Analyzing How Teleconnections Influence Extreme Rainfall Events in the Central U.S. Using Causal Networks

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ABSTRACT

Extreme rainfall events in the central U.S. have caused significant damage, underscoring the need for a better understanding of precipitation changes and their drivers. This study utilizes ERA5 data from 1950 to 2023, focusing on the November to May period, to examine changes in winter and spring precipitation and the influence of teleconnections. Our analysis reveals notable increases in precipitation, particularly in spring, with the most recent period showing the highest values. Employing causal discovery methods, we identify significant causal relationships between teleconnections and extreme rainfall events. The Pacific-North American Pattern (PNA) and the Eastern Pacific Oscillation (EPO) emerge as key teleconnections with strong direct connections to extreme rainfall in the Upper Midwest and Ohio Valley. Furthermore, the study uncovers a complex network of interactions among various teleconnections, suggesting that the combined effects of multiple teleconnections must be considered to fully understand their impact on precipitation. These findings provide insights into the complex dynamics influencing precipitation patterns, hoping to aid in better prediction and management of extreme rainfall events.

1. INTRODUCTION

The central United States is home to some of the most extreme weather phenomena on the planet, frequently experiencing flooding events from extended periods of intense rainfall (Mallakpour and Villarini 2015a). These extreme weather events cause catastrophic damage to infrastructure, agriculture, and properties, costing billions of dollars annually and affecting many lives across the nation (AghaKouchak et al. 2011a; Harding and Snyder 2014a; Zhang and Villarini 2019). This underscores the urgent need to better understand the mechanisms driving extreme precipitation to improve preparedness and mitigation strategies.

In the past, Harding and Snyder (2014) have run simulations using global climate models (GCMs) that have observed an increase in heavy rainfall events, a trend that is predicted to continue throughout the remainder of the century. This anticipated increase highlights the necessity of understanding the formation and dynamics of extreme precipitation events. Analyzing the factors contributing to these events is crucial for developing predictive models and enhancing disaster response and management.

A key aspect of understanding the diverse nature of extreme weather events is the study of teleconnections, which are large-scale climate anomalies that are related to each other over long distances. Teleconnections such as the El Nino-Southern Oscillation (ENSO), the North Atlantic Oscillation (NAO), the Pacific North American Pattern (PNA), the Eastern Pacific Oscillation (EPO), the Western Pacific Oscillation (WPO) and the Arctic Oscillation (AO) can significantly influence weather patterns over vast regions, including the central United States. These teleconnections impact atmospheric circulation and can alter the frequency and intensity of extreme weather events, including heavy rainfall (Bates et al. 2001; Kretschmer et al. 2021; Yang et al. 2023).

In this project we will be incorporating their indices into our causal network analysis. For instance, ENSO is known to have a profound impact on weather patterns across North America, with its positive phase (El Niño) typically associated with wetter conditions in the central United States, while its negative phase (La Niña) often correlates

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with drier conditions (Kretschmer et al. 2021; Ropelewski and Halpert 1986). Similarly, the NAO affects the strength and position of the jet stream, which can influence weather systems and precipitation patterns in the Ohio Valley and Upper Midwest. Positive NAO phases usually result in milder and wetter winters, whereas negative phases bring colder and snowier conditions (Hurrell 1995).

The Pacific-North American (PNA) pattern, when positive, typically brings milder and drier winters to the central U.S., while a negative phase can lead to colder and wetter conditions (Leathers et al. 1991). The Eastern Pacific Oscillation (EPO) affects the temperature and precipitation patterns in the region; positive phases generally result in warmer conditions, while negative phases bring colder weather (Barnston and Livezey 1987). The Western Pacific Oscillation (WPO) can also influence the region's climate, with positive phases associated with milder weather and negative phases linked to colder conditions (Linkin and Nigam 2008). Lastly, the Arctic Oscillation (AO) in its positive phase typically leads to milder winters with reduced cold outbreaks, while its negative phase is associated with colder, more severe winters (Thompson and Wallace 1998).

Despite significant research, a substantial gap remains in understanding the causal relationships between teleconnections and extreme rainfall events in the central United States. Teleconnections play crucial roles in developing extreme rainfall, but traditional methods have limitations in capturing these interactions (Bates et al. 2001; Kretschmer et al. 2021). Traditional statistical models, such as linear regression and correlation analyses, focus on identifying relationships between variables. However, these methods often struggle to distinguish correlation from causation, particularly with complex, nonlinear climate system interactions (Yang et al. 2023). For example, while correlations between teleconnections like ENSO and extreme rainfall patterns can be observed, the underlying mechanisms driving these relationships remain unclear.

