

March 25th, 2020

Dear Dr. Maycock:

Thank you for your prompt response and positive feedback. We have further revised the manuscript according to the reviewer's comments and we would like to resubmit our paper, "Atmospheric Teleconnection Processes Linking Winter Air Stagnation and Haze Extremes in China with Regional Arctic Sea Ice Decline" (manuscript#: acp-2019-1023), for publication in the *Atmospheric Chemistry and Physics*.

Please see the point-by-point response to the review and the revised manuscript with tracked changes in this file for details. A clean version of the revised manuscript without tracked changes is also uploaded to the online submission system.

Thank you again for the time and efforts you and the reviewer put into reviewing this paper.

I look forward to hearing from you soon.

Sincerely,

Yufei Zou

Postdoctoral Research Associate
Atmospheric Sciences and Global Change Division
Pacific Northwest National Laboratory
902 Battelle Blvd
Richland, WA 99354
Email: yufei.zou@pnnl.gov

Response to the referee's comments:

General comments

Thank you very much to the authors for addressing my comments. The issues I raised regarding statistical robustness have now largely been resolved, but I have a few minor comments remaining, which are listed below. Overall, I think that this paper is very interesting and would recommend it for publication, given the new mechanistic insight it provides into the important issue of haze pollution extremes in China.

Response: Thank you very much for the comments and recommendation. We have further revised the manuscript according to your suggestions. Please see below our point-by-point responses (in blue) to your comments and corresponding changes in the revised manuscript.

Specific comments

Section 2.3: Thank-you for addressing my concerns about the autocorrelation. Your results presented in Tables R1 and R2, and Figures R5 and R6, convincingly show that the autocorrelation from month to month is minimal. Could you perhaps add in a sentence saying that the autocorrelation is minimal, to avoid confusion for other readers (perhaps after saying you have 90 samples on line 21 of page 6)?

Response: Thank you for the suggestion. We have added one sentence in line 24 of page 6 as follows: "The autocorrelation between consecutive months in each experiment is minimal, suggesting mutually independent sampling variables for statistical analysis".

Page 9, lines 35-40: With these new 95% confidence ranges from Tables S3 and S4, I am now convinced that the increase in frequency and intensity of ECP_PPI positive extremes is robust for the 30-year simulations (your Figure R3 was also useful for showing this, so thank-you for that). However, I think as well as stating that the increase in ECP_PPI extremes is statistically significant (which you have done on Page 10, lines 2-4), it should be more explicitly stated that the increase in MCA_Z500 extremes is not. This raises a bit of an issue, since the increase in

ECP_PPI extremes is being attributed to the increase in MCA_Z500 extremes; if the latter isn't robust, then it's unclear whether the former is robust. However, given your Figures 4, 5, 6, and S7 in Section 3.3, there do appear to be robust effects of sea-ice loss on atmospheric circulation in the ECP region in the SENSr2 extreme members. This gives me more confidence that there is indeed a dynamical connection between SENSr2 sea-ice loss and increased ECP_PPI extremes. Perhaps this could be highlighted here?

Response: Thank you for the comment. A previous study by Screen et al. (2014) suggested that the detection of thermodynamic responses (such as the change in Z500 in this case) requires an ensemble size approximately twice as large as thermal responses (e.g., temperature). Since PPI is partially based on near-surface temperature gradient (see Eq. (2) in the manuscript), it may be easier to detect a statistically significant response in ECP_PPI than in MCA_Z500 for the given ensemble size in this work.

We have now added a sentence with the explanation in line 4 of page 10: "In contrast, the changes of MCA_Z500 in all experiments are not statistically significant, which might be attributable to the higher difficulty and larger ensemble size requirement for detecting the dynamical-oriented responses (e.g., SLP and geopotential height anomalies) than the thermal-oriented responses (e.g., vertical temperature gradient anomalies and their effects on PPI) (Screen et al., 2014)."

Page 10, lines 1-2: I don't think there's enough evidence to make the following statement: 'The increase in the teleconnection pattern index MCA_Z500 is less significant than that in the regional air stagnation index ECP_PPI, suggesting a potential nonlinear relationship between large-scale circulation and regional stagnation'. In particular, as highlighted by the large 95% confidence range for MCA_Z500, there is large uncertainty in the response of MCA_Z500 extremes due to internal variability. As such, the apparent non-linear relationship between MCA_Z500 and ECP_PPI could equally be due to internal variability / chance. I therefore recommend this sentence is removed.

Response: Thank you for the suggestion. We have removed this sentence in the revised manuscript.

Section 3.3: Just a general comment - I think structuring this section around two questions has helped provide clarity, and that the addition of Figure 5c/f, Figure 6c/f/i/l, and Figure S7 has made it much more convincing that SENSr2 sea-ice loss does indeed have an effect on circulation extremes (and therefore pollution extremes) over the ECP region. This is relevant to my comment two paragraphs above.

Response: Thank you for the comment. These two questions were added in response to your previous concerns. We appreciate your constructive comments to improve the presentation quality and clarity of this work.

Page 14, line 37: not sure what ‘non-linear’ is referring to here.

Response: We removed it and rephrased the sentence as “induced atmospheric responses...” in the revised manuscript.

Page 17, line 1: I’m confused about the phrase ‘forced air stagnation response to internal variability’. How can there be a forced response to internal variability? The two are separate, although they can resemble each other. I presume this is a typo and the response is to some forcing Callahan et al. (2019) prescribe.

Response: In Callahan et al. (2019), they quantify the signal-to-noise ratio of the CESM-LE historical climate by dividing the magnitude of the variable trend in the ensemble mean by the standard deviation in the magnitude of the trends across all realizations. They determine that anthropogenic forcing exerts a robust influence on the system if the signal-to-noise ratio is greater than or equal to one, following Hawkins and Sutton (2009). Therefore, the “forced air stagnation response” here denotes the change of air stagnation conditions in response to anthropogenic forcing in the CESM-LE historical realizations, which is overwhelmed by simulated natural variability given signal-to-noise ratios less than one in multiple regional air stagnation indices.

For clarification, we have rephrased the sentence in line 2 of page 17 to “Callahan et al. (2019) estimated consistent signal-to-noise ratios less than one in multiple regional air stagnation

indices for Beijing based on the CESM-LE historical simulations, demonstrating the dominant role of natural variability rather than anthropogenic forcing in modulating regional circulation and ventilation”.

Technical corrections

Page 2, line 34: I suggest just using ‘correlation’ rather than ‘good correlation’, as no correlation can be said to be ‘good’ or ‘bad’. Also, I suggest splitting this sentence up as follows, as it is currently very long:

‘However, a clear understanding of key dynamic processes linking complex meteorological changes to critical climate factors is still missing. This is necessary to establish a robust causal relationship between remote climate drivers and localized atmospheric responses, because a correlation does not necessarily imply causation.’

Response: Thank you for the suggestion. We have revised the sentence as suggested.

Page 14, line 20: it would help to clarify that this is for positive ECP_PPI extremes (i.e. not MCA_Z500 extremes)

Response: We clarified this in line 23 of page 14 in the revised manuscript.

Page 15, line 42: ‘stratosphere’ should be ‘stratospheric’

Response: Thank you. It’s changed to “stratospheric”.

Page 16, line 42: I would suggest reordering to ‘Callahan et al. (2019) estimated a signal-to-noise ratio of less than one for the forced air stagnation response...’

Response: Thank you. We have rephrased the sentence as suggested.

Reference

Callahan, C. W., Schnell, J. L., and Horton, D. E.: Multi-Index Attribution of Extreme Winter Air Quality in Beijing, China, *J Geophys Res-Atmos*, 124, 4567-4583, <https://doi.org/10.1029/2018jd029738>, 2019.

Hawkins, E., and Sutton, R.: The potential to narrow uncertainty in regional climate predictions. *Bulletin of the American Meteorological Society*, 90, 1095–1108. <https://doi.org/10.1175/2009BAMS2607.1>, 2009.

Screen, J. A., Deser, C., Simmonds, I., and Tomas, R.: Atmospheric impacts of Arctic sea-ice loss, 1979-2009: separating forced change from atmospheric internal variability, *Clim. Dyn.*, 43, 333-344, <https://doi.org/10.1007/s00382-013-1830-9>, 2014.

1 Atmospheric teleconnection processes linking winter air stagnation 2 and haze extremes in China with regional Arctic sea ice decline

3 Yufei Zou¹, Yuhang Wang², Zuowei Xie³, Hailong Wang¹, Philip J. Rasch¹

4 ¹Atmospheric Sciences and Global Change Division, Pacific Northwest National Laboratory, Richland,
5 WA 99354, USA

6 ²School of Earth and Atmospheric Sciences, Georgia Institute of Technology, Atlanta, GA 30332, USA

7 ³International Center for Climate and Environment Sciences, Institute of Atmospheric Physics, Chinese
8 Academy of Sciences, Beijing, 100029, China

9 *Correspondence:* Yufei Zou (yufei.zou@pnnl.gov) and Yuhang Wang (yuhang.wang@eas.gatech.edu)

10 **Abstract.** Recent studies suggested significant impacts of boreal cryosphere changes on wintertime air
11 stagnation and haze pollution extremes in China. However, the underlying mechanisms of such a
12 teleconnection relationship remains unclear. Here we use the Whole Atmosphere Community Climate
13 Model (WACCM) to investigate dynamic processes leading to atmospheric circulation and air
14 stagnation responses to Arctic sea ice changes. We conduct four climate sensitivity experiments by
15 perturbing sea ice concentrations (SIC) and corresponding sea surface temperature (SST) in autumn and
16 early winter over the whole Arctic and three sub-regions in the climate model. The results indicate
17 distinct responses in circulation patterns and regional ventilation to the region-specific Arctic changes,
18 with the largest increase of both the probability (by 132%) and the intensity (by 30%) of monthly air
19 stagnation extremes being found in the experiment driven by SIC and SST changes over the Pacific
20 sector of the Arctic (the East Siberian and Chukchi Seas). The increased air stagnation extremes are
21 mainly driven by an amplified planetary-scale atmospheric teleconnection pattern that resembles the
22 negative phase of the Eurasian (EU) pattern. Dynamical diagnostics suggest that convergence of
23 transient eddy forcing in the vicinity of Scandinavia in winter is largely responsible for the
24 amplification of the teleconnection pattern. Transient eddy vorticity fluxes dominate the transient eddy
25 forcing and produce a barotropic anticyclonic anomaly near Scandinavia and wave-train propagation
26 across Eurasia to the downstream regions in East Asia. The piecewise potential vorticity inversion
27 analysis reveals that this long-range atmospheric teleconnection of Arctic origin takes place primarily
28 via the middle and upper troposphere. The anomalous ridge over East Asia in the middle and upper
29 troposphere worsens regional ventilation conditions by weakening monsoon northwesterlies and
30 enhancing temperature inversions near the surface, leading to more and stronger air stagnation and
31 pollution extremes over eastern China in winter. Ensemble projections based on state-of-the-art climate
32 models in the Coupled Model Intercomparison Project Phase 6 (CMIP6) corroborate this teleconnection
33 relationship between high-latitude environmental changes and middle-latitude weather extremes, though
34 the tendency and magnitude vary considerably among each participating model.

1 Introduction

2 The severe air pollution problem in China has drawn broad attention because of its profound public
3 health (Kan et al., 2012), socioeconomic (Xie et al., 2016), and climatic impacts (Li et al., 2016). In
4 response to an increasing health burden and social costs caused by these environmental stresses, China
5 has prioritized environment protection by implementing ~~a very unprecedentedly~~ stringent air pollution
6 control policy (the State Council of China, 2013) and achieved great success with gradually decreasing
7 annual mean fine particle (PM_{2.5}: particulate matter with aerodynamic diameters of 2.5 micrometers or
8 less) concentrations in recent years (Zhang et al., 2019). However, severe haze pollution associated with
9 PM_{2.5} and PM₁₀ (particulate matter with aerodynamic diameters of 10 micrometers or less) in boreal
10 winter still makes clean air a great challenge for China, especially over the East China Plains (ECP)
11 area (Song et al., 2017). Many studies have investigated possible causes of China's haze pollution from
12 various perspectives: massive primary pollution emissions (Liu et al., 2016; Sun et al., 2016), rapid
13 secondary pollution formation (Cheng et al., 2016; Huang et al., 2014; Guo et al., 2014; Wang et al.,
14 2016), unfavorable regional circulation features (Jia et al., 2015; Niu et al., 2010; Yin and Wang, 2017),
15 and positive aerosol-weather feedback effects (Ding et al., 2016; Lou et al., 2019; Zhang et al., 2018;
16 Zhong et al., 2018) have all been identified as contributing factors. An et al. (2019) provides a recent
17 comprehensive review of the severe haze problem in China and emphasizes the synergy among these
18 contributing factors.

