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Arctic springtime temperature and energy flux interannual variability is driven by 1- to 2-week frequency atmospheric events

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The Arctic is experiencing amplified climate warming, decreasing sea ice extent, increasingly earlier springtime snowmelt, and a related increase in fire activity. The transition from cold to warm season in the Arctic strongly varies between years, but our understanding of temperature and surface energy budget changes over the springtime is limited. Here we investigate intraseasonal variability of Arctic springtime temperature and surface energy budget components and their interannual trends over 40 years (1981–2020) across the terrestrial Arctic (above 60°N) using ERA5-Land reanalysis data. We found the central and western Siberian regions to have the highest interannual variability in spring temperature anomaly among all Arctic regions during the 40-year period. Also in this region, we discovered the strength increased for heat extremes and decreased for cold extremes when comparing the first and the last 20 years of our study. Peaks in composited extreme temperature and surface energy budget anomalies were observed to occur concurrently, indicating temperature extremes are not driven by surface energy budget components. Lastly, by utilizing power spectrum analyses, we identified the primary driver of temperature anomaly interannual variability to be operating at a 1- to 2-week frequency. Based on our findings and observations in the recent literature, we hypothesize that the observed interannual variability in springtime temperature can be attributed to increased Arctic sea ice decline and an increase in the frequency and strength of associated atmospheric blocking events.

1. Introduction

A significantly positive trend in average temperature and temperature extreme frequency and magnitudes have been predicted and already observed in the Arctic (Bintanja, 2018; Bintanja and Selten, 2014; Chylek et al., 2009; Durack et al., 2012; England et al., 2021; Huntington, 2006; Marvel and Bonfils, 2013; Overland et al., 2013; Pithan and Mauritsen, 2014; Screen et al., 2018; Trenberth et al., 2003). Interactions between the Earth’s surface and atmosphere, such as ice-albedo feedback, greatly contribute to amplified Arctic warming (Sudikova and Chechi, 2016; Pithan and Mauritsen, 2014). Amplified Arctic warming coupled with other Arctic phenomena, such as early snowmelt onset and an anomalous Arctic frontal jet, can promote previously unprecedented Tundra fire risk, as evident during the summers of 2019, 2020, and 2021 (Scholten et al., 2022). Such interactions responsible for amplified Arctic warming are directly indicative of changes in surface energy budget (SEB) magnitude and partitioning.

Global climate models, including models participating in the Coupled Model Intercomparison Project, consistently predict an increase in Arctic air temperature (Holland and Bitz, 2003; Smith, 2011; Fischer et al., 2013; Russo et al., 2013; Singh et al., 2013; Spinoni et al., 2015; Davy and Outen, 2020; Casagrande et al., 2021; Hahn et al., 2021), reaching three times the global warming rate between 1971 and 2019 (AMAP, 2021) to nearly four times since 1979 (Descals et al., 2022; Rantanen et al., 2022). Modeled amplified Arctic warming has already been confirmed by in situ observations (Wei et al., 2016).

The Arctic is plagued with temporally and spatially sparse atmospheric in-situ measurements, including gaps in radiosounding data (Liu et al., 2006; Naakka et al., 2019), greenhouse gas measurements (Panov et al., 2021), and eddy covariance sites (Pallandt et al., 2022). The resulting data gaps are expected to be among the top causes of the low skill in Arctic weather forecasts (Jung et al., 2016). Oehri et al. (2022) highlight the importance and extent of Arctic data gaps in SEB measurements. They state Arctic energy flux in situ data gaps are especially

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prevailing during autumn and winter seasons, with turbulent fluxes experiencing the most severe data gaps year-round and across all vegetation types mentioned in the study. The barren tundra vegetation type was identified by Oehri et al. (2022) as being largely absent of SEB measurements. Reanalysis datasets are a valuable resource for filling this gap in data and understanding past climatological changes in spatially and temporally sparsely-measured, difficult to reach and maintain regions, such as the Arctic.

