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Transferability of ML emulators for polar RCM surface melt under different forcings: Limitations and recommendations

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	diversity does not overcome these transferability limitations, highlighting the importance of training on data that are representative of the target application. Future emulator development should focus on incorporating information across multiple temporal scales and systematically evaluate transfer performance to improve generalizability.



Transferability of ML emulators for polar RCM surface melt under different forcings: Limitations and recommendations

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ABSTRACT. Machine learning emulators provide a computationally efficient alternative to physically based regional climate and surface mass balance models, but their applicability depends on their ability to generalize beyond training conditions. In this study, we assess the transferability of a melt emulator trained on output from the regional climate model HIRHAM5 forced by ERA-Interim, CESM2, and EC-Earth under historical and future (SSP5-8.5) climates. Transferability is evaluated across forcing datasets and climate states without retraining. The emulator generalizes reasonably well within a given climate regime, producing biases below the inter-model spread, but exhibits limited transferability between historical and future climate conditions. Predictor distributions analyses, perturbation experiments, and ablation studies indicate that these errors arise from shifts in predictor distributions together with an insufficient representation of the surface state. Although perturbation experiments demonstrate physically plausible relationships between surface energy fluxes and melt generation, physical consistency alone does not ensure robust extrapolation to novel climate conditions. Increasing training data diversity does not overcome these transferability limitations, highlighting the importance of training on data that are representative of the target

application. Future emulator development should focus on incorporating information across multiple temporal scales and systematically evaluate transfer performance to improve generalizability.

INTRODUCTION

Transferability, rather than in-domain accuracy, often determines the practical value of machine learning (ML) emulators. Due to imperfect process understanding, unknown future changes, model assumptions and parametrizations, any individual simulation represents only one realization from a wider ensemble of plausible climate evolutions. Therefore, ensembles of physical model simulations are used to assess the range of possible outcomes. However, due to high computational costs, these ensembles often cover only a limited number of scenarios, forcings, and time periods. While ML emulators are a great opportunity to complement physical simulations, applying them to out-of-domain (OOD) data can lead to unexpectedly high errors, and systematic biases (Quiñonero-Candela and others, 2008; Eyring and others, 2024; Reichstein and others, 2019).

The accuracy and validity of ML emulators is typically determined in-domain, without knowing the area of validity, or exploring the behavior of the emulator outside the tested domain. During development, the available data is split into a training and an (independent) test set, to evaluate the emulator on unseen (but in-domain) data. Splitting data in groups regarding time, location, or other joint characteristics can thereby be necessary to avoid information leakage between training and test data (Roberts and others, 2017; Meyer and Pebesma, 2021). While this strategy can inadvertently generate OOD test data, it is generally considered in-domain, with the test scores indicating interpolation performance. In subsequent applications, it is often not a-priori clear whether the emulator is being applied in an in-domain regime or in an OOD regime, where the emulator might behave unexpectedly.

ML based emulators are increasingly developed for ice sheet and glacier surface mass balance (SMB) modeling (Schlager and others, 2026; Tedesco and others, 2026; Bochow and others, 2026; Jourdain and others, 2025; de Roda Husman and others, 2024; Van Katwyk and others, 2023; Bolibar and others, 2020). The traditional workflow for simulating ice sheet melt and SMB consists of starting with a global climate model (GCM) that is then dynamical downscaled with a regional climate model (RCM), and then the computation of surface meltwater production and runoff using a firn model which may or may not be

integrated into the RCM. The surface mass budget may then be used to force an ice sheet dynamical model and/or to compute the sea level rise contribution of the runoff. Every component in this chain is computationally expensive, limiting the number of simulations for which the entire modeling chain is run and therefore the availability of sufficient simulations to assess true ensemble spread. In the context of international collaborations such as the Coupled Model Intercomparison Project (CMIP), which contributes to IPCC assessments, the Ice Sheet Model Intercomparison Project (ISMIP), is often at the very end of this chain and therefore out of synchrony with other parts of CMIP as there is only a short time window for SMB and ice sheet dynamical simulations to be completed.

Furthermore, ice sheet models and earth system models (ESM) often rely on computationally simpler, but much less accurate approximations such as positive degree day (PDD) models which have important shortcomings when applied to future climate, since coupling full polar RCMs and their associated firn models into the processing chain is also computationally expensive and technically challenging. Emulating the RCM inputs as well as the firn model would speed up that process, enabling the construction of larger ensembles of simulations as well as helping to integrate more sophisticated SMB schemes in ice sheet models and ESMs.

While ML based emulators show great potential in creating melt estimates under additional GCM forcings, and extending simulations in time, the validity of such applications must be rigorously assessed. For example, ML based downscaling is broadly researched, addressing multiple modes of transferability, i.e., spatial, temporal, forcing, and scenario based (Kendon and others, 2025; Bano-Medina and others, 2024; Hernanz and others, 2024; Rampal and others, 2024). For a firn emulator built on RCM outputs, the forcing GCM data does not serve as input to the emulator directly, however, the GCM forcing largely determines the dynamics and biases of the resulting RCM fields (Giorgi, 2019; Hofer and others, 2020; Boberg and others, 2022, 2026; Akperov and others, 2019; Reader and Steiner, 2022). Applying the emulator to simulations from the same RCM but forced by a different GCM than used for training may result in OOD extrapolation and reduced reliability due to differences in the predictor distributions. Similarly, extending simulations in time can place the emulator outside its training distribution, resulting in OOD extrapolation and systematic biases, particularly under high-emission scenarios or for far-away time periods due to shifts in the climate regime (Jourdain and others, 2025; Hernanz and others, 2024). In other words, the emulator learns the functional relationship between the RCM climate and the firn model's surface melt production, but only for the input data region covered by the particular GCM used in training. Even though the

functional relationship of RCM climate and melt production is the same outside this data region, there is no guarantee the emulator behaves the same outside this region, as neural networks are prone to learning localized mappings.

To reduce the risk of extrapolation, ML emulators are typically trained on a wide range of climatic conditions to maximize coverage of the predictor space (Song and Kuang, 2025; Dunmire and others, 2024; Sellevold and Vizcaino, 2021; Veldhuijsen and others, 2025). However, increasing the diversity of the training data does not necessarily improve model fidelity. Instead, when important state variables are missing in the predictor set, the model may be forced to learn a statistical compromise across multiple physical regimes that cannot be fully distinguished from the available predictors. Expanding the training dataset may improve generalization to a wider range of conditions while simultaneously reducing accuracy within specific physical regimes. Consequently, training data selection is not just a question of maximizing coverage of the predictor space, but the optimal choice of training data depends on the intended application of the emulator.

In this work we investigate transferability performance and the cause of OOD biases for daily melt emulation based on the emulator developed in Schlager and others (2026). We first investigate training robustness and the emulator’s capability of reproducing interannual variability via a cross validation study. Then, we assess transferability to data from different forcing GCMs and different time periods via repeated training and evaluation on HIRHAM5 data forced by the reanalysis product ERA-Interim, and historic simulations of CESM2 and EC-Earth for 1990-2016, as well as their high-emission future projections for 2075-2100. While the emulator can accurately extrapolate to higher melt values, temporal extrapolation introduces systematic biases due to the uncertain surface state approximation. In a dedicated perturbation study we demonstrate that the emulator reproduces the expected sensitivities of melt to changes in incoming energy fluxes, indicating that it has learned physically meaningful relationships. Additional experiments further explore the effect of long-term climate variables and precipitation on transferability.

METHODS

Data

The ML emulators in this work have been trained and evaluated on simulation data from the polar RCM HIRHAM5 and its firn model DMIHH. We took simulations that have been forced by (a) the reanalysis product ERA-Interim for 1980–2016 (Langen and others, 2017), (b) the GCM CESM2 (Boberg and others,

2026; Glaude and others, 2024), and (c) the GCM EC-EARTH v3 (Boberg and others, 2022). From the available GCM-forced simulations, we selected the historical period 1980–2016 to align with the reanalysis forced simulation, and the future period 2065–2100 under the SSP5-8.5 scenario, which represents the largest regime shift available among the simulations considered, and therefore provides the "hardest" test for the emulator. We refer to these simulations as *CESM2 future* and *EC-Earth future*, while their historic parts are referred to as *CESM2* and *EC-Earth* only. The first ten years of each simulation are used as aggregated inputs, thus emulator outputs are assessed for the periods 1990–2016 and 2075–2100.

Annual mean surface melt production shows systematic differences across these forcings with respect to forcing and time. The temporal means of the historic simulations show substantial spread, with the ERA-Interim forced simulation showing systematically less melt than the historic ensemble, and the CESM2 forced simulation showing more melt than the historic ensemble across the whole ice sheet (Fig. 1). The future projections show both increased melt production in the already known melting zones and spatial expansion of melt occurrence to the entire ice sheet. The maps of associated annual averages of the main melt drivers are listed in Appendix A Fig. 6, showing the prominent change in downwelling shortwave radiation, the sum of downwelling longwave radiation and turbulent heat fluxes, and precipitation from historical to future simulations (Glaude and others, 2024; Fettweis and others, 2020; Noël and others, 2018; Boberg and others, 2026, 2022). While time-aggregated maps are useful for obtaining a compact overview of overall changes, they hide temporal variability and the total range of the variables, limiting insights into the actual differences between the datasets.

Identifying distribution shifts in multivariate, time-dependent datasets is not trivial, as it is often unclear which aspects of the distribution are most relevant for emulator transferability. Figure 2 shows the different univariate distributions for the main melt driving energy fluxes and the resulting surface melt. The distributions are calculated on randomly subsampled subsets from the whole dataset (2a), the dataset filtered by melt occurrence (i.e. where surface melt is larger than 1 mm. w.e. per day; 2b), and the summer months (JJA) only (2c). For a target like melt, with a very strong spatial and temporal pattern, the choice of filtering criterion can substantially alter the resulting distributions. When comparing the distributions of the full data sets, dominant non-melting conditions may hide actual differences in the data set (2a).

