June 2022 Sea Ice Outlool	k Key Stateme	ents															
Contributer	Туре	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
HEU Group (Zhao, et al.)	Statistical/ML	NA	4.5					18.4					The outlook is based on two statistical methods: climate trends regression prediction and previous bias correction. Based on the consensus that statistic control of the consensus that statistic control of the consensus that statistic trend of sea to concentration in each grid in the Aratic region and then use this trend to predict the value of sea to 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 loc 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 uring 1989-2020. The trend of climate change in the grid is analyzed, and the sea loc 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 loc concentration from January to May 2022 of NSIDC-0081, calculated the curve of sea ice extent natives well a statisfier from January to with the change of sea loc extent from January 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://msidc.org/data/nsidc. 0051.https://msidc.org/data/n sidc-0081,	NA	
Climate Prediction Center	Dynamic Model	CPC sea ice initialization system (CSIS)	4.9	4.85	0.24	4.51	5.35		0.97	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 Pradiction Center Experimental area to ferocast system (CSRs). The forecast is initiatized from the Climate Forecast System Reanalysis (CSRs) for the coam, 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 2007-2020 crospective 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	N/A	4.1		0.5						This is the error measured by the linear regression.	-0.01	This estimate is a linear regression of Moana Los CO2 monthly CO2 concentrations, Northern Hemisphere snow area, and arctic ice area. The idea is to loosely model solar energy absorbed and retained near the Arctic. (Similar estimates care be obtained using CO2 concentration.) For May 2022, the estimate of a September sea ice extent of 4.1MK*2 is no trend. (The anomaly is -0.01MK*2.4 ample linear regression of the September sea ice extent of 4.1MK*2 is not trend. (The anomaly is -0.01MK*2.4 ample linear regression of the September sea ice extent vouid produce the same prediction.) This regression is a minor variant of an approach used by Rob Dekker.	This is a simple linear regression of published May 2022 average now. area is downloaded from https://climate.rutgers.edu/snowcover/table_area.php?ui_s etc-2. The link is the northern hernisphere monthly link. (Due to lintations of my schedule, Tru using an estimated value of 16.66MeV-2 for the May 2022 average sunce value). Moana toa co2 is downloaded from https://gml.noaa.gov/cogg/trendiddtal.html Ice area is obtained from thp://siadas.coibrado.edu DATASETS/NOAA/G02135/north/monthly/dsta/	NA	N/A	
ArCS II Kids	Heuristic	NA	3.52									-0.55	Mean ice extent in this September is expected to be 3.52 million square klömeters. This prediction was made by 22 elementary school children. First, they estimated the sea ice extent for each year from the sea ice distin	The predictions were made by 22 elementary school students divided into these groups. First, each group was given the loc distribution map for September since 2002. Then the loc extent was estimated by approximating the sea iso distribution as a trangle of trapezoid, or by counting the number of sequence on a sheet with squares of the season of the s	10km grid data derived from AMSRE and AMSR2, distributed by Arctic Data Archive Symptomic (https://ada.nipr.ac.jp)	NA	
Applicate Benchmark	Statistical/ML	None	4.57	4.57	0.62	3.33	5.82	18.28			Same as previous years: https://www.arcus.org/ files/sio/32173/applic ate_benchmark.pdf	0.5	Same as previous years: https://www.arcus.org/files/sio/32173/applicate_benc hmark.pdf	Same as previous years: https://www.arcus.org/files/sio/32173/applicate_benchmark. pdf	NSIDC-0081	None	Same as previous years: https://www.arcus.org/files/sio/32173/applicate_bench mark.pdf
CPOM UCL (Gregory et al.)	Statistical/ML	N/A	4.5		0.37	4.13	4.87		0.33	4	Forecasts are Gaussian distributions. Forecast represents the mean, and uncertainties are given by the standard deviation	0.29	This statistical model computes a forecast of pan- Arctic September sea lice extent. Monthly averaged May sea lice concentration and sea-surface temperature fields between 1979 and 2022 were used to create a climate network, based on the approach of Oregory et al 2020). This was then utilised in a Byseast in Livera Regission in order to forecast September extent. The model predicts a part-Arctic settor of 4.5 million square isolimetres. Sea loc control of 5.0 million square isolimetres. Sea loc control of 5.0 million square isolimetres. Sea loc control of 5.0 million square isolimetres. Consideration of the control of 5.0 million of the control of 5.0 million of	Monthly averaged May sea be concentration (SIC) and sea- surface temperature (SST) data between 1979 and 2022 were used to create a May SIC-SST citrate(complex) network. Individual SIC gaid cells were first clustered into regions of spatio-emporal homogenety (and smitish) for SSTS) 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 to extern.	N/A	N/A	
