August 2022 Sea Ice Outlook Key Statements

Contributer	Model Type	Model Name	Arctic Extent	Median	Standard Deviation	Low Error Bound	High Error Bound	Antarctic Extent	Alaska Extent	Maximum Alaska Extent	Uncertainty Estimate Summary	Pan-Arctic Sea Ice Extent Anomaly	Executive Summary	Method Summary	Sea Icea Concentration Data	Sea Ice Thickness Data	Post-Processing Description
Climate Prediction Center	Dynamic Model	Whole Model: CFSm5 Atmospheric component: NCEP GFS Oceanic component: GFDL MOM5	4.69	4.68	0.18	4.34	5.09		0.74	3.97	The uncertainty estimate is calculated from the 20-member ensemble.		The forecast is based on an initialized fully coupled system. Contributing factors include initial oceanic, sea ice and atmospheric conditions, with initial sea ice thickness being the dominant factor.	The outlook is produced from the Climate Prediction Center Experimental sea ice forecast system (CFSm5). The forecast is initialized from the Climate Forecast System Reanalysis (CFSR) for the ocean, land, and atmosphere and from the CPC sea ice initialization system (CSIS) for sea ice. Twenty forecast members are produced. Model bias that is removed is calculated based on 2007-2021 retrospective forecasts and corresponding observations.	NASA Team Analysis from NSIDC	CPC sea ice initialization system (CSIS)	Twenty forecast members are produced. Model bias that is removed is calculated based on 2007-2021 retrospective forecasts.
Simmons, Charles	Statistical/ML		4.73		0.32						This is the error measured by the linear regression.	-0.6	The August Outlook has increased to 4.73 MK^2, mostly because the July ice area anomaly has increased relative to the June ice area anomaly.	This Outlook is a linear regression of northern hemisphere snow area, moana loa co2 concentration, and arctic sea ice area.	N/A	N/A	
University of Washington/APL	Dynamic Model	Pan-Arctic Ice-Ocean Modeling and Assimilation System (PIOMAS, Zhang and Rothrock, 2003), with coupled sea ice and ocean model components. The ocean model is the POP (Parallel Ocean Program) model and sea ice model is the thickness, floe size, and enthalpy distribution (TFED) model (Zhang et al., 2016). Atmospheric forcing is from the NCEP Climate Forecast System (CFS) version 2 (Saha et al., 2014) hindcast and forecast. 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 July 2022 using the CFS hindcast forcing data. We also assimilated CryoSat2 ice thickness available up to April 2020.	4.65		0.4							0.43	Driven by the NCEP CFS forecast atmospheric forcing, PIOMAS is used to predict the total September 2022 Arctic sea ice extent as well as ice thickness field and ice edge location, starting on August 1. The predicted September ice extent is 4.65± 0.40 million square kilometers. The predicted ice thickness fields and ice edge locations for September 2022 are also available (see attachment).	The PIOMAS forecasting system is based on a synthesis of PIOMAS, the NCEP CFS hindcast and forecast atmospheric forcing, satellite observations of ice concentration and sea surface temperature (SST), and CryoSat2 observations of sea ice thickness.	Initial SIC is from PIOMAS hindcast that also assimilates satellite SIC (NASA team) available from NSIDC (https://nsidc.org/data/nsidc-0081).	Initial SIT is from PIOMAS hindcast that also assimilates CrySat2 SIT data up to April 2020 (http://psc.apl.uw.edu/sea_ice_cdr/).	
APPLICATE Benchmark	Statistical/ML		4.72	4.72	0.54	3.64	5.8	18.19			Same as previous submissions		Same as previous submissions	Same as previous submissions	Same as previous submissions	Same as previous submissions	Same as previous submissions
GFDL/NOAA (Bushuk et al.)	Dynamic Model	Model: GFDL-SPEAR_MED Atmosphere AM4 Initialized from nudged atmosphere and SST run Land LM4 Initialized from nudged atmosphere and SST run Ocean MOM6 Initialized from EnKF coupled data assimilation Sea Ice SIS2 Initialized from nudged atmosphere and SST run	4.93	4.93	0.16	4.61	5.4		0.66	3.94	These statistics are computed using our 30 member prediction ensemble.	0.72	Our August 1 prediction for the September-averaged Arctic sea-ice extent is 4.93 million km^2, with an uncertainty range of 4.61-5.40 million km^2. Our prediction is based on the GFDL-SPEAR_MED ensemble forecast system, which is a fully-coupled atmosphere-land-ocean-sea 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 30-member ensemble.	Our forecast is based on the GFDL Seamless system for Prediction and EArth system Research (SPEAR MED) model (Delworth et al., 2020), which is a coupled atmosphere-land-ocean-sea ice model. The ocean model is initialized from an Ensemble Kalman Filter coupled data assimilation system (SPEAR ECDA; Lu et al., 2020), which assimilates observational surface and subsurface ocean data. The sea ice, land, and atmosphere components are initialized from a nudged ensemble run of the coupled SPEAR MED model, which is nudged towards 3-D temperature, wind, and humidity data from CFSR and SST data from OISST. The SST values under sea ice are adjusted to the freezing point of sea water using OISST sea ice concentration data. The performance of this model in seasonal prediction of Arctic sea ice extent has been documented in Bushuk et al. (2022). For an evaluation of the model's September sea ice extent prediction skill from an August 1 initialization, see attached report.	OISST SIC data is used to correct assimilated SST values under sea ice.	No SIT data is explicitly used in our initialization procedure.	These forecasts are bias corrected based on a linear-regression adjustment using a suite of retrospective forecasts spanning 1992-2021.
