

Sub-kilometre scale distribution of snow depth on Arctic sea ice from Soviet drifting stations

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ABSTRACT.

The sub-kilometre scale distribution of snow depth on Arctic sea ice impacts atmosphere-ice fluxes of energy and mass, and is of importance for satellite estimates of sea ice thickness from both radar and lidar altimeters. While information about the mean of this distribution is increasingly available from modelling and remote sensing, the full distribution cannot yet be resolved. We analyse 33539 snow depth measurements from 499 transects taken at Soviet drifting stations between 1955 and 1991 and derive a simple statistical distribution for snow depth over multi-year ice as a function of only the mean snow depth. We then evaluate this snow depth distribution against snow depth transects that span first-year ice to multiyear ice from the MOSAiC, SHEBA and AMSR-Ice field campaigns. Because the distribution can be generated

28 **using only the mean snow depth, it can be used in the downscaling of several**
29 **existing snow depth products for use in flux modelling and altimetry studies.**

30 **INTRODUCTION**

31 The snow cover of Arctic sea ice insulates it from solar radiation in the summer and cold temperatures in the
32 winter. In addition, snow impacts the propagation of laser and radar pulses from satellite altimeters (e.g.
33 Mallett and others, 2020), affecting the timing of their return. This importance has driven the development
34 of a range of modelling and remote sensing approaches to accurately characterise the snow cover (see
35 Zhou and others, 2021, for intercomparison of several products). Satellite remote sensing approaches (e.g.
36 Rostosky and others, 2018; Lawrence and others, 2018) are generally limited by their low (multi-kilometre)
37 spatial resolution, which has the effect of averaging out kilometre and sub-kilometre scale variability.
38 Modelling approaches (e.g. Petty and others, 2018; Liston and others, 2020; Stroeve and others, 2020a)
39 have similar limitations, with grid resolutions not falling below tens of kilometres. This in part reflects the
40 coarse spatial resolution of standard atmospheric reanalysis and sea ice drift products.

41 This lower-bound on spatial resolution is a significant barrier to scientific progress, as the effects of
42 snow on fluxes and sea ice thickness retrievals cannot be characterised solely by the mean snow depth in a
43 grid-cell of a traditional data product (Iacozza and Barber, 1999). To account for the observed variability
44 of snow depth on scales below a grid-cell (e.g. Farrell and others, 2012), a *sub-grid* scale snow depth
45 distribution must be employed (see Petty and others, 2020; Glissenaar and others, 2021, for impacts on sea
46 ice thickness retrievals). For instance, the amount of shortwave solar radiation incident on the ice surface
47 in a multi-kilometre grid cell is sensitive to the fractional coverage of snow which is *optically thin* (<~15
48 cm for dry snow; Warren, 2019). This area cannot be straightforwardly gleaned from modelling or satellite
49 observations of the mean snow depth in the grid cell (Stroeve and others, 2021).

50 In the example above, the area of optically thin snow within a larger area of snow with given mean
51 depth will be primarily dictated by wind redistribution (Moon and others, 2019). Snow is dynamically
52 transported through wind suspension and saltation and is eroded and deposited heterogeneously around
53 any ice topography such as ridges and hummocks (Sturm and others, 2002; Chung and others, 2011).
54 Furthermore, turbulence-induced features such as sastrugi introduce depth variability even on level ice
55 (Eicken and others, 1994; Massom and others, 1997). The probability of snow transport and redistribution

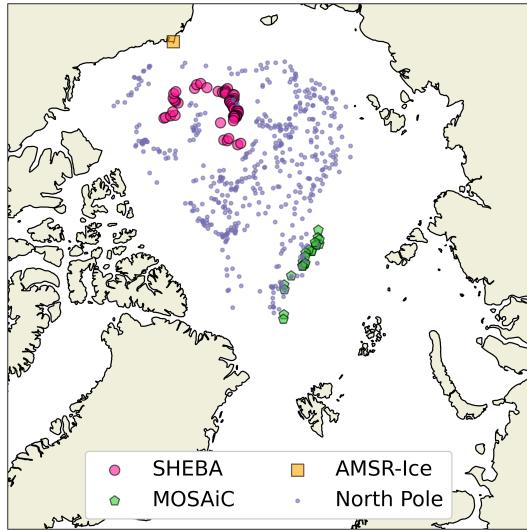


Fig. 1. Map indicating the locations of snow transects used in this study. Small purple dots indicate locations of transects taken at Soviet North Pole drifting stations. Pink circles and green pentagons indicate transects taken on the SHEBA and MOSAiC expeditions respectively. Orange square indicates the locations of the AMSR-Ice transects, which would not be individually well-resolved on the map.

is dependent on its bulk and microstructural properties such as density and bond-radius (Filhol and Sturm, 2015). The combination of these factors makes deterministic modelling of snow redistribution a major challenge when the local ice topography is not known to a high level of detail (e.g. Liston and others, 2018), which is generally the case on sea ice. Because of this limitation on deterministic modelling, in this paper we instead aim to derive a statistical model for the snow depth distribution. The model is trained on the large number of snow depth measurements taken at Soviet drifting stations, and requires only the mean snow depth to generate a distribution.

63 Snow transects from Soviet drifting stations

We analyse the results of snow depth transects performed at Soviet North Pole (NP) drifting stations between 1955 and 1991 (Figures 1 & 2). These were crewed stations that drifted year-round in the Arctic Ocean while measuring a range of atmospheric, oceanographic and cryospheric parameters on what was generally multi-year sea ice. In particular we examine 33539 snow depth measurements from 499 transects from NP stations 5 - 31. Snow transects did not begin until NP 5, and the NP program was halted in 1991. While it was restarted in 2003, these data are not publicly available.

Snow depths were measured every 10 m along a line of either 500 or 1000 m in length when snow depth

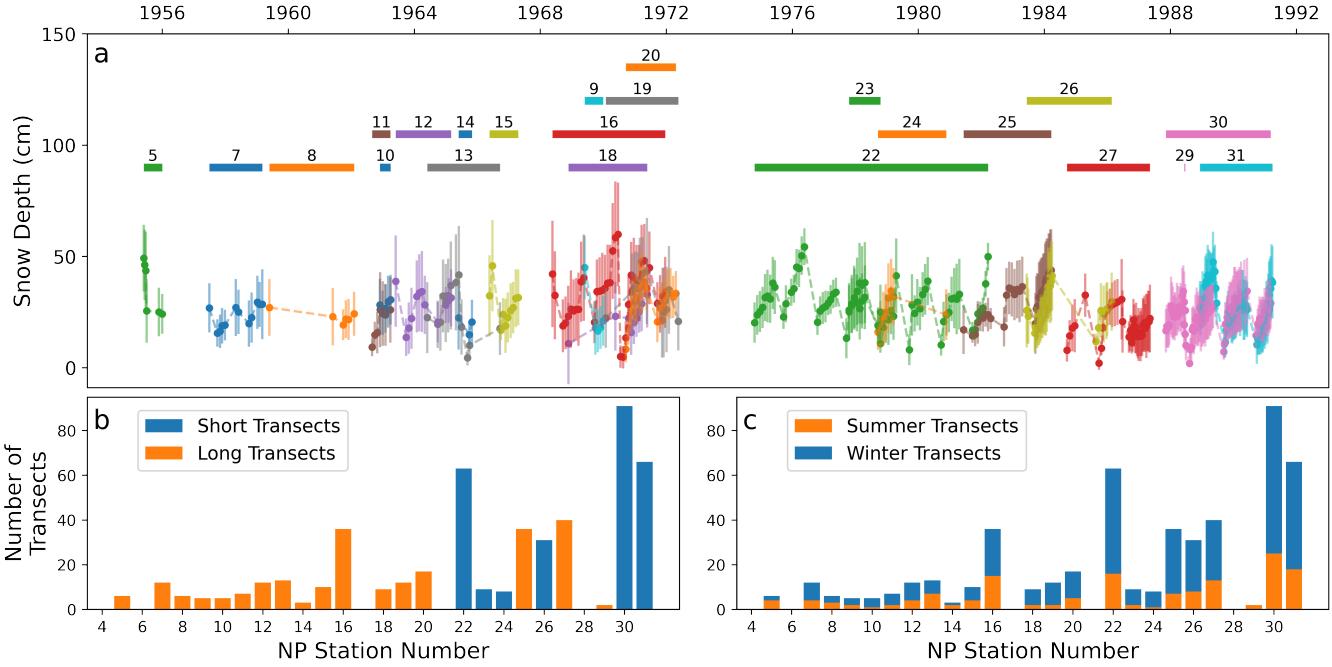


Fig. 2. (a) Operational periods of the Soviet 'North Pole' (NP) stations contributing to this study. Bars at top indicate the time period between the first and last snow depth transect of the station. Solid circles indicate mean snow depth of transects, with vertical bars indicating one standard deviation in snow depth (b) The number of transects measured by each station, broken down by transect length (500m vs. 1000m). (c) Number of transects measured by each station broken down by summer (May-Sep) and winter (Oct-Apr).

71 was at least 5 cm and more than 50% of the surrounding area was snow covered based on a qualitative
 72 assessment. 166 transects were around 500 m long and 333 were around 1000 m long, with transects prior
 73 to 1974 generally being 500 m long (Fig. 2b). The vast majority of transects were of the exact length
 74 specified above, however around 6% of transects were slightly shorter by around 10%: it is unclear why
 75 this was the case, however the operational challenges of Arctic research (e.g. ice dynamics, polar bears,
 76 severe weather) may explain this. The direction of the line was chosen randomly but did deviate where
 77 hummocks were present, and was at least 500 m from the station at its closest point. We note that this
 78 deviation around hummocks may introduce a bias in the snow depth measurements to sample more level
 79 ice with thinner snow. Where successive transects were taken at the same station, each was offset by 3 m
 80 from the previous line.

