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2 **New Constraints on the Volatile Deposit in Mercury's North Polar Crater, Prokofiev**

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15  
16 **Abstract**  
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18 We present new high-resolution topographic, illumination, and thermal models of Mercury's 112  
19 km-diameter north polar crater, Prokofiev. The new models confirm previous results that water ice is  
20 stable at the surface within the permanently shadowed region (PSR) of Prokofiev for geologic timescales.  
21 The largest radar-bright region in Prokofiev is confirmed to extend up to several kilometers past the  
22 boundary of its PSR making it unique on Mercury for hosting a significant radar-bright area outside a  
23 PSR. The near-infrared normal albedo distribution of Prokofiev's PSR suggests the presence of a  
24 darkening agent rather than pure surface ice. Linear mixture models predict at least roughly half of the  
25 surface area to be covered with this dark material. Using improved altimetry in this crater, we place an  
26 upper limit of 26 m on its ice deposit thickness. The 1 km-baseline topographic slope and roughness of  
27 the radar-bright deposit are lower than the non-radar-bright floor although the difference is not statistically  
28 significant when compared to the non-radar-bright floor's natural topographic variations. These results  
29 place new constraints on the nature of Prokofiev's volatile deposit that will inform future missions, such as  
30 BepiColombo.

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32 Keywords: Polar illumination; Mercury; Ice; Volatiles; Permanently shadowed regions

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## 1 Introduction

Due to Mercury's low obliquity, its poles host permanently shadowed regions (PSRs) where temperatures can reach below ~110 K and where water ice and other volatiles could be stable for billions of years. Indeed, there is strong evidence from multi-wavelength, multi-instrument observations and thermal models for the presence of such volatiles in Mercury's north polar PSRs. Ground-based radar measurements identified areas as having backscatter characteristics consistent with ~95% pure ice deposits at least several meters thick on or near the surface (Butler et al. 1993; Harmon 2007; Harmon et al. 2011), which spatially correlate with some, but not all, PSRs identified using MESSENGER data (Deutsch et al. 2016). The Mercury Laser Altimeter (MLA) onboard the MESSENGER spacecraft found that some of the radar-bright deposits appeared bright at 1064 nm while others appeared dark (Neumann et al. 2013). Thermal models based on an MLA-derived polar digital elevation model (DEM) predicted that ice would be stable for geologic timescales on the surfaces of the MLA-bright regions whereas ice would have to lie ~ 10 cm beneath the surface to be long-lived in the MLA-dark regions (Paige et al. 2013). The MESSENGER Gamma Ray and Neutron Spectrometer measured epithermal and fast neutron suppression at the poles consistent with an average two-layer stratigraphy in all the radar-bright regions in which the upper layer was ~10 – 30 cm thick with 0 – 25 wt% water equivalent hydrogen (WEH) and the lower layer was more than tens of cm thick with 12 – 100 wt% WEH (Lawrence et al. 2013). The MESSENGER Mercury Dual Imaging System (MDIS) acquired broadband visible images of PSRs when they were illuminated by scattered light from surrounding terrain, revealing a similar pattern as seen by MLA: dark regions inside radar-bright areas too warm to host stable surface ice and an anomalously bright region in the 112 km-diameter crater, Prokofiev, co-located with a radar-bright and MLA-bright area cold enough to host stable surface ice (Chabot et al. 2014). Most recently, Rivera-Valentín et al. (2022) analyzed new radar data and identified variations in radar scattering behavior between and within the polar deposits indicative of variations in ice purity independent of their brightness at optical wavelengths. They found that although most radar-bright regions were consistent with highly pure ice, some areas, such as Prokofiev's optically bright region, had radar scattering properties consistent with a higher fraction of impurities relative to other nearby areas. Altogether, the observations to date have painted a broadly consistent picture in which the north polar radar-bright regions are predominantly highly pure water ice at least several meters thick. These ice deposits appear optically bright where they are predicted to be exposed at the surface and optically dark where they are modeled to be overlain with an insulating layer of complex organic volatiles typically tens of cm thick that formed as a thermal lag after the surface and near-surface ice sublimated (Paige et al. 2013).