Conversely, restricting the data to melt conditions or to the summer months highlights different aspects of the underlying climate regime. For example, the distributions of the summed energy flux, $E = LW^{\downarrow} +$

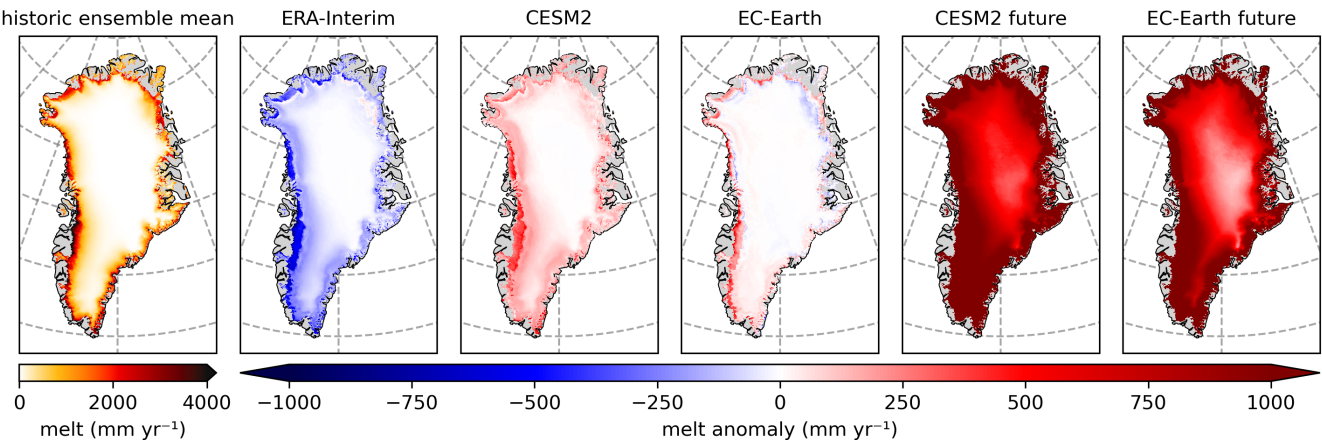


Fig. 1. Mean annual melt of historic ensemble from different forcings (ERA-Interim, CESM2, and EC-Earth for 1990–2016), and the respective anomalies of the historically forced runs, and the future projections for 2075–2100.

LHF + SHF, from simulation data forced by ERA-Interim versus the GCMs (CESM2 and EC-Earth) for the historical period versus their future projection, differ much more from each other for the period of JJA only, compared to the filtering by melt occurrence. Likewise, the relative similarity in shortwave radiation distributions depends on the filtering approach: for melt-based filtering, the ERA-Interim forced data clearly shows lowest maximum $SW^\downarrow$, whereas for JJA-only filtering the future scenarios show lower maximum $SW^\downarrow$ values than the other simulation data. Because melt production depends strongly on the temporal evolution of surface conditions and associated memory effects, it is not obvious which of these distributions is most relevant for assessing model transferability.

The distributional analysis suggests that transferability between historical and future simulations may suffer from OOD extrapolation, as future climate conditions exhibit substantial shifts in several key predictors, most notably in the aggregated energy flux E . In contrast, the two GCM forced simulations in the historic and the future period respectively show similar distributions, especially for E . The ERA-Interim forced simulation shows considerable overlap in the ranges of its distributions with the historic GCM forced simulations, despite differences in their distributional shapes. However, it remains unclear how these distributional differences relate to transferability performance, and whether they are large enough to substantially degrade emulator skill. Moreover, comparisons based solely on univariate distributions may be misleading, as they do not capture dependencies and interactions between variables. Therefore, although distributional comparisons can identify differences between data sets, they are not sufficient on their own to determine whether these differences will translate into reduced transferability, or to quantify the magnitude of any such effect.

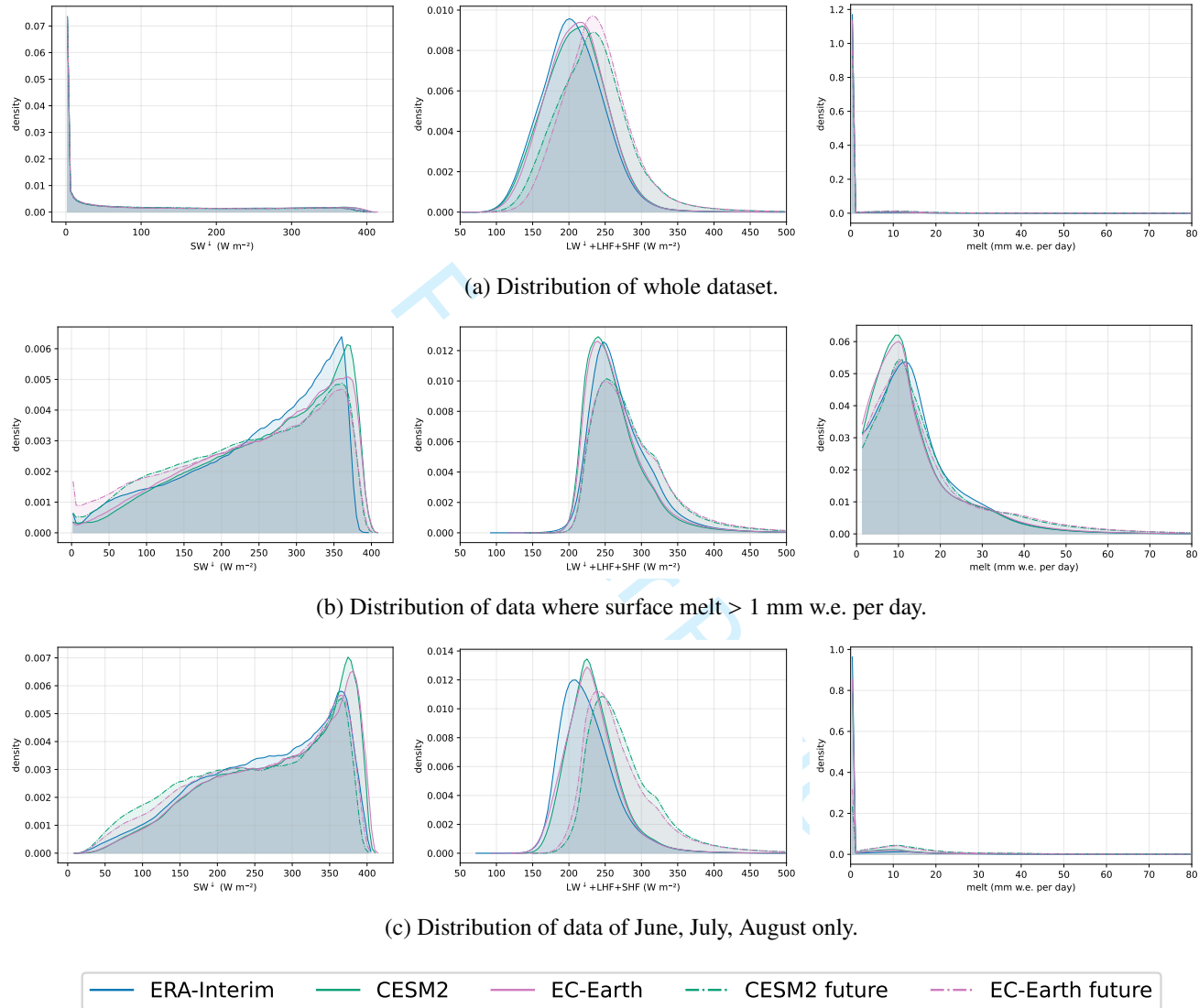


Fig. 2. Distribution of downwelling shortwave radiation $SW^{\downarrow}$, summed energy term $LW^{\downarrow} + LHF + SHF$, and surface melt, randomly subsampled from (a) the whole datasets, (b) from data with daily melt above 1 mm w.e. per day only, and (c) from JJA only. Solid lines indicate historical runs (1990-2016), dashed lines the future projections (SSP5-8.5, 2075-2100).

The emulator

This work builds on the emulator developed in Schlager and others (2026). The emulator is a neural network (NN) using RCM daily downwelling shortwave radiation ($SW^{\downarrow}$), the summed energy term composed of downwelling longwave radiation, latent heat flux, and sensible heat flux ($E = LW^{\downarrow} + LHF + SHF$), rainfall, and snowfall of the current and the nine previous days, alongside the previous' 10 year averages to predict current day surface melt as simulated by the firn model. A cyclic feature encoding the day of the year is included to represent seasonality, but no location information is provided to the emulator. The daily inputs and the 10 year averages are fed into two separate modules, the short-term module and the long-term module, to extract information on both time scales before being merged into the final regression module. While surface albedo is critical to identify net shortwave radiation, a true emulator cannot use albedo as input, as it is itself a prognostic output of the firn model based on the calculated surface state.

Compared to the original NN architecture used in Schlager and others (2026), the network size has been reduced to three layers of 128 neurons each for the short-term module, and four layers of size 160-128-128-64 for the regression module; the long-term module remains unchanged with two layers of 32 neurons each. This reduction in emulator size did reduce model complexity while maintaining model performance, whereas further reductions in network size led to underestimation of high melt values. The NN is trained on samples from all over the Greenland ice sheet, temporally and spatially sub-sampled to counteract the strong data imbalance. The NN is trained by minimizing the mean squared error (MSE) between emulator predictions and the corresponding simulated melt.

The cross validation study

A cross validation study was carried out preliminarily to the transferability study, and guided further methodological decisions. A summary of the results and conclusions is presented here, while further details are given in Appendix B. The cross validation study was performed on simulation data forced by ERA-Interim for 1990-2016, following the blocking approach as in Roberts and others (2017), using one year as validation year, and the remaining years for training. Using in total 13 different validation years results in 13 different folds, each of which is retrained five times with random layer initialization and random shuffling of the training data to investigate training robustness.