81 METHOD

82 We now present a method for transforming an estimate of mean snow depth (from remote sensing or
 83 modelling) into a distribution of snow depths. We first characterise the linear relationship between the
 84 standard deviation of snow depths measured along a transect and the mean of that transect (Fig. 3a). This
 85 ratio is known as the coefficient of variation (CV; Brown, 1998). When a linear regression is performed (and
 86 forced through the origin), the root-mean-square of the residuals is 3.20 cm, meaning that the standard
 87 deviation of the transect depths can be predicted with this standard-error where the mean is known. For
 88 every 10 cm increase in the mean snow depth, we find the standard deviation of the snow depths to increase
 89 by 4.17 cm.

$$\sigma_D = 0.417 \times \bar{D} \quad (1)$$

90 where σ_D is the standard deviation of snow depth in a transect, and \bar{D} the mean depth of the
 91 transect. In the above equation 0.417 represents the coefficient of variation. All NP station snow depth
 92 measurements are then converted into depth-anomalies from their respective transect means. We then
 93 divide all measurements by the standard deviation of their respective transects. These anomalies can then
 94 be plotted as one distribution (Fig. 3b). To this distribution we fit a skew normal curve.

95 Our skew normal distribution function is defined following O'Hagan and Leonard (1976) and Azzalini
 96 and Capitanio (1999) such that:

$$f(a, \xi, \omega, \sigma_D) = \frac{1}{\omega\sqrt{2\pi}} \left(1 + \operatorname{erf}\left(\frac{ax}{\sqrt{2}}\right)\right) e^{-\frac{x^2}{2}} \quad \text{where} \quad x = \frac{\sigma_D - \xi}{\omega} \quad (2)$$

97 with a being the skewness parameter, ξ being a location parameter, ω being a scaling parameter, and erf
 98 being the error function. Through fitting a skew normal curve using the technique of maximum likelihood
 99 estimation (Richards, 1961), we find the best-fit values of the three parameters to be $a = 2.54$, $\xi = -1.11$,
 100 $\omega = 1.50$.

101 We repeat this process for the winter and summer seasons individually (October-April, May-September).
 102 While coefficient of variation is slightly larger in summer (Fig. 3c), the shape of the summer probability
 103 distribution does not depart greatly from the winter distribution (Fig. 3d). This seasonal difference in the
 104 coefficient of variation is relatively small compared to the uncertainty and residuals in the regression, and
 105 as such we opt for a singular analysis, considering all transects from all months. Here we point out that
 106 in summer a measurement bias is introduced in the form of a ‘surface scattering layer’ (e.g. Polashenski
 107 and others, 2012), which forms at the snow-ice interface and can be penetrated by a probe despite being
 108 formed of ice rather than snow. Because this would theoretically increase the mean but not the standard
 109 deviation of depth measurements along a transect, it would introduce a low-bias on the CV in summer. In
 110 reality, we see the summer CV being larger than in winter.

111 The above method allows the standard deviation of the snow depth to be estimated from the mean
 112 snow depth (Fig. 3a). When both of these quantities are known, a statistical model for the snow depth
 113 distribution may be calculated using the skewed normal curve shown in Fig. 3b.

114 For instance, if the mean snow depth is assumed to be 0.5 metres, then the standard deviation of the
 115 snow depth distribution is estimated using Eq. 1 such that $\sigma_D = 0.209 \pm 0.032$. Transforming the x
 116 coordinates of the distribution in Fig. 3b from units of standard deviations to units of snow depth (using
 117 the coefficient of variation), it can be inferred (for example) that the probability of randomly sampled snow
 118 of depth less than 30 cm is 17%, and the chance of sampling snow deeper than 1 metre deep is 1.8%.

119 For calculations of light flux through thin snow, it may be found that for snow with a mean depth of
 120 0.5 m, the probability of snow depth being less than 15 cm is 2.3%. In contrast, this probability for snow
 121 with a mean depth of 25 cm is 16.6%.

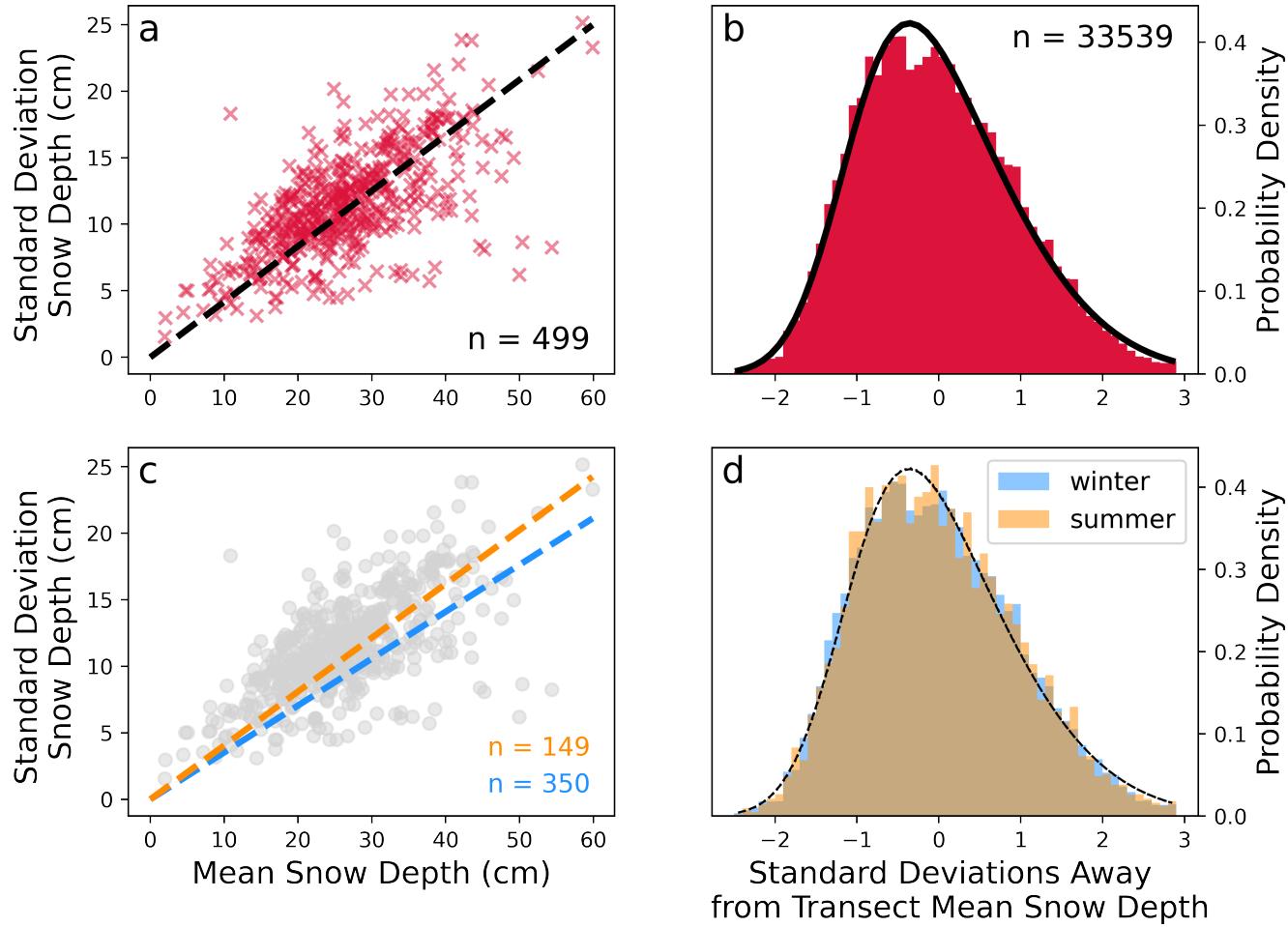


Fig. 3. (a) Relationship between a transect's mean snow depth and the standard deviation. The slope of the regression (forced through the origin) is 0.417, the root-mean-squared-residual is 3.20 cm, and the Pearson correlation coefficient (r value) is 0.66. A visualisation of the point density of this panel is given in Supplementary Fig. SS1. (b) The probability density of a snow depth being measured such that it is a given number of standard deviations from the mean of the transect. The empirical distribution is given in red from drifting station data and a skew normal curve is fitted in black. (c) Same as a, but with individual regressions for winter and summer transects. (d) same as b, but with individual probability density distributions for winter and summer transects. The two seasonal skew normal fits (black) are visually indistinguishable.

122 Choice of Skew Normal Distribution

123 Several authors have characterised terrestrial snow depth distributions with other curves than the skew
124 normal, such as log-normal (Donald and others, 1995; Pomeroy and others, 1998; Marchand and Killingtveit,
125 2004) or gamma distributions (Skaugen, 2007; Egli and others, 2012). Luce and Tarboton (2004) and
126 Kuchment and Gelfan (1996) applied both, with the latter finding the log-normal distribution to provide
127 a superior fit. However, this comparison was over a significantly larger area (basin-scale rather than sub-
128 kilometre). In contrast, Skaugen and Melvold (2019) and Gisnas and others (2016) observed that the
129 gamma distribution offered an improved fit over a log-normal fit.

130 We find that the skew normal curve provides a marginally better fit to the data than both the log-normal
131 and gamma distributions (Fig. 4). We first characterise the goodness of fit of these distributions using
132 the one-sample Kolmogorov-Smirnov test. The test statistics for all three distributions result in extremely
133 small p-values, indicating that none of the distributions fully capture the observed data. However, the
134 test statistic is largest for the gamma and smallest for the skew normal distribution, with the p-value
135 being smallest for the gamma distribution, and largest for the skew normal distribution. This indicates
136 that the skew normal distribution is the best of the three fits to the data, and the gamma the worst. For
137 completeness, we also calculate the RMSE of the observations against the best-fit of all three distributions
138 in bins of 0.1 standard deviations of snow depth. We again find that the skew normal curve performs best,
139 and the gamma distribution worst (Fig. 4b). We note that that the improved performance of the log-normal
140 fit over the gamma distribution is not a contradiction of previous work with the opposite findings (e.g.
141 Skaugen and Melvold, 2019; Gisnas and others, 2016), as these studies concerned terrestrial environments
142 where meteorological forcing, surface topography and snow properties are different.

143 All three of the above distributions have the same number of fitting parameters. Because of the superior
144 goodness-of-fit, we therefore use the skew normal distribution in this paper. However, we also provide the
145 best-fit parameters for the log-normal and gamma distributions in the supplementary material.

