Validation of Pan-Arctic Soil Temperatures in Modern Reanalysis and Data Assimilation Systems

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Abstract. Reanalysis products provide spatially homogeneous coverage for a variety of climate variables in regions where observational data are limited. However, very little validation of reanalysis soil temperatures in the Arctic has been performed to date, because widespread in situ reference observations have historically been unavailable there. Here we validate pan-Arctic soil temperatures from eight reanalysis and ~~LDAS~~ land data assimilation system products, using a newly-assembled database of in situ data from diverse measurement networks across Eurasia and North America. We find that most products have soil temperatures that are biased cold by 2-7 K across the Arctic, and that biases and RMSE are generally largest in the cold season (months where the mean air temperature is $\leq$ -2° C. Monthly mean values from most products correlate well with in situ data (~~R~~ r > 0.9) in the warm season, but show lower correlations (r = 0.6 - 0.8) ~~, in many cases,~~ over the cold season. Similarly, the magnitude of monthly variability in soil temperatures is well captured in summer, but overestimated by 20% to 50% for several products in winter. The suggestion is that soil temperatures in reanalysis products are subject to much higher uncertainty when the soil is frozen and/or when the ground is snow-covered. We also validate the ensemble mean of all available products, and find that, when all seasons ~~,~~ and metrics are considered, the ensemble mean generally outperforms any individual product in terms of its correlation and variability, while maintaining relatively low biases. As such, we recommend the ensemble mean soil temperature product for a wide range of applications ~~-~~, such as the validation of soil temperatures in climate models, and to inform models that require soil temperature inputs, such as hydrological models.

1 Introduction

Soil ~~temperature is~~ temperatures, both near the surface, and at depth, are an important control of many physical, hydrological, and land surface processes, as soils act as a reservoir for energy and moisture underground. ~~It provides~~ They provide an important initial condition for numerical weather prediction, as energy and water fluxes from the land are important for convective processes (Dirmeyer et al., 2006; Kim and Wang, 2007; Siqueira et al., 2009). As soils react relatively slowly to variations in weather, soil temperature is also an important predictor of seasonal and mid-term weather forecasts ~~(Xue et al., 2012)~~ (Xue et al., 2011). Soils over large portions of the Arctic are perennially frozen (permafrost soil). Roughly 800 gigatonnes of carbon (GtC) is estimated to be stored in permafrost soils across the Northern Hemisphere ~~(?)~~(Hugelius et al., 2014); about twice the amount of carbon currently residing in the atmosphere (Tarnocai et al., 2009). Continued warming, and thawing of permafrost soils, and related decomposition of carbon could act as a ~~potentially~~ potential positive feedback on warming, by releasing more methane (CH_4) and carbon dioxide (CO_2) ~~to the atmosphere (??)~~into the atmosphere (Koven et al., 2011).

In situ based soil temperature monitoring networks using thermistor probes, particularly at high latitudes, are limited in terms of their spatial and temporal coverage (Yi et al., 2019), making it difficult to assess hemispheric scale changes in permafrost. Reanalysis products have been used in a variety of weather and climate applications to provide information on a regular spatial grid; particularly in regions where limited or no observational data is available (Koster et al., 2004; Zhang et al., 2008). Previous studies validating reanalysis soil temperature have primarily focused on the middle latitudes, such as across China ~~(?Xu et al., 2019; Zhan et al., 2020)~~(Yang and Zhang, 2018; Xu et al., 2019; Zhan et al., 2020), the Qinqhai-Tibetan Plateau ~~(??Wu et al., 2018)~~(Hu et al., 2019; Qin et al., 2020; Wu et al., 2018), Europe (Albergel et al., 2015; Johannsen et al., 2019), and the continental United States (Albergel et al., 2015; Xia et al., 2013), with a couple of recent studies validating soil temperatures globally ~~(?Ma et al., 2021)~~(Li et al., 2020b). Relative to in situ ground temperature probe networks, most reanalysis products are biased cold by about 2°C - 5°C, on average ~~(???)~~(Hu et al., 2019; Qin et al., 2020; Yang and Zhang, 2018) . Ma et al. (2021) found that most reanalysis products show larger cold biases over polar regions than they do over tropical and temperature regions, while a recent study by ~~?~~ Cao et al. (2020) found that ERA5-Land soil temperatures were biased warm over the Arctic, particularly in winter.

Several explanations have been suggested for the biases in reanalysis soil temperatures, including model parameterizations ~~(Albergel et al., 2015; ?; Chen et al., 2015; Wu et al., 2018; Xiao et al., 2013)~~(Albergel et al., 2015; Cao et al., 2020; Chen et al., 2015; W , air temperature biases ~~(?Hu et al., 2017)~~(Cao et al., 2020; Hu et al., 2017), errors in topography and elevation, arising from the coarse resolution of reanalysis products ~~(?Zhao et al., 2008; Ma et al., 2021)~~(Yang and Zhang, 2018; Zhao et al., 2008; Ma et al., 2021) , and errors in simulated snow cover and snow thermal insulation ~~(??)~~(Cao et al., 2020; Royer et al., 2021).

While soil temperature biases in individual reanalysis products may limit their utility, a consensus is emerging that multi-reanalysis ensemble, based on the same principle as ensemble weather prediction (World Meteorological Organization, 2012), are an effective way to increase the signal-to-noise ratio for many important geophysical variables. Ensemble mean datasets based on combinations of in situ, model, satellite and reanalysis data have been used to reduce biases in estimates of snow water equivalent (Mudryk et al., 2015), soil moisture ~~(Dorigo et al., 2017; Gruber and Scanlon, 2019)~~(Dorigo et al., 2017; Gruber et al., 2019) , precipitation (Beck et al., 2017, 2019), as well as for local scale permafrost simulations ~~? and ?~~ (Cao et al., 2019). Hu et al. (2019) suggest that a similar method could be used to reduce biases in reanalysis soil temperatures.

Reanalysis soil temperatures have been relatively well characterized over the middle latitudes. Studies validating Arctic soil temperatures in reanalysis products, however, have either focused on a singular product ~~(?)~~(Cao et al., 2020), or have only considered a limited spatial extent ~~(?Ma et al., 2021)~~(Li et al., 2020b; Ma et al., 2021).

Here we perform a validation of pan-Arctic (and Boreal) soil temperatures from eight reanalysis and land data assimilation system (LDAS) products. The main objectives are to 1) validate the 8 reanalysis and LDAS soil temperature products in terms of their bias, RMSE, correlation and standard deviation~~of Arctic soil temperatures~~, and 2) investigate whether an ensemble mean soil temperature product outperforms the individual reanalysis products.

2 Data

2.1 Reanalysis and LDAS Data

Table 1 ~~outlines~~ and 2 outline the six reanalysis and two LDAS soil temperature products used in this study. For simplicity, the term "reanalysis" will hereafter be used to describe both reanalysis and LDAS products. A summary of each product follows below. Products were remapped onto the Global Land Data Assimilation System – Catchment Land Surface Model (GLDAS-CLSM) grid for comparison, using three different methods: nearest neighbour, bilinear interpolation, and first-order conservative remapping. The choice of remapping method did not affect the overall conclusions of the study, and the analysis is based on data remapped using the conservative remapping method, as it facilitated the use of the largest number of validation sites and grid cells.

The reanalysis products investigated span a wide range of horizontal resolutions, ranging between 0.1°, in the case of ERA5-Land, to 1.0° for both GLDAS products (Table 1). Most products (CFSR, ERA-Interim, ERA5, ERA5-Land, and GLDAS-Noah) simulate soil temperature across 4 vertical layers, while MERRA2 and GLDAS-CLSM include 6 vertical layers, and JRA-55 calculates soil temperature across a single layer. The topmost soil layer has the highest resolution (7 cm to 10 cm in most cases), while the bottom soil layer often averages soil properties over a metre or more (Table 2).

The Noah Land Surface Model (Noah-LSM) (Chen et al., 1996; Betts et al., 1997; Koren et al., 1999; Ek, 2003) is used by CFSR and GLDAS-Noah. CFSR uses the Noah-LSM in a fully coupled mode to obtain a first-guess land-atmosphere simulation, before operating in a semi-coupled mode with GLDAS to obtain information about the state of the land surface (Saha et al., 2010). GLDAS, however, is run in an offline mode, utilizing meteorological forcing from Princeton University between 1948 to 2000 (Sheffield et al., 2006), and a combination of model and observational data from 2000 - onwards (Rui et al., 2018).

ERA-Interim, ERA5 and ERA5-Land use versions of the Tiled ECMWF Scheme for Surface Exchanges over Land (TESSEL) land model (Viterbo, 1995; Viterbo and Betts, 1999). In the case of ERA-Interim, TESSEL is informed by empirical corrections from 2m (surface) air temperature and humidity (Dee et al., 2011). Meanwhile, ERA5 and ERA5-Land use an updated version of TESSEL, known as the Hydrology-Tiled ECMWF Scheme for Surface Exchanges over Land (HTESSEL) ~~(?)~~(Balsamo et al., 2009). In ERA5, a weak coupling exists between the land surface and atmosphere~~, while~~. It includes an advanced LDAS that incorporates information regarding the near-surface air temperature, relative humidity, as well as snow cover (de Rosnay et al., 2014), along with satellite estimates of soil moisture and soil temperature from the top ~~1m~~ 1 metre of soil (de Rosnay et al., 2013). ERA5-Land, unlike ERA5, does not directly assimilate observational data. Instead, the ERA5 meteorology (such as air temperature, humidity and atmospheric pressure) is used as forcing information for HTESSEL; allowing it to be run at higher resolutions (Muñoz-Sabater et al., 2021). It includes an improved parameterization of soil thermal conductivity allowing for it to account for ice content in frozen soil~~;~~, improvements to soil water balance conservation~~;~~, and the ability to capture rain-on-snow events (Muñoz-Sabater et al., 2021).

Both GLDAS-CLSM and MERRA2 utilize the the Catchment Land Surface Model (CLSM) (Ducharne et al., 2000; Koster et al., 2000). Though MERRA2 does not include a land surface analysis (Gelaro et al., 2017), CLSM is informed using an up-

Table 1. Summary of the 8 reanalysis and LDAS products, their equatorial resolution, land model, and relevant references.

heightProduct	Data Period	Resolution	Land Model	References
~~CFSR1~~ CFSR	1979 - 2010	0.31° x 0.31°	Noah LSM	Saha et al. (2010)
~~CFSR2~~ CFSv2	2011 - Present	0.2° x 0.2°	Noah LSM	Saha et al. (2014)
ERA-Interim	1979 - Aug 2019	0.75° x 0.75°	TESSEL	Dee et al. (2011)
ERA5	1979 - Present	0.25° x 0.25°	HTESSEL	Hersbach et al. (2020)
ERA5-Land	1981 - Present	0.1° x 0.1°	HTESSEL	Muñoz-Sabater et al. (2021)
GLDAS-CLSM	1948 - Present	1.0° x 1.0°	Catchment LSM	Rodell et al. (2004)
GLDAS-Noah	1948 - Present	1.0° x 1.0°	Noah LSM	Rodell et al. (2004)
~~JRA-55~~ JRA55	1956 - Present	0.56° x 0.56°	Simple Biosphere Model	Harada et al. (2016)
				Kobayashi et al. (2015)
MERRA2	1980 - Present	0.5° x 0.625°	Catchment LSM	Gelaro et al. (2017)

Table 2. Summary of the 8 reanalysis and LDAS products and the number and depths of the soil layers included. *The JRA-55 Simple Biosphere Model contains up to three soil layers (whose depths vary depending on vegetation type), but the soil temperature is averaged over all layers to produce a singular value at each grid cell.

heightProduct	~~Data Period Resolution Land Model~~ Soil Layers	~~References~~ Soil Dep
~~CFSR1~~ CFSR	~~1979 - 2010 0.31° x 0.31° Noah LSM~~ 4	~~Saha et al. (2010)~~0 - 10, 10 - 40
~~CFSR2~~ CFSv2	~~2011 - Present 0.2° x 0.2° Noah LSM~~ 4	~~Saha et al. (2014)~~0 - 10, 10 - 40
ERA-Interim	~~1979 - Aug 2018 0.7° x 0.7° TESSEL~~ 4	~~Dee et al. (2011)~~ 0 - 7, 7 - 28,
ERA5	~~1979 - Present 0.27° x 0.27° HTESSEL~~ 4	~~Hersbach et al. (2020)~~ 0 - 7, 7 - 2
ERA5-Land	~~1981 - Present 0.1° x 0.1° HTESSEL~~ 4	~~Muñoz-Sabater et al. (2021)~~ 0 - 7, 7
GLDAS-CLSM	~~1948~~ 6	0 - ~~Present~~ 9.88, 9.88 - 29
	~~1.0° x 1.0°~~	~~Catchment LSM 6 Rodell et al. (2004)~~ 67.99 - 14
GLDAS-Noah	~~1948 - Present 1.0° x 1.0° Noah LSM~~ 4	~~Rodell et al. (2004)~~ 0 - 10, 10 - 4
~~JRA-55~~ JRA55	~~1956 - Present 0.56° x 0.56° Simple Biosphere Model~~ 3*	~~Harada et al. (2016)~~ temperature av
MERRA2	6	~~Kobayashi et al. (2015)~~ 0 - 9.88, 9
~~MERRA2~~	~~1980 - Present~~	~~0.5° x 0.67° Catchment LSM 6 Gelaro et al. (2017)~~ 67.9

~~Summary of the 8 reanalysis and LDAS products, their equatorial resolution, land model, and the number of soil layers included. *The JRA-55 Simple Biosphere Model contains up to three soil layers (depending on vegetation type), but for the purposes of soil temperature, it is calculated as one layer.~~

dated version of the Climate Prediction Center unified gauge-based analysis of global daily precipitation (CPCU) precipitation correction algorithm that originated in MERRA-Land (Chen et al., 2008; Xie et al., 2007). No corrections are available, however, for high latitude regions north of 62.5° N ~~(Reichle et al., 2017b)~~(Reichle et al., 2017a). In the case of GLDAS-CLSM, CLSM is run in an offline mode, in a similar configuration to GLDAS-Noah. Finally, JRA-55 uses the Simple Biosphere Model (SiB) (Onogi et al., 2007; Sato et al., 1988; Sellers et al., 1986) in an offline mode, forced by atmospheric data and data from land surface analyses that incorporate microwave satellite retrievals of snow cover (Kobayashi et al., 2015).

2.2 Observational Data

Owing to the lack of dense soil temperature monitoring networks in the Arctic, most of the observed soil temperature record is characterized by sparse measurements ~~with inconsistencies in the temporal periods that they cover~~ spanning different time periods (Yi et al., 2019). Rather than limit our validation to a small geographic region in the permafrost zone, as several prior studies have done ~~(??Wu et al., 2018; Ma et al., 2021; ?)~~(Hu et al., 2019; Qin et al., 2020; Wu et al., 2018; Ma et al., 2021; Li et al., 2020b , we choose to ~~make use of~~ combine data from a variety of sparse networks. Such an approach has been used to validate soil temperature and permafrost performance in ERA5-Land ~~(?)~~(Cao et al., 2020), and allows for the examination of larger geographic regions, as well as for the inclusion of a more diverse set of vegetation types across the continent (Ma et al., 2021).

