August 2020 Sea Ice Outlook Key Statements															
Contributer	**Type**	**Model Name**	**Arctic Extent**	**Median**	**Standard Deviation**	**Range**	**Antarctic Extent**	**Alaska Extent**	**Maximum Alaska Extrent**	**Estimate Summary**	**Executive Summary**	**Method Summary**	**Sea Icea Concentration Data**	**Sea Ice Thickness Data**	**Processing Description**
GFDL/NOAA (Bushuk et al.)	Dynamic Model	GFDL-FLOR	2.26	2.25	0.49	1.36-3.06		0.05	3.8	These statistics are computed using our 12 member prediction ensemble.	Our August 1 prediction for the September-averaged Arctic sea-ice extent is 2.26 million square km, with an uncertainty range of 1.36-3.06 million square km. Our prediction is based on the GFDL-FLOR 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 12-member ensemble.	Our forecast is based on the GFDL Forecast-oriented Low Ocean Resolution (FLOR) model (Vecchi et al. 2014), which is a coupled atmosphere-land-ocean-sea ice model. The model is initialized from an Ensemble Kalman Filter coupled data assimilation system (ECDA; Zhang et al. 2007), which assimilates observational surface and subsurface ocean data and atmospheric reanalysis data. The system does not assimilate any sea ice concentration or thickness data. The FLOR atmospheric initial conditions are produced from an AMIP run forced by observed SST and sea ice. Historical radiative forcing is used prior to 2005 and the RCP4.5 scenario is used for predictions after 2005. For the predictions initialized after 2004, the aerosols are fixed at the RCP4.5 scenario year of 2004. The performance of this model in seasonal prediction of Arctic sea ice extent has been documented in Msadek et al. (2014), Bushuk et al. (2017), and Bushuk et al. (2018). For an evaluation of the model's September sea ice extent prediction skill from an August 1 initialization, see attached report.	No SIC data is explicitly used in our initialization procedure.	No SIT data is explicitly used in our initialization procedure.	These forecasts are bias corrected based on an additive correction using a suite of retrospective forecasts spanning 1980-2019.
ANSO IAP-LASG	Dynamic Model	CAS-FGOALS-f2 (Atmospheric component: FAMIL2 ; Ocean component: POP; Sea ice component: CICE4; Land component: CLM4) Horizontal resolutions: Approximately 1,î¨¬ºŒìV™,Çß Initial methods: A nudging scheme to assimilate wind components (U and V), Temperature (T) in atmosphere and potential temperature in ocean	3.8	3.6	0.2	3.4-4.2				The uncertainty was estimated by the ensemble member spread.	The prediction for the sea ice outlook Aug 2020 was carried out on China's Tianhe-2 supercomputer, with a dynamic model prediction system CAS FGOALS-f2 S2S V1.3 . The dynamic model prediction system, named FGOALS-f2 (ice-ocean-atmosphere-land model), provides a real-time predictions in the subseasonal-to-seasonal (S2S) timescales. FGOALS-f2 S2S system has been established in 2017 by R&D team of FGOALS-f2 from both LASG Institute of Atmospheric Physics Chinese Academy of Sciences and PAEKL Chengdu University of Information Technology. The FGOALS-f2 S2S prediction results are used in three major national operational prediction centers in China. Basing on the 4-month lead dynamic model prediction from Aug 11, 2020 the outlook predictions of Sea Ice Extent are 3.8 million square kilometers for pan-Arctic in September 2020.	FGOALS-f2 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 Jan 1980 to 11 Aug 2020, and 48 ensemble members are generated by a time-lag method. The predictions are available here for 12 months.	None	None	Model bias that is removed is calculated based on 2019 retrospective forecasts and corresponding observations.
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. PIOMAS hindcast ends on 7/31/2020 and forecast starts on 8/1/2020.	3.81								Driven by the NCEP CFS forecast atmospheric forcing, PIOMAS is used to predict the total September 2020 Arctic sea ice extent as well as ice thickness field and ice edge location, starting on August 1. The predicted September ice extent is 3.81+/- 0.40 million square kilometers. The predicted ice thickness field and ice edge locations for September 2020 are also presented	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. The CFS forecast ranges from hours to months: there are a total of 16 CFS ensemble forecast runs every day, of which four ensemble runs go out to 9 months, three runs go out to 1 season, and nine runs go out to 45 days (Saha et al., 2014). These ensemble runs all create 6-hourly forecast atmospheric data that are widely accessible in real time, thus ideal for forcing PIOMAS forecasts on daily to seasonal time scales. Here we used four CFS forecast ensemble members to drive the PIOMAS ice-ocean ensemble seasonal forecasts. Ensemble mean values from these four members are considered to be the prediction. 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 2020 using the CFS hindcast forcing data. We also assimilated CryoSat2 ice thickness available to April 2020. After the retrospective simulation (hindcast), four ensemble PIOMAS forecast runs were conducted using atmospheric forecast forcing from four CFS ensemble runs. Additional information about PIOMAS prediction can be found in Zhang et al. (2008).	Satellite sea ice concentration data (NASA team) for data assimilation in hindcast.	CryoSat2 sea ice thickness up to 4/2020 for data assimilation in hindcast.	