19 It has also been reported that climate change plays an important role in generating conducive
20 meteorological conditions for the favorable formation and unfavorable ventilation of air pollutants in
21 China and many other regions (Cai et al., 2017; Dawson et al., 2014; Hong et al., 2019; Horton et al.,
22 2014; Wang and Chen, 2016). Several possible climate factors have been investigated for their effects
23 on winter haze pollution in China, including changes in: 1) Arctic sea ice (Wang et al., 2015; Zou et al.,
24 2017); 2) Eurasian snow cover (Yin and Wang, 2018; Zou et al., 2017); 3) El Niño–Southern
25 Oscillation (ENSO; Chang et al., 2016; Sun et al., 2018; Zhao et al., 2018; Zhang et al., 2019); 4)
26 Pacific Decadal Oscillation (PDO; Zhao et al., 2016); and 5) northwestern Pacific sea surface
27 temperature (SST; Pei et al., 2018). In those studies, researchers mainly focused on the relationships of
28 various climate factors with pollution-related weather conditions such as the intensity of East Asia
29 winter monsoon (EAWM), planetary boundary layer height, precipitation, and circulation patterns that
30 correlated with winter haze pollution in China. The data analysis results have been further corroborated
31 by modeling studies (Zhao et al., 2016; Zhao et al., 2018; Zhang et al., 2019; Zou et al., 2017).
32 However, a clear understanding of key dynamic processes linking complex meteorological changes to
33 critical climate factors is still missing, ~~which~~ This is necessary to establish a robust causal relationship
34 between remote climate drivers and localized atmospheric responses, because a ~~good~~ correlation does
35 not necessarily imply causation. Other studies have examined future projections of air stagnation and
36 pollution conditions based on different climate scenarios and ended up with contradictory conclusions
37 over the eastern China region (Cai et al., 2017; Hong et al., 2019; Horton et al., 2014), which further
38 highlights the importance of physical process-based analysis of modeling results.

39 Given the increasing evidence that climate change—especially that occurring in high-latitude
40 regions—may have an influence on middle-latitude circulation and weather extremes (Cohen et al.,
41 2014; IPCC, 2019), it is imperative to identify the key atmospheric processes driving the circulation

1 responses and to understand the underlying physical mechanisms for specific extreme weather events.
2 Several possible dynamic pathways linking Arctic warming to midlatitude weather extremes have been
3 proposed and investigated in the past few years (Barnes and Screen, 2015; Overland et al., 2016).
4 However, the observational data and modeling results are sometimes contradictory and are open to
5 different interpretations (Cohen et al., 2020). Therefore, here we revisit the particular linkage between
6 Arctic sea ice and wintertime air stagnation in China identified by our previous study (Zou et al., 2017)
7 and elucidate a teleconnection mechanism based on new climate model sensitivity experiments and
8 dynamic diagnoses. We describe the analytical methods and datasets in Sect. 2 and analysis of model
9 results in Sect. 3, which is followed by discussion and conclusions in Sect. 4.

10 **2 Analysis methods and datasets**

11 **2.1 Observation and reanalysis data**

12 Monthly gridded Arctic sea ice concentration (SIC) and sea surface temperature (SST) data for 1950–
13 2018 were collected from the Met Office Hadley Centre (HadISST; Rayner et al., 2003) for statistical
14 analysis and comparison with numerical simulation results. We conducted trend analysis for Arctic sea
15 ice changes and examined the statistical correlation between these changes and key atmospheric
16 circulation patterns of interest. The National Centers for Environmental Prediction and National Center
17 of Atmospheric Research (NCEP/NCAR) reanalysis data (Kalnay et al., 1996) was used to calculate
18 indices of a hemispheric-scale Eurasian (EU) pattern (Wallace and Gutzler, 1981) and a regional
19 circulation pattern (MCA_Z500) over East Asia in the 500 hPa geopotential height field (Z500) (Fig. S1
20 in the Supplement). We focused on these two circulation patterns at different spatial scales given their
21 considerable impacts on winter synoptic weather (Liu et al., 2014; Wang and Zhang, 2015) and regional
22 haze pollution in China (Li et al., 2019). We followed the definition of the EU index (EUI) in Wallace
23 and Gutzler (1981) and calculated the EU index in winter (December-January-February; DJF) from
24 1951 to 2019 (years are aligned with January of the winter season in this work),

$$25 \quad EUI = -\frac{1}{4}Z^*(55^\circ N, 20^\circ E) + \frac{1}{2}Z^*(55^\circ N, 75^\circ E) - \frac{1}{4}Z^*(40^\circ N, 145^\circ E) \quad , \quad (1)$$

26 where Z^* denotes the normalized monthly mean geopotential height anomalies at 500 hPa using the
27 1981-2010 average as the climatology. We then regressed the 500 hPa geopotential height anomalies
28 onto this index to get the EU spatial pattern (Fig. 1c/d), which resembles those reported in Liu et al.
29 (2014), Wallace and Gutzler (1981), and Wang and Zhang (2015) quite well.

30 We then used the NCEP/NCAR reanalysis data to calculate gridded pollution potential index (PPI) as
31 a synthetic meteorological proxy for describing regional air stagnation severity (Zou et al., 2017). The
32 monthly PPI in winter (DJF) of 1951–2019 was calculated using Eq. (2) as a weighted average of
33 normalized surface wind speed index (WSI) and near surface air temperature gradient index (ATGI)
34 based on the reanalysis data. WSI was standardized by subtracting time-averaged climatological mean
35 of near-surface wind speed over the 1981-2010 period from the monthly values at each grid cell and
36 then dividing by its standard deviations in the same period. ATGI was the standardized potential
37 temperature gradient field between 925 and 1000 hPa using the same method. These two indices are

1 used to reflect horizontal and vertical dispersions of near-surface air pollutants, respectively. We then
2 estimated grid-scale PPI by weighted averaging WSI and ATGI,

$$3 \quad PPI = \frac{r_1 \times WSI + r_2 \times ATGI}{|r_1| + |r_2|}, \quad (2)$$

4 where r_1 and r_2 are the Pearson correlation coefficients of WSI ($r_1 = -0.73$) and ATGI ($r_2 = 0.70$) with in
5 situ PM_{10} observations over the ECP area (Zou et al., 2017). Regional averaged ECP_PPI was estimated
6 by averaging grid-scale PPI over the ECP area (112° E to 122° E, 30° N to 41° N).

7 Lastly, we applied the Maximum Covariance Analysis (MCA) method (Wilks, 2011) as in our
8 previous study (Zou et al., 2017) to the Z500 and PPI fields and identified the regional MCA_Z500
9 pattern that had the largest covariance with PPI changes in ECP. The MCA analysis performs a singular
10 value decomposition of the covariance matrix of the selected two variables and generates a series of
11 coupled modes in space and time dimensions for both variables (Wilks, 2011). We chose the first
12 couple of modes in the Z500 and PPI fields as the MCA_Z500 and MCA_PPI patterns that show the
13 largest covariance with each other ($r=0.65$; Fig. S1b in the Supplement). The MCA_Z500 pattern
14 resembles a regional manifestation of the planetary-scale EU pattern (in negative phase) with a good
15 correlation between these two indices ($r=-0.67$; Fig. S1b in the Supplement). However, it's worth noting
16 that this regional MCA_Z500 pattern can also be excited by other large-scale teleconnection processes
17 such as the East Atlantic pattern or the East Atlantic/Western Russia pattern associated with both
18 natural variability and perturbed Rossby wave activity (Lim, 2015; Simmons et al., 1983). These
19 variables are assessed as metrics of circulation and ventilation responses to climate forcing in the
20 following sections.

21 2.2 Climate models and numerical sensitivity experiments

22 This study uses the high-top Whole Atmosphere Community Climate Model (WACCM) version 5
23 (Marsh et al., 2013) within the common numerical framework of the NCAR Community Earth System
24 Model (CESM) used for climate sensitivity experiments. WACCM is a comprehensive atmospheric
25 model with a well-resolved stratosphere of 70 vertical layers spanning the surface to the thermosphere
26 (~ 0.001 hPa) at a horizontal resolution of 1.9° (latitude) $\times 2.5^\circ$ (longitude). We conducted 30-year
27 simulations (with an additional unanalyzed 1-year period for the control run as spin-up) as the control
28 (CTRL) run with annually repeating prescribed climatological (1981-2010 average) Arctic SIC and SST
29 from the Met Office Hadley Centre (Rayner et al., 2003) (Table 1). We then performed four climate
30 sensitivity experiments by perturbing SIC and SST in different Arctic regions to investigate the climate
31 sensitivity to regional Arctic sea ice changes and associated local ocean warming (Screen et al., 2013).

32 The spatial distribution of correlation coefficients between SIC and EU indices (Fig. 1b) reveals
33 varying climate sensitivity relationships between regional sea ice changes and circulation responses as
34 suggested by previous studies (Screen, 2017; Sun et al., 2015; McKenna et al., 2018). To test this
35 region-specific climate sensitivity, we first perturbed SIC and SST in the whole Arctic region to
36 evaluate their comprehensive climate effects, and then divided the whole Arctic region into three sub-
37 regions (R1-R3; Fig. 1b) and perturbed regional SIC and SST in three region-specific numerical
38 experiments (Table 1). Specifically, we branched an 8-month simulation from each July of the CTRL
39 run with observed SIC/SST data in autumn and early winter (August-November) of 2012 over the
40 whole Arctic in the first sensitivity experiment (SENSall). We chose 2012 because it had the lowest

1 level of Arctic sea ice concentrations throughout the satellite era of the last four decades
2 (NSIDC/NASA, 2019) and thus provides the strongest sea-ice forcing to the climate system. We only
3 changed the surface boundary conditions (SIC/SST) at modeling grid cells with SIC anomalies larger
4 than 10% to focus on the Arctic regions with the most significant changes. We then added three region-
5 specific sensitivity experiments (SENSr1/r2/r3) by perturbing regional SIC and SST in R1-R3 regions
6 (R1: 30° E to 150° E, 70° N to 85° N; R2: 150° E to 145° W, 60° N to 85° N; R3: 145° W to 30° W,
7 50° N to 85° N; Fig. 1b), respectively, following the same perturbation method in SENSall.

8 We analyzed the consecutive December-January-February monthly data at the end of each sensitivity
9 simulation to examine the seasonal impact of Arctic sea ice changes in comparison with observation and
10 reanalysis data. The simulated EU/MCA_Z500 circulation indices were estimated by projecting
11 modeling differences (SENSx-CTRL, x=all/r1/r2/r3) onto the reanalysis-based EU/MCA_Z500
12 patterns, and the ECP_PPI indices in the model were calculated following the same method of the
13 reanalysis one by using the CTRL ensemble mean as the climatology.

14 Since the default 2000-based emission inventory (Lamarque et al., 2010) in WACCM was prepared
15 for the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC AR5) and is
16 low biased over China, we updated the anthropogenic emission inventory for China by replacing the
17 default one with the 2010-based multi-resolution emission inventory for China (MEIC; Li et al., 2017).
18 The MEIC-MIX inventory was developed for the years 2008 and 2010 and has been widely used for air
19 pollution simulation and health impact assessment studies in China (Geng et al., 2017; Zhang et al.,
20 2017). It is worth noting that the main objective of this study is not to reproduce severe haze pollution
21 extremes in China, but to understand how regional atmosphere and pollution conditions respond to the
22 key climate drivers in the high latitudes. Therefore, we only focused on the relative changes of PPI and
23 surface PM_{2.5} concentrations between SENS and CTRL experiments and investigated dynamic
24 processes associated with these changes in our following analysis.

25 Besides the CESM-WACCM model used in the sensitivity experiments, we also analyzed results
26 from other state-of-the-art climate models in the latest CMIP6 project to examine the teleconnection
27 relationship between Arctic sea ice and regional air stagnation in China. Table S1 in the Supplement
28 lists the 8 CMIP6 models with the same experiment and variant ID (r1i1p1f1) used for historical
29 simulations and future projections of the Arctic sea ice extent (SIE) and ECP_PPI time series. SIE is a
30 measurement of the ocean area where sea ice concentrations exceed 15% (NSIDC, 2019). We analyzed
31 historical simulations (1950-2014; Eying et al., 2016) and future projections (2015-2100) of the Shared
32 Socioeconomic Pathway under a high greenhouse gas emission scenario (SSP5-8.5; O'Neill et al.,
33 2016) by each model to maintain consistency with previous studies (Cai et al., 2017; Horton et al.,
34 2014). We then calculated time series of regional averaged Arctic SIE and ECP_PPI in each CMIP6
35 model to estimate ensemble means and standard deviations of these variables. The estimation of the SIE
36 relative changes and ECP_PPI indices in CMIP6 followed the same method of the observation- and
37 reanalysis-based ones by using 1981-2010 historical runs as the climatology. The whole 150-year
38 CMIP6 time series was equally divided into three time periods (P1-P3) to evaluate regional air
39 stagnation conditions under different Arctic sea ice forcing.