~~To the authors' knowledge, this is one of the first studies to compile~~ The study compiles a comprehensive set of in situ soil temperature measurements across the Eurasian and North American Arctic, from multiple diverse sparse networks. ~~We incorporate~~ The dataset incorporates data from the Yukon Geological Survey (Yukon Geological Survey, 2021), the Northwest Territories (Cameron et al., 2019; Ensom et al., 2020; Gruber et al., 2019; Spence and Hedstrom, 2018a, b; Street et al., 2018) , Roshydromet Network in Russia ~~(?)~~(Sherstiukov, 2012), Nordicana series D (Nordicana) ~~(???????CEN, 2020g)~~(Allard et al., 2020; CEN , Global Terrestrial Network for Permafrost (GTN-P) ~~(?), and ?~~ (GTN-P, 2018), and Kropp et al. (2020) - in an attempt to provide a representative estimate of soil temperature across the circumpolar Arctic. Our validation data also includes sites from outside regions typically underlain by permafrost, in order to facilitate a comparison of the performance of reanalysis soil temperatures at high latitudes with their performance in regions outside the permafrost zone. Thse include data from Kropp et al. (2020) , Sherstiukov (2012), and GTN-P (2018), as well as data from the Manitoba Mesonet network (RoTimi Ojo and Manaigre, 2021) , the Michigan Enviro-weather Network (Enviro-weather, 2022), the North Dakota Mesonet Network (North Dakota Mesonet Netowrk, 202 , and the Alberta Climate Information Service network (Alberta Agriculture, Forestry and Rural Economic Development, 2022) . Data is also sourced from a peatland ecosystem in Metro Vancouver (Beck et al., 2017; Lee et al., 2021), several locations in central and Northern BC (Déry, 2017; Hernández-Henríquez et al., 2018; Morris et al., 2021), and two locations in southern Quebec (Arsenault et al., 2018; Fortier, 2020). This provides a unique baseline upon which to perform a hemispheric wide assessment of soil temperature in reanalysis and LDAS systems, and to the authors' knowledge, presents the most comprehensive analysis to date of soil temperatures across Canada and the Great Lakes basin.

~~The authors do acknowledge that there is a large discrepancy in the sampling of grid cells across North America and Eurasia, however we have done so in order to make use of all available data. Unfortunately, data availability is limited across much of the Canadian North, as it has been historically under-sampled relative to Eurasia (Metcalfe et al., 2018).~~

2.3 Collocation of Station and reanalysis Data

In order to compare with data from reanalysis and LDAS products, temperatures were averaged across two depth bins: a near surface layer (0 cm to 30 cm), and soil temperatures at depth (30 cm to 300 cm). For each site, temperatures from all depths residing within a layer were averaged, producing an estimated layer averaged temperature for every time-step. ~~Data from 51 North American stations, and 247 Eurasian station were used to estimate estimate monthly average temperatures in the near surface layer , while 38 (256) stations from North America (Eurasia) contributed to estimates of monthly average temperatures at depth~~In order to maximize the amount of observational data available, layer-averaged soil temperatures were calculated at each timestep with all available data. This tradeoff meant that layer averages often included a different number of depths at different timesteps, and as such, we needed to limit our analysis of soil temperature trends and variability to locations where layer averages had a consistent number of depths.

Many of the in situ (station) sites reported measurements at hourly or daily frequency, however we chose to perform the analysis at monthly time scales, ~~as soil temperaturesdo not vary much over shorter timescales~~in order to focus on processes controlling the seasonal cycle of soil temperatures. As such, ~~once a layer average had been calculated for a site, a monthly average temperature was then estimated. Daily average temperatures (T_{day}) were calculated for each station with a timestep smaller than 1 day, using all available data, when there was at least one temperature record available on a given date. T_{day} were then used to calculate a station's monthly average temperature (T_{soil}). Outlier detection was performed on in situ data~~ we use monthly averages of soil temperatures for validation purposes. Outlier observations with anomalies greater than $\pm$ 3.5σ were removed before monthly averaging~~, by removing datapoints that fell outside 3.5σ from the mean soil temperature of the dataset~~.

Since the station data often included days with missing observations, the sensitivity of the monthly averages to missing data was tested, by computing monthly averages in five ways: using all months with at least one valid day in a month, using all months with at least 25, 50, and 75 percent valid data, and finally using all months with no missing data in a month. It was found that T_{soil} was not substantially impacted by the inclusion or exclusion of months containing missing data. In order to increase sample size, we therefore included all months with at least 50 percent valid data.

In order to be considered as a validation location, the grid cell was required to include soil temperature data for all eight reanalysis/LDAS products, and be collocated with at least one in situ station. Duplicate stations across datasets were excluded. In situ locations were only included if there was at least 2 years worth of in situ data, in order to properly assess the station's seasonal cycle. For grid cells containing multiple in situ stations, the value used in the comparison is a simple spatial average of the in situ stations in that grid cell on each calendar day.

Over Eurasia, ~~the vast majority of grid cells contain~~ grid cells contained a single in situ measurement location. In North America, however, ~~several Alaskan~~ a number of the grid cells contain ~~three~~ two or more in situ stations. The near surface layer layer includes ~~271~~ 380 validation grid cells ~~,~~ (Figure 1, panel A), while at depth, there are ~~272 grid cells with minimal variation in their location relative to the near surface~~ 346 grid cells (not shown). A subset of stations with longer timeseries and a more complete data record - mostly in Eurasia, are used to calculate soil temperature trends and variability (Section 4.2). Stations included in the soil temperature trend and variability analysis are shown as circles of varying size and colour, while those excluded from the soil temperature trend and variability analysis are shown as an x (Figure 1, ~~panel~~ Panel A). ~~Panel B of Figure 1 shows the spatial standard deviation of monthly surface soil temperatures for grid cells with more than two stationsincluded~~The details of Figure 1 - Panel A will be described further in Section 4.2.

To calculate spatial averages, a simple average of (layer-averaged) soil temperatures from all stations within the bounds of a particular grid cell was calculated at each timestep, using all available stations. This meant that the number of stations included at each timestep wasn't always consistent, and the analysis of soil temperature trends and variability was limited to a subset of grid cells where the following conditions were met:

1. The timeseries included at least 10 years of data.

2. The number of stations included in ~~each grid cell ranges between two to 12. The median standard deviation is generally $\leq 2°$ C, though the temporal variation (spread)is quite large for several stations. This suggests that while differences in T_{soil} at in situ~~ the spatially averaged grid cell temperature was consistent over all timesteps.

3. The number of depths included in the layer averaged soil temperature of each contributing station remained consistent over all timesteps.

As a result, many of the North American grid cells were excluded from the soil temperature trends analysis (except for a subset of 20 grid cells), and the bulk of the analysis is based on grid cells from Eurasia (where grid cells often only contained a single station) (Figure 1, Panel A). Using a subset of North American grid cells that incorporate multiple stations in the spatial average, and include a consistent number of stations and depths in the timeseries, we quantify the variability in soil temperatures between stations within a grid cell~~are generally within a few degrees of one another, there are times when the differences can be quite large~~, and across depths within a layer average. It was found that the median temperature range between stations within a grid cell was approximately 2.3° C, which was roughly two to seven times larger than the median temperature range across depths within the near surface layer of a station (Figure 1, Panel B), suggesting that temperature variability within a grid cell is substantially larger than variations in temperatures within the near surface layer of a particular station.

3 Methods

3.1 Validation Metrics

Reanalysis/LDAS and observational (station) soil temperature data were collocated with one another spatially and temporally. Grid-cell level soil temperatures from each product were compared against in situ soil temperatures using the following statistical metrics: bias (Eq. 1), root-mean-squared-error (RMSE) (Eq. 2), normalized standard deviation (SDV_{norm}) (Eq. 3 and Eq. 4), and the Pearson correlation (R) (Eq. 5). We also include an overall skill score for each model; a Thackeray et al. (2015) type formulation of the Taylor (2001) skill score (Eq. 6). Statistical metrics were calculated as follows:

$$Bias = \frac{1}{N}\sum_{n=1}^{N}(T_p - T_i) \tag{1}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(T_p - T_i)^2} \tag{2}$$

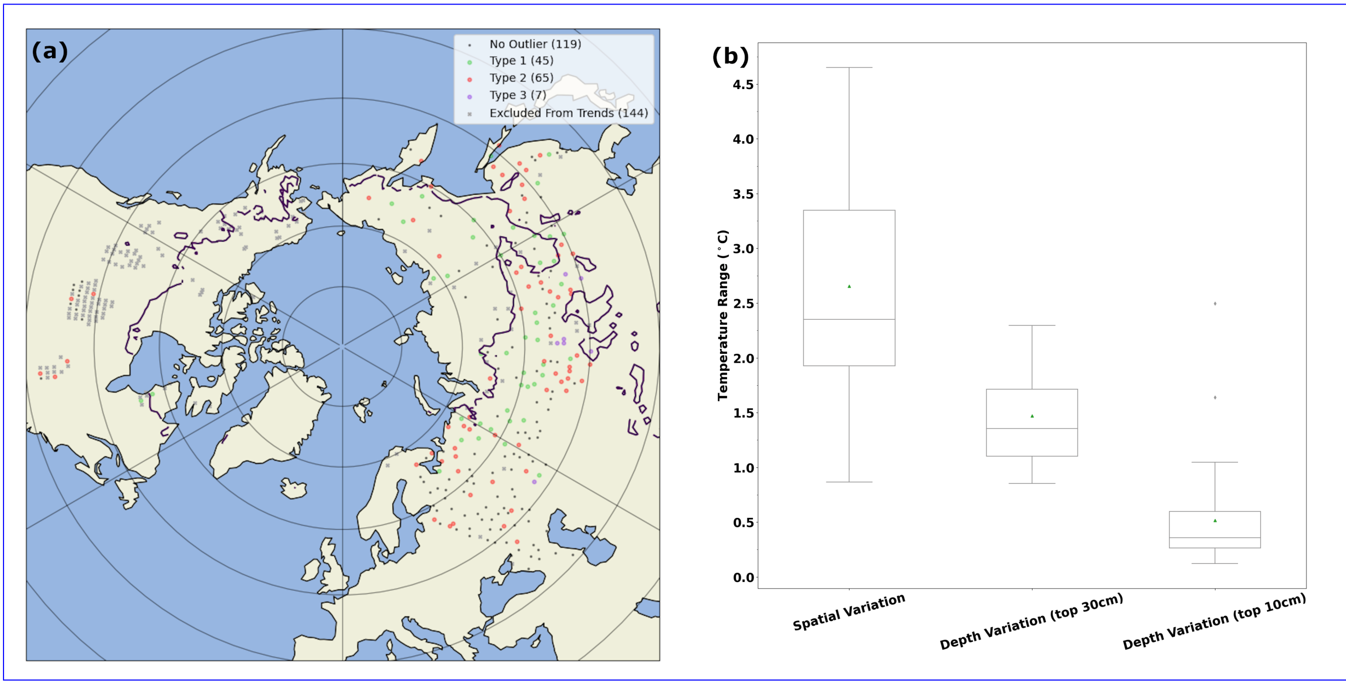


Figure 1. Panel A: location of the validation grid cells collocated with in situ stations in the near-surface layer. Grid cells excluded from the soil temperature trends analysis are ~~colour coded based on~~ shown as an "x". Type 1 refers to grid cells that where the ensemble mean ~~annual air temperature (MAAT);~~ simulates a ~~proxy for permafrost zone~~winter minimum soil temperature that is too cold. ~~The locations of the validation~~ Type 2 refers to grid cells ~~differ minimally in~~ where the ~~depth (30 cm~~ ensemble mean simulates a summer maximum soil temperature that is too cold. Type 3 refers to ~~300 cm) layer~~grid cells where the ensemble mean underestimates the seasonal cycle of soil temperatures. The contour line encircles regions where the Obu et al. (2018) permafrost cover is at least 50 percent. Panel B: ~~temporal spread in~~ Impact of spatial ~~standard deviation~~ variation and depth variation on the spread of ~~monthly~~ soil temperatures ~~near the surface, for grid cells with multiple~~ in ~~situ stations (the number of stations is included in brackets beside the letter)~~a grid cell. ~~Their location~~ The mean is shown ~~in Panel A~~by a green triangle.

$$SDV = \sqrt{\frac{\sum_{n=1}^{N}(x_n-\overline{x})}{N-1}}\sqrt{\frac{\sum_{n=1}^{N}(x_n-\overline{x})^2}{N-1}} \tag{3}$$

$$SDV_{norm} = \frac{SDV_{T_p}}{SDV_{T_i}} \tag{4}$$

$$R = \frac{\frac{1}{N}\sum_{n=1}^{N}(T_p-\overline{T_p})(T_i-\overline{T_i})}{SDV_{T_p}SDV_{T_i}} \tag{5}$$

$$SS = \frac{2(1+R)}{(SDV_{norm} + \frac{1}{SDV_{norm}})^2} \tag{6}$$

Where T_p is the T$_{soil}$ from the reanalysis product, and T_i is the T$_{soil}$ of the in situ data~~,~~. $\overline{T_p}$ and $\overline{T_i}$ refer to the mean T$_{soil}$ of the reanalysis product and in situ data, respectively, while N is the number of monthly soil temperature values~~,~~. SDV_{norm} refers to the normalized standard deviation, while SDV_{T_p} and SDV_{T_i} are the standard deviations of the reanalysis product soil temperatures and in situ soil temperatures, respectively~~, while~~. Finally, x refers to the T$_{soil}$ (~~of a dataset)~~from a particular timestep in a dataset), $\overline{x}$ is the mean T$_{soil}$ of the dataset, R is the Pearson correlation, and SS refers to the skill score.

Metrics were calculated separately for each individual grid cell, and then averaged to ~~calculate a pan-Arctic estimate~~obtain regional values. Estimates for the permafrost zone and the zone with little to no permafrost were also calculated by averaging together metrics from grid cells falling within a particular zone. Skill scores were calculated separately for the near surface, and depth, while the "overall" skill score represents an average of the near surface and depth skill scores.

3.2 Binning of Datasets by Season and ~~Mean Annual Air Temperature~~Permafrost

Datasets were binned into a cold season and warm season using the Berkeley Earth Surface Temperature (BEST) 2m air temperature (T$_{air}$) for each grid cell. Cold season months are those where T$_{air}$ $\leq$ -2° C, while the warm season refers to months with T$_{air}$ > -2° C, where T$_{air}$ is the monthly mean air temperature. Sensitivity testing on the cold/warm season revealed no substantive impact on our conclusions using a threshold of 0° C, -5° C, and -10° C. We also tested the impact of using a different temperature dataset to perform the binning; the ERA5 2m air temperature, which resulted in similar findings.

~~Soil temperatures were also also separated based on the 1981-2010 BEST mean annual air temperature, in order to estimate continuous (≥ 90% permafrost), discontinuous (50 - 89.9% permafrost), and regions with little to no permafrost (< 50% permafrost). **?** found that the continuous permafrost zone is roughly consistent with a MAAT between -6° C to -8° C, while the discontinuous permafrost zone boundary varies somewhat depending on soil organic matter content. For regions with primarily inorganic (mineral) soil, the southern boundary of the discontinuous permafrost zone was roughly consistent with a MAAT of -2° C, whereas for areas underlain by soils with a heavy organic matter content, the boundary was closer to the +1° C MAAT isotherm. As soil organic matter content was not available for the reanalysis products, the following MAAT boundaries were used in this study as a general approximation of permafrost type across the study domain:~~

1. ~~locations with a MAAT ≤ -7° C are referred to as being in the 'continuous permafrost' zone~~
2. ~~locations where -2° C ≤ MAAT > -7° C are referred to as having 'discontinuous permafrost'~~
3. ~~locations with a MAAT > -2° C are referred to as falling within the 'little to no permafrost' zone~~

~~The resultant permafrost distribution (Figure 1) is roughly consistent with the Brown et al. (2002) permafrost map~~Permafrost zonation was estimated using the Obu et al. (2018) permafrost map, which employs a temperature at the top of the permafrost

(TTOP) model based on a 2000-2016 climatology, driven by a combination of remotely sensed land surface temperatures, downscaled atmospheric data from ERA-Interim, and landcover information from The European Space Agency (ESA) Climate Change Initiative (CCI) (Obu et al., 2019). To maximize the sample size in each group, we merge the 'continuous' and 'extensive discontinuous' permafrost zones into a single category called the 'permafrost zone', and compare against the zone with 'little to no permafrost', which includes all regions with <50% permafrost cover.

