

Supplementary Information for
“Sea Ice Darkening of Surviving Arctic Sea Ice
Accelerates Radiative Forcing”

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This Supplementary Information expands on the Online Methods of the main text.
It records the full satellite-in-situ collocation and harmonization procedures, the

25 platform-by-platform validation results underlying the choice of CLARA-A3 as the primary surface albedo record, and the complete ice-edge discrimination analysis. Figure numbers refer to the main manuscript throughout.

S1 Satellite value extraction

For CLARA-A3, each in-situ observation date is bracketed by the two nearest pentad
30 composites; the satellite albedo at the observation location is obtained by temporal interpolation between the area-weighted spatial means of the two pentads, using inverse distance weighting (IDW) over the four nearest valid grid cells within 25 km. We note that due to persistent Arctic cloud cover, a given satellite pentad may effectively represent only a single day of clear-sky observations. While this temporal sparsity
35 could introduce minor interpolation artifacts, the observed negative bias is sufficiently systematic across platforms that temporal sampling alone is unlikely to explain the discrepancy. For fixed Greenland tower sites (Summit, Raven), where the satellite footprint is over a spatially uniform ice sheet, we instead apply a Cartesian 3-D IDW interpolation using the four nearest neighbors without a distance cap, which better
40 handles the pole-proximate grid geometry of CLARA-A3.

For APP-x, which provides daily retrievals at either 04 or 14 UTC, we select the overpass slot whose nominal acquisition time is closest to the in-situ measurement time. If the selected day-of observation yields a masked (cloudy) pixel, we construct a temporal composite from valid retrievals within ± 2 days, weighting each
45 by $\exp(-0.40|\Delta\text{day}|)$ to prioritize temporally proximate observations.

S2 Spatial collocation

Each airborne or surface transect measurement is assigned to the nearest valid satellite grid cell centroid within 12.5 km using a k -d tree based on great-circle distances. Groups of at least three co-located measurements within a single grid cell form a

single comparison point, with the representative in-situ albedo taken as the arithmetic group mean. Drone observations are additionally weighted by the square of the flight altitude, giving proportionally greater influence to larger-footprint, higher-altitude measurements. For the ARISE 2014 campaign, only satellite grid cells with at least one snow-surface observation (`nobs_snow` > 0) are retained, to restrict the comparison to ice covered pixels during the autumn freeze-up period.

Tower observations over sea ice are blended with a SIC-weighted open-ocean albedo prior,

$$\alpha_{\text{tower}}^{\text{blend}} = f_{\text{SIC}} \alpha_{\text{tower}}^{\text{obs}} + (1 - f_{\text{SIC}}) \alpha_{\text{ocn}}(\bar{\Theta}_{\text{sat}}), \quad (\text{S1})$$

to account for the sub-pixel open water fraction unsampled by the point-scale instrument [1, 2], where f_{SIC} is the daily SIC from the NSIDC Climate Data Record [3] at the tower location, and α_{ocn} is the Payne (1972) open-water albedo evaluated at the satellite mean SZA. Tower observations on the Greenland ice sheet are exempt from SIC blending.

S3 Solar zenith angle harmonization

Surface albedo over snow and sea ice varies strongly with SZA [4]. Because instantaneous in-situ observations (Θ_{obs}) often differ from the satellite pentad-mean ($\bar{\Theta}_{\text{sat}}$), we apply distinct SZA harmonization strategies based on the temporal sampling characteristics of each platform [5, 6]:

- **Filtering:** For surface transects, drones, and fixed-wing aircraft campaigns (ARISE, ARCSIX), we retain only observations where $|\Delta\Theta| \leq 3^\circ$, where $\Delta\Theta = \Theta_{\text{obs}} - \bar{\Theta}_{\text{sat}}$.
- **Linear Correction:** For helicopter and HELiPOD flights, which exhibit a systematic time-of-day sampling offset relative to satellite overpasses, we regress the validation bias against $\Delta\Theta$ and apply a linear SZA correction to the in-situ albedo.
- **Matching:** For continuous MOSAiC tower measurements, we isolate and average observations recorded at the SZA of the satellite pentad mean. For Greenland towers

75 (Summit, Raven), which have persistent daily coverage but a natural SZA bias relative to the satellite overpass, we bypass instantaneous SZA filtering and perform a direct pentad (or daily)-mean to pentad (daily)-mean comparison.

Validation statistics (Pearson r , mean bias, RMSE) are computed following these SZA harmonization procedures.