AWI Consortium	Dynamic Model	NAOSIM opt-parameter	3.82		0.17					Ensemble spread.	Scientific curiosity.	For the present outlook the coupled sea ice-ocean model NAOSIM has been forced with atmospheric surface data from January 1948 to August 8th 2020 (combination of NCEP-CFSR and NCEP-CFSv2). All ensemble model experiments have been started from the same initial conditions on August 8th 2020. The model setup has changed compared to the SIO in 2019 with respect to the resolution of the forecasting model (now about 25km) and the forecasting model'sparameters have been optimized with a generic algorithm (Sumata et al, 2019, https://doi.org/10.1175/MWR-D-18-0360.1). We used atmospheric forcing data from each of the years 2010 to 2019 for the ensemble prediction and thus obtain 10 different realizations of potential sea ice evolution for the summer of 2020. The use of an ensemble allows to estimate probabilities of sea-ice extent predictions for September 2020. A variational assimilation system around NAOSIM has been used to initialize the model using the Alfred WegenerInstitute'sCryoSat-2 ice thickness product and the OSI SAF ice concentration. In contrast to previous years no snow depth and sea surface temperature are assimilated due to the lack of these data streams. 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 to with respect to previous years but no bias correction is applied any more to the CryoSat-2 ice thickness - this is not necessary any more due to the optimization of the forecasting model.	OSI SAF EUMETSAT OSI-401b March and April 2020 (http://osisaf.met.no/docs/osisaf_cdop3_ss2_pum_ice conc_v1p6.pdf)	CryoSat-2 SIT from Alfred Wegener Institute of March and April 2020 (Hendricks, S. and Ricker, R. (2019): Product User Guide & Algorithm Specification: AWI CryoSat-2 Sea Ice Thickness (version 2.1), Technical Report, hdl:10013/epic.7dacf2fe-bead-4a1b-a266-c4fdd022877f,https://epic.awi.de/id/eprint/49542/).	None
Simmons, Charles	Statistical	Linear Regression of Northern Hemisphere Snow Area, Arctic Sea Ice Area, and Moana Loa CO2 Concentration using July monthly averages	3.823		0.316 million square kilometers					Standard Error of Linear Regression	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 ocean heat, we use measurements of CO2 concentrations.	This is a variant of Rob Dekker's prediction. Dekker performs a linear regression on northern hemisphere snow area, sea ice area, and sea ice extent. Predictions of more or less similar quality can be obtained by substituting Extent with another series that tends to increase or decrease over time, including the year. We choose to use the CO2 concentration as measured at Mauna Loa as being a particularly provocative measure. Additionally, Dekker performs the regression on a subset of available data, we use all the available data	We do not use SIC nor SIT. We use the following data sources: Average monthly northern hemisphere snow area: https://climate.rutgers.edu/snowcover/table_area.php?ui_set=1 Average monthly northern hemisphere sea ice area: ftp://sidads.colorado.edu/DATASETS/NOAA/G02135/seaice_analysis/Sea_Ice_Index_Monthly_Data_with_Statistics_G02135_v3.0.xlsx Average monthly CO2 concentration at Moana Loa: ftp://aftp.cmdl.noaa.gov/products/trends/co2/co2_mm_mlo.txt		None
McGill Team	Statistical		3.89							RMSE = 0.46 million km2. We compare hindcasts to the observed mean September sea ice extent for the 1993-2019 period.	Our research focuses on seasonal predictability of sea ice in the Arctic Ocean, using observations-based approaches. We are interested in the winter preconditioning effect on the pack ice before the summer melt. Specifically, we investigate how dynamic processes affect preconditioning, in other words, we ask how anomalies in the general circulation of sea ice will influence later conditions of the Arctic Ocean pack ice under a typical melt season. We investigate the skill of different sea ice predictors, including atmospheric forcing parameters that physically connect to wintertime sea ice dynamics. The dovekSIE method builds on the correlation between winter Fram Strait sea ice export and the following September minimum sea ice extent, presented in Williams et al., 2016. A positive anomaly of the winter Fram Strait sea ice export is associated with enhanced circulation of ice through the Transpolar Drift Stream and positive anomalies of coastal divergence of sea ice along the Eurasian coastlines. Increased coastal divergence late in the winter causes anomalies of younger and thinner ice in the peripheral seas, which is more vulnerable to melting in the summer. The dovekSIE forecasts are generated using the sea level pressure difference between Greenland and Svalbard as a proxy for area of ice exported through Fram Strait. Sea ice tends to flow parallel to isobars and the pressure difference across Fram Strait correlates with sea ice export (r=0.44). Sea level pressure fields are available in near-real-time and therefore enable the continuous update of dovekSIE forecasts during winter via the web app. We are supporting the activities of the Sea Ice Prediction Network with great enthusiasm. This is our fourth contribution to the Sea Ice Outlook.	regional SIE is 0.90 (correlation using cross-validated experiments) with RMSE of 0.22 million	Sea ice concentration is not used as an initial condition (such as in a dynamical model). However, we use sea ice extent from the NSIDC Sea Ice Index V3 to fit our statistical model. https://doi.org/10.7265/N5K072F8		
NSIDC (Meier)	Statistical		3.93		0.36		18.09				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 2017 are used, as well as averages over 1981-2010 and 2007-2019. The 2007-2019 average daily rates are used to estimate the official submitted estimate. The predicted September average extent for 2020 is 3.93 (+/-0.36) million square kilometers, which is a substantial decrease from the July estimate of 4.44 million square kilometers. The minimum daily extent is predicted to be 3.81 (+/-0.37) million square kilometers, a decrease from Julys 4.32 million square kilometers and occurs on 14 September. The range of estimates has decreased due to the shorter remainder of the melt season. Based on the last 15 years, two of the projections (2008 and 2012) yield an extent lower than the current record low September extent of 3.57 million sq km in 2012. Thus, there is a roughly a 2 in 15 (13%) of a new record September extent in the ArcticUsing the same method, the predicted Antarctic average extent for September 2020 is 18.09 (+/-0.30) million square kilometers. The maximum daily extent is predicted to be 18.20 (+/-0.32) million square kilometers and occurs on 30 September.	This method applies daily ice loss rates to extrapolate from the start date (1 August) through the end of September. Projected September daily extents are averaged to calculate the projected September average extent. Individual years from 2007 to 2019 are used, as well as averages over 1981-2010 and 2007-2019. The 2007-2019 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.	Maslanik, J. and J. Stroeve. 1999, updated daily. Near-Real-Time DMSP SSMIS Daily Polar Gridded Sea Ice Concentrations, Version 1. Boulder, Colorado USA. NASA National Snow and Ice Data Center Distributed Active Archive Center. doi: https://doi.org/10.5067/U8C09DWVX9LM. Fetterer, F., K. Knowles, W. 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.		Standard deviation of extent projections for years 2007 through 2019.

Cawley, Gavin	Statistical	Gaussian Process Regression	4.0791	4.0791		2.9757 - 5.1825				Bayesian posterior predictive uncertainty from Gaussian Process	September mean pan-Arctic SIE is predicted to be 4.59 million square kilometers (mskm) with	one month at a time. The pan Arctic sea ice extent forecast is calculated by summarizing all cell	Only uses previous mothly September sea ice extent data.		