Given these limitations, more advanced methods are needed to capture the complex, nonlinear interactions within climate systems and provide clearer insights into causal relationships. Causal network-based machine learning models offer a promising solution. These models go beyond simple correlation analysis by employing algorithms that identify and quantify causal links between variables, offering a detailed understanding of how changes in one variable, such as a teleconnection index, can causally influence another, like extreme rainfall events (Kretschmer et al. 2021; Yang et al. 2023).

Therefore, our work leverages causal discovery to better understand how teleconnections influence the central U.S. by gathering and preprocessing data from the ERA5 dataset and the NOAA Physical Sciences Laboratory, focusing on key variables such as total precipitation and teleconnection indices. Utilizing these datasets, we apply causal discovery algorithms to construct causal networks that reveal the relationships between teleconnections and extreme rainfall events. We then analyze climatic precipitation trends and interactions within the causal networks to identify possible links between teleconnections and extreme rainfall events in the central United States.

This study has the general goal of enhancing our understanding of how teleconnections influence extreme rainfall events in the central United States. To accomplish this, we have proposed the following specific objectives: (1) Analyze precipitation patterns over the central U.S. to apply to our causal discovery; (2) Dive deeper into the influence of teleconnections on extreme rainfall within our region; and (3) Develop a successful causal network model that enhances our understanding of extreme rainfall and potential use for prediction strategies.

2. MATERIALS AND METHODS

2.1 *Data and Indices*

The ERA5 dataset is produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) and provides hourly data from 1940 to present with detailed records of atmospheric, oceanic, and land-surface variables (C3S 2018). For this study, we will utilize total precipitation (meters) data selected four times each day at 00, 06, 12, and 18 UTC. It also includes a horizontal resolution of approximately 31 kilometers (0.25°) and includes 137 vertical levels.

Additionally, we will utilize a shapefile obtained from the United States Census Bureau (U.S. Census Bureau 2022) to define the geographic boundaries of the central United States. By integrating this shapefile with the ERA5 dataset, we can accurately map and analyze variables within our specified regions of the Ohio Valley and the Upper Midwest.

We also incorporate daily teleconnection indices from various sources to understand their influence on extreme rainfall events. The ENSO index (Nino 3.4 SST) is obtained from the NOAA Physical Sciences Laboratory (NOAA PSL 2023a). The indices for the NAO, PNA, WPO, and EPO are sourced from the NOAA Physical Sciences Laboratory's daily time series (NOAA PSL 2023b). The AO index is retrieved from the Climate Prediction Center of the National Oceanic and Atmospheric Administration (NOAA CPC 2023).

2.2 *Data Processing*

To gather the necessary precipitation data, we utilized Google Earth Engine (GEE) for our precipitation analysis. We accessed the ERA5 monthly averaged data by the hour, integrating it with the shapefile obtained from the U.S. Census Bureau to focus on our region of interest, the central United States. This process allowed us to collect total precipitation data exclusively for this region, filtered from November to May for the years 1950 to 2023. For all precipitation data we had converted from meters to millimeters and filtered any outlying data deemed unfit.

Next, for our casual discovery, we used the University of Oklahoma's Schooner High-Performance Computing (HPC) system to convert our hourly total precipitation data into daily sums for the period from 1979 to 2023, focusing on November to May. We chose to start from 1979 to streamline the project's temporal scale and ensure consistency with the more reliable and comprehensive datasets available from that year onward. This aggregation was essential for aligning our precipitation data with daily teleconnection indices and for subsequent analysis.

Finally, we processed our teleconnection index values, covering the period from November to May 1979 to 2023. This involved formatting the indices to match the temporal range of our precipitation data. Additionally, we normalized all indices to facilitate better comparison and analysis. Normalization was crucial for minimizing the impact of differing scales and units, thereby enabling a more coherent analysis of the relationships between teleconnection indices and extreme rainfall events.

2.3 *Region of Interest*

This study focuses on two key regions in the central United States: the Ohio Valley (red) and the Upper Midwest (blue) as illustrated in Figure 1. They are defined by the National Centers for Environmental Information of NOAA (NCEI 2024). These regions were selected based on their susceptibility to extreme rainfall events and their unique climatological characteristics. By examining these regions, we aim to capture and quantify their causal relationships between synoptic features, teleconnections, and extreme rainfall.

The Ohio Valley is known for its complex weather patterns influenced by both continental and maritime air masses. This region frequently experiences significant rainfall events, particularly during the spring and summer months, due to its location being between the transition zone of humid subtropical and continental climates (Harding and Snyder 2014; Mallakpour and Villarini 2015). Additionally, the Ohio Valley has the highest winter moisture variability among the regions studied, making it a critical area for understanding its precipitation dynamics and teleconnections during the cold season (Yang et al. 2023). Previous studies have shown that the Ohio Valley is significantly affected by teleconnections such as the ENSO and NAO, which alter precipitation patterns and the frequency of extreme weather events (Groisman et al. 2012; Zhang and Villarini 2019).

