# Electronic Supplementary Material to:
# The Predictability of Ocean Environments that Contributed to the 2020/21 Extreme Cold Events in China: 2020/21 La Niña and 2020 Arctic Sea Ice Loss*

Fei ZHENG[1,2], Ji-Ping LIU[3], Xiang-Hui FANG[4], Mi-Rong SONG[5], Chao-Yuan YANG[6], Yuan YUAN[7], Ke-Xin LI[1,8], Ji WANG[9], and Jiang ZHU[1,8]

[1]*International Center for Climate and Environment Science (ICCES), Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing* 100029, *China*

[2]*Collaborative Innovation Center on Forecast and Evaluation of Meteorological Disasters, Nanjing University of Information Science & Technology, Nanjing* 210044, *China*

[3]*Department of Atmospheric and Environmental Sciences University at Albany, State University of New York, Albany, NY* 12222, *USA*

[4]*Department of Atmospheric and Oceanic Sciences & Institute of Atmospheric Sciences, Fudan University, Shanghai* 200438, *China*

[5]*State Key Laboratory of Numerical Modeling for Atmospheric Sciences and Geophysical Fluid Dynamics (LASG), Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing* 100029, *China*

[6]*School of Atmospheric Sciences, Sun Yat-sen University, Zhuhai* 519082, *China*

[7]*National Climate Center, Beijing* 100081, *China*

[8]*University of Chinese Academy of Sciences, Beijing* 100049, *China*

[9]*Beijing Municipal Climate Center, Beijing* 100089, *China*

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## Introduction:

This file provides supplementary material on the brief descriptions of the IAP EPS and the pan-Arctic prediction systems and components discussed in the main article. The additional figures comparing the best and worst Arctic sea-ice prediction members are also contained in the supplementary file.

## Text S1. Description of the IAP ENSO EPS

The IAP ENSO EPS with 100 ensemble forecast members has three main components: an intermediate coupled model (ICM), an air–sea coupled data assimilation system, and a stochastic model-error model. (1) The ICM was developed by Keenlyside and Kleeman (2002) and Zhang et al. (2005) and consists of a dynamical ocean model, an SST anomaly model that empirically parameterizes the temperature of subsurface water entrained into the mixed layer ($T_e$) based on sea level anomalies, and a statistical wind stress ($\tau$) model. The dynamical component of the ICM consists of linear and nonlinear components. The former is basically the McCreary (1981) modal model but is extended to include horizontally-varying background stratification, ten baroclinic modes, and a parameterization of the local Ekman-driven upwelling. A correction, derived from the residual nonlinear momentum equations, is used to improve the solution where the linear assumptions break down. All coupled model components exchange simulated anomaly fields, such as the wind stress ($\tau$) in the atmosphere and the SST in the ocean, once a day.

(2) The air–sea coupled data assimilation system (Zheng and Zhu, 2010, 2015) uses an ensemble Kalman filter (EnKF) approach to minimize the errors in both the atmospheric and oceanic initial conditions by assimilating available atmosphere and ocean observations simultaneously into the ICM. In the system, the EnKF is implemented by using an ensemble

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square-root filter algorithm with no perturbation of observations (e.g., Evensen, 2004). This EnKF data assimilation scheme was further improved by using a balanced, multivariate model-error approach (Zheng and Zhu, 2008) and was upgraded to use mean preserving transformations in the square-root scheme (Sakov and Oke, 2008; Evensen, 2009). During the assimilation cycle, the state vector contains both atmosphere and ocean states, and the innovation vector is defined as the departure between the observed and modeled ensemble mean wind stress and SST anomalies. Since the background error covariance is constructed from the couple state ensemble member and contains error correlations between atmosphere and ocean states, all the coupled model variables are updated by multiplying the Kalman gain matrix by innovation vector. The atmospheric and oceanic observations can then be consistently assimilated into the coupled model to provide a dynamically consistent and accurate initial condition for real-time SST prediction.

(3) A stochastic error model (Zheng et al., 2009; Zheng and Zhu, 2016) was embedded within the ICM to perturb the modeled SST anomaly field randomly by adding error terms to the right-hand-sides of the model equations with 100 mem-