RASM (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	4.134	4.159	0.148	3.824-4.405		0.508	3.927	The uncertainty of pan-Arctic September sea ice extent was estimated from the 31-member ensemble.	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 uses CFSR/CFSv2 reanalysis output for RASM-WRF lateral boundary conditions and for nudging winds and temperature starting above 500 mb. This model initial condition for ensemble forecast was derived from a hindcast, forced with CFSR/CFSv2 reanalysis for September 1979 through July 2020. 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.	As explained in the "Executive summary", RASM is used for dynamic downscaling of the global NOAA/NCEP CFSv2 7-month forecasts. The initial conditions for the July Sea Ice Outlook were derived from the RASM 1979-2020 hindcast and are physically and internally consistent across all the model components. Neither data assimilation nor bias correction was used. Each of the 31 ensemble members used one of the CFSv2 forcing streams (https://www.ncei.noaa.gov/data/climate-forecast-system/access/operational-9-month-forecast/) initialized at 00:00 between July 1st and July 31st to force RASM 6-month forward integrations starting at 00:00 on August 1st, 2020.	Self-generated from the fully coupled RASM hindcast simulation dynamically downscaling NCEP CFSR/CFSv2 reanalysis for 1979-2020.	As stated above in 7a).	Sea ice grid cells with concentration <=15% and thickness <= 20 cm were not included in the estimates of sea ice extent.
FIO-ESM (Shu et al.)	Dynamic Model	FIO-ESM1.0 Atmosphere CAM3 1992-2020 integration Ocean POP2 DA ŒìVáVú,ÌúV§,Ìú¬® EAKF DA system Ice CICE4 1992-2020 integration Wave MASNUM-wave model 1992-2020 integration	4.18			3.94-4.42					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 2020 is 4.18 (+/-0.24) million square kilometers. 4.18 and 0.24 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-ESM1.0) but with ocean data assimilation. The data assimilation method is Ensemble Adjustment Kalman Filter (EAKF). The data of SST (sea surface temperature) and SLA (sea level anomaly) from 1 January 1992 to 1 August 2020 are assimilated into FIO-ESM1.0 model to get the initial condition for the prediction of the Arctic Sea Ice. There is no sea ice data assimilation.	None.	None.	
Climate Prediction Center	Dynamic Model	Whole Model: CFSm5 Atmospheric component: NCEP GFS Oceanic component: GFDL MOM5	4.19	4.2	0.11	3.97-4.39		0.7		The uncertainty estimate is calculated from the 20-member ensemble.	This contribution is from a 20-member ensemble forecast from the Climate Prediction Center Experimental sea ice forecast system (CFSm5). Model bias that is removed is calculated based on 2007-2019 retrospective forecasts and corresponding observations.	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 2007-2019 retrospective forecasts and corresponding observations.	Both sea ice concentration and sea ice thickness are initialized from the CPC sea ice initialization system (CSIS). The CSIS analysis is produced with GFDL MOM5 which uses surface fields from CFSR and assimilates satellite sea ice concentration retrieval from NSIDC NASA Team	Both sea ice concentration and sea ice thickness are initialized from the CPC sea ice initialization system (CSIS). The CSIS analysis is produced with GFDL MOM5 which uses surface fields from CFSR and assimilates satellite sea ice concentration retrieval from NSIDC NASA Team	Twenty forecast members are produced. Model bias that is removed is calculated based on 2007-2019 retrospective forecasts.
Navy ESPC (Metzger and Barton)	Dynamic Model	Navy Earth System Prediction Capability (ESPC) NAVy Global Environmental Model (NAVGEM) CV2.0 HYbrid Coordinate Ocean Model (HYCOM) V2.2.99DHi Community Ice CodE (CICE) V4.0 All model components are fully coupled and the system is initialized from pre-operational ensemble Navy ESPC run by Fleet Numerical Meteorology and Oceanography Center (FNMOC) at the Navy DoD Supercomputing Resource Center (DSRC).	4.2	4.2 Mkm2		3.7 to 4.6 Mkm2	22	0.76	3.97	The uncertainty estimate is the range of the 16 member ensemble.	The projected Arctic 2020 September mean sea ice extent from the Navy Earth System Prediction Capability (ESPC) is 4.2 million km2. This forecast is the average of a 16 member ensemble using initial conditions on 1 July 2020 from a pre-operational Navy ESPC ensemble with perturbed observations. The range of the ensemble is 3.7 to 4.6 million km2. The projected Antarctic 2020 September mean sea ice extent is 22.0 million km2 with an ensemble range from 21.2 to 22.6 million km2.	We performed a 16 member ensemble forecast with Navy ESPC using initial conditions on 1 July 2020 from the pre-operational system using perturbed observations and run by FNMOC. The pre-operational cycling system assimilates atmospheric observations using the Naval Research Laboratory Atmospheric Variational Data Assimilation System (NAVDAS-AR) (Xu et al., 2005) and the ocean/sea ice assimilate observations using Navy Coupled Ocean Data Assimilation (NCODA) (Cummings, 2005). CICE assimilates passive microwave satellite sea ice concentration observations such as SSMI/S and AMSR2, but does not assimilate sea ice thickness. There was no bias correction performed on the results.	We performed a 16 member ensemble forecast with Navy ESPC using initial conditions on 1 July 2020 from the pre-operational system using perturbed observations and run by FNMOC. SIC initials conditions came from CICE.	We performed a 16 member ensemble forecast with Navy ESPC using initial conditions on 1 July 2020 from the pre-operational system using perturbed observations and run by FNMOC. SIT initials conditions came from CICE.	The Sea Ice Probability (SIP) and Ice-Free Day (IFD) were computed from the Navy ESPC ice output forwarded to the Data Portal.
PolArctic	Other	Model Name: ICE3	4.21								This is PolArctic's second year submitting to the Sea Ice Outlook. Our September extent prediction is 4.21 million square kilometers. Our efforts are to investigate the usefulness of Artificial Intelligence and Machine Learning (AI/ML) as a predictive tool for Arctic sea ice extent. Hidden and non-linear relationships can be exposed through the use of AI/ML when high quality data is available. NSIDC's daily record of sea ice extent creates the perfect test bed to leverage and assess the power of AI/ML.	PolArctic's September SIO extent was generated using our Artificial Intelligence algorithm, and trained with historical NSIDC daily ice extent data. Our initial modeling efforts are to generate high quality seasonal forecasts of daily, spatial and temporal sea ice extents. To calculate our September extent outlook, daily results in September 2019 from our model are averaged.	NOAA/NSIDC, Sea Ice Index, Version 3. https://doi.org/10.7265/N5K072F8.		