1 2.3 Statistical analysis methods

2 We examined long-term linear trends of observed SIC in each grid cell in Fig. 1a using the Mann-
3 Kendall test, a non-parametric (i.e., distribution free) method that is based on the relative ranking of
4 data values. After trend detection, we estimated the Pearson correlation between the gridded sea ice
5 variations and the EU index. To evaluate the circulation impact on regional ventilation, we conducted
6 composite analysis of gridded PPIs over the middle latitude regions (Fig. 1b) and examined their
7 statistical significance using the two-sided Student's t-test. The t-test was also used to evaluate
8 statistical significance of surface heat flux changes and atmospheric responses in the modeling results,
9 such as the ensemble mean differences of atmospheric variables between the WACCM SENS and
10 CTRL experiments.

11 To further evaluate the modeling sensitivity results, we used statistical functions in the Python SciPy
12 v1.4.1 module (<https://docs.scipy.org/doc/scipy/reference/stats.html>; last access: 24 October, 2019) to
13 evaluate statistical properties of the modeling samples and estimate their cumulative distribution
14 functions (CDFs) and probability density functions (PDFs) following proper distributions. We first
15 examined the statistics of the MCA_Z500 and ECP_PPI indices in each experiment in terms of their
16 location, scale, and shape (Table S2), and then conducted the Shapiro-Wilk normality test (Wilks, 2011;
17 the “shapiro” function in SciPy v1.4.1) to examine whether the data conform to normal distributions
18 (Fig. S2 and Fig. S3 in the Supplement). The null hypothesis of the normality test is that the sampling
19 data from each experiment are drawn from a normal distribution. If the p-value is larger than 0.05, we
20 failed to reject the null hypothesis and fitted normal distribution (the “norm.fit” function in SciPy
21 v1.4.1) CDF/PDF curves to the modeling data (30 years \times 3 winter months = 90 samples). Otherwise,
22 we rejected the null hypothesis and chose a proper non-Gaussian distribution (e.g., the
23 “gumble_r.fit”/“gumble_l.fit” functions in SciPy v1.4.1 for right-skewed/left-skewed distributions) to
24 fit CDF/PDF curves to the data. The autocorrelation between consecutive months in each experiment is
25 minimal, suggesting mutually independent sampling variables for statistical analysis. Table S2 shows
26 ~~these~~ statistical properties and test results of each experiment, ~~which suggests that~~ that indicate the data
27 in most experiments conform to normal distributions except MCA_Z500 in SENSall and
28 MCA_Z500/ECP_PPI in SENSr2. The statistics and histograms of the SENSall MCA_Z500 indices
29 suggest a skew distribution to the left, while those of the SENSr2 MCA_Z500/ECP_PPI indices suggest
30 a skew distribution to the right. Therefore, we fitted a left-skewed Gumbel distribution to the SENSall
31 MCA_Z500 data and a right-skewed Gumbel distribution to the SENSr2 data, respectively. The
32 goodness-of-fit results are shown in the Q-Q plots of Fig. S2 and Fig. S3 in the Supplement. After
33 distribution fitting, we chose the 95th percentiles of the MCA_Z500 and ECP_PPI indices in CTRL as
34 the thresholds of positive extremes and estimated the probability of positive extremes in the four SENS
35 experiments based on their fitted CDF curves (i.e., $P_{PPI_{SENS} \geq PPI_{CTRL}^{95th}}$). The average intensity of positive
36 extreme values in each experiment was estimated by weighted ~~averaging~~ averaging values with their
37 probabilities as weights. The fitted CDFs for all the WACCM experiments are shown in Fig. 3 and
38 discussed below. For CMIP6 data, we used the same approach to fit CDF curves for each modeling and
39 the reanalysis data in different time periods. The CDFs for three time periods over 1950-2000 (P1),
40 2001-2050 (P2), and 2051-2100 (P3) are shown in Fig. 7 and discussed later near that figure. The P1
41 time period over 1951-2000 was chosen as the reference period for the NCEP reanalysis and CMIP6

1 modeling data. The thresholds of positive extremes in the reanalysis and CMIP6 models were defined as
 2 the 95th percentiles of ECP_PPI values in this reference time period, which were then used to evaluate
 3 probability changes of positive extremes in the other two periods (i.e., $P_{PPI_{P2/3} \geq PPI_{P1}^{95th}}$).

4 Such extreme value analyses provide an alternative perspective to the traditional ensemble mean
 5 statistical analysis, lending a more comprehensive understanding of atmospheric responses to climate
 6 forcing based on full distribution curves. A special report of the Intergovernmental Panel on Climate
 7 Change (IPCC, 2012) focusing on the risks of climate extreme events discussed three kinds of responses
 8 including “shifted mean”, “increased variability”, and “changed symmetry” in climate variable
 9 distributions to climate change. These distinct responses demonstrate that changes in extremes can be
 10 linked to changes in the mean, variance, and shape of probability distributions (IPCC, 2012). We
 11 followed this analysis framework to examine statistical distribution changes in regional circulation
 12 (MCA_Z500) and ventilation (ECP_PPI) with consideration of both natural variability and perturbation-
 13 induced responses in our climate sensitivity experiments. The uncertainty of the extreme probabilities
 14 and intensities in each experiment was estimated using 95% percentile ranges (i.e., values between the
 15 2.5th percentile to 97.5th percentile) via a bootstrap method by resampling the model simulated samples
 16 with replacement (10000 times) and re-estimating those statistics based on the repeatedly fitted CDFs
 17 (Tables S3 and S4 in the Supplement).

18 2.4 Diagnostics of atmospheric dynamics

19 To understand the atmospheric pathways from the Arctic sea ice forcing to regional circulation
 20 responses, we employed multiple dynamic diagnostic tools to investigate storm-track characteristics and
 21 local interactions between transient eddy forcing and the time-mean flow. The properties of transient
 22 eddies were depicted by eddy kinetic energy (EKE) in Eq. (3) and the horizontal components of
 23 extended Eliassen-Palm vectors (**E** vectors) in Eq. (4) given by Trenberth (1986),

$$24 \quad EKE = \frac{1}{2} (\overline{u'^2} + \overline{v'^2}) \quad , \quad (3)$$

$$25 \quad \mathbf{E} \text{ vector} = \frac{1}{2} (\overline{v'^2} - \overline{u'^2}) \mathbf{i} - \overline{u'v'} \mathbf{j} \quad , \quad (4)$$

26 where u and v are the daily zonal and meridional wind components, respectively. The prime denotes the
 27 2–8-day band-pass-filtered quantities and the overbar denotes temporal averaging over a month.

28 The direction of **E** vectors approximately points to the wave energy propagation relative to the local
 29 time-mean flow, while the divergence and curl of **E** vectors indicate eddy-induced acceleration of local
 30 mean zonal and meridional winds (Trenberth, 1986).

31 We then illustrated transient eddy feedback to the quasi-stationary flow by eddy-induced
 32 geopotential height tendencies due to the convergence and divergence of transient eddy vorticity and
 33 heat fluxes (Lau and Holopainen, 1984; Lau and Nath, 1991),

$$34 \quad \left\{ \frac{1}{f} \nabla^2 + f \frac{\partial}{\partial p} \left(\frac{1}{\sigma} \frac{\partial}{\partial p} \right) \right\} \left(\frac{\partial \phi}{\partial t} \right) = D^V + D^H, \text{ where } D^V = -\nabla \cdot (\overline{V' \zeta'}) \text{ and } D^H = f \frac{\partial}{\partial p} \left(\frac{\nabla \cdot (\overline{V' \theta'})}{S} \right). \quad (5)$$

35 In Eq. (5), D^V and D^H are the eddy forcing due to heat and vorticity fluxes, respectively. f is the
 36 Coriolis parameter, $\phi = gz$ is geopotential, $\sigma = -\left(\frac{\alpha}{\theta}\right) \left(\frac{\partial \theta}{\partial p}\right)$ is static stability, α is specific volume, θ is

37 potential temperature with $S = -\frac{\partial \theta}{\partial p}$, V is horizontal wind, and ζ is relative vorticity. Here the prime

1 and overbar are the same with those in Eqs. (3) and (4). By inverting the eddy forcing terms D^V and D^H
 2 on its right-hand side separately and solving the equation, we could distinguish independent effects of
 3 vorticity and heat fluxes induced by transient eddies on the corresponding height tendencies Z_t^V and Z_t^H .
 4 The net tendency associated with the combination of D^V and D^H is denoted as Z_t^{V+H} .

5 Moreover, we used the phase-independent 3-dimensional wave activity flux (WAF; Takaya and
 6 Nakamura, 2001) based on the monthly averaged reanalysis and modeling data to diagnose zonal and
 7 vertical propagation of locally forced wave packet induced by quasi-geostrophic (QG) eddy
 8 disturbances embedded in a zonally varying basic flow,

$$9 \quad \mathbf{W} = \frac{p \cos \phi}{2|\mathbf{U}|} \left[\begin{array}{l} \frac{u}{a^2 \cos^2 \phi} \left[\left(\frac{\partial \psi'}{\partial \lambda} \right)^2 - \psi' \frac{\partial^2 \psi'}{\partial \lambda^2} \right] + \frac{v}{a^2 \cos \phi} \left[\frac{\partial \psi'}{\partial \lambda} \frac{\partial \psi'}{\partial \phi} - \psi' \frac{\partial^2 \psi'}{\partial \lambda \partial \phi} \right] \\ \frac{u}{a^2 \cos^2 \phi} \left[\frac{\partial \psi'}{\partial \lambda} \frac{\partial \psi'}{\partial \phi} - \psi' \frac{\partial^2 \psi'}{\partial \lambda \partial \phi} \right] + \frac{v}{a^2} \left[\left(\frac{\partial \psi'}{\partial \phi} \right)^2 - \psi' \frac{\partial^2 \psi'}{\partial \phi^2} \right] \\ \frac{f_0^2}{N^2} \left\{ \frac{u}{a \cos \phi} \left[\frac{\partial \psi'}{\partial \lambda} \frac{\partial \psi'}{\partial z} - \psi' \frac{\partial^2 \psi'}{\partial \lambda \partial z} \right] + \frac{v}{a} \left[\frac{\partial \psi'}{\partial \lambda} \frac{\partial \psi'}{\partial z} - \psi' \frac{\partial^2 \psi'}{\partial \lambda \partial z} \right] \right\} \end{array} \right] + \mathbf{C}_U M \quad (6)$$

10 Here u and v are the zonal and meridional wind components, respectively. $\mathbf{U} = (u, v, 0)^T$ is a steady
 11 zonally inhomogeneous basic flow. $p = (\text{pressure}/1000 \text{ hPa})$ is normalized pressure, ψ' is a
 12 streamfunction perturbation relative to the climatological mean, (ϕ, λ) are latitude and longitude, a is
 13 the earth's radius, $N^2 = (R_a p^\kappa / H)(\partial \theta / \partial z)$ is the squared buoyancy frequency, \mathbf{C}_U represents the phase
 14 propagation in the direction of \mathbf{U} , and M can be interpreted as a generalization of small-amplitude
 15 pseudo-momentum for QG eddies onto a zonally varying basic flow.

16 Lastly, we quantified the influence of circulation anomalies at different vertical levels using a
 17 piecewise potential vorticity (PV) inversion method (Black and McDaniel, 2004; Xie et al., 2019). The
 18 PV anomalies were calculated with reanalysis and simulation data for all troposphere pressure levels
 19 from 1000 hPa to 100 hPa in Eq. (7),

$$20 \quad q' = \frac{1}{f} \left[\frac{1}{(a \cos \phi)^2} \frac{\partial^2}{\partial \lambda^2} + \frac{f}{a^2 \cos \phi} \frac{\partial}{\partial \phi} \left(\frac{\cos \phi}{f} \frac{\partial}{\partial x} \right) + f^2 \frac{\partial}{\partial p} \left(\frac{\partial}{\partial p} \right) \right] \Phi' \quad (7)$$

21 where q is the PV, ϕ is the geopotential, f is the Coriolis parameter, and a prime represents the deviation
 22 from the smoothed climatological annual cycle. We then inverted individual PV “pieces” at different
 23 levels to evaluate [near-surface low-level](#) (850 hPa) horizontal wind anomalies related to these PV
 24 anomalies. The horizontal anomalous wind field that will be presented in Fig. 6 was derived from the
 25 geopotential height field based on geostrophic balance. We partitioned the 1000-100 hPa PV anomalies
 26 into the lower (1000-850 hPa) and the middle to upper troposphere (700-100 hPa) PV anomalies and
 27 compared their impacts on the [near-surface low-level](#) wind field in Sect. 3.