4 ~~Validation of Reanalysis and LDAS Products~~

3.1 ~~Warm Season~~Calculation of Ensemble Mean Product

~~Most products show small to moderate negative (cold) biases over the warm season (Figure 2); a finding similar to previous studies investigating reanalysis soil temperatures over the mid-latitudes and the Qinghai-Tibetan Plateau (Hu et al., 2017; **?**; Yang et al., 202~~ ~~. Warm season biases (Figure 2, Panels C and D)tend to be slightly larger at depth for most products (by ~1° C –~~ The ensemble mean soil temperature product is a "blended" soil temperature product based on a simple average of soil temperatures from each of the individual soil temperature products (CFSR, ERA-Interim, ERA5, ERA5-Land, GLDAS-CLSM, GLDAS-Noah, JRA55 and MERRA2). Two soil temperature estimates: one of the "near-surface", and another of soil temperatures at depth are calculated for each timestep. The near-surface soil temperature is based on the average soil temperature of the top 2 ~~° C).~~ ~~JRA-55, however, displays substantially more negative biases near the surface~~ soil layers from each product – ~~suggesting that it underestimates summer soil temperatures near the surface.~~ representing an estimate of the average soil temperature in the top 30cm. The "deep" soil temperature estimate is based on an average of the soil temperatures from layers further down the soil column, down to a maximum depth of about 300cm. While the vertical discretization is coarser than that of the individual products, this approach allows the ensemble mean product to incorporate soil temperatures from products with different land models, whose vertical resolution is not constant.

~~Bias (stippling) and Root Mean Square Error (RMSE) (solid colour) for the cold season (blue) (≤ -2° C) and the warm season (red) (> -2° C) performance of reanalysis products. Panel A displays the bias and RMSE for the near surface (0 cm to 30 cm) layer, while panel B displays the bias and RMSE at depth (30 cm to 300 cm). Models are ordered based on cold season RMSE (from the smallest to largest). The ensemble mean is shown beside for comparison.~~

~~Over the warm season, most reanalysis products display correlations greater than 0.95 near the surface, and close to 0.9 at depth (Figure 6, Panels C and D). JRA-55, however, displays a correlation of 0.4 near the surface ; arising from the fact that its~~ ~~T_{soil} display a large spread for a given station temperature (red scatter)(Figure 4, top row). For example, while the histogram for the station data shows that T_{soil} rarely falls below 0° C near the surface, in the warm season, frozen soil occurs relatively regularly in~~ All products were first re-gridded to the GLDAS-CLSM grid using a first-order conservative remapping technique (Jones, 1999). The near surface soil layers were calculated as a simple average of the top 2 soil layers in each reanalysis product (except for JRA-55 ~~during the warm season (Figure 4); likely suggesting that JRA-55's single soil layer is more representative of deeper soil layers (which are more likely to remain frozen year round). Most products generally capture the warm season variability in T_{soil}, and are within 20% of the observed – both at depth and near the surface (Figure 6, Panels C and D)~~which only includes a single soil layer that represents the temperature averaged over the entire soil column). Soil temperatures at depth were calculated as a simple average of all layers whose bottom depth is within the top 300 cm of soil. For CFSR/CFSv2, ERA-Interim, ERA5 and ERA5-Land, this represented the third and fourth soil layers, while the third, fourth and fifth soil layers were included from MERRA2 and GLDAS-CLSM. For JRA55, we were again limited to the single averaged soil layer. Readers are referred to Table S1 for further information.

After the near surface and deep soil layer average temperatures were calculated for each product, the ensemble mean soil temperature, for each layer, was calculated as the unweighted arithmetic mean of the eight products for each month and for each grid cell.

~~Taylor Diagram of the cold season (≤ -2° C) and the warm season (> -2° C) performance of reanalysis products. Panels A and B refer to the cold season, while panels C and D refer to the warm season. The top panels (panels A and B) are for the near surface (0 cm to 30 cm) while the bottom panels (panels C and D) refer to soil temperatures at depth (30 cm to 300 cm).~~

4 Validation of reanalysis and LDAS Products

~~Scatterplot matrix of station and reanalysis soil temperatures. The top triangle (right of the histograms) refers to soil temperatures in the near-surface (0 cm to 30 cm) layer, while the bottom triangle represents soil temperatures at depth (30 cm to 300 cm). Seasons are stratified by the ERA5 air temperature, with the cold season (≤ -2° C) in green and the warm season (>-2° C) in red.~~

4.1 Extratropical Northern Hemisphere Mean

4.2 ~~Cold Season~~

~~Over the cold season, biases tend to be larger (more negative)~~ Most products show annual mean skill scores (purple) ranging between 0.8 and 0.95. In general, skill scores are higher near the surface ~~, relative to the warm season; particularly in the cases of GLDAS-Noah, GLDAS-CLSM, and ERA-Interim, where cold season biases are several degrees larger~~ where soil temperatures are more correlated with air temperatures (Figure 2~~, Panels A and B). ERA5-Land, however, shows a slight overall positive (warm)bias, because of substantial positive biases over the coldest temperature ranges (Figure 3), and over Siberia and North America (Figure S1); qualitatively similar to the findings of ?. At depth, half of the products show smaller coldseason biases (relative to the warmseason)~~). JRA55 is a noticeable outlier (skill score = 0.68), ~~while the biases are of a similar magnitude for the remaining products. Most~~ as it uses a simplified land model where the soil temperatures are averaged across the soil column. Thus its soil temperatures underestimate the seasonal cycle of observed soil temperatures in the near surface, and the timing of annual maximum and minimum soil temperatures is offset by roughly a month (as deep soil temperatures are slower to react to changes in air temperature or surface energy balance changes) (not shown).

For the most part, reanalyses show small to moderate negative (cold) biases in both seasons, though ERA5-Land exhibits a small positive (warm) bias in winter (Figure 2). JRA55 exhibits larger biases with respect to near surface soil temperatures, as it underestimates the annual range of near surface temperatures, whereas, at depth, biases are smaller, and the skill score is higher, reflective of the fact that its soil temperatures are more reflective of deeper soil layers. Generally speaking, most products show a maximum bias when ~~T_{soil} is~~ soil temperatures are between -2° C to -10° C, and there is a tendency for biases to decrease or flip sign over the coldest temperatures. There is also a larger spread in bias over the coldest range of temperatures (Figure 3).

~~Reanalysis soil temperature bias as a function of station soil temperature for a) the near surface (0 cm to 30 cm) layer, and b) at depth (30 cm to 300 cm). Station temperatures are binned into 4° C intervals, beginning with the -32° C to -28° C bin, and ending with the 28° C to 32° C bin. The midpoint of each temperature bin is plotted along the x-axis.~~

~~Cold season correlations are generally lower; particularly near the surface, where correlations are often 25% to 35% smaller than they are over~~ In addition, there is a larger range of temperatures displayed for a given observed soil temperature in the cold season (blue scatter) than in the warm season (~~Figure 6, panel A). In addition, there is less agreement between products~~red scatter) (Figure 4), ~~with a spread of 0.26 between the product with the lowest correlation (JRA-55), and the product most correlated with in situ (Ensemble Mean) . At depth, seasonal differences in correlations are smaller, though cold season correlations for most products are 5~~suggesting a reduced agreement between reanalyses and observations in winter. For individual products, the variability in reanalysis soil temperature for a given observed soil temperature (as measured by their standard deviation) is generally greatest over frozen soil conditions (particularly temperatures below -20° C) - further evidence of the reduced agreement between product soil temperatures and observations. The spread in standard deviation between products (similar to their biases), is also largest over the coldest temperatures - providing evidence of increased disagreement between different reanalyses. JRA55 is an exception, as it shows a maximum standard deviation when soil temperatures are near freezing, and variance decreases thereafter (Figure 5) - likely due to the fact that it underestimates the coldest temperatures.

4.2 Temporal Variability

Strong seasonal differences exist in reanalysis performance - particularly near the surface, where skill scores are often 25% to ~~10~~38% lower ~~than their warm seasoncounterparts (Figure 6, panel B) .~~

~~Several productsoverestimate the in situ standard deviation in the cold season~~ during the cold season than in warm season, and there is a noticeably larger spread (greater disagreement) between products. The skill at depth shows less seasonal variation, but is still noticeably lower during the cold season, with most products show a decline in skill of between 3% and 14%. The decline in cold season skill is mirrored by increases in near surface bias and RMSE for several products - particularly ~~over Eurasia, though ERA5-Land underestimates the cold season standard deviation by approximately 25% to 50% (Figure 6, panel A and B)~~ ERA-Interim, GLDAS-CLSM, and GLDAS-Noah whose biases are 4.1° C, 2.4° C and 1.7° C colder, respectively. Interestingly, biases for all products are somewhat larger in the warm season at depth, though seasonal differences are also generally smaller in the deeper soil layers (Figure 2).

JRA55 shows a 3.6° C positive (warm) bias during the cold season, and a 6.5° C negative (cold) bias in the warm season 2) - ~~arising in part due to the wintertime positive biases over large portions of the northern hemisphere (see Figure S2 and~~

~~? for further details) . The increased variance in T_{soil} in~~ suggesting that the seasonal cycle in soil temperatures is too small. Meanwhile, ERA5-Land displays a small warm (positive) bias during the cold season~~suggests that reanalysis products have a greater degree of temperature variability in the winter. Along the topmost row (near-surface)and leftmost column (depth)of Figure 4 are scatterplots of soil temperatures from each of the eight reanalysis products, relative to in situ data. There is a larger range of temperatures for a given~~ ; a feature not present in the warm season. This is suggestive that snow cover properties may be driving the winter warm bias in ERA5-Land (which will be discussed further in Section 6).

Similar seasonal variation is present in reanalysis soil temperature correlations (against station data), as most products show warm season correlations of greater than 0.95 near the surface 6). Meanwhile near surface cold season correlations are generally lower by approximately 0.2 to 0.3 (Figure 6) - which contributes to lower skill scores (Figure 2). The poor JRA55 correlation near the surface arises from its mismatched seasonal cycle.

Most products generally capture the observed soil temperature ~~in the cold season(blue scatter) than there is over the~~ variance during the warm season~~(red scatter), both at depth, and near the surface. Second~~, as normalized standard deviations are within 25% of the observed for all products. This is contrasted by the cold season, where several products overestimate soil temperature variability, contributing to a decline in product skill. Moreover, there is a ~~greater spread in standard deviations between products at colder temperatures. The spread is largest over the coldest temperature ranges (Figure 5), which suggests that colder climate regimes are likely an important controlling factor on reanalysis performance. Snow has a low thermal conductivity that insulates the soil , decoupling the air temperature above from the soil below the snow pack Zhang (2005). ? note that winter warm biases in T_{soil} in~~ larger spread in variance during the cold season - suggesting that there is less agreement between the products themselves (Figure 6). ERA5-Land~~could be partially explained by HTESSEL having a snow density that was biased low (relative to observations), leading to a snowpack thermal conductivity that was too low, and an associated overestimate of the insulating effects of snow. Snow was also cited as a major controlling factor in soil temperature biases in ECMWF's Integrated Forecast System, which also uses the HTESSEL land surface model (Albergel et al., 2015).~~

~~Reanalysis soil temperature standard deviation as a function of station soil temperature for a) the near surface (0 cm to 30 cm) layer, and b) at depth (30 cm to 300 cm). Station temperatures are binned into 4° C intervals, beginning with the -32° C to -28° C bin, and ending with the 28° C to 32° C bin. The midpoint of each temperature bin is plotted along the x-axis.~~

~~Most products show a maximum standard deviation over the coldest T_{soil}, whereas JRA-55 shows a maximum standard deviation when the observed T_{soil} are near freezing and shows a decline in standard deviation over the coldest temperatures (Figure 5), particularly near the surface (panel A)~~'s (blue) cold season skill is impacted by its underestimation of cold season soil temperature variability (which is roughly half of the observed variance), and arises in part because of its warm (positive) bias in winter (Figure 2). ERA-Interim (lime-green), GLDAS-Noah (black) and GLDAS-CLSM (grey) show unrealistically large soil temperature variability over the cold season (Figure 6), contributing to a substantial decline in their cold season skill (Figure 2).

4.3 ~~Influence of Frozen Soils~~Spatial Variability

~~Over our domain, there are grid cells over regions with substantial permafrost cover, as well as grid cells that fall outside the region typically covered by permafrost. As there are differences in the physical processes governing soil temperatures across regions covered by permafrost, it is important to mention differences in performance between these two regions. Bias and RMSE are typically~~ Soil temperature performance over the permafrost zone is typically worse relative to the performance over the zone with little to no permafrost, while skill scores are generally reduced by 0.05 - 0.1, and by as much as 0.2 for ERA-Interim and ERA5-Land (Figure SRMSE are typically 2° C ~~to~~ - 4° C larger over the permafrost zone (~~in both seasons)(Fig. S2). The mean bias and RMSE are typically 1° C to 3° C smaller over North America~~Figure S1 and Figure 7). The spread in standard deviation between products, at depth, is around 2.5 times larger over permafrost zone, relative to the ~~permafrost zone in Eurasia (see Figure S3); however with fewer grid cells over North America, the uncertainty is also larger - as evidenced by the larger error bars.~~

~~Correlations~~ zone with little to no permafrost (Figure S2), because of substantial differences in the variance of ERA5-Land, JRA55 and ERA-Interim. It is not clear whether these differences are due to the regions being colder, or due to structural issues with the land models, though this is beyond scope of paper. Interestingly, the differences in correlation and standard deviation between the permafrost ~~region~~ zone, and the zone with little to no permafrost~~are generally quite similar, rarely differing by more than 0.1 (not shown). Individual models are more likely to overestimate the near surface variance over the zone with little to no permafrost , while the opposite is true at depth (not shown).~~, in the near surface soil layers are less dramatic (Figure S2).

