Chapter 9: Ocean, cryosphere, and sea level change – Supplementary Material

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Table of Content

9.SM.1 Additional ocean information

9.SM.1.1 Details for Figure 9.10

Lower right panel: In all experiments an additional surface freshwater flux (hosing) is applied over the subpolar North Atlantic (regions vary between studies) for a limited time. The total amount of fresh water added is then this flux multiplied by the number of years applied (in Gt). While hosing is applied the AMOC weakens. In some models the AMOC recovers quickly, in other the AMOC hasn't recovered after 200 years, and in some the AMOC is starting to recover after 200 years. These are represented by circles, downward and upward triangles respectively which show the percentage AMOC change after 200 years. Sizes of symbols represent the magnitude of the hosing (from 0.1-1Sv) and colours indicate the different studies these results were taken from (de Vries and Weber, 2005; Stouffer et al., 2006; Yin and Stouffer, 2007; Meehl et al., 2009; Jackson, 2013; Liu and Liu, 2013; Timmermans et al., 2014; Hutchings et al., 2015; Jackson and Wood, 2018; Haskins et al., 2019).

9.SM.2 Additional ice sheet information

[START TABLE 9.SM.1 HERE]

Table 9.SM.1: Observed mass loss of Greenland (The IMBIE Team, 2020, 2021) and Antarctic (The IMBIE Team et al., 2018, 2021) ice sheets for three different periods. Values are expressed as the total loss over each period (Gt) along with the equivalent rate (Gt yr^{-1}) and *very likely* ranges. Periods include both end years. The cumulative mass loss uncertainty from IMBIE is assumed to be zero at the start of each period.

Observed mass loss		**1992-1999**	**2000-2009**	**2010-2019**
Greenland (The IMBIE Team, 2019)	Δ (Gt)	309 [-24 to 642]	1753 [1308 to 2199]	2433 [1968 to 2897]
	Gt yr^{-1}	39 [-3 to 80]	175 [131 to 220]	243 [197 to 290]
Antarctica (The IMBIE Team et al., 2018)	Δ (Gt)	392 [-18 to 802]	703 [220 to 1187]	1482 [942 to 2022]
	Gt yr^{-1}	49 [-2 to 100]	70 [22 to 119]	148 [94 to 202]

[END TABLE 9.SM.1 HERE]

9.SM.3 Additional glacier information

9.SM.3.1 Details for Figure 9.21

1960-2019 time series annual and decadal values from (Zemp et al., 2019, 2020). Glacier mass change rates estimated from GRACE 2002-2016 from (Wouters et al., 2019). Glacier mass change rate between 2006-2016 and its respective uncertainty as it was assessed in SROCC (Hock et al., 2019b). Glacier mass change rates between 2000-2009 and 2010-2019 and its respective uncertainty obtained by (Hugonnet et al., 9998)

9.SM.3.2 Details for Figure 9.22

Glacier mass relative to 2015 between 1902 and 2100. Glacier change in 20th century is from (Marzeion et al., 2015). Observed mass change between 1961-2016 from (Zemp et al., 2019). Median and ± 1 standard deviation (shaded areas) projected mass change between 2015 and 2100 for RCP2.6, RCP 4.6, and RCP8.5 scenarios obtained from GlacierMIP (Marzeion et al., 2020). Data from (Bamber et al., 2018b) included in some regions

[START TABLE 9.SM.2 HERE]

Table 9.SM.2: Regional and global glacier-covered area, glacier mass (presented as potential sea level rise equivalent) in year 2000, glacier mass change rate in period 2000-2019, and projected glacier mass change between 2015 and 2100. The glacier-covered area is derived from the RGI 6.0 (RGI Consortium, 2017) and glacier-covered area uncertainties are extracted from (Pfeffer et al., 2014). Glacier mass and uncertainties are derived from Farinotti et al. (2019), based on RGI 6.0. Recent (2000-2019) mass change rate is based on (Hugonnet et al., 9998), except: [a] mean of Menounos et al. (2019) and (Hugonnet et al., 9998); [b] mean of (Aðalgeirsdóttir et al., 2020) and (Hugonnet et al., 9998); [c] mean of (Schuler et al., 2020) and (Hugonnet et al., 9998); [d] mean of (Davaze et al., 2020), (Sommer et al., 2020) and (Hugonnet et al., 9998); [e] mean of Shean et al. (2020) and (Hugonnet et al., 9998); and [f] mean of (Dussaillant et al., 2019) and (Hugonnet et al., 9998). The total projected glacier mass change between 2015-2100 is derived from (Marzeion et al., 2020). See Figure 9.22 for the time series of changes in each region.

Region	Glacier-covered area in 2000 (km^2)	Glacier mass in 2000 (mm SLE)	Glacier mass change rate 2000-2019 ($kg\ m^{-2}\ yr^{-1}$)	Projected glacier mass change between 2015-2100 (mm SLE)		
				RCP 2.6	RCP 4.5	RCP 8.5
Alaska (1)	86700 ± 4600	43 ± 11	-770 ± 60	14 ± 11	19 ± 13	25 ± 15
Western Canada and US (2)	14500 ± 1400	2.6 ± 0.7	-490 ± 170[a]	1.5 ± 0.9	2.0 ± 0.7	2.2 ± 0.7
Arctic Canada North (3)	105100 ±3400	65 ± 17	-290 ± 20	10 ± 10	16 ± 15	24 ± 20
Arctic Canada South (4)	40900 ± 2000	21 ± 5	-650 ± 50	5 ± 5	7 ± 7	11 ± 7
Greenland Periphery (5)	89700 ± 4500	34 ± 9	-430 ± 40	9 ± 10	12 ± 11	18 ± 11
Iceland (6)	11000 ± 300	9 ± 2	-860 ± 100[b]	2 ± 3	3 ± 3	5 ± 3
Svalbard (7)	34000 ± 1200	17 ± 4	-270 ± 180[c]	7 ± 7	11 ± 9	14 ± 8
Scandinavia (8)	2900 ± 300	0.7 ± 0.2	-580 ± 60	0.3 ± 0.2	0.4 ± 0.2	0.4 ± 0.2
	51600 ± 1400	32 ± 8	-200 ± 20	10 ± 8	14 ± 11	20 ± 12

Russian Arctic (9)						
North Asia (10)	2400 ± 200	0.3 ± 0.1	-500 ± 70	0.2 ± 0.2	0.3 ± 0.2	0.3 ± 0.2
Central Europe (11)	2100 ± 200	0.3 ± 0.1	-760 ± 260[d]	0.2 ± 0.1	0.3 ± 0.1	0.3 ± 0.1
Caucasus and Middle East (12)	1300 ± 100	0.2 ± 0.1	-430 ± 60	0.1 ± 0.05	0.11 ± 0.04	0.13 ± 0.04
High Mountain Asia (13 to 15)	97600 ± 7800	17 ± 3	-205 ±40[e]	8 ± 3	11 ± 4	13 ± 5
Low Latitudes (16)	2300 ± 200	0.2 ± 0.1	-450 ±60	0.13 ± 0.12	0.17 ± 0.12	0.19 ± 0.11
Southern Andes (17)	29400 ± 1700	13 ± 3	-720 ± 230[f]	3 ± 4	4 ± 3	6 ± 4
New Zealand (18)	1200 ± 100	0.2 ± 0.1	-720 ± 110	0.06 ± 0.06	0.09 ± 0.05	0.13 ± 0.04
Antarctic and Subantarctic (19)	132900 ± 2500	69 ± 18	-170 ± 20	9 ± 15	16 ± 13	20 ± 24
World	705700 ± 33200	324 ± 84	-460 ± 10	79 ± 56	119 ± 75	159 ± 86

[END TABLE 9.SM.2 HERE]

9.SM.4 Additional sea level information

9.SM.4.1 Framework for Assessing Changes To Sea-level (FACTS)

Projections of the probability distributions of global-mean and relative sea-level change are produced using the Framework for Assessing Changes to Sea-level (FACTS), a Python-based modularized framework. Contributors to sea-level change (e.g., ice sheets, ocean dynamics, etc.) are represented as individual modules which are then organized into user-defined projection workflows. The modularity of the framework enables efficient application of the different methodologies described in the chapter. The code for FACTS and its accompanying modules are open source and available through GitHub (https://github.com/radical-collaboration/facts). In the application here, the different drivers are treated as conditionally independent given GSAT.