IceNet1 (Andersson et al.)	Other		4.21		0.47	3.74-4.68				This is the standard deviation of the September SIE error when initialised in August, computed over the 6 held-out validation years from 2012-17	IceNet is an interdisciplinary data science project aimed at improving Arctic sea ice forecasts and understanding, with a team of both sea ice and computer science experts. IceNet is currently at version 1, and the model is called IceNet1. The design of IceNet1 is inspired by AIŒìVáVñs ability to automatically learn complex relationships between variables from large amounts of raw data. In particular, IceNet1 takes the form of a U-Net architecture - a model that receives image inputs and produces image outputs - which has achieved widespread success in medical imaging segmentation problems. IceNet1 is trained to predict the future 12 months of spatial pan-Arctic sea ice classification maps based on the past 12 months of SIC, as well as the past few months of other climatological variables (such as atmosphere and ocean temperature anomalies, sea level pressure, and surface wind). IceNet1 was presented at a SIPN2 Webinar, available from this link at 35.07: https://youtu.be/l-R8PNL5Hdo?t=2107. Note that at the time of writing IceNet is under continual development and results from a research project funded by the Alan Turing InstituteŒìVáVñs Data Science for Science programme.	At each 25x25 km ocean grid cell in the Arctic and at each forecast leadtime from 1 to 12 months ahead, IceNet1 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 sea ice probability (SIP) for this SIO submission, we sum the probability of the two ice classes to obtain the probability that SIC > 15%. To compute the SIE, we sum the area of grid cells whose SIP > 0.5. IceNet learns to predict sea ice through gradient descent optimisation with over 10 million free parameters. This process is called training, and attempts to minimise the error between predictions and reality over a training dataset. To account for the limited amount of observational months available, we leverage >10,000 months of climate model data by pre-training IceNet1 on historical and future scenario runs from the MRI-ESM2.0 climate model, a concept known as transfer learning. After pre-training, we fine-tune IceNet1ŒìVáVñs parameters on the observational data record from 1979-2011. We use NSIDC NASA Team for the SIC data and ERA5 reanalysis for the climatological data. The observational data period from 2012-2017 is held out and used to assess IceNet1ŒìVáVñs hindcast predictive skill during the development process. IceNet1 contains over 43 million trainable parameters and comprises an ensemble of four neural networks trained with different parameter initialisations. The ensemble member predictions are averaged to produce the final prediction.	NSIDC NASA Team, https://nsidc.org/data/nsidc-0081, https://doi.org/10.5067/U8C09DWVX9LM.		
APPLICATE (UCLouvain)	Dynamic Model	NEMO3.6 (ocean) LIM3 (sea-ice) JRA-55 (atmospheric forcing) Initialized from 1958 01 01 - 2019 12 31 forced simulation	4.23	4.23 million km sq	0.67 million km sq	2.73 million km sq	20.77	0.47	5.39	The uncertainty is given as the range between minimum and maximum extents in the ensemble.	Our estimate is based on results from ensemble runs with the global ocean-sea ice coupled model NEMO3.6-LIM3. Each member is initialized from a reference run on Jan 1, 2020, then forced with the JRA-55 atmospheric reanalysis from one year between 2009 and 2019 except 2015, which caused the model to crash. Our final estimate 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 ensemble runs with the global ocean-sea ice coupled model NEMO3.6-LIM3. The ensemble members are expected to sample the atmospheric variability that may prevail this summer. In practice, the model is forced with JRA-55 atmospheric reanalysis data from 1948 to Dec 31, 2019. No data are assimilated during this simulation. Ten ensemble members are then started from the obtained model state, each using atmospheric forcing from one year between 2009 and 2019 (forcing year 2015 was not used as it caused the model to crash). This choice of 10 members forced by 10 forcings from previous years is a compromise between a sufficiently large ensemble and the rapidly changing Arctic atmospheric conditions in recent decades. The estimate given above corresponds to the ensemble median monthly September extent. No bias-correction is applied.	Initial sea ice concentrations come from a model free run on Jan 1, 2020	Initial sea ice thicknesses come from a model free run on Jan 1, 2020	None.
Lamont (Yuan and Li)	Statistical	Lamont Linear Markov Model for seasonal Arctic sea ice prediction	4.24				18.65	0.64		The uncertainty of SIC prediction was measured by root-mean-square error (RMSE). They were estimated based on 34 years cross-val	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 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. These anomalies are relative to the 1979-2012 climatology. The September mean pan-Arctic SIE is predicted to be 4.24 million square kilometers (mskm) with an RMSE of 0.33 mskm, at the two-month lead. It is slightly lower than the September SIE in 2019. The Alaskan regional SIE is predicted to be 0.64 mskm with an RMSE of 0.20 mskm. A similar statistical models was also developed to predict the SIE in the Antarctic (Chen and Yuan, 2004). The September mean pan Antarctic SIE is predicted to be 18.65, with an RMSE of 0.66 mskm.	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 2012. 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%. The predictive skill of the model was evaluated by anomaly correlation between predictions and observations, and root-mean-square errors (RMSE) in a (take one-year out) cross-validated fashion (Yuan et al, 2016). For the two-month lead prediction of September sea ice concentrations, the model has the higher skill (anomaly correlation) and lower RMSE in the Chukchi Sea and Beaufort Sea than in other regions (figure 4). The skill of the two-month lead prediction of the pan Arctic sea ice extent in September is 0.94 with an RMSE of 0.33 million square kilometers. The Alaskan regional SIE prediction is produced by a regional linear Markov model developed by using SIC, SST, SAT, and in a rotated-EOF space. Following the NSIDC regional mask, the Alaska SIE forecast is calculated from predicted SIC. The skill of the regional SIE is 0.92 with RMSE of 0.20 million square kilometers. A similar model is used for Antarctic SIE forecast (Chen and Yuan 2004).	Sea ice concentration: NSIDC NASA Team, https://nsidc.org/data/nsidc-0081, https://doi.org/10.5067/U8C09DWVX9LM.		A constant bias correction was applied to Arctic SIC prediction at each grid point.Then a constant SIE bias was applied too.