GFDL/NOAA (Bushuk et al.)	Dynamic Model	No SIT data is explicitly used in our initialization procedure.	4.56	4.58	0.21	4.01	4.94		0.53	3.94	These statistics are computed using our 30 member prediction ensemble.	0.35	Our June 1 prediction for the September-averaged Arctic sea-ice extent is 4.56 million square kilometers, with an uncertainty range of 4.01-4.94 million square kilometers. Our prediction is based on the GPU-SPEAR JMEO ensemble forecast system, which is a fully-coupled artimosphere-land-cosen-area ice model initialized using a coupled data assimilation system. Our prediction is the bas-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 (Deborth et al., 2023), which is a coupled in property of the system of the system of the system of the property of the system of the system of the system of sasimilation system (SPEAR ECDA, Lu et al., 2020), which assimilates observational surface and subsurface ocean data. The sea ice, land, and arthrosphere components are initiatized from a nudged ensemble run of the coupled SPEAR, MED model, which is nudged towards 3-0 temperature, wind, and humidity data from CFSR and SST data from OSIST. The SST values under sea ice are adjusted to the freezing point of sea water using OISST data from OSIST. The SST values under sea ice are adjusted to the freezing point of sea water using OISST data from OSIST. The SST values under sea loca are adjusted to the freezing point of sea water using OISST data from OSIST. The SST values under sea loca are adjusted to the freezing point of sea water using OISST data from OSIST. The SST values under sea for documented in Bushuk et al. (2022, For an evaluation of the model's September sea loc exchant prediction skill from a June 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 (orecasts are bias corrected based on a linear- regression adjustment using a suite of retrospective forecasts spanning 1992-2021.

University of Washington/APL	. Dynamic Model	Initial SIT is from PIOMAS hindcast that also assimilates CrySat2 SIT data up to April 2020 (http://psc.apl.uw.e du/sea_ice_cdr/).	3.41		0.4						-0.81	Driven by the NCEP CFS forecast atmospheric forcing. PIOMAS is used to predict the total of Springer and the springer of the product of Springer and the springer of the springer and sprin	he 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_ic e_cdr/).	
NCEP-EMC (Wu et al.)	Dynamic Model	NCEP CFSv2 model guess (May 1-31, 2022)	4.34		0.37			18.37				The projected Antic minimum sea ice extent from the NCEP CFSV crodel May hital conditions (IGO) using 124-member ensemble forecast (4 cycles each day May 1-31) is 4.34 million square klometers with a standard deviation of 0.37 million square klometers. The corresponding number for the Antactic (maximum) is 18.37 million square klometers with a standard deviation of 0.71 million square klometers with a standard deviation of 0.71 million square klometers.	We used the NCEP CFSv2 model with 124-case of May 2022 Initial conditions (4 cycles each day May 1-31) and model (bias-connected for the Arctic).	NCEP Sea Ice Concentration Analysis for the CFSv2 (May 1-31, 2022)	NCEP CFSv2 model guess (May 1-31, 2022)	
loeTFT (Bin Mu et al.)	Mixed/Other	NA	4.85	0.15								Ico TFT is a SIE forecasting AI system which predicts 12-month SIE up to 12 months ahead at Sea Ice Index from NSIDC MASA Team. Ice TFT is based on a deep basming Temporal Fusion Transformer model Index from NSIDC MASA Team. Ice TFT is based on a deep basming Temporal Fusion Transformer model Index of the Index of Temporal Fusion Transformer model Index of Temporal Temp	coEFTs inputs include thme types dataset, and each type of they is selected by spanishe variable selection network. to fifter unnecessary noises. The first input type is static metadata which are acclusited by counting the days from start (1982-01-01). Gated Residual Network (GRN) in DET generates different context vectors which are inlead to the different Deaton, and static covariate encorder condition temporal dynamics though these context vectors. The second input is SIE and three inputs are vectors. The second input is SIE and three inputs are sufficient to the second input is SIE and three project and incomplete, decided the prediction LeTFT use an LSTM encoder-decoder to enhance boally fromation of these time series. In addition, loefTF uses a interpretable multi-head self-attentive mechanism to learn ong-term features at different time seleps. Note that LeTFT use SIE as input instead of SIC, and the output of loeTFT are 12-month SIE.	NSIDC NASA Team.Sea ice Index, Version 3(https://doi.org/10.7265/NS K072F8)	NA .	