80 S4 Angular sampling geometry and the MOSAiC negative bias

An additional structural limitation affects the MOSAiC validation in particular. The AVHRR constellation's orbital geometry at the latitudes of the MOSAiC drift (~ 83 – 87°N) restricts valid, cloud-free retrievals to the backward-scattering hemisphere only; 85 the forward-scattering hemisphere is never sampled at these latitudes. Because snow and sea ice reflectance is systematically lower in the backward-scattering direction relative to the hemispherical mean apart from high zenith angle views [4], this angular undersampling introduces a geometric low bias into CLARA-A3 retrievals that is independent of surface or atmospheric retrieval errors. This effect is compounded by 90 known visible-channel calibration drift in the 2020 AVHRR constellation. Extended Data Fig. 10 illustrates this sampling asymmetry directly, showing the observed broadband directional reflectances over the MOSAiC drift at global area coverage (GAC) resolution alongside polar plots of the valid observation geometries for the drift locations and two reference sites at lower latitudes. The contrast is pronounced: at sites 95 near Svalbard (78°N), both scattering hemispheres are sampled, while at MOSAiC latitudes the coverage collapses almost entirely into the backward-scattering region. This geometric bias provides a physically consistent explanation for the larger negative bias observed at MOSAiC relative to earlier campaigns such as SHEBA, which drifted at lower latitudes where more balanced angular sampling is achieved.

100 S5 Validation performance by platform and product selection

Across the eight validation platforms, CLARA-A3 exhibits a consistent systematic negative bias ranging from -0.01 to -0.20 . Correlations are strongest for spatially integrated melt-season observations (i.e., surface transects, helicopter, and drone), as
105 their larger footprints are highly representative of the satellite grid cell. Note that the transects (Fig. 6B) likely undersampled open water that may have been in the satellite view, a potential explanation for differences at intermediate values. Robust agreement is achieved with the MOSAiC tower data (Fig. 6a), where extended temporal averaging helps compensate for the localized nature of the point measurement. Because
110 the MOSAiC towers were deployed on the thickest, most stable snow-covered ice to ensure survivability, their unblended measurements inherently lack the dark-surface contribution of summer melt ponds. However, our SIC-blending methodology partially mitigates this sampling bias. Passive microwave SIC retrievals notoriously misclassify summer melt ponds as open ocean [7]; consequently, blending the tower data with
115 a low-biased SIC record preferentially weights the final validation target downward with open-ocean albedo, inadvertently but effectively representing the missing melt-pond contribution. The Greenland comparisons (Fig. 6D,L), which are uniformly snow and do not suffer this spatial limitation for the in-situ observations, are consistent with Fig. 6a. Indeed, CLARA-A3 artificially compresses the albedo distribution at its
120 extremes—a known artifact of NTBC algorithms that tends to underestimate highly reflective surfaces while overestimating darker features [8]. In contrast, correlations are weakest during the ARISE freeze-up campaign (September–October), where rapidly evolving surface conditions, geometrically complex new ice, and reduced AVHRR polar coverage collectively degrade retrieval accuracy.

125 Despite offering daily temporal coverage, APP-x generally performs worse across most platforms, exhibiting larger biases, lower correlations, and greater scatter. It

notably fails to retrieve valid matchups for the ARISE 2014 freeze-up campaign, likely because its neural network retrieval scheme was trained on summer surface conditions and degrades severely when new ice types dominate the surface. The Summit and
130 Raven comparisons reveal an additional structural limitation: neither retrieval scheme performs well in representing the natural variance of snow albedo over the ice sheet. APP-x overestimates this variance, whereas CLARA-A3 underestimates it, effectively collapsing snow albedo retrievals toward a fixed value of approximately 0.84 [9].

Because CLARA-A3 more closely captures the physical surface state across the
135 full range of Arctic melt-season conditions, it serves as the primary surface albedo record for this analysis. However, its retrieval algorithm applies a strict SZA cutoff of 70° for the surface-albedo (SAL) retrieval to minimize atmospheric correction errors [9, 10], whereas APP-x permits retrievals up to 85° [11]. As solar zenith angles increase late in the melt season, CLARA-A3 develops a large unretrieved polar hole. Because
140 solar zenith angles are highest at the start and end of the melt season, CLARA-A3 develops an unretrieved polar hole in April and again—most severely—in September. To prevent spatial gaps in the SIAF decomposition, APP-x is used to fill missing CLARA-A3 values in the early melt season, and we transition entirely to APP-x for September. While albedo retrievals at these extreme SZAs inherently carry higher
145 observational uncertainty, the RS in September is substantially smaller than in the early-to-mid melt season; thus, the influence of this elevated albedo uncertainty on the final SIAF magnitude is likely negligible.