28 3 Results

29 3.1 Observation- and reanalysis-data based relationships among Arctic sea ice, atmospheric 30 circulation, and boundary-layer ventilation

31 We first examined the long-term variations of Arctic sea ice in autumn and early winter (August to
 32 November, ASON) of the past four decades during the satellite era. Figure 1a shows strong decreasing
 33 trends in Arctic SIC, especially in the Eurasian and Pacific sectors such as the northern Barents Sea,

1 Kara Sea, East Siberian Sea, and Chukchi Sea. The winter EUI shows positive correlations with
2 regional Arctic sea ice concentrations with the strongest correlation over the East Siberian Sea and
3 Chukchi Sea (Fig. 1b), suggesting a decrease of EUI in winter following the sea ice decline over these
4 regions in preceding months. The correlation coefficient between EU and regional averaged SIC over
5 these positively correlated R2 grids is 0.38 ($p=0.02$). Positive correlations are also present when the
6 long-term trend in regional sea ice changes is removed, suggesting a consistent relationship between EU
7 variations and sea ice changes in these Arctic regions on both long-term (interdecadal) and short-term
8 (interannual) time scales.

9 To evaluate the impact of EU phases on regional ventilation, we conducted composite analysis and
10 compared wintertime boundary-layer PPI differences over the Northern Hemisphere corresponding to
11 different EU phases. In general, PPI and EU show an in-phase relation with high (low) PPI anomalies
12 corresponding to positive (negative) height anomalies in the EU pattern (Fig. 1c, d). Europe and East
13 Asia become two hot-spot regions in the negative EU phase (Fig. 1d), implying significant sensitivity
14 (i.e., lower ventilation capability and higher air pollution potential) in these regions. Since the EUI
15 shows a positive correlation with declining sea ice in the Pacific sector of the Arctic, we would expect
16 more severe air stagnation over East Asia coinciding with the decrease of EUI and regional Arctic sea
17 ice.

18 3.2 WACCM sensitivity simulations

19 The statistical analysis suggests a potential linkage between the Arctic sea ice decline and the regional
20 ventilation deterioration through a circulation change in the negative EU phase. We evaluate [this](#)
21 teleconnection relationship using ensemble WACCM sensitivity experiments (Table 1). Figure 2 shows
22 the mean surface sensible plus latent heat flux changes between the SENSall and CTRL experiments
23 during autumn and winter. Since we perturbed the Arctic SIC and SST in the model surface boundary
24 conditions from August to November, most Arctic regions show significantly increased heat fluxes in
25 autumn and early winter, especially over the Kara Sea, Laptev Sea, East Siberian Sea, and Beaufort Sea
26 (Fig. 2a). The heat flux changes are much weaker in winter with some remnant influence over the Kara
27 Sea (Fig. 2b) due to the strong perturbation in this region. The comparison of monthly variations in
28 regional averaged heat fluxes over the Arctic confirms the much stronger forcing in ASON (seasonal
29 mean heat fluxes increased by 3.3 W/m^2 or +16% over the Arctic in SENSall) than in DJF (seasonal
30 mean heat fluxes decreased by 0.17 W/m^2 or -1% over the Arctic in SENSall) (Fig. 2c).

31 To examine the regional circulation and ventilation responses to these changes in the high latitudes,
32 we fit the CDF and PDF curves of MCA_Z500 and ECP_PPI based on CTRL and SENS monthly
33 results in winter. Figure 3 shows the CDF changes of simulated MCA_Z500 (Fig. 3a) and ECP_PPI
34 indices (Fig. 3b) between sensitivity and CTRL experiments. It is clear that both indices show more
35 significant changes in their extreme members than in medians or ensemble means, especially in SENSr2
36 driven by SIC and SST changes in the Pacific sector of the Arctic (R2 in Fig. 1b). In SENSr2, the
37 occurrence probability of MCA_Z500 positive extremes increases by 50% from 5.0 to 7.5% (95th
38 percentile range: 0.8-16.4%) (Fig. 3a; Table S3 in the Supplement), while the ECP_PPI positive
39 extremes increases by 132% to 11.6% (95% percentile range: 5.2-18.4%) (Fig. 3b; Table S3 in the
40 Supplement). Meanwhile, the intensity of positive extreme values of the two indices also increases by

1 11% and 30%, respectively (Table S4 in the Supplement). ~~The increase in the teleconnection pattern~~
2 ~~index MCA_Z500 is less significant than that in the regional air stagnation index ECP_PPI, suggesting~~
3 ~~a potential nonlinear relationship between large-scale circulation and regional stagnation.~~ Only SENSr2
4 shows statistically significant increases of ECP_PPI in terms of positive extreme probability and
5 intensity, and the significance of such increases is independent of the fitting method being used (i.e.,
6 still valid with nonparametric curve fitting). In contrast, the changes of MCA_Z500 in all experiments
7 are not statistically significant, which might be attributable to the higher difficulty and larger ensemble
8 size requirement for detecting the dynamical-oriented responses (e.g., SLP and geopotential height
9 anomalies) than the thermal-oriented responses (e.g., vertical temperature gradient anomalies and their
10 effects on PPI) (Screen et al., 2014). The substantially increased ECP_PPI positive extremes in SENSr2
11 contribute to the positive responses in its ensemble mean, making SENSr2 the only sensitivity
12 experiment with positive ensemble mean ECP_PPI (0.03, not statistically significant). In comparison,
13 other SENS experiments generally show negative ensemble mean ECP_PPI values due to left-shifted
14 CDF curves at most percentiles. For instance, SENSr1 is the only experiment showing robustly
15 decreased ECP_PPI at all percentiles in its CDF curve (Fig. 3b), contributing to its negative ensemble
16 mean of ECP_PPI (-0.13) that is statistically significant at the 0.05 significance level (Table S2 in the
17 supplement). This result implies an overall improvement of the ECP regional ventilation driven by the
18 SIC and SST changes in the Barents-Kara Seas (R1 in Fig. 1b), while the ventilation responses are more
19 ~~random-erratic~~ driven by sea ice loss in other Arctic regions.

20 The disparate results among the sensitivity experiments highlight distinct climate effects of regional
21 SIC/SST changes as suggested by both statistical analysis in the last section and previous climate
22 modeling studies. Screen (2017) and McKenna et al. (2018) investigated atmospheric responses to
23 regional sea ice loss by perturbing regional SIC and SST or surface temperature. McKenna et al. (2018)
24 focused on the climate impacts of sea ice loss in the Atlantic (the Barents-Kara Seas) and the Pacific
25 sectors (the Chukchi-Bering Seas) of the Arctic, while Screen (2017) conducted more comprehensive
26 investigation by dividing the whole Arctic region into nine sub-regions. These region-specific modeling
27 studies suggested quite different or even opposite effects of regional sea ice forcing on general
28 circulation in the stratosphere and troposphere. However, it is worth noting that they mainly focused on
29 the responses in the stratospheric polar vortex and in the tropospheric Arctic Oscillation (AO) and North
30 Atlantic Oscillation (NAO), which are different from the EU and MCA_Z500 patterns of interest in this
31 work.

32 The differences in the MCA_Z500 and ECP_PPI responses among the four sensitivity experiments
33 in extreme members and ensemble means also suggest complex relationships between Arctic sea ice
34 loss and mid-latitude weather changes. Two distinct patterns of Asian winter climate responses to Arctic
35 sea ice loss were identified in a previous study (Wu et al., 2015), one (the “Siberian High” pattern) in
36 positive phase associated with the strengthened Siberia High and EAWM systems while the other (the
37 “Asia-Arctic” pattern) in negative phase associated with weakened EAWM and enhanced precipitation
38 in East Asia. Such opposite responses in regional climate and weather systems partly explain the
39 concurrent changes in the two tails of distribution curves in our sensitivity experiments. An IPCC report
40 (IPCC, 2012) demonstrated three kinds of responses in variable probability distributions to climate
41 change, and our ECP_PPI results in the four SENS experiments agree with the proposed “increased
42 variability”, “shifted mean”, “changed symmetry”, and “increased variability” responses, respectively

1 (see section 2.3 and Table S2 and Fig. S3 in the Supplement for explanations). These distinct responses
2 reflect complex interactions between atmospheric anomalies driven by climate forcing and atmospheric
3 circulation associated with the natural variability.

4 Coupling processes among different components of the climate system can compound such
5 complexity by amplifying or dampening signal-to-noise ratios and expanding responsive regions (Deser
6 et al., 2015; Deser et al., 2016). Smith et al. (2017) pointed out the importance of ocean-atmosphere
7 coupling and the background state in modulating atmosphere responses to Arctic sea ice changes. They
8 found that the background state plays a key role in determining the sign of the NAO responses to Arctic
9 sea ice loss via the refraction of planetary waves by the climatological flow (Smith et al., 2017). These
10 findings shed light on the diverse responses in our simulated distributions of MCA_Z500 and ECP_PPI
11 because of the varying background flow in each modeling year. It is worth noting that we only changed
12 the surface boundary conditions (SIC/SST) at these model grid cells with sea ice changes larger than
13 10% and kept other grid cells unperturbed. Because our modeling study ~~design~~ used prescribed ocean
14 data, the ice-ocean-atmosphere coupling is constrained and it might attenuate other atmospheric
15 responses to sea ice changes as discussed in previous studies (Deser et al., 2015; Deser et al., 2016;
16 Smith et al., 2017).

17 Exacerbated haze pollution represented by positive anomalous PM_{2.5} surface concentrations in eastern
18 China regions appears concurrently with increased ECP_PPI extreme values in all SENS experiments.
19 The changes in surface PM_{2.5} concentration fields correspond well with the PPI changes with the most
20 significant increases in SENSr2 (Fig. S4c in the Supplement) due to the largest number of positive
21 extreme members in this case (Fig. 3b). These positive PPI extremes in SENSr2 are attributable to both
22 reduced surface wind speed and enhanced near surface temperature inversion (Fig. S5 in the
23 Supplement). The agreement between PPI and surface PM_{2.5} concentration changes demonstrates the
24 promising capability of PPI for describing regional air stagnation and pollution potentials. Since the
25 cause of increasing air stagnation extremes is the major concern of this work, we conduct more dynamic
26 diagnosis in the next section to understand the following two questions: (1) how does severe air
27 stagnation occur in these SENSr2 extreme members? (2) why are there more and intensified air
28 stagnation extremes in SENSr2?

29 3.3 Diagnosis of dynamic processes

30 To answer the first question raised in the previous section, we examine atmospheric anomalies induced
31 by sea ice perturbations in the SENSr2 extreme members from the perspective of wave activity fluxes
32 and transient eddy feedback forcing. We also evaluate climate impacts of the anomalous circulations
33 and teleconnection patterns in these extremes on regional ventilation using the piecewise PV inversion
34 method. We first compare the anomalous geopotential height field in the upper troposphere (250 hPa,
35 Fig. 4a) and sea level pressure anomalies (Fig. 4b), both of which share similar features with strong
36 positive anomalies over the North Pacific and Northern Europe and negative ones over central Siberia.
37 This quasi-barotropic structure over most regions of the Northern Hemisphere agrees with prior findings
38 regarding Arctic sea ice induced atmospheric responses at interseasonal scales (Deser et al., 2010). The
39 geopotential height anomalies in the upper troposphere manifest wave-train patterns with enhanced
40 Rossby wave propagation from the North Pacific to North America and over the Eurasian continent

1 (Fig. 4a). The sea level pressure anomalies exhibit eastward displacements with respect to the upper-
2 troposphere anomalies over Eurasia (Fig. 4b). In particular, the negative sea level pressure anomaly
3 over Siberia extends southeastward to southeastern China, suggesting a weakened Siberia high. In
4 response, anomalous surface southerlies are seen along the coastal region of eastern China that offset
5 the prevalent winter monsoon and thus increase the air stagnation in winter over eastern China.

6 We then compare the difference of EKE and \mathbf{E} vectors (section 2.4) between SENSr2 extreme
7 members and CTRL ensemble mean and calculated anomalous 250 hPa geopotential height tendencies
8 driven by transient eddies using Eq. (5). The most prominent features in the anomalous zonal wind and
9 transient eddy fields are zonal positive anomalies over middle latitudes from the northeastern Pacific to
10 North Africa that are to the south of the upper-troposphere negative height anomalies (Fig. 4c).
11 Meanwhile, both zonal wind and EKE fields feature a moderate dipole around the positive height
12 anomaly. The divergence of \mathbf{E} vectors is seen from the northeastern Pacific to the North Atlantic, which
13 results in amplifications of zonal winds and a climatology-like pattern of transient eddy feedback
14 forcing with zonally elongated positive height tendencies to the south of negative height tendencies
15 (Fig. 4d). In contrast, the \mathbf{E} vectors converge over the vicinity of the Scandinavian region (Fig. 4d),
16 suggesting a weakened zonal wind and thereby depress transient eddy activity. Accordingly, significant
17 geopotential height tendencies driven by transient eddy forcing emerge in the upper troposphere,
18 showing pronounced positive anomalies near the Scandinavian region. These tendencies are dominated
19 by transient eddy vorticity forcing rather than transient eddy heat forcing, the latter of which shows
20 opposite but much weaker effects on the upper level geopotential height field (Fig. S6a, b in the
21 Supplement). Both transient eddy vorticity and heat flux forcing contribute constructively in the lower
22 troposphere (Fig. S6c, d in the Supplement).