ANSO IAP-LASG	Dynamic Model	None	3.78	3.82	0.29	3.14	4.34			The uncertainty was estimated by the ensemble member spread.		established in 2017 byte & R&D team of FGOALS-f2	FGOALS-42 S2S V1.3 is a global coupled dynamic rediction system. The initialization of this prediction system is based on a rudging scheme, which assimilates wind omponents (U and V). Temperature (I) in atmosphere and coloniatel temperature in ocean from 1 an 1980 to 1 June 2022, and 46 ensemble members are generated by a time-lag method. The predictions are evaluable here for 12 months of the colonial system	None	None	The systematic biases have been corrected based on reforecast datasets
KOPRI (Chi et al.)	Statistical/ML	NA	5	4.97	0.19	4.68	5.22			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 Aracic sea (ex concentration) (SIC). The predicted September extent for 2022 is 5.00 million square kilometers using data from June 2021 to May 2022.	KOPRI's laby data-driven model was trained on historical NSIDC's day's Cotal from 1979 to 2021 using a combination of convolutional and recurrent neural networks. Since we observed a large visual discrepancy coording to the neural network is loss functions, a new loss unction was developed to improve both statistical accuracy and visual agreement. The 6-month prediction model is urrently turning up to improve predictability. Pleases find our recent published paper. Chi J, Bas J, Kwon VJ. Two-Stream Convolutional Long-and Short-Term Memory Model Using Perceptual Loss for Sequence-to-Sequence Artic's Sea to Prediction. Remote Sensing. 2021; 13(17):3413. https://doi.org/10.3390/in1373413	NSIDC NASA Team, https://insidc.org/data/nsidc- log/lines/corg/data/nsidc- log/lines/corg/data/nsidc- org/data/nsidc.org/data/nsidc- org/data/nsidc.org/data/nsidc- log/lines/corg/data/nsidc- org/data/nsidc- org/data/nsidc-	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 coes 100% were set to 100%. SIC data
Kondrashov (UCLA)	Statistical/ML	NA	4.9		0.16				0.55	his uncertainty corresponds to standard deviation of stochastic ensemble spread.	0.5	This model forecast is based on statistical/ML stochastic modeling techniques applied to the regional Arctic Sea Ice Extent (SIE) dataset.	StatisticalML stochastic modeling techniques have been applied to the regional Article Sea lee Extent (SE) from Sea lee index Version 3 dataset. The daly SE data were aggregated to provide weekly-amplied dataset over several Articl section. The predictive model has been derived from SE anomales with annual cycle removed, and is initialized from lates SIE conditions by ensemble of stochastic noise realizations to provide probabilistic regional Articl forecasts in September.	NA NA	NA NA	
FIO-ESM (Shu et al.)	Dynamic Model	PIOMAS, http://psc.apt.uw.e du/research/project s/arctic-sea-ice- volume- anomaly/data/mod el_grid	4.3									Our prediction is based on HO-ESM (the First Institute of Oceanography-Earth System Model) with data assimilation. The prediction of September pan-Arctic extent in 2022 is 4.30 (+/0-39) million square kilometers. 4.30 and 0.39 million square kilometers is the average and one standard deviation of 10 ensemble members, respectively.	Our prediction is based on a climate model named FIC-SBM v1.0 (Cliao et al., 2013). Ocean and sea ice data are assimilated to initialize the model (Chen et al., 2016; Statellite observed daily sea surface temperature (from OISST), sea level anomaly (from OKEMS), sea ice concentration (from OSISAF), and PIOMAS sea ice thickness are assimilated to initialize the model.	OSISAF, OSI-430-b, https://losi- saf.eumetsat.int/products/osi- 430-b-complementing-osi- 450	PIOMAS, http://psc.apl.uw.edu/researc h/projects/arctic-sea-ice- volume- anomaly/data/model_grid	
METNO-SPARSE-ST	Statistical/ML	NA	4.639	4.639	0.36	4.279	5	17.773	0.497		0.015	AR model with NSIDC sea ice extent data. We used an updated adaptive length to construct the AR model.	AR model with NSIDC sea ice extent data	NA	NA	