The ERA5-Land warm (positive) bias in the cold season is largest over permafrost regions (Figure S1) - particularly over Siberia and across North America (Figure S3). In the ~~permafrost zone~~case of JRA55, however, the ~~spread in standard deviation, at depth, is about 2.75 times larger than it is over the zone with little to no permafrost (~~warm biases over the cold season are largest further south. In fact, over many grid cells in the permafrost zone, JRA55 exhibits a cold (negative) bias during the cold season (not shown). ~~Over North America, several products overestimate the observed standard deviation in the warm season, while there is good agreement between the reanalysis products and the observed standard deviation in Eurasia. Conversely, the cold season variance is more likely to be overestimated over Eurasia (not shown). It is likely that sampling variability in~~ ~~T_{soil}~~ ~~is a large contributing factor to the differences in variance between North America and Europe.~~

~~Several factors may explain the increased variability in soil temperatures over permafrost regions. First - snow cover is present for longer, and may persist for longer on slopes with a northern aspect or where it has accumulated around vegetation. Munkhjargal et al. (2020) observed an average difference in soil temperatures of 3° C to 4° C across the Qinghai-Tibetan plateau in response to aspect. Second, near surface soil temperature is particularly sensitive to vegetation cover; shrub height and vegetation type were found to account for roughly half the variability in late winter and spring soil temperatures in the low Arctic (Grünberg et al., 2020). Moreover, in the discontinuous permafrost zone,~~ Generally speaking, the ~~presence of permafrost is often ecosystem protected or ecosystem driven. Variability in vegetation and drainage, for example, may lead to localized portions of the landscape where soil temperaturesare colder than in surrounding areas (Jorgenson et al., 2010). Thirdly, latent heat interactions in the active layer during spring can lead to long periods of time where the soil remains at or close to freezing (~~skill is higher over Eurasia than over North America (Figure S4). The lower skill in North America arises in part due to the underestimation of seasonal cycle over many grid cells in the Yukon, and an overestimation of variability of cold season temperatures over much of the ~~zero-curtain period). In regions where the active layer is deep (such as over the discontinuous permafrost zone), the zero curtain period is often longer and more pronounced (Chen et al., 2021) than it is over the continuous permafrost zone or regions with seasonally frozen soil. Many of the processes that control the zero-curtain effect, such as freeze-thaw parameterizations are relatively simplistic in many land models (?Chen et al., 2015), and their coarse resolution would fail to capture local scale variations in the zero-curtain period.~~ Great Lakes Region (Figure S5). CFSR, GLDAS-CLSM and JRA55 are an exception, however, as they greatly overestimate the cold season variability over much of western Eurasia (Figure S5), and consequently exhibit lower Eurasian skill scores. Product soil temperature correlations (with in situ soil temperatures) are also lower by about 0.05 to 0.1 in both seasons over North America, relative to Eurasia (Figure S6), which further contributes to reduced skill over North America.

5 Ensemble Mean Product

5.1 Validation

~~Having validated the performance of the individual products, here we construct a soil temperature product based on the ensemble mean of the products, and investigate its performance. Taking the ensemble mean of all eight soil temperature products~~ The ensemble mean soil temperature product produces a soil temperature dataset that shows closer agreement with observed soil temperatures than most/all individual products. The ~~ensemble mean bias and RMSE are~~ annual mean, ensemble mean skill score is higher than any individual product over the extratropical northern hemisphere (Figure 2). The bias of the ensemble mean soil temperature generally quite close in magnitude to the best performing products over ~~all regions, seasons , and~~ both seasons depths (Figure 2). Moreover, ~~by sequentially increasing the number of products included in the ensemble mean , we are able to demonstrate that~~ the ensemble mean product (pink) displays a temporal variance within 20% of the observed variability over all depths. We find that the inclusion of a greater number of products in the ensemble mean ~~leads to a reduction in overall~~ yields greater reductions in bias and RMSE, and analogous improvements in correlation (Figure 8, panels A and B)~~. Interestingly, the number of products included appears to be of greater importance to the performance of the ensemble mean than which products are included, suggesting that most products share similar uncertainties and signal-to-noise ratios, and resulting, to a certain degree, in the offsetting of biases or errors.~~ , though the incremental improvement in skill begins to saturate beyond four products (Figure 8.

~~In addition,~~ The value of using the ensemble mean soil temperature is particularly noticeable in the cold season when individual products see a decline in skill, and a larger spread in performance. The near surface skill of the ensemble mean ~~maintains a high correlation (often the highest of all products) over all seasons and depths (Figure 6), and analogous improvements to correlation are seen as a greater number of models are included (Figure 8). Finally, the ensemble mean standard deviation is close to the observed value over all seasons and~~ in the cold season is nearly 10% than the next best product (Figure 2). While many products fail to capture the cold season temperature variance, the variance of the ensemble mean product remains within 25% of the observed variability (Figure 2). In addition, the extratropical northern hemisphere mean cold season biases are

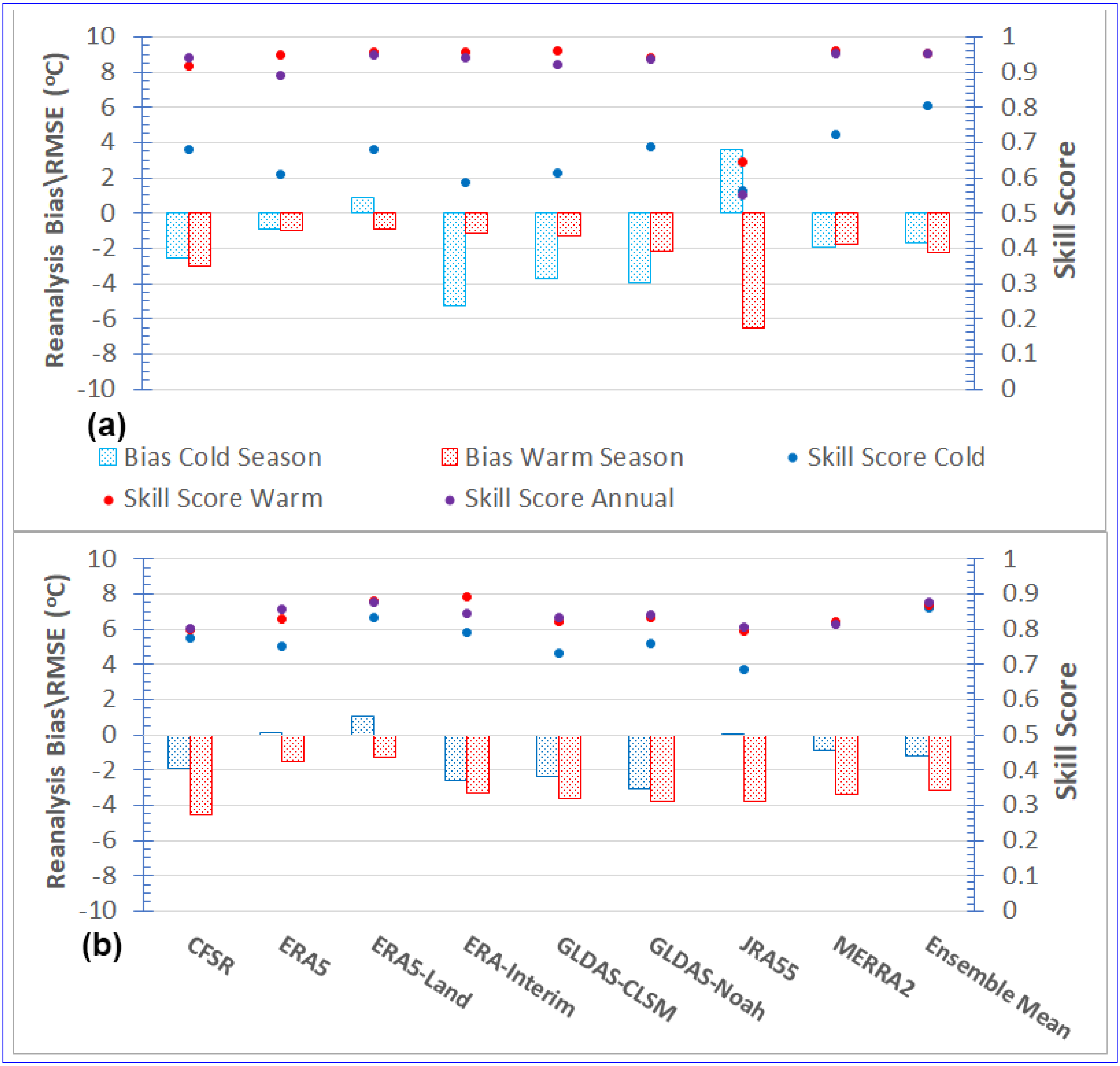


Figure 2. Bias (stippling) and skill scores (small circles) of each product the cold season (blue) (≤ -2° C) and the warm season (red) (> -2° C) performance of reanalysis products. Panel A displays the bias and skill score for the near surface (0 cm to 30 cm) layer, while panel B displays the bias and skill score at depth (30 cm to 300 cm). The ensemble mean is shown beside for comparison.

close in magnitude to best performing product (Figure 2) over both depths, and its correlations are generally larger, by roughly 0.05, than the best performing product over both depths (Figure 6)~~, suggesting that the seasonal variability in T_{soil} is similar to~~

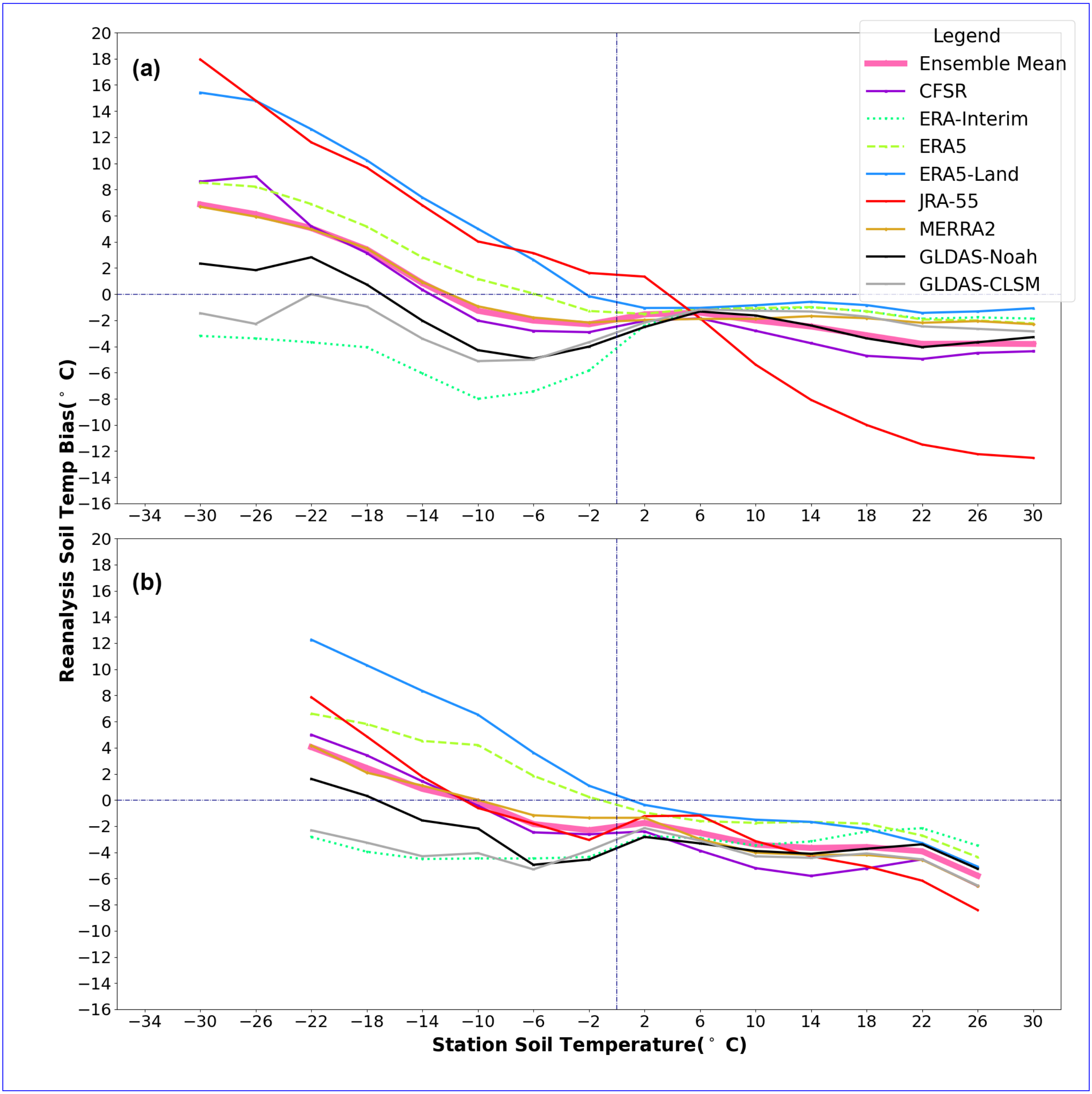
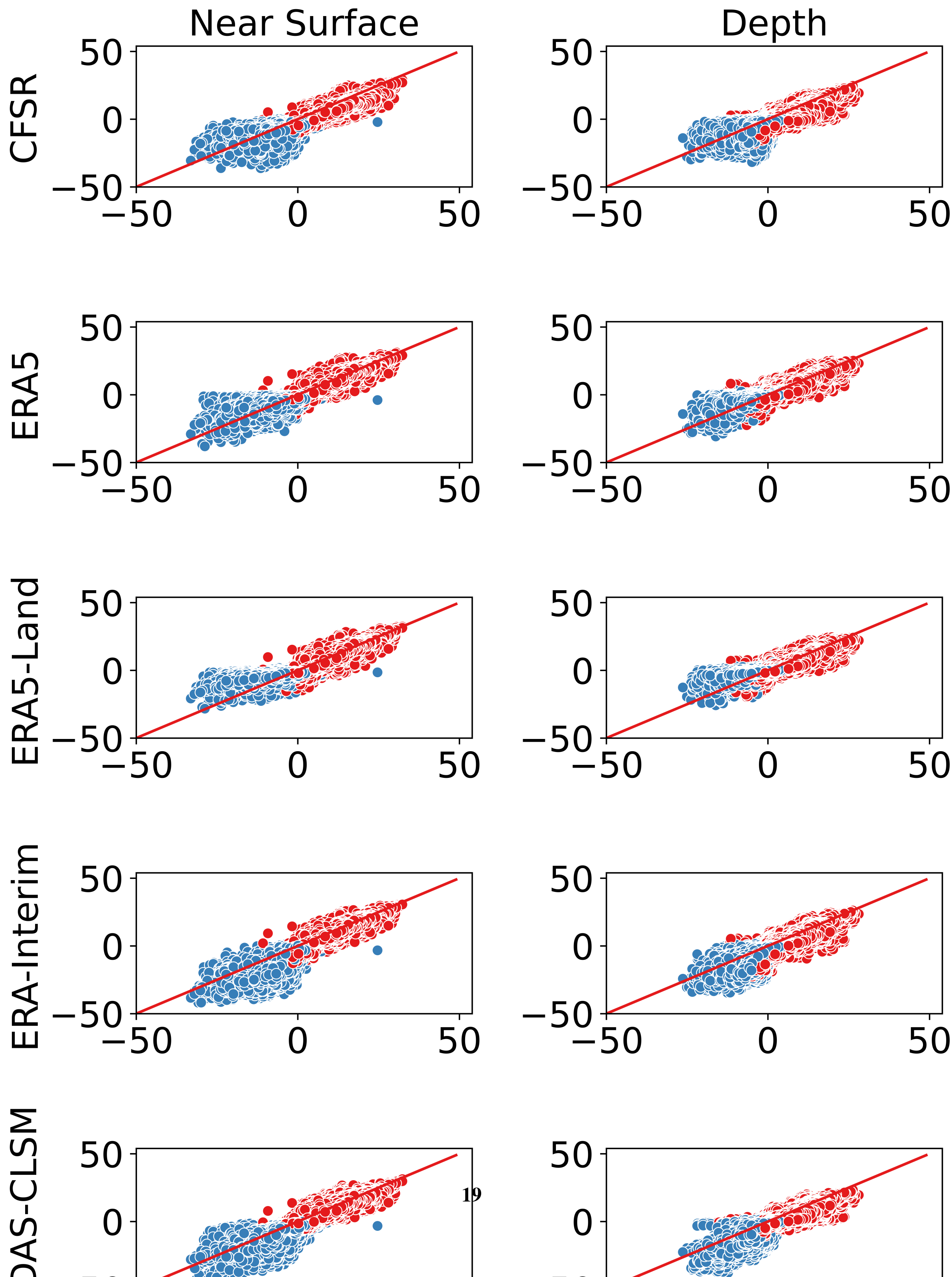


Figure 3. Reanalysis soil temperature bias as a function of station soil temperature for a) the near surface (0 cm to 30 cm) layer, and b) at depth (30 cm to 300 cm). Station temperatures are binned into 4° C intervals, beginning with the -32° C to -28° C bin, and ending with the 28° C to 32° C bin. The midpoint of each temperature bin is plotted along the x-axis.