The data shows high interannual variability in both melt and the melt driving climate variables, such that evaluation on only some selected years can give a skewed view of the emulator performance. The

cross validation shows that the scores depend heavily on the year evaluated, with some years showing strong positive or negative biases across multiple model realizations. Therefore, an ensemble of emulator realizations obtained through repeated retraining captures uncertainty associated with model training, rather than predictive uncertainty, and can therefore not be reliably used for quantification of predictive uncertainty. However, the emulator score for a given year is largely independent of whether that year was included in the training set or reserved for validation. Similarly, the study by Tedesco and others (2026) showed that emulator performance was largely unaffected by the choice of splitting the data into a train and test set randomly or temporally blocked.

In the rest of this study we therefore do not use a disjoint train-test-split, but train and evaluate on the entire respective data sets. This allows the use of a large variety of training data, while avoiding the risk of a biased assessment due to few selected validation years. Furthermore, the repeated training of each fold shows poor training robustness with convergence to local minima with errors of different magnitudes, and non-consistent biases. We therefore re-train the emulator multiple times for each data set and evaluate transferability both using the best-performing realization and across all re-trainings. While the latter allows conclusions to be based on systematic behavior rather than on a potentially exceptional realization, it also includes models that may have converged to suboptimal local minima. The best-performing realization, in contrast, represents the transferability skill of a well-converged emulator and, when considered alongside the ensemble of retrained models, provides a robust assessment of transferability skill. To identify this best realization, performance is assessed across multiple years rather than a single year, yielding a more robust estimate of overall model skill.

The transferability study

For each dataset, we train the emulator 20 times with random layer initialization and training data shuffling. Training is performed on all but the last year, which is used for additional loss monitoring, while evaluation is done on all years (1990–2016 for the historical data sets, 2075–2100 for the future data sets). The trained emulators are applied to the simulation data the emulator has been trained on (as baseline), and to simulation data from the other forcings. This evaluates zero-shot transferability, i.e., transferability without any re-training. For each dataset we then select the emulator with lowest baseline MAE as the *best-performing* emulator. However, we also look at the ensemble of all the 20 training runs, to see if transferability biases are systematic across multiple runs, rather than the result of a single realization.

The emulators are evaluated in terms of mean absolute error (MAE; in mm w.e. per day) and aggregated residuals (mean of predicted minus simulated melt; in Gt). The errors are calculated per year, and then averaged across all years, which gives us the respective errors per emulator–data–pair. Relative MAE and residuals are also calculated as their relative errors per year, and then averaged across the years. For evaluating the scores across the 20 repeated trainings per training set up, we use the median, minimum and maximum of the emulators’ averages across all years. However, the evaluation of the 20 re-trainings should not be interpreted as a valid ensemble characterizing predictive uncertainty, but rather account for training instability.

Experiments to explore influences on transferability

While certain emulator modifications can enhance in-domain accuracy, they may come at the expense of OOD generalization, and vice versa. We therefore perform several additional experiments, to explore the factors influencing transferability. To assess transferability when complete information is available, we train an emulator that includes daily albedo as an input feature. While this emulator setup shows almost perfect in-domain performance (Schlager and others, 2026), transferability could still fail due to input covariate shift under different forcings. This albedo-driven emulator is trained and evaluated on simulation data forced by CESM2, CESM2 future, and EC-Earth future, to explore transferability across both a different forcing GCM and future climate conditions.

To investigate the influence of specific emulator components and climate variables on the transferability, we retrain the emulator excluding certain inputs. While rainfall, snowfall, and 10 year averages of the climate variables do improve in-domain performance (Schlager and others, 2026), they might degrade transferability. These additional experiments are trained on simulation data forced by CESM2 future, and evaluated on data forced by CESM2 future (for in-domain performance), CESM2 (for temporal transferability), and EC-Earth future (for forcing transferability).

Future projections show markedly different precipitation patterns compared to historical ones, which are also reflected in the downscaled RCM fields. We therefore train emulator variations excluding rainfall, or precipitation (i.e, rainfall and snowfall), to explore the role of precipitation changes in transferability. Rainfall and precipitation are thereby excluded from both the emulator’s daily and long-term module.

To assess the impact of of the long-term information, we further train the emulator without the long-term module. Since 10 year averages are rather static input, the emulator does not see much variability of

these inputs during training. However, long-term climate conditions change considerably from the historical period to end-of-century simulations under a high-emission scenario, potentially increasing the OOD effect when transferring emulators trained on historical data to future projections or the other way round.

With not including albedo, the emulator can only approximate the surface state from imperfect climate variables (as net radiation rates are not known, and climate information is aggregated temporally). We investigate to what extent the emulator learns physically plausible relationships, as physical plausibility is not only linked to improved generalization but crucial for interpretability. We therefore perform a perturbation study by separately increasing $SW^\downarrow$ and $LW^\downarrow + LHF + SHF$ relative to the current day by 10 W m^{-2} and assess the associated changes in melt production. Only instances where the predictions under unperturbed conditions already exceed 10 mm w.e. per day are assessed, such that the surface is already at melting conditions and the additional energy is supposed to increase melt production. This perturbation experiment is carried out for the respective best emulator realizations trained on data forced by CESM2 future, using the default emulator, the albedo-driven emulator, the emulator without long-term inputs, and two emulators that were trained with additional physics-informed loss terms.

By training with physics-informed loss terms we assess whether we can guide the emulator toward more physically consistent behavior, and whether this leads to improved transferability. The first physics-informed loss term considered penalizes negative melt gradients with respect to the daily energy inputs, to prevent unphysical negative change of melt production. Alternatively, the second loss term encodes the physically intended behavior more directly: For each instance with melt exceeding 10 mm w.e., the melt change due to perturbing current day's $SW^\downarrow$ or $LW^\downarrow + LHF + SHF$ by 10 W m^{-2} is calculated. The loss term then penalizes melt changes outside the range of $[0.19, 1.76]$ for $SW^\downarrow$, and $[2.4, 2.8]$ for $LW^\downarrow + LHF + SHF$. More details on the motivation and implementation of these physics-informed loss terms are provided in Appendix C.

RESULTS AND DISCUSSION

Inter-model transferability within same climate regimes

MAE and residual of the respectively best-performing emulators across the 20 re-trainings are shown in Table 1. The inter-model transferability within the same climate regimes can be seen in the top left quadrants (transferability between historical simulation data), and bottom right quadrants (transferability between future projections). Overall, transferability between data sets forced by different reanalysis products or

GCMs are reasonable, with biases smaller than the inter-model spread in mean annual simulated melt.

Emulators trained on historical GCM simulations transfer well to ERA-Interim forcing, with the emulator trained on EC-Earth forced data outperforming that trained on CESM2 forced data. MAE increases slightly compared to the baseline performance (from 15% for the baseline mean, to 17% for the EC-Earth trained emulator, and 18% for the CESM2 trained emulator). Furthermore, the EC-Earth trained emulator results in a negligible mean bias on ERA-Interim forced data, while the CESM2 trained emulator results in a positive mean bias of 4%. The MAE on data forced by the historic GCM-forced simulations show better transferability between the two GCM-forcings, compared to transferability from the emulator trained on ERA-Interim forced data to the data forced by the GCMs, with the ERA-Interim trained emulator leading to a relative MAE 3-4% higher than the respective other GCM-trained emulator.

However, emulator transfer does introduce some significant biases despite a reasonable MAE. On EC-Earth forced data both emulators, trained on ERA-Interim or CESM2 forced data, introduce a bias of 8%, while having different skill in terms of MAE. On the other hand, the emulator trained on EC-Earth forced data results in negligible mean bias on the ERA-Interim forced data set. Moreover, for CESM2 forced data the ERA-Interim trained emulator shows a negligible bias of 1% compared to a bias of -5% for the EC-Earth trained emulator. Thus, transferability skill is not symmetric, and an apparent good skill in terms of MAE can suffer from systematic bias. The emulator trained on the combined data set from both forcings, ERA-Interim & CESM2, did not change MAE on either set, nor did it improve transferability to the EC-Earth forced data. This is surprising since melt amount of EC-Earth is between that of ERA-Interim and CESM2, and one might intuitively consider this a relatively easy interpolation task.

Figure 3a,c shows that the baseline performances and transferability skills with respect to MAE are robust across the 20 model re-trainings and in agreement with the best performing models. Also the transfer-induced biases are mostly consistent across re-trainings (Fig. 3b,d). Especially the introduction of substantial biases, e.g., the emulator transfer from ERA-Interim or CESM2 forced data to EC-Earth forced data, are consistent between the best-performing model and the median of the 20 re-trainings. However, for some emulator-dataset combinations, the median bias is small and the sign of the bias varies across training realizations, indicating that the transfer-induced signal is not robust relative to the variability introduced by retraining (e.g., EC-EARTH forced data with its baseline model).

For future simulations, the baseline MAEs are substantially higher than for the historic runs due to much higher melt extent; the relative absolute error is, however, lower (11-12%, Table 1 bottom right

Table 1. Mean annual MAE and residual of transferability of the best-performing emulator realizations trained on the forcing dataset indicated by the row labels and evaluated on the datasets indicated by the column labels. Total and relative scores show the mean of the annual MAE and residuals across all years, ranges indicate minimum and maximum annual total scores. Performance on the dataset used for training (i.e., without transfer) serves as the baseline and is highlighted in bold. Comparisons are only meaningful within columns, where all models are evaluated on the same dataset; differences between columns additionally reflect varying difficulty and error scales of the evaluation datasets.

