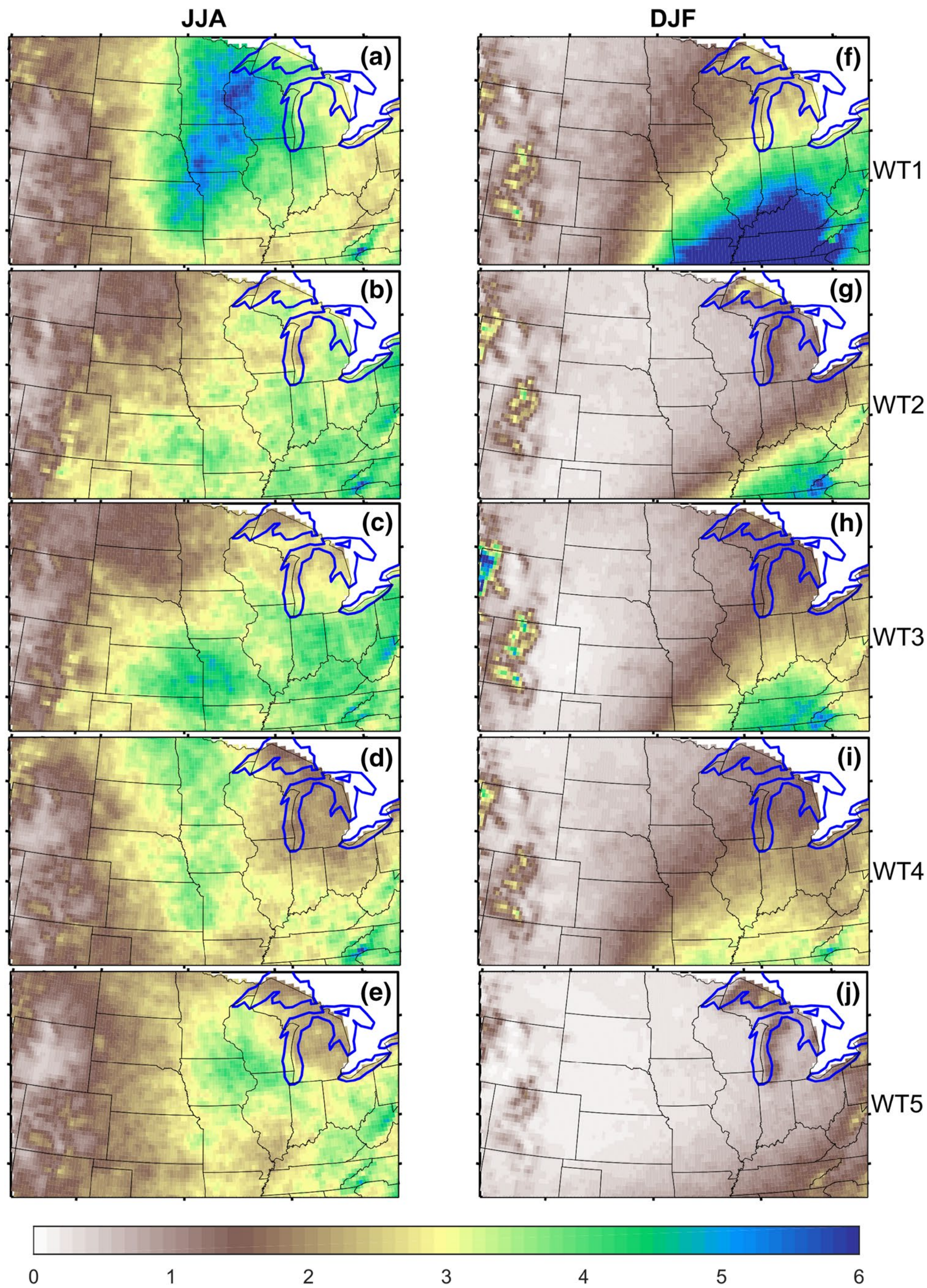

Fig. 7 Composite precipitation rate (unit: mm) during (left panels) JJA and (right panels) DJF in the Midwest for each weather type (WT1-5)

significant upward trend in WT5 and persistent WT5, leading to heavy rainfall in the Midwest. In contrast to WT1 and WT5, WT3 exhibits a significant downward trend in frequency over the historical period. The upward trend in the frequency of WT1 for each season and the decreasing trend in the frequency of WT3 are significant across all the seasons, while the trend for WT5 is significant only during DJF and MAM. Overall, the weather types during JJA and DJF are consistent with those derived from the entire year, though the weather types during DJF have a larger amplitude. The WT1 during both JJA and DJF accounts for the largest contribution to total precipitation in the Midwest, particularly during DJF where it accounts for ~ 40% of the total precipitation. Focusing on MAM, Robertson et al. (2015) and Farnham et al. (2018) identified a weather type similar to WT1 that exerts strong impacts on precipitation and flooding across the Midwest. In particular, the weather type found in Robertson et al. (2015) was closely associated with the La Niña phase of the El Niño Southern Oscillation (ENSO) and phase 5 of the Madden–Julian

