July 2019 Sea Ice Outlook Key Statements														
Contributor	Type	Dynamic Model Type	Arctic Extent	Antarcti Extent			Median	Range	Standard Deviation	Estimate Summary	Executive Summary	Method Summary	Sea Ice Concentration Data	Sea Ice Thickness Data
Sanwa Elementary School (lihoshi et al.)	Heuristic		3.06								Monthly mean ice extent in September will be about 3.06 million square kilometers.  We estimated the minimum ice area through discussion among 22 students based on the ice map from 2004 to 2018.	Monthly mean ice extent in September of 2004,2006,2008,2010,2012,2014,2016 and 2018 from the ice concentration map, by approximating the ice cover with a triangle or trapezoid.  Based on this rough estimation, we discussed a yearly change of the ice area and calculated the ice area of this September.	SIC is not used.	Sit is not used.
Navy ESPC (Metager et al.)	Dynamic Model	Coupled	3.6	20.3	0.25	. 0		3.1 - 4.1 M km2		The uncertainty estimate is the range of the 10 member ensemble.	The projected Arctic 2015 September mean sea ice extent from the Nays famth System Prediction Capability (1525); 3.5 million km2. This projection is the average of a 10 member time-larged ensemble using initial conditions from 1 line to 11 June 2015. The range of the ensemble is 3.1 to 4.1 million km2. The projected Antarctic 2013 is 1.3 to 4.1 million km2. The projected Antarctic 2013 are extended an area of the control o	We performed ensemble forecasts with the Navy ESPC using Initial conditions on 2019-06-01 122. through 2019-06-11 122. The stanospheric Initial conditions are from NAVDAS-AR (for et al., 2005), to gard of the NAVEM (Hospan et al. 2014) operations also five on expectage for initial conditions are from the Navy's 20xx NCOSA size assimilation system (Cumming 2005), which is a component of G075-21 using WCOM and CIG (Merage et al. 2014).	Sea ice concentration in the Navy ESPC forecasts was initialized from GGF 3.1 (https://www.7320.nrissc.navy.mil/GLBhycomcicel-12).	Sea ice thickness in the Navy ESPC forecasts was initialized from GOFS 3.1 (https://www7320.nrissc.navy.mil/GL Bhycomcice1-12).
GFDL/NOAA (Bushuk et al.)	Dynamic Model	Not Specifier	d 3.67		0.1	0	3.57	3.16-4.31	0.38	These statistics are computed using our 12 member prediction ensemble.	Our July 1 prediction for the September-averaged Arctic sea-ice extent is 3.67 million km²2, with an uncertainty range of 3.16-4.31 million km²2, Our prediction is been on the GFR-1-10 ensemble floreast system, which is a fully coupled amosphere-land-ocean-sea ice model initialized using a coupled data assimilation system. Our prediction is the bias-corrected ensemble enam, and the uncertainty range reflects the lowest and highest sea ice extents in the 12-member ensemble.	Our forecast is based on the EGN. Forecast-oriented four Ocean Resolution (FLOR) model (Vecchi et al., 2014), which is coupled strongsher-bard ocean-sea (see model 1: The model is institulated from an Ensemble Kalman Filter coupled data assimilation system (ECDA; Zhang et al., 2007), which assimilates otherwistional surface and subsourface ocean data and atmospheric readapsity data. The system does not assimilate any sea let concentration or thickness data. The FLOR atmospheric intral conditions are produced from an AMP run forced by observed ST3 and sea (ix. Historical radiative forcing is used prior to 2005 and the RPG4's scenario is used for predictions after 2005, for the predictions initialized after 2004, the aeroscio ser flusted at the RCP4's scenario is used to predictions after 2005. For the predictions initialized after 2004, the aeroscio ser flusted at the RCP4's scenario is used more read to the second prediction of Artici scale section has been documented in Masdel et al. (2017), and Bushuk et al. (2018). For an evaluation of the model's September sea (se extent prediction skill from a July 1 intilization, see attached pdf.	No SIC is assimilated, but the sea ice state is constrained by ocean and atmosphere assimilation.	No SIT is assimilated, but the sea ice state is constrained by ocean and atmosphere assimilation.