	Model training data	Evaluation data				
		ERA-Interim	CESM2	EC-Earth	CESM2 future	EC-Earth future
	simulated melt	621±141	962±190	850±166	2734±462	2582±380
MAE (mm w.e.)	ERA-Interim	0.14 (15%) [0.10,0.20]	0.37 (25%) [0.27,0.45]	0.36 (28%) [0.32,0.44]	0.94 (22%) [0.59,1.28]	0.86 (22%) [0.69,1.11]
	CESM2	0.17 (18%) [0.13,0.22]	0.30 (21%) [0.23,0.36]	0.30 (24%) [0.26,0.38]		
	EC-Earth	0.16 (17%) [0.11,0.22]	0.32 (22%) [0.23,0.40]	0.26 (21%) [0.23,0.35]		
	ERA-Interim & CESM2	0.14 (15%) [0.10,0.19]	0.29 (20%) [0.22,0.37]	0.31 (24%) [0.25,0.39]		
	CESM2 future		0.54 (38%) [0.47,0.63]		0.47 (12%) [0.41,0.61]	0.59 (15%) [0.49,0.68]
	EC-Earth future			0.43 (34%) [0.34,0.53]	0.59 (15%) [0.42,0.75]	0.42 (11%) [0.36,0.53]
	ERA-Interim & CESM2 future	0.15 (16%) [0.10,0.20]	0.41 (29%) [0.34,0.52]	0.38 (30%) [0.33,0.47]	0.50 (12%) [0.42,0.62]	0.70 (18%) [0.59,0.81]
residual (Gt)	ERA-Interim	-13.13 (-2%) [-56.54,30.01]	-16.41 (-1%) [-128.98,107.59]	57.65 (8%) [-4.61,140.65]	313.82 (11%) [137.18,571.79]	332.30 (13%) [193.53,485.59]
	CESM2	24.44 (4%) [-25.70,82.49]	-6.61 (-0%) [-103.58,119.76]	62.07 (8%) [0.85,135.36]		
	EC-Earth	-4.39 (-0%) [-50.57,41.65]	-52.94 (-5%) [-156.67,55.19]	10.29 (2%) [-37.97,82.56]		
	ERA-Interim & CESM2	10.03 (2%) [-36.74,58.76]	2.74 (1%) [-93.00,139.24]	74.84 (10%) [10.39,147.59]		
	CESM2 future		-94.89 (-9%) [-192.79,-0.63]		-34.49 (-1%) [-120.21,69.14]	123.22 (5%) [28.23,221.85]
	EC-Earth future			-131.73 (-15%) [-214.61,-35.07]	-174.90 (-7%) [-284.49,-18.01]	-49.46 (-2%) [-108.25,34.83]
	ERA-Interim & CESM2 future	-6.74 (-1%) [-46.93,32.91]	-1.34 (0%) [-91.77,88.60]	48.36 (6%) [-8.76,125.24]	49.41 (2%) [-20.15,155.96]	257.34 (10%) [132.03,390.42]

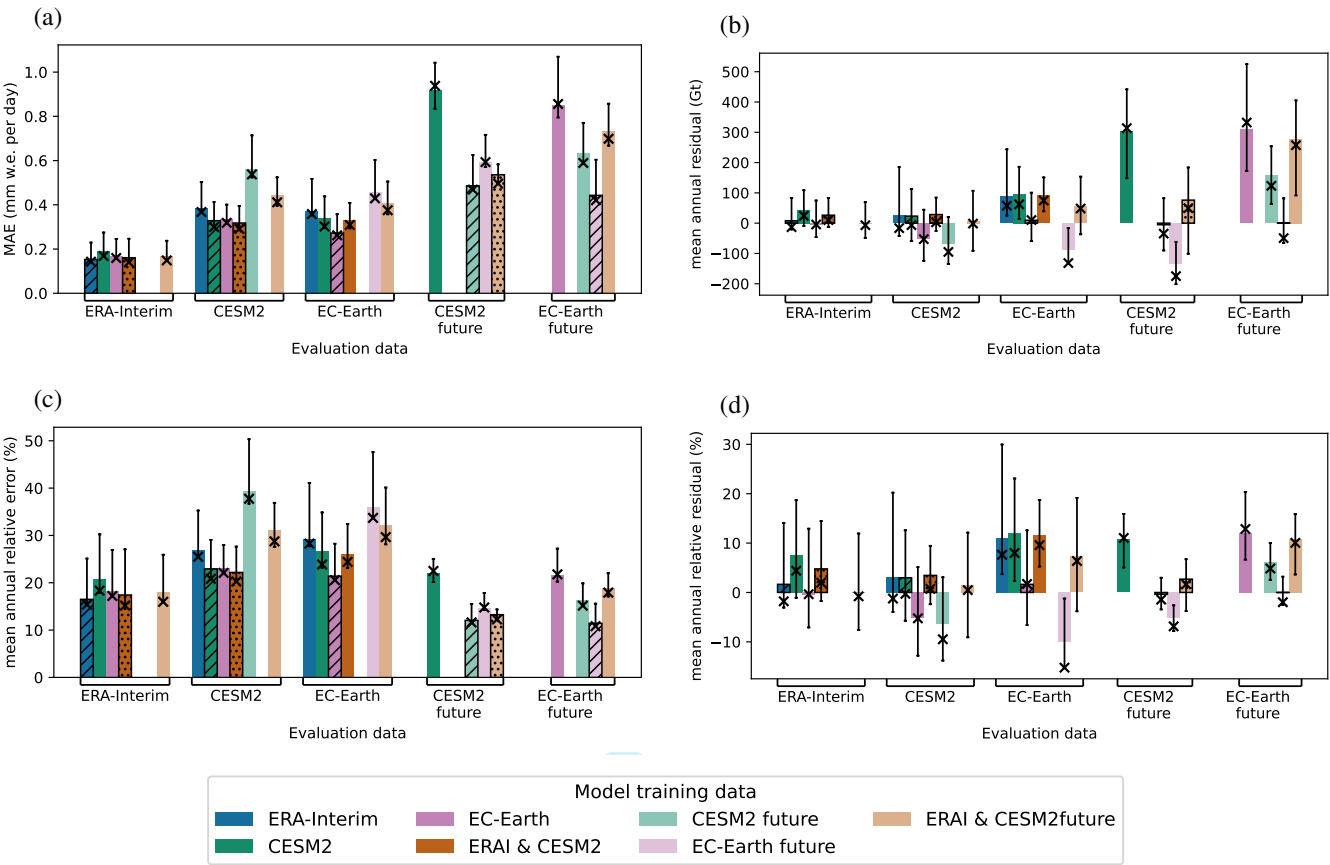


Fig. 3. MAE and residuals as totals and in percentage of total annual melt across all 20 repeated training runs. Each group of bars shows the scores on one specific data set w.r.t. the different model trainings, analogously to the columns in Table 1. The scores are calculated annually and then averaged across the the years. The bar heights indicate the median of the average scores across the repeated training runs, and the error bars show the minimum and maximum score. The black ‘x’ shows the scores of the respectively best-performing model listed in Table 1. Models evaluated on its own training set are shown with hatched bars (baseline), and models evaluated on data which are part of the training set are shown with dotted pattern since they do not reflect zero-shot transferability.

quadrants). Transfer between the two GCM-forced datasets for the future period increases the relative absolute errors by another 2-3%, which is of similar magnitude as for the historical transferability. Also, similarly to the transferability between the historic data sets, transfer from CESM2 to EC-Earth does introduce a positive bias, while transferring the emulator trained on EC-Earth forced data introduces negative bias on CESM2 forced data (Fig. 3b,d).

Transferability between historic and future climate states

Transferring the best-performing historic emulators to their respective future counterparts (2075–2100) almost doubles absolute errors to 22% of the annual melt amount, and introduces a positive bias across all years, averaging to 11% and 13% of CESM2 future and EC-EARTH future forced data respectively

(Table 1 top right quadrants). Transfer backwards in time also shows substantially higher MAE than transfer between the historical emulators, and introduces a negative bias across all years, averaging to -9% and -15% for CESM2 and EC-Earth forced data respectively (Table 1 bottom left quadrants). This behavior can be seen not only for the best performing emulators, but clearly across all repeated model trainings (Fig. 3).

With ERA-Interim yielding the least melt in the physical model simulations, and the future projection of CESM2 resulting in the most melt, we decided to train our emulator with a combination of both datasets, to see if there is improved transferability to other datasets due to interpolation instead of extrapolation. This combined emulator shows good performance on the two training sets themselves, so the model complexity is high enough to cover both climate regimes. For CESM2, the MAE improved significantly compared to its respective future emulator alone, but still shows worse MAE than the other historically trained emulators (Fig. 3a,c). However, residual on CESM2 data has improved compared to its baseline, with the combined emulator training showing a lower median residual, but higher range (Fig. 3b,d). On EC-Earth forced data, the combined emulator shows similar performance to the ERA-Interim forced emulator only. Thus the combined emulator shows fairly good transferability to the historical datasets.

However, transferability to data forced by the EC-Earth future projection shows degraded performance in terms of absolute error and residual compared to the emulator trained on CESM2 future projection data only. So, although the EC-Earth future projection produces less melt than CESM2 future, including the low melt historical data set degrades performance instead of improving it.

Overall, the transferability results are broadly consistent with the expectations based on the predictor distributions shown in Fig. 2: transferability between historical and future climate states is limited, whereas transferability within the historical and future climate states is generally reasonable. However, transferability is neither symmetric across all simulation combinations nor free of systematic biases. The univariate distribution plots do not reveal a clear explanation for the observed differences in transferability. These differences may arise from subtle distributional discrepancies visible in the predictor distributions, but could equally be related to changes in the remaining input variables, and in multivariate dependencies or temporal characteristics that are not captured by these plots.

Exploring influences on transferability

To better understand the drivers of successful and failed transferability, this subsection explores different factors that may influence transferability. By identifying which aspects of the input data and model setup most strongly affect transferability skill, this analysis provides insight into the behavior of the emulator and helps inform future efforts to improve its robustness.