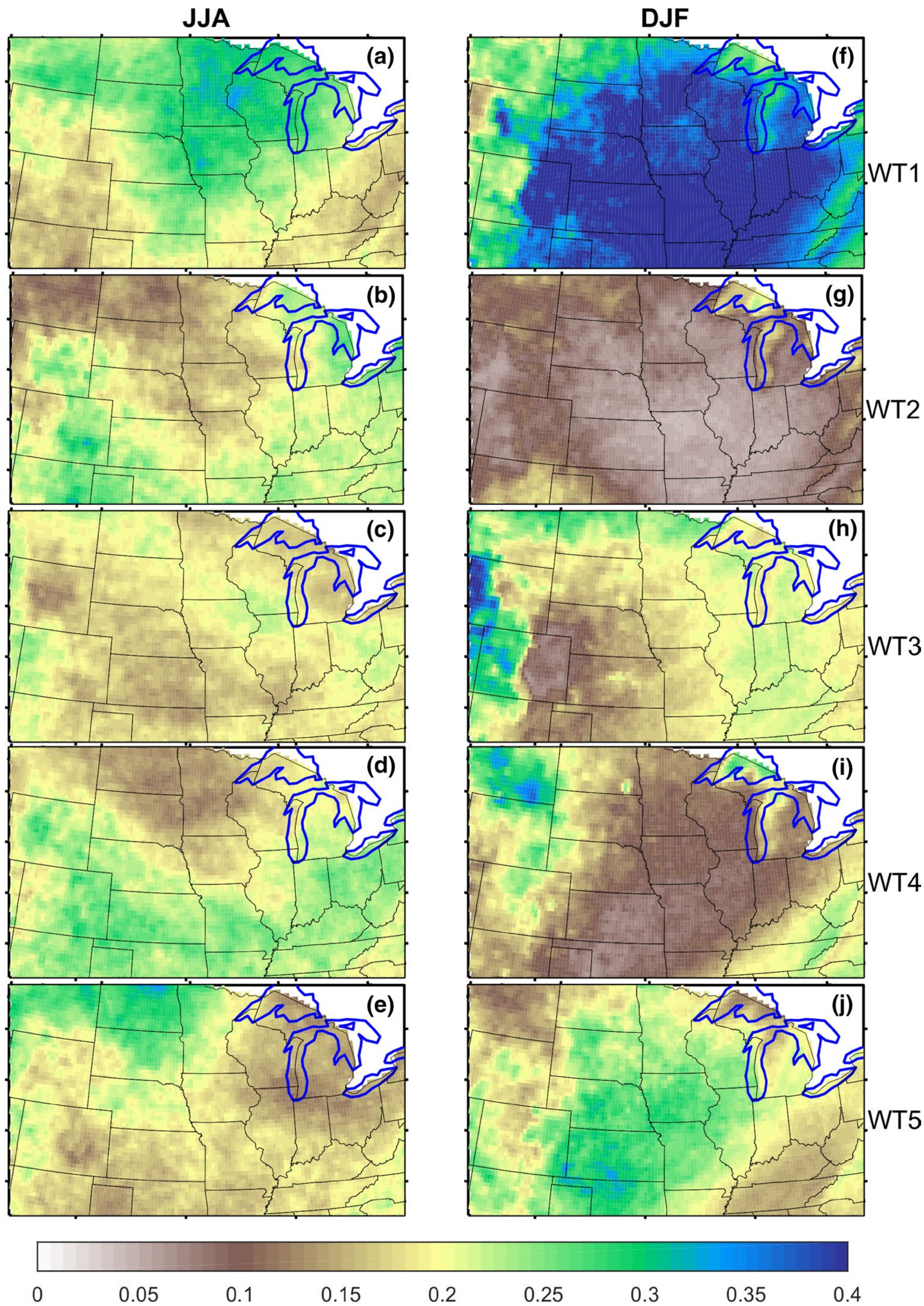

Fig. 8 Fractional contribution of precipitation associated with each weather type to total precipitation during (left) JJA and (right) DJF

Oscillation (MJO) during MAM. Following Robertson et al. (2015), future studies should focus on identifying the drivers of this weather type during all seasons based on observations and climate models.