Morison, James	Meuristic		3.8								email rec'd 11:00 pm (AKDT) on12 June: Hi Betsy, Well we just got back from the historic last C-130H mission from USCS Air Station Kodiast. The long serving it is are being NSCS Air Station Kodiast. The long serving it is are being Recommissioner Survey (SIZRS) flight was successful. We flee wu p150M* washing coencengraphic stations with expendable probes every degree for 72 to 76 and then flee back at higher attitude doing amongher is dations with expendable probes every degree for 72 to 76 and then flee back at higher attitude doing amongher is dations with expendable probes every degree for 75 to 76 and then flee back at higher attitude doing amongher is dations with expendable probes every degree for 75 to 76 and then flee was as lot of often water even up to 76 kl. The zinou is already grozes. I usually account flee Arctic Cocean and look at the AO, but not time for that, it's already midnight Pacific Daylight Time. To be any later and still be on the 121th, if the AO, but not time for that, it's already midnight Pacific Daylight Time. To be any later and still be on the 121th, if the AO, but not must prove the control of the provided provided provided the provided provided the provided provided provided the provided provided the provided provid			
Sun, Nico	Statistical		3.95		0.21	. 0	3.95	3.61-4.17		The uncertainty is based on the 2007- 2018 remaining melt condition variations.	The forecast model is based on ice persistence. It uses incoming solar radiation and sea ice albedo derived from a predicted Sea ice Concentration (SIV) value to calculate daily thickness losses for every MSIDC. 25km grid cell: The install thickness is calculated from AMRST as lea (volume and MSIDC SIC data.  The mean forecast uses the 2007-2018 mean 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 0.385toh for previously observed SIC for this day and a 10% increased bottom melt. The light forecast increase the predicted SIC by 0.205tdv and a 10% decreased bottom melt.	cell using the exact solar radiation energy and the predicted sea lec concentration as an albedo value.  Ice-loss(m) = Energy(solar in MU)*(1-SIC) / icemeltenergy SIC = sea lec concentration icemeltenergy = Meltenergy per m3, (333.55 KJ/kg*1000(m3/dm)*0·92(density)/1000(MJ/kJ)	NSIDC NASA Team, https://midc.org/data/msidc-0081, https://doi.org/10.5967/URD990WV93M. Initial SIC. 1st June 2019. The model used observed SIC until 11th July 2019 to calculate melt.	AMSR2 Sea Ice Volume model (v.1.5), 31st May 2019, developed by Nico Sun https://cryospherecomputing.kl/StTJ
Simmons, Charles	Statistical		3.978						0.385 million square kilometers		We loosely model the contributions of ocean heat and insolation to sea Ice melting. To model insolation, we use measurements of northern hemisphere snow area and sea ice area. To model cocean heat, we use measurements of CO2 concentrations.	This is a variant of Rob Dekker's prediction. Dekker performs a linear regression on northern hemisphere strow area, sea fac area, and sea ice catent.  Predictions of more of least control and transfer of the control and trans	We do not use SIC nor SIT. We use the following data was a constant of the size of the siz	
McGill Team	Statistical		3.99							BMSE: 0.50 million square kilometers. From comparison of hindcasts to the observed minimum September sea ice extent.		The doweldE prediction for the minimum Segember ice extents 3.99 million square kilometers. The doweldE prediction is compated as a sum of the linear trend climatide(s) and departure from the trend toteraman variability). We take the long-term inner trend in a time series of the minimum september so ice extent one the 1953-2018 product of her particular to the control of the con	NOAA/NSIDC, See Ice Index, Version 3. https://doi.org/10.7265/NSX072F8	

NASA GISS / McGill University	Statistical		4			0.44 million sqr km	An error analysis of a hindcast using this method was done in Williams et al (2016)	It has been shown that the September sea-ice extent anomaly is significantly correlated with the mean Artic Oscillation (AC) index during the previous writer. The mean Artic oscillation (AC) index during the previous writer the sea-ice circulation during the writer. In other words, the writer circulation during the writer. In other words, the writer partners associated with the policy phase of the AO (mailey) increased number and strength of cyclones penetrating deep into the Arctic region) lead to enhanced sea-ice export through Fram strait, and an anomalousity younger / thinner ice cover in the Siberian shelf seas. These two processes provide a preconditioning effect which sets the stage for additional ice loss when compared to a typical melts season. We, therefore, use the writer mean AO (midex as a predictor for the September) writer mean AO (midex as a predictor for the September).	We perform a linear regression between the detrended September mean SIE and the winter mean (IDFAM) AD index during the period 1993-2018. This allows us to form a prediction for the 2019 for this year, the winter mean AD index was 0.481, which translates into a Sept SIE anomaly of -0.41 million Mazz. This anomaly of-cests it then added to an estapolation of the linear trend line from 1993-2018. The linear trend forecast for 2019 is 4.14 million km2. Summing it up, we get a par-Avctic forecast for the September mean SIE of 4.00 million km2.	NSIDC Sea Ice Index Version 3: https://midc.org/data/G02135/versions/3	
								sea-ice extent anomaly. This anomaly forecast is then superimposed on the longer term trend of September sea- ice loss to form a seasonal forecast of the Pan-Arctic September sea-ice extent.			
LASG, JAP	Dynamic Mode	I Not Specified	d 4.01	3.98	3.67-4.60	0.19	The uncertainty was estimated by the ensemble member spread.	The prediction for the sai ice outlook June 2019 was carried dut on China's Tainhe-2 supercompater, with a dynamic model prediction system CAS FGOALS-12 32 3 V.13. The dynamic model prediction system CAS FGOALS-12 32 3 V.13. (Ice-ocean-atmosphere-land model), provides a real-time predictions in the subseasonal-to-seasonal (1253) timescales. FGOALS-12 325 system has been established in 2021 Tay R&D beam of FGOALS-12 from both LASS institute of Atmospheric Physics Chinese Academy of Sciences and CAS Taylor of FGOALS-12 Tay	FGGALS-12 S2S V1.3 is a global coupled dynamic prediction system. The initialization of this prediction system is based on a nudging scheme, which assimilates wind components (U and V), Temperature (T) in atmosphere and potential temperature in ocean from 1 and 1880 to 1 June 2013, and 40 ensemble members are generated by a time-lag method. The predictions are available here for 6 months. This rea time 52S prediction system is fully operated on China's Tlanhe-2 supercomputer.	The sea ice is constrained by atmosphere and ocean initialization	None