NSIDC (Horvath et al.)	Statistical		4.3								This statistical model computes the probability that sea ice will be present (concentration above15%) 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 SetID:G02135), all other variables are from NASA's MERRA2 dataset	Yearly data from 1980 through the present are used in a Bayesian logistic regression to predict the probability that sea ice concentration will be above 15%. To estimate 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 (DataSet ID:G02135), all other variables are from NASA's MERRA2 dataset	NSIDC's Sea Ice Index V3 (Data Set ID:G02135)		
METNO SPARSE (Wang et al.)	Dynamic Model	METROMS, a coupled model based on ROMS and CICE. The initial field is from CMEMS NEMO analysis on 5 August	4.3								We use initial ocean and sea ice data from the analysis of NEMO operational result, use the forcing data from the SEAS5 atmospheric seasonal forecast, and the initial ice concentration is assimilated with amsr2 from University of Bremen. With these configuration, we use the METROMS model to make the prediction.	The method is a dynamic coupled ocean-sea ice model. The initial field is from NEMO opertional data, with assimilation of AMSR2 ice concentration. The atmospheric forcing is from the ECMWF SEAS5 product.	AMSR2 ice concentration from University of Bremen.	ice thickness is from NEMO analysis on 5 August 2020.	

Kondrashov, Dmitri (UCLA)	Statistical		4.3		0.12 million Km2			0.57		This uncertainty corresponds to standard deviation of stochastic ensemble spread.	This statistical model forecast is based on nonlinear stochastic modeling techniques applied to the regional Arctic Sea Ice Extent dataset.	Nonlinear inverse stochastic modeling techniques have been applied to the regional Arctic Sea Ice Extent (SIE) from Sea Ice Index Version 3 dataset. 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 (August 2020) by ensemble of stochastic noise realizations to provide probabilistic regional Arctic forecasts in September, as well as pan-Arctic ones. References: 1. Kondrashov, D., M. D. Chekroun, and M. Ghil, 2018: Data-adaptive harmonic decomposition and prediction of Arctic sea ice extent, Dynamics and Statistics of the Climate System, 3(1), doi:10.1093/climsys/dzy001. 2. Kondrashov, D., M.D. Chekroun, and M. Ghil, 2015: Data-driven non-Markovian closure models, Physica D, 297, 33-55, doi:10.1016/j.physd.2014.12.005.			
CPOM UCL (Gregory et al.)	Statistical		4.3		Pan-Arctic: 0.3, Beaufort: 0.09, Chukchi: 0.07			0.384		Forecasts are Gaussian distributions. Forecast represents the mean, and uncertainties are given by the standard deviation	This statistical model computes a forecast of pan-Arctic September sea ice extent . Monthly averaged July sea ice concentration and sea surface temperature fields between 1979 and 2020 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 Septemver extent. The model predicts a pan-Arctic extent of 4.1 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 2020 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 alforithm (see Gregory et al, 2020). Lonks 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.	NSIDC NASA Team Sea Ice Concentrations: 1979 - 1987: Nimbus-7 SMMR 1987 - 2007: DMSP F-8, F-11 SSM/Is. 2007-2018 DMSP F-18 SSM/I 2018 - 2020: Near-real time SIC		
CPOM	Statistical		4.3		0.5					Mean forecast error based on forecasts for the years 1984 to 2019.	We predict the September ice extent 2020 to be 3.8 (3.3-4.3) million km2. This is the lowest prediction we have made based on spring melt pond fraction. The likehood is around 30% that this September extent will be a new minimum record. In our model simulation since 1979, May 2020 has the highest mean melt pond fraction for May including some unprecedented melt pond formation in the Central Arctic during 15-18 May when air temperature exceeded 0deg C.	This is a statistical prediction based on the correlation between the ice area covered by melt-ponds in May and ice extent in September. The melt pond area is derived from a simulation with the sea ice model CICE in which we incorporated a physically based melt-pond model1. See our publication in Nature Climate Change http://www.nature.com/nclimate/journal/v4/n5/full/nclimate2203.html for details2.References:1. Flocco, D., Schroeder, D., Feltham, D. L. & Hunke, E. C., 2012: Impact of melt ponds on Arctic sea ice simulations from 1990 to 2007. J. Geophys. Res. 117, C09032.2. Schroeder D., D. L. Feltham, D. Flocco, M. Tsamados, 2014: September Arctic sea-ice minimum predicted by spring melt-pond fraction. Nature Clim. Change 4, 353-357, DOI: 10.1038/NCLIMATE2203.	None.	None.	See references in Section 6.
NCAR/CU-Boulder	Heuristic		4.3	4.37	4.89	3.14				The uncertainty estimate is based on the scatter in entries in our informal pool.	An informal pool of 31 climate scientists in early June 2020 estimates that the September 2020 ice extent will be 4.30 million sq. km. (stdev. 0.34, min. 3.14, max. 4.89). Since its inception in 2008, the NCAR/CU sea 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 appendix of Stroeve et al. 2014 in GRL doi:10.1002/2014GL059388 ; Witness the Arctic article by Hamilton et al. 2014 http://www.arcus.org/witness-the-arctic/2014/2/article/21066). We think our informal pool provides a useful benchmark and reality check for Sea Ice Prediction efforts based on more sophisticated physical models and statistical techniques.	An informal pool of 31 climate scientists in early June 2020 estimates that the September 2020 ice extent will be 4.30 million sq. km. (stdev. 0.34, min. 3.14, max. 4.89). Guesses were collected by sending an e-mail out to the scientists and tempting them with local bragging rights and with local ice cream.			