In future projections, melt production reaches higher daily peak values compared to the historical runs. However, the increase in total melt production is not caused by these higher absolute values, but by more frequent occurrence of low and medium surface melt. This might be expected to favor transferability of emulators trained on historical data, as future conditions mainly require applying learned melt relationships across a larger spatial and temporal extent, rather than predicting substantially higher melt rates than encountered during training.

Surprisingly, the models trained on historic data can in fact successfully extrapolate to future peak melt values. For such strong melt values the climate signal is very clear, and the model can extrapolate to melt values much higher than seen during training (maximum melt in the historic data sets 300 mm w.e. per day compared to 485 mm w.e. per day in the CESM2 future projection). In contrast, the emulator shows uncertainty when predicting no/low melt, as it only approximates the surface state from the provided climate data. The learned approximate relationship might work well in a specific climate regime, but fail when moving to another climate regime which shows a different relationship between forcing and surface conditions.

If missing surface-state information contributes to the observed transferability limitations, transferability should improve when albedo is provided to the emulator. To test this hypothesis, we compare transferability for an albedo-driven emulator in which albedo is included as a daily input variable. The albedo-driven emulator shows strong transferability with almost no degradation in performance (Fig. 4, Table 2). Feeding albedo as model input does not only enable the emulator to determine net solar radiation, but it is also a direct indicator of whether a snow-covered surface is at the melting point. However, the emulator must still learn the relationship between the surface energy balance and melt amount generation. Remarkably, the learned relationship remains valid even under the pronounced distribution shifts observed between the historical and future simulations.

Given that the model including albedo transfers well, whereas the emulator without albedo exhibits poor transferability for low melt values, we further investigate the emulator’s physical plausibility. The

Table 2. Mean annual MAE and residual of transferability of the best-performing model runs with albedo included as predictors. For each training setup, the model achieving the lowest MAE across all 20 repeated trainings was selected and evaluated on the other data sets. Scores were computed annually and are reported as the mean absolute residual and mean relative residual; ranges indicate the full range of annual residuals. Performance on the dataset used for training (i.e., without transfer) serves as the baseline and is highlighted in bold.

	Model training data	Evaluation data		
		CESM2	CESM2 future	EC-Earth future
MAE (mm w.e.)	CESM2	0.06 (4%) [0.03,0.07]	0.17 (4%) [0.12,0.22]	0.17 (4%) [0.13,0.24]
	CESM2 future	0.07 (5%) [0.05,0.10]	0.14 (3%) [0.11,0.17]	0.14 (4%) [0.13,0.19]
	EC-Earth future	0.08 (5%) [0.05,0.11]	0.16 (4%) [0.12,0.20]	0.13 (3%) [0.11,0.17]
residual (Gt)	CESM2	3.70 (0%) [-3.11,10.00]	6.77 (0%) [-14.51,34.34]	19.39 (1%) [6.35,33.43]
	CESM2 future	7.68 (1%) [-5.05,16.94]	-9.19 (-0%) [-40.68,13.72]	-17.43 (-1%) [-33.09,-1.53]
	EC-Earth future	19.00 (2%) [4.32,32.01]	21.56 (1%) [-12.92,52.26]	9.93 (0%) [-5.98,27.06]

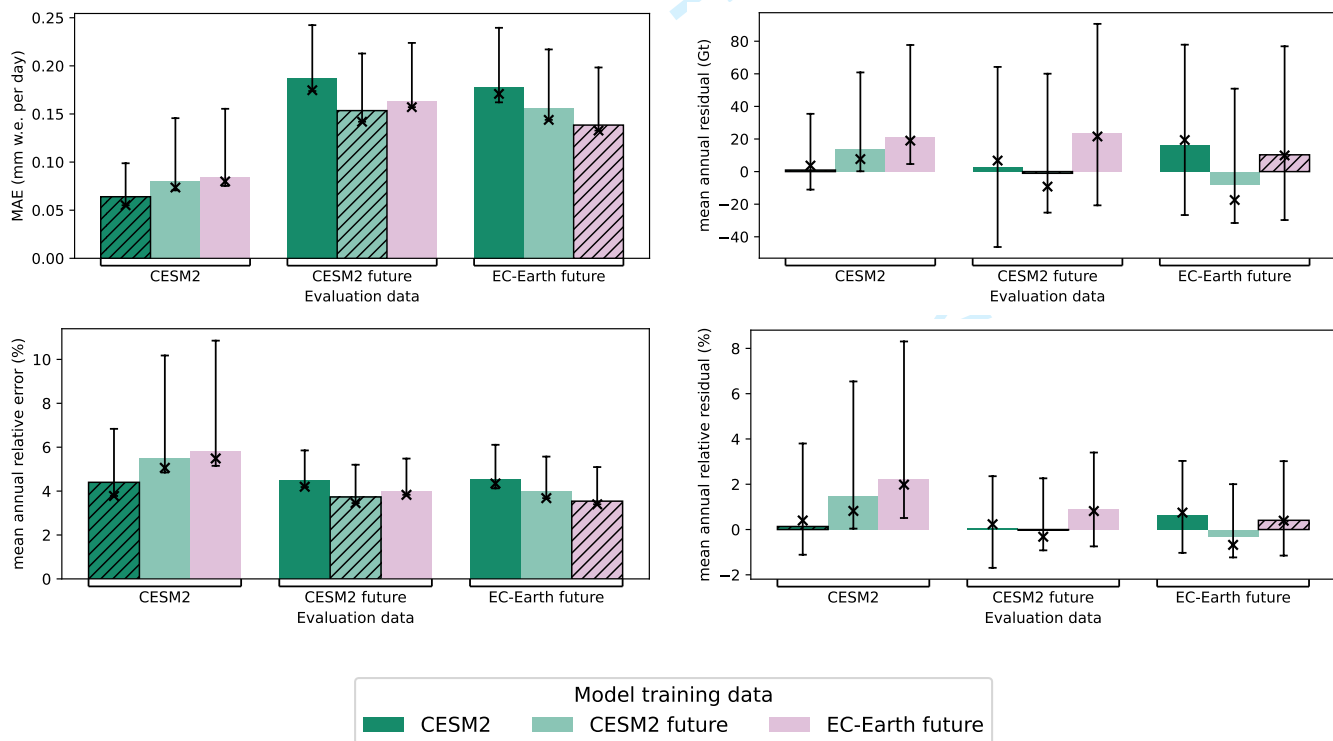


Fig. 4. MAE and residuals as totals and in percentage of total annual melt across all repeated training runs for models including albedo as inputs. Bar heights, error bars, and markers analogously as in Fig. 3.

successful transferability of the albedo-driven emulator across markedly different predictor distributions suggests that it has captured physically meaningful relationships that remain valid under changing climate conditions. We therefore examine whether the emulator without albedo has learned a physically meaningful relationship between the surface energy balance and melt generation, or whether its poor transferability arises from learning climate-specific statistical relationships that do not generalize across climate states. To this end we perform an input perturbation study, where we perturb the input energy fluxes, $SW^\downarrow$ and $LW^\downarrow + LHF + SHF$, and analyze the resulting changes in simulated melt.

While the emulator without albedo as input can only approximate the surface state, it does so in a physical manner when compared to the emulator trained with albedo as input. The perturbation experiment for the emulator with albedo shows a median melt sensitivity with respect to $SW^\downarrow$ of 0.9 mm w.e., and 2.4 mm w.e. with respect to $LW^\downarrow + LHF + SHF$ (Fig. 5a) for data samples showing substantial melt (i.e., unperturbed melt exceeding 10 mm w.e.). The change in melt production to the increased $SW^\downarrow$ shows a strong dependence on albedo, with a median melt increase of 1.5 mm w.e. at bare ice (calculated where albedo $\alpha \in [0.4, 0.42]$), and a lower median melt increase of 0.8 mm w.e. where the surface is snow covered and at the melting point (where $\alpha \in [0.65, 0.67]$). The melt sensitivities show some spread with respect to the energy flux disturbances, which decreases with higher melt production. We speculate that this spread arises from the temporal aggregation to daily values, where the temporal aggregation can represent a variety of distinct physical conditions that lead to different melt outcomes, especially at lower melt signals.

The perturbation experiment for the emulator trained without albedo shows large overlaps with the sensitivities of the emulator that uses albedo as input. While melt changes show a larger spread and even some unphysical negative values, their dominant ranges overlap with those of the albedo-driven emulator (Fig. 5b). Moreover, although albedo is not known to the model, the emulator shows systematic relationship between melt increase and albedo largely consistent with the albedo-driven model. This suggests that the emulator is able to infer information about surface conditions from the available predictors.

An additional experiment of training a variation of the emulator using daily inputs only, but excluding 10 year averages, shows a weaker distinction between the albedo regimes (Fig. 5c), and larger spread of melt increase for low and medium melt values, indicating that the 10 year averages provide useful information to approximate the surface state, and to differentiate between snow covered and bare-ice conditions. Excluding long-term information also leads to higher absolute errors both in-domain (CESM2

future) and also when being transferred to the CESM2 and the EC-Earth future forced climate data (Appendix D Fig. 8). However, the median residual is lower than for the other experiments, thus the model seems to not introduce such a systematic bias, indicating that long-term information is a good proxy for surface state, but it is not transferable. Since the 10 year average is a rather static input, the model does not see much variability of these inputs during training. However, long-term climate conditions change considerably from the historical period to end-of-century simulations under a high-emission scenario, such that this 10 year averages potentially increase the OOD effect when transferring models trained on historical data to future projections.

To encourage physically consistent behavior, we also trained the emulator with two physics-informed loss functions. An additional gradient-based monotonicity term was introduced to penalize decrease in melt although energy input is increased (Appendix D). Training with this monotonicity term discouraged unphysical negative sensitivities, such that negative melt change is eliminated to a large extent, but large positive values for Δmelt remain (Fig. 5d). By comparison, the physical loss term directly enforcing specific sensitivity ranges shows a much narrower spread of Δmelt (Fig. 5e). However, the median values of melt change due to increased energy fluxes deviate further from the albedo-driven emulator than the model with the monotonicity loss and even the default model. Especially the sensitivity with respect to $SW^\downarrow$ does not show such a strong separation regarding albedo. Further refinement of the physical loss term, by penalizing the sensitivity based on the albedo value, could improve this behavior further.