UCL (Gregory et al.)	Statistical		4.021	0.2		Pan-Arctic = 0.076, feather 5 = 0.076, feather 5 = 0.057, Chukchi = 0.037	Forecast method produces estimates which are Gaussian. Therefore each forecast is presented with a mean and standard deviation.	This statistical model computes a forecast of pan-Arctic and regional mean September soa ice extents (regions were defined based on NSDICs data mask (Fetterer et al., 2010)). Monthly averaged June sea ice concentration fields between 1579 and 2019 were used to create a climate network of June sea lee concentration of both. This was then utilised in a Bayesian Linear Regression in order to the control of the	Monthly averaged lune sea ice concentration (SIC) data between 1979 and 2019 were used to create a lane SIC climate/compled) network. Includesal SIC grid cells were first clustered into regions of spatio- temporal homogeneity by using a community detection algorithm. Units between each of these network regions (cooxinance) were then passed into a Bayesian Invest Regression to devine 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 extents.	NSIDC NASA Team Sea Ice Concentrations: 1979 - 1987: Mimbus-7 SSMR 1987 - 2007 DMSP F-8, F-11, F-11 SSM/Is 2007 - 2017: DMSP F-18 SSM/I 2017 - 2019: Near-real time SIC	
UIUC (Zhan)	Statistical		4.04		+/- 0.2 million km2		The uncertainty range is estimated from the standard error of the correlation between June TOA-RSR and September SIE.	Our prediction is based on the strong correlation between deterneded June top-of-atmosphere (TOA) reflected solar radiation (RSR) and September Sec. bec Extent (SIS) anomalies, as proposed by Zhan and Davies (2017). This method is letting because the main contribution of TOA RSR anomaly in a time is from a because the order of the contribution of TOA RSR anomaly in a time is from a because the order of underlying surfaces and the contribution of the contribution	Our contribution is formulated by adding the main contribution part from Segember SIz treed (2002*2018) with the anomalous part from the June TDA-RSE (2019) anomaly. The detailed description of calculation is at follows:  The determedial user RSE anomaly (2019) is 3.25 W/m2.  The corresponding September SIE anomaly is -0.25 (-3.25 * 0.0781) million km2.  The trending anomaly of September SIE (0.08 million km2 per year.  The 2019 September SIE (from the trend) is 4.29 million km2.  The predicted September SIE (6.02 to 6.02 km) willion km2.  Note that the coefficient of 0.0781 is estimated from the detrended anomalies of June TDA-RSR and September SIE between 2002 and 2018.	We do not use SIC dataset. Instead, we use sea Ice index (Version 3.0) product (NSIDC, NASA Team, https://issic.org/data/20135, doi: https://doi.org/10.7265/NSX072F8).	
CPOM (Schroeder)	Statistical		4.1		3.6 - 4.6	0.5	The given uncertainty is the mean forecast error based on forecasts for the years 1984 to 2018.	We predict the September 2019 (se extent will be 4.1+/- 0.5 million km2. This means there is a 79% (ikehood it will be among the lowest 3, 66% among the lowest 2, and it it will be a newmininum record. The simulated melt pond fraction in June 2019 has been higher when in any June before.	This is a statistical prediction based on the correlation between the ice area covered bymelt-ponds in May and ice active in September. The med pond area is derived from a simulationwith the sea ice model CCE in which we incorporated a physically based melt-pond model i.5ee our publication in Nature Climate Chapethyl/www. nature compricinate/pomanyl-Anfe/ful/primate/2018. Intel of details. Zenferences. I. Floco, D., Sch/Mfder, D., Feltham, D. L. & Hunke, E. C., 2012: Impact of melt ponds conductic seas cismilations from 1990 to 2007. I. Geophys. Res. 111, 2009232. 25ch/Mfder D., L. Feltham, D. Floco, M. Tsamados, 2014. September Arctic sea-teeninimum predicted by spring melt-pond fraction. Nature Clim. Canage 4, 333-337, 00.101.0038/NCMMATE203.		
NASA GSFC (Petty)	Statistical		4.13			0.39	The uncertainty represents one standard deviation of the prediction interval.		In this forecast we use sax ice concentration (SIC) data (1979-present day), derived from passive microwave brightness temperature using the NMSA. Team algorithm. The SIC data are detrended spatially using linear tend persistence (from the given forecast year) then averaged, to generate deterended SIC dataset. A least-squares linear regression model is fit from the mean deterended SIC/SIC data. To produce he SIC forecast, the relevant monthly many-feterended SIC date are applied to the linear regression model. See my website (http://slexpetry.com/blog/2017Arcticf-orecasts) for more details.	NSIDC NASA Team, https://nsidc.org/data/nsidc-0081, https://doi.org/10.5067/U8CD9DWVX9LM.	
Univ. of East Anglia (Cawley)	Statistical		4.1452	2 4.1452	3.0324 - 5.2580 (Bayesian credible region)		Gaussian Process models provide the posterior predictive distribution. Doesn't includehyper-parameter uncertainty.	This is a purely statistical method (related to krigging) to extrapolate the long term trend fromprevious observations of September Arctic sea ice extent. As this uses only Septemberobrevations, the prediction is not altered by observations made during the Summer of 2019.	A Gaussian Process model, with a squared exponential covariance function, is used to model thehistorical SMICS September Arctices aire center data. The hyper-parameters are optimized bymaximizing the marginal illusthood for the model (marginalizing them would probably be betteto include the additional predictive uncertainty due to uncertainty in estimating thehyper-parameters). The model was implemented in MATLAL using the GPML toolbox(http://www.gaussienprocess.org/gpmi/code/matlab/dox/). An images has hopefully beenuplicaded showing how the predictive uncertainty increase as the model extrapolates into thefuture. For an animation showing how the model charges as the amount of californicals, see things://withstc.com/Gavin_Cardyststatus/1004897805037464448.		NSIDC September average Arctic sea ice extent data.