~~the variability seen in the station data~~. Thus, the ensemble mean soil temperature dataset provides the best estimate of in situ temperatures for the broadest range of conditions.


Near Surface
Depth
CFSR
ERA5
ERA5-Land
ERA-Interim
DAS-CLSM
50
0
−50
−50
0
50

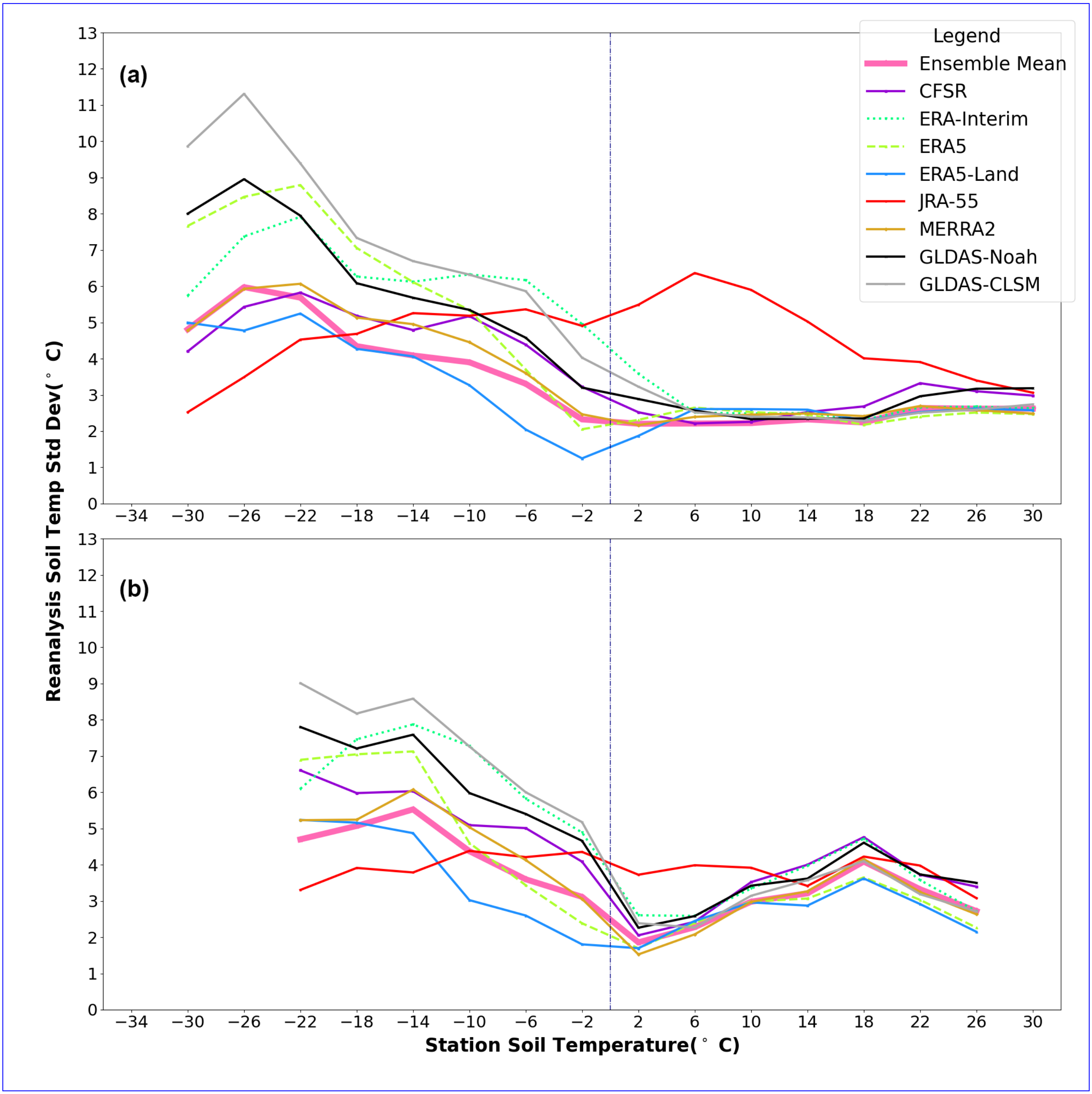


Figure 5. Reanalysis soil temperature standard deviation as a function of station soil temperature for a) the near surface (0 cm to 30 cm) layer, and b) at depth (30 cm to 300 cm). Station temperatures are binned into 4° C intervals, beginning with the -32° C to -28° C bin, and ending with the 28° C to 32° C bin. The midpoint of each temperature bin is plotted along the x-axis.

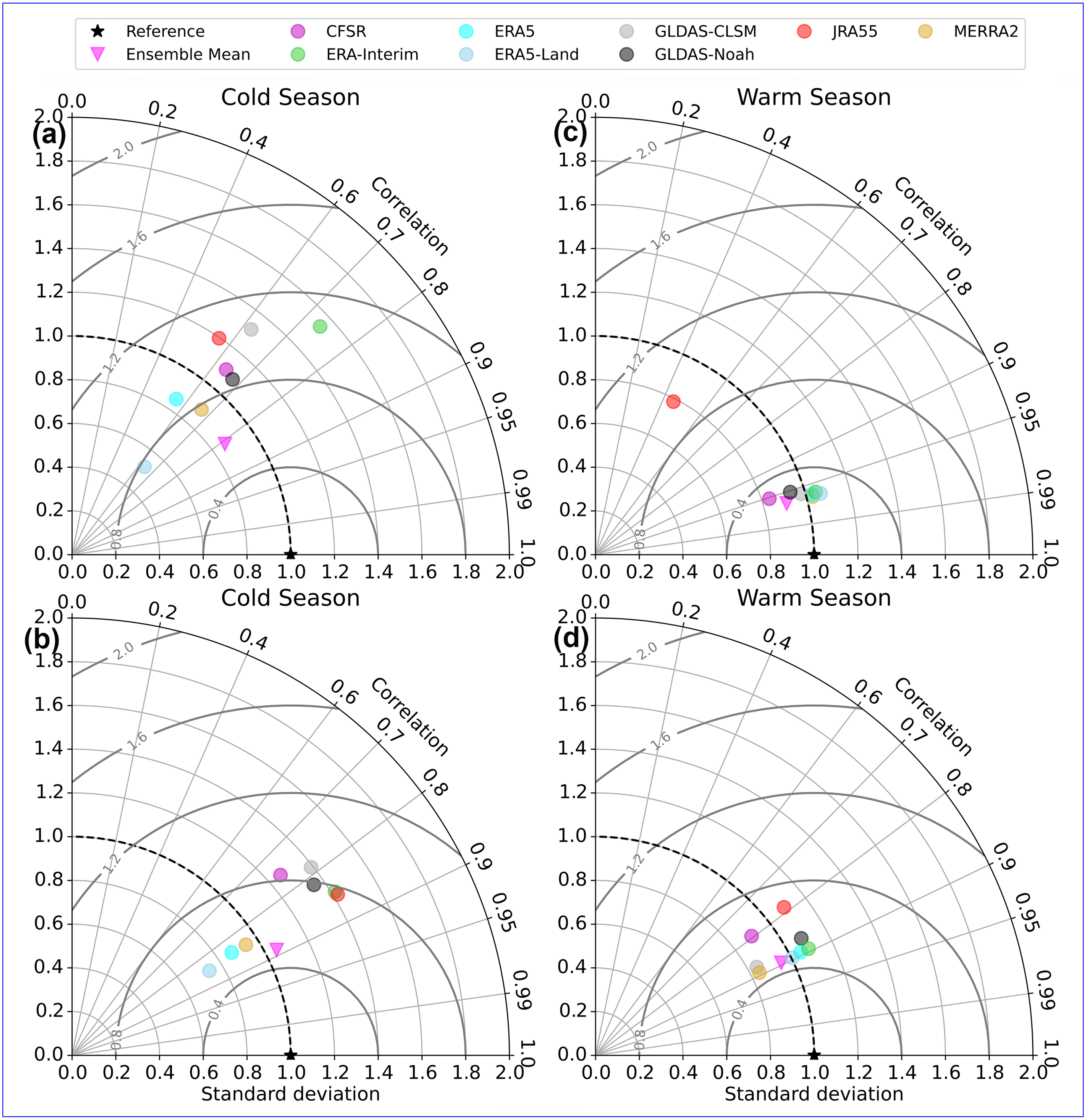


Figure 6. Taylor Diagram of the cold season (≤ -2° C) and the warm season (> -2° C) performance of reanalysis products. Panels A and B refer to the cold season, while panels C and D refer to the warm season. The top panels (panels A and C) are for the near surface (0 cm to 30 cm) while the bottom panels (panels B and D) refer to soil temperatures at depth (30 cm to 300 cm). The concentric rings (solid grey lines) refer to the centralized root mean square error (CRMSE)

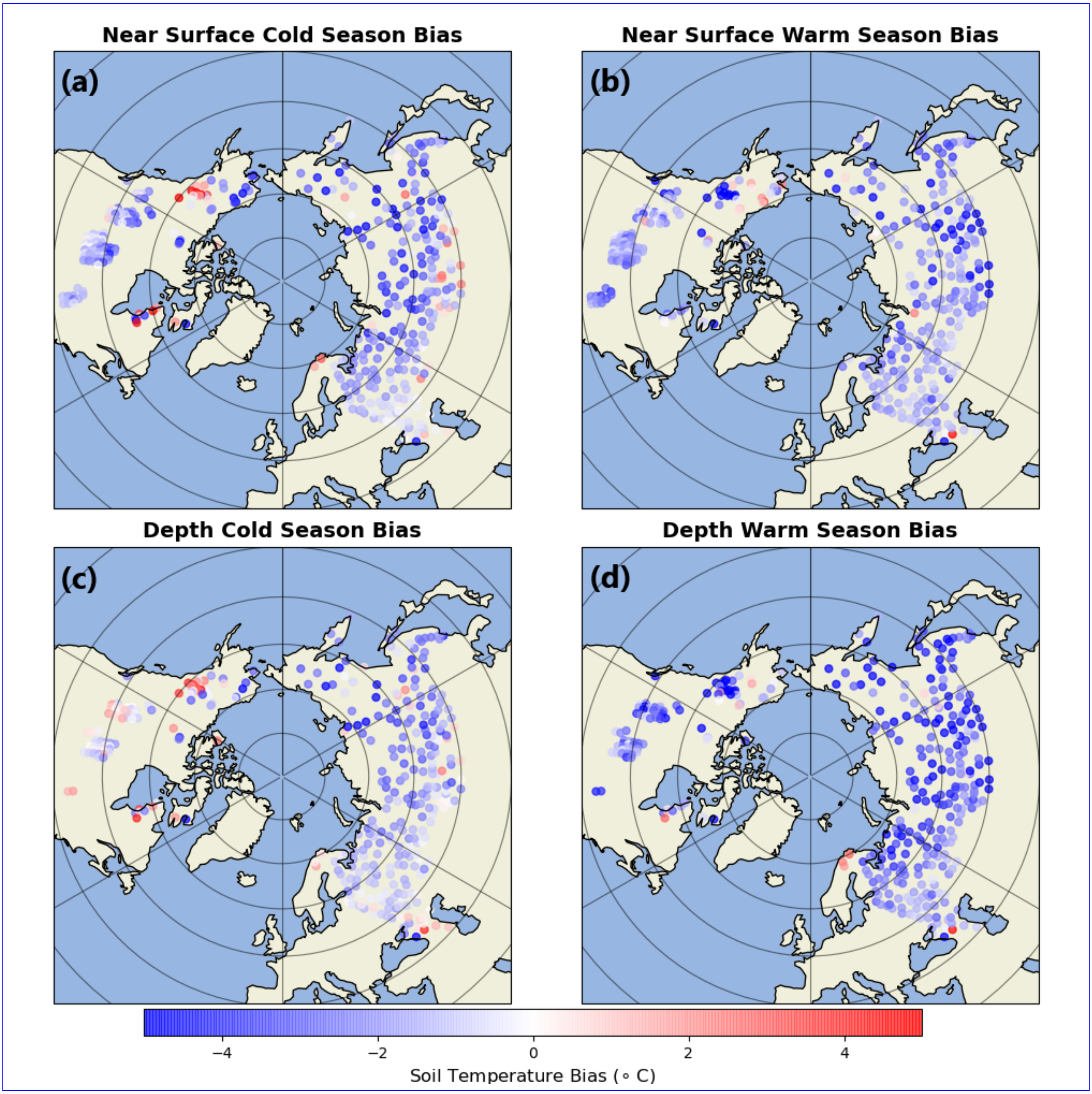


Figure 7. Spatial map of bias for the Ensemble Mean product. Values for the cold season are shown in the left hand panels, and those for the warm season are shown in the right hand panels. Panels A and B show the near surface bias, while biases at depth are shown in Panels C and D.