Ideally, a FACTS module contains a sample-generation method through some sort of statistical or process-based model for the particular component. For example, the module for projecting thermal expansion and dynamic sea-level generates samples from statistical distributions calibrated within the module itself. For modules that use externally-provided ensembles for this report, which include the Emulated ISMIP6 ice sheets simulations, Emulated GlacierMIP glaciers simulations, the LARMIP-2 Antarctic ice sheet simulations, the Marine Ice Cliff Instability Antarctic ice sheet simulations, and the Structure Expert Judgement ice sheets simulations, a bootstrap sampling approach is used. This provides a consistent number of samples across all modules within an integrated projection workflow. However, due to this sampling method, the number of samples in the provided ensemble for the module, and the seed value for the random-number generator, small differences may exist between the values of the FACTS produced projections and the values published in the paper for a particular method.

9.SM.4.2 Obtaining Global Mean Thermosteric Sea-Level Rise and Ocean Dynamic Sea-Level Change from CMIP6

We obtained monthly mean values for the CMIP6 variables 'zos' (sea-surface height above geoid), 'zostoga' (global mean thermosteric sea-level change) and 'psl' (air pressure at sea level; required to apply the inverse barometer effect). The data files were extracted from the Earth System Grid Federation (ESGF) database between 22-30 September 2020. Data were obtained for both the historical experiment (1850-2014) and the five core SSPs (2015-2100 and up to 2300 where available) with corresponding variant labels ('ripf' identifier). Additionally, models were required to provide the pre-industrial control output from which the 'zos' and 'zostoga' experiments were initialized, so that 'zos' and 'zostoga' simulations could be corrected for model ocean drift (Gupta et al., 2013; Hobbs et al., 2016b). Thus, the total number of available models used for each emissions scenario depends on the availability of these simulations (and of grid information required to carry out the preprocessing steps detailed in the next paragraph, such as ocean grid cell area 'areacello'). We obtained all available data with an experiment variant with a realization equal to one ('ripf' having 'r'=1). For each model, we use the first of the remaining experiment variants for which most SSP experiments are available, and the first alternative experiment variant for the SSPs for which that variant is not available. For UKESM1-0-LL, the air pressure sea level field yielded an anomalously large inverse barometer effect, so this was model not included.

Then, the timeseries of 'zos' and 'zostoga' were corrected for ocean model drift (Gupta et al., 2013; Hobbs et al., 2016b). This was done by fitting a linear trend to the full pre-industrial control run of each model, and subtracting the resulting linear trend from the historical and scenario runs. Since the drift in 'zostoga' is nearly linear for most CMIP6 models, quadratic or linear drift correction yields little difference compared to the magnitude of projected GTE under the emissions scenarios (Hermans et al., 2021). Additionally, the area-weighted mean of the 'zos' field was removed at each timestep for each model, since 'zos' is defined as the sea-surface height above a time-invariant geoid. Next, 'zos' and 'psl' were bilinearly interpolated to a common regular 1° by 1° grid using the ESMValTool regridding routine (Eyring et al., 2020) . Finally, the inverse barometer effect was derived from sea-level pressure anomalies with respect to the area-weighted ocean mean sea-level pressure (following Stammer and Hüttemann, 2008) and applied to 'zos' in order to obtain ocean dynamic sea-level fields (Gregory et al., 2019). Note that the inverse barometer effect due to sea-ice (e.g., Lyu et al., 2020a) was not applied here.

9.SM.4.3 Global Mean Thermosteric Sea-Level and Ocean Dynamic Sea-Level Projections based on the Two-Layer Emulator

To convert the ocean heat content projections based upon the AR6 assessment of equilibrium climate sensitivity and transient climate response (Appendix 7.A.2) to global mean thermosteric sea-level rise projections, the emulated ocean heat content projections were multiplied with expansion coefficients estimated from CMIP6. A distribution of expansion coefficients was derived by fitting drift-corrected global mean thermosteric sea-level rise (9.SM.4.2) from individual CMIP6 GCMs against total ocean heat content output of a two-layer emulator configured with CMIP6 calibration parameters (Smith et al., 2020b). Both thermosteric sea-level rise and ocean heat content were referenced to their mean values in 1995-2014. The two-layer model was forced with scenario-dependent effective radiative forcing from the RCMIP protocol (Nicholls et al., 2020) for the SSPs. Expansion coefficients were derived through linear regression with a fixed 0-intercept for the period 2015-2100 for all SSPs combined.

The resulting distribution was clipped based on the root mean square error cumulative across scenarios between the GSAT projections of individual CMIP6 models and the GSAT projection of the two-layer model calibrated to that model. Only the expansion coefficients of models with an RMSE less than or equal to the 85th percentile of the cumulative distribution function of RMSEs were considered. Thus, the expansion coefficients for CNRM-ESM2-1 and EC-Earth3-Veg were dropped. Expansion coefficients were then randomly drawn from a normal fit to the distribution of remaining expansion coefficients, which has a mean and standard deviation of 0.113 ± 0.013 m/YJ.

To produce ocean dynamic sea-level projections consistent with the global mean thermosteric projections described in this section, we follow the approach of (Kopp et al., 2014). We fit a multivariate t-distribution to the ocean dynamic sea-level terms from CMIP6 (9.SM.4.2), and drawing from this distribution, combine the ocean dynamic sea-level terms with the emulator-based global mean thermosteric projections, accounting for the underlying correlation between global mean thermosteric sea-level rise and ocean dynamic sea-level change in CMIP6. While if the CMIP6 ensemble represented a complete representation of all relevant uncertainties, its 5th-95th percentile range would represent a *very likely* range, it is not a perfect representation, so following practice in the AR5, we treat its 5th-95th percentile range as a *likely range* (i.e., a 17th-83rd percentile range). We therefore scale the standard deviation of the t-distribution of ocean dynamic sea-level change by 1.64, so that ±1 standard deviation of the scaled fitted distribution corresponds to a central 66% *likely range*. To account for identifiable, model-specific problems in specific grid cells (e.g., in inland seas), projections for a grid cell are removed if they have an amplitude in 2099 more than ten times the median local amplitude. In cases where, after removal of extreme outliers, the standard deviation of projections in 2099 is greater than 20 cm, we also remove models that deviate from the mean by more than three standard deviations.

9.SM.4.4 Parametric fit to ISMIP6 Greenland Ice Sheet projections

Since the ISMIP6 emulator does not account for temporal correlation, a polynomial fit to the ISMIP6 results is employed to calculate rates of change. The parametric fit is a cubic fit to temperature and a quadratic fit over time:

$$\frac{\partial s}{\partial t} = \beta_0 + \beta_1 T + \beta_2 T^2 + \beta_3 T^3 + \beta_4 t + \beta_5 t^2$$

Where s indicates the sea-level equivalent contribution in mm, T is GSAT in °C, and t is time in years. For the purposes of fitting this function, T and t are anomalies to their respective values in year 2015. Fitting is done using maximum a posteriori estimation.

[START TABLE 9.SM.3 HERE]

Table 9.SM.3: Parameters for the fit to the ISMIP6 Greenland Ice Sheet models.