One open question concerned the observation that the boundary of Prokofiev's optically-bright region was offset by several kilometers inward from the edges of both its radar-bright region and its PSR

70 estimated from MDIS imaging (Chabot et al. 2014). Such an offset, if true, could have implications for the  
71 ice properties and its delivery and destruction mechanisms. For example, lateral mixing by impact  
72 gardening was hypothesized to have covered the outer edge of the surface ice leading to the boundary  
73 offset (Chabot et al. 2014). However, the boundary of the optically-bright region closely matched the PSR  
74 computed with an alternative method based on the polar MLA DEM (Neumann et al. 2013; Deutsch et al.  
75 2016). If there really is an offset between the PSR and radar-bright boundaries, then this area would be  
76 unique on Mercury since all other large radar-bright regions are closely associated with PSRs (Deutsch et  
77 al. 2016), including Mercury's south polar region (Chabot et al. 2018a). Such an offset could have  
78 implications for the ice deposit characteristics, like depth, age, and evolution. It was unclear whether the  
79 MDIS images were sufficiently sensitive to detect dimly sunlit areas along the margins of the radar-bright  
80 region when building the MDIS-based PSR map (Chabot et al. 2014). This could lead to an overestimate  
81 of the PSR size. Additionally, inaccuracies in the low-resolution MLA DEM ( $500 \text{ m pix}^{-1}$ ), particularly on  
82 the crater wall, could have caused the MLA-based PSR to be too small (Deutsch et al. 2016). Improved  
83 topographic and illumination models were, therefore, needed to settle the question of the true extent of  
84 Prokofiev's PSR. In the present work, we address these issues by developing new higher-resolution and  
85 more accurate topographic, illumination, and thermal models of Prokofiev.

86 In addition, previous work has noted that the MLA-bright polar regions have a reflectance value of  
87  $\sim 0.4$ , roughly  $\sim 2$  times brighter than average Mercury regolith (Neumann et al. 2013; Deutsch et al. 2017;  
88 Rubanenko et al. 2018). This fact suggests the presence of a darker material to reduce the observed  
89 MLA reflectance below the expected value of  $\sim 1.0$  for pure ice. The composition and abundance of this  
90 dark material are unknown but can help constrain the origin and evolution of the ice and dark material.  
91 Therefore, we also study the MLA reflectance data in Prokofiev to quantitatively estimate the ice and dark  
92 material's abundances.

93 Other recent work on the Moon and Mercury's PSRs has found evidence that ice or sub-surface  
94 ice may affect surface geomorphologic characteristics. This evidence includes smaller depth-to-diameter  
95 ratios of craters hosting PSRs and lower surface roughness inside PSRs compared to outside PSRs  
96 (e.g., Rubanenko et al. 2019; Moon et al. 2021; Deutsch et al. 2021a; Deutsch et al. 2021b). Studies have  
97 also estimated the average thickness of Mercury's polar ice deposits to be  $50 \pm 35 \text{ m}$  (Eke et al. 2017)  
98 and  $41^{+30}_{-14} \text{ m}$  (Deutsch et al. 2018). Susorney et al. (2019) placed a tighter upper limit of  $15 \text{ m}$  on the  
99 average thickness in 4 north polar craters including Prokofiev where they estimated a thickness of  $36 \pm 60$   
100 m. Here we use a similar approach and a more comprehensive set of improved MLA tracks for this crater  
101 to examine whether the ice deposit has any topographic expression in terms of surface height, slope, and  
102 roughness.

103 This paper is organized as follows: In Section 2, we describe the new topographic, thermal and  
104 illumination models. Then, in Section 3, we apply linear mixture models to the MLA reflectance data in  
105 Prokofiev to constrain the abundance of surface ice and dark material. In Section 4, we examine the

106 topography of the volatile deposit. In Section 5, we discuss the results and implications for Prokofiev's  
107 volatile deposit and compare it to the Moon. Finally, we summarize the results in Section 6.