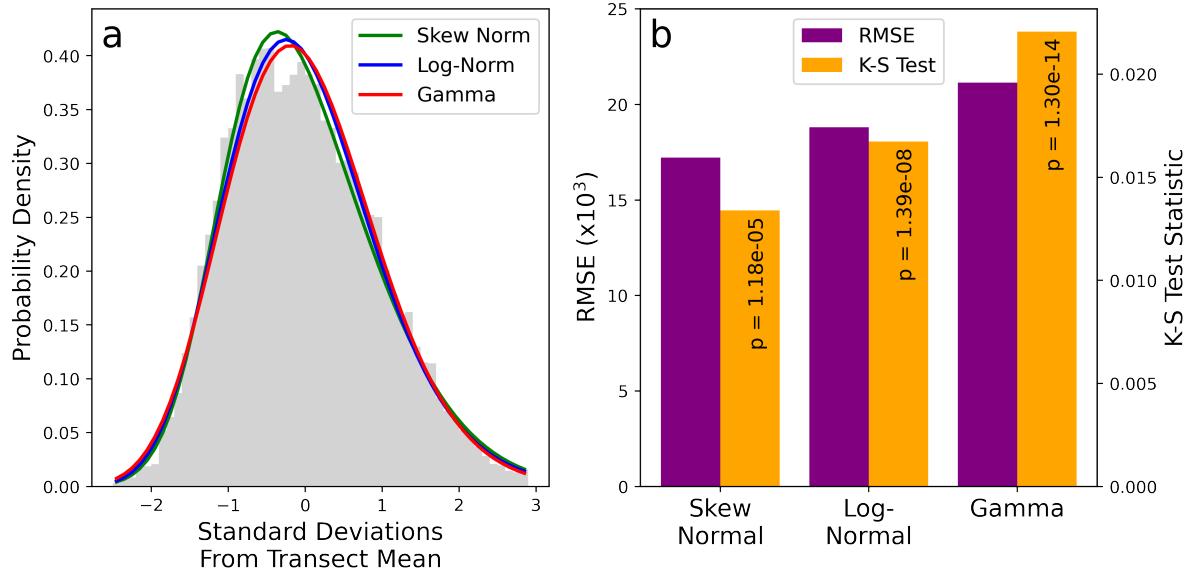


Fig. 4. (a) The best-fit curves of the skew normal, log-normal and gamma distributions. The log-normal and gamma distributions have historically been fitted to terrestrial snow depth distributions, however we find that the skew normal distribution provides a superior fit to our data. (b) The RMSE and one-sample Kolmogorov-Smirnov test statistics. Both metrics for goodness of fit indicate that skew normal has the best fit, and gamma the worst. The quantities of Probability Density, RMSE and the K-S Test statistic have the same units as the number of standard deviations, which is unitless.

RESULTS**Cross-validation**

We now evaluate the consistency of our snow depth distribution model with a leave-one-out-cross-validation (LOOCV) approach (Stone, 1978). To do this we select a single transect and recalculate the skewed-normal curve using the remaining 498 transects. We then assess the goodness-of-fit of the curve against the selected transect. This is performed iteratively for each transect such that 499 goodness-of-fit statistics are generated. We calculate the goodness-of-fit using the root-mean-square error (RMSE) for the fitted probability distribution and that of the transect, using ten equal-width depth bins that span from 0 cm to the maximum depth measured.

This cross-validation exercise allows for the estimation of model skill as a function of different variables, such as the transect's length, its mean depth and the month in which it was performed (Fig. 5a - c). We also investigate whether the snow depth distribution of a transect can be better predicted with the NP Station based model presented here (the 'NP model') when its corresponding station has contributed many other transects to the distribution (Fig. 5d).

We first show that the NP model's skill is very similar when applied to both long and short NP transects (Fig. 5a). The mean RMSE for long and short transects is 0.053 and 0.057 cm respectively (a difference of 7%). This similarity is to be expected, with the difference likely reflecting the more incomplete sampling of the local snow depth distribution by a shorter transect. We also show that the skill of the NP distribution is relatively independent of the depth of the transect. The skill of the model is maximal for snow distributions with means in the range of 20 - 40 cm. Transects where the model exhibited lowest skill had very shallow depths (<10 cm). In this category the model's skill is halved relative to the 20 - 40 cm range (which represents 69% of all transects). This mean-depth dependent skill reflects the relative representation of transects that contribute to the NP model: the model performs best when predicting transects similar to those on which it was trained (Fig. 3a).

The model's skill is relatively insensitive to the month of the year with the exception of July and August (Fig. 5c). In these two summer months its skill is diminished with the RMSE being on average 67% higher in these two months by comparison to the average of the other months. Again, this is ostensibly a reflection of the low contributions of these months to the total number of transects: July and August contribute three and six transects to the NP model respectively, whereas the other months on average each contribute 49

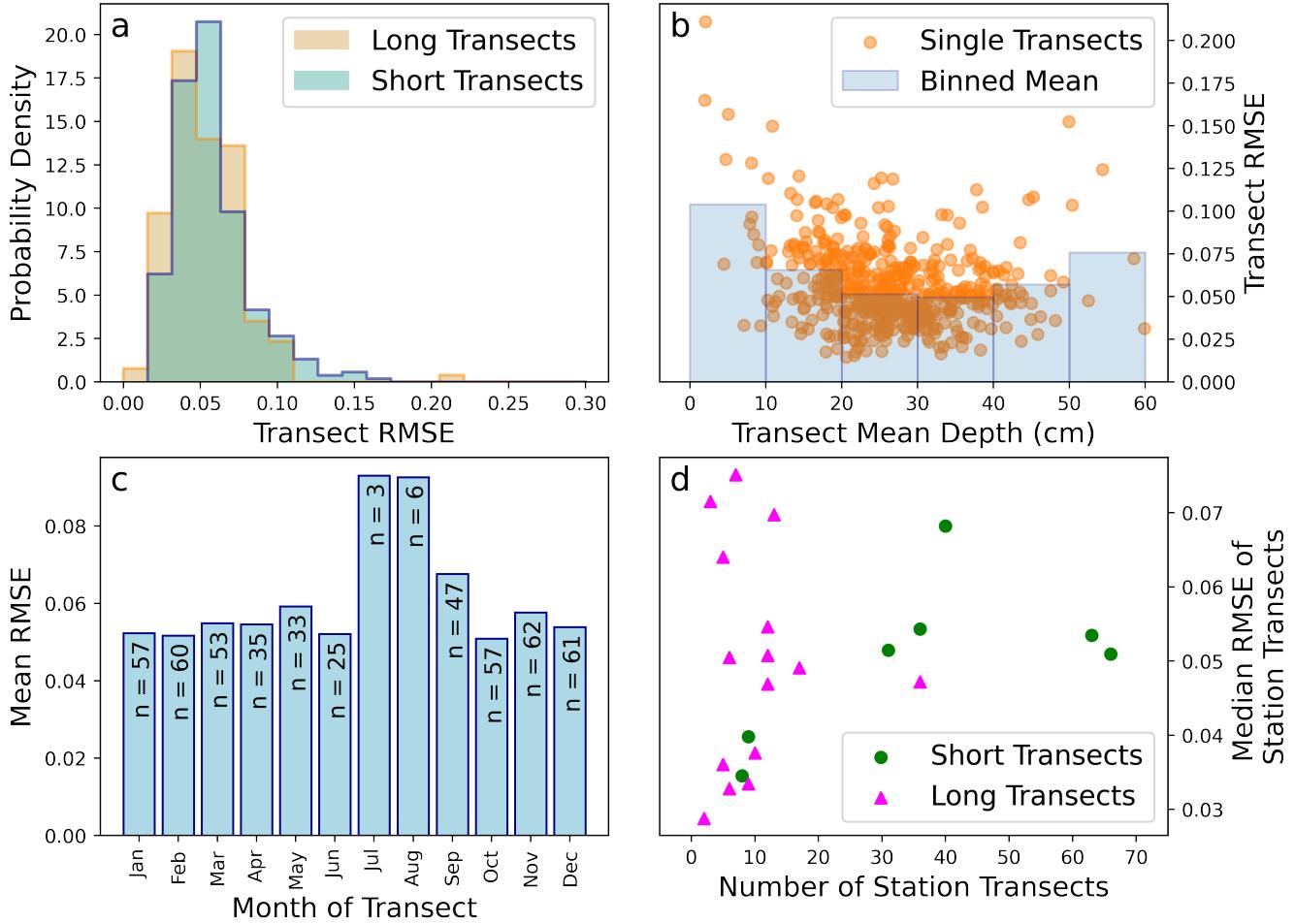


Fig. 5. (a) Histograms of the RMSE for long transects (1km) and short transects (500m) separately. (b) RMSE of the NP distribution against observed transects shown as a function of transect mean depth. (c) NP distribution RMSE as a function of month. ‘n’ indicates the number of transects contributing to the model from that month (d) Mean RMSE of all transects at a given station, shown as a function of the number of transects at that station. RMSE values are unitless as they represent the error in a probability distribution.

transects. Low skill in these months is also likely a reflection of the snow depths being lowest, which is also associated with low skill (see Fig. 5b).

We finally address the potential lack of independence between successive transects at the same station. Our LOOCV approach assumes that by not training the model with the transect being validated against, the validation transect is independent. But the potential exists that information about the validation transect enters the model through previous and subsequent transects at the same station that are included. If successive transects are strongly related, we would expect stations that contribute more transects to the model to have their transects perform better in the LOOCV exercise. Application of the non-parametric Spearman's Rank test for correlation reveals no statistically significant relationship ($p < 0.05$) between the number of transects contributed by a station to the model and the mean or median RMSE of its transects in the LOOCV exercise (Fig. 5d). This supports the premise that LOOCV is an appropriate tool with which to evaluate the skill of the NP model.

Evaluation against MOSAiC Measurements

We compare our regression and fitted curve (Fig. 3a, b) against the snow surveys taken on the MOSAiC expedition using a magnaprobe (Figs 6, 7). To do this we select snow suveys of the "Northern Transect" (Stroeve and others, 2020b), which predominantly consisted of second-year ice.