John, Christian	Statistical		4.17	4.17		0.33	Its the Standard deviations of the difference between Model and Observation (1980-2016)	The Model is based on the idea, that June has the possible power to reflect triggering of powerfull feedbacks, e.g. Albedo-Feedback is hows up, that the June is very able to forecast the September Sea Ice Extent (NSIDC).	a = (Air-Temperatur (10)- Air-Temperatur (1-1)- Sea Surface Temperatur (10)- Sea Surface Temperatur (10		

Dekler, Rob	Statistical		4.22							380 k km^2		The concept behind my method pertains to estimating albedo-based Arctic amplification during the melting also the "whiteness" of the Arctic in Jane as a predictor for how much loc will mel tout between June and September.  I use three variables (lands now cover, lec concentration, ice area) of "whiteness" that are available in June, in a regression formal which shows particularly storegor correlation with Sept sac lec entert missimum. September ice extent over the past 25 pers shown in a graph here: https://lorum.arctic.sea-lice.net/index.php?action-dilatacht.pojc-292.0.attach=1.04 209/image.  The interesting finding is that the June land snow coversignal is clearly present in the September ice extent numbers, suggesting land snow cover could be used to improve sea ice estimates in other models as well.	The concept behind my method pertains to estimating albedo-based Artic amplification during the melting season.  I use the "whiteness" of the Artic in June as a precition for how much lice will melt out between June and September.  Specifically, I set up a formula which reflects how "dark" areas near the Artic in June would create heat that will meet out see over the months until the September minimum.  As an educated guess, such a formula could take the following form:  As an educated guess, such a formula could take the following form:  For (Extent - Area): 1.0 (assuming that ALL solar adulation not one-time (se and into polyvia will cause in the control of the control o	Land snow cover from Rutgers Snow Lab. https://climate.rutgers.edu/snowcover/fable_area.php Nu_Set=Table_Jort=0 Sea ice Area and Estent from NSIGC: ftp://sidads.colorado.edu/DATASETS/NOAA/G02135/n orth/monthly/data/	
NSIDC, CU Boulder (Horvath et al.)	Statistical		4.25	i								This statistical model computes the probability that sea ice will be present (concentrationabove15%) for each grid cell in INSIDCS polar steeperagnishic projection. Versify data from 13980through the present are used in a bayesian logistic regression. Predictors include local surface alteremperature, downwelling longwave radiation, and sea interconcentration, as well as the first-principal component of geopotential height at 300mbars, and Pacific and Adlantic sea surfacemperatures. This model predicts a minimum September sea ice extent of 5.50 million Segarethic. Sea ice concentration data was dodlined from NSIDC. Sea lectioned Vigilia Sea Set 1000 MSID, all other violables are from NASAS MRRRAZ dataset.	Yearly data from 1980 through the present are used in a bayesian logistic regression to predictibe probability that sea lice concentration will be above 15%. To estimate total sea lice extent_grid cells with a percentage above a certain threshold (noisen from a drop-one cross-validationtest) are multiplied by the pieal reagy fill dataset provided by MOSCs polar stereographicotolest and their summed. This mode predicts a minimum September sea (se extent of 5.5million Intr.). Sea leconcentration data was obtained from NSIDCS Sea Ice Index 3 (2014 Sectio GOISS), all other variables are from NASA'S MERRAZ distaset.	NSIDC's Sea Ice Index V3 (Data Set ID: G02135) NASA's MERRA2 dataset	
University of Washington/APL, Zhang and Schweiger	Dynamic Mode	I Not Specified	1 4.26	i								Driven by the NCEP Climate Forecast System (CFS) forecast atmospheric forcing, PIOMAS is used to predict the total September 2019 Access some context and the context September 2019 Access some context and per only is the predicted September (se extent is 4.26&5.0 Ab million square kilometers. The predicted test thickness fields and ice edge locations for September 2019 are also presented in the attached document.	See above.	Real-time satellite sea ice concentration data (NASA team) from NSIDC for data assimilation in hindcast.	CryoSat2 sea ice thickness up to 4/2019 used for data assimilation in hindcast.
NASA GMAG	Dynamic Mode	l Coupled	4.27			0.41	0.00294	Pan-Arctic: 4.28; Alaska region: 0.42; Hudson Bay: 0.00299	Pan-Arctic: 3.64 to 4.99; Alaska region: 0.07 to 0.81; Hudson Bay: 0.00000 to 0.00599	Pan-Arctic: 0.38; Alaska region: 0.23; Hudson Bay: 0.00225	The given uncertainty is the standard deviation of the 10 member ensemble.	An experiment of the GMAO seasonal forecasting system using CryoSat-2 derived ice thickness predicts a September average Arctic ice extent of 4.27 ± 0.38 million him. The experiment test site application of ice thickness data in a near-real time setting for the seasonal forecast system. The forecast suggests reduced less cover for 2019 as compared to the previous year.	The forecast uses a prototype the GEOS, 5.35 westion 2 coupled system that was modified for this forecast. The mode has na appointaine grid spacing of 1° to be the the strong-time and the ocean. The ocean data assimilation system is driven by a near real-time atmospheric analysis that is similar to MERRA-2, and uses the Local Ensemble Transform Kalman Filter (EETRF) for assimilation of available observations and along-track ocean altimetry.  A branch of the ODAS system was integrated from 1-December 2018 to 26-Apr 2019 that included undging to CrydSa5-2 sea ice thickness fields over the available time period until 12-Apr. The ensemble used a staggered institutional of 11-Apr, 16-Apr, 21-Apr, and seven additional ensemble members on 26 Apr based on institul continue perturbation of the atmosphere and cosen states.	The sea ic concentration was taken from MERRA-2 dickin 10.0001/WORDLIZEAR, which make he retrieved from the Godderd Earth Sciences Data and Information Services Centre (IGS DISC, 1 he MERRA-2 sea ice conventration is derived from the Operational Sea Surface Temperature and Sea lex Analysis system (DSTIA) Domion et al. doi:10.1016/j.nez.2010.10.017). Which in turn dollins sea lex from the UMETSAT Satellite Application Facility on Ocean and Sea Ice (DSI SAF).	CryoSat-2 Level-4 Sea Ice Elevation, Freeboard, and Thickness, Version 1, https://nsidc.org/data/RDEFT4/, doi:10.5067/96100KIFDASs. The data were incorporated into the DDAS over a four month period. The ODAS integrated for an additional 14 days after the end of the CryoSat-2 data period.