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## 2 New Topographic, Illumination and Thermal Models

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111 Previously, Hamill et al. 2020 (hereafter H20) derived new topographic, illumination, and thermal  
112 models for 8 northern craters hosting dark surface deposits. Here, we follow the same procedures used  
113 by H20 to derive new models for Prokofiev. We used MLA altimetry and MDIS images together with the  
114 Ames Stereo Pipeline (ASP) shape-from-shading (SfS) tool (Alexandrov & Beyer 2018). The ASP SfS tool  
115 uses the technique of photogrammetry to derive a topographic model based on the pixel shading  
116 variations observed in images. The tool requires an initial *a priori* model, for which we used a locally  
117 optimized MLA-only DEM obtained by bundle adjustment of the MLA tracks in a manner similar to that  
118 used with Lunar Orbiter Laser Altimeter data for the lunar crater, Shackleton (Zuber et al. 2012). For the  
119 image data, we used a set of 34 MDIS images of Prokofiev with pixel scales of  $\sim 70$  to  $170$  m  $\text{pix}^{-1}$   
120 sampling a wide range of Sun azimuth.

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122 The final hybrid MLA+SfS DEM (Figure 1a), with a pixel scale of  $125$  m  $\text{pix}^{-1}$ , is more complete  
123 than either an MDIS-only or MLA-only DEM alone. The MLA-only DEM fills in areas shadowed in all  
124 images (including PSRs) which correspond to most of the southern half of the crater floor, while the  
125 images provide denser coverage of illuminated terrain including the crater rim, which is important for  
126 determining the true extent of PSRs. The topography of Prokofiev's floor is relatively flat on large  
127 baselines, but numerous small craters give it a mottled appearance. Some fraction of these craters are  
128 likely secondaries from Kandinsky indicating that the surface ice in Prokofiev must post-date that crater  
(Chabot et al. 2014).