We first note that the NP-based coefficient of variation (CV) is lower than that observed on the MOSAiC transects (Fig. 6a). The effect of this is that the width of the modelled depth distribution is too high in standard-deviation space (Fig. 6b), i.e. the NP model distribution is insufficiently 'peaked'. Symptoms of this are underestimation of the two modal bins (relative to the MOSAiC data), and overestimation of the low tail probabilities. This extra width can be understood because the standard deviations are themselves smaller.

Despite this bias, the NP model generally provides a good fit to the individual MOSAiC transects (Fig. 7). The skewness parameter of the NP model ($a = 2.54$) is smaller than when a skew normal fit is applied to the MOSAiC transects ($a = 6.4$). This results in the modal depth bin often being overestimated by the NP model (Fig. 7). For clarity, the skewness parameter (a) of the skew normal distribution is different to the commonly calculated *sample skewness* (γ), although both quantities consistently have the same sign. We calculate and report the sample skewness for the NP data and all evaluation data in Supplementary Figure S2.

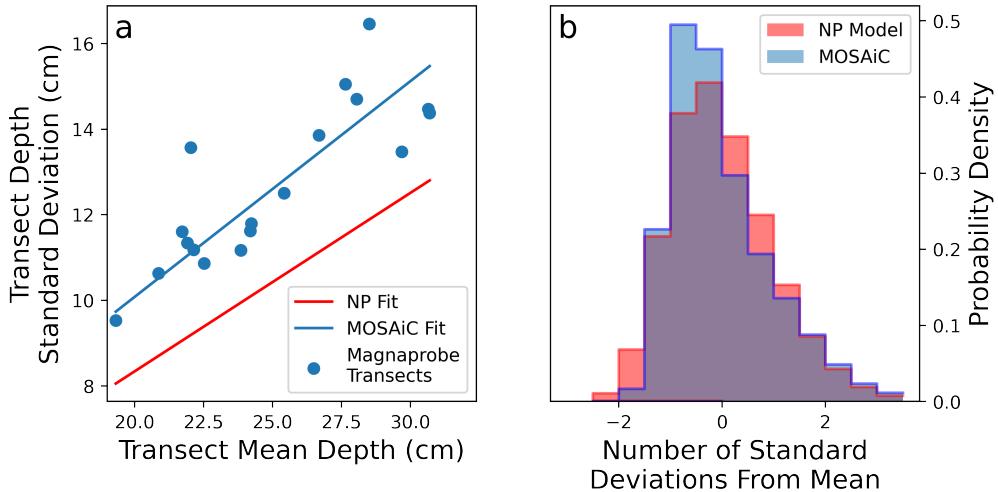


Fig. 6. (a) Snow depth variability for a given mean depth was larger on the MOSAiC transects than on average for the NP stations. Regression for NP station data shown in red, MOSAiC transects in blue. (b) Because the depth variability is lower in the NP model, the probability distribution in standard deviation space is wider (as the standard deviations themselves are smaller).

204 A corollary to this underestimation of skewness by the NP model is that where the modal bin is
 205 overestimated by the model, the probability (or fractional coverage) of the depth bin is underestimated.
 206 This can be seen (for example) in the panel of Fig. 7 corresponding to January 30th. The skewness
 207 parameter of data in this panel is 13.7, higher than that of the NP model. This results in the model's
 208 modal depth bin being one too high (20 - 25 cm vs 15 - 20 cm), and the probability of the modal bin being
 209 3.5% too low. However, we recognise that the binning process involved in this comparison places a lower
 210 resolution limit on any comparison of modal values. As such, we also compare the modal value of the NP
 211 model with that of a skew normal curve fitted to each magnaprobe transect (Supplementary Fig. S3). We
 212 find that, similarly to Fig. 7, the modal depth of the NP model is higher by comparison to the mode of
 213 the skew normal curve of best fit to the observations. This discrepancy grows over the winter from 2.7
 214 cm at the start of October to 9.5 cm by the end of February. We stress that although a precise number
 215 can be determined for the difference in the mode of the NP model and the observationally-derived curves,
 216 the curve-fitting process to the magnaprobe observations does not necessarily fully capture the underlying
 217 data, particularly with regard to the position of the modal value.

218 The fractional coverage of shallow snow is a key parameter for energy flux modelling, so is now given
 219 specific consideration. We find the NP model underestimates the coverage of thin snow (<10 cm) in early
 220 winter (end of October - mid December) with respect to MOSAiC observations. The observed coverage is

6.1%, and the NP model produces a coverage of 4.3%. After mid December the model begins to overestimate the thin snow coverage. On average it was observed to be 1.5%, and modelled to be 2.1%, an overestimate by 0.6 percentage points. With regard to heat fluxes, an overestimation of the thin snow coverage would lead to an overestimate of the heat flux from the ice to the atmosphere (and accompanying overestimation of sea ice growth rate).

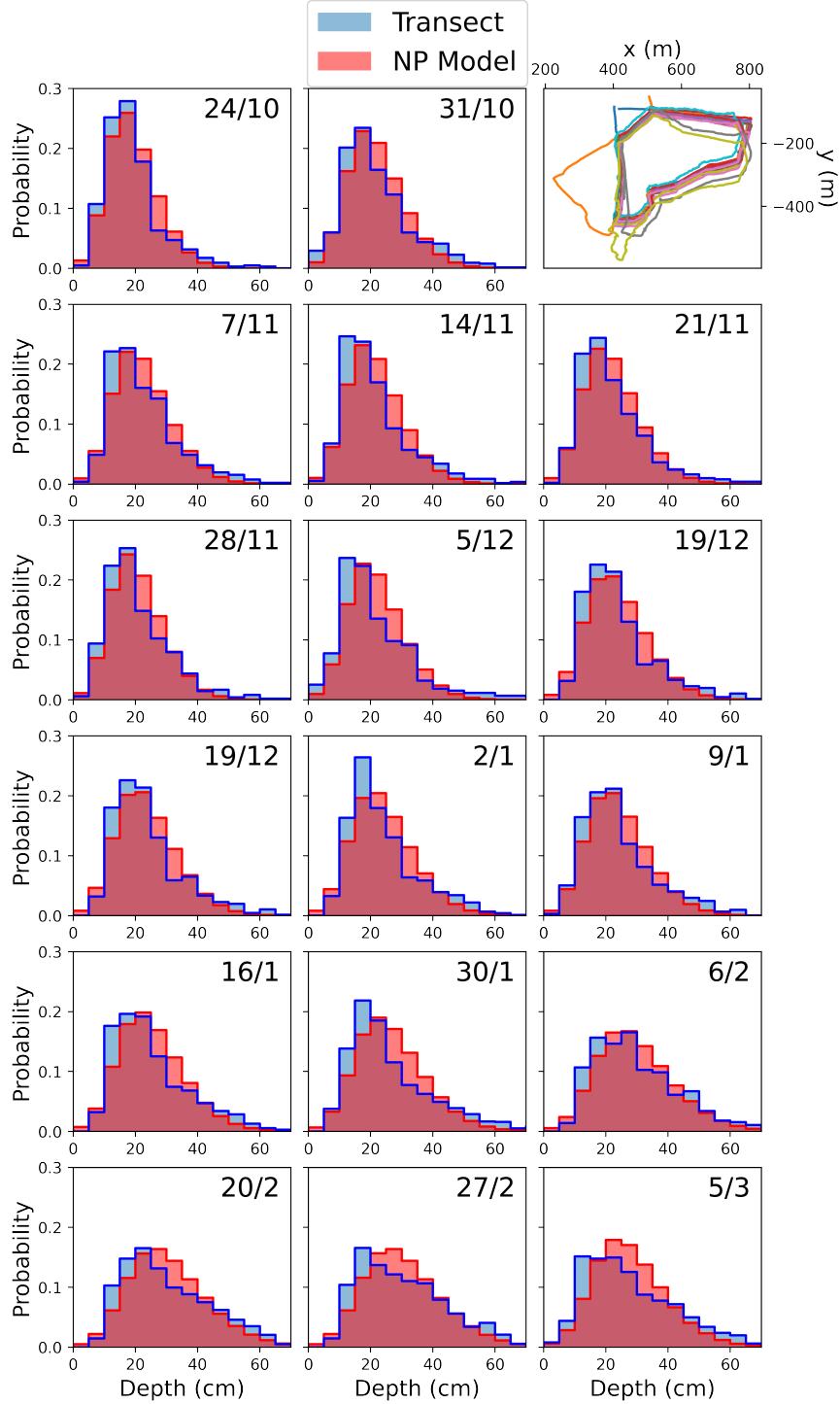


Fig. 7. Winter evolution of the snow depth distribution on the MOSAiC Northern Transect (blue histograms, 5 cm bins). The modelled depth distribution described in this paper shown in red. Top right: plots of the fourteen transects contributing to the MOSAiC evaluation exercise, with panel coordinates being the relative coordinates of the floe with the research vessel Polarstern at the origin orientated upwards).

226 Evaluation against SHEBA Measurements

227 We now evaluate our model using snow depth transect data from the Surface Heat Budget of the Arctic
228 (SHEBA) expedition (Uttal and others, 2002; Sturm and others, 2002). Snow transects were taken over a
229 variety of ice types during the SHEBA expedition, and here we opt to compare our model to transects taken
230 in the ‘Atlanta’ and ‘Tuktoyaktuk’ (henceforth ‘Tuk’) areas which were dominated by multi-year ice (for
231 best comparison with the NP data). These areas were described using ice-class codes, and were indicated
232 as 2-3 and 4 respectively. Class 2 indicates ‘Refrozen melt ponds’, 3 ‘Hummocky’, and 4 ‘Deformed’
233 (Sturm and others, 2002). Snow depths were initially measured with a marked ski-pole, with a prototype
234 magnaprobe being used later. While the NP-model provides a good fit to the Atlanta transects, it is less
235 appropriate for Tuk transects (where the RMSE is on average doubled compared to Atlanta).