Modified CanSIPS	Dynamic Mode	l Not Specified	i 4.28	1				4.19	min=3.94, max=4.74	1 standard deviation = 0.27, uncertainty = ±0.52 (95% CI)	The uncertainty values were calculates from the ensemble of 20 fcst biascorrected SIE anomalies (see section 5).	Our Outlook of forecast total bias-corrected Arctic sea ice extent [SIE] and calibrated sea ice probability [SIP] was produced using the Canadian Seasonal to Internamual Prediction System (CanSIPS), but (as 10.021 and 2018) in modified experimental configuration intended to test updates to the sea ice forecast methodology. These updates include changes to the data used to initialize both sea ice concentration [SIC] and sea ice thickness (SIT].	CALSES combines forecasts from two models, CarcM3 and CarcM4, with a total of 20 exemble members (10 from CarcM3, 15 from CarcM4). Early the ArcC15 st annahy succellulated for each includudal ensemble member relative to a piecewise linear trend fitted to the respective model's ensemble member little fitted so the respective model's ensemble member little fitted so the respective fitted to the respective model's ensemble member little fitted so the respective fitted and the fitted so the respective fitted and the respective fitted so that fitted so the respective fitted and the respective fitted fi	SIC is initialized by rudging model SIC to the Meteorological Service of Canada analysis (MSC) with a 3 day time construct, initial conditions for the sluly submission are from June 30 nudged SIC.	SIT was estimated using the statistical model SMX3' described in Dirkson et al., 2017 (dic1):175/(LIC1-0-16-0321.1). The parameters in SMx3 were fit using a blended SIC product (Hud2CDS-Hud3STZ-Büce Charts) and POMAS SIT date over the period 2003. Dilla The daily MXC SIC described above for June 2014 was then used as the real-time predictor field in SMx3 to estimate real-time SYT.
UC Louvain (Massonnet et al.)	Dynamic Mode	I Ocean-sea ice	e 4.32	: :	20.9	0.5	0.81	4.31	Arctic: 2.86-5.02 (min- max); Antarctic: 20.14- 21.82 (min-max)	Arctic: 0.62; Antarctic: 0.50	The projection uncertainty is given as the range between minimum and maximum extents in the ensemble. Although relatively wide,	Our estimate is based on results from ensemble runs with the global ocean-sea ice coupled model NEMO3.6-LIM3. 1, Each member is intitialized from a reference run on 11, 2015, then forced with the IRA-55 atmospheric reanalysis from one year between 2009 and 2018. Our final earlier is the ensemble median, and the given range corresponds to the lowest and highest extents in the ensemble.	Our estimate is based on results from estemble runs with the global ocean-sea lice coupled model NRMO36-NMO. The enounthe membles are expected to sample the tempospher centality that may prevail this summer. In practice, the model is forced with IRA-53 atmospheric reanalysis data from 154t to be £1, 20.88 No data are assimilated during this summation. The ensemble members are then started from the obtained model state, each using atmospheric forcing from one year between 2009 and 2018. This choice is componnise between a sufficiently large ensemble and the rapid changing actions atmospheric conditions in recent décades. The estimate given above corresponds to the ensemble median mostify segémente extent. No blac-correction is applica-	Initial sea ice concentrations come from a model free run on Jan 1, 2019	initial sea ice thicknesses come from a model free run on Jan 1, 2019
NSIDE (Meier)	Statistical		4.34	1 1	17.46					0.53	Standard deviation of the projections using individual years' rates of change	This method applies daily ice loss rates to extrapolate from the start date (July 3) Through the end of September. Projected September daily vectors are averaged to calculate the projected September awarge extent. Individual years from 2005 to 2017 are used, as well as averaged over 100 years of 100 years and 100 years of 100 years and	This method applies daily ice loss rates to extrapolate from the start date (July 1) through the end of September Projected September daily extents are a weraged to calculate the projected September 2007 to 2018 are used as werage soor 1501-2010 and 2019 are used as werages over 1501-2010 and 2019 are used as werages over 1501-2010 and 2019 are used to 2019 2019 a	Maslanik, J. and J. Stroeve. 1999, updated daily, Near- Real-Time DMSP \$55MS Daily Polar Gridded Sea Ice Concentrations, Venion I. Boulder, Colorado USA. MASA National Sarva and Ce Data Centre Destrobuted https://doi.org/10.5067/USCOBOW/VSSUM. Fetterer, F. K. Knowles, W. Meier, M. Savice, and A. K. Windragel. 2017, updated daily. Sea Ice Meiox, Version 3. Boulder, Colorado USA. NSIOC National Snow and ice Data Center. doi. https://doi.org/10.7285/MSIOC7278.	