The Upper Midwest is particularly vulnerable to extreme rainfall events that can lead to severe flooding, especially in the late spring and early summer (AghaKouchak et al. 2011). The Upper Midwest is influenced by teleconnections such as the PDO and ENSO, which affects the regional climate variability and extreme weather patterns (Groisman et al. 2012; Harding and Snyder 2014). The Upper Midwest experiences significant winter and spring precipitation variability influenced by these teleconnections (Yang et al. 2023). Studying this region provides valuable insights into how teleconnections interact with local weather systems and extreme weather formation.

The selection of these two regions allows for an analysis of the causal relationships between synoptic features and extreme rainfall events across multiple climatological zones. This diversity enhances a broader understanding of how teleconnections and local synoptic conditions interact to form extreme weather events. Using causal network-based machine learning models, we aim to uncover the complex non-linear interactions between these regions.

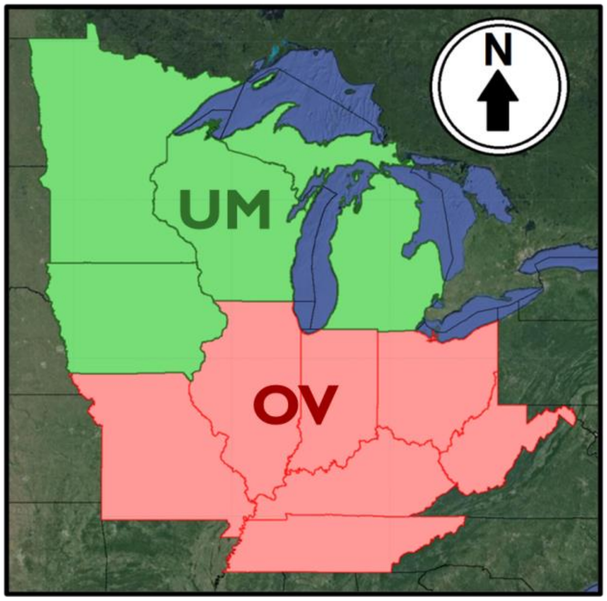

Figure 1. Our region of study making up the central United States consisting of the Upper Midwest (green) and the Ohio Valley (red) defined by the National Centers for Environmental Information of NOAA (NCEI 2024).

2.4 *Time Series Analysis*

2.4.1 *Annual Total Precipitation*

Total precipitation (mm) values will be segmented into monthly intervals from November to May for each year between 1950 and 2023. This temporal range was selected due to the pronounced influence of teleconnections during these transitional periods. Teleconnections exhibit significant impacts on regional weather patterns during the fall to spring months (Groisman et al. 2012; Yang et al. 2023). We analyze annual total precipitation data for winter and spring, split into three climate normals: 1950-1980, 1980-2010, and 2010-2023. A climate normal is a 30-year average of climatic data, like total precipitation for our project, and is used as a standard to compare current observations with past data. We hope to gain an understanding of precipitation variability between winter and spring compared by each climate normal.

2.4.2 *Monthly Mean Precipitation Analysis*

The same climate normal concept was used for mean precipitation (mm) by sectioning values into 30-year intervals: 1950-1980, 1980-2010, and 2010-2023. For this analysis, we used months for our x-axis to gain an understanding of what time of year precipitation was falling the most during which climate normal in our region of interest. We are apple to visualize a side-by-side of winter into spring of when exactly precipitation varies between the seasons.

2.4.3 *Winter and Spring Precipitation Trends*

For our spatial analysis we wanted the representation of areas experiencing significant changes in precipitation (mm) patterns during the current climate normal period 2010-2023, compared to historical maximum averages from 1950-2010. These spatial trend maps are crucial for identifying hotspots of increasing or decreasing precipitation. We took the monthly maximum values from 2010-2023 and subtracted them from the monthly mean maximum values from 1950-2010, this then gives us a positive or negative trend value. A threshold was applied to determine the positive and negative trend: regions with changes of more or less than 10 mm from normal were considered to have a significant trend, while areas with lower magnitude changes were excluded from the analysis.