This study highlights the role of WT1 in shaping the spatial pattern, magnitude and fractional contribution of precipitation in the Midwest. Further research is required to understand the drivers of this weather type at various time scales. If WT1 can be properly predicted using numerical weather prediction systems, we will likely be able to achieve better prediction skill for precipitation patterns and extremes across the Midwest. In particular, persistent weather types (e.g., WT1) can provide potentially useful information that can be leveraged to increase the skill in forecasting extreme precipitation. The identification and forecasting of persistent weather types and sequencing of

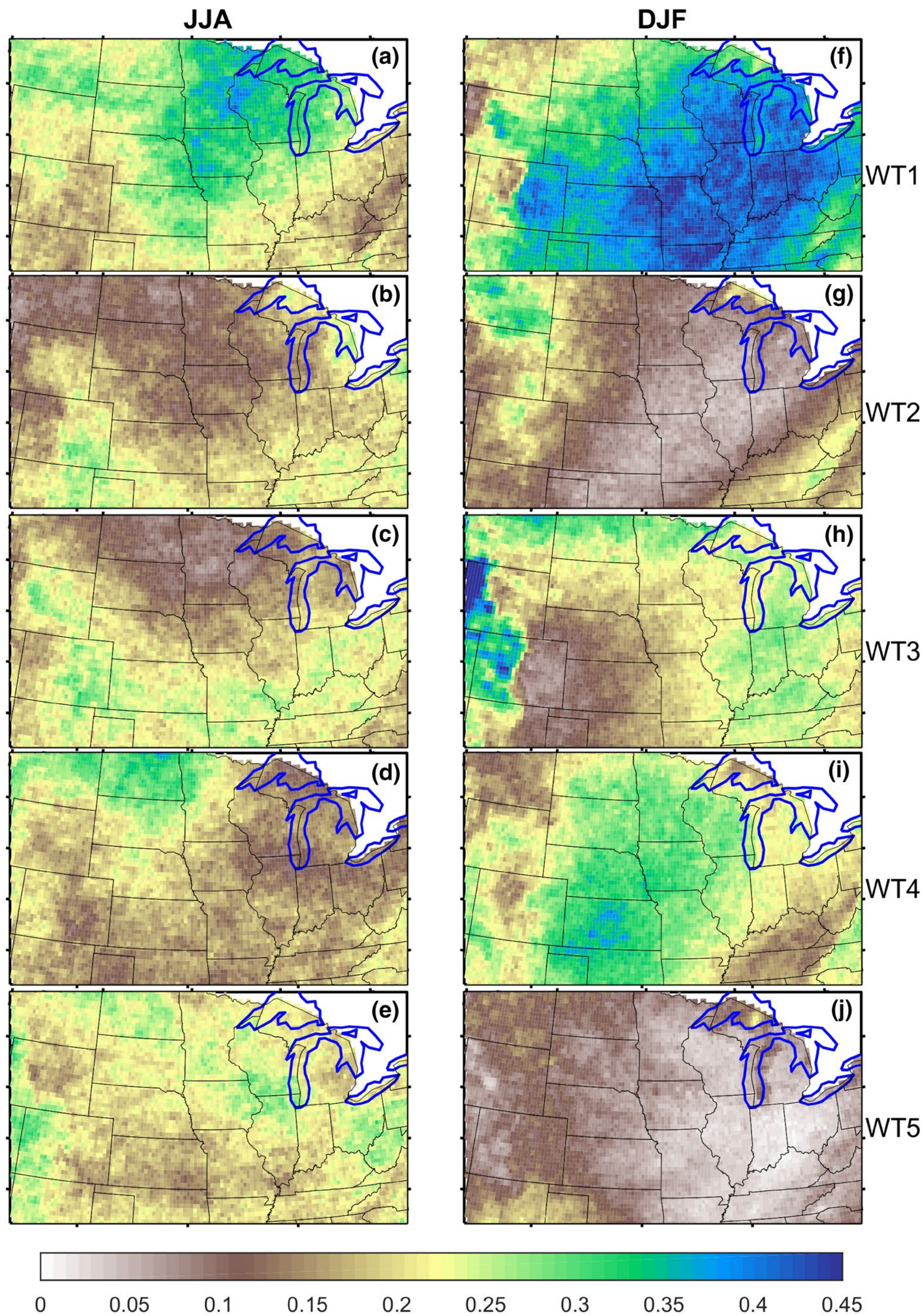

Fig. 9 Fractional contribution of precipitation associated with each weather type to heavy rainfall events during (left) JJA and (right) DJF

weather patterns can provide useful tools for understanding and predicting extreme precipitation, leading to valuable tools for operational forecasters. Moreover, the significant trends detected in WT1, WT5 and WT3 may suggest the modulation of external forcing, which should be further examined by experiments performed by general circulation models. In the context of storm types, Kunkel et al. (2012) quantified the contribution of frontal precipitation, extratropical cyclones, and mesoscale convective systems to the rainfall in the Midwest. In particular, they reported that the increasing trend in extreme rainfall over the Upper Midwest had significant contributions from both frontal precipitation and extratropical cyclones. Further analysis of precipitation associated with weather types following Kunkel et al. (2012) should be the topic of future studies.

Acknowledgments The authors thank the anonymous reviewers for insightful comments. The authors acknowledge the financial support from the Center for Global and Regional Environmental Research (Seed Grant Program). The second author also acknowledges financial support by the USACE Institute for Water Resources, Iowa State University under Iowa Economic Development Authority Award No. 13- NDRP-016 through funding from the U.S. Department of Housing and Urban Development, and the National Science Foundation under CAREER Grant AGS-1349827.

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