23 We further compare the simulated atmospheric anomalies relative to the ensemble average of the 30
24 strongest negative EU years (10 minimums for each Dec/Jan/Feb month) in winter since 1950 in the
25 reanalysis data. Figure 5 shows the horizontal (250 hPa) and vertical structures of wave propagation in
26 reanalysis-based negative EU extremes (Fig. 5a, d) and model-based SENSr2 extreme members (Fig.
27 5b, e; hereafter SENSr2_{extreme}) and their CTRL counterparts (Fig. 5c, f; hereafter CTRL_{counterpart}). The
28 comparison between the last two modeling results shed light on the question of why more extremes
29 occur in SENSr2 than in CTRL. It's apparent that SENSr2_{extreme} shares more similar features of wave
30 train propagation with the reanalysis data than the CTRL_{counterpart} does, characterized by two anomalous
31 troughs over the North Atlantic (region A in Fig. 5a, b) and the Siberian (region C in Fig. 5a, b) areas
32 and two anomalous ridges over the Scandinavian Peninsula (region B in Fig. 5a, b) and East Asia
33 (region D in Fig. 5a, b) areas. These wave train patterns exhibit barotropic vertical structures in the
34 troposphere in both cases (Fig. 5d, e). Unlike the reanalysis data, the wave train pattern of SENSr2_{extreme}
35 shows a westward tilt in the lower troposphere with evident downward energy propagation. In contrast,
36 such prominent configurations fade in CTRL_{counterpart} with much weaker wave activity, resulting in
37 disappeared key features along the propagation pathway (Fig. 5c, f). Though these CTRL_{counterpart}
38 members share the same initial condition with SENSr2_{extreme}, they show different vertical structures of
39 wave train patterns in both upstream regions (e.g., the lower troposphere over region B) and the
40 downstream region of East Asia (region D). Meanwhile, the anomalous centers of CTRL_{counterpart}
41 members are higher than SENSr2_{extreme} and the reanalysis data, which is unfavorable for the lateral
42 Rossby wave propagation to help the formation of the positive height anomalies over East Asia. In

1 contrast to negative to neutral height anomalies in CTRL_{counterpart}, SENSR2_{extreme} manifests positive
2 anomalies in the middle to upper troposphere over this region ([region D in Fig. 5e](#)). To highlight such
3 difference between SENSR2_{extreme} and CTRL_{counterpart}, we isolate the sea ice perturbation-induced
4 anomalies in SENSR2_{extreme} (shading in Fig. S7c, d in the Supplement) by subtracting CTRL_{counterpart}
5 from SENSR2_{extreme} and overlay them with the internal variability-induced anomalies in CTRL_{counterpart}
6 (contours in Fig. S7d in the Supplement). The sea ice-induced anomalous Rossby wave constructively
7 interferes with the internal variability-induced one over the upstream regions including Northern Europe
8 and Central Siberia, contributing to the enhanced wave propagation to downstream regions with
9 emerging high-pressure anomalies over East Asia in SENSR2_{extreme} (Fig. S7d in the Supplement). This
10 critical difference appears to be the key to more frequent ECP_PPI extremes in the SENSR2 experiment.

11 To illustrate this point, we use the piecewise PV inversion method to examine the impact of the
12 circulation anomalies in region D (the red box in Fig. 5a) on regional ventilation over eastern China in
13 both the negative EU reanalysis data and modeling results from SENSR2_{extreme} and CTRL_{counterpart}. We
14 first partition tropospheric PV anomalies into two parts: the lower troposphere (1000-850 hPa) and the
15 middle to upper troposphere (700-100 hPa) and then invert each PV piece at two levels to estimate the
16 [near-surface low-level](#) (850 hPa) horizontal anomalous winds associated with these PV anomalies. We
17 find significantly weakened wind fields in eastern China in the reanalysis data and SENSR2_{extreme}, but
18 not in CTRL_{counterpart}. In contrast to strong climatological northwesterly winds over northeastern Asia
19 (Fig. 6a, b, c), PV anomalies in the middle to upper troposphere in both reanalysis-based negative EU
20 and model-based SENSR2_{extreme} induce anomalous southeasterly winds [at-in](#) the lower troposphere over
21 the ECP region (Fig. 6d, e), which is not the case in CTRL_{counterpart} (Fig. 6f). These anomalous
22 southeasterlies weaken the monsoon northwesterlies and strengthen air stagnation in this region in the
23 first two cases. We also compare the contribution of PV anomalies at different levels and find that the
24 ventilation suppression effect is dominated by anomalous PV in the middle to upper troposphere (700
25 hPa and above) rather than that in the lower troposphere (below 700 hPa) in both reanalysis and
26 SENSR2_{extreme} data. Comparing to anomalous southerly winds induced by PV anomalies [in-at](#) middle to
27 upper levels (Fig. 6d, e), those PV anomalies in the lower troposphere mainly tend to strengthen
28 northerly climatological winds over the ECP region, though the circulation patterns in the reanalysis and
29 SENSR2_{extreme} results (Fig. 6g, h) are quite different from CTRL_{counterpart} (Fig. 6i). In general, the
30 ventilation suppression effect associated with middle- and upper-level PV anomalies overwhelms the
31 enhancement effect associated with lower-level PV anomalies and finally suppresses monsoon winds as
32 a net effect in the reanalysis and SENSR2_{extreme} results (Fig. 6j, k), while CTRL_{counterpart} manifests an
33 opposite net effect with the dominant role of lower-level PV anomalies (Fig. 6l).

34 3.4 Historical simulations and future projections in CMIP6

35 Lastly, we examine the historical simulations and future projections of Arctic SIE and ECP_PPI under
36 the SSP5-8.5 scenario based on 8 currently available CMIP6 climate models (Eying et al., 2016; see
37 Table S1 in the Supplement for model details) to understand how this teleconnection relationship might
38 change in the future. Figure 7 shows the time series of the Arctic sea ice and ECP_PPI and the statistical
39 distribution changes of ECP_PPI among three time periods: P1 (1951-2000) defined as the reference
40 period with slowly declining Arctic SIE, P2 (2001-2050) as the near-term projection with rapidly

1 decreasing Arctic SIE, and P3 (2051-2100) as the long-term projection with an almost ice-free Arctic in
2 boreal Autumn. A similar figure is available in the Supplement to show the relationship between Arctic
3 SIE change and MCA_Z500 time series (Fig. S8). Although the CMIP6 model ensemble captures the
4 observed decreasing trend in Arctic SIE, it generally shows less interannual and interdecadal variability
5 of Arctic SIE and ECP_PPI than the reanalysis data. Low decadal variations in the CMIP6 models are
6 also evident in the CDF distributions of simulated ECP_PPI. For instance, the simulated ECP_PPI CDF
7 curve in P1 is positively shifted over the whole distribution range in comparison with the reanalysis-
8 based one (Fig. 7b), while the simulated CDF curve in P2 is negatively shifted relative to the reanalysis
9 data (Fig. 7c) especially over the lower ends of the distribution. Therefore, the shift to positive PPI
10 distributions from P1 to P2 in the NCEP reanalysis data is much more significant than the CMIP6
11 ensemble, which is understandable since the reanalysis data is just a single realization and the CMIP6
12 modeling result is ensemble average. This shrunken interdecadal change in the CMIP6 model ensemble
13 is also found in MCA_Z500 but to a less prominent extent (Fig. S8b-d in the Supplement).
14 Consequently, the ensemble mean values and averaged probability of simulated ECP_PPI positive
15 extremes increase from -0.05/5% in P1 to 0.07/7% in P2 (Fig. 7c), which is smaller than those presented
16 in the reanalysis data (-0.38/5% in P1 to 0.30/19% in P2). With the greatest change of Arctic SIE in P3,
17 the ensemble averaged probability of ECP_PPI positive extremes nearly doubles and increases to 9%
18 with the ECP_PPI mean value of 0.09 (Fig. 7d), in concurrence with substantially increased positive
19 extremes of MCA_Z500 in the same time period (Fig. S8d in the Supplement). The model-specific
20 projections of ECP_PPI positive extreme probabilities range between 2%-11% in P2, and between 2-
21 13% in P3 (Table S5 and Fig. S9 in the Supplement).

22 For more direct comparison with the CESM-WACCM sensitivity results in previous sections, we
23 specifically looked into the two newer versions of CESM (CESM2 and CESM2-WACCM; Table S1 in
24 the Supplement) that were developed in the same CESM project as the CESM-WACCM model used in
25 this study. The ensemble mean and probability of ECP_PPI positive extremes in the low-top CESM2
26 model increase from -0.07/5% in P1 to 0.20/11% in P2 and to 0.11/13% in P3, while these values in the
27 high-top CESM2-WACCM model increase from 0.03/5% in P1 to 0.36/10% in P2 and to 0.27/6% in P3
28 (Table S5 and Fig. S9 in the Supplement). Both model results are much closer to the changes between
29 P1 and P2 shown in the reanalysis data than the other CMIP6 models. These increments are also more
30 significant than the SENSall results of the sensitivity experiment in this study, which might be
31 attributable to the much stronger climate forcing and fully coupled modeling settings in the CMIP6
32 simulations.

33 **4 Discussion and conclusions**

34 The connection between Arctic sea ice decline and winter air stagnation has been re-examined as a
35 cause of pollution extremes in China, and the mechanisms for the teleconnection have been explored.
36 We identified a tropospheric pathway linking the remote sea ice changes in the Arctic to regional
37 circulation and ventilation responses in eastern China based on statistical analysis and diagnosis of
38 atmospheric dynamics using the NCEP reanalysis and climate model sensitivity simulation data. The
39 teleconnection mechanism's evolution can be summarized as follows: In autumn and early winter of

1 recent years, substantial declines in sea ice in most regions of the Arctic significantly increased upward
2 heat fluxes during the same period. These changes in surface boundary conditions, especially those that
3 occurred in the Pacific sector of the Arctic (the East Siberian and Chukchi Seas), induced ~~non-linear~~
4 ~~responses in the atmosphere~~atmospheric responses during the following winter producing strengthened
5 eddy kinetic energy fluxes over the mid-latitudes from the northeastern Pacific to North Africa and
6 strong convergence of anomalous transient eddy vorticity fluxes in the vicinity of Scandinavia. This
7 transient eddy forcing led to positive geopotential height tendencies as well as an anomalous ridge in
8 this region throughout the troposphere. Constructive interference between eddy-induced wave packets
9 and background flow enhanced wave train propagation across Eurasia, resembling the negative phase of
10 the EU pattern. The high-pressure anomalies over eastern Asia in the middle and upper troposphere of
11 this teleconnection pattern finally weakened boundary-layer air ventilation and exacerbated air
12 stagnation extremes in eastern China by suppressing monsoon northwesterlies and enhancing near
13 surface temperature inversions in this region. Such meteorological conditions are favorable to air
14 pollutant accumulation and secondary formation.

15 The occurrence of these teleconnection processes depends on complex interactions between climate
16 disturbances and its internal variability, which are reflected by diverse climate sensitivity responses in
17 the full statistical distributions of circulation and ventilation variables. The largest increase of both the
18 probability (by 132%) and the intensity (by 30%) of monthly air stagnation extremes is found in the
19 experiment driven by sea ice perturbations over the Pacific sector of the Arctic (the East Siberian and
20 Chukchi Seas). We emphasize the importance of a full-distribution evaluation, especially for climate
21 extreme assessment and attribution, considering vastly distinct responses between mean conditions and
22 extremes and the tendency of underestimated impacts of climate extremes (Schewe et al., 2019). We
23 note some relevant issues to our analysis that deserve more attention and further investigations.

24 Firstly, Screen and Simmonds (2014) examined the regional impact of planetary wave changes on
25 mid-latitude weather extremes and found distinct relationships between quasi-stationary planetary wave
26 anomalies and regional weather extremes in terms of temperature and precipitation. Specifically, they
27 found attenuated (amplified) planetary-wave amplitudes accompanying positive temperature extremes
28 (near-average temperature) over eastern Asia that is different from other regions like central Asia and
29 western North America (Screen and Simmonds, 2014). This region-dependent relationship can be
30 attributed to the interaction between anomalous planetary waves and climatological waves that show
31 quasi-stationary phases. The EU-like teleconnection pattern tends to amplify climatological planetary
32 waves in the upstream regions such as the North Atlantic and Europe but attenuate climatological waves
33 in the downstream regions over central and eastern Asia, leading to regional dynamic and
34 thermodynamic responses as demonstrated in this study. It's worth noting that atmospheric
35 teleconnection patterns like EU with smaller wave numbers might also be excited by quasi-stationary
36 spatially inhomogeneous diabatic sources/sinks and orography other than the thermal forcing associated
37 with the SIC/SST perturbation used in this study. Therefore, we have mainly focused on the relative
38 changes of teleconnection occurrence probability between the CTRL and sensitivity experiments to
39 isolate the contributions from this single forcing in the simulated atmospheric system.