2.5 *Causal Networks*

Causal networks, also known as causal influence models, are powerful tools in climate science for uncovering and quantifying the complex relationships between various atmospheric variables. These networks are constructed using nodes that represent variables (such as teleconnections like ENSO, AO, NAO, EPO, WPO, and PNA) and use directed vectors that denote causal relationships between these variables. The direction of a vector from one node to another indicates that changes in the first variable causally influence changes in the second (Kretschmer et al. 2021; Yang et al. 2023). By applying causal influence techniques, these networks help differentiate correlation from causation, providing a clearer understanding of how different factors contribute to extreme weather events.

One of the main advantages of causal networks is their ability to model complex, nonlinear interactions within the climate system. Traditional statistical models often struggle to capture the complicated dependencies and feedback mechanisms present in atmospheric processes

(Yang et al. 2023). Causal networks, however, are designed to handle these complexities, making them particularly well-suited for analyzing the interactions between teleconnections and extreme rainfall events. For our study, we employ the PCMCI (Peter and Clark Momentary Conditional Independence) method, as detailed by Runge et al. (2019), which is specifically developed to deal with high-dimensional and autocorrelated time series data.

The PCMCI method begins with data collection and preprocessing to ensure data quality suitable for analysis. This includes atmospheric variables from reanalysis datasets (such as ERA5) and teleconnection indices. PCMCI then applies a combination of constraint-based and model-based approaches to identify potential causal links between variables, considering both direct and indirect effects. The connections and their strengths are represented by the thickness and color of the edges (lines) between the nodes (teleconnections and Upper Midwest). The edges in the graph are color-coded and vary in thickness. Thicker and more intensely colored edges represent stronger causal relationships. The color gradient from blue to red represents the strength and direction of the causal relationship (MCI - Momentary Conditional Independence). Redder edges indicate positive causal effects, while bluer edges indicate negative effects. This method effectively reduces the complexity of the network by focusing on significant causal pathways while controlling for the influence of other variables in the dataset (Runge et al. 2019).

By utilizing the PCMCI method, we can robustly estimate the strength and direction of causal relationships between teleconnections and extreme rainfall events. This approach helps elucidate the pathways through which teleconnections like ENSO, AO, NAO, EPO, WPO, and PNA influence extreme rainfall. The resulting causal networks provide a detailed map of these interactions, offering valuable insights into the mechanisms driving extreme weather events in the central United States.

To practically apply the PCMCI method, we first preprocess the data to address issues such as missing values and reformatting to our temporal resolution. Next, the PCMCI algorithm is run to perform momentary conditional independence tests, which are crucial for detecting causal links in time series data. The algorithm refines the network by testing the conditional dependencies between variables at multiple time lags. This helps in identifying both instantaneous and time-lagged causal relationships. Numbers on the edges (e.g., 1, 2, 5) denote the time lags (in days) at which these causal relationships are significant. For instance, a link labeled with "1" indicates a one-day lag, meaning the causal effect from one node to another occurs with a one-day delay. For our study, we had first tested a time lag of 30 days but to simplify our current discovery, we had chosen a time lag of 10. Finally, the significance of these causal links is assessed, and the resulting network is interpreted to understand the causal mechanisms at play (Runge et al. 2019). This systematic approach ensures a robust analysis of the causal dynamics between teleconnections and extreme rainfall events.

The ability to uncover these complex causal relationships is crucial for improving predictive models and enhancing our understanding of climate dynamics. By integrating diverse data sources and revealing hidden interactions, causal networks provide a more robust framework for predicting and understanding extreme rainfall events, thereby contributing to more effective climate adaptation and mitigation strategies (Runge et al. 2019; Kretschmer et al. 2021; Yang et al. 2023).

3. RESULTS

3.1 *Time Series Analysis*

3.1.1 *Annual Total Precipitation*

Figure 2 presents the annual total precipitation in millimeters for the winter and spring seasons across three climate normals: 1950-1980, 1980-2010, and 2010-2023. Each climate normal is represented by different colors for winter and spring, making it easier to compare the precipitation trends across these periods.

During the 1950-1980 period, we can see the clear indication of seasonal variability between winter (blue) and spring (light blue). Winter ranges between 100 mm and 200 mm and shows a relatively consistent jump between dry and wet years, with one exceptionally dry winter in 1976. Spring has ranges roughly from 350 mm to 475 mm but is showing a larger but also consistent variation in precipitation through the years.

For 1980-2010, at the start of the climate normal we see how it remains semi-consistent with the period before but with more years having higher values. Nearing 2000, the precipitation trends seem to change. For winter (red), it seems as though the precipitation accumulation is steading, and maximums are lower than before. Although, for spring (light red) there is quite the opposite. Maximum values are increasing through time and becoming more frequent. Overall, the seasonal variation is changing in opposite directions.