236 *Atlanta Transects*

237 We find the coefficient of variation to be very similar between the SHEBA and NP transects (Fig. 8a).
238 Removing transects from the high-melting month of July from the SHEBA data marginally improves this
239 agreement, but not greatly relative to the uncertainty in the regressions. We note that no transects were
240 taken in the Atlanta region in August.

241 Unlike the coefficient of variation, the agreement of the snow depth distribution is clearly improved by
242 removing July transects from the SHEBA distribution (Fig. 8b). We attribute this to strong alteration of
243 the snow depth distribution by melt ponds in this month, which developed at the site in the second half of
244 June (Webster and others, 2015). Outside of this period the snow depth distribution is primarily dictated
245 by wind redistribution, but within the period it is dictated by the production of liquid water at the surface
246 of the snow, consequent runoff and potential melt pond formation.

247 The poor performance of our model in July and its association with intense snow melting is shown
248 in Fig. 8c. After strong melting (decreasing snow depth) in June, the snow depth distribution begins to
249 diverge from the NP model during the transition from June to July, and increases throughout July.

250 *Tuk Transects*

251 The NP model performs considerably less well when applied to Tuk transects (Fig. 9). Unlike Atlanta, the
252 standard deviation of snow depth on Tuk transects is significantly underestimated by the NP regression.
253 Furthermore, the skew-parameter of the NP model ($a = 2.54$) is less than half that of a skew normal curve

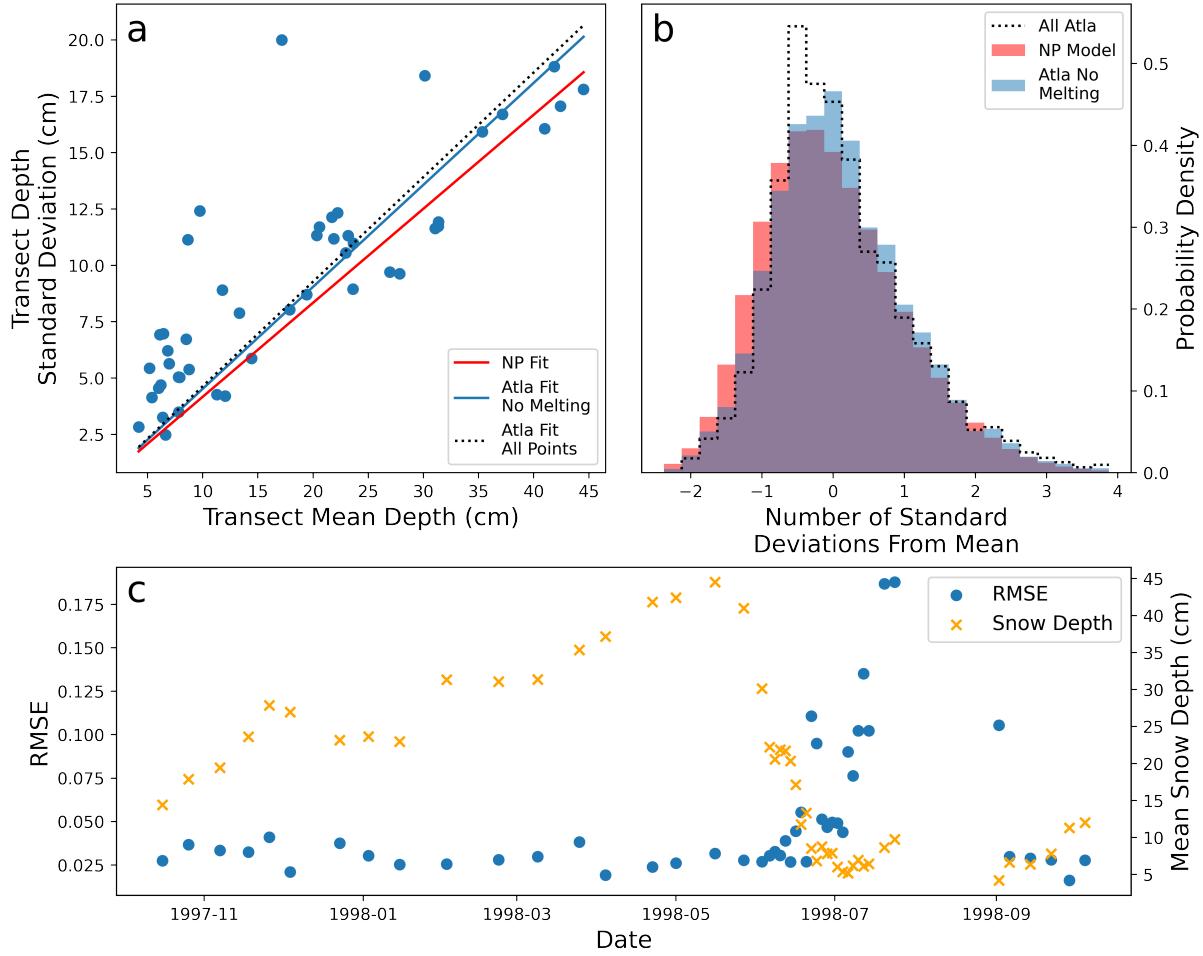


Fig. 8. (a) Relationship between the mean snow depth and standard deviation of the snow depth on SHEBA ‘Atlanta’ transects (blue scatter). Linear regressions through the points are shown both including and excluding data points from July and August (blue solid and black dotted respectively). Linear regression from all NP transects shown by red line. (b) The snow depth distribution on the SHEBA ‘Atlanta’ transect excluding July and August (blue) and from NP stations (red). The SHEBA fit from all transects including July and August shown by black dotted line. (c) Time evolution of the error in this paper’s model (blue scatter). RMSE is higher during July and August than in other months, which coincides with melted snow (depth in orange scatter).

254 fitted to the Tuk transects ($a = 6.27$). The corresponding value for Atlanta is 2.9.

255 It is striking that the mismatch in the skewness parameter for the Tuk transects is slightly smaller than
256 the MOSAiC transects, but the model-observations mismatch is much larger. Furthermore it is notable
257 that although the skewness of the Tuk transects is larger than the NP model, the NP model still does a
258 good job of predicting the modal depth bin. We would expect the modal bin to correspond to snow depth
259 that is too deep where the skewness is underestimated (see Fig. 7). These features are explained by the
260 fact that a skew normal curve cannot be easily fitted to the Tuk transects in standard deviation space (Fig.
261 10).

262 To illustrate, we display the transect data alongside the best possible skew normal fit (not involving
263 the NP data) to the data. The agreement is good for the Atlanta and MOSAiC data sets, but noticeably
264 less good for the Tuk data (Fig. 10). This indicates that unlike the MOSAiC northern transects and the
265 SHEBA Atlanta transects, the SHEBA Tuk transects do not display a skew normal distribution of snow
266 depths.

267 We attribute the deviation of the Tuk data from the skew normal distribution to the highly deformed
268 nature of the ice relative to that seen at Atlanta and the MOSAiC northern transects, and at most of the
269 NP stations. Firstly we point out that over strongly deformed ice the wind dynamics may cause snow to
270 be distributed differently. Secondly we raise the fact that NP transects deviated around highly deformed
271 ice such as that dominating the Tuk transects. There is a related sampling bias for the MOSAiC Northern
272 transect, because the transect layout was chosen such that a snowmobile could drive around it.

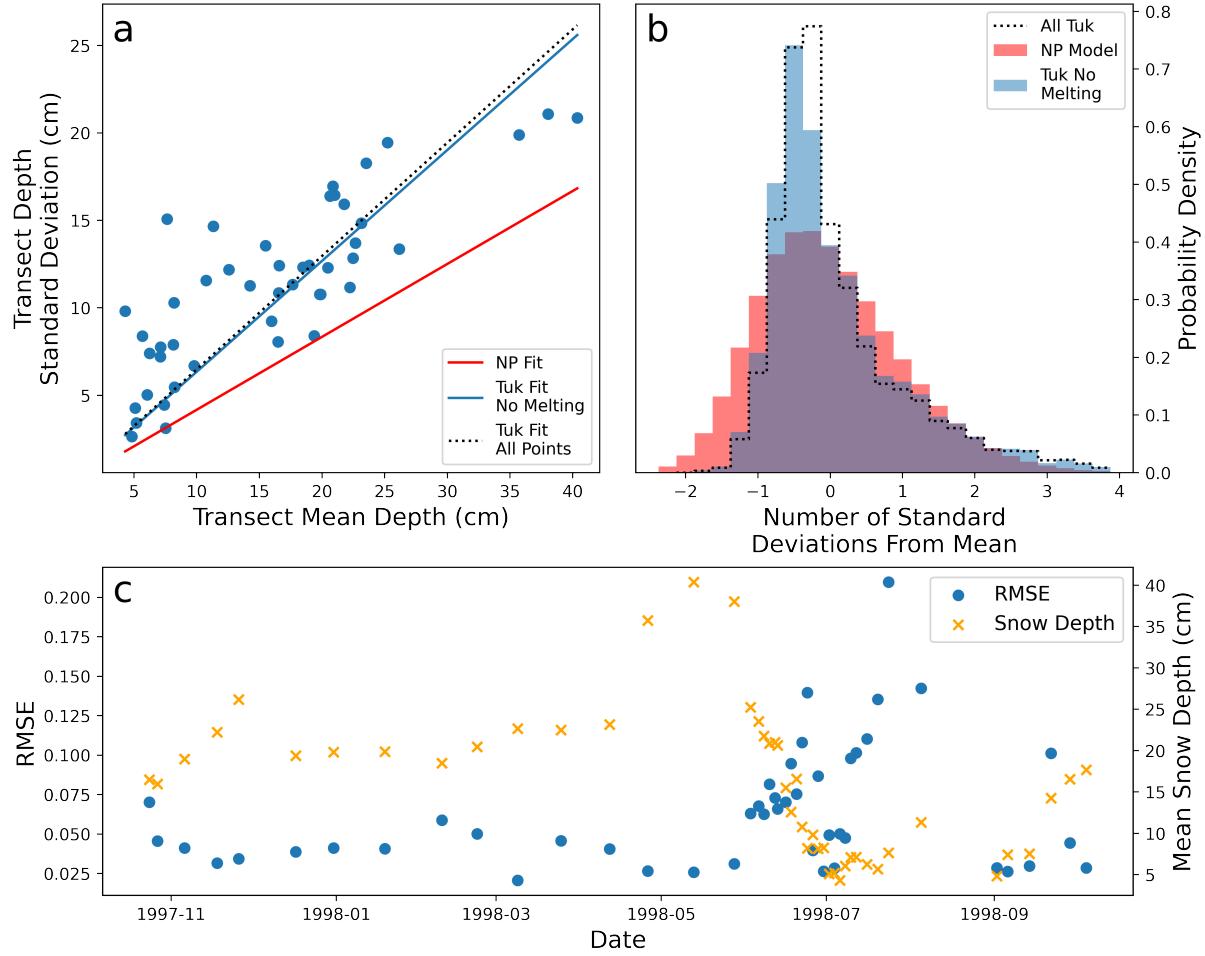


Fig. 9. (a) Relationship between the mean snow depth and standard deviation of the snow depth on SHEBA 'Tuk' transects (blue scatter). Linear regressions through the points are shown both including and excluding datapoints from July and August (blue solid and black dotted lines respectively). Linear regression from all NP transects shown by red line. (b) The snow depth distribution on the SHEBA 'Tuk' transect excluding July and August (blue) and from NP stations (red). The SHEBA fit from all transects including July and August shown by black dotted line. (c) Time evolution of the error in this paper's model (blue scatter). RMSE is significantly higher during July and August than in other months, which coincides with melted snow (depth in orange scatter).