40 Secondly, the climate impacts may vary in response to differing location and magnitude of climate
41 forcing as we found in our regional sensitivity experiments and this issue is often discussed in other
42 modeling studies (Screen, 2017; Sun et al., 2015; McKenna et al., 2018). The different responses might

1 be attributable to different physical mechanisms and atmospheric processes associated with specific
2 forcing-response relationships. Previous studies proposed multiple pathways of Arctic sea ice impacts
3 on middle-latitude atmospheric circulation through troposphere-stratosphere coupling and/or
4 tropospheric processes only (Overland et al., 2016). It is an intriguing question to quantify the relative
5 importance of different pathways in different case studies. Screen (2017) proposed that a **stratosphere**
6 **stratospheric** pathway dominated the atmosphere responses to sea ice loss in the Barents-Kara Seas
7 whereas tropospheric processes governed wave train responses to sea ice loss in other regions, which is
8 partly consistent with what we found in this study. Similarly, McKenna et al. (2018) also found opposite
9 effects of the regional sea ice forcing on the stratospheric polar vortex in their full-magnitude and half-
10 magnitude forcing experiments, but the tropospheric responses were different between the two
11 experiments with different forcing magnitudes. They suggested that tropospheric processes become
12 more important than stratospheric pathways as the sea ice loss magnitude increases (McKenna et al.,
13 2018). Our modeling results indicate that the tropospheric processes are the key to understand the
14 forcing-response relationship of interest. However, we cannot rule out the possible role of stratospheric
15 changes in midlatitude weather extreme events through stratosphere-troposphere coupling processes
16 (Zhang et al., 2018), and the CESM2 model's sensitivity appears to be stronger when the stratosphere is
17 reasonably resolved in its high-top WACCM version. Multiple dynamic processes and teleconnection
18 pathways associated with different forcing source regions increase the detection difficulty in the whole
19 Arctic perturbation experiment. More detailed sensitivity experiments need to be designed and
20 conducted to evaluate such pathway-dependent effects of Arctic sea ice loss on regional circulation and
21 pollution conditions.

22 Thirdly, climate responses to Arctic sea ice forcing may also vary on intra-seasonal scales. In a
23 recent study, Lu et al. (2019) revealed an important role of the autumn Arctic sea ice in the phase
24 reversal of the Siberian high in November and December-January. They suggested that the autumn
25 Arctic sea ice loss, especially in the Barents Sea, could induce anomalous upward (downward) surface
26 turbulent heat fluxes in November (December-January). This would strengthen (weaken) the
27 development of the storm track in northeastern Europe and decrease (increase) Ural blockings with
28 accelerated (decelerated) westerlies. With inhibited (enhanced) cold air transport from the Arctic to the
29 Siberian area, a weaker (stronger) Siberian high in November (December-January) would occur
30 thereafter. In our modeling results, we also found significant intra-seasonal variations in simulated
31 atmosphere responses. Figure S10 in the Supplement shows weekly evolution of geopotential height
32 tendencies and anomalies in SENSr2 from late November to February. The negative phases of the EU
33 pattern are more prominent in early winter than in late winter. Better understanding of such intra-
34 seasonal variations could benefit seasonal and sub-seasonal forecasts of regional ventilation and
35 pollution potentials.

36 Last but not the least, the concurrence of multiple climate drivers and their synergistic climate
37 impacts should be considered. Since many other climate factors such as Eurasian snow cover, ENSO,
38 and PDO also show considerable influence on regional circulation and air pollution in China (Chang et
39 al., 2016; Sun et al., 2018; Zhao et al., 2016; Zhao et al., 2018; Zhang et al., 2019; Zou et al., 2017),
40 more studies with concurrent climate drivers could be conducted to obtain a more comprehensive
41 understanding of climate change impacts. However, these climate drivers may interact with each other
42 in either synergistic or antagonistic ways (Li et al., 2019). Fully sea ice-ocean-atmosphere coupling also

1 allows more interactive dynamic and thermodynamic feedbacks with expanded and enhanced climate
2 responses as suggested by previous studies (Deser et al., 2015; Smith et al., 2017) and by the CMIP6
3 fully coupled projections in this study. It's a great challenge to distinguish robust and significant
4 responses to climate change from atmospheric internal variability due to relatively low signal-to-noise
5 ratios (Barnes and Screen, 2014). Callahan et al. (2019) estimated ~~less than one signal~~consistent signal-
6 to-noise ratios of less than one in multiple regional air stagnation indices for the forced air stagnation
7 response to internal variability-Beijing in-based on the CESM-LE historical simulations, demonstrating
8 the dominant role of natural variability rather than anthropogenic forcing in modulating regional
9 circulation and ventilation. Divergent consensus on the climate impact of Arctic amplification on
10 midlatitude severe weather remain an open question for the whole climate science community (Cohen et
11 al., 2020). Therefore, long-term climate simulations with larger ensemble sizes should be conducted to
12 achieve more robust modeling-based findings (Screen and Blackport, 2019). Furthermore, the Arctic sea
13 ice cover reached its historical minimum in the fall of 2012 (Fig. 7a; NSIDC/NASA, 2019). The
14 slowdown of Arctic sea ice loss since then may reflect regional climate internal variability and may
15 have weakened the effect of the Arctic sea ice loss on winter extreme haze occurrence in China in recent
16 years.

17 **Code and dData availability**

18 The NCEP Reanalysis data is provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, USA, from
19 their web site at <https://www.esrl.noaa.gov/psd/data/gridded/data.ncep.reanalysis.html> (last access: 18
20 July, 2019). The MEIC-MIX emission inventory data is available at [http://www.meicmodel.org/dataset-](http://www.meicmodel.org/dataset-mix)
21 [mix](http://www.meicmodel.org/dataset-mix) (last access: 18 July, 2019). The CMIP6 model outputs are distributed by the Earth System Grid
22 Federation (ESGF) at <https://esgf-node.llnl.gov/search/cmip6/> (last access: 24 October, 2019). All the
23 CESM-WACCM modeling input and output data are archived on the GLADE and HPSS file systems
24 managed by the Computational & Information Systems Lab (CISL) of NCAR. The simulation results of
25 the control and sensitivity experiments used for the analysis in the main text are deposited at the
26 Figshare website (<https://doi.org/10.6084/m9.figshare.11894439>). The modeling source code and data
27 materials are available upon request, which should be addressed to Yufei Zou (yufei.zou@pnnl.gov).

28 **Author contributions**

29 YZ and YW conceived the research idea and designed the climate sensitivity experiments. YZ
30 conducted the modeling experiments and analyzed modeling results with ZX. YZ prepared all the
31 figures and wrote the draft manuscript. All authors discussed the results and revised the manuscript.

32 **Competing interests.**

33 The authors declare no conflict of interest.

34

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1 **Table 1. The modeling settings of the climate sensitivity experiments using CESM-WACCM**

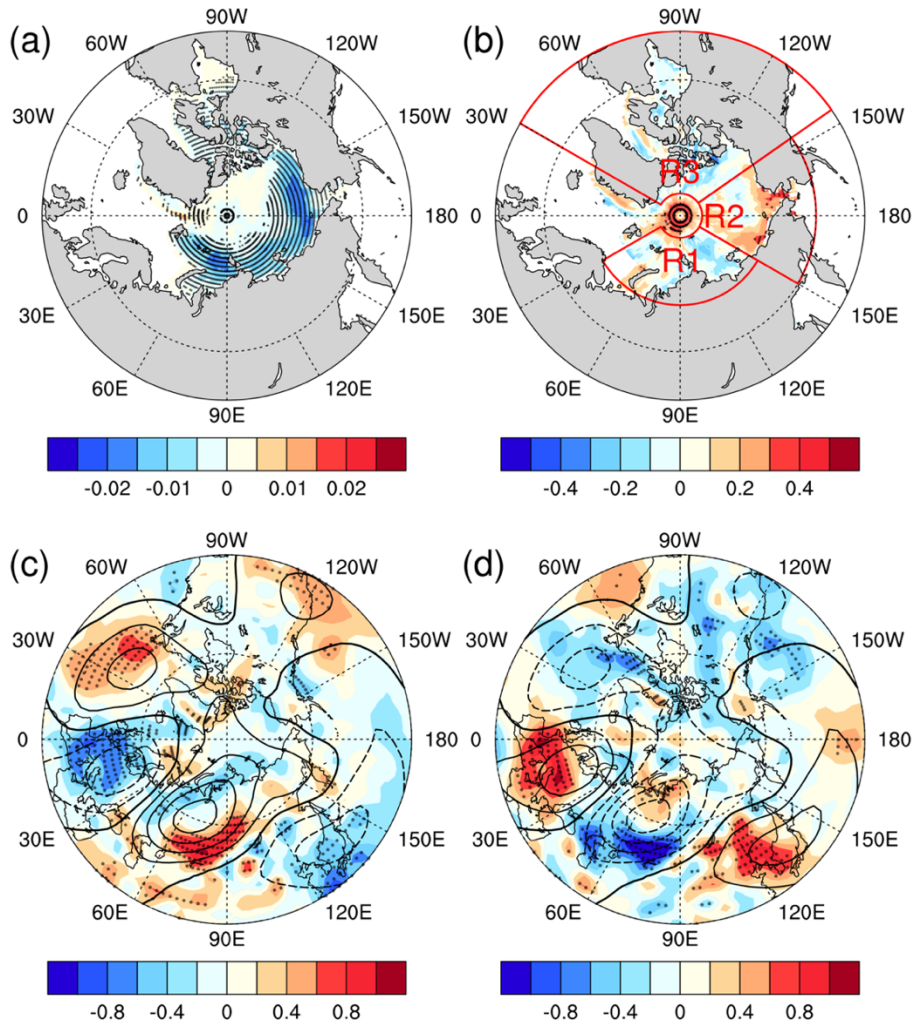
Experiment	CTRL	SENSall	SENSr1	SENSr2	SENSr3
Time period	30 years	30 years	30 years	30 years	30 years
Horizontal resolution	1.9°×2.5°	1.9°×2.5°	1.9°×2.5°	1.9°×2.5°	1.9°×2.5°
Vertical level	70	70	70	70	70
Atmosphere	WACCM ^(a)	WACCM	WACCM	WACCM	WACCM
Land	CLM4.0	CLM4.0	CLM4.0	CLM4.0	CLM4.0
Ocean	Climatology ^(b)	2012 Arctic SST	2012 R1 SST ^(c)	2012 R2 SST	2012 R3 SST
Sea ice	Climatology ^(b)	2012 Arctic SIC	2012 R1 SIC	2012 R2 SIC	2012 R3 SIC
China emissions	MEIC-MIX	MEIC-MIX	MEIC-MIX	MEIC-MIX	MEIC-MIX
Other emissions	IPCC AR5	IPCC AR5	IPCC AR5	IPCC AR5	IPCC AR5

2 ^(a): using CAM5 physics package and WACCM_MOZART_MAM3 chemistry package;

3 ^(b): 1981-2010 average based on the HadISST SST and SIC data (Rayner et al., 2003);

4 ^(c): see the main text and Fig. 1b for the R1-R3 region definition;