For our current climate normal 2010-2023, our maximum values for winter (yellow) and spring (light yellow) are at their highest ever. Winter seems to have a lowering trend in values compared to the last period, apart from the wettest winter at around 250 mm occurring in 2015. Spring on the other hand, is showing the largest increase in total precipitation with some consistently high seasons at around 500 mm and the wettest spring at 550 mm. Although this is the shortest period of data, the graph suggests that the spring season is on the rise accumulating more precipitation through the years. While winter has a somewhat steady decline in precipitation, increasing the variability between winter and spring.

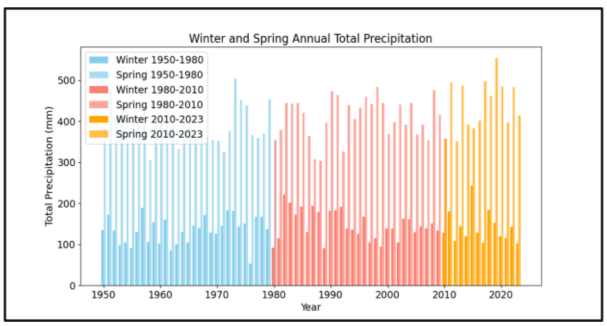

Figure 2. Total Precipitation (mm) distributed by climate normal 1950-1980 (blue), 1980-2010 (red), and 2010-2023 (yellow). The lower histogram depicts winter and the upper depicts spring.

3.1.2 *Monthly Mean Precipitation Analysis*

The graph displays the monthly climate normal for the mean precipitation across three different time periods: 1950-1980 (blue), 1980-2010 (red), and 2010-present (yellow). The precipitation patterns show a consistent seasonal cycle across all three periods, with a pronounced peak during the late spring and early summer months (April to June). The highest mean precipitation values are observed in June for all periods, indicating this month as the wettest period annually.

For 1950-1980 (Blue), starting in winter with mean precipitation values in decline and at the lowest during this time of year but as we go towards spring there is a sharp incline through February and March with mean values steading out at around 100 mm in May, being the lowest out of all the climate normals.

Starting in winter of 1980-2010 (Red), we can already see the higher mean precipitation on the decline as it bottoms out almost exactly as the last period. Around the same time at February precipitation increases at an almost constant rate all the way through up to May. A Maximum of 115 mm now being higher than the previous climate normal by 15 mm.

2010-2023 (Yellow) shows the highest mean precipitation values of all other climate normals at around 118 mm, which is a slight increase from the last period. A significant difference is the presence of the highest precipitation values during winter than the others. This could be because of the smaller range of data we still see all the way to spring that values remain the highest for most months.

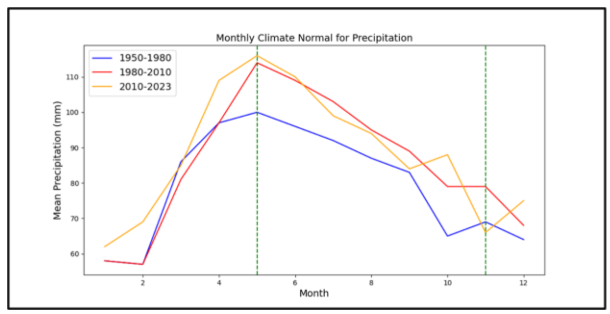

Figure 3. Mean precipitation (mm) per month for each climate normal 1950-1980 (blue), 1980-2010 (red) and 2010-2023 (yellow). Between the green lines from Nov to May depicts our temporal range of focus.

3.1.3 *Winter and Spring Precipitation Trends*

The spatial distribution of precipitation trends for the central United States is illustrated in Figure 4, which highlights regions with positive (blue) and negative (red) precipitation trends for spring (Figure 4a.) and winter (Figure 4b.) seasons. This approach allowed us to identify significant changes in precipitation trends over the selected periods. A threshold was considered for our positive and negative trends: regions with changes of more or less than 10 mm from normal were considered to have a significant trend, and areas with lower magnitude changes were excluded from the analysis. This method focuses on regions experiencing the most notable shifts in precipitation patterns, aligning with previous research methodologies (Groisman et al. 2012; Yang et al. 2023).

For the spring season (Fig. 4a), we observe widespread regions with positive precipitation trends, particularly in northern areas such as Minnesota, Wisconsin, and Michigan. There are also significant positive trends in parts of Iowa, Illinois, and Missouri. Conversely, a band of negative precipitation trends is evident across southern Michigan, northern Indiana, and parts of Ohio, suggesting areas that have experienced a decrease in spring precipitation.

In the winter season (Fig. 4b), positive precipitation trends dominate much of the central United States, with notable increases in Indiana, Illinois, and Ohio. This widespread increase in winter precipitation aligns with the overall trend towards wetter conditions observed in the temporal analysis. There are fewer regions with negative trends in winter, but some areas in Indiana and Kentucky exhibit decreasing precipitation trends.