NCAR/CU (Cay, Balley, and Holland)	Heuristic	4.38		4.44	3.14 (min) to 5.03 (max)	0.40	The uncertainty estimate is based on the scatter in entiries in our informal pool.	An informal pool of 20 climate scientists in early, June 2010 estimates that the September 2010 is centre will be 4.3 an million sq. km (stidere, O.A), min. 3.14, max. 5.03). Since this inception in 2008, the NOAR/OL see ice pool has easily rivaled much more sophisticated efforts based on statistical methods and physical models to predict the September monthly mean Arctic sea ice extent (e.g. see appende of Storeev et al. 2014 in GRI. doi:10.1007/2014c01059388. Withress the Arctic article by Hamilton et al. 2014 http://www.arcc.org/withress-the-arctic/2014/2/article/210560, We think our informal pool provides a useful benchmark and reality heck for Sea for the Prediction efforts based on more sophisticated physical models and statistical refortingues.	An informal pool of 29 climate scientists in early June 2019 estimates that the September 2019 ice extent will be 4.18 million sq. km. (stddee. 0.40, min. 3.14, max. 5.03). Guesses were collected by sending an e-mail out to the scientists and tempting them with local bragging rights and with local ice cream.	
NSIDC (Group)	Heuristic	4.4				0.33 million square kilometers	The uncertainty is the standard deviation of the 10 individual estimates.	This estimate is based on polling NSIDC employees for their estimates of the September extent. The submitted group estimate is the average of 10 individual contributions.	The method is to simply average 10 individual heuristic estimates.  No specific dataset was used for initialization, but contributions were provided NISIC Sea (se Index extent Values to Inform their estimation). SIT was not used values to Inform their estimates.	ed in this method.
NSIDC (Barrett/Slater)	Statistical	4.46						This projection was made using the Slater Probabilistic Ice Etent model developed by Drew Slater (http://crest.colorado.edu/~salter/SEAEE/). 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 lice exeents. A September mean ice cetter its calculated from daily forecast Issued on July 1. While the model has predictive skill at lead times up to 90 days, NISIC rust the forecast model with a 50 day read time. Forecasts issued on July 1 for September have lead time spaming 62 to 91 days. Therefore we consider the mean September ice extent forecast for the July sea ice outdook to have some 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. Probabilities are computed using data from the past 10 years. These probabilities are adjusted using data from the past 10 years. These probabilities are adjusted using data from the past 10 years. These probabilities are adjusted using data from the past 10 years. These probabilities are adjusted using data product of grid-box areas the probability of a grid-box containing ice on the forecast date.  While not as sophisticated as a coughele coachie-campositien models, this statistical method has the advantage that the forecast for all points are completely independent in both space and time; that is, the forecast story given point not of the particular date of the partic	
JARC (Brettschneider et al.)	Statistical	4.524		4.524	Upper: 4.965 million sq. km. Lower: 4.006 million sq. km.		The range assessments represent 95th and 5th percentile confidence intervals.	The International Arctic Research Center has developed a prototype model to estimate Arctic sea ice extent using an analogs approach. The analogs approach looks at prior years and finisk the best matches that most closely represent the current state of the atmosphere in 2019. The model run in early by 2019 indicates September 2019 sea ice will be slightly righer than the extrapolated linear trend of the previous four decades. We estimate a monthly extent of 4,524 million square followerers.	Our statistical model uses the NCEP/NCAP [R1] Reanalysis data sets to develop analog matches of atmospheric variables that correlates with seal ce extent. The R1 data covers the time period of 349± present. The model generates an estimated deviation from the 1979-2018 Septembers sa ice linear trend line by levidaritying the top matching the top the seal of coasie and atmospheric variables using the June Through July time periods of seath year, and then follows the seasonal decline in sea ice through the following September. The variables used are 11) sea level persoure, 2 500 mblepits, 312 -meter temperatures, 4) 925 mb temperatures, and 5) sea surface temperatures. A composite forecast is developed from a regression-weighted model.  **Deviation**  **Deviation*	
NCEP CPC	Dynamic Model Not Specified	4.55	0.61			0.24	The standard deviation is calculated from the 20-member ensemble.	This contribution is from a 20-member ensemble forecast from the Climate Prediction Center Experimental sea is forecast system (CS:mS). Model bias that is removed is calculated based on 2006-2018 retrospective forecasts and corresponding observations.	The outlook is produced from the Climate Prediction Center Experimental sea ice forecast system (CSGN). The forecast is initialized from the Climate forecast System Reanalysis (CSSI) for the ocean, Ice, and the Cost as it is initialized from the Cost as it is initialized from the Cost as it is initialized from the CSG as a legislation system (SSI) for sea (CSSI). The Cost analysis is produced with GFDL MOMS all costs are initialized from the CSG analysis is produced with GFDL MOMS which cost surface fields from CFS and sea free this cost and cost	s is produced with h uses surface fields ssimilates satellite ition retrieval from
UCLA (Kondrashov)	Statistical	4.56	0.47			0.3 MKm2	This uncertainty corresponds to standard deviation of stochastic ensemble spread.	This statistical model forecast is based on inverse modeling techniques applied to the regional Arctic Sea Ice Extent (SIE) dataset.	Nonlinear inverse modeling techniques have been applied to the regional Arctic Sea (oc Exect (SIS) from Sea (oc Index Version 3 dataset. The daily) if disk were aggregated to provide weetly-sampled dataset sea (or a sea of the sea	
RASM (Maslowski et al.)	Oynamic Model Coupled	4.57	0.393 2.96E-07	4.59	4.23 to 4.90	0.181	The uncertainty of pan-Arctic sea ice extent was estimated from the 27 ensemble members.	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), Lox Alamos National Laboratory (LANL) Parallel Ocean Program (POP) and Sea ke Model (CICL), variable infiltration Capastry (VIC) land hydriology and routing scheme (RIVI) model components (Maskowski et al. 2012; Falmman et al. 2015; Hamman et al. 2015; Hamman et al. 2015; Hamman et al. 2017; Cassano et al. 2017; The model uses CFSR/CFSv2 reanalysis output for RASM/WRF lateral boundary conditions and for sudging winds and temperature starting some control of the co	As explained in the "Executive summary", RASM is used for dynamic down-scaling of the global NOAA/NCEP CFS/Q 7- month forecasts. The initial conditions for the July Sea Ice Outlook were derived from the RASM 1979- 2018 bindsx1 and are physically and internally consistent across all the model components. Notifier data assimilation not be correction was used. Each of the 27 exemble members and roward for for morths using outputs from GFS/V reanalysis. The CFSV forcing streams used for the ensemble members were instituted every disk of 2000 (persecution user) for long tractams used for the ensemble members are instituted every disk of 2000 (persecution see assimable between 28th and 30th of June) and used for RASM forcing at 00:00 on July 1st, 2019.	