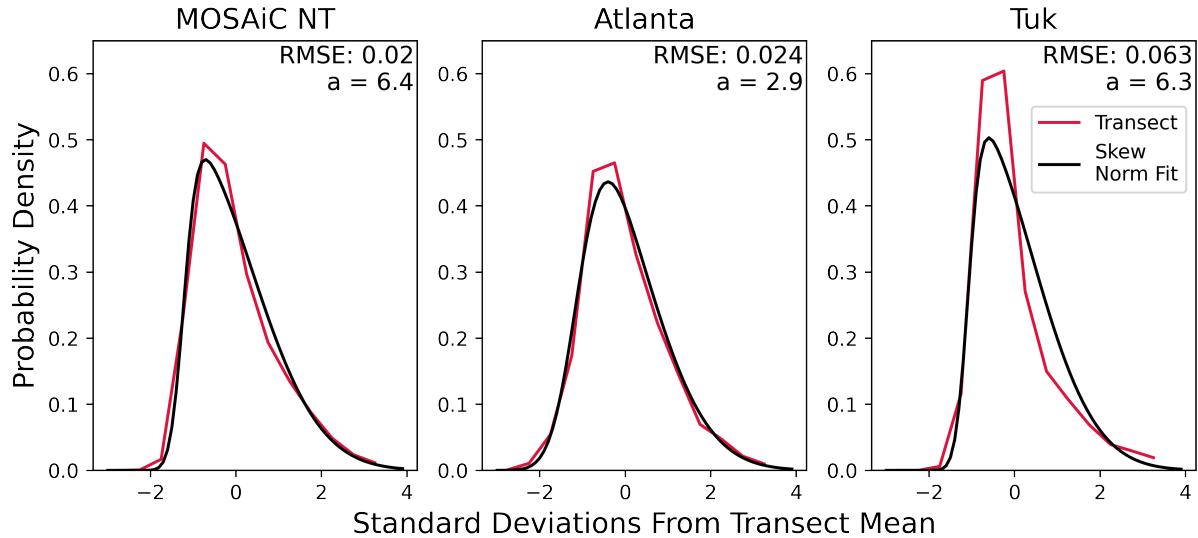


Fig. 10. Distribution of relative depth anomalies for the three evaluation data sets used in this paper (red). Distributions were generated with a bin width of 0.5 standard deviations. Skew normal distributions are fitted to each and show variable agreement (black).

273 DISCUSSION

274 Negative Snow Depths

275 The use of a skewed normal distribution results in a small fraction of negative snow depths. The total
 276 fraction is relatively constant at 0.1% in the 0 - 50 cm range of mean snow depths. Above this range, it
 277 transitions to a linear decline with increasing mean snow depth, dropping below 0.075% for snow depths
 278 larger than 200 cm (Supplementary Fig. SS4).

279 Because the fraction of negative snow depths does not exceed 0.1%, we treat it as negligible in our
 280 analysis. However, if this distribution were implemented in a snow-conserving model it would be necessary
 281 to modify the low-tail of the distribution. This could be done by merging the distribution with an
 282 exponential curve at low values, or by truncating it at zero and redistributing the coverage so that the area
 283 under the probability distribution is unity. In the redistribution case, it would be possible to either scale
 284 the whole curve by a small amount, or instead preferentially add the 'lost' coverage to the low-end of the
 285 distribution. We stress however that the effect of this would be extremely small (and not noticeable in the
 286 analysis of this paper), and so is only necessary for applications where snow must be precisely conserved.
 287 For completeness we point out that when a log-normal distribution is fitted to the data in Fig. 3a (instead
 288 of a skew normal), the fraction of negative snow depths is a similar function of the mean depth as in the

289 skew normal case, but around 100 times smaller in magnitude.

290 Potential for Application to First Year Ice

291 No multi-station data similar to the NP transects exist for first year ice (FYI). This is in part because first
292 year ice cannot be drifted on for long before experiencing a melt season, but also because FYI is thinner
293 and more liable to break up, making crewed research installations difficult to establish. Because of these
294 difficulties, it is natural to wonder whether the NP snow depth distribution can be applied to FYI and
295 with what uncertainty. To investigate this we apply the NP model to FYI snow depth transects taken
296 on the AMSR-Ice03, AMSR-Ice06 (Sturm and others, 2006) and MOSAiC field campaigns (Krumpen and
297 others, 2020). Several of these transects were performed in Elson Lagoon (EL in Fig. 11), which consists of
298 level ice. This contrasts with the more deformed ice on the nearby Beaufort sea measured during AMSR-
299 Ice03 (BS in Fig. 11). During AMSR-Ice06 a level-ice section in the Chukchi Sea was also surveyed (CS
300 in Fig. 11). Finally, during the MOSAiC expedition, successive transects were taken on a refrozen lead
301 (nicknamed the ‘runway’, described in Stroeve and others (2020b)), which provides some information about
302 the thin-snow regime on FYI (Fig. 11 g, h & i). For the eight transects described above we calculate the
303 RMSE of the NP model when applied based on the mean value, calculated with 5 cm bins. We also fit a
304 skew normal curve to the transect data and investigate the skewness-parameter (a) to shed light on the
305 mismatch between the NP model and the observations.

306 We first observe that all eight FYI transects have coefficients of variation (CV) roughly consistent with
307 that observed in the NP stations (Fig. 11a), particularly those from AMSR-Ice06. The average difference
308 between the FYI CV values and that of the NP model is 0.74 (a unitless quantity), or around 17% of
309 the CV of the NP model. We display the CV values for all FYI data in Supplementary Figure S5. We
310 also note that the skewness parameter of the AMSR-Ice06 data ($a = 1.6$ & 2.2) is close to the skewness
311 parameter of the NP-model ($a = 2.54$). These characteristics lead to the NP model performing better
312 on the AMSR-Ice06 data than the AMSR-Ice03 data. The AMSR-Ice06 survey on Elson Lagoon has the
313 lowest RMSE of all eight FYI transects (0.012) when compared to the NP model - this is related to it
314 having the most closely matching skewness parameter to the NP model.

315 While all three AMSR-Ice03 transects have very similar mean snow depths to each other (~ 30 cm),
316 the coefficient of variation is lower than for the NP station transects for the Elson Lagoon transects, but
317 higher for the Beaufort Sea (Fig. 11a). That is to say, the snow over the deformed first year ice in the