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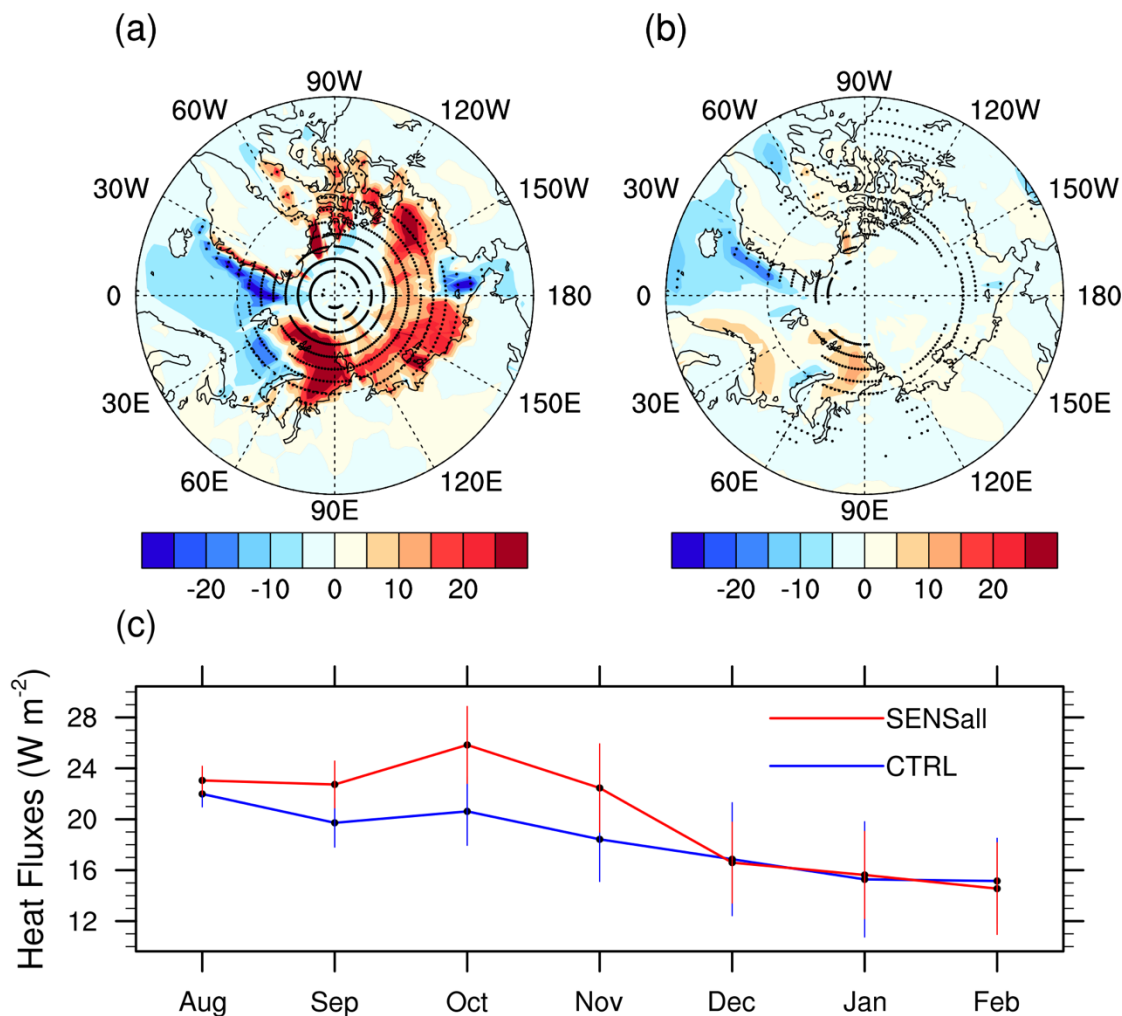
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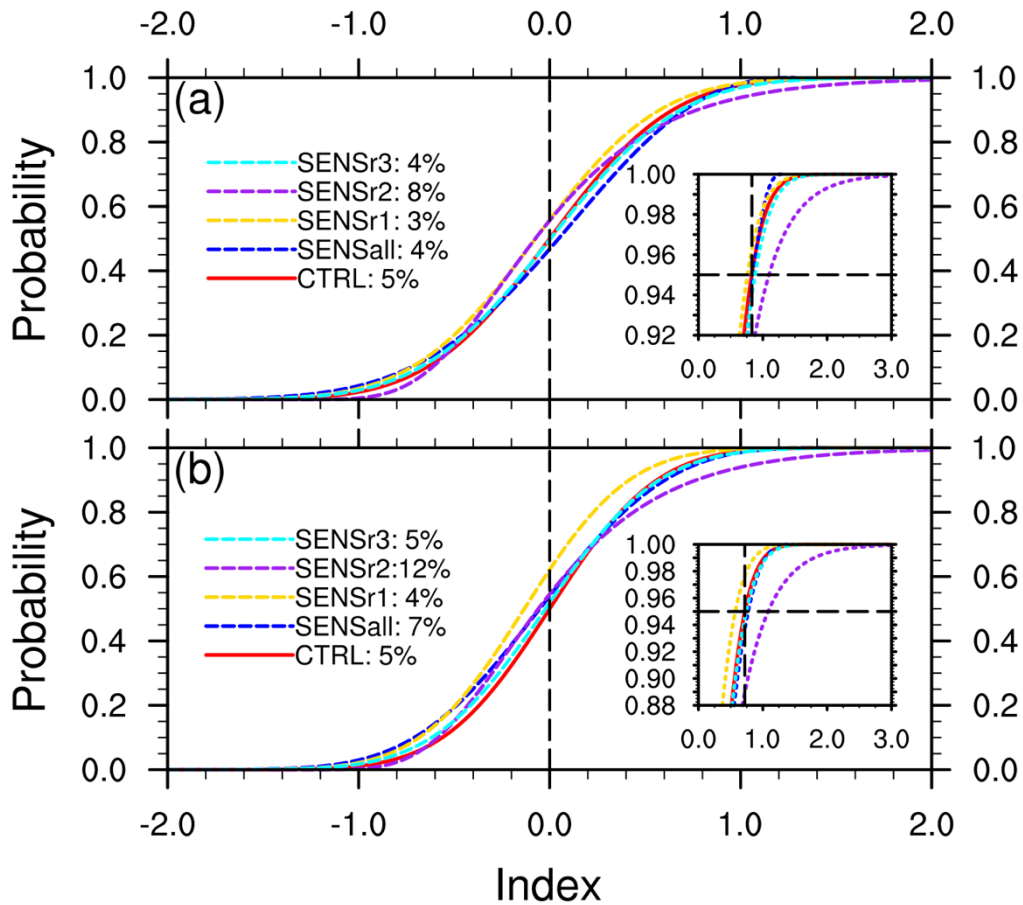
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Figure 1. Relationship between Arctic sea ice changes, EU teleconnection, and pollution ventilation conditions in the Northern Hemisphere based on the reanalysis and observational data. (a) trends of Arctic sea ice changes in autumn and early winter (ASON) of 1980-2017 (color shading in the Arctic region, year⁻¹); (b) correlation between the winter EU index and preceding Arctic sea ice concentrations (color shading in the Arctic region, unitless); R1-3 denote the perturbation regions in the three region-specific sensitivity experiments; (c) PPI spatial distributions (color shading, unitless) during the positive phase of EU (contours with interval of 20 m; dashed/solid lines indicate negative/positive geopotential heights at 500 hPa); (d) PPI spatial distributions (color shading, unitless) during the negative phase of EU (contours with interval of 20 m; dashed/solid lines indicate negative/positive geopotential heights at 500 hPa). The stipples over color shading denote the 0.05 significance level based on the two-tailed Student's t-test.

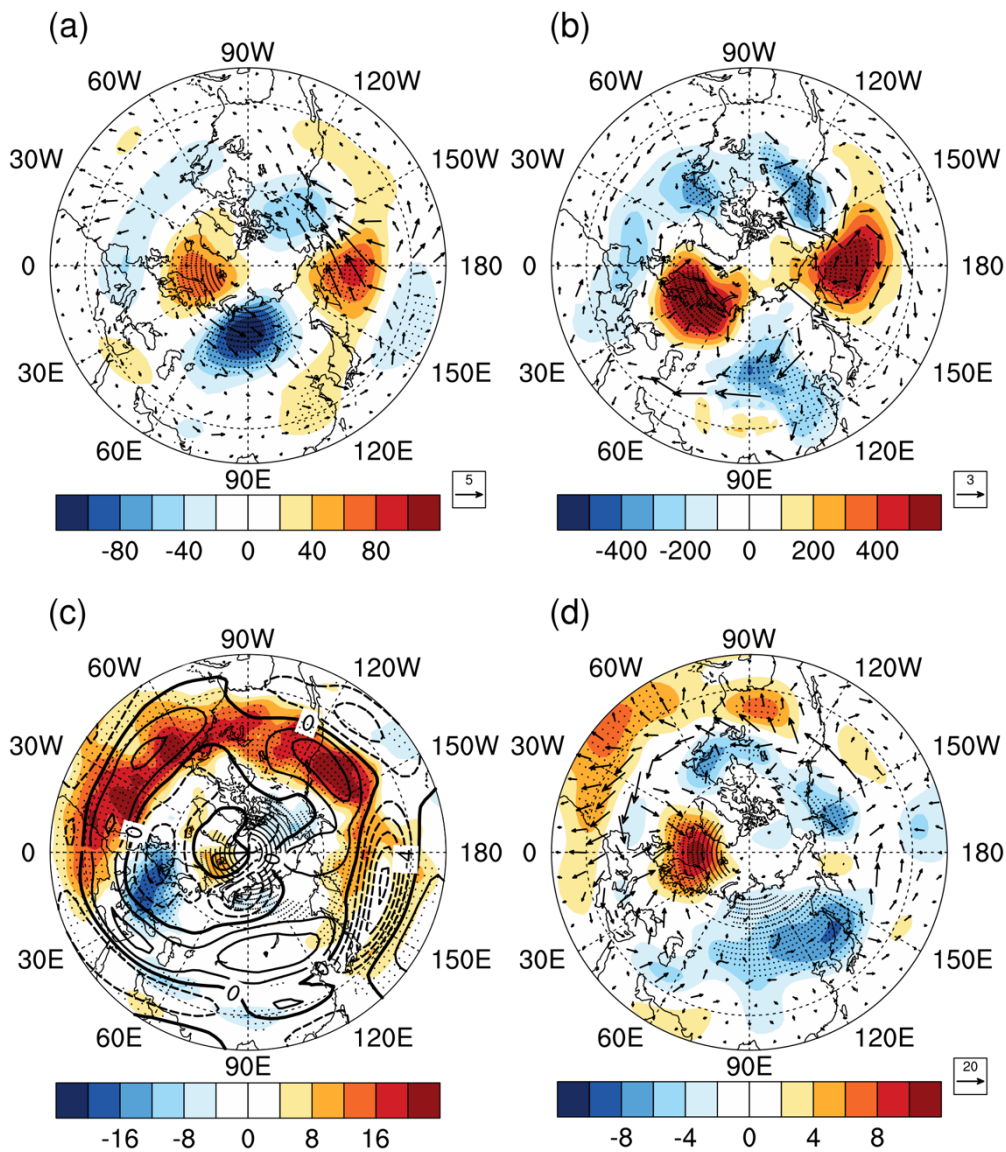


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2 **Figure 2. Surface heat flux changes over the Arctic in the WACCM SENSall simulation. (a)**
3 **differences of surface sensible plus latent heat fluxes (positive upward) between SENSall and**
4 **CTRL during Aug-Nov; (b) differences of surface sensible plus latent heat fluxes between**
5 **SENSall and CTRL during Dec-Feb; (c) comparison of regional averaged surface heat fluxes over**
6 **the Arctic (north of 66.6° N) from August to February. The stipples in (a)/(b) denote the 0.05**
7 **significance level. The error bars in (c) denote one standard deviation of the 30-member**
8 **ensembles in CTRL and SENSall, respectively.**

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1
2 **Figure 3. Comparison of the statistical distributions of atmospheric circulation and regional air**
3 **stagnation indices in the WACCM climate sensitivity experiments. (a) comparison of cumulative**
4 **distribution functions (CDFs) of the MCA_Z500 index in winter months (Dec, Jan, and Feb). The**
5 **percentages in the legend are the occurrence probabilities of positive extreme members based on**
6 **the bootstrap estimation in Table S3 in the Supplement; the inset shows the zoomed-in**
7 **distributions of positive MCA_Z500 extremes ($\geq MCA_Z500_{CTRL}^{95^{th}}$) and the black dashed lines in**
8 **the inset denote the positive extreme threshold ($MCA_Z500_{CTRL}^{95^{th}} = 0.83$); (b) same as (a) but for**
9 **the regional averaged ECP_PPI index; the inset shows the zoomed-in distributions of positive PPI**
10 **extremes ($\geq ECP_PPI_{CTRL}^{95^{th}}$) and the black dashed lines in the inset denote the positive extreme**
11 **threshold ($ECP_PPI_{CTRL}^{95^{th}} = 0.72$).**