CSU-REU21	Statistical/ML		4.81										We consider the importance of the boreal winter mean large-scale atmospheric circulation (Icelandic Low, Arctic Oscillation) and the state of Arctic sea-ice concentration and thickness at the beginning of summer for predicting September sea ice. In particular, our simple statistical model uses mean Arctic sea-ice thickness in the Beaufort Sea region as an important predictor for September sea-ice extent. Myint, H., & Labe, Z. M. (2022). Predicting September Arctic Sea-ice Using a Hierarchy of Statistical Models. In 102nd American Meteorological Society Annual Meeting. AMS.	We use a multiple linear regression model with regional climate predictors from boreal winter (focused on sea ice motion/drift) and early summer (focused on the mean state of sea-ice concentration and sea-ice thickness). Our data is derived from ERA5 reanalysis and PIOMAS. This work has been supported by the National Science Foundation Research Experiences for Undergraduates Site in Earth System Science at Colorado State University under the cooperative agreement No. AGS-1950172.	ERA5 Reanalysis - Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., ... & Thépaut, J. N. (2020). The ERA5 global reanalysis. Quarterly Journal of the Royal Meteorological Society, 146(730), 1999-2049. https://doi.org/10.1002/qj.3803	Pan-Arctic Ice Ocean Modeling and Assimilation System (PIOMAS) - Zhang, J., & Rothrock, D. A. (2003). Modeling global sea ice with a thickness and enthalpy distribution model in generalized curvilinear coordinates. Monthly Weather Review, 131(5), 845-861. https://doi.org/10.1175/1520-0493(2003)131<0845:MGSIWA>2.0.CO;2	
ASIC, NIPR	Statistical/ML		4.64									0.19	Monthly mean ice extent in September will be about 4.64 million square kilometers. Our prediction is based on a statistical way using data from satellite microwave sensor. We used the ice thickness (accumulated ice convergence) and ice age on June 30. Predicted ice concentration map from July 1 to September 20 is available in our website : https://www.nipr.ac.jp/sea_ice/e/forecast/2022-08-01-1/	We predicted the Arctic sea-ice cover from coming July 1 to September 20, using the data from satellite microwave sensors, AMSR-E (2002/03-2010/11) and AMSR2 (2012/13-2021/22). The analysis method is based on our research (Kimura et al., 2013). First, we expect the ice thickness distribution on June 30 from redistribution (divergence/convergence) of sea ice during December and June. Additionally, ice age distribution on June 30 was estimated from the backward tracking of sea ice. Then, we calculated the summer ice concentration by multiple regression analysis based on the derived ice thickness and ice age.	10km grid data distributed by Arctic Data archive System (https://ads.nipr.ac.jp)	NA	
CPOM UCL (Gregory et al.)	Statistical/ML		4.94		0.34	4.6	5.28		0.54	4	Forecasts are Gaussian distributions. Forecast represents the mean, and uncertainties are given by the standard deviation	0.73	This statistical model computes a forecast of pan-Arctic September sea ice extent . Monthly averaged July sea ice concentration fields between 1979 and 2022 were used to create a climate network (based on the approach of Gregory et al 2020). This was then utilised in a Bayesian Linear Regression in order to forecast September extent. The model predicts a pan-Arctic extent of 4.94 million square kilometres. Sea ice concentration data were taken from NSIDC (Cavalieri et al., 1996; Maslanik and Stroeve,1999)	Monthly averaged July sea ice concentration (SIC) data between 1979 and 2022 were used to create a July SIC climate(complex) network. Individual SIC grid cells were first clustered into regions of spatio-temporal homogeneity by using a community detection algorithm (see Gregory et al, 2020). Links between each of these network regions (covariance) were then passed into a Bayesian Linear Regression to derive an estimate on the prior distribution 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.	N/A	N/A	
KOPRI (Chi et al.)	Statistical/ML		5.18	5.22	0.1	5.05	5.37				We selected ten most accurate models in the training process and then use them for the uncertainty estimate.		KOPRI's prediction model uses the past 12-month data as inputs for the six-month predictions of Arctic sea ice concentration (SIC). The predicted September extent for 2022 is 5.18 million square kilometers using data from August 2021 to July 2022.	KOPRI's fully data-driven model was trained on historical NSIDC's daily SIC data from 1979 to 2021 using a combination of convolutional and recurrent neural networks. Since we observed a large visual discrepancy according to the neural network's loss functions, a new loss function was developed to improve both statistical accuracy and visual agreement. The 6-month prediction model is currently tuning up to improve predictability. Please find our recent published paper: Chi J, Bae J, Kwon Y-J. Two-Stream Convolutional Long- and Short-Term Memory Model Using Perceptual Loss for Sequence-to-Sequence Arctic Sea Ice Prediction. Remote Sensing. 2021; 13(17):3413. https://doi.org/10.3390/rs13173413	NSIDC NASA Team, https://nsidc.org/data/nsidc-0051, https://doi.org/10.5067/8GQ8LZQVL0VL, https://nsidc.org/data/nsidc-0081, https://doi.org/10.5067/YTTHO2FJQ97K	NA	Negative SIC predictions over ocean pixels were set to 0% and SIC predictions over 100% were set to 100%. We also used land and coastline masks from NSIDC's SIC data
METNO-SPARSE-ST (Wang et al.)	Statistical/ML		4.78	4.78	0.26	4.23	5.3	17.72					AR model using NSIDC SIE	AR model using NSIDC SIE	NA	NA	
