

June 2020 Sea Ice Outlook Key Statements	Contributor	Type	Dynamic Model Type	Arctic Extent	Median	Standard Deviation	Range	Arctic Minimum	Arctic Maximum	Antarctic Extent	Antarctic Minimum	Antarctic Maximum	Alaska Extent	Possible Max Extent	Estimate Summary	Executive Summary	Method Summary	Sea Ice Concentration Data	Sea Ice Thickness Data	Processing Description
	University of Washington/APL	Dynamic Model	Dynamic model: Pan-Arctic Ice-Ocean Modeling and Assimilation System (PIMAS; Zhang and Rothrock, 2005), with coupled sea ice and ocean model components. The ocean model is the PDP (Parallel Ocean Program) and sea ice model is the thickness, flow, and embay distribution (TFED) model (Zhang et al., 2004). Atmospheric forcing is from the NCEP Climate Forecast System (CFS) version 2 (Saha et al., 2014) hindcast and forecast.	3.2											Driven by the NCEP CFS forecast atmospheric forcing, PIMAS is used to predict the total September 2020 Arctic sea ice extent as well as ice thickness, field and ice edge location, starting on June 1. The predicted September ice extent is 3.26 ± 0.22 million square kilometers. The predicted ice thickness fields and ice edge locations for September 2020 are also presented.	The PIMAS forecasting system is based on a synthesis of PIMAS, the NCEP CFS hindcast and forecast atmospheric forcing, satellite observations of ice concentration and sea surface temperature (SST), and CryoSat-2 observations of sea ice thickness. The CFS forecast ranges from hours to months. There are a total of 16 CFS ensemble forecast runs every day, of which four ensemble runs go out to 9 months, three runs go out to 1 season, and one run goes out to 60 days (Saha et al., 2014). These ensemble runs all cover 6-hourly forecast atmospheric data that are widely available in real time. This ideal for forcing PIMAS forecasts on a daily to seasonal time scales. There are four CFS ensemble members to allow the PIMAS ice-ocean-iceberg seasonal forecasts. Ensemble mean values from these four members are considered to be the predictions. To obtain the best possible, initial ice-ocean conditions for the forecasts, we conducted a retrospective simulation that assimilates satellite ice concentration and SST data through the end of May 2020 using the CFS hindcast forcing data. We also assimilated CryoSat-2 ice thickness available to April 2020. After the retrospective simulation (hindcast), four ensemble PIMAS forecast runs were conducted using atmospheric forecast forcing from four CFS ensemble runs. Additional information about PIMAS prediction can be found in Zhang et al. (2006).	Satellite sea ice concentration data (NASA team) for data assimilation in hindcast.	CryoSat-2 ice thickness up to 4/2020 data assimilation in hindcast.		
	GFZ/NOAA (Bashak et al.)	Dynamic Model	GFZ-FLOR	3.5	3.47	0.2	3.26-3.93	3.26	3.93				0.14	1.8	Our June 1 prediction for the September average Arctic sea ice extent is 3.50 million square km, with an uncertainty range of 3.26-3.93 million square km. Our prediction is based on the GFZ-FLOR ensemble forecast system, which is a fully-coupled ice-ocean-atmosphere-land-ice-ice model initialized using a coupled data assimilation system. Our prediction is the bias-corrected ensemble mean, and the uncertainty range reflects the lowest and highest sea ice extents in the 12-member ensemble.	Our June 1 prediction for the September average Arctic sea ice extent is 3.50 million square km, with an uncertainty range of 3.26-3.93 million square km. Our prediction is based on the GFZ-FLOR ensemble forecast system, which is a fully-coupled ice-ocean-atmosphere-land-ice-ice model initialized using a coupled data assimilation system. Our prediction is the bias-corrected ensemble mean, and the uncertainty range reflects the lowest and highest sea ice extents in the 12-member ensemble.	Sea forecast is based on the GFZ-FLOR forecast-oriented Low Ocean Resolution (FLOR) model (Vinnits et al., 2014), which is a coupled atmosphere-land-ocean-sea ice model. The model is initialized from an ensemble Kalman filter coupled data assimilation system (EKDA; Cheng et al., 2007), which assimilates observational surface and subsurface ocean data and atmospheric reanalysis data. The system does not assimilate sea ice concentration or thickness data. The FLOR atmospheric initial conditions are produced from an AR6-Pre-Operational Observing System (AR6-POS) reanalysis. Radiative forcing is used prior to 2020 and the RCP4.5 scenario is used for predictions after 2020. For the predictions initiated after 2020, the aerosols are fixed at the RCP4.5 scenario year of 2020. The performance of this model in seasonal prediction of Arctic sea ice extent has been documented in Bashak et al. (2014), Bashak et al. (2017), and Bashak et al. (2020). For an evaluation of the model's September sea ice extent prediction skill from a June 1 initialization, we attached report.	No sea data is explicitly used in our initialization procedure.	No SST data is explicitly used in our initialization procedure.	These forecasts are bias-corrected based on an additional correction using a suite of retrospective forecasts spanning 1980-2020.