Sun, Nico	Statisticat/ML	NSIDC SIC * 2m	4.86			4.3	5.2	18.73	0.555	4	variation in Sea Ice Concetration	0.31	The forecast model is based on ice pensistence. It uses incoming solar radiation and sea is a sibedo derived from a predicted Sea to Concentration (SIC) value to calculate daily hinkness bases for every MSIDC 20 in the calculate daily hinkness bases for every MSIDC 20 in MSIDC 20 in the calculated from AMSIDC area is volume and MSIDC 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, Years with a very high correlation. For his month the mean field as made up of: 2007.2010.2010.2010.2010.2013.2013.2013.2014.2014. The mean forecast uses the SIC (1/4 weight) and mean SIC change per day (3/4 weight) a predict future SIC. The low forecast reduces the predicted future SIC. The low forecast reduces the predicted forces and a 10% decreased bottom met. The high foncast increases the predicted SIC by 0.105bt/ or previously observed SIC for this day and a 10% increased bottom met. In high foncast increases the predicted SIC by 0.105bt/ or previously observed SIC for this day and a 10% increased bottom met. Since 3 and a 10% increased bottom met. Since 3 and 3 10% increased bottom met	Each grid-cell is initialized with a thickness derived from the AMSF2 Sea los Volume model (NSIDC NASA Team, https://maidc.org/data/naidc-https://maidc.org/10.5067/U8CO 9DWVX9LM	NSIDC SIC * 2m	none
EMCINCEP (UFS)	Dynamic Model	CPC sea ice initialization system (CSIS) (May 3 to May 9, 2022)	5.2		0.29			18.41					The projected Article minimum sea loce within from the NCEP Unified Fonecast System (UFS) model May initial conditions (GJ) using 7-member ensemble fonecast (00Z May 3 to May 9 with C192) is 5.20 million square kilometers with a standard deviation of 0.29 million square kilometers. The corresponding number for the Antanctic (maximum) is 18.41 million square kilometers with a standard deviation of 0.31 million square kilometers.	We used the NCEP UFS model with 7-case of May 2022 initial conditions (May 3 to May 9 with C192) and biascorrected for the Arctic.	NASA Team Analysis from NSIDC (May 3 to May 9, 2022)	CPC sea ice initialization system (CSIS) (May 3 to May 9, 2022)	
СРОМ	Statistical/ML	NA	4.3		0.5						Mean forecast error based on forecasts for the years 1984 to 2021.	0.05	We predict the September ice extent 2022 to be 4.3 (3.8-4.8) million km ² . This is just above the trend line. In spite of the large sea ice extent in May 2022, sea ice thickness and melt pland cover are quite normal with respect to the last decade.	This is a statistical prediction based on the correlation between the toe area covered by melb-conds in Mey and ce starts in September. The melt pond sizes is defined from a simulation with lawse set amonder LOE for interest of the condition of the set of the condition of the c	NA	NA	See references above
Met Office	Dynamic Model	Sea ice thickness (as al variables) is initialised using the operational FOAM ocean-sea ice analysis. Sea ice thickness is not assimilated in FOAM.	3.7		0.65	2.4	5	18			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 (GioSea). GioSea is a fully coupled Armosphere-Ocean-sea Ice Land (AOIL) model that produces a small 2-member ensemble of 210-day forecasts each day. Forecasts initialisation var a 21-day pendia mused together to create a 42-member lagged ensemble or forecasts of September sea ice cover.	Ensemble coupled model seasonal forecast from the GloSade 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 initiatized between 22 May and 11 June (2 per day) from an ocean and sea ice analysis (FOAMNEMDVAR) [Blockley et al., 2014; Peterson et al., 2015] and an atmospheric analysis (MO-WWP/4DVA) (Pawlis et al., 2007) using observations from the previous Concentration observations from EUMETSAF CSI-SAF (GSI-SAF (GSI-SAF)) (SAF) were assimilated in the ocean and sea ice analysis, along with stabilitie and in-situ SST, sub surface temperature and sainty profiles, and sea level anomalies from altimeter data. No assimilation of ice thickness was performed.	Sea ice concentration (as all variables) is initialled using the operational FOAM ocean sea ice analysis. SSMS sea ice concentration is assimilated using the EMETENT OSSAF (IOSI- http://ossaf.met.nodiocsolos af_cdop3_ssZ_umi_ce- conc_vtp6.pdf)	Sea ice thickness (as all variables) is infalled using the operational FOAM coeanse 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. +14 million sq. km. Antarctic0.1 million sq. km.