NSIDC (Meier)	Statistical/ML		4.88		0.35			17.4			Standard deviation of projections from the individual years, 2007 to 2021.	0.67	This method applies daily ice loss rates to extrapolate from the start date (August 1) through the end of September. Projected September daily extents are averaged to calculate the projected September average extent. Individual years from 2005 to 2021 are used, as well as averages over 1981-2010 and 2007-2021. The 2007-2021 average daily rates are used to estimate the official submitted estimate. The predicted September average extent for 2022 is 4.88 (±0.35) million square kilometers. The minimum daily extent is predicted to be 4.76 (±0.36) million square kilometers and occurs on 16 September. The range of estimates reflects the variability in ice loss rates over the final ~1.5 months of the melt season. Based on the last 17 years (2005-2021), there is a 0% chance that 2022 will be lower than the current record low September extent of 3.57 million sq km in 2012. Using the same method, the predicted Antarctic average extent for September 2022 is 17.40 (±0.34) million square kilometers. The maximum daily extent is predicted to be 17.48 (±0.34) million square kilometers and occurs on 26 September.	This method applies daily ice loss rates to extrapolate from the start date (August 1) through the end of September. Projected September daily extents are averaged to calculate the projected September average extent. Individual years from 2005 to 2021 are used, as well as averages over 1981-2010 and 2007-2021. The 2007-2021 average daily rates are used to estimate the official submitted estimate. The method essentially provides the range of September extents that can be expected based on how the ice has declined in past years, though it is possible that record fast or slow daily loss rates may yield a value outside the projected range. It also can provide a probability of a new record by comparing how many years of loss rates yield a record relative to all years. It has the benefit that it can easily and frequently (daily if desired) be updated to provide updated estimates and probabilities and as the minimum approaches the "window" of possible outcomes narrows.	NASA Team algorithm extents from the NSIDC Sea Ice Index, Version 3 (http://nsidc.org/data/seaice_index/)	NA	
Kondrashov, Dmitri (UCLA)	Statistical/ML		4.82		0.14				0.48		This uncertainty corresponds to standard deviation of stochastic ensemble spread.	0.4	This model forecast is based on statistical/ML stochastic modeling techniques applied to the regional Arctic Sea Ice Extent (SIE) dataset.	Statistical/ML stochastic modeling techniques have been applied to the regional Arctic Sea Ice Extent (SIE) from Sea Ice Index Version 3 dataset (G02135). The daily SIE data were aggregated to provide weekly-sampled dataset over several Arctic sectors. The predictive model has been derived from SIE anomalies with annual cycle removed, and is initialized from latest SIE conditions by ensemble of stochastic noise realizations to provide probabilistic regional Arctic forecasts in September. The Alaskan region is defined using the mask file, "Arctic_region_mask_Meier_AnnGlaciol2007.msk, created by Meier et al. (2007)" (from documentation of Sea Ice Index G02135).	NA	NA	

Slater-Barrett (NSIDC)	Statistical/ML		5.02										This projection was made using the Slater Probabilistic Ice Extent model developed by Drew Slater (http://cires1.colorado.edu/~aslater/SEAICE/). The model computes the probability of sea ice concentration greater than 15% for Arctic Ocean grid cells in the EASE 25 km grid. These probabilities are aggregated over the model domain to arrive at daily ice extents. A September mean ice extent is calculated from daily forecasts issued on August 1. While the model has predictive skill at lead times up to 90 days, NSIDC runs the forecast model with a 50 day lead time. Forecasts issued on August 1 for September have lead times spanning 31 to 61 days. Therefore we consider the mean September ice extent forecast for the August sea ice outlook to have reasonable skill.	This is a non-parametric statistical model of Arctic sea ice extent. The model computes the probability of whether ice concentration greater than 15% will exist at a particular location for a particular lead time into the future, given current ice concentration. The only input is sea ice concentration. Probabilities are computed using data from the past 10 years. These probabilities are adjusted using daily near-real-time concentrations to make a forecast. Pan- Arctic Ice extent is the sum of the product of grid-box area and the probability of a grid-box containing ice on the forecast date. While not as sophisticated as a coupled ocean-ice- atmosphere models, this statistical method has the advantage that the forecasts for all points are completely independent in both space and time; that is, the forecast at any given point is not affected by its neighbors, nor its result from the prior day. Therefore, the model can adapt to changing conditions and is not inherently subject to drift. The model has performed well in comparison to others in the 2013/2014 SIPN Outlooks, in both extent value and spatial distribution. For 2012, a September mean forecast of below 4 million square kilometers was given. However, the model has also missed by as much as 0.6 million square kilometers in some years. Forecasting is difficult, but the model does have genuine skill at lead times as long as 90 days. Skill improves as lead time decreases, and September is the month with highest skill.	https://nsidc.org/data/nsidc-0081	NA	