	ANDS IAP/ASG	Dynamic Model	CAS-GOALS-F2 (Atmospheric component: FAML2; Ocean component: POP; Sea ice component: OCEA; Land component: CLM4)	3.8	3.4	0.4	2.2-4.2	2.2	4.2						The prediction for the sea ice outlook June 2020 was carried out on China's Tianhe-2 supercomputer, with a dynamic model prediction system CAS-GOALS-F2 V2.11.3. The dynamic model prediction system, named FGOALS-F2 (ice-ocean-atmosphere-land model), provides a real-time prediction in a subsurface to seasonal (S2S) timescale. FGOALS-F2 system has been established in 2017 by IAP team of FGOALS-F2 from both IAP Institute of Atmospheric Physics, Chinese Academy of Sciences and IAP Chinese Academy of Information Technology. The FGOALS-F2 S2S prediction results are used in three major national operational prediction centers in China. Based on the a month lead dynamic model prediction from June 9th, 2020, the actual prediction of sea ice extent are 3.8 million square kilometers for pan-Arctic in September 2020.	The uncertainty was estimated by the ensemble member spread.	FGOALS-F2 V2.11.3 is a global coupled dynamic prediction system. The initialization of the prediction system is based on a reanalysis of sea ice concentration and thickness (1° resolution), Temperature (1°) atmosphere and potential temperature in ocean from 1 Jan 1980 to 1 June 2020, and the RCP4.5 scenario members are generated by a time slicing method. The predictions are available here for 12 months. This real-time S2S prediction system is fully operated on China, Tianhe-2 supercomputer.			Model bias that is removed is calculated based on 2019 retrospective forecasts and corresponding observations.
	CPOM	Statistical		3.8		0.5									We predict the September ice extent 2020 to be 3.8 (3.3-4.3) million km ² . This is the lowest prediction we have made based on spring melt pond fraction. The likelihood is around 30% that this September extent will be a new minimum record in our model simulation since 1979. May 2020 is the highest mean melt pond fraction for May including some unprecedented melt pond formation in the Central Arctic during 15-18 May when air temperature exceeded 0°C.	Mean forecast error based on forecasts for the years 1984 to 2020.	Reference: 1. Flood, D., Schneider, N., Poffenberger, D. L. & Ramanam, C., 2012. Impact of melt ponds on Arctic sea ice simulations from 1990 to 2007. J. Geophys. Res., 117, C09022. 2. Schivinski, B., D. L. Floren, D. F. Hare, M. T. Williams, 2018. September Arctic sea-ice minimum predicted by spring melt-pond fraction. Nature Climate Change, 8, 383-387. DOI: 10.1038/s41467-018-2203-3			See references in Section 6.