The ERA5-Land reanalysis dataset is an enhanced version of the ERA5 reanalysis dataset that captures the evolution of over-land variables from January 1950 to 2-3 months prior to present with a high spatial and temporal resolution (Muñoz-Sabater et al., 2021). The spatial resolution of 0.1° × 0.1° allows for more accurate capturing of details around small-scale land features (e.g. water bodies or topography) compared to the 0.25° × 0.25° spatial resolution of ERA5. The high temporal resolution (hourly) of ERA5-Land is required to capture short-term atmospheric phenomena, even as short as an individual storm, which can have long-lasting impacts on intraseasonal variability and interannual variability (IAV) in atmospheric variables (Kim et al., 2017). ERA5-Land can be utilized to characterize atmospheric temperature or SEB extremes and their variability within season and year-to-year.

The change in frequency and intensity of extreme heat events as a driver of increased climate variability has been the subject of previous studies (Alexander et al., 2006) and is particularly relevant for the understudied Arctic region. Temperature extremes, which are becoming more frequent and extreme (Shabbar and Bonsal, 2003; Tomczyk and Bednorz, 2014; Vikhamar-Schuler et al., 2016; Wei et al., 2016; Graham et al., 2017; Sui and Yu, 2018; Yu et al., 2021), can be characterized using multiple methods. A common method is through the use of a temperature extreme absolute index (TEAI; Curry et al., 2014; Abatan et al., 2018; Vogel et al., 2018; Wang et al., 2018; Xu and Wang, 2019; Wehner et al., 2020; Almazroui et al., 2021; Chen et al., 2022; Yang et al., 2022). The TEAI methodology captures the magnitude and strength of temperature extremes, but misses detail about the development or duration of extreme events. Shorter-scale extreme temperature events are frequently identified using percentile-based climate indices that were developed by the Expert Team on Climate Change Detection and Indices (ETCCDI; Klein-Tank et al., 2009). Power spectrum analysis Li et al. (2020a), in combination with ETCCDI percentile-based climate extreme composite analysis of temperature extremes and temperature anomaly IAV, is an effective method for filling the temperature extreme identification gap created by the low temporal scale of TEAI indices.

The goals of this study are to: 1) quantify Arctic spring temperature trends and variability, 2) identify the shift in temperature extreme events and relation with SEB component anomalies over time and, 3) determine Arctic spring temperature anomaly spatial extent and temporal scales. Section 2 introduces the data and methods used in this study. Spatial and temporal patterns of temperature trends and variability findings are introduced in Section 3.1, while Section 3.2 identifies the change over time of Arctic-wide temperature extremes and their SEB influence. The dominant temporal frequency driving IAV in western and central Siberia is the focus of Section 3.3. We discuss the findings and outlook of our study in Section 3.4. In Section 4, we summarize and conclude our study.

2. Data and methods

2.1. Data

We used 0.1° × 0.1° hourly ERA5-Land reanalysis data for the 40 year period of 1981–2020 because of the dataset’s high spatial resolution, long temporal coverage, and extensive list of available data products (Muñoz-Sabater et al., 2021). All data were resampled to a daily temporal resolution by averaging hourly data. The following ERA5-Land products were selected: 2-m air temperature (hereafter referred to simply as temperature), surface sensible heat flux (H), surface latent heat flux (LE), surface net solar radiation (SWnet), and surface net thermal radiation (LWnet). Sign conventions for H and LE were altered from the standard ERA5-Land convention and made to be positive away from the surface. SWnet and LWnet sign convention remained as the standard ERA5-Land convention and are therefore positive towards the surface.

The spatial and temporal extent of this study is confined to the under-studied region of the Arctic, defined as north of 60°N, during the spring months of March, April, and May (MAM) from 1981 to 2020. Spring was chosen for our study because it is among the seasons with the largest expected Arctic temperature variability, strongest expected temperature trends, and strongest variability in temperature trends under a changing climate (Overland et al., 2004; Fröybylak, 2007). Additionally, we focused on spring for its variability in snow cover, a dominant driving factor behind temperature variability (Cohen and Rind, 1991; Dutra et al., 2011; Xu and Dirmeyer, 2011; Qu and Hall, 2014; Diro et al., 2018; Gross et al., 2020).