RASM@NPS (Maslowski et al.)	Dynamic Model	The version of Regional Arctic System Model (RASM v2_1_00) used for this contribution consists of the following components: Ocean: POP2.1 Atmosphere: WRF3.7.1 Sea-ice: CICE 5.1.2 Land hydrology: VIC 4.0.6 River streamflow routing: RVIC 1.0.0 Flux Coupler: CPL 7 This model initial condition for ensemble forecast was derived from a hindcast, forced with CFSR/CFSv2 reanalysis for September 1979 through July 2022. The ocean and sea ice initial conditions at the beginning of the hindcast were derived from the 32-year spin-up of the ocean-sea ice model only (RASM G-case) forced with CORE2 reanalysis for 1948-1979.	4.593	4.574	0.14	4.248	4.859		0.456	3.927	The uncertainty of pan-Arctic September sea ice extent was estimated from the 30 ensemble members: see also Fig.4 in the supplementary material.	-0.04	The Arctic sea ice extent September 2022 minimum is predicted to roughly continue the September declining trend (of -0.528x10^6 km^2/decade) based on 2000-2021 output from the Regional Arctic System Model (RASM) hindcast simulation. The difference between the 31-member ensemble mean September sea ice extent prediction and the extrapolation 2000-2021 linear trend into 2022 is 0.040x10^6 km^2. Compared to the RASM September 2021 sea ice extent minimum (4.695x10^6 km^2) from the hindcast, the ensemble mean forecast for 2022 minimum is slightly lower by 0.102x10^6 km^2, suggesting a continuous decline of sea ice after a brief rebound. According to the RASM ensemble mean predicted September sea ice thickness distribution, the majority of surviving ice thickness ranges between 1.0 m and 1.5 m, with the thickest sea ice north of the Canadian Archipelago and Greenland within the range of 1.5 m-2.5 m, and almost no sea ice thicker than 3.0 m (see Fig. 3 in the supplementary material). The RASM September outlook has been commonly biased high in recent years (bias of 0.070x10^6 km^2 and standard deviation of 0.415x10^6 km^2) compared to the NSIDC observation (2000-2021), especially in the northern Barents/Kara and East Siberian seas.	We used RASM2_1_00, which is a recent version of the limited-area, fully coupled climate model consisting of the Weather Research and Forecasting (WRF), Los Alamos National Laboratory (LANL) Parallel Ocean Program (POP) and Sea Ice Model (CICE), Variable Infiltration Capacity (VIC) land hydrology and routing scheme (RVIC) model components (Maslowski et al. 2012; Roberts et al. or 2015; DuVivier et al. 2015; Hamman et al. 2016; Hamman et al. 2017; Cassano et al. 2017). The model is forced with CFSR/CFSv2 reanalysis output for RASM-WRF lateral boundary conditions and for nudging winds and temperature starting above 500 mb for September 1979-July 2022. Then, RASM is used for dynamic down-scaling of the global NOAA/NCEP CFSv2 7-month forecasts. The CFSv2 forcing (https://www.ncei.noaa.gov/data/climate-forecast-system/access/operational-9-month-forecast/) streams used for the ensemble members were initialized every day (at 00:00) between July 1st and July 31st and used for RASM forcing at 00:00 on August 1st, 2022 and onward until the end of January 2023. Each of the 31 ensemble members ran forward for 6 months using outputs from CFSv2 forecasts since we skip the first calendar month of each CFSv2 forcing.	The initial sea ice conditions for the August Sea Ice Outlook were derived from the RASM 1979-2022 hindcast and are physically and internally consistent across all the model components. Neither data assimilation nor bias correction was used.	See the above.	Daily mean sea ice with concentration <=15% and thickness <= 20 cm was excluded in the estimates of September sea ice extent.
HEU Group (Zhao, et al.)	Statistical/ML		4.58					18.24					The outlook is based on two statistical methods: climate trends regression prediction and previous bias correction. Based on the consensus that arctic sea ice is significantly decreasing, we calculate the trend of sea ice concentration in each grid in the Arctic region and then use this trend to predict the value of sea ice concentration in that grid this year. The satellite observation data of this year before the prediction are used to calculate the real change of this year, and further correct the change trend obtained by the regression of climate trend. This is the meaning of the previous bias correction. By combining the above two methods, a more reasonable distribution field of sea ice concentration is obtained, and then the sea ice extent is calculated.	When obtaining the regression prediction results of climate trend, we used the NSIDC-0051 sea ice concentration dataset of NSIDC NASATEAM algorithm, with a time range of 1989-2020 and a spatial resolution of 25km. Firstly, we calculated the linear regression coefficients of each grid during 1989-2020. The trend of climate change in the grid is analyzed, and the sea ice concentration of each grid in 2022 is calculated by using the linear regression coefficient. In the previous bias correction part, we also used the value of sea ice concentration from January to July 2022 of NSIDC-0081, calculated the curve of sea ice extent retrieved by satellite from January to July 2022, and compared it with the change of sea ice extent from January to July 2022 predicted by climate trend regression. The average difference between the two was obtained as a basis for previous bias corrections, climate trend predictions for September 2022 were then revised to obtain the final results.	NSIDC NASA Team, https://nsidc.org/data/nsidc-0051,https://nsidc.org/data/nsidc-0081,	NA	
Sun, Nico	Statistical/ML		5.55	5.55		5.31	5.69	18.23	0.755	4	SIC uncertainty	1	The forecast model is based on ice persistence. It uses incoming solar radiation and sea ice albedo derived from a predicted Sea Ice Concentration (SIC) value to calculate daily thickness losses for every NSIDC 25km grid cell. The initial thickness is calculated from AMSR2 sea ice volume and NSIDC SIC data. Instead of a long-term mean, the 2022 model predicts SIC change based on correlation to previous years. A special formula calculates a best new mean field based on past years. Years with a very high correlation get weighted more. For this month the mean field is made up of: 2007,2007,2010,2010,2012,2013,2013,2013,2015,2015,2016,2016,2017 The mean forecast uses the SIC (1/4 weight) and mean SIC change per day (3/4 weight) to predict future SIC. The low forecast reduces the predicted SIC by 0.3Stdv for previously observed SIC for this day and a 10% increased bottom melt. The high forecast increases the predicted SIC by 0.10Stdv and a 10% decreased bottom melt. Since 2020 model includes a bias correction layer to reduce persistent errors of underprediction or overprediction based on past forecasts. This layer simulates ice drift or cold freezing air blowing from landmasses causing refreezing.	Each grid-cell is initialized with a thickness derived from the AMSR2 Sea Ice Volume model (https://cryospherecomputing.tk/SIT). For each day the model calculates average thickness loss per grid cell using the exact solar radiation energy and the predicted sea ice concentration as an albedo value. Ice-loss(m) = Energy(solar in MJ)*(1-SIC) / icemeltenergy SIC = sea ice concentration icemeltenergy = Meltenergy per m3, (333.55 KJ/kg*1000(m3/dm)*0.92(density)/1000(MJ/KJ) In 2020 the model was updated a bias correction layer to approximate sea ice drift.	NSIDC NASA Team, https://nsidc.org/data/nsidc-0081	SIC * 1.4m	None