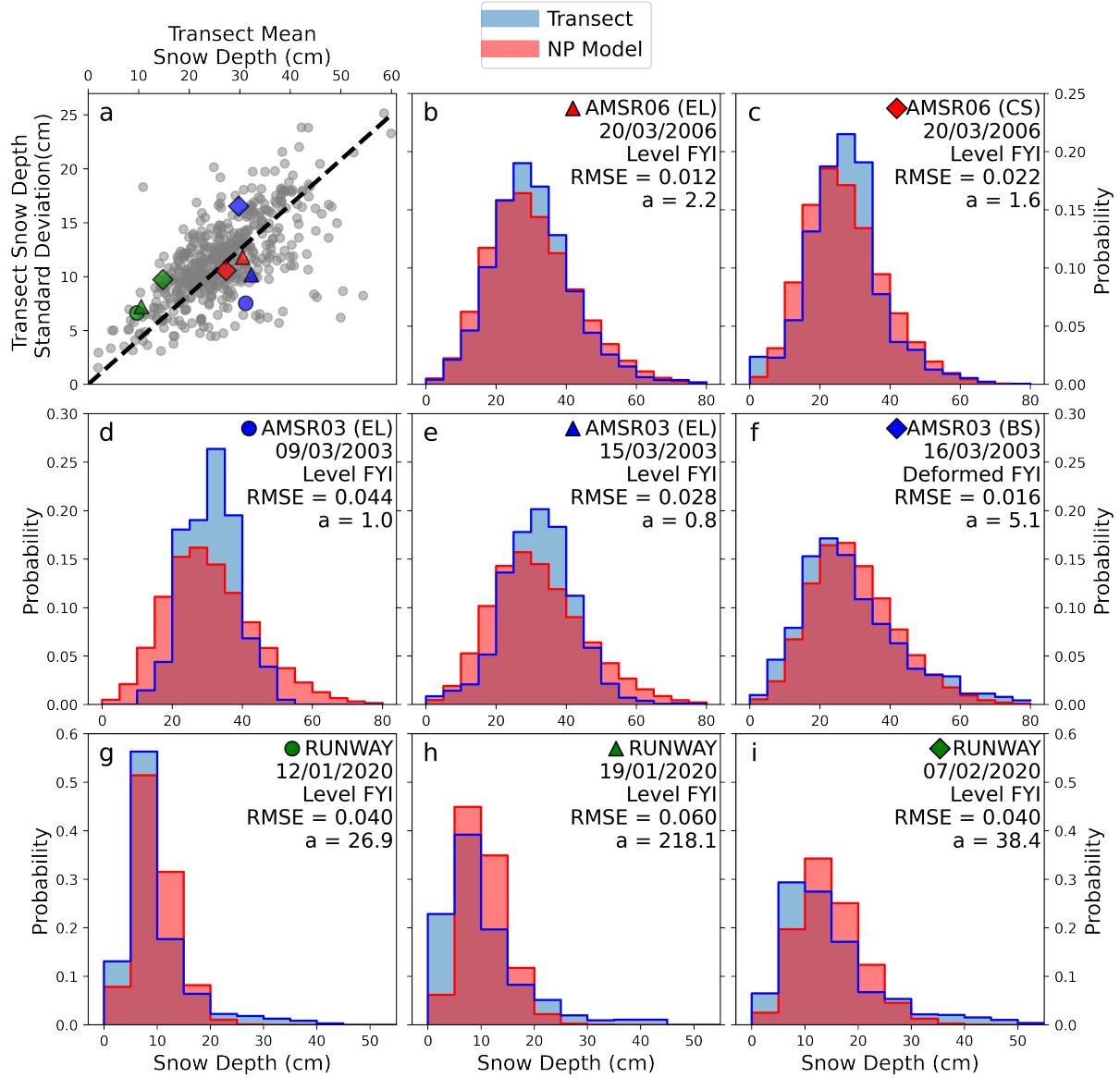


Fig. 11. Comparison of the NP model with data from first year ice transects taken during the AMSR-Ice 03, AMSR-Ice 06, and MOSAiC field campaigns. Panel (a) shows the ratio of snow depth standard-deviation to transect mean depths (the coefficient of variation, CV) for the FYI transects (large markers) as well as for the NP transects (gray dots). All other panels show the snow depth distribution produced by the NP model (red) against the transects (blue), with 5 cm wide depth bins for comparative purposes. Panels represent (in order b-i) Elson Lagoon (EL) and level ice on the Chukchi Sea (b & c), two transects on Elson Lagoon one week apart (d & e), a transect on FYI of the Beaufort sea near Elson Lagoon (f). Bottom row (g - i) displays snow transects taken on a refrozen lead during the MOSAiC expedition.

318 Beaufort Sea exhibited considerably more variability than that over the level ice in Elson Lagoon during
319 AMSR-Ice03. In addition to being more variable, the Beaufort Sea transect showed a much higher skewness
320 parameter ($a = 5.14$) than those on Elson Lagoon ($a = 1.02$ & 0.844). The transect over deformed ice
321 exhibits the lowest RMSE value of the AMSR-Ice03 transects by some margin.

322 We attribute the low-skewness (symmetry) of the 2003 Elson Lagoon data to a lack of ice topography
323 around which to build up a ‘long tail’ of drifted, thick snow. Conversely, the highly deformed ice of the
324 Beaufort Sea produces a noticeable long tail of thick snow, such that the probability of finding snow deeper
325 than 55 cm is underestimated by the NP model (Fig. 11f). However, it is striking that the AMSR-Ice06
326 transects at Elson Lagoon are more weakly governed by this: while the skewness parameters are still lower
327 than for the NP transects, there is a smaller difference. It is possible that this variability is produced by
328 the cumulative effect of wind redistribution, and particularly strong wind events. Investigating the role of
329 strong-wind events on the coefficient of variation and skewness of the snow depth distribution may form
330 the basis for future work.

331 We now turn to the thin snow cover of the three MOSAiC ‘runway’ transects (Fig. 11 g, h & i). We first
332 point out that a skew normal curve cannot be easily fitted to these data (Supplementary Fig. S6; similar to
333 the situation with the SHEBA ‘Tuk’ transects above). This indicates that the NP model will not be a good
334 fit, even before it is applied. Because of this feature, the skewness-parameter values listed in the panels of
335 Fig. 11 should not be assumed to properly capture the underlying transect data. When the NP model is
336 applied and compared, it exhibits a high RMSE relative to the other FYI transects. As well as being related
337 to the poor approximation with a skew normal curve, this performance is also linked to the three ‘runway’
338 transects having the highest error in the coefficient of variation (Fig. 11a) by comparison to the NP
339 transects. One key physical difference between the runway transects and the other FYI surveys is the low
340 average snow depth. However, other contextual differences exist: for example the transects were performed
341 in a colder region (near the pole), and at a colder time of year (January/February). This may result in a
342 more weakly bonded snowpack at the time of measurement, susceptible to more wind-redistribution and
343 resulting in a higher coefficient of variation (by comparison to the AMSR-Ice transects).

344 Because of the differences in the age of the snow (and the ice topography over level ice), there is
345 no a priori reason that the NP-model for the snow depth distribution derived in this paper should be
346 applicable to FYI, and indeed our model works relatively poorly when simulating the ‘symmetrical’ snow
347 depth distributions at Elson Lagoon in 2003, and the thin snow on the MOSAiC runway.

348 However in the instance where the ice was deformed (Fig. 11f) the model performs relatively well.
 349 Perhaps counterintuitively given the 2003 results, the NP model also performed well in 2006 over both
 350 level ice transects. The RMSE of the NP Model when applied to the Beaufort Sea transect was 0.016,
 351 which is in fact lower than the corresponding values for the MOSAiC Northern Transects (Fig. 7), which
 352 ranged from 0.019 - 0.031. By this metric the performance of the model over FYI in 2006 was also better
 353 (lower RMSE, 0.012) and comparable (similar RMSE, 0.022).

354 In summary, we have shown that the NP model is capable of performing well over deformed FYI,
 355 and even over level ice in the case of 2006 (where ‘well’ is defined with reference to its performance over
 356 MYI at MOSAiC). But despite this capability, it also clearly performs poorly in the case of thin snow (at
 357 MOSAiC runway, where we observed that the measurements could not be well-represented by any skew
 358 normal distribution), and also in the case of highly symmetrical (low-skew) snow distributions over FYI
 359 (Elson Lagoon in 2003).

360 Application to point-measurements of snow depth

361 There are several drifting, autonomous platforms in existence that record the snow depth at a single point,
 362 such as snow buoys and ice mass balance buoys (Nicolaus and others, 2021). If the buoy is deployed at
 363 random, it is most likely to sample the modal snow depth. In reality these instruments are often not
 364 deployed at random, and a conscious choice is made to sample what is perceived to be the modal depth.
 365 However, for applications such as laser and radar altimetry retrievals of sea ice thickness, the mean snow
 366 depth is the quantity required for characterising the floe’s hydrostatic equilibrium (e.g. Mallett and others,
 367 2021). We now present a simple method of relating these point measurements to the mean snow depth of
 368 the surrounding area.

369 If the mean snow depth (\bar{D}) is related linearly to the standard deviation (σ_D , Fig. 3a, Eq. 1) by the
 370 coefficient of variation (CV), and we observe the modal snow depth to be X standard deviations below the
 371 mean (Fig. 3b), then we can relate the modal depth to the mean depth as follows:

$$\sigma_D = CV \times \bar{D} \quad \& \quad \bar{D} = D_{mode} + X\sigma_D \quad (3)$$

$$\bar{D} = \frac{D_{mode}}{1 - (X \times CV)} \quad (4)$$

Using the NP data from Fig. (3) we now calculate that $X = 0.35$. The CV was found earlier (Eq. 1) to be 0.417. We therefore calculate that the mean snow depth is 17% larger than the modal depth. Where singular drifting instruments are assumed to retrieve the modal snow depth in their environment, we recommend this correction for estimation of the mean.

Length Scales

The NP station transects were performed over distances of 500 - 1000 m, and this characterises the length scale on which our distribution is relevant. If the same transects were theoretically performed over just a few centimetres, the coefficient of variation (Fig. 3a) would be lower, and the distribution about the mean would likely be different. The distribution would be sensitive to the small-scale roughness of the snow surface, rather than larger scale features like sastrugi and snow drifts around ice topography. If the transects were performed (again, theoretically) over thousands of kilometres then the snow distribution would again be different, and more representative of synoptic variability in snowfall and ice type. As such we stress that the distribution of snow depths has been characterised at the *sub-kilometre* length scale (on the order of hundreds of metres).

We also investigate the sensitivity of our analysis to the spatial sampling interval of the transects, which was 10 m for the NP stations. In particular, we consider the possibility that adjacent (and near-adjacent) snow depth measurements on a given transect may be correlated (Moon and others, 2019), and the impact that this might have on our main results. To do this we perform an autocorrelation analysis for each of the 499 transects, testing the correlation of a spatially-lagged series against the original set of measurements. We find that for a lag of one measurement (10 m), 26% of transects show a statistically significant autocorrelation ($p < 0.05$). To put this another way, we detect that adjacent points are correlated in 26% of transects. This fraction drops by roughly half at a lag of 2 measurements (20 m, 12%), and half again for a lag of 3 (30 m, 7%; Fig. 12a). We performed our test for correlation at the 5% level (i.e. significance at $p < 0.05$), and as such would predict one in twenty transects to exhibit a correlation even in the case where all snow depth measurements were sampled randomly from a normal distribution. As such, we see the fraction of statistically significant transects tend to this level at higher lag values (Fig. 12a). We also analyse the strength of positive autocorrelations where they are statistically significant. The typical strength (r value) of these statistically significant correlations is broadly similar (0.364, 0.315 & 0.31 respectively for lag = 1, 2 & 3; Fig. 12b).