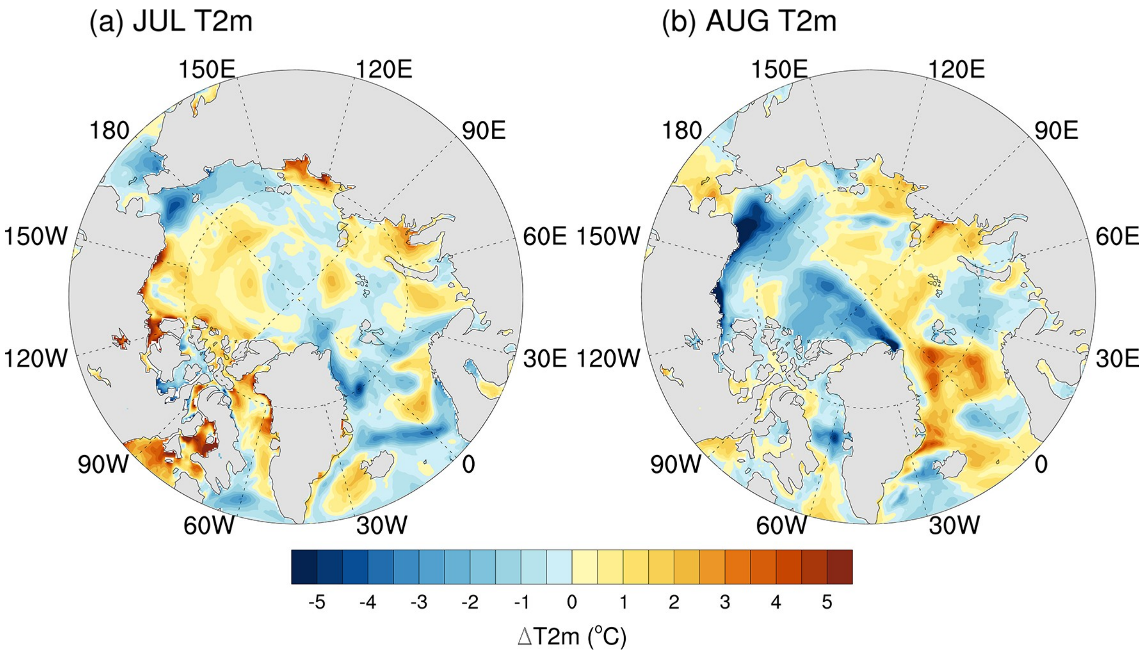


**Fig. S1.** Difference in surface air temperature (°C) between the best and worse members.

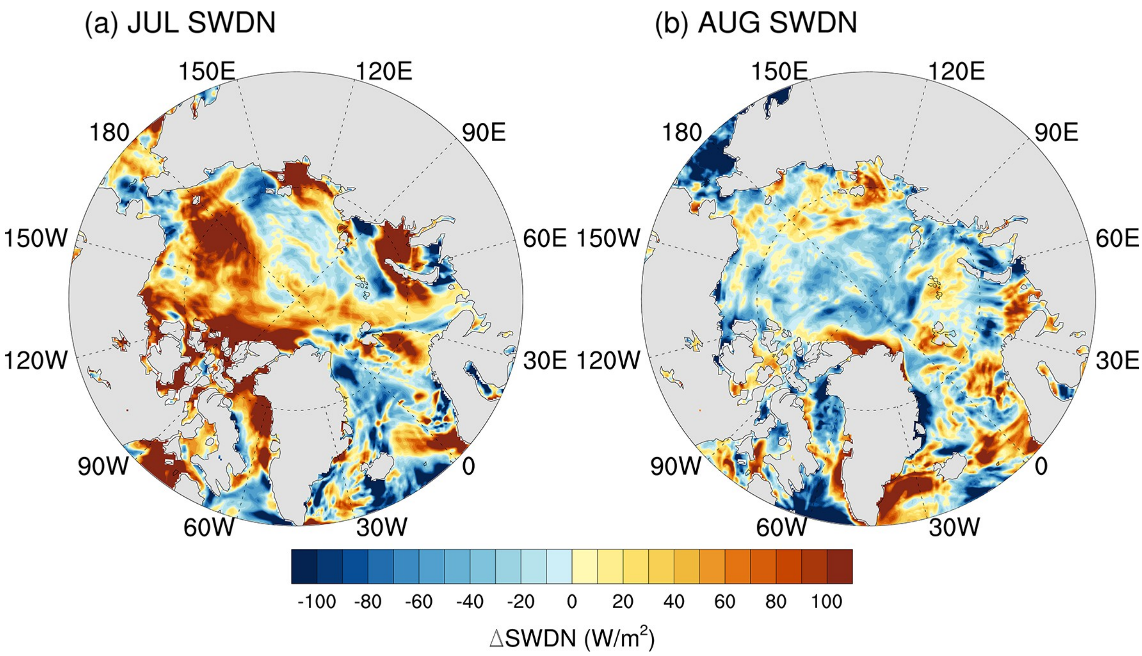


**Fig. S2.** As in Fig. S1, but for the surface downward shortwave radiation (W m$^{-2}$).

bers. This stochastic error model is designed to account for the time evolutions of the forecasted uncertainties in the SST anomaly field. The performance of this prediction system has been documented in Zheng and Zhu (2016), where a 20-year retrospective forecast comparison shows that good forecast skill of the EPS with a prediction lead time of up to one year is possible (Zheng and Yu, 2017).

## Text S2. Description of the Arctic sea ice prediction model

The Arctic sea ice predictions are performed by a regional coupled prediction system with eight ensemble members, and the prediction system is built on the Weather Research and Forecasting model (WRF), the Regional Ocean Modeling System (ROMS), the Community Ice CodE (CICE), and the data assimilation based on the Local Error Subspace Transform Kalman Filter (LESTKF). The WRF and ROMS models are initialized with the Climate Forecast System version 2 (CFSv2, Saha et al., 2014) operational forecast archived at the National Centers for Environmental Prediction (NCEP; http://nomads.ncep.noaa.gov/pub/data/nccf/com/cfs/prod/). To reduce ice thickness biases inherited from the CFSv2 simulations/forecasts (Saha et al., 2014), satellite-observed sea ice concentration and thickness products are assimilated. The details of configurations of physical parameterizations, model domain, and the assimilation procedures of the coupled prediction system are described in Yang et al. (2020).

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