NASA GMAO	Dynamic Model	Model-derived.	4.75	0.36	0.37	4.4	5.11		0.97	4.00193	The uncertainty is based on the spread of 10 ensemble members.		An experiment of the new GMAO seasonal forecasting system version 3 predicts a September average Arctic sea loe actent of 4.75 to 3.77 million km2, or slighly less than last year's value of 4.92 million km2 here experiment is a test of the new version 3 ODAS and forecast ensemble sub-esting method in a near-real time setting. Comparison with NSIDC values suggest the system has more initial ice extent, which may be due to discrepancies between OSI SAF and the NSIDC near-real-time values.	The forecast uses a prototype the GEOS_S2S version 3 coupled system that was modified for this forecast. The model has an approximate grid spacing of ½" in the atmosphere and ½" in the ocean. An offline version of the ocean data assimilation system (DDAS) was integrated through May 2022. The ODAS is driven by GMAO floward-processing atmospheric analysis. The ODAS assimilates available ocean-propphs to besverious and along-lank available ocean-propphs to besverious and along-lank available ocean-propphs to besverious and along-lank available ocean-propphs to be sometimes that the control of the atmosphere-perturbed ensemble members are stated on the last day of the month. A total of 45 ensemble members were run through July, at which point the ensemble is sub-amplied based on an error growth assessment, with 10 ensemble members continuing the forecast integration through September.	OSTIA. (https://doi.org/10.3390/ss12 040720). The OSTIM sea for concept of	Model-derived.	Fields have been regridded to the NSIDC polar- stereographic grid. A template file from NSIDC contains the grid-box area.
UQAM (VARCTIC)	Statistical/ML	PIOMAS, http://psc.apl.uv. du/wordpress/wp- content/uploads/sc hweiger/ice_volume e/PIOMAS, thick.daily,1979.20 22. Current.v2.1.da t.gz.	4.5056	4.5056		3.8966	5.0896				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 I comes to forecasting sea loc, there is tension between oping for statistical methods so 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 differents for years. One model, Vector Autoregressions, have been an increasingly they are a compromise between theory-based methods and statistical ones. As a result, it is possible to obtain an explanable forecast which are the results of dynamic interactions between key Arctic variables. Hence, our forecast simplicity uses physical transmission mechanisms in the data, whous specifying them applicitly.	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 mecroeconomic time sense. Hence, the VARCTIC is a paraimonious compromise between full-blown climate models and purely statistical approaches that usually offer title explanation of the underlying mechanism. Autoregression (VAR) with 12 gap and a constant which we refer to as the VARCTIC. We estimate the model over the period from January 1880 until February 2022. A detailed description can be found in the following paper: https://journals.ametos.org/view/pumals/clim/34/13/JCLI-D-20-324.1.xml	Fettemr, F., K. Knowles, W. N. Meier, M. Sarole, and A. K. Windnager, 2017. updated daily. Sea Ice Index, Version 3. Boulder, Colorado USA. NSIDC: National Snow and Ice Data Center. doi: https://doi.org/10.7256/SKO 72F8.	PIOMAS, http://pca.apl.uw.edu/wordpr content/uplacific-brweiger/ic content/uplacific-brweiger/ic thick.daily.1979.2022.Curren t.v2.1.dat.gr.	