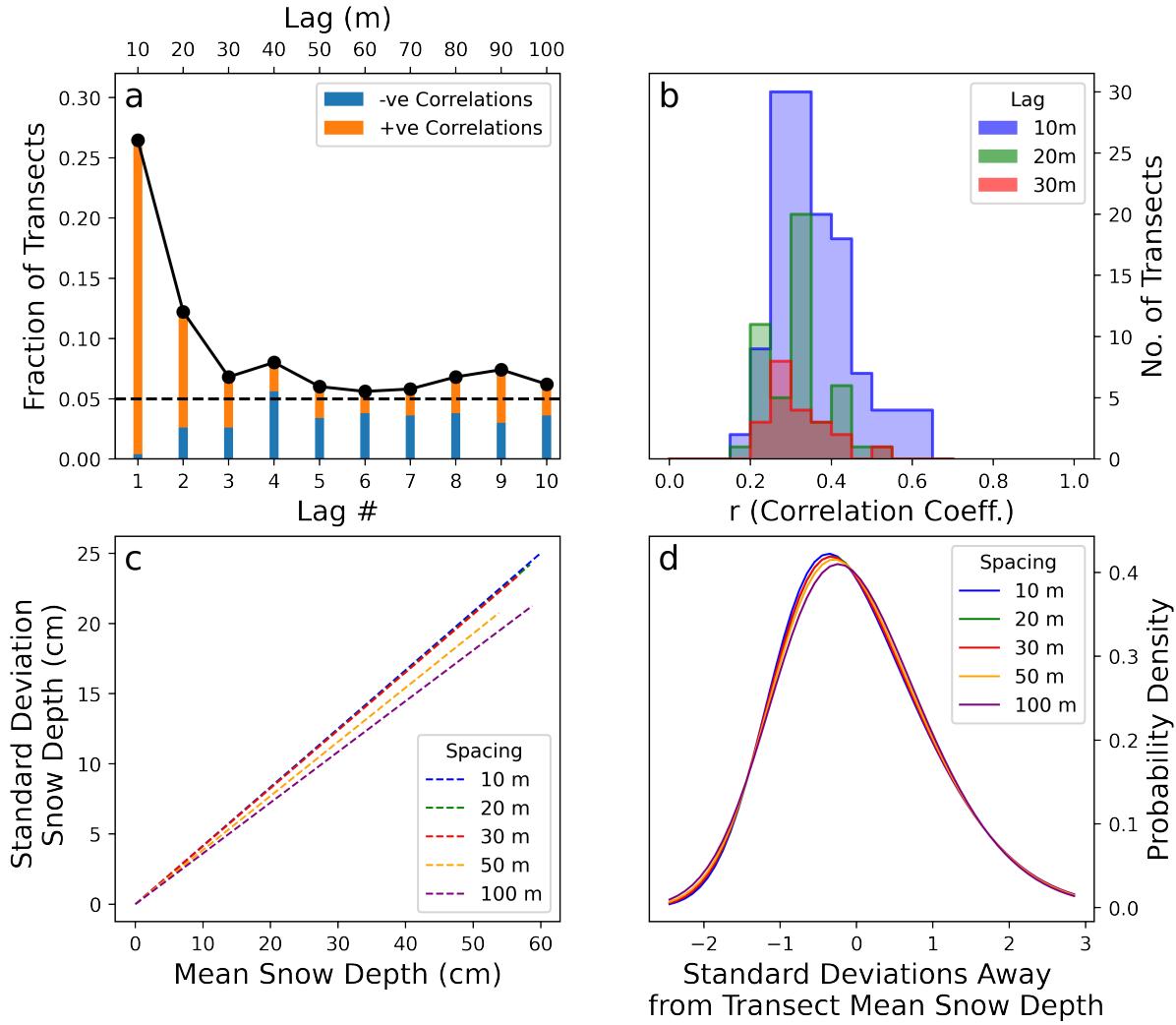


Fig. 12. (a) Fraction of transects with a statistically significant autocorrelation at various lags. 26% of transects exhibit correlated adjacent measurements at lag = 1. (b) The distribution of Pearson r correlation coefficients for various lags, where correlations are statistically significant. The mean strength of the statistically significant correlations decreases slowly as the lag increases. (c) Impact of undersampling the transect by taking every second, third, fifth and tenth measurement on coefficient of variation, and (d) the probability density distribution in standard deviation space. The impact of this sampling is small for the double-spacing and triple-spacing, indicating that the correlation of adjacent points in 28% of transects has a negligible impact on the main results in this paper.

401 The effect of adjacent points being correlated on our main analysis can be obviated by only analysing
402 every other transect measurement. To remove the effect of autocorrelation for a lag of two samples, we can
403 perform our analysis again but only consider every third measurement, etc. The results of this exercise on
404 the main results are displayed in Fig. 12 c & d (c.f. Fig. 3 a & b). The coefficient of variation (Fig. 12
405 c) is essentially unchanged by only analysing every second or third measurement from the transects, and
406 this is also true for the calculated skew normal distribution (Fig. 12 d). To stretch this approach, we also
407 display the results of taking every fifth and tenth sample from transects. When comparing a 10 m sampling
408 interval to a 100 m sampling interval, the coefficient of variation decreases from 0.416 to 0.361, and the
409 skewness parameter decreases from 2.54 to 1.84. Extrapolating from this trend, magnaprobe samples used
410 in the validation data sets which have a very low sampling interval of 1 m may therefore have a high-skew
411 and high coefficient of variation bias relative to transects from NP stations. However, the corresponding
412 analysis for these datasets is significantly more complex as, unlike the NP transects, the samples were
413 generally neither regularly spaced nor taken along a straight line.

414 For completeness we also investigate a common statistic for correlation between adjacent measurements:
415 the *autocorrelation length* (Supplementary Fig. S7). This is calculated for a transect by, as above,
416 calculating the correlation of lagged transects with the original transect at increasing lags. The *correlation*
417 *length* is then defined as the lag at which the correlation drops to a value of $1/e$. Because only a minority
418 (28%) of transects have statistically significant correlations for adjacent points (Lag = 1 sample, 10m), the
419 correlation lengths for the transects are generally below 10 m. Because of the coarse spatial resolution of
420 the measurements, we must interpolate to get the correlation length, and this was done linearly. When
421 calculating in this way, we find the modal correlation length of the transects to be 6.8 m (Supp. Fig. S7 b),
422 although this would be highly sensitive to the interpolation method. 9.4% of transects had a correlation
423 length of 10 m or greater.

424 Relevance in a changing Arctic Ocean and other limitations

425 The potential for application of the NP-model to first year ice was discussed above, and it was found that
426 while the NP model was capable of performing well over FYI, it performed poorly when simulating the
427 distribution of thin snow, and overestimated the skew in some cases. Here we point out that the Arctic
428 Ocean is becoming increasingly dominated by first year ice, so arguably the relevance of this MYI-trained
429 model is in slow decline.

430 There may also be spatial limitations on applicability. The NP drifting stations generally operated in
431 the Central Arctic Ocean (Fig. 1) rather than in the marginal regions such as the Kara, Beaufort and
432 Barents Seas (Warren and others, 1999). However, these areas are generally dominated by first year ice,
433 so this geographic constraint is less strict than the ice-type one described above.

434 The average age of multi-year ice is in decline, with the coverage of ice aged five years or more shrinking
435 from 28% to 1.9% between 1984 and 2018 (Stroeve and Notz, 2018). The mean thickness of sea ice is also
436 in decline (Kwok, 2018). Because we produce our statistical model using drifting station data from 1955
437 - 1991, it likely reflects snow conditions on ice older and thicker than that which currently exists in the
438 Arctic. We note however that our model does still display good skill with respect to the MOSAiC transects,
439 which were generally performed on ice that had only experienced one melt season.

440 SUMMARY

441 In this paper we have developed a generic snow depth distribution for multi-year ice that can be fully
442 characterised by the mean snow depth. This allows it to be superimposed onto estimates of mean snow
443 depth from satellites and models for the purposes of flux modelling and altimetry studies.

444 We performed a cross-validation exercise and found the model's skill to be highest in winter, and lowest
445 during the summer months of intense melt and sparse measurements. We then evaluated the distribution
446 against snow depth transects from the MOSAiC, SHEBA and AMSR-Ice field campaigns. These analyses
447 revealed that the model generally overestimated the variability in snow depths for the MOSAiC campaign,
448 but the fit parameters were otherwise broadly appropriate. On the smoother multiyear ice of the SHEBA
449 campaign the model performed well, but the model performed poorly on transects executed over highly
450 deformed ice. This was related to the fact that the snow depth distribution in this area was not well
451 approximated by the skewed normal distribution used in the NP model. Application of the distribution
452 to eight transects conducted over first year ice shows that while the NP-model was capable of performing
453 well (over deformed FYI and in two cases over level ice), it performed poorly when simulating thin snow
454 on a refrozen lead in the Central Arctic, and also when simulating a highly symmetrical snow distribution
455 over level ice.

456 Acknowledgements

457 This work was funded primarily by the London Natural Environment Research Council (NERC) Doctoral
458 Training Partnership (DTP) grant (NE/L002485/1). JCS acknowledges support from the Canada 150
459 Chair Program and NASA grants NNX16AJ92G, 80NSSC20K1121 & 19-ICESAT2-19-0088; ‘Sunlight
460 under sea ice’. MT acknowledges support from the European Space Agency ‘Polarice’ grant ESA/AO/1-
461 9132/17/NL/MP, NERC grant NE/S002510/1, NERC “PRE-MELT” NE/T000546/1 project and from the
462 ESA “EXPRO+ Snow” (ESA AO/1-10061/19/I-EF) project. VN was supported by JCS, in part thanks to
463 the Canada 150 Chair Program. RW was supported by NERC grant NE/S002510/1. PI acknowledges
464 funding from the Research Council of Norway (RCN287871, SIDRIFT) and the US National Science
465 Foundation (NSF) (NSF1820927, MiSNOW). MO acknowledges funding from the NSF (OPP1735862).
466 MJ acknowledges funding from the NSF (NSF1820927, MiSNOW). JL acknowledges support from the
467 Centre for Integrated Remote Sensing and Forecasting for Arctic Operations (CIRFA) project through the
468 Research Council of Norway (RCN) under Grant RCN237906.

469 Code and Data Availability

470 All code and data required to reproduce this analysis can be downloaded from:
471 www.github.com/robbiemallett/sub_km.

472 Author Contributions

473 RM developed the NP model in consultation with JS, MT, RW and VN. JL, PI, MO, MJ and DP were
474 involved with collecting, providing, and advising on the evaluation data. All authors contributed to and
475 provided feedback on the manuscript.

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