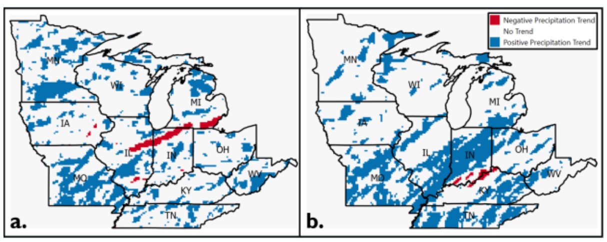

Figure 4. (a) Spring precipitation trends as of 2010-2023 showing a notable positive trend (blue) for the central United States. (b) Winter precipitation trends as of 2010-2023 show similar results to spring with a notable increase in precipitation.

3.2 *Causal Discovery*

3.2.1 *Upper Midwest*

Figure 5 provides a visual representation of the causal relationships between different teleconnections (PNA, ENSO, EPO, NAO, WPO, AO) and their influence on extreme rainfall events in the Upper Midwest (UM). The connections and their strengths are represented by the thickness and color of the edges (lines) between the nodes (teleconnections and UM).

PNA and EPO are shown to each have both positive and negative direct causal links to the Upper Midwest. These links are significant as they suggest that variations in these teleconnections directly influence extreme rainfall events in the region. Although the arrows from PNA and EPO to UM are lighter in coloring representing a weaker link, they indicate a directional influence, implying that changes in PNA and EPO likely lead to changes in the rainfall patterns in the Upper Midwest.

There is no direct causal link from ENSO to the Upper Midwest. This absence might suggest that ENSO's influence on extreme rainfall in the Upper Midwest is either indirect or less significant compared to other teleconnections. Whereas NAO did not show many causal links to other nodes as well other than a strong possible indirect link to the AO. Perhaps if we had chosen a longer time lag than 10, these direct links would show if more time is required.

AO and WPO are also shown to have numerous connections with other teleconnections as well as PNA and EPO, suggesting a complex interplay that could indirectly affect the Upper Midwest.

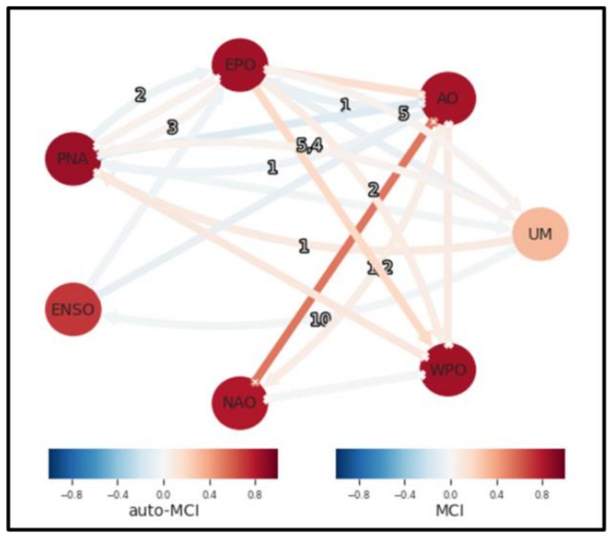

Figure 5. Upper Midwest causal discovery between teleconnections (ENSO, NAO, PNA, EPO, WPO, and AO). These connections and their strengths are represented by the thickness and color of the edges (lines) between the nodes (teleconnections and UM). Red represents a positive relationship and blue represents a negative relationship.

3.2.2 *Ohio Valley*

Figure 6 Illustrates the causal relationships between various teleconnections (PNA, ENSO, EPO, NAO, WPO, AO) and their influence on extreme rainfall events in the Ohio Valley (OV). The edges between the nodes indicate the direction, strength, and lag of these causal connections.

The PNA has an inverse causal relationship with the Ohio Valley, as indicated by the blue edge connecting PNA to OV. This suggests that when PNA experiences a positive phase for example, it leads to an inversive effect on the Ohio Valley, typically lowering rainfall amounts over the Ohio Valley (Leathers et al. 1991).

Like the Upper Midwest, ENSO does not have a direct causal link to the Ohio Valley. This implies that ENSO's impact on extreme rainfall in the Ohio Valley is either indirect or less significant compared to other teleconnections. Teleconnections exhibit numerous causal links among themselves, indicating a complex network of interactions. For example, EPO, AO, WPO, and NAO as well as the PNA, all show multiple interconnections. These interactions can potentially amplify or modulate the influence of individual teleconnections on the Ohio Valley.