ERA5-Land temperature data were validated with in situ temperature measurements from Arctic sites registered with the World Meteorological Organization. To cover a broader Arctic area, temperature measurements were added from sites in the International Arctic Systems for Observing the Atmosphere archives, the Arctic Observatory Network, the National Science Foundation National Ecological Observatory Network, and the European Fluxes Database Center resulting in a
total of 47 sites spread across the Arctic (Figure A1a). 18 of the 47 in situ sites were excluded from the validation analysis due to low quality (i.e. short temporal coverage, data gaps, etc.), with 29 sites left for final validation.

To quantitatively evaluate the quality of the ERA5-Land reanalysis dataset relative to in situ measurements, we implemented a scoring system (Equation A.4) developed by Graham et al. (2019). ERA5-Land reanalysis data scored well for all averaging periods with scores ranging from 9.45 to 9.59 out of 10, which would rank among the top-scoring reanalysis datasets analyzed by Graham et al. (2019). As a result of the strong performance of the ERA5-Land dataset in estimating in situ temperature measurements, we proceeded with using the ERA5-Land reanalysis dataset for our subsequent analyses. For full details on ERA5-Land data validation, see Appendix A.

2.2. Methods

Using ERA5-Land reanalysis data, we calculated 40-year temperature trends as the slope of mean yearly MAM temperature using the Python SciPy package, version 1.5.0 (Virtanen et al., 2020) — Python version 3.7.6 was used for all analyses unless otherwise stated (Van Rossum and Drake, 2009). 40-year MAM temperature anomalies intra-seasonal standard deviations were also calculated using the daily ERA5-Land data. Normalized intraseasonal standard deviations (NISD) were calculated by applying a min-max scaling normalization function (Equation (1)) to the previously-calculated intraseasonal standard deviations. NISD was normalized using min-max normalizing over a Z-score normalizing method for its simplicity and our lack of expected extreme outliers within the dataset. Temperature trend and NISD calculations were applied to all available ERA5-Land reanalysis grid cells from 1981 to 2020. It is important to note that NISD values were calculated using 40 years of daily MAM (92-day) datasets, therefore capturing an average of the normalized standard deviation within each of the 40 spring seasons.

\[
X_{\text{normalized}} = \frac{X - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}} \tag{1}
\]

Temperature extremes were identified and composited for the 47 ERA5-Land 0.1° × 0.1° grid cells corresponding to the 47 in situ measurement sites by first identifying the extreme events of raw temperature, normalizing the extreme temperature events to equal length and centered about the middle of the event, then averaging all identified normalized extreme temperature events into an extreme temperature event composite. The first step of creating our temperature anomaly composites was to separate our 40-year time period into two distinct time windows: 1981–2000 (Time Window 1; TW1) and 2001–2020 (Time Window 2; TW2). We identified temperature extreme events using raw temperature, then calculated anomalies for the days identified within the events — raw temperature percentiles and climatological means were unique to each time window. Our two time windows were chosen based on distinct shifts observed around this time associated with a warming climate, such as an accelerated decline in sea ice extent (Comiso, 2006; Stroeve and Notz, 2018). All extreme temperature events, regardless of event length, were normalized to 3 days using normalization methodology as described in the appendix of Schemm et al. (2018). The days leading up to and following the extreme temperature event were appended to either side of the event and included in the composites and will hereafter be referred to as “wings.” An extreme heat- or cold event-day can be identified using percentile-based indices based on indices defined by the ETCCDI. Temperature extremes calculated using a 40-year percentile, rather than percentiles unique to each time window, yielded similar results and can be found summarized in Appendix C. TW1- and TW2-unique thresholds were chosen as the primary method for analysis because this method accounts for the change in climate warming over time.

Extreme heat event-days were identified as days with a mean daily raw temperature greater than the 90th percentile of the mean monthly raw temperature. Extreme cold event-days were identified as days with a mean daily raw temperature less than the 10th percentile of the mean monthly raw temperature. Mean daily raw temperatures were calculated as the average of the mean hourly raw temperature for each day. Mean monthly raw temperatures were calculated for MAM using the calculated mean daily raw temperatures, separated into months.