GROUP	Model	β_0	β_1	β_2	β_3	β_4	β_5
UCIJPL	ISSM1	0.11	0.68	-0.16	0.03	-0.009	1.5E-04
UAF	PISM1	0.11	2.23	-0.69	0.08	-0.046	4.7E-04
NCAR	CISM	0.31	1.60	-0.44	0.06	-0.030	2.7E-04
MUN	GSM2601	0.26	1.92	-0.64	0.07	-0.048	5.4E-04
AWI	ISSM1	0.15	0.57	-0.06	0.02	-0.002	2.6E-05
JPL	ISSMPALEO	0.08	0.67	-0.13	0.02	-0.016	1.9E-04
BGC	BISICLES	0.15	0.82	-0.24	0.04	-0.017	2.2E-04
GSFC	ISSM	0.17	1.94	-0.62	0.08	-0.035	3.8E-04
UCIJPL	ISSM2	0.22	0.34	0.05	-0.02	-0.004	8.5E-05

IMAU	IMAUICE2	0.20	2.30	-0.71	0.09	-0.044	4.5E-04
VUB	GISMHOMv1	0.39	0.85	-0.19	0.04	-0.002	-1.1E-05
IMAU	IMAUICE1	0.28	0.84	-0.13	0.03	-0.002	-7.9E-06
MUN	GSM2611	0.32	0.39	0.15	-0.04	-0.016	2.1E-04
UAF	PISM2	0.22	0.22	-0.03	0.02	0.002	-1.0E-05
VUW	PISM	0.00	1.54	-0.52	0.06	-0.037	4.6E-04
AWI	ISSM2	0.15	0.58	-0.06	0.02	-0.001	1.6E-05
ILTS_PIK	SICOPOLIS2	0.23	0.64	-0.06	0.02	-0.005	6.9E-05
ILTS_PIK	SICOPOLIS1	0.18	1.83	-0.52	0.07	-0.036	3.7E-04
AWI	ISSM3	0.09	2.12	-0.65	0.08	-0.042	4.2E-04
JPL	ISSM	0.20	0.73	-0.13	0.03	-0.004	4.9E-05
LSCE	GRISLI2	0.22	0.39	-0.04	0.02	-0.006	5.7E-05

[END TABLE 9.A.3 HERE]

9.SM.4.5 Parametric fit to GlacierMIP2 projections

Since the GlacierMIP2 emulator does not account for temporal correlation and terminates, along with the GlacierMIP2 simulations, in 2100, we employ a power law fit to the GlacierMIP2 simulations (Marzeion et al., 2020), with a functional form similar to that employed by the AR5, to calculate rates of change and extrapolate changes beyond 2100 (up to a maximum potential contribution of 0.32 m). As in the AR5 (Church et al., 2013), the glacier contribution is the integral of $fI(t)^{\rho}$, where $I(t)$ is the time integral of GSAT from 2006 to time t in degrees Celsius year, and the constants f and ρ used for each glacier model are shown in Table 9.SM.4. The spread of the results around this median projection has a coefficient of variation (standard deviation divided by the mean) σ which is determined on a per-model basis. As in the AR5, this variation is incorporated by taking for each Monte Carlo sample a normally distributed random number. This number is multiplied by the time-dependent standard deviation and added to the sample. All models are equally weighted.

[START TABLE 9.SM.4 HERE]

Table 9.SM.4: Parameters for the fit to the global glacier models.

Global Glacier Model	f (mm °C^{-1} yr^{-1})	ρ	σ
GLIMB	3.7	0.66	0.21
GloGEM	4.08	0.72	0.16
JULES	5.5	0.56	0.19
MAR2012	4.89	0.65	0.14
OGGM	4.26	0.72	0.16
RAD2014	5.18	0.71	0.14
WAL2001	2.66	0.73	0.21

[END TABLE 9.SM.4 HERE]

9.SM.4.6 Background rates of relative sea-level change

Background rates of RSL change, including glacial-isostatic adjustment as well as other factors contributing to long-term vertical land motion, are estimated from tide-gauge data following the Gaussian-process regression method of Kopp et al. (Kopp et al., 2014). The method was applied to annual-mean tide-gauge data downloaded from the Permanent Service for Mean Sea Level (Holgate et al., 2013) on 18 October 2020. As in Kopp et al. (Kopp et al., 2014), RSL is represented as the sum of three Gaussian processes: (1) a regionally varying, temporally linear process, (2) a globally-uniform process, and (3) a regionally varying, temporally autocorrelated non-linear process. The posterior estimate of the first (temporally linear) process is used as the estimate of the background rate. The analysis is conducted separately for each of 15 regions: Iceland/Svalbard, Scandinavia, Northern Europe, Russia, Mediterranean/Africa, US Pacific, US Atlantic, Gulf of Mexico, Northeastern Canada, Alaska, Latin America, Oceania, Japan, South/East Asia, and Antarctica (see Kopp et al., 2014, for details). Within each region, available tide-gauge data are used together with the GMSL curve of (Dangendorf et al., 2019) (treated as a noisy observation of the second term) to estimate the Gaussian-process model.

9.SM.4.7 Warming Level Scenarios

Because GMSL projections are more strongly related to integrated warming rather than to instantaneous warming, warming-level-based scenarios cannot be defined based on the time-slice method used for atmospheric variables (Cross-Chapter Box 11.1). Instead, consistent with the approaches of (Jackson et al., 2018; Rasmussen et al., 2018), all available SSP-based projections are pooled, then assigned to temperature levels based on the 2081-2100 GSAT anomaly projected by the two-layer energy budget emulator, using a ±0.25°C window around the targeted temperature level. For example, the 2.0°C projections are based on all realizations from all scenarios where 2081-2100 GSAT falls between 1.75°C and 2.25°C. A certain warming level may therefore include a mixture of one or more SSP scenarios.

9.SM.4.8 Analysis of future changes in extreme sea level return frequency

Frequency amplification factors for the 1% average annual-probability of extreme still-water levels are computed by combining the projected regional sea-level change (Section 9.6.3.3) with historical distributions of observed extreme events derived from the Global Extreme Sea Level Analysis 2 (GESLA2;(Woodworth et al., 2016b)) , following the approach of the SROCC and (Frederikse et al., 2020a). GESLA2 stations are included in the analysis when hourly mean data was available for at least 6,000 hours per year (250 days) for at least 20 years. For each station, the annual means were removed before fitting a General Pareto Distribution (GPD) to the hourly mean GESLA2 data using a peak-over-threshold (POT) method with a threshold of 99.7%. The extremes are de-clustered using a minimum of 72 hours between subsequent extremes. The estimated GPD location (the 99.7% threshold), scale and shape parameters are generally in agreement with (Frederikse et al., 2020a). We note that our results are sensitive to the statistical method used (Wahl et al., 2017) and may therefore differ from previous analyses.

Following the SROCC and (Frederikse et al., 2020a), we computed an ensemble of historical return curves for each station using the location parameter in combination with 50,000 random pairs of the shape and scale parameters drawn from the mean estimated shape and scale parameters and their covariance matrices. To compute the future return curves, we use the same scale and shape parameter samples but increase the location parameter at each station by the local projected mean sea-level change, effectively shifting the return curve up. The uncertainty in the local projected mean sea-level change is estimated by drawing 50,000 samples from the projected probability distribution of local mean sea-level change, clipped at its 5th and 95th percentiles. This differs from SROCC, where sea-level change samples were drawn from a normal distribution using the central value and a standard error.

Using the resulting 50,000 future return curves for each station, we calculated the frequency amplification factor of a 1% average annual-probability (i.e., once in 100 years) of extreme still-water level by dividing the frequency of that water level in the future return curves by the historical frequency. This resulted in a probability distribution of frequency amplification factors that represents both the uncertainty in projected sea-level change and in the historical distribution of extremes.

Using the POT method, the frequency of extreme events is only defined for water levels above the POT threshold. If the projected sea-level change for a given location is higher than the exceedance of the historical location parameter by the historical 1% annual probability event, the historical 1% annual-probability event would have a return level below the future location parameter. Thus, for the stations where this occurs the frequency amplification factor cannot be fully determined. Therefore, we used the approach of (Buchanan et al., 2016) to describe the return frequency of return heights below the POT threshold. We fit a Gumbel distribution between Mean Higher-High Water (MHHW) and the location parameter, assuming the frequency of exceedance of the MHHW to be 182.6/year. The MHHW was estimated from the GESLA2 data as the long-term mean of 2-daily maxima for each location. Therefore, by construction, the maximum projected frequency amplification factor in our analysis is 18,262.5.

[START TABLE 9.SM.5 HERE]

Table 9.SM.5: Integrated GMSL projections for 2050, relative to 1996-2014, from the post-AR5 literature.