UPenn-UQAM Group	Statistical/ML	NA .	4.32	4.32	0.56	3.2	5.44			estimated stochastic model. The standard deviation computed from last 10 years prediction errors from a recursive pseudo- out-of-sample exercise.		The UPenn-UCAM group is composed of economists and statisticans interested in predictive modeling of many aspects of climate in its relation to economic activity. The Arctic - and Arctic sea tex in particular-late in a construction of the arctic angle factor in sufficient and arctic angle factor in sufficient	p, and stochastic shocks, in the modeling process we regation of the underlying attended to the underlying attended to the underlying attended the underlying that previous pseudo-out-of-tuse) are approximately making our out-of-sample The predictive deneaty is a milion square kloreless. By milion square kloreless. By median coincide. The we report is the mean plus	NA NA	NA	
NCAR/CU (Kay/Balley/Holland)	Heuristic	NA	4.28	4.33	0.4	3.14	4.82			An informal pool of 27 climate scientists in early June 2022 estimates that the September 2029 ice extent will be 4.28 million sq. km, (stdew. 0.4, min. 3.14, max. 4.82). The uncertainty estimate is based on the scatter in entries in our informal pool.	0.14	An informal pool of 27 climate scientists in early June 2022 cell states that the September 2022 (see June 1997) and the September 2022	cientists in early June 2022 2022 (se extent will be 4.28 3.14, max. 4.82), Guesses e-mail out to the scientists regigning rights and with lose ree farthest quesses. The staken from the October attonal Snow and Ice Data	NA NA	NA.	none
Lamont (Yuan and Li)	Statistical/ML	N/A	5.18	5.18	0.4	4.78	5.58	18.42	0.57	Ardic SIE uncertainty is 0.40, measured by RMSE using forecast of 2013-2020.		A linear Markov model is used to predict monthly Arctic sea lec concentration (SIC) at all grid points in the pan-Arctic region (Yuan et al. 2016). The model may be pan-Arctic sea loc extent (SIE) is calculated from predicted SIC. The model predicts negative SIC anomalies throughout the pan-Arctic region. These anomalies are relative to the 1979-2012 climatology in the September anapan-Arctic SIE is predicted to be 5.18 million square kilometers (makin) with an ARMSE of 0.40 means, at the four-month lead. The MRMSE of 0.40 means, at the four-month lead. The MRMSE of 0.40 means, at the four-month lead. The MRMSE of 0.40 means are the sea loc extra temperature of the sea of t	i pan Arctic region at the employs 6 variables: NASA sea surface temperature re, GH300, vector winds at https://n e EOF space. The model of uses a Markov process to ints forward one month at a ent forecast is calculated by where predicted sea ice	IDC NASA Team, nsidc.org/data/nsidc- 0081, 0061, 0061, 00710.5067/USC0 9DWYX9LM.	N/A	First, a constant bias correction was applied to Arctic SIC prediction at each grid point. These biases were estimated based on the table-on-sper-out cross settlemated based on the table-on-sper-out cross settlemated based on the settlemate of th
Horvath, et al.	Statistical/ML	NA NA	5.07									Yearly data from 1980 through the present are used in a Bayesian logistic regression to predict the windows and a superbalbity that sea ce concentration at the above 15%. To estimate total sea tice extent, grid cells with a percentage above a certain threshold (chosen from a drop-one cross-validation test) are multiplied by the piber lares grid dataset provided by NSIDCS polar stereographic blobet and then surmers. Sea to concentration data was obtained from NSIDCS Sea los index VS (Dias Bit ID 002/135), all other van ID 002/135, al	oove 15%) for each grid cell projection. Yearly data from used in a Bayesian logistic cal surface air temperature, idiation, and sea ice irst principal component of rs, and Pacific and Allantic ice concentration data was loe Index V3 (Data Set	NA	NA	