Although the physical loss terms seem to have improved the physical plausibility of the emulator, they did not improve in-domain performance, nor did they decrease absolute error when being transferred backward in time (to data forced by CESM2), or to another forcing (EC-Earth future) (Appendix D Fig. 8). However, the bias of the backwards in time transferability has improved, as the residual on historical CESM2 forced data decreased for the respectively best models and the median values of the model ensembles.

Additional experiments training emulators without rainfall, or without precipitation altogether, did not improve transferability either. As shown in Appendix D Fig. 8, excluding rainfall leads to slightly worse in-domain performance, while excluding both rainfall and snowfall substantially degrades performance. For transferability, the rainfall-free emulator exhibits similar absolute errors to the default configuration, whereas removing all precipitation increases errors both in-domain and for future climate forced by CESM2 and EC-Earth. Excluding rainfall reduces bias for CESM2-driven simulations but slightly increases it for

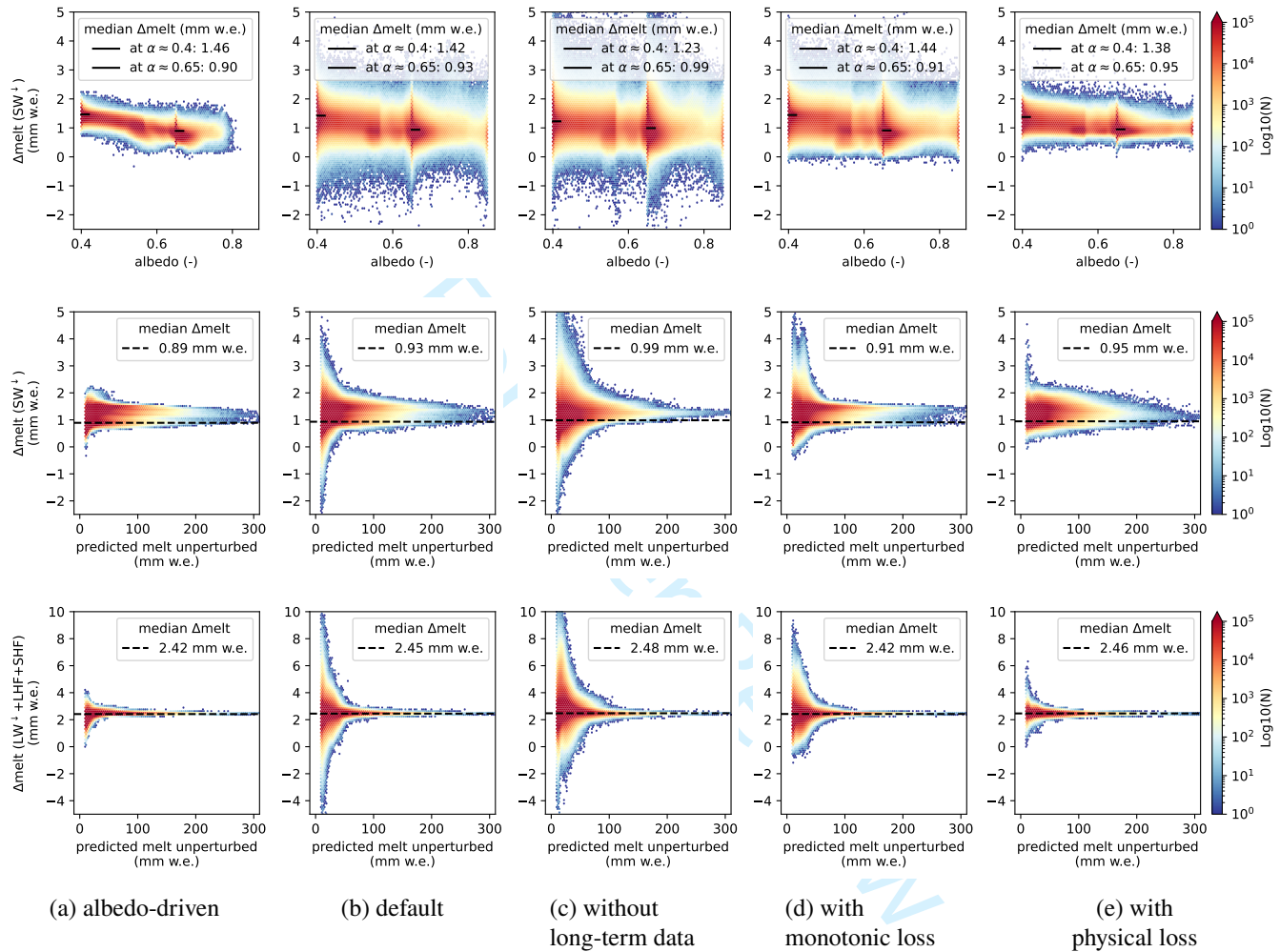


Fig. 5. Change in melt production (Δmelt) due to increase in $SW^\downarrow$ or $LW^\downarrow + LHF + SHF$ by 10 W m^{-2} for emulator trained and assessed on simulation data forced by CESM2 future. Top row shows Δmelt due to increase in $SW^\downarrow$ with respect to albedo, and median melt changes are calculated for the indicated intervals of $\alpha \in [0.4, 0.42]$ and $\alpha \in [0.65, 0.67]$. Middle and bottom row shows Δmelt due to increase in $SW^\downarrow$ and $LW^\downarrow + LHF + SHF$ with respect to unperturbed predicted melt respectively. Emulator including daily albedo as input (a), the default emulator (b), emulator without long-term data (c), and the two emulator variations with additional loss terms (d,e) are evaluated. Only data points where unperturbed predicted melt exceeds 10 mm w.e. were evaluated.

EC-Earth, while removing all precipitation results in similarly mixed effects on transfer bias. Given the clear increase in absolute errors when snowfall is excluded, we recommend retaining snowfall as a predictor. In contrast, the impact of rainfall remains inconclusive.

CONCLUSIONS AND FUTURE PERSPECTIVES

We investigated the skill and limitations of transferability of surface melt emulation to different forcing GCMs and between historical and future high-emission data, based on an NN-based emulator (Schlager and others, 2026) with HIRHAM5 simulation data.

The emulator is capable of learning an approximate relationship between RCM climate variables and surface melt production, resulting in good in-domain performance. While the transfer to simulation data forced by other GCMs and time periods show reasonable extrapolation to higher melt values, approximation uncertainty at lower melt values leads to error accumulation and systematic biases. The inferred relationship represents a compromise learned from the training dataset and does not necessarily generalize to data produced under different forcing conditions. Consequently, transfer of the emulators trained on historic climate data to high emission future projections or vice versa introduce high errors and systematic biases, while transferability within a climate regime (historical, or high emission future scenario) shows acceptable performance.

Training the emulator on a combined data set consisting of simulation data under different forcings does also not improve transferability. Instead, the emulator learns an overall compromise that fits across all data provided during training, but does not fit better to the forcing specific relationships of the individual data sets. While climate conditions at the end of the twenty-first century under SSP5-8.5 represent the most extreme case considered here, transferability between historical data and lower-emission scenarios can generally be expected to be better. However, climate projections are increasingly being extended to 2300, and even under lower-emission scenarios these longer simulations exhibit substantial climate regime shifts that challenge emulator transferability.

A perturbation study on the input energy fluxes showed that the emulator behaves in a physically consistent manner, and that the poor transferability is not caused by unphysical short-cut learning. However, although the model learned meaningful physics, the necessary state information can only be approximated. Using physics-informed loss terms neither improved in-domain performance, nor transferability. Also providing more state information to the model by using an auto-regressive approach or using albedo as an

466 additional target did not improve state encoding, a result previously reported by Schlager and others
467 (2026). We therefore consider further improvements through refinement of the physics-based loss alone to
468 be unlikely, unless additional contextual information is provided to improve the encoding of the system
469 state.

470 Based on these results, we recommend the following considerations for the application of and further
471 development of firn emulators in general:

472 *Univariate predictor distributions can indicate where transferability may fail, but they do not guarantee*
473 *successful emulator transfer.* Large shifts in univariate predictor distributions can indicate situations in
474 which transferability is likely to deteriorate. However, similar distributions do not guarantee successful
475 transfer and even relatively small distributional differences may lead to systematic biases and increased
476 errors after model transfer. Assessments based solely on univariate, time-independent distributions may
477 underestimate relevant differences between data sets, as they neglect predictor correlations and the temporal
478 evolution of surface conditions. It also remains unclear which filtering strategy, such as summer-only
479 conditions or melt occurrence, provides the most informative basis for assessing transferability. Future
480 research should assess transferability across a wider range of forcing datasets and climate scenarios to
481 better understand the impact of distributions shifts on emulator transferability.

482 *When applying a trained emulator to a different data set, staying in the same emission scenario and*
483 *period of time is more important than using the same GCM-forcing.* Transfer of the emulators trained on
484 historic climate data to high emission future projections or vice versa introduces higher errors and bias,
485 compared to emulators trained on the same climate regime but forced by a different GCM. Hence, similarity
486 in climate regime is a stronger determinant of transferability than similarity in the driving GCM. However,
487 also transferability within the same climate regime introduces systematic biases to some extent.

488 *Neither training on more diverse data, nor on more extreme data results in a better emulator.* Training
489 the emulator on simulation data from multiple forcings or from different time periods simultaneously did
490 not improve transferability, but rather degraded performance. Since the model can only approximate the
491 surface state insufficiently, the learned relationship is only a compromise across the whole training data.
492 Including data from very different simulations can therefore introduce higher errors and systematic biases
493 on the individual datasets. Similarly, the narrative of training on the ‘more extreme’ future projection
494 data, so that the emulator can interpolate on historic and lower emission data does not hold true in general
495 but introduces negative bias on the historic data.