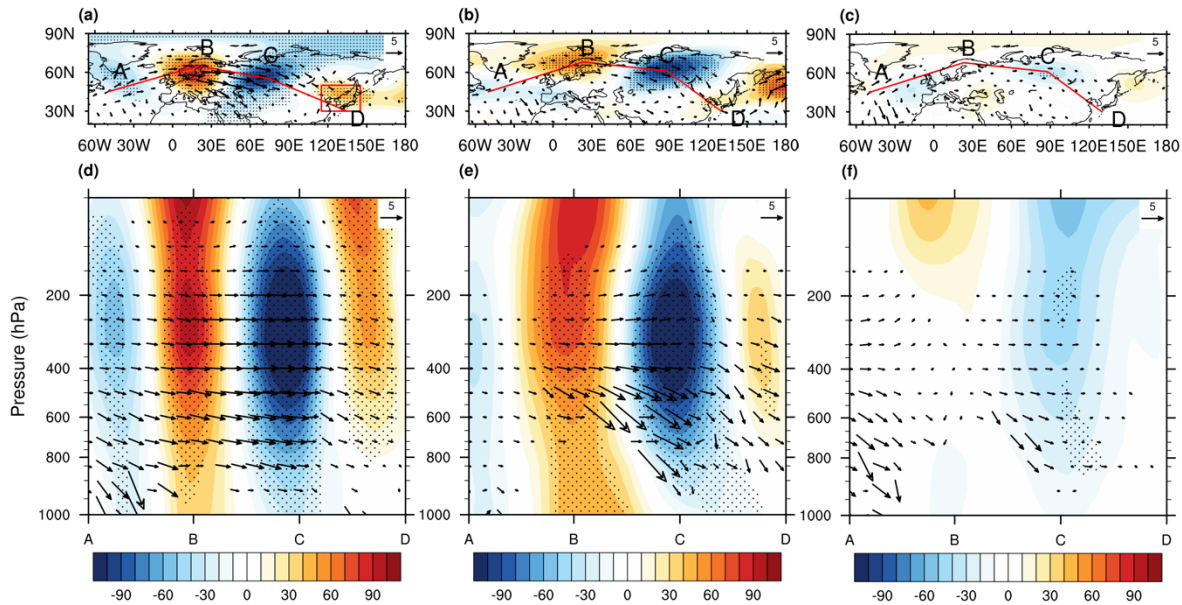


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2 **Figure 4. Atmospheric anomalies in WACCM SENSr2 extreme members with respect to the**
 3 **CTRL ensemble mean. (a) geopotential height (color shading, m) and wave activity flux (vectors,**
 4 **$\text{m}^2 \text{s}^{-2}$) anomalies at 250 hPa; (b) sea level pressure (color shading, Pa) and surface wind**
 5 **circulation (vectors, m s^{-1}) anomalies; (c) Anomalous transient eddy kinetic energy (color shading,**
 6 **$\text{m}^2 \text{s}^{-2}$) and zonal wind (contours, m s^{-1}) anomalies at 250 hPa; (d) Anomalous E vectors (vectors,**
 7 **$\text{m}^2 \text{s}^{-2}$) and transient eddy-induced geopotential height tendencies (Z_t^{V+H}) (color shading, m day^{-1})**
 8 **at 250 hPa. The stipples denote the 0.05 significance level.**

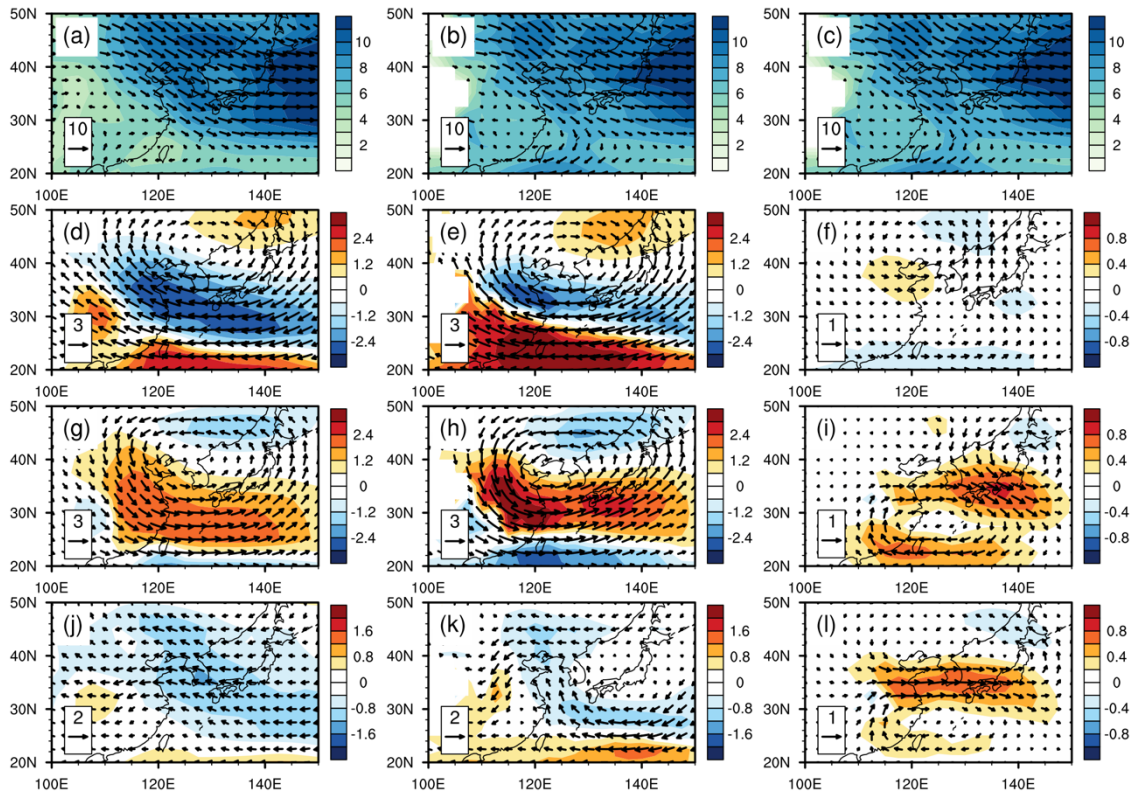
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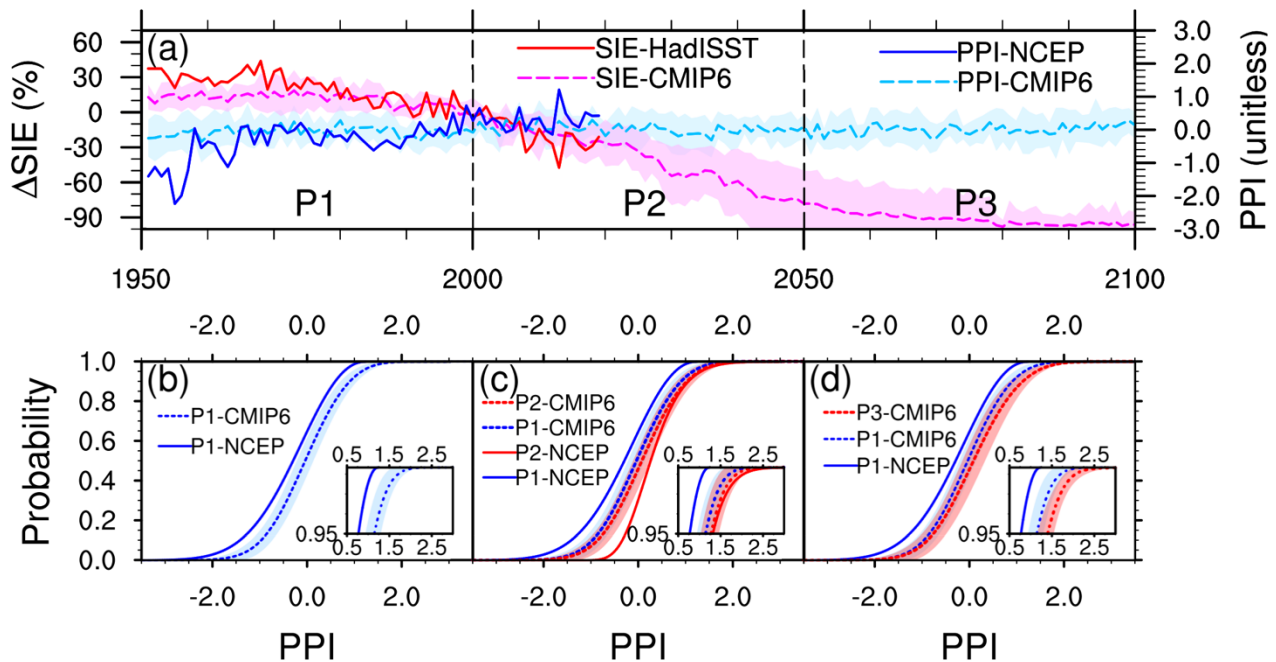


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5 **Figure 5. Comparison of atmospheric anomalies in the NCEP reanalysis data and WACCM**
6 **experiments. (a) reanalysis-based ensemble mean geopotential heights at 500 hPa (color shading,**
7 **m) and wave activity flux (WAF) at 250 hPa (vectors, $m^2 s^{-2}$) of the 30 strongest negative EU**
8 **months in winter (DJF) of 1951-2019 (relative to the 1981-2010 climatology); (b) same as (a) but**
9 **based on the SENSR2 extreme members (relative to the CTRL ensemble mean); (c) same as (b)**
10 **but based on the CTRL counterparts of the SENSR2 extreme members (relative to the CTRL**
11 **ensemble mean); (d) reanalysis-based vertical cross section of geopotential heights (color shading,**
12 **m) and WAF (vectors, $m^2 s^{-2}$) of the ensemble mean negative EU months (relative to the 1981-2010**
13 **climatology) along the wave propagation path shown in (a); (e) same as (d) but based on the**
14 **SENsr2 extreme members (relative to the CTRL ensemble mean); (f) same as (e) but based on the**
15 **CTRL counterparts of the SENSR2 extreme members (relative to the CTRL ensemble mean).**
16 **Note that the vertical components of WAF in (c)-(d) were scaled up by 200 for clear illustration.**
17 **The stipples denote the 0.05 significance level.**



1
 2 **Figure 6. Comparison of winter circulation in East Asia based on the piecwise PV inversion**
 3 **analysis with the NCEP reanalysis and WACCM modeling data. (a) climatological wind speed**
 4 **(color shading, m) and directions (vector, m) at 850 hPa based on the reanalysis data; (b)-(c) same**
 5 **as (a) but based on the WACCM CTRL ensemble mean; (d) reanalysis-based wind circulation**
 6 **change at 850 hPa induced by East Asia PV anomalies (see the red box in Fig. 5a) in the middle to**
 7 **upper troposphere (700-100 hPa) during strong negative EU months in winter; (e) model-based**
 8 **wind circulation change at 850 hPa associated with the middle to upper troposphere PV**
 9 **anomalies over East Asia in the SENSr2 extreme members (relative to the CTRL ensemble**
 10 **mean); (f) same as (e) but in the CTRL counterparts of the SENSr2 extreme members (relative to**
 11 **the CTRL ensemble mean); (g) reanalysis-based wind circulation change at 850 hPa induced by**
 12 **East Asia PV anomalies in the lower troposphere (1000-850 hPa) during strong negative EU**
 13 **months in winter; (h) model-based wind circulation change at 850 hPa associated with the lower**
 14 **troposphere PV anomalies in the SENSr2 extreme members (relative to the CTRL ensemble**
 15 **mean); (i) same as (h) but in the CTRL counterparts of the SENSr2 extreme members (relative to**
 16 **the CTRL ensemble mean); (j) reanalysis-based wind circulation change at 850 hPa induced by**
 17 **East Asia PV anomalies in the whole troposphere (1000-100 hPa) during strong negative EU**
 18 **months in winter; (k) model-based wind circulation change at 850 hPa associated with the whole**
 19 **troposphere PV anomalies in the SENSr2 extreme members (relative to the CTRL ensemble**
 20 **mean); (l) same as (k) but in the CTRL counterparts of the SENSr2 extreme members (relative to**
 21 **the CTRL ensemble mean).**



1
2 **Figure 7. Historical simulations and future projections (under the SSP5-8.5 scenario) of Arctic sea**
3 **ice and regional air stagnation in observational and reanalysis data and CMIP6 models. (a) time**
4 **series of the Arctic SIE relative changes (unit: %; relative to the 1981-2010 climatology) in**
5 **preceding September and ECP_PPI (unitless) in DJF of the following winter (using years of**
6 **January for X-axis labeling). The solid lines denote observation- and reanalysis-based Arctic SIE**
7 **and ECP_PPI from 1950 to 2019. The dashed lines denote ensemble mean and the color shading**
8 **denotes ± 1 standard deviation of the 8 CMIP6 models (see Table S1 for model details) from 1950**
9 **to 2100. Note that the SIE time series were shifted one year after to be aligned with the ECP_PPI**
10 **data; (b) comparison of ECP_PPI CDF curves between the NCEP reanalysis data and the CMIP6**
11 **models in the P1 time period from 1951 to 2000. The inset denotes the distributions of positive**
12 **extremes ($\geq PPI_{P1}^{95th}$). The color shading denotes ± 1 standard deviations in the 8 CMIP6 models;**
13 **(c) Same as (b) but for the comparison between P1 and P2 (2001-2050) time periods as well as**
14 **between the NCEP reanalysis data and the CMIP6 models; (d) same as (b) but for the comparison**
15 **between P1 and P3 (2051-2100) time periods as well as between the NCEP reanalysis data and the**
16 **CMIP6 models. The model-specific comparison in (b)-(d) are shown in Table S5 and Fig. S9 in the**
17 **Supplement.**