Study	Grouping	RCP 2.6		RCP 4.5		RCP 8.5	
		67%	90%	67%	90%	67%	90%
Bakker et al., 2017	MED		0.16--0.29		0.18--0.31		0.20--0.34
Kopp et al., 2014	MED	0.19--0.27	0.16--0.31	0.19--0.29	0.16--0.33	0.22--0.32	0.19--0.36
Mengel et al., 2016	MED		0.10--0.20		0.11--0.21		0.12--0.25
Nicholls et al., 2018	MED						0.16--0.29
Kopp et al., 2017	MICI	0.14--0.31	0.10--0.39	0.16--0.34	0.12--0.41	0.20--0.38	0.15--0.46
Wong et al., 2017	MICI		0.18--0.31		0.20--0.33		0.23--0.38
Jackson and Jevrejeva, 2016	SEJ					0.19--0.34	0.15--0.45
Bamber et al., 2019	SEJ					0.25--0.45	0.19--0.59

All projections are adjusted to a 1995-2014 baseline and 2050 end year. For projections baselined to 1986-2005 or to 2000, adjustments are made assuming a 3 mm/yr rate. For projections ending in 2046-2065, adjustments are made assuming a constant acceleration from 1996-2014 to the end year.

[END TABLE 9.SM.5 HERE]

[START TABLE 9.SM.6 HERE]

Table 9.SM.6: Integrated GMSL projections for 2100, relative to 1996-2014, from the post-AR5 literature.

Study	Grouping	RCP 2.6		RCP 4.5		RCP 8.5	
		67%	90%	67%	90%	67%	90%
Bakker et al., 2017	MED		0.37--0.68		0.51--0.94		0.82--1.56
Jackson and Jevrejeva, 2016	MED			0.33--0.69	0.19--0.82	0.51--0.95	0.34--1.15
Kopp et al., 2014	MED	0.35--0.63	0.27--0.80	0.43--0.75	0.34--0.91	0.60--0.98	0.50--1.19
Kopp et al., 2016	MED	0.26--0.49	0.22--0.59	0.37--0.67	0.31--0.83	0.57--1.03	0.50--1.29
Mengel et al., 2016	MED		0.25--0.53		0.34--0.74		0.54--1.28
Nauels et al., 2017	MED	0.34--0.56		0.45--0.71		0.65--1.06	
Slangen et al., 2014	MED			0.36--0.83		0.46--1.15	
Le Bars, 2018	MED			0.39--0.67	0.31--0.82	0.59--0.98	0.48--1.18
Le Cozannet et al., 2019	MED	0.20--0.42	0.14--0.49	0.32--0.54	0.24--0.60	0.55--0.80	0.45--0.89
Goodwin et al., 2017	MED		0.51--0.88		0.52--0.79		0.73--1.00
Nicholls et al., 2018	MED						0.51--0.88
Kopp et al., 2017	MICI	0.35--0.76	0.24--0.96	0.64--1.23	0.48--1.56	1.07--2.07	0.91--2.41
Wong et al., 2017	MICI		0.41--0.72		0.54--1.28		1.07--2.05
Grinsted et al., 2015	SEJ					0.56--1.18	0.43--1.81
Jackson and Jevrejeva, 2016	SEJ					0.60--1.18	0.48--1.64
Jevrejeva et al., 2014	SEJ						0.44--1.78
Bamber et al., 2019	SEJ					0.77--1.72	0.60--2.36
Horton et al., 2020	Survey	0.28--0.63	0.19--0.80			0.61--1.30	0.43--1.63

All projections are adjusted to a 1995-2014 baseline and 2100 end year. For projections baselined to 1986-2005 or to 2000, adjustments are made assuming a 3 mm/yr rate. For projections ending in 2081-2100, adjustments are made assuming a constant acceleration from 1996-2014 to the end year.

[END TABLE 9.SM.6 HERE]

[START TABLE 9.SM.7 HERE]

Table 9.SM.7: Global mean sea-level projections for 5 SSP scenarios, for total change and individual contributions, median values, (*likely*) ranges of the process-based model ensemble, for 1995-2014 to 2050 and 2150 in meters. Average rates for total sea-level change in mm yr^{-1}.

	SSP1-1.9	SSP1-2.6	SSP2-4.5	SSP3-7.0	SSP5-8.5	SSP5-8.5 *Low Confidence*
2050						
Thermal expansion	0.07 (0.06--0.08)	0.07 (0.06--0.09)	0.08 (0.07--0.10)	0.09 (0.07--0.10)	0.09 (0.08--0.11)	0.07 (0.06--0.09)
Greenland	0.03 (0.02--0.04)	0.03 (0.02--0.04)	0.03 (0.02--0.04)	0.03 (0.02--0.04)	0.03 (0.02--0.04)	0.03 (0.02--0.10)
Antarctica	0.03 (0.01--0.08)	0.03 (0.01--0.08)	0.03 (0.01--0.08)	0.03 (0.01--0.08)	0.03 (0.01--0.08)	0.03 (-0.00--0.08)
Glaciers	0.04 (0.03--0.05)	0.05 (0.04--0.06)	0.05 (0.05--0.06)	0.06 (0.05--0.07)	0.07 (0.06--0.08)	0.05 (0.04--0.06)
Land Water Storage	0.01 (0.00--0.02)	0.01 (0.00--0.02)	0.01 (0.00--0.02)	0.01 (0.00--0.02)	0.01 (0.00--0.02)	0.01 (0.00--0.02)
Total (2050)	0.18 (0.15--0.23)	0.19 (0.16--0.25)	0.21 (0.18--0.26)	0.22 (0.19--0.28)	0.23 (0.20--0.30)	0.20 (0.16--0.31)
2150						
Thermal expansion	0.14 (0.11--0.18)	0.18 (0.14--0.23)	0.30 (0.24--0.38)	0.46 (0.38--0.57)	0.55 (0.45--0.68)	0.55 (0.45--0.68)
Greenland	0.10 (0.08--0.13)	0.13 (0.10--0.17)	0.19 (0.15--0.24)	0.24 (0.19--0.28)	0.27 (0.22--0.35)	0.31 (0.18--0.98)
Antarctica	0.17 (-0.01--0.44)	0.18 (-0.03--0.49)	0.18 (-0.05--0.55)	0.17 (-0.07--0.61)	0.17 (-0.09--0.68)	0.77 (-0.09--3.68)
Glaciers	0.10 (0.07--0.14)	0.13 (0.09--0.18)	0.19 (0.13--0.26)	0.27 (0.18--0.32)	0.31 (0.20--0.32)	0.31 (0.20--0.32)
Land Water Storage	0.05 (0.03--0.06)	0.05 (0.03--0.06)	0.05 (0.03--0.07)	0.07 (0.04--0.09)	0.05 (0.03--0.06)	0.05 (0.03--0.06)
Total (2150)	0.57 (0.37--0.85)	0.69 (0.46--1.00)	0.93 (0.67--1.33)	1.21 (0.92--1.67)	1.35 (1.02--1.89)	1.99 (1.02--4.83)

[END TABLE 9.SM.7 HERE]

[START TABLE 9.SM.8 HERE]

Table 9.SM.8: Global mean sea-level rise projections for 2000-2300 from literature (m), for different RCP scenarios.

Study	Grouping	RCP 2.6		RCP 4.5		RCP 8.5	
		67%	90%	67%	90%	67%	90%
Kopp et al., (2014)	MED	0.3--2.9	-0.2--4.7	0.7--3.5	0.0--5.3	1.8--5.2	1.0--7.4
Nauels et al., (2017)	MED	0.8--1.4		1.8--2.3		3.4--6.8	
Palmer et al. (2020)*	MED	0.6--2.2		0.9--2.6		1.7--4.5	
Kopp et al., (2017)	MICI	0.8—2.3	0.5--3.0	2.8--6.0	2.1--7.0	9.8--14.1	9.1--15.5
Bamber et al. (2019)*	SEJ	1.2--3.6	0.5--5.3			2.6--6.5	1.8--11.8
Horton et al. (2020)	Survey	0.54-2.15	0.24-3.11			1.67-5.61	0.88-7.83

*Bamber et al. (2019) 2°C scenario is listed under the RCP 2.6 column, but GSAT does not decline in this 2°C scenario as it does in RCP 2.6. Bamber et al. (2019) "RCP 8.5" scenario assumes GSAT stabilization at 5°C above pre-industrial after 2100 and so becomes cooler than RCP 8.5 over the 22nd and 23rd century. Palmer et al. (2020) 5th-95th percentile of simulated projections are constructed to be analogous to AR5/SROCC *likely* ranges and so are presented here as 17th-83rd percentile projections.