Future research should focus on increasing the temporal resolution of climate inputs or incorporating additional contextual information to better approximate the surface state. While 10 year averages successfully provide some surface state information, adding the variables at higher temporal resolution from the preceding year or months, could provide more context to better approximate the surface state. Furthermore, complementing temporal averages with measures of variability, such as variances or ranges over selected time periods, could help characterize different climate regimes more effectively. Together with more detailed temporal information, approaches like a physics-informed loss, auto-regressive model, or multi-target learning may become beneficial again. Also, alternative ML approaches designated for timeseries data such as LSTMs or transformer based networks are promising future directions. However, increasing the temporal resolution of the input data introduces additional variability and complexities beyond those present in decadal averages, potentially amplifying OOD effects.

Consequently, further emulator development should always go together with testing transferability, to avoid improving in-domain performance at the expense of stagnant or even degraded transferability skill. Improvements measured on a single dataset do not necessarily translate into improved transferability. Consequently, the evaluation of new emulator developments should routinely include testing on independent forcing datasets, climate regimes, or simulation periods. At the same time, repeatedly using the same transferability datasets to guide model development risks overfitting to a small set of benchmark cases. Transferability test sets should therefore be used sparingly for model selection and complemented by additional independent datasets whenever available.

To emulate the whole SMB modeling pipeline, we need to also consider emulating the RCM, and the coupling of the RCM and firn emulator. To advance the emulation of the complete SMB modeling chain, ML-based downscaling could replace the RCM component, although the propagation of errors through the resulting modeling chain would need to be carefully evaluated. Nevertheless, we consider separate emulation of the downscaling and firn processes crucial for quantifying process-specific uncertainties and attributing model behavior to individual processes, as compensating errors may otherwise obscure their respective contributions. Future emulator development must therefore also address how ML-based downscaling and firn emulation can be coupled consistently while retaining process-level interpretability.

DATA AVAILABILITY STATEMENT

Code can be accessed via the GitHub repository <https://github.com/eschlager/MeltEmulationRobustness>. The data produced in this study is available at <https://anon.erda.au.dk/sharelink/CIWflqtI0i>. The code repository and the data will be archived with a DOI upon acceptance.

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COMPETING INTERESTS

The authors declare none.

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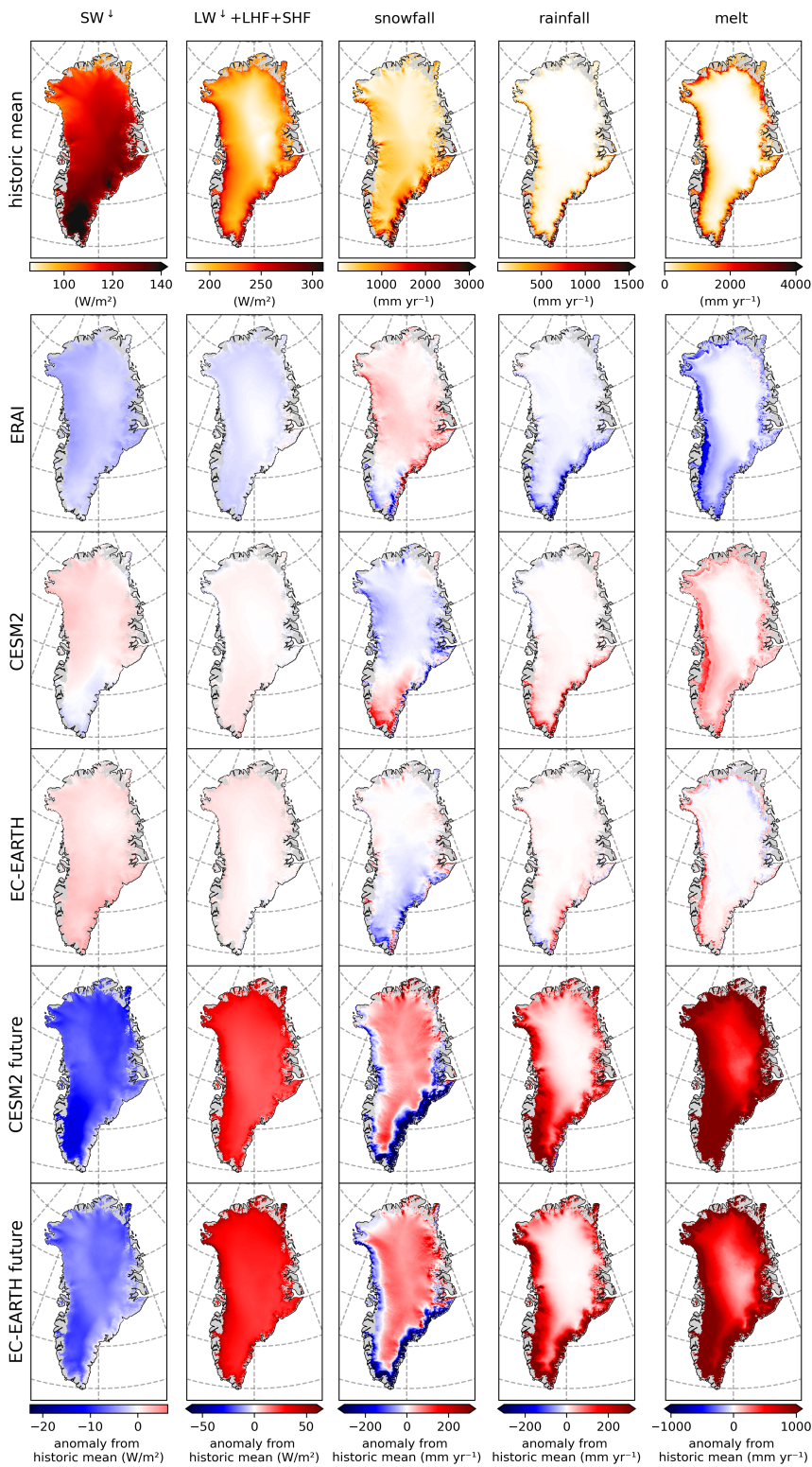
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APPENDIX A. DIFFERENCE BETWEEN MODEL’S MEANS AND HISTORICAL

635

ENSEMBLE MEAN.



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Fig. 6. Anomaly of model’s means to historical ensemble mean (ERA, CESM2, and EC-EARTH, 1990-2016).

APPENDIX B. CROSS VALIDATION

Cross validation was done on ERA-Interim forced data. The cross validation follows the blocking approach as in Roberts and others (2017), using one year as validation year, and the remaining years for training. Even years starting from 1992 up to 2016 are selected as validation years, resulting in 13 different validation models. Furthermore, we retrain each model five times with random layer initialization and random shuffling of the training data to investigate training robustness. Figure 7 shows the resulting MAE and residual in totals and relative to annual melt extents of all trained models (including the five repeated trainings per fold). For each fold, the best resulting model regarding lowest absolute MAE across all years among the five re-trainings has been calculated. For a given evaluation year, the best model from the fold in which that year served as the validation year is highlighted with a pink cross; the scores of the other four re-training of that fold are marked in green. The scores of each fold's best model on their respective non-validation years are shown as blue dots. The evaluations of all other remaining model runs are shown in gray.

The repeated training of each fold shows that the randomness of the layer initialization and the training data order leads to convergence to different local minima (green and pink elements per year, which show strong spread within each year). The model needs to infer the surface state indirectly from the provided climate input, and the approximation of it seems to be sensitive to the model initialization and the gradient direction imposed by the data shuffling. Also, some model runs converge to a non-optimal local minimum, resulting in high errors, and consistent bias across all years. Thus, it is important to re-train multiple times to reach an optimal minimum.

Looking at the best runs per fold, we can see that the scores depend more on the year they are computed on, rather than on the trained model (blue dots, whose variability over different years is larger than their spread within single years). The training fold itself does mostly not impact the performance for the single years. The best model of the respective fold (pink crosses) is mostly in the same range as the scores of the best models of the other folds (blue circles), except for the MAE in 1996, which is one of the lowest melt years in the data set. However, this worse performance w.r.t. some metrics for some specific years, can also be by chance due to the limited number of re-trainings per fold.

Figure 7c shows the annual residuals in Gt for the different model runs. The residuals for the best 13 models across all years averages to approximately -6 Gt. However, residuals for the single years range from

666 -72 to 58 Gt, or in relative numbers, from -11 to +13% of the respective annual melt. While the MAE
667 correlates with the total annual melt, the residual does not show such a relationship. However, there are
668 years, where the models tend to under- or overestimated respectively, irrespective of the year's total melt
669 amount. Thus it is advised to include as many years as possible in the training set, to include as many
670 different melt regimes as possible, but also to evaluate on various years. Since the model is not prone to
671 over-fitting, and performance of each year does not depend on whether the data was used in the training
672 or not, we do not need a disjoint train-test-split, but can train and evaluate on the same data set.