S6 Ice-edge representation and albedo discrimination

Our spatial decomposition of SIAF into area-loss and darkening components rests on
150 an assumption: that satellite-derived SIAL and satellite-derived SIC identify ice cover in the same geophysical locations. If the two products disagree about where the ice edge is—if SIAL is reporting bright, ice-like conditions in locations where SIC reports

open ocean, or vice versa—then it is less likely that our albedo-based darkening signal is actually located on ice that SIC confirms is present, and the sea ice albedo feedback (SIAF) derivation breaks down. This section tests that assumption directly.

We first show that even in the Central Arctic, where SIC remains consistently high throughout the satellite era, monthly mean SIAL continues to decline (Extended Data Fig. 1). This confirms that SIAL responds to surface processes (e.g., snow loss, ice thinning, melt pond formation) that are partially independent of ice concentration, which is the physical basis for treating darkening as distinct from area-loss in interior, ice-covered regions. However, it also means we cannot assume the two products agree at the ice edge. We therefore assess, directly and quantitatively, whether SIAL and SIC identify the same ice-covered regions by testing whether SIAL carries a physically meaningful ice–ocean contrast: whether ice-covered pixels ($\text{SIC} \geq 15\%$) are reliably brighter than open-ocean pixels ($\text{SIC} < 15\%$), and by how much.

We quantify ice-edge representation using two complementary classification metrics applied to both the full Arctic domain and a dynamically defined Marginal Ice Zone (MIZ). First, we evaluate the separability of the albedo distributions using receiver operating characteristic (ROC) analysis [12] (Extended Data Fig. 7). For a given albedo threshold α^* , pixels are classified as ice if $\alpha \geq \alpha^*$. The true positive rate (TPR; fraction of $\text{SIC} \geq 15\%$ pixels correctly identified) and false positive rate (FPR; fraction of $\text{SIC} < 15\%$ pixels misclassified as ice) are computed across a range of thresholds, and the area under the ROC curve (AUC) is used as a summary metric of discrimination skill.

Crucially, evaluating ROC across the entire Arctic domain (Extended Data Fig. 7a) artificially inflates the AUC, as the bulk of the region consists of saturated pixels (e.g., 100% sea ice or 0% open ocean). Because the sea ice albedo feedback (SIAF) area-loss signal is concentrated almost entirely within the dynamic ice fringe, we recalculate the ROC curve strictly within the MIZ—defined here as pixels within a localized

dilation of the SIC = 15% contour (Extended Data Fig. 7b). This MIZ-restricted AUC rigorously tests albedo discrimination exactly where the ice edge is actively melting.

Second, we identify the optimal albedo threshold for ice detection using Youden’s J statistic [13],

$$J = \text{TPR} - \text{FPR}, \quad (\text{S2})$$

which maximizes the combined sensitivity and specificity of the classification. By extracting this optimal threshold specifically from the MIZ-restricted ROC curves, we provide a physically interpretable estimate of the effective albedo contrast at the active ice edge.

All metrics are computed for each year and month, with inter-annual mean curves and variability reported. Grid cells with fewer than 100 valid ice or ocean pixels are excluded to ensure robust statistics. This method isolates the fundamental requirement for albedo-based ice-edge detection (that ice-covered pixels are systematically brighter than open ocean) while avoiding ambiguities associated with spatial mismatch metrics.

S7 CMIP6 ensemble composition and per-model results

Table 1 lists every model in the 31-model ensemble, its assignment to one of the 18 model families used for the family-weighted multi-model mean, its ensemble size, native atmospheric grid spacing, sea ice component, and its SIAF components. Family assignment groups configurations sharing a common base model, so that no lineage is weighted by the number of variants its centre contributed. Sea ice components were read from the `source` global attribute of each model’s CMIP6 output, except for the CESM2 configurations, whose archived files do not populate a `seaIce` field.

The table also substantiates the observation in the main text that skill is not inherited from the choice of sea ice component. Eight components appear in more than one model, and in most such cases the constituent models differ widely in SIAF_{drk}: Gelato

205 6.1 spans 0.038–0.070, CICE4.0 spans 0.031–0.068, and CICE-HadGEM3-GSI8 0.048–
 0.072. The three CESM2 configurations, which share CICE5, are the most tightly
 clustered (0.045–0.054), so a shared component does not preclude agreement—it
 simply does not ensure it.