FIO-ESM (Shu et al.)	Dynamic Model	FIO-ESM1.0 Atmosphere CAM3 2000-2022 integration Ocean POP2 ocean data assimilation Ice CICE4 sea ice data assimilation Wave MASNUM-wave model 2000-2022 integration	4.06										Our prediction is based on FIO-ESM (the First Institute of Oceanography-Earth System Model) with data assimilation. The prediction of September pan-Arctic extent in 2022 is 4.06 (+/-0.17) million square kilometers. 4.06 and 0.17 million square kilometers is the average and one standard deviation of 10 ensemble members, respectively.	Our prediction is based on a climate model named FIO-ESM v1.0 (Qiao et al., 2013). Ocean and sea ice data are assimilated to initialize the model (Chen et al., 2016; Shu et al., 2021). The system bias was removed to get bias corrected pan-Arctic September monthly-mean sea ice extent. The system bias is the mean error between reforecast sea ice extent and satellite derived sea ice extent during 2000 to 2009.	OSISAF, OSI-430-b, https://osi-saf.eumetsat.int/products/osi-430-b-complementing-osi-450	PIOMAS, http://psc.apl.uw.edu/research/projects/arctic-sea-ice-volume-anomaly/data/model_grid	
NCEP-EMC (Wu et al.)	Dynamic Model	a) Model Name: NCEP CFSv2 b) Component Name Initialization Atmosphere NCEP GFS NCEP CDAS Ocean GFDL MOM4 NCEP GODAS ICE Modified GFDL SIS SIC nudging c) 124 ensemble members (July 1-July 31 2022, each day from all 4 cycles)	4.83		0.14			19.64					The projected Arctic minimum sea ice extent from the NCEP CFSv2 model July initial conditions (ICs) using 124-member ensemble forecast (4 cycles each day July 1 to July 31) is 4.83 million square kilometers with a standard deviation of 0.14 million square kilometers. The corresponding number for the Antarctic (maximum) is 19.64 million square kilometers with a standard deviation of 0.62 million square kilometers.	We used the NCEP CFSv2 model with 124-case of July 2022 initial conditions (4 cycles each day July 1-31) and model.	NCEP Sea Ice Concentration Analysis for the CFSv2 (July 1 to July 31, 2022)	NCEP CFSv2 model guess (July 1-July 31, 2022)	
EMC/NCEP (UFS)	Dynamic Model	a) Model Name: NCEP UFS b) Component Name Initialization Atmosphere NCEP GFS/FV3 NCEP CDAS Ocean GFDL MOM6 NCEP GODAS ICE CICE6 CPC CSIS c) 21 ensemble members (May 3-9, June 3-9 and July 3-9 2022, each day 00Z with C192)	5.06		0.32			18.56					The projected Arctic minimum sea ice extent from the NCEP Unified Forecast System (UFS) model May-July initial conditions (ICs) using 21-member ensemble forecast (00Z May 3-9, June 3-9, and July 3-9 with C192) is 5.06 million square kilometers with a standard deviation of 0.32 million square kilometers. The corresponding number for the Antarctic (maximum) is 18.56 million square kilometers with a standard deviation of 0.25 million square kilometers.	We used the NCEP UFS model with 21-case of May to July 2022 initial conditions (May 3-9, June 3-9 and July 3-9 with C192) and bias-corrected for the Arctic.	NASA Team Analysis from NSIDC (May 3-9, June 3-9 and July 3-9, 2022)	CPC sea ice initialization system (CSIS) (May 3-9, June 3-9 and July 3-9, 2022)	
UQAM (VARCTIC)	Statistical/ML		4.56	4.56		3.99	5.12				The lower bound constitutes the 5th percentile and the upper bound the 95th percentile of the credible region. Done via the posterior distribution obtained by standard Bayesian Methods for linear Vector Autoregressions.		When it comes to forecasting sea ice, there is tension between opting for statistical methods vs forecasts based on climate models. While the former are explicitly designed for the prediction task, they usually lack interpretative potential. That is, we may get a good forecast, but it is hard to know why. Institutions in charge of macroeconomic policy have been facing such dilemmas for years. One model, Vector Autoregressions, have been an increasingly popular tool to forecast economic aggregates as they are a compromise between theory-based methods and statistical ones. As a result, it is possible to obtain an explainable forecast which are the results of dynamic interactions between key Arctic variables. Hence, our forecast implicitly uses physical transmission mechanisms in the data, without specifying them explicitly.	The VARCTIC, which is a Vector Autoregression (VAR) designed to capture and extrapolate Arctic feedback loops. VARs are dynamic simultaneous systems of equations, routinely estimated to predict and understand the interactions of multiple macroeconomic time series. Hence, the VARCTIC is a parsimonious compromise between full-blown climate models and purely statistical approaches that usually offer little explanation of the underlying mechanism. Precisely, we use an 7-variable Bayesian Vector Autoregression (VAR) with 12 lags and a constant which we refer to as the VARCTIC. We estimate the model over the period from January 1980 until June 2022. A detailed description can be found in the following paper: https://journals.ametsoc.org/view/journals/clim/34/13/JCLI-D-20-0324.1.xml	Fetterer, F., K. Knowles, W. N. Meier, M. Savoie, and A. K. Windnagel. 2017, updated daily. Sea Ice Index, Version 3. Boulder, Colorado USA. NSIDC: National Snow and Ice Data Center. doi: https://doi.org/10.7265/N5K072F8.	PIOMAS, http://psc.apl.uw.edu/wordpress/wp-content/uploads/schweiger/ice_volume/PIOMAS.thick.daily.1979.2022.Current.v2.1.dat.gz.	