[END TABLE 9.SM.8 HERE]

9.SM.5 Data Table

[START TABLE 9.SM.9 HERE]

Table 9.SM.9: Input datasets and code in the chapter.

Figure number	**Dataset / Code name**	**Type**	**Filename / Specificities**	**License type**	**Dataset / Code citation**	**Dataset / Code URL**	**Related publications / Software used**	**Notes**
Figure 9.2, panel b	OSCAR third degree resolution ocean surface currents. Ver. 1	Input dataset (observations)		open	10.5067/OSCAR-03D01	https://doi.org/10.5067/OSCAR-03D01	Bonjean, F., and G. S. E. Lagerloef, 2002.	time averaged over 1993-2018
	ETOPO20	Input dataset (topography)		open	doi:10.7289/V5C8276M.	http://www.ngdc.noaa.gov/mgg/global/etopo2.html	Amante, C.; Eakins, B.W. (2009). "ETOPO1 1 Arc-Minute Global Relief Model: Procedures,	

							Data Sources and Analysis". *NOAA Technical Memorandum NESDIS NGDC-24*.	
	Permafrost gridded map	input dataset		open		https://data.tpdc.ac.cn/en/data/c66bf4a7-8f20-443c-9412-53ac675bd964/	Brown, J., O. Ferrians, J. A. Heginbottom, E. Melnikov, Tingjun Zhang Tingjun Zhang Tingjun Zhang. **Circum-Arctic map of permafrost and ground ice conditions (v2) (1997)**. National Tibetan Plateau Data Center, 2011.	all permafrost types combined
	Snow water equivalent map	Input dataset		Open	https://doi.org/10.5067/KIGGFNVROX9V	https://doi.org/10.5067/KIGGFNVROX9V	Brodzik, M. J., R. Armstrong, and M. Savoie. 2007. Global EASE-Grid 8-day Blended SSM/I and MODIS Snow Cover, Version 1. [Indicate subset used]. Boulder, Colorado USA. NASA National Snow and Ice Data Center Distributed Active Archive Center. doi: https://doi.org/10.5067/KIGGFNVROX9V.	SWE converted to distribution of snowy regions and locations of ice sheets
	Northern Hemisphere sea ice data	Input dataset		Open			Meier, W. N., F. Fetterer, M. Savoie, S. Mallory, R. Duerr, and J. Stroeve. 2017. NOAA/NSIDC Climate	Annual average concentration

							Data Record of Passive Microwave Sea Ice Concentration, Version 3. [Indicate subset used]. Boulder, Colorado USA. NSIDC: National Snow and Ice Data Center. doi: https://doi.org/10.7265/N59P2ZTG.	
	Southern Hemisphere sea ice data	Input dataset		Open			Peng, et al. 2013. https://doi.org/10.5194/essd-5-311-2013	Annual average concentration
	Glacier inventory	Input dataset		Open			RGI Consortium (2017). Randolph Glacier Inventory – A Dataset of Global Glacier Outlines: Version 6.0: Technical Report, Global Land Ice Measurements from Space, Colorado, USA. Digital Media. DOI: **https://doi.org/10.7265/N5-RGI-60**	
Figure 9.3a (left: paleo panel)Figure 9.3a (left: paleo panel)	Paleo MPWP observation	Input dataset (observations)					Foley, et al. (2019) https://doi.org/10.5066/P9YP3DTV. . McClymont, et al. (2020). https://doi.org/10.5194/cp-2019-161	Anomalized relative to 1950-1980. These data used a different ‘modern’ period so a +0.2 correction was applied based on HadCM3.
	Paleo LIG observati	Input dataset (observ					Fischer, et al. (2018). https://doi.org/10.103	Anomalized relative to 1950-1980.

	on	ations)					8/s41561-018-0146-0; Turney, et al. (2020). https://doi.org/10.5194/essd-12-3341-2020; Hoffman et al., 2017	The references used varying 'modern' periods so the following corrections were applied; +0.2 for Fischer et al. (2018) and -0.1 for Turney et al. (2020). These corrections were based on HadCM3.
	Paleo LGM observation	Input dataset (observations)					Paul, et al. (2020). https://doi.org/10.1038/s41586-020-2617-x; MARGO (2009)	Anomalized relative to 1950-1980. The references used varying 'modern' periods so the following corrections were applied; +0.2 for Paul et al. (2021) & MARGO (2009) and +0.1 for Tierney et al., 2020. These corrections were based on HadCM3 and PAGES12K (Kaufman et al., 2020) respectively.
	Paleo MPWP Models	Model dataset					Haywood, et al. (2020).	Anomalized relative to 1950-1980. These data used a different 'modern' period so a +0.2 correction was applied based on

								HadCM3.
	Paleo LIG Models	Model dataset					Otto-Bliesner, et al. (2021).	Anomalized relative to 1950-1980. Otto-Bliesner et al. (2021) used a different 'modern' period so a +0.2 correction was applied based on HadCM3.
	Paleo LGM Models	Model dataset					Kageyama, et al. (2021). https://doi.org/10.5194/cp-2019-169	Anomalized relative to 1950-1980. Kageyama et al. (2021) used a different 'modern' reference perios so the following was applied; +0.2. This correction was based on HadCM3.
Figure 9.3a (middle and right panels)	Hadley Centre Sea Ice and Sea Surface Temperature dataset (HadISST)	Input dataset (observational reanlyses)		Crown Copyright		https://www.metoffice.gov.uk/hadobs/hadisst/	Rayner, et al.. (2003), ESMValTool v2	Reformatted with ESMValTool v2.0 (March 20th 2020)
	CMIP6 (CMIP, ScenarioMIP, HighResMIP)	Model dataset						
Figure 9.3b	Hadley Centre Sea Ice and Sea Surface Temperature dataset (HadISST)	Input dataset (observational reanlyses)		Crown Copyright		https://www.metoffice.gov.uk/hadobs/hadisst/	See Figure 9.3a (middle and right panels)	Monthly data averaged between 1995 and 2014. Reformatted with ESMValTool v2.0 (March 20th

								2020)
Figure 9.3c	Hadley Centre Sea Ice and Sea Surface Temperature dataset (HadISST)	Input dataset (observational reanlyses)		Crown Copyright		https://www.metoffice.gov.uk/hadobs/hadisst/	See Figure 9.3a (middle and right panels)	Change rate calculated between the 2005-2014 mean and 1950-1959 mean.
Figure 9.3d	CMIP6 (CMIP)	Model dataset						Change rate calculated between the 2091-2100 mean and the 2005-2014 mean.
Figure 9.3e	CMIP6 (CMIP)	Model dataset						See Fig. 9.3b
Figure 9.3f	CMIP6 (CMIP)	Model dataset						See Fig. 9.3c
Figure 9.3g	CMIP6 (CMIP)	Model dataset						Change rate calculated between the 2041-2050 mean and the 2005-2014.
Figure 9.3h	CMIP6 (HighResMIP)	Model dataset						See Fig. 9.3b
Figure 9.3i	CMIP6 (HighResMIP)	Model dataset						See Fig. 9.3c
Figure 9.3j	CMIP6 (HighResMIP)	Model dataset						See Fig. 9.3g
Figure 9.4a,b,d,e,g,h	CERES EBAF v4 (Heat fluxes); OAFlux-HR (heat, freshwater and momentum fluxes); GPCP (precipitation)	Input datasets (observation-based products)				https://ceres.larc.nasa.gov/data/ ; http://oaflux.whoi.edu/ ; https://rda.ucar.edu/datasets/ds728.3/		Details of dataset merging and trend calculation to be added
Figure 9.4c,f,i	CMIP6 (CMIP, Scenario	Model datasets						Change rate calculated between

	MIP)							2081-2100 mean and 1995-2014 mean (CHECK THIS). Models include river runoff, observations do not.
Figure 9.5a,b,e,f	Argo Mixed Layers	Input datasets (observations)		Open		http://mixedlayer.ucsd.edu	Holte, et al. (2017).	Climatology of monthly mixed layer depths. Dec 2019 version. MLDs calculated using de Boyer Montégut et al.'s (2004) threshold values. DJF and JJA averages ignore missing gridpoints. Afterward, isolated missing gridpoints infilled as average of four neighbors.
Figure 9.5b,f	CMIP6 (CMIP)	Model datasets						Change rate calculated across 1995-2014 period.
Figure 9.5c,d,g,h	CMIP6 (ScenarioMIP, CMIP)	Model datasets						Change rate calculated between 2081-2100 average and 1995-2014 average.
Figure 9.6a	Observations (Ishii)	Input dataset (observations)	ishii_ohc_global_1955.txt			https://www.data.jma.go.jp/gmd/kaiyou/english/ohc/ohc_data_en.html (Downloaded 12th Jan.	Ishii et al. 2017	Anomalized relative to 2004-2015 mean.