	MSUJ Team	Statistical		3.89											Our research focuses on seasonal predictability of sea ice in the Arctic Ocean, using observations-based approaches. We are interested in the winter preconditioning effect on the pack ice before the summer melt. Specifically, we investigate how dynamic processes affect preconditioning, in other words, we ask how anomalies in the general circulation of sea ice will influence later conditions of the Arctic Ocean pack ice under a spring melt season. We investigate the skill of different sea ice predictors, including atmospheric forcing parameters and the following September minimum sea ice extent. The downdice method builds on the correlation between winter Fram Strait sea ice extent and the following September minimum sea ice extent, presented in Williams et al., 2016. A positive anomaly of the winter Fram Strait sea ice extent is associated with enhanced circulation of sea through Fram Strait (drift stream) and positive anomalies of coastal divergence of sea ice along the Eurasian coasts, increased coastal divergence leads to the winter ocean convergence of warmer and thicker ice preference, which is more favorable to melting in the summer.	RMSE = 0.46 million km ² . We compare hindcasts to the observed mean September sea ice extent for the 1984-2020 period.	The downdice method builds on the correlation between winter Fram Strait sea ice extent and the following September minimum sea ice extent, presented in Williams et al., 2016. A positive anomaly of the winter Fram Strait sea ice extent is associated with enhanced circulation of sea through Fram Strait (drift stream) and positive anomalies of coastal divergence of sea ice along the Eurasian coasts, increased coastal divergence leads to the winter ocean convergence of warmer and thicker ice preference, which is more favorable to melting in the summer.	Sea ice concentration is not used as an initial condition (push) in a dynamical model. However, we use sea ice extent from the NSIDC. See ice index V3 to fit our statistical model. https://doi.org/10.7926/H4972718		
	Simmons, Charles	Statistical	This is a variant of Decker's model. This is a simple linear regression on three variables from 1979 through 2020, used to predict NSIDC September mean sea ice extent. * May average northern hemisphere sea ice area (https://nsidc.columbia.edu/data/products/figs/area_nh05a.html) * May average northern hemisphere snow area (https://climate.geog.udel.edu/arcviewer/citable_area.php?cat=42) * May average atmospheric CO2 as measured at Mauna Loa (https://www.esrl.noaa.gov/gcd/trace/gtrends/data.html)	3.949		0.495 million square kilometers									The model used here assumes September sea ice extent is mostly based on three things: - the temperature of the ocean and atmosphere, - the albedo of the earth and the energy it reflects away from the Arctic, - weather patterns in August. Mauna Loa CO2 measurements are used as a proxy for the temperature of the earth. The northern hemisphere snow and ice area is used as a proxy for the amount of energy reflected away from the Arctic. The residual error is assumed to be due to weather patterns in August that we don't know how to predict.	Standard Error of Linear Regression	This is a variant of Decker's model. This is a simple linear regression on three variables from 1979 through 2020, used to predict NSIDC September mean sea ice extent. * May average northern hemisphere sea ice area (https://nsidc.columbia.edu/data/products/figs/area_nh05a.html) * May average northern hemisphere snow area (https://climate.geog.udel.edu/arcviewer/citable_area.php?cat=42) * May average atmospheric CO2 as measured at Mauna Loa (https://www.esrl.noaa.gov/gcd/trace/gtrends/data.html)			None
	CPOM UCL (Gregory et al.)	Statistical		3.96		0.34									This statistical model compares a forecast of pan-Arctic September sea ice extent. Monthly averaged May sea ice concentration and surface temperature fields between May 2015 and 2020 were used to train a Bayesian Network (based on the approach of Gregory et al. 2020). This was then utilized in a Bayesian Network in order to forecast September 2020. Model predicts a pan-Arctic extent of 3.96 million square kilometers. Sea ice concentration data were taken from NSIDC Globalv2 et al., 1996. Reanalysis data were taken from ERA5 reanalysis.	Forecasts are Gaussian distribution. Forecast reports the mean, and uncertainties are given by the standard deviation	Monthly averaged May sea ice concentration (SIC) data between 1979 and 2020 were used to create a May SIC climatology (complex) network, and similarly for sea surface temperature (SST). Individual SIC(S15) grid cells were first clustered into regions of spatial-temporal homogeneity by using a community detection algorithm (see Gregory et al., 2020). Links between each of these network regions (clusters) were then passed into a Bayesian Network Regression to derive an estimate on the joint probability of the regression parameters. Subsequently a posterior distribution of the regression parameters was then derived in order to generate the forecast of September sea ice extent.	NSIDC NASA Team Sea Ice Concentrations: 1979 - 2020; ERA5: 1950 - 2020; MERRA-2: 1980 - 2020; MERRA-2: 1980 - 2020; MERRA-2: 1980 - 2020; MERRA-2: 1980 - 2020		
	Climate Prediction Center	Dynamic Model	Whole Model: CFSv5 Atmospheric component: NCEP GFS Ocean component: GFDL MOM5	4.01	4.01	0.176	3.72-4.45	3.72	4.45				0.56		This contribution from a 20-member ensemble forecast from the Climate Prediction Center uses ice fluxes to predict September 2020 sea ice extent that is removed is calculated based on 2007-2019 retrospective forecasts and corresponding observations.	The outlook is produced from the Climate Prediction Center's Experimental Model using ice fluxes to predict September 2020 sea ice extent. The outlook is produced from the Climate Prediction Center's Experimental Model using ice fluxes to predict September 2020 sea ice extent. Twenty forecast members are produced. Model bias that is removed is calculated based on 2007-2019 retrospective forecasts and corresponding observations.	Both sea ice concentration and sea ice thickness are initialized from the CPC sea ice initialization system (CIS). The CIS analysis is produced with GFDL MOM5 which uses surface fluxes from CFS and assimilates satellite sea ice concentration retrieval from NSIDC/NASA Team	Both sea ice concentration and sea ice thickness are initialized from the CPC sea ice initialization system (CIS). The CIS analysis is produced with GFDL MOM5 which uses surface fluxes from CFS and assimilates satellite sea ice concentration retrieval from NSIDC/NASA Team	Twenty forecast members are produced. Model bias that is removed is calculated based on 2007-2019 retrospective forecasts.	