Wu, Tallapragada and Grumbine	Dynamic Model Coupled	4.58	20.18					kilometers with a standard deviation of 0.61 million square kilometers.	from previous years' sea ice outlook). If this thinning would have eliminated ice from areas observed to have sea ice, a minimum thickness of 10 cm was left in place for the ice ICs. Bias correction was applied  30, 2019	
NMEFC of China (Li and Li )	Statistical	4.59						We predict the September monthly average sea ice extent of Arctic by statistic method and based on monthly sea ice concentration and extent from National Snow and ice Data Center.  The predicted monthly average ice extent of September 2019 is 4.59 million square kilometers .	A simple statistical model is used to predict September average Arctic sea ice extent. The sea ice extent of September is well related with the sea ice extent of Juni net head repeated and optimal climate normal method, the predicted september sea ice extent in 2019 is 4.59 million square kilometers.	
PolArctic LLC	Other	4.6						This is PolArctic's first submission to the Sea Ice Outlook. Our September sedent prediction is 4.6 million square klometers. Our efforts are to investigate the sucefures of Artificial intelligence and Machine Learning (ANA) as a predictive tool for Arctic sea ic section. Hidden air or predictive tool for Arctic sea ic section. Hidden air or Artificial intelligence and arctic arctic arctic arctic arctic Arctic Arctic sea in a contract of Artificial intelligence arctic arctic arctic arctic arctic precord of sea ice section creates the preferct test bed to leverage and assess the power of Ar/ML.	PolArctic's inaugural September SIO extent was generated using our Artificial intelligence algorithm, and trained with historical HSIOS daily ice extent data. Our initial modeling efforts are to generate high quality season	

FIO-ESM (Shu et al.)	Dynamic Model	Coupled	4.63	4.63 ± 0.32	uncertainty = ±0.32	Our prediction is based on FIO-ESM (the First Institute of Oceanograph-Earth System Model) with data assimilation. The prediction of September pan-Arctic extent in 2019 is 4.63 (1-0.32) million square kilometers. 4.63 and 0.32 million square kilometers is the average and one standard deviation of 10 ensemble members, respectively.	This is a model contribution. The initialization is also from the same model (FIO-ESM) but with data assimilation. The data assimilation method is Ensemble Adjustment Kalman Filter (EAKF). The data of SST (see surface temperature) and SLA (see level anomaly) from 1 January 1992 to 1 Jun 2019 are assimilated into FIO-ESM model to get the initial condition or the prediction of the Arctic Sea (see . There is no sea lee data assimilation.	No dataset are used for initial sea ice concentration.	No dataset are used for initial sea ice thickness.
UTokyo (Kimura et al.)	Statistical		4.7			Monthly mean lice settent in September will be about 4.70 million opeans elimenters. Our eritative is based on a statistical vary using data from satellitie microwave serior. We used the lot etilicials in December and le momentor from Discember to June. Predicted les concentration map from July to September is a sailable in our website: http://csr.aori.u-tokyoa.cji/-limura_n/arctic/2019-2e.html  loc retreat in the Beaufort Sea will be faster than a normal year. Though lice cover in the East Siberian Sea will retreat with merry same speed as a normal year, ice retreat around the New Siberian Islands will be faster than a normal year. On the other hand, the retreat speed around Severnaya Zemiya will be slower than a normal year.	We predicted the Arctic sea-ice cover from coming July 1 to November 1, using the data from satellite microwave sensors, AMSR-E (2002/03-2010/11) and AMSR2 (2012/13-2018/19). The analysis method is based on our recent research (formure et al., 2013). First, we expect the ice thickness distribution in with 5 from redistribution (liewgenec/forwegenec) of sea ice during Becember and June, Based on the daily ice velocity data. Then, we predict the summer ice area depending on the assumption that thick ice remains later and thin ice melts sooner than the average.		