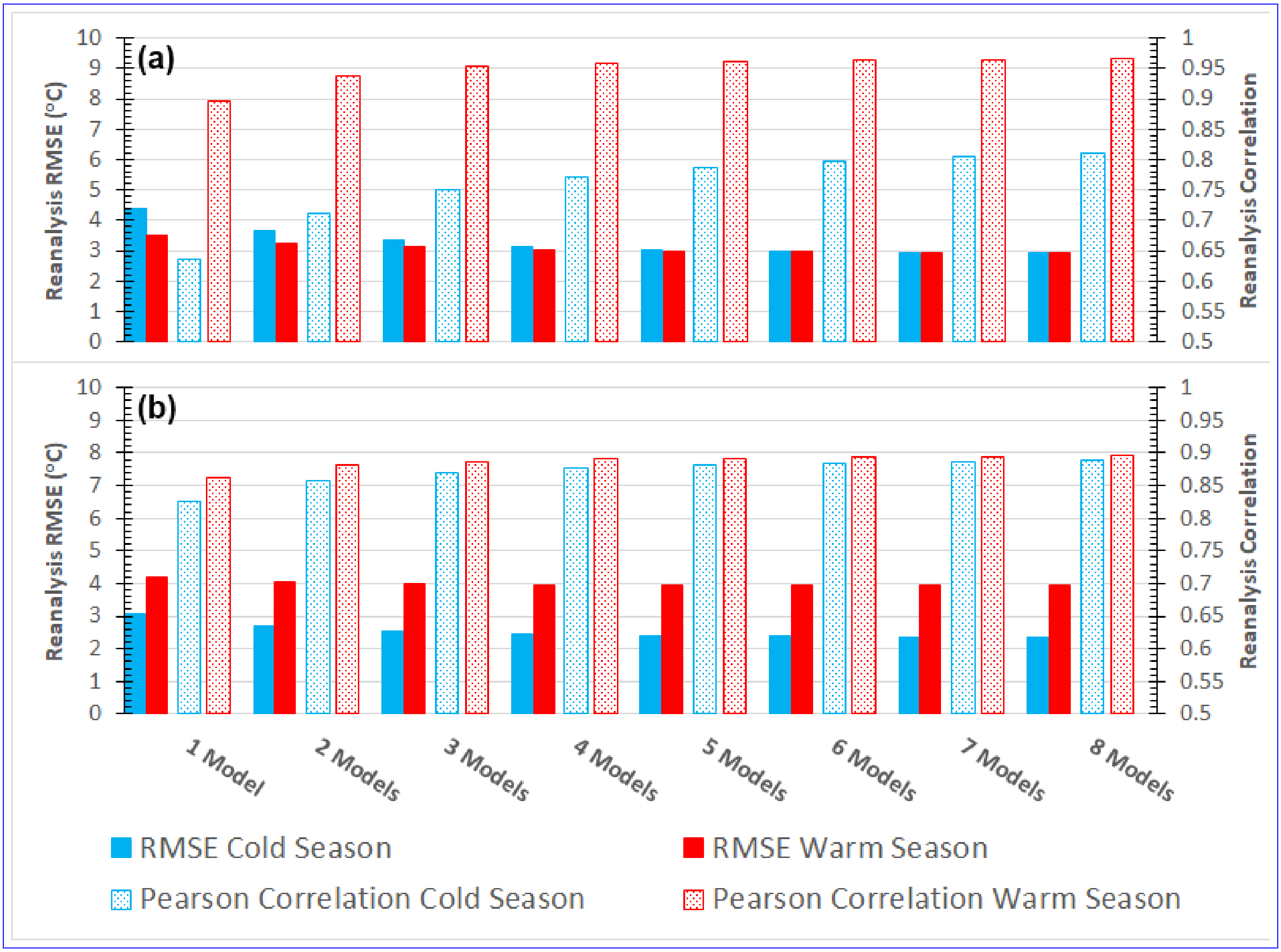


Figure 8. Root Mean Square Error (RMSE) (solid colour), and Pearson Correlation (stippling) for the cold season (blue) (≤ -2° C) and the warm season (red) (> -2° C) averaged over all combinations of 1 model through to 8 model ensemble means. Panel A displays the RMSE and correlation for the near surface (0 cm to 30 cm) layer, while panel B displays the RMSE and correlation at depth (30 cm to 300 cm). Values are ordered based on cold season RMSE (from smallest to largest). Note that the y-axis scale is from -8° C to +10° C (rather than -10° C to +10° C).

~~Ensemble mean 1981-2010 near-surface climatology (panels A and B), variability (panels C and D), and 30-year trend (panels E and F). Values for DJF are shown in the left hand panels, and those for JJA are shown in the right hand panels.~~

5.2 ~~Climatology (1981-2010)~~Trends and Variability in Seasonal Extremes in the Ensemble Mean Product

~~Having established that an ensemble mean of products provides the best choice for T$_{soil}$ in most situations, in this Section we characterize the pan-Arctic mean,~~ We focus our analysis of variability and trends ~~of the ensemble mean T$_{soil}$ product. Unlike in previous sections, where the air temperature of a grid cell was used to separate the cold and warm season, this was not possible for a discussion of the climatology. Henceforth, in Sections 5.3 and 5.4, we use the DJF climatology to represent winter, and JJA climatology to represent summer~~on the near surface data, as the spatial pattern of soil temperature trends near the surface and at depth show a pattern correlation of greater than 0.95 (not shown), and the conclusions regarding performance are generally similar. The authors highlight any major differences where applicable and readers are referred to Supplemental Figures A5 and A6 for further information.

~~Near surface soil temperatures generally range between -12~~The ensemble mean soil temperature dataset shows that most regions see small positive annual mean soil temperature trends of $\leq 1°$ ~~C and -30° C for most regions north of 60° N in DJF~~C decade^{-1}, with slightly ~~warmer temperatures over the Yukon, Alaska, and Scandinavia (Figure **??**, panel~~ larger trends in the Canadian Arctic Archipelago and in Siberia, for example. Portions of Western North America and Siberia exhibit slight cooling trends of $< 0.5°$ C decade^{-1} (Figure 9, Panel A). ~~Temperatures are often a few degrees warmer at depth, but the temperature pattern remains quite similar (DJF pattern correlation > 0.95 over the extratropical NH north of 45° N).~~

~~In JJA, most of the near surface soil temperatures across the Arctic rise above freezing, with the exception of a few locations along Baffin Island and Ellesmere Island (as the top 30 cm is representative of the active layer). Temperatures generally range between 6° C to 12° C, with cooler areas across Eastern~~ Annual mean soil temperature trends in the Ensemble Mean over Eurasia show a moderate correlation of 0.5 with observations (Figure 9 Panel B). The ensemble mean generally correctly predicts both the magnitude and the sign of the station trend. There are several cases where the station shows a warming trend over North America, and ~~along the northern coast of Siberia (Figure **??**, panel~~ the Ensemble Mean predicts a small cooling trend, however these trends are not statistically significant (Figure 9 Panel B). ~~At depth , (not shown) , much of the Canadian Arctic Archipelago and the northern portions of Siberia remain below freezing, with most other regions showing soil temperatures between 0° C to 6° C (except for Scandinavia). JJA pattern correlations in near-surface and depth soil temperature climatologies are > 0.95~~Figure S7 shows that the spatial pattern in soil temperature trends at depth is nearly identical (Panel A) - displaying a pattern correlation of 0.99. Panel B of Figure S7 highlights a similar performance of the Ensemble Mean product at depth - with most grid cells showing a small positive soil temperature trend, and a moderate correlation with in situ soil temperature trends of 0.45 (not shown).

~~Spatial map of bias for the Ensemble Mean product. Values for the cold season are shown in the left hand panels, and those for the warm season are shown in the right hand panels. Panels A and B show the near surface bias, while biases at depth are shown in Panels C and D.~~

~~While, not directly comparable to the climatology figure, cold season biases in the Ensemble Mean product are typically -4° C to -5° C over~~ Referring to Figure 1, Panel A, several different types of grid cells are denoted. The first group - Type 1 (45 occurrences) are typically located in regions within the permafrost zone~~, and -2° C to -3° C over much of the zone with little to no permafrost (Figure 7, panel~~ ; particularly in continental regions of Siberia. Type 1 grid cells are characterized by a strong cold bias in (underestimate) the winter minimum soil temperature (Figure **??**, Panel A). ~~There is little difference in the cold season biases at depth, except for being slightly smaller in western Eurasia~~ A second grouping of grid cells, which we refer to as Type 2 (~~Figure 7, panel C).~~

~~In the warm season,~~ 65 occurrences), are generally located outside the permafrost zone, in grid cells that are further south, or in western Eurasia. Type 2 grid cells are defined as those which have a strong warm bias in (overestimate) the summer maximum temperature (Figure **??**, Panel B). A common feature of the third group, Type 3 (7 occurrences), is that they underestimate the observed seasonal cycle of soil temperatures (Figure **??**, Panel C). Often the situ station(s) located within Type 3 grid cells are located in areas devoid of vegetation, and it is likely that disagreements in the ~~near surface biases are generally small (around -1° Cover much of Eurasia), except for a few grid cells south of Siberia, where they are similar in magnitude to the cold season (around -4° C). Alaska and~~ simulated vegetation cover in the contributing reanalysis products may partially account for the reduced seasonal cycle. Many grid cells in the Yukon, ~~however, appear to show a small to moderate warm bias on the order of +1° C to +~~whose comprising stations are similarly located in areas devoid of vegetation, would also meet the criteria for a Type 3 ~~° (Figure 7, panel B)~~outlier, as the ensemble mean normalized standard deviation (a measure of soil temperature variability) is substantially smaller than 1.0 in both seasons (Figure S7), though these grid cells were excluded as their timeseries were too short. If we examine all grid cells over North America, a fourth group can be identified: instances where the ensemble mean simulates a seasonal cycle of soil temperatures that is too large. This is evident in Figure S6, where a cluster of grid cells in the Great Lakes region show a normalized standard deviation much larger than 1.0. This is also true for a number of grid cells in western Eurasia. ~~At depth,~~

As discussed in earlier sections, the ~~biases are somewhat larger than they are at the surface, particularly over Eurasia, but the pattern remains similar to the near surface (Figure 7, panel D) .~~ mean soil temperatures in the ensemble mean product is generally biased cold (negative) over most grid cells in both seasons. For many grid cells, this cold bias also extends to both the winter minimum (Figure 11, Panel A) and the summer maximum (Figure 11, Panel B) soil temperature.

5.3 ~~Variance and Trends (1981-2010)~~

~~Generally speaking, coastal regions show the greatest variability in T_{soil}, with inland regions showing substantially smaller variation. Temperature variability is larger in DJF than it is for JJA (Figure **??**, Panels Cand~~ Most products exhibit a cold bias over all latitude bands in both their zonal mean winter minimum (Figure 11, Panel C) and summer maximum temperature (Figure 11, Panel D). ~~A similar pattern is generally seen at depth, but with reduced variability (pattern correlation greater than 0.9 in DJF). In JJA, the pattern in variability is generally similar, though pattern correlations between surface and depth are closer to 0.58, owing to an increased sensitivity to small changes standard deviation~~ While the spread between products remains relatively consistent across latitudinal bands over summer, the spread between products increases at higher latitudes

Table 3. Standard Deviation of the Mean Winter Minimum and Summer Maximum Soil Temperature as a Function of Latitude and Depth. Latitude bands are 10 degrees in width, such that the 40° N latitude band is an average between 40° N and 50° N, while the 60° N latitude band is an average between 60° N and 70° N, for example.

Latitude Band		
40°N	2.60° C ~~per decade along the northern coastlines. Inland regions typically see smaller DJF trends; closer to a degree pe~~	
50°N		2.90° C ~~per decade~~
60°N		

over winter (Table 3). Using the standard deviation as a measure of spread between product biases, the standard deviation in winter minimum bias increases from 2.60° C over the 40° N latitude band, to 3.73° C north of 60 ° N. This is in large part to substantially colder biases in ERA-Interim (green) at higher latitudes. Meanwhile the standard deviation in the mean summer maximum bias only sees small increases (from 2.30° C at 40° N, to 2.73° C at 60° N) (Table 3).

~~Decadal temperature trends (Figure ??) are the largest in DJF (panel E) ; reaching as large as~~ Winter warm (positive) biases in ERA5-Land (sky-blue) are most prevalent over higher latitudes. The ensemble mean (pink line) exhibits somewhat larger cold (negative) biases in winter minimum temperature in the highest latitude band (Figure 10, Panel C). Interestingly, ERA-Interim (green) shows similar biases to ERA5 (cyan) and ERA5-Land (sky-blue) in summer and is one of the best performing products. This is suggestive that ERA-Interim's degraded performance over winter could be related to snow cover.

The conclusions regarding variability in soil temperature extremes, at depth, are generally similar to those near the surface. Both the winter minimum and summer maximum soil temperatures are biased cold at depth (Figure S8, Panels A and B), however the winter minimum soil temperature sees a larger spread at high latitudes (increasing from a standard deviation of 1.21° C at 40° N to 2.70° C at 60° N), while the spread in the summer maximum sees little variation with latitude (Table 3).

Figure S8 Panel B shows that there is a noticeably greater disagreement between the ensemble mean and in situ soil temperatures; especially over colder regions. It is also apparent that the latitudinally averaged biases in the summer maximum temperature (Figure S8, Panel C) are larger than their winter minimum counterparts (Figure S8, Panel D) - consistent with the findings that the extratropical mean bias in the warm season is larger than the bias in the cold season (Figure 2).

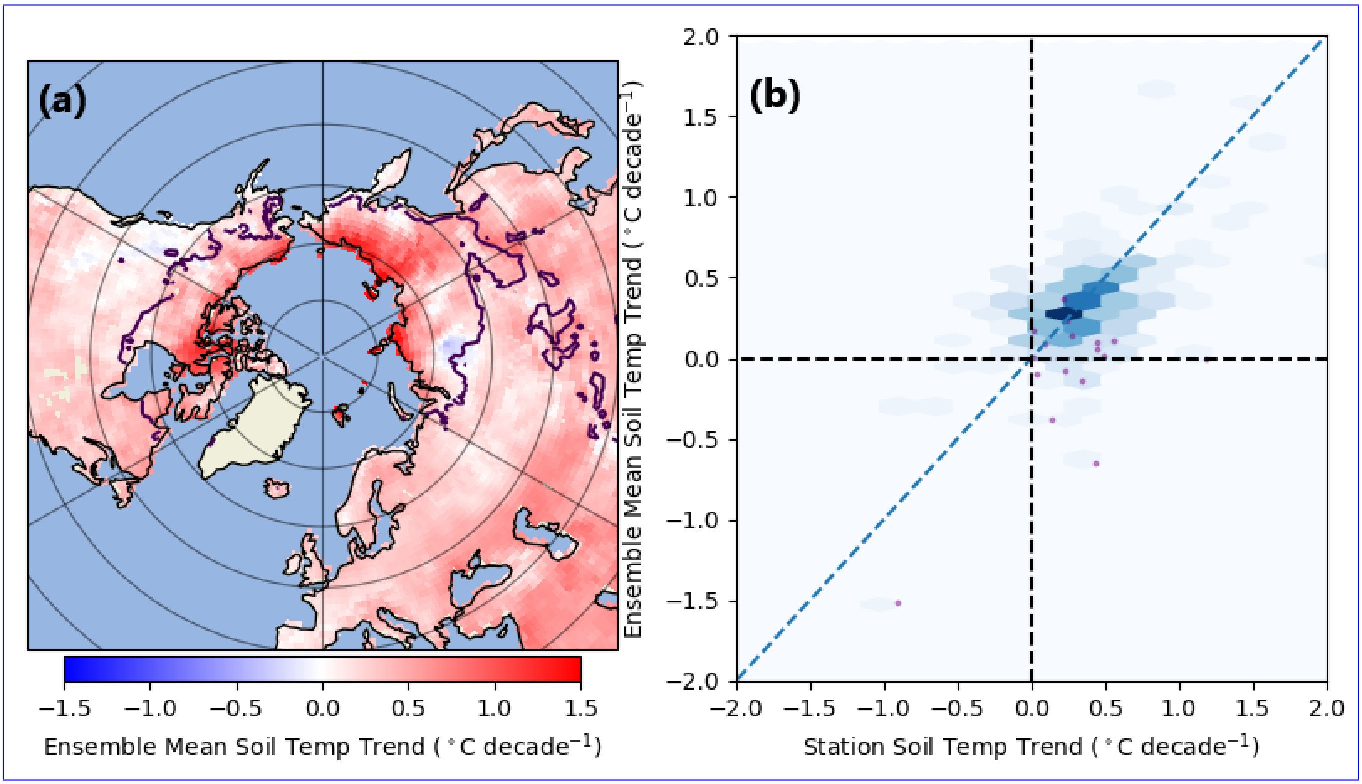


Figure 9. Panel A: 1981-2010 Ensemble Mean decadal soil temperature trends, with the locations of validation grid cells included in the trend analysis. Panel B: Relationship between Ensemble Mean and Station soil temperature trends (per decade). The red dots refer to North American grid cells. Note that the time periods over which the soil temperature trends are calculated in Panel B do not necessarily match those calculated in Panel A (as they are calculated over the time period that station data is available). The black line represents the boundary of the permafrost zone (regions with at least 50% permafrost cover).