S8 Sensitivity of the decomposition to native grid

210 resolution

Because the classification of Ω_{area} and Ω_{drk} depends on how finely each model resolves
 the ice edge, coarse- and fine-resolution models could in principle partition the feedback
 differently for reasons unrelated to their physics. We test this in two ways.

First, across the 31 models—whose atmospheric grids span 0.56° to 2.81° latitude
 215 spacing, a factor of five—we correlate each quantity against the logarithm of the total
 number of native grid cells (Table 2). Neither the total SIAF nor either component cor-
 relates significantly with resolution. The footprint-normalized ice sensitivity $\text{IS}_{\text{local,drk}}$
 does increase weakly but significantly with resolution, which is expected: it divides by
 the area of Ω_{drk} , and that area is precisely what a better-resolved ice edge changes. The
 220 globally normalized SIAF divides by Earth’s area instead and is therefore insulated.

Second, five lineages contribute both a coarse and a fine configuration, isolating
 resolution with the rest of the model held largely fixed (Table 3). The sign of the
 resolution difference is inconsistent: SIAF_{drk} increases with refinement in two pairs
 and decreases in three. Resolution therefore does not impose a systematic bias on the
 225 decomposition. Consistent with this, the model reproducing the observed darkening-
 region ice sensitivity most closely, CNRM-ESM2-1, runs at 1.41° , coarser than the
 ensemble median.

Table 1 CMIP6 models analysed, grouped by family. n is the number of ensemble members passing all data requirements; Δlat is the native atmospheric grid latitude spacing in degrees. SIAF components are ensemble means in $\text{W m}^{-2} \text{K}^{-1}$, expressed as a global-mean forcing; $\text{IS}_{\text{local}, \text{drk}}$ is the ice sensitivity averaged over Ω_{drk} alone, in K^{-1} .

Model	Family	n	Δlat	Sea ice	SIAF _{area}	SIAF _{drk}	SIAF _{tot}	IS _{local, drk}
ACCESS-ESM1-5	ACCESS	39	1.24	CICE4.1	0.051	0.046	0.098	0.0647
ACCESS-CM2		10	1.25	CICE5.1.2	0.103	0.030	0.133	0.0542
BCC-CSM2-MR	BCC	3	1.12	SIS2	0.038	0.037	0.075	0.0663
BCC-ESM1		3	2.81	SIS2	0.040	0.038	0.078	0.0547
CESM2	CESM2	10	0.94	CICE5	0.065	0.045	0.109	0.0795
CESM2-WACCM		3	0.94	CICE5	0.072	0.048	0.121	0.0843
CESM2-FV2		4	1.88	CICE5	0.072	0.054	0.126	0.0957
CMCC-CM2-SR5	CMCC	11	0.94	CICE4.0	0.070	0.031	0.102	0.0803
CNRM-CM6-1	CNRM	11	1.41	Gelato 6.1	0.048	0.038	0.085	0.0738
CNRM-ESM2-1		5	1.41	Gelato 6.1	0.070	0.070	0.140	0.0965
CanESM5	CanESM5	29	2.81	LIM2	0.105	0.053	0.159	0.0620
E3SM-1-0	E3SM	5	1.00	MPAS-Seaiice	0.095	0.054	0.149	0.0895
EC-Earth3-Veg	EC-Earth3	5	0.70	LIM3	0.066	0.081	0.147	0.0953
EC-Earth3-Veg-LR		3	1.12	LIM3	0.104	0.082	0.187	0.0819
FGOALS-f3-L	FGOALS	3	1.00	CICE4.0	0.042	0.054	0.097	0.0644
FGOALS-g3		6	2.25	CICE4.0	0.037	0.068	0.105	0.0618
GISS-E2-1-H	GISS	10	2.00	GISS SI	0.095	0.058	0.153	0.0662
UKESM1-0-LL	HadGEM3/UKESM	16	1.25	CICE-HadGEM3-GSIS	0.090	0.049	0.139	0.0534
HadGEM3-GC31-LL		5	1.25	CICE-HadGEM3-GSIS	0.108	0.048	0.156	0.0600
HadGEM3-GC31-MM		4	0.56	CICE-HadGEM3-GSIS	0.092	0.072	0.164	0.0767
INM-CM5-0	INM	10	1.50	INM-ICE1	0.055	0.056	0.111	0.0606
IPSL-CM6A-LR	IPSL	31	1.26	NEMO-LIM3	0.083	0.059	0.142	0.0839
MIROC-ES2L	MIROC	3	2.81	COCO4.9	0.049	0.031	0.079	0.0564
MIROC6		43	1.41	COCO4.9	0.064	0.043	0.107	0.0659
MPI-ESM1-2-LR	MPI/ICON	50	1.88	Sentner/Hibler	0.053	0.039	0.092	0.0699
MPI-ESM1-2-HR		10	0.94	Sentner/Hibler	0.066	0.049	0.115	0.0905
MPI-ESM1-2-HAM		3	1.88	Sentner/Hibler	0.083	0.059	0.143	0.0873
MRI-ESM2-0	MRI-ESM2-0	5	1.12	MRI.COM4.4	0.082	0.078	0.160	0.0927
NESM3	NESM3	5	1.88	CICE4.1	0.135	0.031	0.166	0.0446
NorCPM1	NorESM/NorCPM	30	1.88	CICE4	0.030	0.050	0.080	0.0637
NorESM2-LM		3	1.88	CICE	0.037	0.061	0.098	0.0907