Met Office	Dynamic Model	Model: HadGEM3 [Hewitt et al., 2011], Global Coupled Model 3.2 [Williams et al., 2018] in use within the GloSea6 seasonal prediction system. The model configuration has been updated, but all other details of the system (forecast members, hindcast members, anomaly calculations) are as described in MacLachlan et al. (2015). Sea ice component: CICE5.1 [Hunke et al., 2015] model using Global Sea Ice 8.1 configuration [Ridley et al., 2018]. Initialised using the Met Office FOAM ocean and sea ice analysis [Blockley et al., 2014], which assimilates the SSMIS sea ice concentration observation product from EUMETSAT OSI-SAF. Ocean component: NEMO [Madec, 2016] ocean model using Global Ocean 6.0 configuration [Storkey et al., 2018]. Initialised using Met Office FOAM ocean and sea ice analysis [Blockley et al., 2014] assimilating in-situ and satellite observations of SST [GHRSST], satellite observations of sea level anomaly [AVISO/CLS] and temperature and salinity sub-surface profiles. Atmospheric Component: Met Office Unified Model (MetUM) [Brown et al., 2012] using Global Atmosphere 7.2 configuration [Walters et al., 2019]. Initialised using Met Office operational numerical weather prediction (NWP) 4D-Var data assimilation system [Rawlins et al., 2007]. Land Component: Joint UK Land Environment Simulator (JULES) [Best et al., 2011] using Global Land 7.0 configuration [Walters et al., 2019]. Soil temperature, soil moisture, and snow over land are initialised from running the land surface model forced with the JRA-55 analysis. Coupling: Ocean and sea ice are hard coupled. Atmosphere and land are hard coupled. The combined ocean/ice and atmosphere/land configurations are coupled using the OASIS3 coupled [Valcke et al., 2015]	4.4		0.6	3.2	5.6	17.5			Uncertainty range is provided as +/- 2 two standard deviations of the (42 member) ensemble spread around the ensemble mean.		A dynamic model forecast made using the Met Office's seasonal forecasting system (GloSea). GloSea is a fully coupled Atmosphere-Ocean-sea Ice-Land (AOIL) model that produces a small 2-member ensemble of 210-day forecasts each day. Forecasts initialised over a 21-day period are used together to create a 42-member lagged ensemble or forecasts of September sea ice cover.	Ensemble coupled model seasonal forecast from the GloSea6 seasonal prediction system [based on, MacLachlan et al., 2015], using the Global Coupled 3 (GC3) version [Williams et al., 2018] of the HadGEM3 coupled model [Hewitt et al., 2011]. Forecast compiled together from forecasts initialized between 22 July and 11 August (2 per day) from an ocean and sea ice analysis (FOAM/NEMOVAR) [Blockley et al., 2014; Peterson et al., 2015] and an atmospheric analysis (MO-NWP/4DVar) [Rawlins et al., 2007] using observations from the previous day. Special Sensor Microwave Imager Sensor (SSMIS) ice concentration observations from EUMETSAF OSI-SAF [OSI-SAF] were assimilated in the ocean and sea ice analysis, along with satellite and in-situ SST, sub surface temperature and salinity profiles, and sea level anomalies from altimeter data. No assimilation of ice thickness was performed.	Sea ice concentration (as all variables) is initialised using the operational FOAM ocean-sea ice analysis. SSMIS sea ice concentration is assimilated using the EUMETSAT OSI-SAF (OSI-401b; See http://osisaf.met.no/docs/osisaf_cdop3_ss2_pum_ice-conc_v1p6.pdf)	Sea ice thickness (as all variables) is initialised using the operational FOAM ocean-sea ice analysis. Sea ice thickness is not assimilated in FOAM.	Bias correction in each hemisphere, calculated by evaluation of hindcasts over 1993-2016. Bias correction calculated from hindcast evaluation over 1993-2016. Arctic: 2.5 million sq. km; Antarctic: -0.6 million sq. km
AWI Consortium	Dynamic Model	NAOSIM v36, 1/4 degree, parameter optimized (opt5.3)	4.51		0.26						Ensemble spread		Forced sea ice - ocean model initialized in March and April with satellite products. Ensemble forecast is generated by using the forcing from ten previous years. Prediction potential comesfrom the initialization in March and April with satellite observations (sea ice thickness, snow depth, SST, and sea ice concentration). Deliberately no observations are assimilated later in the year because the potential of state estimation in March and April with respect to summer sea ice conditions should be evaluated.	