Extreme heat events (HE) (cold events (CE)) were defined as instances of three or more consecutive extreme heat (cold) event-days. Event wings incorporate the five days pre- and post-event and were appended to the event to capture the temperature anomaly behavior leading up to and following the event. The minimum event length, including wings, is therefore 13 days—5 days pre-event, the normalized 3-day event, and 5 days post-event. Composites of mean daily H, LE, SWnet, and LWnet were created for all 47 sites during periods identified as HEs or CEs.

We utilized mean power spectrum analyses to assess the temporal scale of the intraseasonal variability of temperature and SEB anomalies. Following the methodology used in Li et al. (2020b), mean power spectrum analyses were utilized to analyze springtime daily temperature, H, LE, SWnet, and LWnet, anomalies. Daily anomalies were calculated by subtracting the 40-year mean daily value from the mean daily value of each day during spring.

Springtime power spectra were created for each season from 1981 to 2020 using the National Center for Atmospheric Research Command Language, more commonly referred to as NCL, version 6.6.2 (NCAR Command Language, 2019). 40-year mean power spectra were created by averaging all 40 yearly power spectra by frequency. Four sub-seasonal frequency bins were selected within the 40-year power spectra to capture sub-seasonal interactions (<2-week bin), synoptic scale interactions (1- to 2-week bin), mesoscale events (4- to 7-day bin), and multi-day or daily-scale processes (<4-day bin) (Figure B1). For example, if the largest power-frequency sum (P-FS) response is observed within the 1- to 2-week bin, we can infer a physical process that occurs within this timescale (i.e. frontal passage) is responsible for the observed variability. This 40-year mean power spectrum methodology was applied to daily anomalies in temperature, H, LE, SWnet, and LWnet anomalies for each grid cell of the 0.1° × 0.1° ERA5-Land Dataset. These four sub-seasonal bins were chosen in order to identify the temporal scale of the variability and relationships between atmospheric variables. It is essential to consider sub-seasonal or shorter timescales to quantify the short-term temporal covariances that drive Arctic climate interactions, as emphasized in previous studies (Luo et al., 2020; Semmler et al., 2020; Rudeva and Simmonds, 2021; Yao et al., 2024). Studies focusing on Arctic climate interactions that only consider longer, monthly or seasonal time scales are therefore less effective at accounting for the effects short timescale processes have on the Arctic climate.

Instances of significant abnormal P-FSs were identified using the 95% anomaly P-FS confidence interval (CI) for all frequencies within each 40-year mean power spectrum. Anomaly P-FSs above the 95% anomaly P-FS CI were flagged as significant. Mean anomaly P-FS significance thresholds were calculated for each of the four frequency bins. Anomaly P-FSs were normalized using Equation (1) in order to easily compare between frequency bins. Anomaly P-FS significance was primarily analyzed through a change in anomaly P-FS significance between TW1 and TW2. For example, areas flagged as significant in TW1 and insignificant in TW2 were considered significant change in P-FS. The P-FS significance was normalized to identify regions with significantly changing anomaly P-FSs over time — in other words, we identified areas that became more variable over time.

Spearman rank correlations for temperature anomaly P-FSs versus H, LE, SWnet, and LWnet anomaly P-FSs were calculated for the 1- to 2-week frequency bin. The Spearman correlation was used over the Pearson correlation because of its lower sensitivity to extreme values and better handling of monotonic data. Spearman rank correlations calculations were shown only for the 1- to 2-week frequency bin because
of the strong and significant normalized temperature anomaly P-FS response over central and western Siberia observed in this frequency window.