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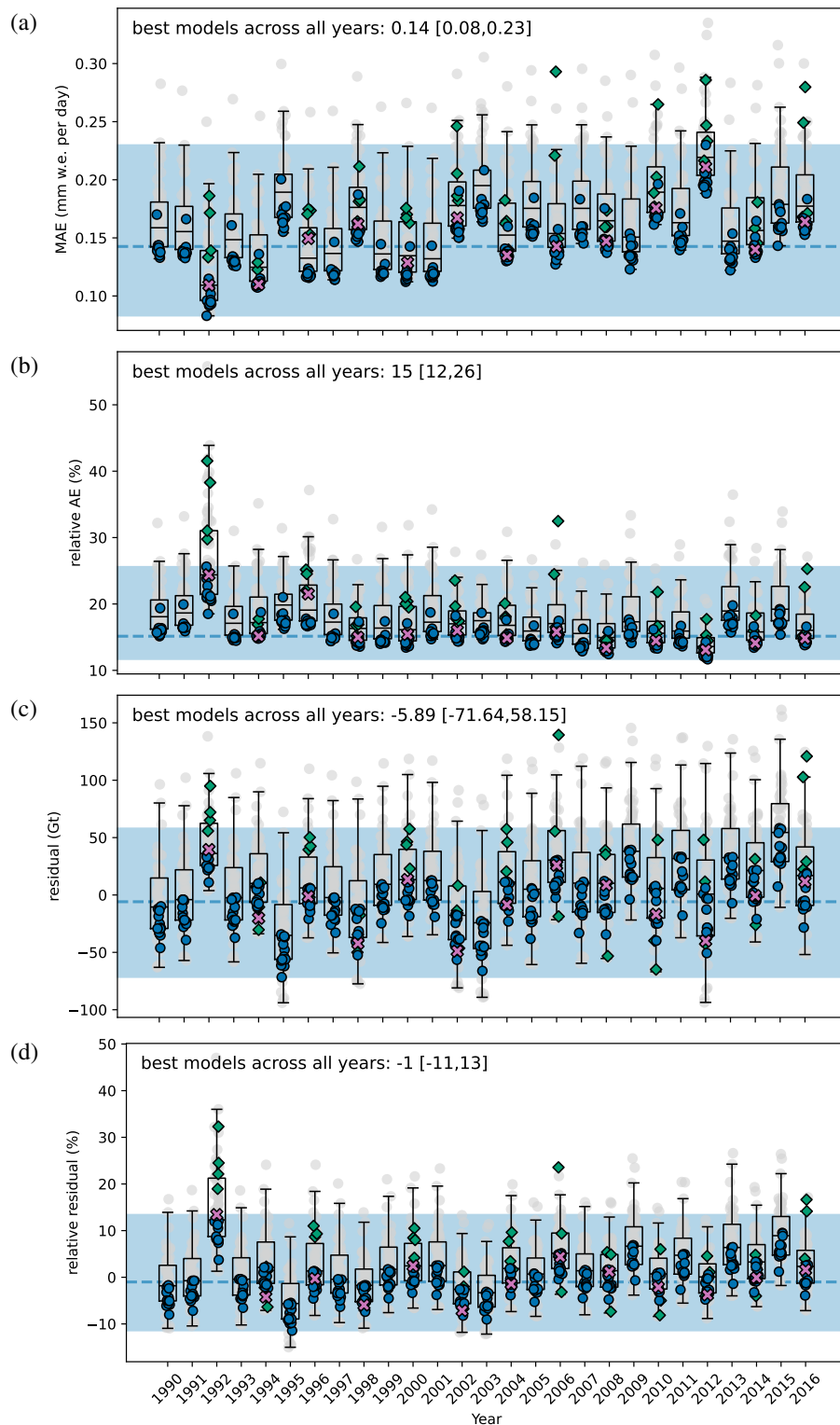


Fig. 7. MAE and residual across all years of the repeatedly trained model folds (on ERA-Interim forced data). The gray circles indicate the scores of all the trained models applied to the respective year, the blue circles are the scores of the respective best model (i.e. lowest MAE on all years) per fold, the green diamonds are the scores of the model of this fold (i.e. applied year was not seen during training), and the pink crosses indicate the best model per fold.

APPENDIX C. PHYSICALLY INFORMED LOSS TERMS

The monotonic loss term penalizes negative gradients with respect to the daily energy inputs:

$$\mathcal{L}_{mono} = \sum_{r=0}^9 \left[\min(0, \partial \hat{S}M_t / \partial E_{t-r})^2 + \min(0, \partial \hat{S}M_t / \partial SW_{t-r}^\downarrow)^2 \right],$$

with $SW_s^\downarrow$ and $E_s = LW_s^\downarrow + LHF_s + SHF_s$ being the respective energy flux inputs of day s . The respective emulator is trained with the loss $\mathcal{L} = MSE + 100 \cdot \mathcal{L}_{mono}$.

The physical loss term is based on

$$L_{dswrad} = \frac{1}{|M|} \sum_{i \in M} \left[\max(\delta_{min}^{SW} - \Delta melt_i^{SW}, 0)^2 + \max(\Delta melt_i^{SW} - \delta_{max}^{SW}, 0)^2 \right],$$

and

$$L_{energyin} = \frac{1}{|M|} \sum_{i \in M} \left[\max(\delta_{min}^E - \Delta melt_i^E, 0)^2 + \max(\Delta melt_i^E - \delta_{max}^E, 0)^2 \right],$$

where M are the instances with unperturbed predicted melt exceeding 10 mm w.e., $\Delta melt_i^{SW}$ and $\Delta melt_i^E$ indicate the change in melt production due to increase of current day's $SW^\downarrow$ or E by 10 W m^{-2} . The range limits, outside of which melt change is penalized, are $\delta_{min}^{SW} = 0.19$, $\delta_{max}^{SW} = 1.76$, $\delta_{min}^E = 2.4$, and $\delta_{max}^E = 2.8$. These values are based on the instantaneous extra melt production from an additional energy flux of 10 W m^{-2} for surface already at the melting point. With latent heat of fusion of ice $333.55 \text{ kJ kg}^{-1}$ and density of water at 0°C (999.84 kg m^{-3}), 10 W m^{-2} extra energy produces about 2.6 mm w.e. extra melt (Ismail and others, 2023). Since for $SW^\downarrow$ only a ratio of $(1 - \alpha)$ is absorbed by the surface, an increase in $SW^\downarrow$ by 10 W m^{-2} is expected to show lower melt increase depending on the albedo, with 0.39 mm w.e. for cold snow covered surfaces ($\alpha = 0.85$), and 1.56 mm w.e. at bare ice locations ($\alpha = 0.4$). However, the emulator works with daily aggregated data, not instantaneous energy fluxes and surface state conditions, thus some deviation from these theoretical values is expected. We therefore add a tolerance of 0.2 to each limits. The respective emulator is trained with the loss $\mathcal{L} = MSE + 20 \cdot (L_{dswrad} + \mathcal{L}_{energyin})$.

692 APPENDIX D. TRANSFERABILITY OF EXTRA MODEL EXPERIMENTS

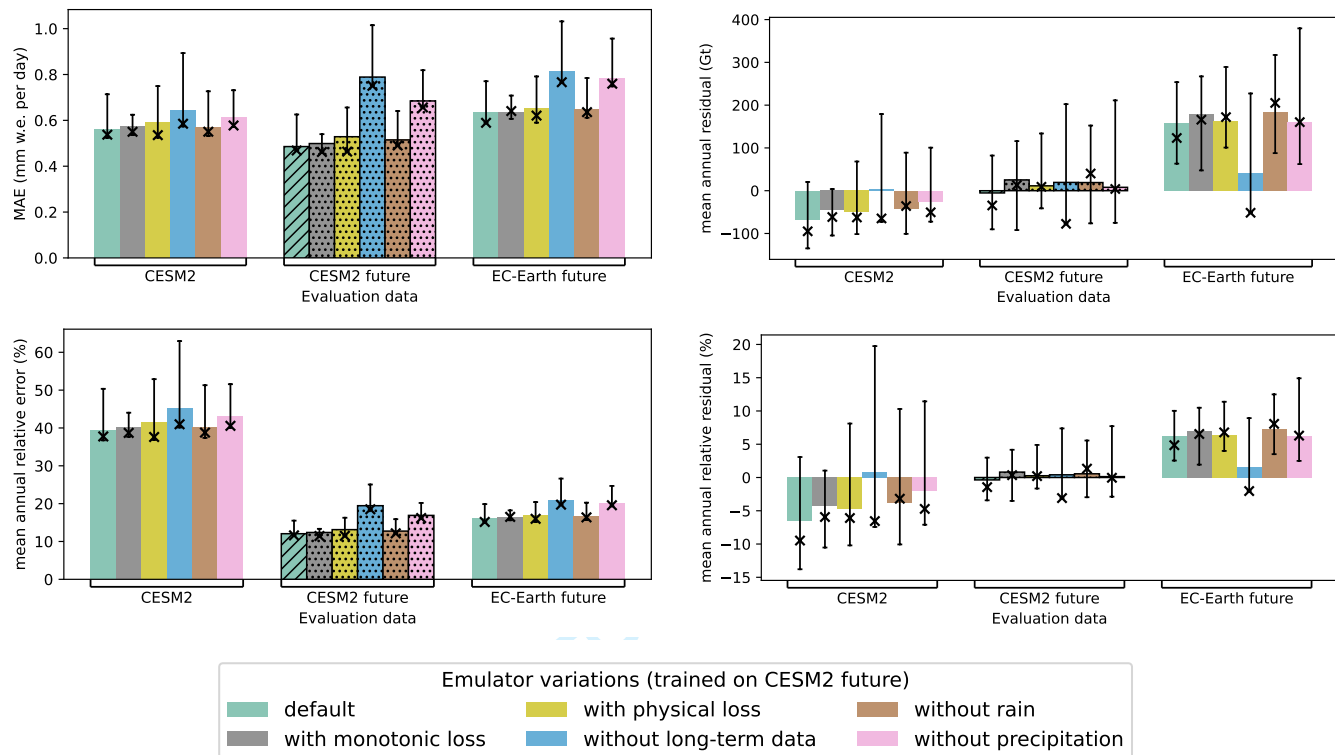


Fig. 8. MAE and residuals as totals and in percentage of total annual melt across all repeated training runs for models trained on simulation data forced by CESM2 future. The default emulator refers to the emulator used in the main transferability study trained with MSE loss. The variations with monotonic loss and physical loss also use the default emulator, but trained with the additional respective loss terms. The emulators without long-term data, rain, or precipitation (rain and snowfall) use MSE loss only. Bar heights, error bars, and markers analogously as in Fig. 3. The in-domain evaluation of the default model is marked with hatching, the in-domain evaluation of the emulator variations are marked with dots.