For the present outlook the coupled sea ice-ocean model NAOSIM has been forced with atmospheric surface data from January 1948 to August 11th 2022 (combination of NCEP-CFSR and NCEP-CFSv2). All ensemble model experiments have been started from the same initial conditions on August 11th 2022. The model setup is identical to the SIO 2019-2021 setup - a forecasting model (about 25km horizontal resolution) with optimized parameters (with the help of a generic algorithm (Sumata et al, 2019, https://doi.org/10.1175/MWR-D-18-0360.1)) is employed. We used atmospheric forcing data from each of the years 2012 to 2021 for the ensemble prediction and thus obtain 10 different realizations of potential sea ice evolution for summer of 2022. The use of an ensemble allows to estimate probabilities of sea-ice extent predictions for September 2022. A variational data assimilation system around NAOSIM is applied to initialize the model using the Alfred Wegener Institute's CryoSat-2 ice thickness product, University of Bremen's snow depth and the OSI SAF ice concentration product 430b (interim Climate Data record). In contrast to previous years no sea surface temperature is assimilated due to the lack of this data stream. Only observations from March and April were used. The assimilation system (Kauker et al, 2015, http://www.the-cryosphere-discuss.net/tc-2015-171) is unchanged but no bias correction is applied any more to the CryoSat-2 ice thickness - this is not necessary anymore due to the optimization of the forecast model.	OSI SAF EUMETSAT OSI-430b, https://osi-saf.eumetsat.int/products/osi-430-b- complementing-osi-450	CryoSat-2 SIT from Alfred Wegener Institute v2.4, Hendricks, S. and Ricker R. (2020): Product User Guide & Algorithm Specification: AWI CryoSat-2 Sea IceThickness (version 2.3), Technical Report, https://epic.awi.de/id/eprint/53331/1/AWI-CryoSat2-ProductUserGuide- v2p3.pdf	None performed.
UPenn-UQAM Group	Statistical/ML		5.12	5.12	0.23	4.66	5.58				estimated stochastic model. The standard deviation computed from last 10 years prediction errors from a recursive pseudo-out-of-sample exercise.		The UPenn-UQAM group is composed of economists and statisticians interested in predictive modeling of many aspects of climate in its relation to economic activity. The Arctic -- and Arctic sea ice in particular -- is of particular interest to us. As is well known, the Arctic is warming about twice as fast as the global average, and the Arctic amplification in surface air temperature is of course closely connected to the dramatic multi-decade reduction in Northern sea ice. This loss of sea ice is one of the most conspicuous warning signs of \textit{current} climate change, and it also plays an integral role in the timing and intensity of \textit{future} global climate change. Not surprisingly then, we are keenly interested in predictive modeling of Arctic sea ice, particularly summer ice.	We have supplied a forecast based on a statistical model with trend, a feed-forward loop, and stochastic shocks, estimated by direct projection. In the modeling process we explore different levels of aggregation of the underlying high-frequency (daily) concentration data and associated sea ice extent, and we tune the aggregation to optimize the predictive bias/variance tradeoff in forecasting September extent. It turns out that previous pseudo-out-of-sample forecast errors (residuals) are approximately Gaussian, which we exploit in making our out-of-sample forecast for this September. The predictive density is Gaussian, with the mean 5.12 million square kilometers and standard deviation of 0.23 million square kilometers. (By symmetry, the mean and median coincide.) The approximate 95\% interval that we report is the mean plus or minus 2 standard deviations. See https://chairemacro.esg.uqam.ca/arctic-sea-ice-forecasting/?lang=en.	NA	NA	
Horvath, et al.	Statistical/ML		4.98										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 total sea ice extent, grid cells with a percentage above a certain threshold (chosen from a drop-one cross-validation test) are multiplied by the pixel area grid dataset provided by NSIDC's polar stereographic toolset and then summed. Sea ice concentration data was obtained from NSIDC's Sea Ice Index V3 (Data Set ID:G02135), all other variables are from ERA5	This statistical model computes the probability that sea ice will be present (concentration above 15%) for each grid cell in NSIDC's polar stereographic projection. Yearly data from 1980 through the present are used in a Bayesian logistic regression. Predictors include local surface air temperature, downwelling longwave radiation, and sea ice concentration, as well as the first principal component of geopotential height at 500mbars, and Pacific and Atlantic sea surface temperatures. Sea ice concentration data was obtained from NSIDC's Sea Ice Index V3 (Data Set ID:G02135), all other variables are from ERA5	NA	NA	
IceNet1	Statistical/ML		5.13										IceNet is a sea ice forecasting AI system which predicts monthly-averaged sea ice probability (SIP; probability of sea ice concentration > 15%) up to 6 months ahead at 25 km resolution on an EASE2 grid. IceNet is based on a deep learning U-Net architecture, and has been trained on climate simulations (CMIP6) covering 1850-2100 and observational data (OSI-SAF SIC and ERA5) from 1979-2011. IceNet's monthly-averaged inputs comprise SIC, 11 climate variables, statistical SIC forecasts, and metadata. IceNet is introduced in a study in Nature Communications: https://www.nature.com/articles/s41467-021-25257-4. IceNet was also presented at the Oxford ML and Physics Seminar Series: https://youtu.be/JAKWhEU09Xo.	At each 25x25 km ocean grid cell in the Arctic and at each forecast lead time from 1 to 6 months ahead, IceNet produces a probability that the SIC will be less than 15% (no ice), between 15% and 80% (marginal ice), or above 80% (full ice). To compute the SIP map for this SIO submission, we sum the probability of the two ice classes to obtain P(SIC > 15%). IceNet comprises 25 different U-Net models, whose output SIPs are averaged to produce the final SIP forecast. To compute the SIE, we sum the area of grid cells whose SIP > 0.5. Note that IceNet's SIE prediction corresponds to the SIE of monthly-averaged sea ice, not the monthly-averaged SIE of daily sea ice.	EUMETSAT OSI-SAF, OSI-450/OSI-430-b (http://osisaf.met.no/p/ice/ice_conc_reprocessed.html, https://doi.org/10.15770/EUM_SAF_OSI_0008)	N/A	