3. Results and discussion

3.1. Spatial and temporal patterns of arctic spring temperature trends and variability

We found spring ERA5-Land Arctic temperature trends to be consistent with what was found by Vose et al.'s (2021) analysis of 1981–2018 monthly mean 5° × 5° NOAA GlobalTemp version 5 and Interim temperature data — a strong increase in spring temperature across the majority of the Arctic with strongest increases of greater than 1 °C decade−1 over central and western Siberia (Fig. 1a). These regions do not only show the strongest positive temperature trends across the 40 years, but also the highest NISD, approaching 1.0 (Fig. 1b). Here we find our first evidence of the central and western Siberian region experiencing a combination of both the strongest positive temperature trend and intraseasonal variation in the Arctic.

![Normalized composites of anomalous temperature, H, LE, SWnet, and LWnet](image-url)

**Fig. 2.** Normalized composites of anomalous temperature (a), H (b), LE (c), SWnet (d), and LWnet (e) up to five days prior to extreme event, during extreme event, and up to five days post extreme event. The 95% CI is illustrated for all composites.
3.2. Temporal shift in temperature extreme events and relation with SEB component anomalies

Temperature extremes have previously been proven to be increasing in frequency and intensity over time (Shabbar and Bonsal, 2003; Alexander et al., 2006; Tomczyk and Bednorz, 2014; Vikhamar-Schuler et al., 2016; Wei et al., 2016; Graham et al., 2017; Sui and Yu, 2018; Yu et al., 2021). Due to their potential strong impact on yearly temperature anomalies, we expect the change in temperature extremes over time to be closely linked with our observed IAV (Dangjing et al., 2010; Kim et al., 2017).

Normalized 13-day raw temperature composites (Figure D1a) and temperature anomaly composites (Fig. 2a) were analyzed for HEs and CEs for each of the 47 selected sites. Across all sites, 2,335 HEs (2,492 CEs) were identified throughout the 40 year analysis period, with 1,178 and 1,577 occurring during TW1 and TW2, respectively (Table 1). As expected with our temperature extreme event identification method, we did not see a shift in occurrence of HEs or CEs between time windows. However, we did discover, although slight, an increase in mean non-normalized HE event length of 7.3% and decrease in CE event length of 2.8% between time windows, providing our first evidence of increasing intensity in Arctic temperature extremes.

Within-CE temperature was significantly less anomalously cold during TW2 than TW1, indicating a decrease in CE intensity over time (Fig. 2a). No significant difference in within-HE temperature anomaly intensity could be identified between TW1 and TW2. Interestingly, TW1 HE temperature anomalies were slightly warmer than TW2 HE temperature anomalies, though not significantly.

Composites of H, LE, SWnet, and LWnet anomalies (Fig. 2b-e) were created for all 47 sites during HEs and CEs (for composites using raw values, see Figure D1). Anomaly composite peak values for all variables, excluding HE LWnet (Fig. 2e), occur within the identified temperature extreme events and are not leading or lagging extreme temperature events. However, a few SEB components are not synchronized with the temperature anomaly evolution. For example, the H anomaly peak is on the first day of the extreme event, before the temperature anomaly. This is likely driven by the extreme temperature event resulting in the highest difference between surface temperature and air temperature during the beginning of the event, decreasing over time. However, since there are no SEB anomaly peaks during the five days preceding the temperature anomaly peak, we can conclude SEB components are not driving the extreme temperature events.

The impact of HEs and CEs on SEB anomalies long outlasts the extreme temperature event — this is particularly true for the turbulent fluxes, which experienced a large increase in anomaly magnitude over the extreme temperature event. In other words, SEB anomalies (excluding HE LWnet) take longer to recover to pre-extreme event levels than temperature anomalies. Based on the temperature extreme event analysis, we conclude that SEB component anomalies were not driving the observed Arctic springtime temperature anomalies.

When analyzing the distribution of HE occurrences as a function of event length (Fig. 3a), we can see a shift towards longer events, reflected in both event number and likelihood of occurrence between TW1 and TW2. The opposite relationship was observed for CE occurrences (Fig. 3b), where we observed a shift towards shorter events between TW1 and TW2. The shift in preference of occurrence likelihood for HEs and CEs between time windows both occurred for event lengths between 4 and 5 days.