						2021)		
	Hybrid (Zanna)	Input dataset (hybrid)	OHC_GF_1870_2018_Zanna.nc			Zanna, Laure, Khatiwala, Samar, Gregory, Jonathan, Ison, Jonathan, & Heimbach, Patrick. (2019). Global reconstruction of historical ocean heat storage and transport (Version v1) [Data set]. Zenodo. http://doi.org/10.5281/zenodo.4603700	Zanna, et al. (2019)	Anomalized relative to 2004-2015 mean.
	Hybrid (Cheng)	Input dataset (hybrid)	Cheng_2016_Global_OHC_13_Jan_2021.txt			http://159.226.119.60/cheng/images_files/OHC2000m_annual_timeseries.txt	Cheng, et al. 2019	Anomalized relative to 2004-2015 mean.
	Paleo (LIG)	Input dataset (LIG)	Stored in Excel file for Fig 9.9: 9.2.2_ACM_Fig_9.9_OHC_Paleo_Data_update_2020_12_06.xls				Shackleton, S. et al. (2020).	Last Inter-Glacial OHC anomaly relative to preindustrial. This mean is between -129 ka and -116 ka CE, and the timeseries is shown in Fig. 9.9
	Paleo (LGM)	Input dataset (LGM)	Stored in Excel file for Fig 9.9: 9.2.2_ACM_Fig_9.9				Baggenstos, D., Häberli, M., Schmitt, J., Shackleton, S. A., Birner,	Last Glacial Maximum OHC anomaly relative to

			_OHC_Paleo_Data_update_2020_12_06.xls				B., Severinghaus, J. P., Kellerhals, T & Fischer, H. (2019). Earth's radiative imbalance from the Last Glacial Maximum to the present. Proceedings of the National Academy of Sciences, 116(30), 14881-14886. DOI: 10.1073/pnas.1905447116	preindustrial. This mean is between -23 ka and -19 ka CE, and the timeseries is shown in Fig. 9.9
	Paleo (MH)	Input dataset (MH)	Stored in Excel file for Fig 9.9: 9.2.2_ACM_Fig_9.9_OHC_Paleo_Data_update_2020_12_06.xls				Baggenstos, D. et al. (2019).	Mid-holocene OHC anomaly relative to preindustrial. This mean is between -6.5 ka and -5.5 ka CE, and the timeseries is shown in Fig. 9.9
	CMIP6 (CMIP, ScenarioMIP)	Model dataset						Timeseries across 1850-2014 (CMIP) and 2015-2100 (ScenarioMIP). Anomalized relative to 2005-2014 mean
Figure 9.6b-g	Observations	Input dataset (observational reanlyses)				https://climate.mri-jma.go.jp/pub/ocean/ts/v7.3/2021-02-01/		0-700m calculated between 1971-2014 and 0-2000m calculated between 2005-2014.
	CMIP6 (CMIP)	Model dataset						0-700m Bias calculated across 1971-

								2014 mean. 0-2000m Bias calculated across 2005-2014 mean
	CMIP6 (ScenarioMIP)	Model dataset						Change rate calculated between 2091-2100 mean and 2005-2014 mean.
Figure 9.7 1st and 2nd columns	Argo (observations)	Input dataset (observational reanlyses)				https://argo.ucsd.edu/		
	CMIP6 (CMIP)	Model dataset						
Figure 9.7 3rd and 4th columns	CMIP6 (CMIP, ScenarioMIP)	Model dataset						Change rate calculated between 2005-2014 mean (CMIP) and 2091-2100 mean (ScenarioMIP).
Figure 9.8 Panels a-f	CMIP5 and observation based product	Model and observation analysis dataset			https://doi.org/10.1038/s41586-020-2573-5	https://doi.org/10.1038/s41586-020-2573-5	Bronselaer, B. and Zanna, L., 2020.	These data are the same as used in the paper, but projections are redrawn so as to match the chapter standards
Figure 9.8 Panel g	RAPID array	Input dataset (observations)					**Version v2015.1** Smeed D. et al. (2016).	
	CMIP6 (HighResMIP)	Model dataset					Roberts, et al. 2020.	This analysis is similar to that in the paper but combines multiple panels from the paper into one.
Figure 9.9a,b,d	Ocean heat content (OHC)	Input dataset				Inset OHC updated values	Shackleton et al, 2019; 2020; Baggenstos et	Rebased to PI: Baggenstos et al. (2019)

	estimates					from Levitus et al., 2012; https://www.nodc.noaa.gov/OC5/3M_HEAT_CONTENT/basin_tsl_data.html	al., 2019; Levitus et al. 2012 updated NOAA NODC, 2020	MOT-PI= MOT-1.51; Shackleton et al. (2019) MOT-PI = MOT+0.50 (aligned to Baggenstos et al. 2019); Shackleton et al. (2020) MOT-PI = MOT+0.25 (aligned to Baggenstos et al. 2019); assumption, Baggenstos et al. (2019) at 1000 BP =PI.
	Southern Ocean SST estimates from marine cores	Input dataset					Uemera et al., 2018	Restacked 11 records from average of three low-variability intervals, 4-8 ka, 18-22ka, and 25-29 ka, binned and averaged at 1000-year intervals.
	Southern Ocean SST estimates from ice core source	Input dataset					Uemera et al., 2018	As published, moisture source temperature based on deuterium excess
	OHC from HadCM3	Input dataset				https://crudata.uea.ac.uk/cru/projects/soap/pw/data/model/hadcm3/hadcm3_sealevel.htm	Gregory et al., 2006	Inset only, Natural + Anthropogenic forcing
Figure 9.9c	Model OHC projections	Model dataset					Clark et al., 2016	Projected OHC in response to four GHG emissions scenarios
	Model SAT	Model dataset					Clark et al., 2016	Projected SAT in

								response to four GHG emissions scenarios
Figure 9.10 Top left panel	CMIP6 (PMIP)	Model dataset						
Figure 9.10 Top right panel	CMIP6 (DAMIP, ScenarioMIP), CMIP5	Model dataset					Menary, et al., 2020.	
Figure 9.10 Bottom panels	Simulated AMOC changes	Model datasets					Based on literature search from Jackson and Wood, 2018; Yin and Stouffer, 2007; Liu and Liu, 2013; Haskins et al. 2019; De Vries and Weber, 2005; Jackson 2013; Stouffer et al. 2006.	Extracted from timeseries and descriptions of models from these papers.
Figure 9.11 Maps	CMIP6 (CMIP, ScenarioMIP)	Model dataset						Change rates calculated between 1995-2014 mean (CMIP) and 2081-2100 mean (ScenarioMIP).
Figure 9.11 Right column (scatter plots)	CMIP6 (CMIP, ScenarioMIP)	Model dataset					Hu et al., 2015	
Figure 9.12g	AVISO Sea Surface Altimetry	Input dataset (observations)				https://www.aviso.altimetry.fr/en/home.html		Standard deviation across 2005-2014.
Figure 9.12h,i	CMIP6 (OMIP)	Model dataset				HYCOM low-res is from ftp://ftp.coaps.fsu.edu/pub/abozec/OMIP2-GLBt0.7		Standard deviation across last 10 years.