Lamont (Yuan and Li)	Statistical/ML		5.04			4.63	5.45	18.54	0.68	3.93	The uncertainty of SIC prediction was measured by root-mean-square error (RMSE). They were estimated based on 42 (1980-2021) years (take-one-year-out) cross-validated model experiments.	0.83	A linear Markov model is used to predict monthly Arctic sea ice concentration (SIC) at all grid points in the pan-Arctic region (Yuan et al., 2016). The model has been retrained this month using SIC, atmosphere variables and SST from 1979 to 2021. It is capable of capturing the co-variability in the ocean-sea ice-atmosphere system. The September pan-Arctic sea ice extent (SIE) is calculated from predicted SIC. The model predicts negative SIC anomalies throughout the pan-Arctic region. The September mean pan-Arctic SIE is predicted to be 5.04 million square kilometers (mskm) with an RMSE of 0.41 mskm based on model cross-validation experiments, at the two-month lead. The Alaskan regional SIE is predicted to be 0.68 mskm. A Similar statistical model was also developed to predict the SIE in the Antarctic (Chen and Yuan, 2004). The September mean pan Antarctic SIE is predicted to be 18.54 mskm, close to September 2021 (18.45), with an RMSE of 0.66 mskm. The RMSE is estimated based on our model forward forecasts from 2003-2017.	The linear Markov model has been developed to predict sea ice concentrations in the pan Arctic region at the seasonal time scale. The model employs 6 variables: NASA Team sea ice concentration, sea surface temperature (ERSST), surface air temperature, GH300, vector winds at GH300 (NCEP/NCAR reanalysis) for the period of 1979 to 2021. It is built in multi-variate EOF space. The model utilizes first 11 mEOF modes and uses a Markov process to predict these principal components forward one month at a time. The pan Arctic sea ice extent forecast is calculated by summarizing all cell areas where predicted sea ice concentration exceeds 15%.	Sea ice concentration: NSIDC NASA Team, https://nsidc.org/data/nsidc-0081, https://doi.org/10.5067/U8C09DWVX9LM.	N/A	First, a constant bias correction was applied to Arctic SIC prediction at each grid point. Then a constant SIE bias also derived from the cross-validation experiments from 1980 to 2021 was corrected from the September SIE prediction. Finally, the model uses lower resolution sea ice concentration data (2-degree longitude x 0.5-degree latitude), introducing a 0.10 million square kilometers bias compared to 25kmx25km original satellite data. This resolution bias is corrected in the final Arctic SIE prediction.
SYSU/SML-KNN	Statistical/ML	NA	5.68	5.68	0.31	5.37	5.99				We estimate our uncertainty with root-mean-square-error(RMSE) calculated from 2015-2020 hindcast.	1.48	A machine learning KNN model is used to predict the daily sea ice concentration (SIC) and the sea ice extent (SIE) of September 2022 in pan-Arctic. Daily averaged sea ice concentration ("NSIDC NASA Team, https://nsidc.org/data/nsidc-0081) fields between 1979 and 2021 were used to predict. The model predicts a pan-Arctic sea ice extent of 5.04(±0.31) million square kilometers and has a positive anomaly of 0.8.		NA	NA	

SYSU/SML-MLM	Statistical/ML		5.3	5.3	0.5	4.8	5.8		1.01		We estimate our uncertainty with root-mean-square-error(RMSE) calculated from 1979-2019 hindcast.	1.09	A multivariate linear Markov model is used to predict monthly sea ice concentration (SIC), from which sea ice extent prediction of monthly September 2021 in Artic is calculated to be 4.63±0.51 million square kilometers, and the Alaskan regional SIE is predicted to be 0.71±0.25 million square kilometers.	The multivariate linear Markov model is a statistical model that combines principal component analysis and linear Markov model together, it can identify the large scale atmospheric and oceanic variability through principal component analysis and make linear Markov predictions based on its results (Yuan et al., 2016). To make predictions, first we extract time and space component from the data matrix, and we use linear Markov model to predict the target time component, which will be multiplied with space component to make a final prediction. Besides the parameters used in Yuan et al. (2016), e.g., sea ice concentration (SIC), sea surface temperature (SST), surface air temperature (SAT), here we further use monthly surface net radiation flux (NR) data from 1979 to 2019 to train our model. For this attempt, we use 2021 May monthly mean SIC data to initiate our model and make monthly SIC and SIE prediction.	NA	NA	No post-processing.