UTokyo (Kimura et al.)	Statistical		4.32								Monthly mean ice extent in September will be about 4.32 million square kilometers. Our estimate is based on a statistical way using data from satellite microwave sensor. We used the ice concentration on July 15 and ice age of the day. Predicted ice concentration map from August 1 to September 30 is available in our website: http://ccsr.aori.u-tokyo.ac.jp/~kimura_n/arctic/2020-3e.html	We predicted the Arctic sea-ice cover from coming August 1 to September 30, using the data from satellite microwave sensors, AMSR-E (2002/03-2010/11) and AMSR2 (2012/13-2019/20). For the prediction, we used the ice concentration on July 15 and ice age of the day estimated by the backward tracking of sea ice up to 730 days. Predicted ice concentration map from August 1 to September 30 is available in our website: http://ccsr.aori.u-tokyo.ac.jp/~kimura_n/arctic/2020-3e.html	Sea ice concentration on July 15 distributed by ADS/NIPR (https://ads.nipr.ac.jp).	No ice thickness data	
Metservice (Yizhe Zhan)	Statistical	The June TOA-RSR model is a statistical model based on the strong correlation between the June top-of-atmosphere (TOA) reflected solar radiation (RSR) and the September Sea Ice Extent (SIE) [Zhan and Davies, 2017, JGR]. To achieve a timely pan-Arctic September SIE prediction, we use Multi-angle Imaging SpectroRadiometer (MISR) first-look TOA albedo product (MISR_AM1_CGAL_1_DEG_FIRSTLOOK_JUN_yyyy_F06_0024). The relationship between the detrended June TOA-RSR anomaly and the detrended September sea ice extent anomaly is calculated from the MISR_AM1_CGAL_JUN_yyyy_F06_0024 product and NSIDC G02135 (Version 3.0) in the previous years (2002~2019 in this case).	4.33			+/- 0.3 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 detrended June top-of-atmosphere (TOA) reflected solar radiation (RSR) and September Sea Ice Extent (SIE) anomalies, as proposed by Zhan and Davies [2017]. This method is telling because the main contributor of TOA RSR anomaly in June is from the change of underlying surfaces and the sea ice state in early summer (June) largely determines the total absorbed shortwave solar radiation during the whole melt season.	Our contribution is formulated by adding the main contribution part from the September SIE trend (2002~2019) with the anomalous part from the June TOA-RSR (2020) anomaly. The detailed description of the calculation is as follows. The detrended pan-Arctic June RSR anomaly (2020) is 1.24 W/m2. The corresponding September SIE anomaly is 0.10 (1.24 * 0.0765) million km2. The trending anomaly of September SIE is -0.08 million km2 per year. The 2020 September SIE (from the trend) is 4.23 million km2. The predicted September SIE of 2020 is 4.33 (4.23 + 0.1) million km2. Note that the coefficient of 0.0765 is estimated from the detrended anomalies of June TOA-RSR and September SIE between 2002 and 2019.	We do not use SIC dataset. Instead, we use sea ice index (Version 3.0) product (NSIDC, NASA Team, https://nsidc.org/data/G02135, doi:https://doi.org/10.7265/N5K072F8).	Not used.	
ARCUS Team (Wiggins et al.)	Heuristic		4.34	4.34		Range: 3.79 - 4.86					The ARCUS team submission is the median of the September monthly average mean sea ice extent values contributed by 10 ARCUS team members.	ARCUS staff and board members were invited to provide an informal guess of the 2020 September minimum sea ice extent, defined as the September monthly average. Ten individuals participated.			
Sun, Nico	Statistical	Sun_SIPN_forecast_v2.2020.06	4.36	4.36		4.13 - 4.50		0.491	4		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. The mean forecast uses the 2007-2019 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 0.3Stdv 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. The 2020 model includes an extra cooling/heating layer to simulate sea ice drift. In re-forecasts it eliminated the persistent underprediction of sea ice in the Eastern Beaufort sea, the Canadian Archipelago and Eastern Greenland Sea during the late melt season.	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) For 2019 the model was upgraded with a bottom-melt model and a radiation of thermal energy back to space. This allowed the model to forecast the initial refreezing period during late September.	NSIDC NASA Team, https://nsidc.org/data/nsidc-0081, https://doi.org/10.5067/U8C09DWVX9LM. Initial SIC 1st June 2019. The model used observed SIC until 11th August 2020 to calculate melt.	AMSR2 Sea Ice Volume model (v1.5), 31st May 2020, developed by Nico Sun https://cryospherecomputing.tk/SIT) The average thickness of this model was used to initialise thickness on the NSIDC SIC field on the 1st June.	
NSIDC Hivemind	Heuristic		4.36		0.26 million sq km					Uncertainty is based on the standard deviation of the 18 guesses.	The approach is heuristic expert elicitation method based on entries to an informal NSIDC sea ice contest. Interested employees submitted their guesses and the ensemble average of all guesses. There were 18 total entries, with an average guess of 4.26 million sq km for the September average.	The approach is heuristic expert elicitation method based on entries to an informal NSIDC sea ice contest.	Guesses were based on the NASA Team algorithm extents from the NSIDC Sea Ice Index, Version 3 (http://nsidc.org/data/seaice_index/).		
Goulet Coulombe and Gobel	Statistical	VARCTIC	4.37	4.37		percentile 5: 3.76, percentile 95: 5.00				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 8-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 December 2019. The variables and their data-source can be found in our original paper. Due to the observable time-series data for Thickness ending in December 2019, we could not feed our model with any further observations from 2020, which would have allowed us to further enhance our forecast. That is, we forecast September 2020 starting from December 2019 using a 9-months ahead recursive forecast.	-	-	

Met Office (Blockley et al.)	Dynamic Model	Model: HadGEM3 [Hewitt et al., 2011], Global Coupled Model 2.0 [Williams et al., 2015] in use within the GloSea5 seasonal prediction system [MacLachlan et al., 2015]. Sea ice component: CICE4.1 [Hunke and Lipscomb, 2010] model using Global Sea Ice 6.0 configuration [Rae et al., 2015]. 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, 2008] ocean model using Global Ocean 5.0 configuration [Megann et al., 2014]. 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 6.0 configuration [Walters et al., 2017]. 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 6.0 configuration [Walters et al., 2017]. Initialised using soil temperature and snow over land from atmospheric 4D-Var analysis [Rawlins et al., 2007]. Soil moisture is model climatology. Coupling: Ocean and sea ice are hard coupled. Atmosphere and land are hard coupled. Ocean/ice and atmosphere/land are coupled using the OASIS3 coupled [Valcke, 2006].	4.4		Arctic: +/- 0.25 million sq km; Antarctic: +/- 0.3 million sq km	Arctic: +/- 0.5 million sq km; Antarctic: +/- 0.6 million sq km	18.4			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, centred on the 1st of the month, are used together to create a 42-member lagged ensemble or forecasts of September sea ice cover.	Ensemble coupled model seasonal forecast from the GloSea5 seasonal prediction system [MacLachlan et al., 2015], using the Global Coupled 2 (GC2) version [Williams et al., 2015] of the HadGEM3 coupled model [Hewitt et al., 2011]. Forecast compiled together from forecasts initialized between 22nd July and 11th 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 calculated from hindcast evaluation over 1993-2016. Arctic: +0.9 million sq km; Antarctic: -0.3 million sq km
Sanwa school (Lihoshi et al.)	Heuristic	A dynamic model is not used.	4.4								Monthly mean ice extent in September will be about 4.40 million square kilometers. We estimated the minimum ice area through discussion among 20 students based on the ice map from 2004 to 2019.	We first estimated total ice area for September of 2004,2006,2008,2010,2012,2014,2016,2018 and 2019 from the ice concentration map, by approximating the ice cover with triangle or trapezoid and so on. 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.	