						2/. HYCOM high-res is from ftp://ftp.coaps.fsu.edu/pub/abozec/GLBb0.08/.		
Figure 9.12a-f	CMIP6 (CMIP, ScenarioMIP)	Model dataset						Changes are between 1995-2014 and 2081-2100 means.
Figure 9.13 Left panel	UHH SIA	Input datasets	SeaIceArea__NorthernHemisphere__monthly__UHH__v2019_fv0.01.nc	Creative Commons Attribution 4.0 International	Doerr, Jakob, Notz, Dirk, & Kern, Stefan. (2021). UHH Sea Ice Area Product (Version 2019_fv0.01) [Data set].	http://doi.org/10.25592/uhhfdm.8559		
Figure 9.13 Left panel	Plotting code	Code	plot_9_13_and_9_15.py					
Figure 9.13 Maps (except right column)	OSISAF/CCI 450	Input datasets			EUMETSAT Ocean and Sea Ice Satellite Application Facility. *Global sea ice concentration climate data record 1979-2015* (v2.0, 2017),	http://doi/10.15770/EUM_SAF_OSI_0008	*Lavergne et al., 2019*	
	OSISAF/CCI 430-b	Input datasets			EUMETSAT Ocean and Sea Ice Satellite Application Facility. *Global sea ice concentration interim climate data record 2016 onwards* (v2.0, 2019), [Online]. Norwegian and Danish Meteorological Institutes.	http://osisaf.met.no/p/ice/#conc-reproc-v2 [last accessed: 2020-08-14] at time of writing available at	*Lavergne et al., 2019*	

						ftp://osisaf.met.no/reprocessed/ice/conc-cont-reproc/v2p0/		
	NASA Team and Bootstrap algorithm data as included in the NOAA/NSIDC Climate data record	Input data set			Meier, W. N., F. Fetterer, M. Savoie, S. Mallory, R. Duerr, and J. Stroeve. 2017. *NOAA/NSIDC Climate Data Record of Passive Microwave Sea Ice Concentration, Version 3*. [Indicate subset used]. Boulder, Colorado USA. NSIDC: National Snow and Ice Data Center. Cavalieri, D. J., C. L. Parkinson, P. Gloersen, and H. J. Zwally. 1996, updated yearly. *Sea Ice Concentrations from Nimbus-7 SMMR and DMSP SSM/I-SSMIS Passive Microwave Data, Version 1*. Comiso, J. C. 2017. *Bootstrap Sea Ice Concentrations from Nimbus-7 SMMR and DMSP SSM/I-SSMIS, Version 3*. Boulder, Colorado USA. NASA National Snow and Ice Data Center Distributed Active Archive Center.	https://doi.org/10.7265/N59P2ZTG	Cavalieri et al., 1996; Comiso et al., 2017	

Figure 9.13 Right column	Plotting code	Code	plot_Fig_9_13_RIGHT_and_Fig_9_15_RIGHT.py					
Figure 9.13 Right column	CMIP6 (CMIP, ScenarioMIP)	Model dataset						
Figure 9.14	Plotting code	Code	plot_Fig_9_14.py					
Figure 9.14	CMIP6 Sea-Ice Model Intercomparison Project SIMIP	Model dataset					SIMIP Community, 2020	
Figure 9.15 Left panel	UHH SIA	Input datasets	SeaIceArea__NorthernHemisphere__monthly__UHH__v2019_fv0.01.nc	Creative Commons Attribution 4.0 International	Doerr, Jakob, Notz, Dirk, & Kern, Stefan. (2021). UHH Sea Ice Area Product (Version 2019_fv0.01) [Data set].	http://doi.org/10.25592/uhhfdm.8559		
Figure 9.15 Left panel	Plotting code	Code	plot_9_13_and_9_15.py					
Figure 9.15 Maps (except right column)	OSISAF/CCI 450	Input datasets			EUMETSAT Ocean and Sea Ice Satellite Application Facility. *Global sea ice concentration climate data record 1979-2015* (v2.0, 2017),	http://doi/10.15770/EUM_SAF_OSI_0008	*Lavergne et al., 2019*	
	OSISAF/CCI 430-b	Input datasets			EUMETSAT Ocean and Sea Ice Satellite Application Facility. *Global sea ice concentration interim climate data record 2016 onwards* (v2.0, 2019), [Online]. Norwegian and Danish Meteorological	http://osisaf.met.no/p/ice/#conc-reproc-v2 [last accessed: 2020-08-14] at time of writing	*Lavergne et al., 2019*	

					Institutes.	available at ftp://osisaf.met.no/reprocessed/ice/conc-cont-reproc/v2p0/		
	NASA Team and Bootstrap algorithm data as included in the NOAA/ NSIDC Climate data record	Input data set			Meier, W. N., F. Fetterer, M. Savoie, S. Mallory, R. Duerr, and J. Stroeve. 2017. *NOAA/NSIDC Climate Data Record of Passive Microwave Sea Ice Concentration, Version 3*. [Indicate subset used]. Boulder, Colorado USA. NSIDC: National Snow and Ice Data Center. Cavalieri, D. J., C. L. Parkinson, P. Gloersen, and H. J. Zwally. 1996, updated yearly. *Sea Ice Concentrations from Nimbus-7 SMMR and DMSP SSM/I-SSMIS Passive Microwave Data, Version 1*. Comiso, J. C. 2017. *Bootstrap Sea Ice Concentrations from Nimbus-7 SMMR and DMSP SSM/I-SSMIS, Version 3*. Boulder, Colorado USA. NASA National Snow and Ice Data Center Distributed	https://doi.org/10.7265/N59P2ZTG	Cavalieri et al., 1996; Comiso et al., 2017	

					Active Archive Center.				
Figure 9.15 Right column	CMIP6 (CMIP, ScenarioMIP)	Model dataset							
Figure 9.15 Right column	Plotting code	Code	plot_Fig_9_13_RIGHT_and_Fig_9_15_RIGHT.py						
Figure 9.16 Top left panel	Regional Mass Change in Greenland	Input dataset						Colgan et al., 2019; Mouginot et al., 2019	Referenced to 2015
Figure 9.16 Top right panel	Regional Mass Change in Antarctic	Input dataset						Bamber et al., 2018a; IMBIE Team, 2018	Referenced to 2015
Figure 9.16 Lower panels	Regional Mass Change in Greenland	Input dataset						Mankoff et al., 2019; Mouginot et al., 2019; King et al., 2020	
Figure 9.17 Top-left panel	Greenland Paleo observations (MPWP)	Input dataset						Dolan et al (2011); Koenig et al. (2015); Miller et al. (2012); de Boer et al. (2017); Dolan et al. (2015); Contoux et al. (2015)	The mean of each of these studies means is plotted as a circle. The range shows the maximum and minimum of range values across all these studies.
	Greenland Paleo observations (LIG)	Input dataset						Robinson et al. (2011); Colville et al. (2011); Fyke et al. (2011); Born & Nisancioglu (2012); Quiqet et al. (2013); Dahl-Jensen et al. (2013); Helsen et al. (2013);	The mean of each of these studies means is plotted as a circle. The range shows the maximum and minimum of range values across all these studies.

							Stone et al. (2013); Colleoni et al., (2014); Robinson & Goelzer (2014); Calov et al., (2015); Dutton et al. (2015); Goezler et al (2017); Yau et al., (2016) Bradley et al. (2018); Tabone et al. (2018); Plach et al. (2019); Clark et al. (2020)	
	Greenland Paleo observations (LGM)	Input dataset					Simpson et al. (2009); Lecavalier et al. (2014); Peltier et al. (2015); Khan et al. (2016); Simms et al. (2019); Stuhne et al. (2015); Argus & Peltier (2010).; Bradley et al. (2018); Tabone et al. (2018)	The mean of each of these studies means is plotted as a circle. The range shows the maximum and minimum of range values across all these studies.
Figure 9.17 Top-right panel	Greenland mass loss historical data	Input dataset					Box and Colgan 2013; Kjeldsenet al., 2015; Mouginot et al., 2019; Bamber et al., 2018b; The UMBIE Team, 2019	
	Greenland mass loss projection (ISMIP6)	Model datasets					Goelzer et al., 2020; Payne et al., submitted	
	Greenlan	Model					Edwards et al.,	

	d mass loss projection (ISMIP6 emulation)	dataset					submitted	
Figure 9.17 Bottom panels	Paleo reconstructions (left 3 panels)	Input dataset					Lecavalier et al., 2014; Koenig et al., 2015; Goelzer et al., 2017	
	CryoSat 2 radar altimetry	Input Dataset					Bamber et al., 2018b	
	ISMIP6 projection	Input dataset					Goelzer et al., 2020	
Figure 9.18 Top-left panel	Antarctica Paleo observations (MPWP)	Input dataset					Dolan et al (2011); Miller et al. (2012); Pollard et al (2015); de Boer et al. (2015); de Boer et al. (2017); Deconto & Pollard (2016); Yan et al. (2016); Gasson et al. (2016); Golledge et al. (2017)	The mean of each of these studies means is plotted as a circle. The range shows the maximum and minimum of range values across all these studies.
	Antarctica Paleo observations (LIG)	Input dataset					Bamber et al. (2009); Dutton et al. (2015); Goezler et al (2017); Briggs et al. (2014) Clark et al. (2020) Albrecht et al. (2020)	The mean of each of these studies means is plotted as a circle. The range shows the maximum and minimum of range values across all these studies.
	Antarctica Paleo observations (LGM)	Input dataset					Whitehouse et al. (2012) Golledge et al. (2012) Golledge et al. (2013) Mackintosh et al. (2011)	The mean of each of these studies means is plotted as a circle. The range shows the