	Gayley, Gavin	Statistical	Gaussian Process Regression	4.091	4.091		2.9757 - 5.1825	2.9757	5.1825						This is a purely statistical method (related to kriging) to estimate the long term trend from previous observations of September Arctic sea ice extent. As this uses September observations, the prediction is altered by observations made during the Summer of 2020.	Bayesian posterior predictive uncertainty from Gaussian Process	This is a purely statistical method, which uses a Gaussian process regression (i.e. kriging) method to estimate the (non-linear) long term trend from previous observed September Arctic sea ice extent. The model uses a radial basis covariance function and the parameters are optimized through maximum likelihood using the GPRM toolbox for MATLAB. As this uses only September observations, the prediction is not altered by observations made during the Summer of 2020.	Only uses previous monthly September sea ice extent data.		
	NSIDC (Mayer)	Statistical		4.13		0.66				18.19					This method applies daily sea ice loss rates to extrapolate from the start date (June 1) through the end of September. Projected September average daily sea ice loss rates are averaged to calculate the projected September average extent. Individual years from 2007 to 2021 are used, as well as averages from 1980-2003 and 2007-2020. The 2007-2020 average daily rates are used to estimate the official statistical estimate.	Standard deviation of September extents of projections from year 2007-2020	This method applies daily sea ice loss rates to extrapolate from the start date (June 1) through the end of September. Projected September average daily sea ice loss rates are averaged to calculate the projected September average extent. Individual years from 2007 to 2021 are used, as well as averages from 1980-2003 and 2007-2020. The 2007-2020 average daily rates are used to estimate the official statistical estimate. The method estimates provides the range of September 2020 average daily rates that can be expected based on how the ice has declined in past years. Though it is possible that a recent loss of sea ice daily loss rates may yield a value outside the projected range, it is not as probable a probability of a new record by comparing how many years of loss rates and a record relative to 4 years. It has the benefit that it can easily and frequently daily (if desired) be updated to provide updated estimates and probabilities and is the minimum approaches the "Alternative A" of possible outcomes names.	NSA Team algorithm extends from the NSIDC Sea Ice Index, Version 1 (http://nsidc.org/data/sea_ice/index_v1)		
	NSIDC (Horvath et al.)	Statistical	Bayesian Logistic Regression	4.19											This statistical model compares the probability that sea ice will be present (concentration above 15%) for each grid cell in NSIDC's polar stereographic projection. Training data from 1980 through the present are used to develop logistic regression. Predictors include local surface air temperature, precipitation, and sea ice concentration. The model is trained using the first principal component of geopotential height at 500mbars, and Pacific and Atlantic sea surface temperatures. Sea ice concentration data were obtained from NSIDC. Sea ice Index V3 (Data Set ID:G2131), all other variables are from NASA's MERRA2 dataset.	Yearly data from 1980 through the present are used in a Bayesian logistic regression to predict the probability that sea ice concentration will be above 15%. To estimate sea ice extent, a grid cell with a percentage above a certain threshold (above 50%) is considered to be present. The model is trained using the first principal component of geopotential height at 500mbars, and Pacific and Atlantic sea surface temperatures. Sea ice concentration data were obtained from NSIDC. Sea ice Index V3 (Data Set ID:G2131), all other variables are from NASA's MERRA2 dataset.	NSIDC's Sea Ice Index V3 (Data Set ID:G2131)			