PolArctic	Statistical/ML	NA NA	4.71									This is PoArctic's fourth year submitting to the Sea too Outlook. Our September eather prediction is 4.7 to Outlook. Our September eather prediction is 4.7 to our set of the Sea to our set of the Sea to our set of the Sea to our set our s	and trained with historical rinitial modeling efforts are laid forecasts of daily, spatial for calculate our September September 2022 from our	A/NSIDC, Sea Ice idex, Version 3. Joi.org/10.7265/N5K0 72F8.	NA	
NSIDC (Meiler)	Statistical/ML	NA NA	4.97		0.6			17.34		Standard deviation of the projections from using the 15 years between 2007 and 2021	0.78	This method applies daily ice loss rates to extrapolate from the start date (June 1) through the end of September Projected September daily extents are averaged to calculate the projected September average other. Individual years from 2005 to 2021 are used, as well as averages over 1981-2010 and 2007-2021. The 2007-2021 averaged daily lates are used to estimate the Official submitted daily lates are used to estimate the Official submitted of the September Cally of the September	hit he end of September, sextents are averaged to tember average extent. 2021 are used, a severage 2021 are used, a severage extent. 2021 are used, a severage extent. 2021 are used, and a severage extent are to be expected based of a sesentially provide a few past years, though it is daily loss rates may yield a comparing how many years free to all years. If had off be self-ranked and probabilities as the "window" of possible set the window" of possible set the window	iik, J. and J. Stroeve. updated dally. Near- Time DMSP SSMS olion Gridded Sea Ice ntrations, Version 1. der, Colorado USA color Colorado USA color Distribute Center Distribute Archive Center, doi: 10.io.gr/10.5087/U8C0 9DWVXSLM.	NA	

Slater-Barrett (NSIDC)	Statistical/ML	None	4.83							Standard deviation of		This projection was made using the Siater Probabilistic loe Extent model developed by Drew Stater (http://cires 1.cobrado.edu/-asiater/SEA/CE/). The model computes the probabilisty of sea ice concentration greater than 15% for Autic Ocean grid concentration for extended or the probabilistic are aggregated over the model domain to arrive at draily lot of the probabilistic and grid of the probabil	non-parametric statistical model of Arctic sea ice emodel computes the probability of whether ice action greater than 15% wil exist at a particular for a particular loss of the 15% will exist at a particular for a particular loss time in the failure, given to the properties of the	https://nsidc.org/data/nsid c-0081	None	
NSIDC Hivemind	Heuristic	NA	4.48		0.35					all individual submissions		NSIDC Sea Ice Contest	September extent estimate.	NA	NA NA	
ASIC, NIPR	Statistical/ML	NA	4.549								0.103	Monthly mean ice extent in September will be about 4.549 million square klönneters. Our prediction is based on a statistical way using data from satellite microwave sensor. We used the ice thickness (corumitated ice convergence), ice age, and mean ice divergence on April 30. Predicted ice concentration may from July 110 September 20 is the thickness of the concentration may from July 110 September 20 is the thickness of the concentration may from July 110 September 20 is the thickness of the concentration may be supported by the concentration of the	ad the Arctic sea-ice cover from coming July 1 to be 720, using the data from satellite microwave rs. AMSR-E (2002/03-2010/11) and AMSR2 2021/122). The analysis method is based on our (Kimura et al., 2013). First, we expect the ice ses distribution on April 30 from redistribution elconvergence) of sea ice during December and elconvergence) of sea ice during December and distribution which represents how much area of or distribution which represents how much area of or so contained in the old ice on Apd 30 were from the backward tracking of sea ice. Then, we treat the summer ice concentration by multiple analysis based on the derived ice thickness, ice age, and mean to divergence.	10km grid data distributed by Arctic Data archive System (https://ads.nipr.ac.jp)	NA	