Table 2 Pearson correlation of each quantity with $\log_{10}$ of the number of native atmospheric grid cells, across the 31 models.

Quantity	r	p	Significant at $p < 0.05$
SIAF_{tot}	+0.26	0.156	no
SIAF_{area}	+0.13	0.485	no
SIAF_{drk}	+0.32	0.079	no
$\text{IS}_{local,drk}$	+0.46	0.010	yes

Table 3 Within-lineage resolution pairs. SIAF_{drk} in $\text{W m}^{-2} \text{K}^{-1}$; Δlat in degrees.

Coarse $\rightarrow$ fine configuration	Δlat	SIAF_{drk}	Effect of refinement
HadGEM3-GC31-LL $\rightarrow$ HadGEM3-GC31-MM	1.25 $\rightarrow$ 0.56	0.048 $\rightarrow$ 0.072	increase
MPI-ESM1-2-LR $\rightarrow$ MPI-ESM1-2-HR	1.88 $\rightarrow$ 0.94	0.039 $\rightarrow$ 0.049	increase
CESM2-FV2 $\rightarrow$ CESM2	1.88 $\rightarrow$ 0.94	0.054 $\rightarrow$ 0.045	decrease
EC-Earth3-Veg-LR $\rightarrow$ EC-Earth3-Veg	1.12 $\rightarrow$ 0.70	0.083 $\rightarrow$ 0.081	decrease
FGOALS-g3 $\rightarrow$ FGOALS-f3-L	2.25 $\rightarrow$ 1.00	0.068 $\rightarrow$ 0.054	decrease

S9 Bayesian model averaging weights

Table 4 gives the BMA weight of every model in the 21-model, 346-member subset used
 230 for the probability distributions of the main text, computed separately for each SIAF
 component. Weights are the likelihood that the observation arose from each model’s
 distribution inflated by the observational uncertainty, normalized to sum to unity.

The weights make explicit that skill in one component does not imply skill in the
 other. NESM3 carries the highest weight on SIAF_{area} (0.127) and the lowest but one
 235 on SIAF_{drk} (0.011), while FGOALS-g3 receives essentially zero weight on the area
 component and 0.071 on darkening. MRI-ESM2-0 is the only model ranking in the
 upper third on both.

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Table 4 BMA weights by component for the 21 CMIP6 models retaining at least five ensemble members, ordered by weight on the total SIAF.

Model	w (SIAF _{area})	w (SIAF _{drk})	w (SIAF _{tot})
NESM3	0.127	0.011	0.125
MRI-ESM2-0	0.074	0.086	0.113
CanESM5	0.118	0.054	0.099
GISS-E2-1-H	0.094	0.065	0.093
HadGEM3-GC31-LL	0.117	0.040	0.081
IPSL-CM6A-LR	0.071	0.067	0.075
CNRM-ESM2-1	0.052	0.082	0.075
EC-Earth3-Veg	0.033	0.076	0.070
INM-CM5-0	0.045	0.050	0.055
UKESM1-0-LL	0.065	0.045	0.052
E3SM-1-0	0.040	0.055	0.043
ACCESS-CM2	0.111	0.027	0.033
MPI-ESM1-2-HR	0.028	0.045	0.029
FGOALS-g3	0.000	0.071	0.015
ACCESS-ESM1-5	0.005	0.041	0.009
CNRM-CM6-1	0.002	0.032	0.009
CESM2	0.003	0.032	0.008
MIROC6	0.011	0.030	0.008
MPI-ESM1-2-LR	0.003	0.030	0.003
CMCC-CM2-SR5	0.004	0.012	0.003
NorCPM1	0.000	0.048	0.001

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