ECCC-CanSIPSv2	Dynamic Model	CanSIPSv2: CanCM4i & GEM-NEMO (https://doi.org/10.1175/WAF-D-19-0259.1)CanCM4i; Component Name/Description InitializationAtmosphere CanAM4 CCMEP GDPSOcean CanOM4 CCMEP GIOPSSea Ice Cavitating Fluid CCMEP GDPS SIC, SMv3 SITGEM-NEMOComponent Name/Description InitializationAtmosphere GEM v4.8-LTS.16 CCMEP GEPSOcean NEMO v3.1 CCMEP GIOPSSea Ice CICE4.0 CCMEP GIOPS SIC/SIT	4.41	4.37	0.22	min=3.96, max=4.68				The uncertainty values were calculated from the bias-corrected SIE across the 20 ensemble members (see section 6).	Our outlook for bias-corrected Arctic sea ice extent (SIE), bias-corrected sea ice concentration (SIC), calibrated sea ice probability (SIP), and bias-corrected ice free dates (IFD) and ice advance dates (IAD) was produced using the Canadian Seasonal to Interannual Prediction System version 2 (CanSIPSv2). CanSIPSv2 is now the operational seasonal forecasting system for Environment and Climate Change Canada.	CanSIPv2 combines ensemble forecasts from two models, CanCM4i and GEM-NEMO, with a total of 20 ensemble members (10 from each model). Our pan-Arctic SIE estimate was formulated by calculating (for each ensemble member) the SIE anomaly relative to a piecewise linear trend fitted to the respective model's ensemble-mean SIE time series over 1980-2019. These anomalies were then added to the fitted piecewise linear trend for the NSIDC sea ice index SIE time series, and then averaged over all 20 ensemble members to yield a total SIE of 4.41 million square kilometers. The piecewise linear fit, including the breakpoint year, was found using non-linear least squares. Sea ice probability maps were produced by first calibrating the ensemble SIC forecasts for each respective model using trend-adjusted quantile mapping (TAQM), computing the probability for SIC>15%, and then averaging those probabilities across both models. Our outlook for the 80% SIC contour was prepared by first bias correcting the full ensemble SIC fields for each model separately using a 2011-2019 baseline, and then averaging the ensemble mean SIC across both models. The resultant SIC field was then converted to 0's and 1's corresponding to which grid cells have SIC<80% and which have SIC>=80%, respectively. Similarly, our IFD/IAD forecasts have been bias corrected based on the 2011-2019 mean IFD/IAD.	CanCM4i: CCMEP GDPS analysis (assimilates SSM/I and SSMIS satellite & CIS ice charts) (https://doi.org/10.1175/MWR-D-14-00354.1) GEM-NEMO: CCMEP GIOPS analysis (assimilates SSM/I and SSMIS satellite & CIS ice charts) (https://doi.org/10.1002/qj.2555)	CanCM4i: SMv3 statistical model (SIT trends from PIOMAS + anomalies proportional to observed SIC anomalies; https://doi.org/10.1175/JCLI-D-16-0437.1) GEM-NEMO: CCMEP GIOPS analysis (~constrained by SIC projection onto each thickness category; https://doi.org/10.1002/qj.2555)	This is described in section 6.
EMC/NCEP (Wu, et al.)	Dynamic Model	a) Model Name: NCEP CFSv2 b)ComponentNameInitialization AtmosphereNCEP GFSNCEP CDAS OceanGFDL MOM4 NCEP GODAS ICE Modified GFDL SISSIC nudging c) 368 ensemble members (May 1-July 31 2020, each day from all 4 cycles)	4.45				20.01				The projected Arctic minimum sea ice extent from the NCEP CFSv2 model May-July initial conditions (ICs) using 368-member ensemble forecast (4 cycles each day from May 1 to July 31) is 4.45 million square kilometers with a standard deviation of 0.18 million square kilometers. The corresponding number for the Antarctic (maximum) is 20.01 million square kilometers with a standard deviation of 1.03 million square kilometers.	We used the NCEP CFSv2 model with 368-case of May-July 2020 initial conditions (4 cycles each day from May 1 to July 31) and model forecast.	NCEP Sea Ice Concentration Analysis for the CFSv2 (May 1 to July 31, 2020)	NCEP CFSv2 model guess (May 1 to July 31, 2020)	
UColorado/NSIDC (Slater-Barrett)	Statistical	Slater Probabilistic Ice Extent Model	4.48								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 60 days. Therefore we consider the mean September ice extent forecast for the August sea ice outlook to have 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 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.	NSIDC daily sea ice concentrations NSIDC-0051	None	
APPLICATE Benchmark	Statistical		4.58	4.58 million km sq		3.90-5.26 million km sq (95% confidence interval)	18.35				We forecast that the September 2020 monthly mean Arctic sea ice extent will be between 3.90 and 5.26 million km sq (95% confidence interval), with 4.58 million km sq as our best estimate. We estimate that the 2012 minimum is exceptionally unlikely (0.2% chance) to be broken (medium confidence statement).	The APPLICATE-benchmark outlook is a simple statistical forecast based exclusively on the knowledge of past daily Arctic sea ice extent. It is produced in three steps: Step 1: Sea ice extent is forecasted for each day between the initial time (August 11st, 2020) and December 31st, 2020, as the August 11 sea ice extent anomaly (calculated with respect to the quadratic trend line computed over 1979-2019) added to the relevant day background estimate. The background estimate itself is calculated as the 1979-2019 quadratic trend of extent for that day extrapolated to 2020. A weight is applied to the anomaly term, equal to the correlation between the relevant day and August 11 anomalies estimated over 1979-2019 so that more weight is put on the anomaly term when the autocorrelation of the time series is high, and more weight is put on the background term when the autocorrelation tends to zero. Step 2: The September mean of daily forecasts is then estimated and is used to produce an initial 2020 forecast. Step 3: The 2020 forecast is finally recalibrated by linearly regressing the 1991-2019 forecasts onto the verification data. A 95% confidence interval is calculated around the recalibrated value and provided as an uncertainty estimate. The code used to produce this APPLICATE-benchmark is publicly available, see			
NMEFC of China (Li and Li)	Statistical		4.59								the pan-Arctic region. These anomalies are relative to the 1979-2012 climatology. The	first 11 mEOF modes and uses a Markov process to predict these principal components forward	Sea Ice Index - Daily sea ice concentration(NASA Team) and monthly sea ice extent from National Snow and Ice Data Center.		