Lamont (Vuen and Li)	Statistical		4.87	18.63 0.31	The uncertainty is accessed by RNSE derived from cross-validation experiments. See details in the report.	A linear Markov model is used to predict monthly Arctic sea ice concentration (SIC) at all grid points in the pan- Arctic region (Twan et al., 2016). The model is capable of capturing the countability in the coean-sea ice- atmosphere system. The September pan-Arctic sea ice extert (SIF) is Caudiated from predicted SiC. The model predicts negative SiC anomalies throughout the pan Arctic region. These anomalies are relative to the 1979-2012 climatology. The September mean pan-Arctic SIF is predicted to be 4.37 million spane in Bottmerters (makin) with an RMSC of O.48 mism, at the three-month lead to the SIF in the Alaksan region (11 et al., in revision) and the 4.58 mism, and the simple sea of the simple sea of the Antarctic (Chen and Yuan, 2004). The Alaskan regional SIE is predicted to be 3.31 mism with an RMSC of 0.22 mism, which is only about 50% of the last year Alaska SIE. The September mean pan Antarctic SIE is predicted to be 18.63, at the same level of September 2018, with an RMSC of 0.42 mism.	modes and uses a Markov process to predict these principal components forward one month at a time. Be pan Arctic se all center forecast is calculated by summaring all cell areas where predicted sea ic econcentration exceeds 15%. Bias corrections have been applied to ice concentration predictions at grid M points as well as the total sea ice recent prediction. The prediction self-prediction self-predictions and point and provided to the concentration predictions and point and consideration between predictions and observations, and most mean-square errors (RMSE) in a Citake one-year out press which predictions are predictions by anomally persistence, damped anomaly persistence, and climatology (Yuan et al., 2016). For the three-month lead prediction of September sea ice concentrations, the model is superiors, the places sill promatyly	NSIDC NASA Team, https://nsidc.org/data/nsidc.0081, https://lobi.org/10.5087/URGD9WVVSUM.  IOAA NCEP/NCAR Reanalysis-1 atmospheric variables, rttp://indil.deloc.columba.edu/SDUNCES/NOAU/NCEP- NOAA NCCE RESST version3b sst. Extended reconstructed sea surface temperature data, /NCDC/ERSST/version3bl/sst/	
AWI Consortium (Kauker et al.)	Dynamic Model	Ocean-sea ice	e 4.89		0.17 Ensemble spread			OSI SAF EUMETSAT OSI-401b March and April 2019 http://osisaf.met.no/dosc/doisaf_cdop3_ss2_pum_te- conc_vtp6.pdf.)	CryoSat-2 from Alfred Wegener Institute of March and April 2019 (Hendricks, S. and Ricker, R. (2019): Product User Guide & Algorithm Specification: AWI CryoSat-2 Sea Lee Thickness(yees) 21.). Technical Report, Indi: 2013/ejec.736at72-bead-data-265-267. April 2013/ejec.736at72-bead-data-265-27. Introp. // ejec.awi.de/id/eprint/49542/).
NMEFC (Zhao, et al.)	Dynamic Model	Ocean-sea ice	5.11			This Sea Ice Outlook is a part of the official sea ice service for Chinese Arctic activities during this summer, targeting for icebreakers and commercial ships.	The sea ice prediction was carried out by National Marine Environmental Forecasting Center (China), using a occan-sea le coupled model, MTRgcm. The prediction was initialized on July 2, 2019 and run for 4 months forced by GTS operational forecast. The 9-month GTS forecast initialized on June 27, 28, 29 and 30 was used to obtain atmospheric forcing in this study. The initial condition came from a operational assimilation system by assimilating sea lice concentration and thickness daily and 10 radom initial conditions on July 1 were produced for this study. The sea (ce outlook was a mean value from 40 ensemble runs.	AMSR2	SMOS, CryoSat-2
Met Office (Blockley et al.)	Dynamic Model	Not Specified	5.2		Arctic: 4/- 0.7 million million sq km; and arctic: 1/- 0.8 million sq km; and arctic: 1/- 0.8 million sq km; mi	A dynamic model forecast made using the Met Office's seasonal forecasting system (GloSea) GloSea is a fully coupled Atmosphere-Decean-sea (e-Land (AOI) model that produces a small 2-member ensemble of 210-day forecasts each day. Forecasts initialised over a 21-day period ine use of agenter to resear & 2-f emember lagged ensemble or forecasts of September sea lec cover.	centred on the 1st July 2019 (2 per day; 42 in total) from an ocean and sea ice analysis (FOAM/NEMOVAR) [Blockley et al., 2014, Peterson et al., 2015] and an atmospheric analysis (MO- NWP/ADVar) [Rawlins et al., 2007] using observations from the previous day. Special Sensor Microwave	Sea ice concentration (as all variables) is initialised using the operational FOAM ocean-sea ice analysis. SSMS sea ice concentration is assimilated using the EUMETSAT OS-SAF (OS-400) Use to EUMETSAT OS-SAF (OS-400) using 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.
METNO SPARSE (Wang et al.)	Dynamic Model	Ocean-sea ice	5.896	5		This contribution is part of the Nonvegian Research Cood's profess SPARSE (Developing and advancing Cood's profess SPARSE (Developing and advancing Seasonal Predictability of Arctic Sea (cs.) Here we use the regional Coupled ocean-sea is emoded to make the prediction. We initialize the model with remote seesing sea ice concentration and thickness, and with remanalysis ocean stars from the EU Copernicus and efficient (SFAR) is used to drive the model. The model started prediction from 15 May 2015, and run writt 1 October 2019. We have saved the daily mean and mortafy means saic secretar for this period. The September sea ice extent is calculated from the mortafy neares as rise creater.	The Outlook is a straightforward result of the dynamic model prediction.	University of Bremen, AMSR2 sea ice concentration, https://seaice.uni-bremen.de/data/amsr2/	UCL Centre for Polar Observation and Modeling, Latest Sim Grid of 28-day hickness, http://www.cpom.cd.ac.uk/csop/sea ice.timl