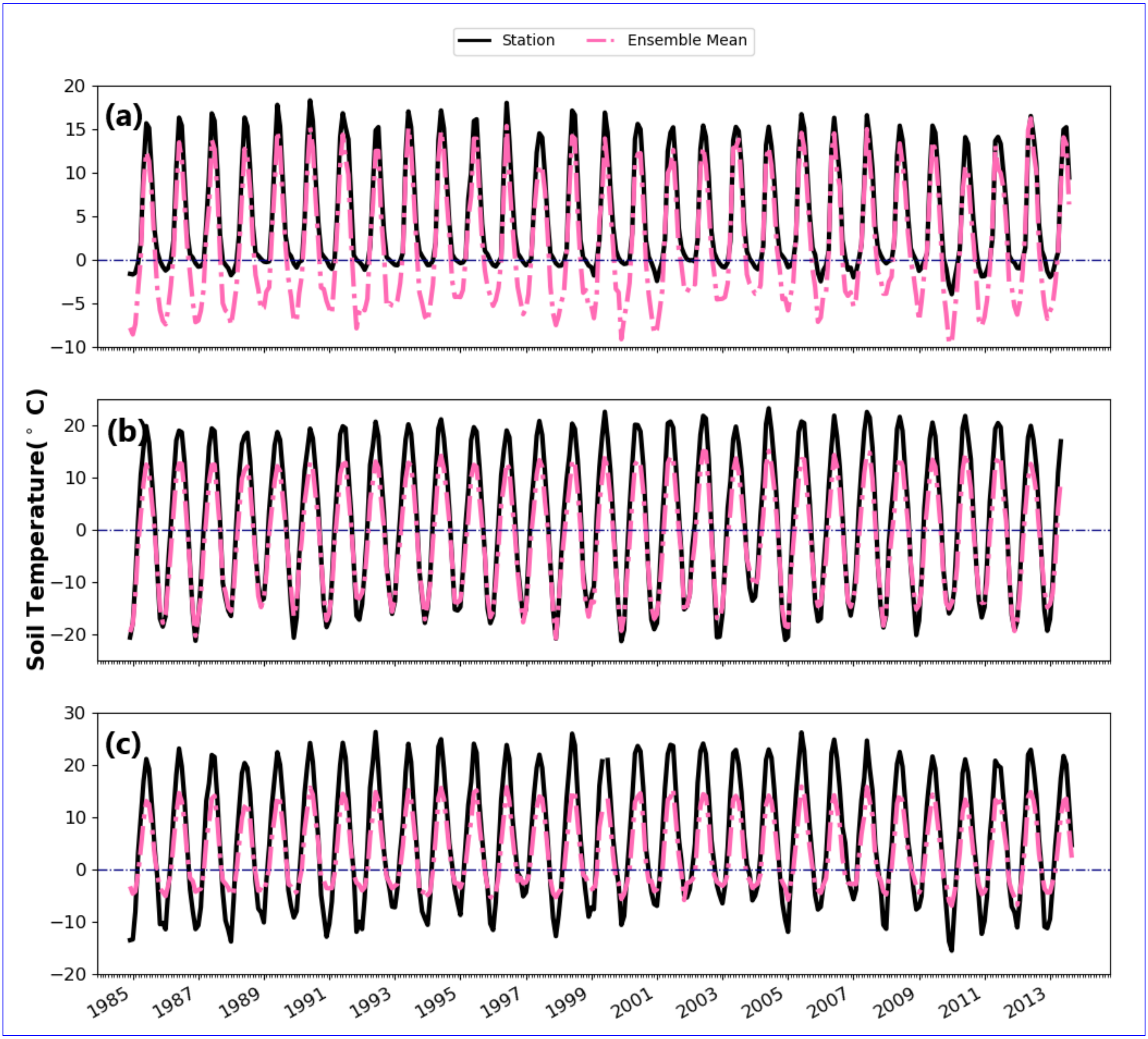


Figure 10. Timeseries from selected grid cells showing the ensemble mean (pink) and station (black) soil temperatures. Panel A: Timeseries where the ensemble mean simulates a winter minima that is too cold. Panel B: Timeseries where the ensemble mean simulates a summer maxima that is too cold. Panel C: Timeseries where the ensemble mean underestimates the seasonal cycle of soil temperatures.

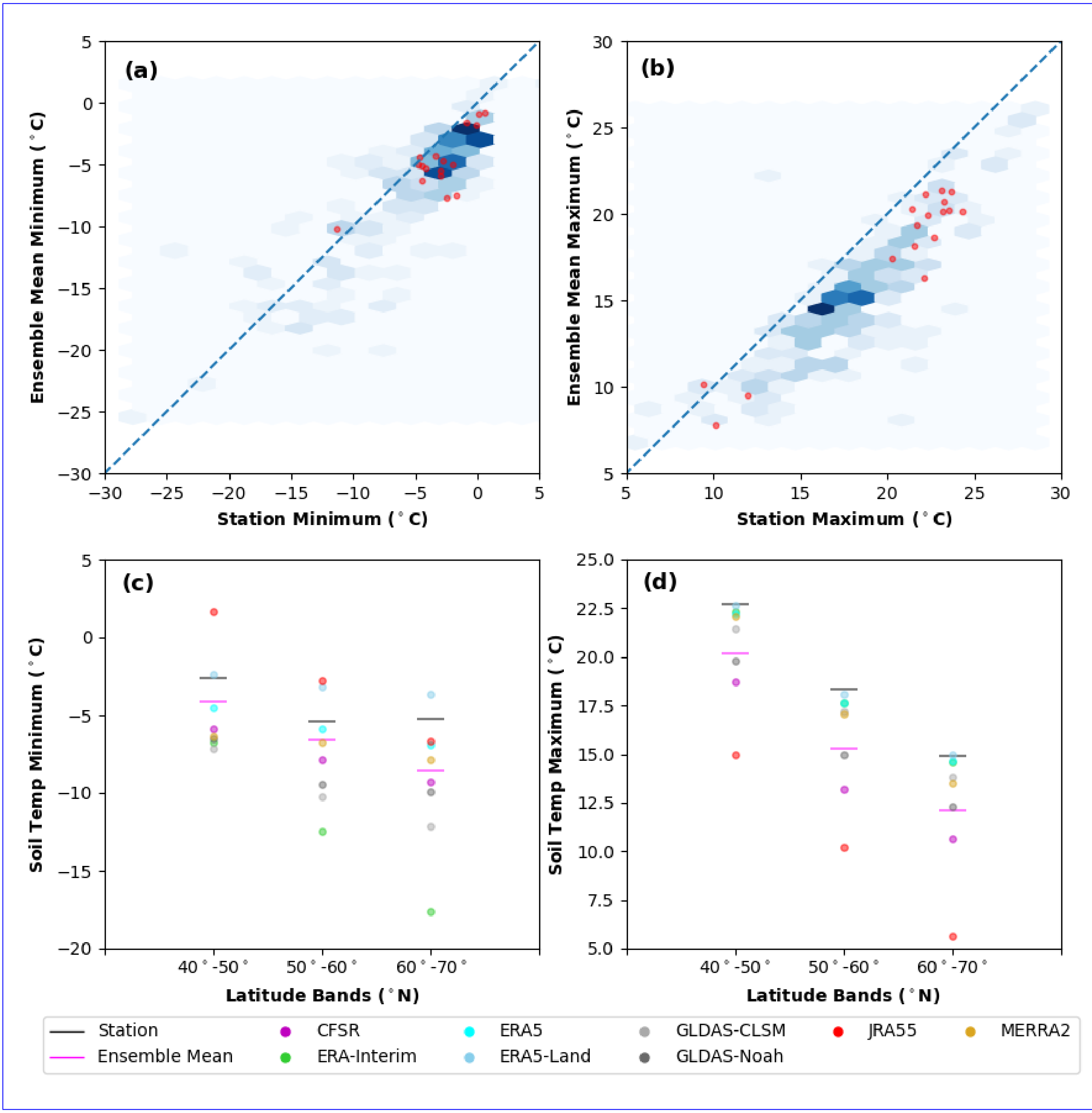


Figure 11. Performance of the near surface soil temperature variability in the Ensemble Mean. Panel A: Scatterplot of the station and ensemble mean winter minimum soil temperature. Panel B: Scatterplot of the station and ensemble mean summer maximum soil temperature. Panel C: latitudinal averages (from Eurasian grid cells) of near surface soil temperature winter minimum for the ensemble mean and contributing products. Panel D: latitudinal averages (from Eurasian grid cells) of near surface soil temperature summer maximum for the ensemble mean and contributing products.

6 Discussion and Conclusions

This study conducted a validation of pan-Arctic soil temperatures for eight reanalysis products, and validated a new ensemble mean pan-Arctic soil temperature dataset. ~~Most reanalysis products show a negative (cold) soil temperature bias of several degrees across the Arctic; one that is most prominent during the cold season, and over the highest latitudes. There is also greater disagreement between~~ The results are qualitatively similar to the findings of previous studies exploring reanalysis soil temperature performance in the extratropical northern hemisphere, which generally highlighted a cold bias in most products (Hu et al., 2019; Qin et al., 2020; Wu et al., 2018; Xu et al., 2019; Yang and Zhang, 2018; Zhan et al., 2020) . Similar to (Li et al., 2021), we note greater biases in cold season soil temperatures, and our results qualitatively reflect the findings of Cao et al. (2020), who found that ERA5-Land exhibited warm soil temperature biases - particularly over higher latitudes.

The soil temperature trends reported here are slightly larger than those reported by Biskaborn et al. (2019), who found that permafrost soil temperatures generally warmed at a rate of 0.39° C $\pm$ 0.15° C decade^{-1}, however we report near surface soil temperature trends, whereas Biskaborn et al. (2019) used soil temperatures near the depth of zero amplitude to calculate soil temperature trends.

Other major differences here are that we develop an ensemble mean soil temperature product, and had a greater focus on higher latitude regions than most other studies. We also note a strong difference in seasonal performance. Relative to the warm season, the cold season is generally characterized by lower skill, larger near surface temperature biases, a larger spread in the reanalysis products' ~~estimates of~~ soil temperature variability and ~~correlation during the cold season~~lower correlations with in situ soil temperatures. When all depths and seasons are considered, the ensemble mean product performs better than any individual product, exhibiting a consistently high skill, realistic soil temperature variability, and relatively small biases over all seasons.

~~All estimates of T$_{soil}$ are subject to uncertainty , and while we have not been able to present a~~ Here we show an approximate estimate of the magnitude of soil temperature uncertainty associated with instrumental uncertainties, and those associated with structural differences and parameterizations in land models, using the standard deviation in soil temperature across time and as a function of station temperature. A complete quantitative assessment of ~~these~~ the contributions of various sources of uncertainty ~~, we have made some progress in their characterization. In particular, we identify four main categories of uncertainty, and provide qualitative estimates of their importance:~~ is not possible using this dataset, as time-series did not have a consistent start or end date and consequently, the metrics are calculated using different climatologies across different grid cells. A more complete uncertainty analysis is beyond the scope here, but in the future could be achieved by limiting analysis to a subset of grid cells with consistent timeseries; for example by focusing on soil temperature networks such as the Michigan Enviro-weather Network, or the North Dakota Mesonet Network, or limiting the uncertainty analysis to a smaller portion of the permafrost region.

~~Uncertainties in data assimilation and configurations of atmospheric model~~

~~Many reanalysis products exhibit a positive air temperaturebias near the surface over the Arctic (Beesley et al., 2000; Lindsay et al., 2014 ; particularly in winter, in association with temperature inversions that are weaker than observed (Serreze et al., 2012; Tjernström and Grave . Differences between products in the parameterization of cloud cover and small scale turbulent mixing have been highlighted as key sources of uncertainty in atmospheric reanalyses (Boisvert et al., 2018; Taylor et al., 2018),~~ We find that the median spread in the spatially averaged soil temperature of stations in a grid cell is approximately 2.5° C (Figure 1, Panel B) – an order of magnitude smaller than the standard deviation of reanalysis soil temperatures for a given station soil temperature; particularly over frozen soils (Figure 5). For example, when soil temperatures are below –20 ° C, soil temperature standard deviations increase to near 10° C in several products. Reanalysis air temperatures maintain a relatively consistent standard deviation between 1.25° C to 1.75° C for most products, except over the coldest in situ temperatures (not shown). Unlike with soil temperature, the standard deviation of reanalysis two metre air temperature only increases modestly over the cold season; along with the ~~near surface Arctic energy budget (Graham et al., 2019). Reanalysis estimates of precipitation amount and phase are another important source of uncertainty , and are especially hard to constrain~~ spread in standard deviation between products (not shown). This would suggest that the largest degree of uncertainty in reanalysis soil temperatures over the Arctic ~~, due to a lack of observations (Boisvert et al., 2018)~~is most likely contributed by differences in the land models between products, rather than from uncertainties in observed soil temperatures, or from differences in product air temperatures.

~~Uncertainties in the land model configuration and /or parameterizations :~~

~~The methods used here did not allow for explicit study of the impacts of land model configuration on soil temperature . Nevertheless, it is important to acknowledge that most land models fail to simulate important aspects of permafrost soils, such as the influence of phase change on thermal conductivity (?), or include relatively crude parameterizations of~~

6.1 Uncertainties Associated with Land Model Parameterizations and Structural Differences

Uncertainties in soil temperatures associated with structural differences and parameterizations in land models can be grouped into several categories. The first surrounds the simplified parameterizations controlling frozen soil processes. For example in the Noah LSM - utilized by CFSR and GLDAS-Noah, freeze-thaw ~~processes (Chen et al., 2015). Moreover, many current generation land models fail to capture feedbacks that exist between vegetation and permafrost (?)~~ processes are highly simplified, and unsuited for permafrost simulations (Hu et al., 2019) - ~~a factor particularly important in the discontinuous permafrost zone, where permafrost presence (or absence)is heavily influenced by vegetation (Jorgenson et al., 2010). Land surface models,~~ and may have contributed to the relatively large soil temperature biases simulated in these products. Even the best performing products: ERA5 and ERA5-Land, are unsuited for simulation of permafrost soil temperatures, as they fail to simulate phase-dependent changes in soil thermal conductivity (Cao et al., 2020).

Yang et al. (2020) noted that larger soil temperature biases over the Qinghai-Tibetan Plateau in deeper soil layers were likely related to the fact that soil temperatures are less constrained by air temperature observations (and soil properties). This could also explain why soil temperature biases in the warm season are larger at depth than near the surface in this study. Moreover, the near surface soil layers tend to fall within the active layer (which undergoes seasonal freeze/thaw), while deeper soil layers are more likely to contain permafrost. Permafrost has a high degree of impermeability, which prevents soil water from infiltrating below the bottom of the active layer, and owing to latent heat considerations, leads to soil water freezing at the base of the active later (Zhao et al., 2000), however these processes are not well represented in reanalysis LSMs Yang et al. (2020); Hu et al. (2019).