RASM@NPS (Maslowski et al.)) Dynamic Model		4.91	4.877	0.33	4.392	5.689	0.546	3.927	The uncertainty of pan-Arctic September sea ice extent was sestimated from the 31 ensemble members see also Fig 4 the supplementary material.	-0.357	accuring yield of U-22-Vin term the Regional Arctic on 2002-2021 output from the Regional Arctic of September 2021 set of the Arctic of	RASM2_1_00, which is a recent version of the limited-area, fully coupled climate sixting of the Weather Research and Forecasting os Alamos National Laboratory (LANL) Parallel grain (POP) and Sea lee Model (CICE), Variable on Capacity (VIC) land hydrology and routing VIC) model components (Malsowise 4 et al. 2012; al. or 2015; Dul'wer et al. 2015; Harmann et al. 2017; Cassano et al. 2017). The forced with CFSRVETSV2 reanalysis output for vice of the CFSRVETSV2 reanalysis output for vice vice of the CFSRVETSV2 reanalysis output for vice vice vice vice vice vice vice vice	The initial sea ice conditions for the June Sea Ice Outlook was defived from the RSA by the Property of the RSA by the RS	See the above	Daly mean sea ice with concentration <=15% and thickness <= 20 cm was excluded in the estimates of September sea ice extent.
NMEFC of China (Li and Li)	Statistical/ML	Sea Ice Index - Daily sea ice concentration(NSI DC NASA Team) and monthly sea ice extent from NSIDC.	4.54									extent from National Snow and Ice Data Center. The predicted monthly average ice extent of September 2022 is 4.54 million square kilometers.	imal climate normal method is used to predict eptember average Arctic sea ice extent.	N/A	Sea Ice Index - Daily sea ice concentration(NSIDC NASA Team) and monthly sea ice extent from NSIDC.	
SYSU/SML-KNN	Statistical/ML	NA	5.04	5.04	0.31	4.73	5.35			We estimate our uncertainty with root-mean-square-emr(RMSE) calculated from 2015-2020 hindcast.	0.8	A machine learning KNN model is used to predict the daily sea ice concentration (SIC) and the sea ice content (ISIC) of September 2022 in pan-Artic. Daily averaged sea ice concentration (YISIDC NASA Team, https://mick.org/data/nico/0011 fleids between 1979 and 2021 were used to predict. The model predicts pan-Artic beals ce settent of 5.04(±0.31) million square kilometers and has a positive anomaly of 0.8.	saming algorithm (KNI) (K-Namerst Neighbors) is a prediction. The principle is to find the K-naerst for the input variables from the training data set of the input variables from the training data set the time the kind of the size of the input variables from the training data. At the time the kind year, organises simulated climate elected in the same and adjacent date as the time the kind year. The size of the	NA	NA	NA.
SYSU/SML-MLM	Statistical/ML	NA	4.41	4.41	0.5	3.91	4.91	0.63		We estimate our uncertainty with root-mean-equare-error(RMSE) calculated from 1979-2019 hindcast.	0.2	A multivariate linear Markov model is used to precide monthly sea ice concentration (SIC), from which sea ice concentration (SIC), from which sea ice setter precident on from this yealpreher 2021 in Artic is calculated to be 4.63:20 51 million square klometers, and the Alisakan regional SIE is predicted to be 0.71:20.25 million square klometers. The property of the concentration of t	watest lener Markov model is a statistical model bribbes principal component analysis and linear model together, it can identify the large scale here and oceanic vanishily through principal nt analysis and make linear Markov prediction for its results (line and space component form or its results (line and space component form first we extract line and space component form in the state of the state of the state of the time component, which will be matigated with mponent to make a final prediction. Besides the tration (SIC), sea surface temperature (SST), temperature (SAT), here we further use monthly et radiation flux (NI) data from 1979 to 2019 to dot! For this attempt, we use 2021 May monthly data to intate our model and make monthly SIC and SIE prediction.	NA.	NA .	No post-processing.
ARCUS Team (Wiggins et al.)	Heuristic	NA	4.75									The ARCUS Team submission is the median of all the values contributed by ARCUS team members.		NA	NA NA	