The increase in extreme temperature event intensity is evident when comparing the air temperature cumulative density curves and percentile thresholds for TW1 and TW2 (Fig. 3c). The cumulative density curves not only highlight the general shift towards warmer temperatures, but also warmer minimum and cooler maximum temperatures when comparing TW1 with TW2. The importance of the shift in HE and CE percentile thresholds is particularly apparent when a threshold is applied to the opposite time window. For example if the TW1 (TW2) HE threshold is applied to TW2 (TW1), 13.9% (6.4%) of the days would be considered extreme. Conversely, if the TW1 (TW2) CE threshold is applied to TW2 (TW1), 7.7% (12.0%) of the study period would be considered extreme. In other words, due to the nature of our percentile methodology, an increase in temperature extreme intensity cannot be seen through an increase in frequency, but through an increase in temperature magnitude between the two time windows.

### Table 1

Change in ERA5-Land reanalysis MAM extreme temperature event occurrence and mean temperature event length (days event$^{-1}$) between TW1 (1981–2000) and TW2 (2001–2020) for 47 selected grid cells with in situ measurement sites across the Arctic. The percent increase in HE and CE occurrence and mean HE and CE event length between TW1 and TW2 is also presented.

<table>
<thead>
<tr>
<th></th>
<th>HE Occurrences</th>
<th>CE Occurrences</th>
<th>Mean HE Length (days event$^{-1}$)</th>
<th>Mean CE Length (days event$^{-1}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>TW1</td>
<td>1,178</td>
<td>1,224</td>
<td>4.40</td>
<td>4.69</td>
</tr>
<tr>
<td>TW2</td>
<td>1,157</td>
<td>1,268</td>
<td>4.72</td>
<td>4.56</td>
</tr>
<tr>
<td>Percent Increase</td>
<td>-1.8%</td>
<td>3.6%</td>
<td>7.3%</td>
<td>-2.8%</td>
</tr>
</tbody>
</table>
widespread.

1- to 2-week frequency temperature anomaly P-FSs experienced some of their strongest and most significant correlation with H anomaly P-FSs in the central and western Siberian region, where we observed the strongest trends and highest temporal variability in temperature between TW1 and TW2. We therefore hypothesize that the mechanism driving the temporal temperature anomaly variation is also driving the variation in SEB anomalies, particularly H and LW\textsubscript{net} anomalies. A strong temperature anomaly correlation between H anomalies, via flux advection (Miralles et al., 2014; Schumacher et al., 2019; Tian et al., 2023), and LW\textsubscript{net} anomalies, via cloud insulative effects (Luo et al., 2022; Ojo et al., 2021; Tian et al., 2023), was expected and has been confirmed in many previous studies, further supporting our findings. When considering the conclusions from Section 3.2, we suspect the primary driver of our observed temperature IAV to be a large-scale driver of temperature extremes that operates within a 1- to 2-week frequency.

3.4. Discussion

Our leading hypothesis for a common driving mechanism between increasing HE and decreasing CE frequency and temperature anomaly IAV that operates within a 1- to 2-week frequency would be the change in occurrence of Arctic synoptic-scale atmospheric blocking patterns resulting from an Arctic-wide decrease in sea ice extent. Arctic atmospheric blocking patterns are defined as the synoptic-scale obstruction of eastward-moving (northern hemisphere) cyclonic or anticyclonic progression (James, 1994), persisting for roughly one week or longer (Treidl et al., 1981; James, 1994; Diao et al., 2006; McLeod and Mote, 2016; Luo et al., 2018). Despite being a known phenomenon for decades, research around atmospheric blocks is still developing, with new identification and analysis methods being developed every year (Li et al., 2023). Atmospheric blocking duration, frequency, and intensity have been observed to be increasing over time in the North American and North Atlantic Arctic (Francis and Vavrus, 2012; McLeod and Mote, 2016), primarily during spring (Francis and Vavrus, 2012; McLeod and Mote, 2016; Luo et al., 2017). Increasingly frequent winter (summer) blocking patterns have also been observed over the western (eastern) Siberian Arctic (You et al., 2022).