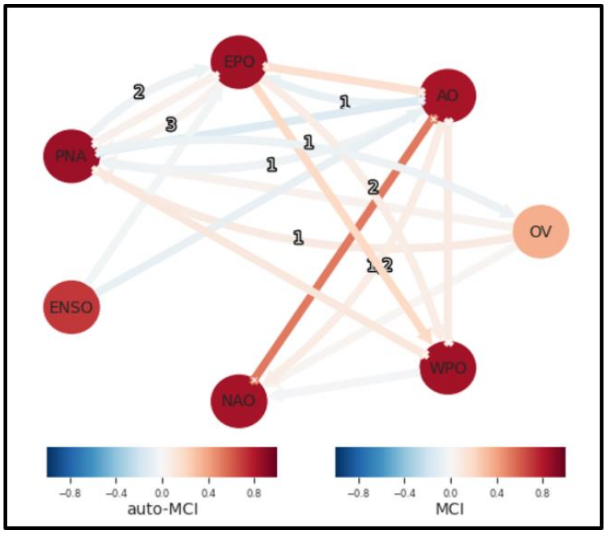

Figure 6. Ohio Valley causal discovery between teleconnections (ENSO, NAO, PNA, EPO, WPO, and AO). These connections and their strengths are represented by the thickness and color of the edges (lines) between the nodes (teleconnections and UM). Red represents a positive relationship and blue represents a negative relationship.

4. DISCUSSION

4.1 *Time Series Analysis*

4.1.1 *Annual Total Precipitation*

The analysis of annual total precipitation (Fig. 2) reveals significant variability in seasonal precipitation trends across the different climate normals. From 1950-1980 we see a relatively stable range of winter and spring precipitation, similar to Groisman et al. (2012), who highlighted consistent precipitation patterns during these decades.

From 1980 to 2010, we observe a shift towards higher precipitation values, particularly in spring. This change lines up with findings by Leathers et al. (1991), who identified increasing precipitation trends in the central U.S. during the late 20th century. The contrasting trends between winter and spring during this period might suggest a changing seasonal distribution, which could be influenced by shifts in atmospheric circulation patterns (Leathers et al. 1991).

The current climate normal (2010-2023) shows the highest precipitation values, with spring having the largest increase of all seasons. This aligns with recent studies indicating an intensification of the hydrological cycle due to global warming (Yang et al. 2023). The observed trends suggest that the region may be experiencing more frequent and intense precipitation events, especially in spring, which could be attributed to changes in teleconnections such as the PDO and the NAO (Runge et al. 2019).

4.1.2 *Monthly Mean Precipitation Analysis*

The monthly mean precipitation analysis (Fig. 3) reveals consistent seasonal cycles across all periods, with a peak during late spring and early summer. The increasing mean precipitation values from 1950 to the present suggest a gradual intensification of precipitation events. The higher mean values observed during the 1980-2010 period, particularly in May, support Groisman et al. (2012)'s findings on increased precipitation variability.

The current period (2010-2023) shows the highest mean precipitation values, indicating a potential shift towards wetter conditions. This trend is consistent with Yang et al. (2023), who reported an increase in extreme precipitation events in recent years. The significant winter precipitation values during this period could be linked to the influence of teleconnections such as the AO and the WPO, which have been shown to affect winter precipitation patterns in the central U.S. (Runge et al. 2019).

4.1.3 *Winter and Spring Precipitation Trends*

The spatial distribution of precipitation trends highlights notable regional differences. The positive precipitation trends in the northern areas during spring (Fig. 4a) align with studies indicating increased precipitation in the Midwest (Groisman et al. 2012). The negative trends in southern Michigan and parts of Ohio suggest potential localized drying, possibly linked to changes in regional atmospheric circulation patterns (Leathers et al. 1991).

In winter (Fig. 4b), the widespread positive trends across the central U.S. align with the overall increase in winter precipitation observed in the temporal analysis. These trends are consistent with the findings of Yang et al. (2023), who reported an increase in winter precipitation in the region. The few areas with negative trends, such as parts of Indiana and Kentucky, may be influenced by local factors such as changes in land use and urbanization (Groisman et al. 2012).

4.2 *Causal Discovery*

4.2.1 *Upper Midwest*

The causal discovery analysis for the Upper Midwest reveals significant connections between teleconnections and extreme rainfall events. The direct causal links from PNA and EPO to the Upper Midwest suggest that these teleconnections play a crucial role in influencing regional precipitation patterns. They both share a positive and a negative relationship to the Upper Midwest. This might suggest that the influence of a certain phase of PNA and EPO on precipitation in the Upper Midwest may not be immediate and can vary with time lags. For instance, the atmospheric circulation changes produced by these teleconnections may take days or weeks to influence the regions weather patterns. This can result in complex relationships where the same teleconnection can cause both positive and negative impacts depending on the time lag considered (Runge et al. 2019).