LSMs such as the Simple Biosphere Model (used in ~~JRA-55~~JRA55), that use the force restore method to estimate soil temperature, are prone to overestimating diurnal soil temperature range (Gao et al., 2004; Kahan et al., 2006), as well as the seasonal cycle of soil temperatures (Luo et al., 2003). This is because they underestimate heat capacity, and overestimate temporal variation in ground heat flux compared to more complex land models (Hong and Kim, 2010). ~~The~~ Moreover, the force restore method assumes a strong diurnal forcing from above~~. In regions with substantial snow cover, such as the Arctic, this assumption~~ , an assumption that is likely violated ~~(Tilley and Lynch, 1998)~~ when snow cover is present (Tilley and Lynch, 1998; Slater et al., 2001) , because snow cover leads to a decoupling of the surface forcing from the soil below~~, and may , in part, explain why JRA-55 displays a reduced standard deviation in temperature over the cold season relative to most other products .~~

~~Instrumental uncertainties~~

~~The approach used here assumes that uncertainties in the in situ data are negligible~~. These factors may help explain why JRA55 is unable to simulate near surface soil temperatures as accurately as the other products explored in this study explicitly incorporate representations of soil heat flux between soil layers (Niu et al., 2011; Koster et al., 2000; van den Hurk et al., 2000; Balsamo et , and hence ~~are the 'true' soil temperature in a particular grid cell. In situ soil temperature measurements, however, are taken as a point measurement, and as such they may not be representative of the average soil temperature over a grid cell. As this is hard to explicitly account for in linear metrics such as bias, RMSE, and correlation, it can result in non-negligible errors (Crow et al., 2012; Loew and Schlenz, 2011); particularly when a limited number of stations are contributing to the spatially averaged station temperature (as is the case over large parts of Eurasia) . While the use of data from dense networks may improve the spatial representativeness of validation data (Zeng et al., 2015), their drawback is that they are often limited in terms of the land cover types they represent (Zeng et al., 2015; Ma et al., 2021).). This is particularly true in the Arctic where data from dense networks is extremely limited.~~ they are able to simulate a dampening of seasonal variability of soil temperatures at depth (and greater variability near the surface).

~~An estimate of~~ Burke et al. (2020) note that differences in snow cover properties were important in explaining soil temperature biases of several Coupled Model Intercomparison Project 6 (CMIP6) models, and it is likely that differences in snow cover properties between the LSMs studied here could account for some of the observed spread - particularly in the ~~uncertainty of the validation data was calculated using grid cells where multiple stations were available. The uncertainty is represented by the standard deviation of soil temperatures between stations within a grid cell for a particular timestep. While the median standard deviation of soil temperature between stations is generally~~ ~~$\leq 2^\circ$ C for eight of the nine grid cells, there are periods of time when the standard deviation is substantially larger than this (Figure 1, Panel B); consistent with the findings of in situ studies examining soil temperature variability at the site level (Scharringa, 1976; Gubler et al., 2011; Gruber et al., 2018) and at regional scales (Kropp et al., 2021; Grünberg et al., 2020; Way and Lapalme, 2021; Zhang et al., 2021). Kropp et al. (2021) note that~~ ~~T_{soil} can vary widely over small spatial scales in response to vegetation canopy structure; on scales of tens of metres in many cases Gruber et al. (2018). This is particularly true in the cold season, as the presence or absence of vegetation has~~

~~a strong control on snow accumulation. By trapping snow, trees and shrubs lead to substantially warmer soil temperatures in their vicinity (Way and Lapalme, 2021). Moreover, the impact of snow cover on soil temperature is generally more pronounced over permafrost regions (regions of seasonal frost) (Chen et al., 2021).~~ cases of ERA-Interim, ERA5 and ERA5-Land, because during the warm season, these products have similar soil temperature biases, but their performance varies widely during the cold season (Figures 2 and 11), in large part because of snow density biases (Cao et al., 2020; Gao et al., 2022). In ERA-Interim, the large cold (negative) bias during the cold season is strongly related to the fact that it overestimates the observed snow density (Gao et al., 2022), and consequently also overestimates the thermal conductivity of the snow pack. Conversely, snow density (and thermal conductivity) in ERA5-Land (and ERA5) are too low, and hence biases in snow density are a large contributing factor to the warm (positive) bias during the cold season (Cao et al., 2020). Snow was also cited as a major controlling factor in soil temperature biases in ECMWF's Integrated Forecast System, which also uses the HTESSEL land surface model (Albergel et al., 2015). In the case of the Noah LSM, which is included in CFSR/CFSv2 and GLDAS-Noah, Li et al. (2021) found that an overestimation of snow cover was a major contributor to larger soil temperature biases in winter over the Qinghai-Tibetan Plateau.

~~Uncertainties can also arise from processes that occur within the soil itself; particularly in seasonally frozen and permafrost soils. For example, rapid temperature fluctuations are often seen during the melt period, as melt-water can induce strong, localized latent heat fluxes in the active layer~~

6.2 Impacts of Discontinuities in Reanalysis Timeseries

Discontinuities in the timeseries of reanalysis products may arise due to changes in data assimilation. This is particularly problematic when calculating soil temperature trends in reanalysis products, but will also influence correlation and variance on a Taylor diagram (such as Figure 6). Over the course of the nearly 40 year period explored in this study (1981 - ~~factors not easily captured in monthly mean temperatures over large areas (Hinkel and Outcalt, 1995). Frost heave can lead to seasonal shifts in the position of the soil temperature probes, resulting in seasonal discontinuities in soil temperature datasets between summer and winter (Streletskiy et al., 2017; Urban and Clow, 2017)~~2018), CFSR and the two GLDAS products (GLDAS-CLSM, and GLDAS-Noah) see substantial changes in interannual variability in soil temperatures arising due to changes in data assimilation. GLDAS 2.0 (covering the period between 1948-1999) is forced using the Princeton meteorological forcing dataset, whereas GLDAS 2.1 (2000-onwards) uses a combination of modelled and observed data (Rodell et al., 2004). In a number of locations, there is a clear step-wise change in soil temperature variability around 2000 in both GLDAS products (not shown), coinciding with the shift from GLDAS 2.0 to GLDAS 2.1. CFSR sees a stepwise increase in soil temperature variability associated with the assimilation of Advanced TIROS Operational Vertical Sounder (ATOVS) radiance data beginning in 1998 (Saha et al., 2010; Xue et al., 201 . A decline in variability occurs around 2011, associated with the change from CFSR to CFSv2 (Saha et al., 2014). Unfortunately it is not trivial to remove the effects of temperature discontinuities in a timeseries; particularly when several products are being incorporated into an ensemble mean.

~~Sampling uncertainties~~

6.3 Uncertainties Associated with Scale Effects

~~Uncertainties exist due to inconsistencies in data availability, both temporally and spatially. Some sites (particularly those in Siberia, for example), included 30 years or more of data, while others were limited to a data record of a few years; resulting in inconsistencies in the time period over which metrics were calculated for each grid cell. The authors also acknowledge there are substantially more validation grid cells over Eurasia, than over North America. In order to test the impact of this, a Monte Carlo type simulation was constructed, whereby 25 (19)grid cells from the continuous and discontinuous permafrost zones of Eurasia were randomly selected, alongside the 25 (19)North American grid cells, and the mean bias, RMSE, standard deviation and Pearson Correlation were calculated for the 50 (38) grid cell subsample from the near surface (at depth) . This process was repeated 10000 times, and the bias, RMSE, standard deviation, and Pearson Correlation from the subsamples were compared against those calculated over the entire continuous and discontinuous permafrost domain. Generally speaking, the bias, RMSE, standard deviation and correlation over the entire continuous and discontinuous permafrost domain fall within~~ Here we evaluated soil temperatures at a relatively coarse resolution of 1~~quartile of the median value from the Monte Carlo Simulations; particularly in the top 30 cm. At depth, the median bias was ~1°C smaller than the mean over the entire permafrost domain, and correlations were ~0.1 lower in many cases. However, the sampling error was not large enough to alter the fundamental conclusions of the study.~~ . As such, it is difficult for reanalysis products to capture local scale variability in soil temperature. The sub-grid scale variability in soil temperatures calculated in Figure 1, Panel B is of a similar magnitude to those calculated by previous studies exploring sub-grid scale variability in cryospheric soil temperatures (Gubler et al., 2011; Morse et al., 2012; Gisnås et al., 2014), though is smaller than those reported by Cao et al. (2019). If the strict requirements surrounding consistency in the number of stations and depths are relaxed, allowing for stations in permafrost regions to be included, spatial variability in soil temperatures is larger than 10° C at times in a couple of high latitude grid cells (not shown) - similar to the findings of Cao et al. (2019).

~~It is possible that validation sites in the discontinuous permafrost zone were preferentially located in regions where permafrost is present. In parts of Alaska, and northern Quebec, for example, there are localized areas where warm biases exist (Figure 7). This may be expected in regions where permafrost presence is ecosystem protected, as reanalysis products are unable to account for local scale feedbacks of vegetation on permafrost presence. Given, however, that the discontinuous zone is a relatively small part of the validation dataset, and that warm biases in the discontinuous zone are generally limited to a few localized areas, the authors do not believe that selection bias has fundamentally influenced the overall conclusions~~Moreover, as many grid cells in Eurasia only included a single in situ station, there is a large chance that this single in situ station may not necessarily be reflective of conditions elsewhere in the grid cell (Gubler et al., 2011). When multiple in situ stations were available, we took the spatial mean of all stations, in an attempt to estimate the mean soil temperature over the grid cell.

6.4 Uncertainties Arising from Sampling Variability

~~Time-series did not have a consistent start or end date - meaning that the metrics are calculated using different climatologies across different grid cells . Thus, it is not possible to calculate a true uncertainty estimate. We've qualitatively acknowledged~~

~~the main sources of uncertainty, and here we show an approximate estimate of the magnitude of uncertainty associated with each component, using the standard deviationin soil temperature across time and as a function of station temperature. The median standard deviation of in situ soil temperatures, for grid cells with more than 2 stations, is generally between 0.5° C and 2° C (~~As was described in Section 5.2, the presence of missing data created a challenge for calculating in situ soil temperature averages. While most grid cells in Eurasia had relatively consistent timeseries, and fewer issues with missing data, this was not the case over North America. Rather than limit our analysis to a small number of grid cells with little to no missing data (as we did for the calculation of soil temperature trends), we chose to make use of all available data at each timestep when calculating our validation metrics (bias, RMSE, standard deviation, correlation and skill score). Thus, the spatially averaged in situ soil temperature did not always contain a constant number of depths or grid cells at each timestep in many grid cells over North America.

From Figure 1, Panel B~~) - an order of magnitude smaller than the standard deviation of reanalysis soil temperatures for a given station soil temperature; particularly over the cold season (Figure 5) . Reanalysis air temperatures maintain a relatively consistent standard deviation between 1.25° C to 1.75° C for most products, except over the coldest in situ temperatures (not shown). Unlike with soil temperature, the standard deviation of reanalysis 2m air temperature only increases modestly over the cold season; along with the spread in standard deviation between products (not shown). This would suggest that the largest degree of uncertainty~~, it is apparent that the median variability of soil temperatures between stations within a grid cell (spatial variation) is roughly two to three times larger than the median variability of soil temperatures at different depths, in ~~reanalysis soil temperatures over the Arctic is most likely contributed by differences in the land models between products, rather than from uncertainties in observed soil temperatures, or from differences in product air temperatures.~~ the top 30 cm, for a particular station (depth variation). Thus, it would appear that fluctuations in the number of stations comprising the spatially averaged soil temperature are responsible for a greater proportion of the uncertainty than fluctuations in the number of depths included. However it is also apparent that the uncertainties arising from variations in the number of grid cells included in a station average are smaller than the spread between reanalysis products; by a factor of two to three in the cold season.

~~Future work should aim to investigate how differences in snow cover and snow density between the reanalysis products may influence biases in the individual products. On a related note, future studies should emphasize how differences in the land models of reanalysis productsmay account for the spread in soil temperatures.~~

6.5 Applications for the Ensemble Mean Product and Suggestions for Future Work

The ensemble mean data product ~~has potential applications in several fields, including the validation of model soil temperatures , species distribution models and to inform~~ provides gridded, monthly-averaged soil temperature estimates of near surface, and deeper soil temperatures at a 1° resolution. Therefore, it is most suitable to regional or hemispheric-scale analyses of soil temperature climatologies, or their seasonal cycle, or to explore recent trends in soil temperatures. The product could also be used to provide boundary conditions for models that require soil temperature inputs, such as hydrological models, ~~or for permafrost simulations.~~ and for the validation of model soil temperatures. While the ensemble mean product still exhibits substantial cold biases over permafrost regions, and therefore is likely unsuitable for permafrost modeling, the RMSE of the ensemble mean product outperforms the RMSE of the best performing product by 2° C, on average, and hence it may still provide some added value for estimation of high latitude soil temperatures relative to the individual products.

A robust ensemble mean can be computed with four products (Figure 8), which means a higher resolution ensemble mean data product could be created using a subset of higher resolution reanalysis products. For example, ERA-Interim, MERRA2, and ~~JRA-55~~ CFSR have resolutions lower than 0.5 degrees. ~~A~~ Using a similar blending methodology, we have been investigating the performance of a 0.31~~degree ensemble mean product~~ -degree product (using a smaller subset of products that provide data at higher spatial resolution). We have also performed similar analyses with a 0.05-degree soil temperature product, using interpolated soil temperatures from the Arctic System Reanalysis version 2 (ASR), ~~based on ERA5,~~ ERA5-Land, ~~CFSR, and GLDAS-Noah is being explored, using a similar methodology.~~ and the Famine Early Warning Systems Network (FLDAS). The goal has been to assess the impact of spatial resolution on performance of the ensemble mean product. We are hoping to include these results in a follow-up paper. Future work should aim to investigate how differences in snow cover and snow density between the reanalysis products may influence biases in the individual products. On a related note, future studies should emphasize how differences in the land model structure and parameterization may account for the spread in soil temperatures.

Data availability. GTN-P data (GTN-P, 2018) is available from The Global Terrestrial Network for Permafrost, while the Kropp et al. (2020) dataset is available from Heather Kropp's Arctic Data Center page. Russian Hydromet (Sherstiukov, 2012) data are available from RIHMI-WDC, while Nordicana data can be obtained from Nordicana D. CFSR (Saha et al., 2010), CFSv2 (Saha and Coauthors, 2012), ERA-Interim (European Centre for Medium-Range Weather Forecasts, 2012), ERA5 (European Centre for Medium-Range Weather Forecasts, 2019) and JRA-55 (Japan Meteorological Agency, 2013) data were obtained from the National Center for Atmospheric Research (NCAR)'s Research Data Archive (RDA). GLDAS-CLSM (Li et al., 2020a), GLDAS-Noah (Beaudoing et al., 2020), and MERRA2 (Global Modeling and Assimilation Office, 2015) were obtained from the Goddard Earth Sciences Data and Information Services Center (GES DISC), while ERA5-Land data (Muñoz-Sabater, 2019) was downloaded from the Copernicus Climate Change Service (C3S) Climate Data Store (CDS). The ensemble mean soil temperature dataset has been made available on the Arctic Data Center.

Author contributions. TH and CGF conceived of the study, TH gathered, and analyzed the data, and TH, CGF interpreted the data. HK provided in situ data to the study, and TH, and CGF wrote the manuscript, with contributions from HK.

Competing interests. The authors declare that they have no known conflicts - financial or personal, that could have appeared to influence this work.

Acknowledgements. This work was funded under a National Science and Engineering Research Council (NSERC) PGS-D scholarship. The authors would like to thank the two anonymous referees, as well as Dr. Hugh Brendan O'Neill ~~as well as~~ and Dr. Andre Erler for their helpful comments.

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