NMEFC (Jiechen Zhao)	Dynamic Model	MITgcm	4.6								This Sea Ice Outlook is a part of the official sea ice service for Chinese Arctic activities, targeting for icebreakers and commerical ships. This prediciton was carried out by National Marine Environmental Forecasting Center (China), using a ocean-sea ice coupled model, MITgcm.	September sea ice concentrations, the model has the higher skill (anomaly correlation) and	AMSR2	SMOS, CryoSat-2	
UPenn Group (Diebold et al.)	Statistical		4.813	4.813	0.26	[4.293, 5.333] (approximate 95% confidence interval)				estimated stochastic model	The UPenn-Diebold Predictive Modeling Team (``UPenn group") is composed of econometricians 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 the group. 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, the UPenn group is keenly interested in predictive modeling of Arctic sea ice, particularly September 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 our in-sample forecast errors (residuals) are approximately Gaussian, which we exploit in making our out-of-sample forecast for September. The predictive density is Gaussian, with mean 4.813 million square kilometers and standard deviation 0.260 million square kilometers. (By symmetry of the normal distribution, the mean and median coincide.) The approximate 95\% interval that we report [4.293, 5.333] is the mean plus or minus 2 standard deviations.			

NASA GMAO	Dynamic Model	Atmosphere: Goddard Earth Observing System model (GEOS), version Icarus3.3p2 (modified for coupled model); GMAO Forward Processing for Instrument Teams (FPIT). Ocean: GFDL Modular Ocean Model version 5 (MOM5); Modified version of GMAO GEOS_S2S_3 ODAS. Sea Ice: modified version of the Los Alamos Community Ice CodE version 4.1 (CICE4.1); MERRA-2/OSTIA.	4.87	Pan-Arctic, 4.81 ; Alaskan region, 1.02	Pan-Arctic, 0.28 ; Alaskan region, 0.20	Pan-Arctic, 4.45 to 5.31 ; Alaskan region, 0.68 to 1.28		0.98	4.37	The given uncertainty is the standard deviation of the 7 member ensemble.	An experiment of the GMAO seasonal forecasting system using CryoSat-2 derived ice thickness predicts a September average Arctic ice extent of 4.87 +/- 0.28 million km2. The experiment tests the application of ice thickness data in a near-real time setting for the seasonal forecast system. The forecast suggests an enhanced ice cover for 2020 as compared to the previous year.	The forecast uses a prototype the GEOS_S2S version 3 coupled system that was modified for this forecast. 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 (LETKF) for assimilation of available observations and along-track ocean altimetry.A branch of the ODAS system was integrated that included nudging to CryoSat-2 sea ice thickness fields over the available time period until 2-Apr. The ensemble used a staggered initialization of every fifth day beginning 01-May for a total of 7 ensemble members.	The concentration was initialized with the MERRA-2 sea ice field, which is taken from the OSI SAF product OSI-401-b that is paired with the OSTIA real-time SST analysis.	From 1-December 2019 until 2-April 2020, the GMAO Ocean Data Assimilation System (ODAS) had ingested sea ice thickness fields from the CryoSat-2 Level-4 Sea Ice Elevation, Freeboard, and Thickness, Version 1 (doi:10.5067/96JO0KIFDAS8). After that time, the ODAS continued to integrate up to the start point of the forecasts.	The model output was re-gridded to the standard Northern Hemisphere passive microwave grid.
APPLICATE CNRM (Batte, et al.)	Dynamic Model	CNRM-CM6-1 HR (Meteo-France system 7) Ocean: NEMO 3.6 0.25,î¨¬ºŒì√™,Çß initialized from NEMO-GELATO run constrained to GLORYS12V1 Sea ice: GELATO v6 0.25,î¨¬ºŒì√™,Çß initialized from NEMO-GELATO run constrained to GLORYS12V1 Atmosphere: ARPEGE-Climat v6.4 0.5,î¨¬ºŒì√™,Çß reduced Gaussian grid initialized from IFS analysis Land surface: SURFEX v8.1 0.5,î¨¬ºŒì√™,Çß reduced Gaussian grid initialized from IFS analysis	4.95	4.98 million km2	0.22 million km2	4.38 to 5.43 million km2				These estimates are based on a 51-member ensemble	This contribution is part of the H2020-APPLICATE project and based on Meteo-France System 7 June initialization forecast. It is a 51-member ensemble forecast initialized from three sets of ocean/ice and atmosphere/land initial conditions from May 21 (25 members), May 28 (25 members), and June 1st (1 member).	0.46 million square kilometers. The Alaskan regional SIE prediction is produced by a regional	Initial conditions for the ocean and sea ice (both concentration and thickness) are provided by Mercator Ocean International. These are based on the Mercator Ocean International operational analysis, run at 1/12 horizontal resolution with NEMO-LIM. This analysis is upscaled to the 1/4 ocean resolution of CNRM-CM6 HR used for Meteo-France system 7, and fields are used to nudge a NEMO-GELATO run (Meteo-France configuration) forced by IFS operational analysis and restoring SST towards Mercator. Sea ice concentration and thickness (and ocean fields) are used to initialize forecasts.	See above.	Data was corrected for systematic error in SIC, as well as trend in SIE, based on hindcast data for the corresponding starts.