The underlying cause of the increase in Arctic blocking activity and subsequent driver of our observed temperature IAV is likely the observed decline in Arctic sea ice (Luo et al., 2018; Li et al., 2020b; Simmonds and Li, 2021). Seasonal sea ice decline has become an increasingly researched topic as it has been linked to the increase in
continental hot and cold anomalies due to its impact on large-scale atmospheric circulations (Overland et al., 2008; Screen and Simmonds 2013; Simmonds and Govekar 2014; Luo et al., 2018). For example, the Barents-Kara Sea has experienced a rapid decline in sea ice extent over the past three decades (Stroeve et al., 2005; Comiso 2006; Simmonds, 2015). This sea ice decline has been observed to increase the frequency and duration of anticyclonic Ural blocks in the region, which often result in strong HEs in the northern western and central Siberian region (Luo et al., 2018) — corresponding well to our identified areas of largest temperature trends and IAV. Simmonds and Li (2021) found a general significant increase in fall, winter, and spring Arctic baroclinicity, which, when paired with decreased midlatitude baroclinicity, indicate a poleward shift towards and increase in frequency of synoptic-scale atmospheric events.

Sea ice extent has been observed to be both significantly decreasing during the 1979–2020 time window and accelerating in decline in recent years, with strong seasonal variance (Stroeve and Notz, 2018; Simmonds and Li, 2021). A distinct increase in sea ice decline across all seasons was identified around the year 2000, corresponding well to our two identified time windows used throughout our study. For example, the winter sea ice decline, the weakest decline of all seasons, accelerated from roughly 2.4% per decade from 1979 to 1999 to 3.4% from 2000 onwards (Stroeve and Notz, 2018). Additionally, summer/fall sea ice declined at a rate of nearly 17% per decade. This summer/fall rate of decline was not consistent throughout the study period. For example, the 2000-onward September sea ice decline was about 3.5 times the sea ice decline rate of 1979–1999 (Stroeve and Notz, 2018). We hypothesize this observed, accelerating sea ice decline to be responsible for our observed temperature IAV through its governance of Arctic synoptic-scale atmospheric circulations, such as atmospheric blocking circulations.

Particularly for warm extremes, slow-moving and persistent atmospheric blocking circulations have been proven to be important for the development of such temperature extremes across the midlatitudes and into Arctic latitudes (Kunkel et al., 1996; Athar and Lupo, 2010; Cassano et al., 2017; Li et al., 2020c). The increased atmospheric subsidence and therefore shortwave radiation associated with atmospheric blocking patterns is the primary link between atmospheric blocking and trends of regional warming (You et al., 2022).

The impact of atmospheric blocks is, of course, regionally dependent. For example, Arctic atmospheric blocks tend to also induce CEs through eastern Asia (Dong et al., 2020). However, Arctic amplification, through the differential warming of the Arctic relative to midlatitudes (Francis and Vavrus, 2012), has the potential to reduce the occurrence of atmospheric blocking over northern Europe, subsequently reducing the frequency of Eurasian CEs through reduced eastward transport of cold, maritime air (Kennedy et al., 2016).

Despite the impressive accuracy and resolution of ERA5-Land reanalysis data, widespread spatial and temporal validation of the data is vital to ensure the reanalysis data are representing all surface types well across the Arctic. Our validation of ERA5-Land reanalysis data is currently limited to 29 sites, due to the lacking spatial and/or temporal coverage of in situ measurement stations in the Arctic. The scarcity of in situ measurements is relevant for all variables, but even more so for less commonly-measured variables such as H, LE, SW_{net}, and LW_{net}. We therefore want to further emphasize the importance and necessity of
Arctic in situ measurements, especially in understudied regions and landscape types.