The absence of a direct causal link from ENSO to the Upper Midwest could be from too short of a time lag. Another possibility is that ENSO's influence on the central U.S. is more indirect and modulated by other teleconnections (Leathers et al. 1991). The complex network of interactions among teleconnections, such as AO and WPO, highlights the need for further research to understand the combined effects of these patterns on regional climate (Runge et al. 2019). Perhaps if we had chosen a longer time lag than 10, these direct links would show if more time were required for stronger relationships to appear.

4.2.2 *Ohio Valley*

For the Ohio Valley, the inverse causal relationship between PNA and extreme rainfall events supports previous studies that have shown the PNA’s significant impact on regional climate variability (Leathers et al. 1991). Other teleconnections such as the WPO can interact with the PNA since a direct link is shown which could have a possible impact on the region. When PNA is in its negative phase, it may enhance the moisture transport from the Gulf of Mexico and other sources into the Ohio Valley, thus leading to an increase in precipitation (Leathers et al. 1991).

ENSO's primary impacts are more pronounced in regions closer to the Pacific Ocean, such as the western United States, and tropical regions (Ropelewski and Halpert 1986). The Ohio Valley is further from the direct atmospheric circulation produced by ENSO. As a result, ENSO's influence on the Ohio Valley could be indirect by this manner. The Ohio Valley could be affected through changes in other teleconnections or global circulation patterns that later affect the region. The multiple interconnections among teleconnections, such as EPO, AO, WPO, and NAO, suggest a complex network that can amplify or modulate the influence of individual teleconnections on the Ohio Valley. This complexity underscores the importance of considering the combined effects of multiple teleconnections in climate studies (Runge et al. 2019).

5. CONCLUSIONS

This study provides significant insights into the complex causal relationships between teleconnections and extreme rainfall events in the central United States, specifically focusing on the Upper Midwest and Ohio Valley regions. Utilizing causal network-based machine learning models, such as the PCMCI method, allowed for a robust analysis of these relationships and revealed several key findings:

1. **Increasing Precipitation Trends**: Analysis of annual total precipitation and monthly mean precipitation indicates a

trend towards increasing precipitation, particularly in the spring season, over the past decades. The 2010-2023 period shows the highest precipitation values, with significant increases in both winter and spring, aligning with recent studies that suggest an intensification of the hydrological cycle due to global warming. The spatial distribution of precipitation trends reveals notable regional differences, with positive trends observed in Missouri, Minnesota, Illinois, and Michigan during spring and widespread positive trends across Missouri, Illinois, Indian, and Tennessee during winter. Although negative trends are not as prevalent, but observed across small parts of Illinois, Indiana, and Michigan during the spring and a narrow region of Kentucky and Indiana for winter.

2. **Causal Relationships with Teleconnections**: The causal discovery analysis identified significant positive and negative direct causal links between the Pacific-North American Pattern (PNA) and the Eastern Pacific Oscillation (EPO) with extreme rainfall events in the Upper Midwest. Interestingly, ENSO does not show a direct causal link with extreme rainfall in these regions, suggesting its influence may be indirect or less significant compared to other teleconnections. The inverse causal relationship between PNA and extreme rainfall events in the Ohio Valley supports previous studies highlighting PNA's impact on regional climate variability.

3. **Complex Interactions**: Furthermore, the study reveals a complex network of interactions among various teleconnections, including the Arctic Oscillation (AO) and the Western Pacific Oscillation (WPO), which influence extreme rainfall events indirectly through their interactions with PNA and EPO. These multiple interconnections suggest that the combined effects of these teleconnections must be considered to understand their full impact on regional precipitation patterns. The findings underscore the limitations of traditional statistical models in capturing these complex, nonlinear interactions and highlight the advantages of using causal network-based approaches. This intricate network of relationships underscores the importance of considering multiple teleconnections simultaneously to understand their combined effects on regional weather patterns.

4. **Future Research Directions**: Future studies should explore longer time lags and additional teleconnections to better understand the delayed effects and direct influences on regional precipitation patterns. Further research is needed to refine causal discovery algorithms to capture the dynamics of climate systems more accurately.

In conclusion, this study demonstrates the utility of causal network-based machine learning models in climate science, particularly for understanding the drivers of extreme weather events. The findings highlight the critical roles of PNA and EPO in influencing extreme rainfall in the central United States and emphasize the importance of considering complex interactions among multiple teleconnections. These insights can inform the development of more effective predictive models and mitigation strategies, ultimately contributing to better preparedness in the face of changing climatic conditions.

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