							Golledge et al. (2014) Ivins et al. (2013) Maris et al. (2014) Argus et al. (2014) Simms et al. (2019) Argus et al. (2014) Argus & Peltier (2010)	maximum and minimum of range values across all these studies.
Figure 9.18 Top-right panel	Antarctic mass loss historical data	Input dataset					WCRP Global Sea Level Budget Group, 2018	
	Antarctic mass loss projection (ISMIP6)	Model datasets					Seroussi et al., 2019; Payne et al., submitted	
	Antarctic mass loss projection (ISMIP6 emulation)	Model dataset					Edwards et al., submitted	
Figure 9.18 Bottom panels	Paleo reconstructions (left 3 panels)	Input dataset					Anderson et al., 2002; Bentley et al., 2014; De Boer et al., 2015; Goelzer et al., 2016	
	Restored analog radar records	Input Dataset					Schroeder et al., 2019	
	ISMIP6 projection	Input dataset					Seroussi et al., 2019	
Figure 9.19 Top-left panel	Present-day melt rates (input-output method)	Input dataset					Rignot et al., 2013	
Figure 9.19 Top-middle panel	Present-day melt rates (non-local PIGL)	Input dataset					Jourdain et al., 2020	
Figure 9.19	Present-day melt	Input dataset					Naughten et al., 2018	

Top-right panel	rates (FESOM simulation)							
Figure 9.19 Bottom panels	ISMIP6 projections	Input dataset						Future anomalies are calculated as 2081-2100 minus present-day using the ISMIP6 non-local-MeanAnt and non-local-PIGL parameterizations ((Jourdain et al., 2020) lower left and centre respectively) based on projections from the NorESM1-M CMIP5 model, and the FESOM-MMM projection (lower right).
Figure 9.20	Glacier change rates	Input dataset					Zemp et al., 2019; Zemp et al., 2020; Wouters et al., 2019; Hugonnet et al., submitted	
Figure 9.21	Historical glacier mass	Input dataset					Marzeion et al., 2015; Zemp et al., 2019; Bamber et al., 2018.	
	CMIP6 (Glacier MIP Phase 2)	Model dataset					Marzeion et al., 2020	
Figure 9.22	Global mean annual ground temperature data (GTN-P)	Input dataset			GTN-P, 2018			
Figure 9.22	CMIP6 (CMIP,	Model dataset	pf15m_amip_NH_19	Creative				

Left panel	AMIP, land-hist), CMIP5		79-1998.txt; pf15m_CMIP5historical_NH_1979-1998.txt; pf15m_historical_NH_1979-1998.txt; pf15m_land-hist_NH_1979-1998.txt	Commons Attribution 4.0 International				
	Observed and reanalysis-based permafrost extent	Input dataset	3 values extracted manually from the cited references	No license required	Obu et al., 2018; Zhang et al., 1999; Gruber et al., 2012	-	Obu et al., 2018; Zhang et al., 1999; Gruber et al., 2012	-
Figure 9.22 Right panel	CMIP6 (CMIP, ScenarioMIP)	Model dataset	pfvolbin-3m.tgz	Creative Commons Attribution 4.0 International			Python, Fortran	Change calculated relative to 1995-2014 over historical period and up to 2100
Figure 9.23	Observed snow trends	Input dataset	Figure directly from publication	Creative Commons Attribution 4.0 International	Mudryk et al., 2020		Mudryk et al., 2020	Trends and anomalies calculated over 1981-2018.
Figure 9.24 Left panel	Observed snow cover extent	Input dataset	Mudryk_scf_1981-2014.txt	Creative Commons Attribution 4.0 International	Mudryk et al., 2020	-	Mudryk et al., 2020	
	CMIP6 (CMIP)	Model dataset	snc_clim_CMIP6_historical_1981-2014.txt	Creative Commons Attribution 4.0 International	Mudryk et al., 2020		Mudryk et al., 2020	1981-2014
Figure 9.24 Right panel	CMIP6 (CMIP, ScenarioMIP)	Model dataset	sncbin.tgz	Creative Commons Attribution 4.0	Mudryk et al., 2020		Mudryk et al., 2020	1850-2100, relative to 1995-2014

				International				
Figure 9.25	Literature global mean sea leavel projections	Input dataset					Bakker et al. 2017 Jackson and Jevrejeva 2016 Kopp et al. 2014 Kopp et al. 2016 Mengel et al. 2016 Nauels et al. 2017a Slangen et al. 2014 LeBars et al. 2018 LeCozannet et al. 2019 Goodwin et al. 2017 Nicholls et al. 2018 Kopp et al. 2017 Wong et al. 2017 Grinsted et al. 2015 Jackson and Jevrejeva 2016 Jevrejeva et al. 2014 Bamber et al. 2019 Horton et al. 2020	See Appendix Tables 9.A.5 and 9.A.6
Figure 9.26	Sea level projections							See 9.6.3.2, Table 9.7, and Appendix 9.A.4 for methods
	Figure 9.26 Plotting code	Code	Plot_SL_Contribution_Maps.m					
	Figure 9.26 Plotting Code	Code	Plot_SL_Contribution_Timeseries.m					
Figure 9.27	GMSL projections							See 9.6.3.2, Table 9.7, and Appendix 9.A.4 for methods
	Figure 9.27	Code	Plot_GMSL_Projecte					

	Plotting Code		d_Scenarios.m					
Figure 9.28	Sea level projections							See 9.6.3.2, Table 9.7, and Appedix 9.A.4 for methods
	Figure 9.28 Plotting Code	Code	Plot_RSL_Scenario_Maps.m					
Figure 9.29	Sea level timing projections							See 9.6.3.2, Table 9.7, and Appedix 9.A.4 for methods
	Figure 9.29 Plotting Code	Code	plot_exceedance_year.r					
Figure 9.30	GMSL commitment (models)	Input dataset					Clark et al., 2016; Van Breedam et al,. 2020; Garbe et al., 2020; DeConto and Pollard, 2016; Gregory et al, 2020	
	GMSL Commitment (paleo records)	Input dataset						Assessed in 2.3.3.3
	Figure 9.30 Plotting Code	Code	plot_SLR_commitments.m					
Figure 9.31A	Observed minor tidal flood frequency trend	Input dataset (observations)			Woodworth et al. (2017) ( )	Gesla.org ( )	Woodworth et al. (2017) ( )	Trends determined over 1950-2020
Figure 9.31B	Observed minor tidal flood frequency trend	Input dataset (observations)			Woodworth et al. (2017) ( )	Gesla.org ( )	Woodworth et al. (2017) ( )	Trends determined over 1950-2020
Figure 9.32	Sea level projections	Input dataset					Buchanan et al., 2016; Oppenheimer et al., 2019; Frederikse et al., 2020	See Appendix 9.A.4.8 for methods
	Global Extreme Sea Level Analysis	Input dataset	private_14032017.zip public_11092018.zip			https://www.gesla.org/	Woodworth et al, 2017	Public and private parts of dataset

	2 (GESLA 2)							
	Figure 9.32 Plotting Code	Code	Plot_fig9_32_ESL.m					

[END TABLE 9.SM.9 HERE]