4. Conclusion

ERA5-Land 1981–2020 reanalysis temperature data, validated using in situ temperature measurements, were used to analyze springtime temperature IAV at pan-Arctic scale to 1) quantify Arctic spring temperature trends and variability, 2) identify the shift in temperature extreme events and relation with SEB component anomalies over time, and 3) determine Arctic spring temperature anomaly spatial extent and temporal scales. Analysis of temperature temporal and spatial variability was conducted for the seldom-studied region of the Arctic via three primary methods: 1) a temperature trend and NISD analysis paired with 2) an evaluation of temperature extreme temporal evolution and its influence on temperature and SEB anomaly IAV followed by 3) an in depth power spectrum analysis of anomalies in temperature and SEB components. We observed an Arctic-wide increasing temperature trend and a temperature trend peak coupled with a peak in NISD focused around the central and western Siberian region.

An increase in HE frequency and decrease in CE frequency between TW1 and TW2 was discovered when analyzing the change in temperature extremes over time. Similar to the findings and projections proposed in many previous studies, we provide further evidence of the manner and magnitude of not only developing Arctic climate warming, but also Arctic temperature extremes shifting towards more intense warmer events (Smith, 2011; Fischer et al., 2013; Russo et al., 2013; Singh et al., 2013; Spinoni et al., 2015; Pörtner et al., 2022; etc.). We were unable to determine a change in temperature extreme frequency or identify a shift in dominant temperature extreme type due to the extreme identification methodology. We did observe an increase in mean HE length and a decrease in mean CE length between TW1 and TW2, indicating a shift towards longer and shorter events, respectively. Lastly, we identified a general shift towards warmer temperatures, warmer minimum temperatures, and much cooler maximum temperatures when comparing TW1 to TW2, as indicated in the TW1 and TW2 cumulative distributions.

We found temperature and SEB anomalies to share a common temporal length scale, which is indicated by all anomaly peaks in SEB components (excluding LW\textsubscript{net} during HEs), occurring within the extreme temperature event window. If SEB anomaly peaks were leading the extreme temperature event, this would indicate SEB component-driven temperature extremes, however, this was not the case.

Evidence of pronounced temperature IAV in central and western Siberian was gained through power spectrum analyses, within the 1- to 2-week temporal bin showing the most widespread shift in temperature anomaly P-FSs in this region between TW1 and TW2. This finding indicates that western and central Siberian temperature anomaly variance is driven by a process operating within the 1- to 2-week timescale.

1- to 2-week binned P-FSs of temperature and H anomalies showed the highest and most significant Spearman rank correlations across the Arctic, including over the central and western Siberian region, relative to the P-FS anomalies of LE, SW\textsubscript{net}, and LW\textsubscript{net}. LW\textsubscript{net} P-FS anomalies also displayed a mostly significant Spearman rank correlation across the Arctic, though across a smaller spatial extent than for H P-FS anomalies. The significantly strong relationship between temperature and SEB P-FS
anomalies in this region is indicative of a common driving mechanism of variability between the parameters.

In conclusion, Arctic sea ice decline has been proven in previous studies to enable the development of atmospheric circulations conducive to temperature extreme development, such as atmospheric blocking events. Such circulations have been increasing in frequency and intensity partly due to an Arctic-wide increase in rate of sea ice decline, which experienced a stark increase in intensity roughly around the year 2000, coinciding well with the two time windows chosen in this study. Additionally, our identified IAV maxima occurring within the 1- to 2-week bin and across the Arctic matches well with the temporal operating period and spatial extent of atmospheric blocking events. These two points, in combination with the increase in heat extreme and decrease in cold extreme intensity found in this study, lead us to the following hypothesis. We hypothesize that the observed spatial and temporal IAV in springtime temperature and surface energy fluxes can be attributed to increased Arctic sea ice decline and an increase in the frequency and strength of associated atmospheric blocking events.

CRediT authorship contribution statement

Raleigh Grysko: Writing – review & editing. Writing – original draft. Visualization, Validation, Software, Methodology, Investigation, Formal analysis. Data curation, Conceptualization. Jin-Soo Kim: Writing – review & editing. Supervision, Software, Project administration. Methodology, Data curation, Conceptualization. Gabriela Schaepman-Strub: Writing – review & editing. Supervision, Project administration. Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

All data used in this study are publicly available.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.wace.2024.100650.

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