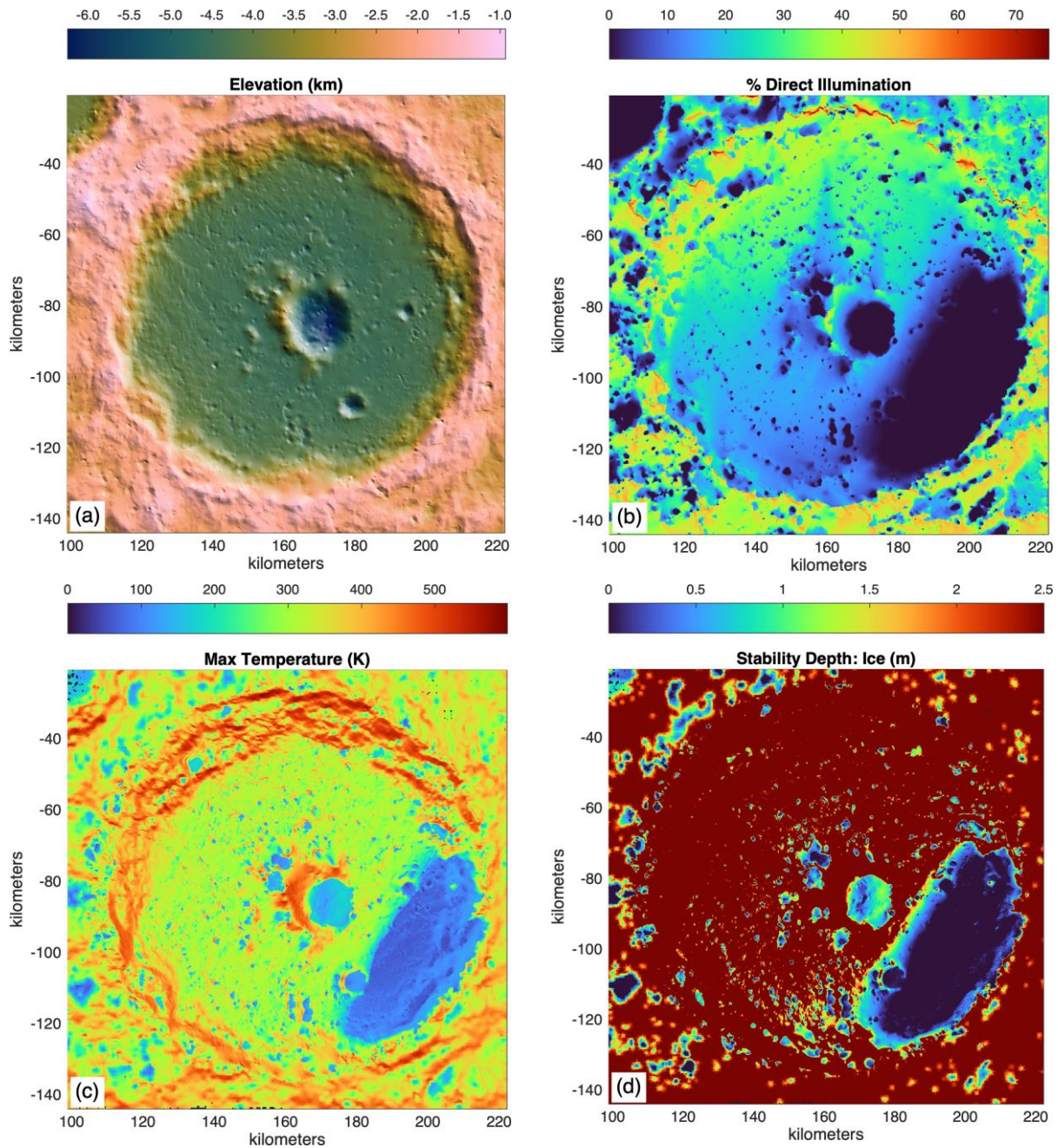


Figure 1 – High-resolution polar stereographic models of Prokofiev at  $125 \text{ m pix}^{-1}$  with the origin at the north pole and  $0^\circ$  longitude to the bottom. (a) Colorized hillshade of MLA+SfS DEM. (b) Average illumination over one Mercury solar day. Dark blue regions are PSRs. (c) Maximum surface temperature throughout a Mercury solar day. (d) Depth below the surface needed for the long-term stability of ice. Dark blue regions are areas where ice is thermally stable at the surface. Dark red areas are where no ice is stable within the upper 2.5 m, and generally, therefore, where ice is unstable at any depth.

129           This new topographic model allows a more detailed look at the illumination and thermal  
130 conditions inside Prokofiev than was previously possible with the polar MLA DEM. To that end, we ran  
131 illumination and thermal models using the same approach as in H20. The illumination model computed  
132 the direct incident solar flux and fraction of the Sun (treated as a 2-dimensional limb-darkened source)  
133 visible at hourly timesteps for a whole Mercury day (~176 Earth days). The thermal model and its  
134 parameters (0.04 albedo, 0.9 emissivity, and a two-layer temperature dependent thermal inertia) follows  
135 Paige et al. (2010, 2013) and accounts for reflected visible and reradiated infrared radiation to produce  
136 temperature profiles (here, to 2.5 m depth, several times the thermal skin depth). Solar declination and  
137 obliquity were taken from the JPL Horizons<sup>1</sup> ephemeris. Ice stability depth is calculated assuming lunar  
138 regolith diffusion (Schorghofer and Taylor, 2007) to find the depth at which ice would be lost at a rate of 1  
139 m Gyr<sup>-1</sup>. The properties of Mercury's regolith and the potential presence of complex organics as observed  
140 in other PSRs might make the conditions within Prokofiev different than the lunar regolith model.  
141 However, given our limited knowledge about Mercury's regolith and composition, application of the lunar  
142 regolith model to Mercury is appropriate. Dark material overlying subsurface ice may be more or less  
143 porous than regolith, but due to the exponential dependence of volatile loss on temperature, this does not  
144 substantially affect the stability boundaries, which appear to align well with the regolith assumption.  
145 Finally, all thermal and illumination model calculations were done in 3-dimensional Cartesian coordinates  
146 and treated the Sun as a 2-dimensional limb-darkened source sub-divided into 128 sub-sources with full  
147 3-dimensional ray-tracing from each. Thus, the models account for the planet's curvature and penumbral  
148 effects.

149           The PSRs within Prokofiev appear as dark blue regions in the map of average illumination (Figure  
150 1b) and are dominated by a large area along the southern portion of the crater and the central peak-ring  
151 crater, with many smaller PSRs distributed throughout the floor inside the aforementioned small craters.  
152 The large southern PSR also stands out in the thermal model with maximum temperature  $T_{\max} < 110$  K  
153 (Figure 1c), and surface-stable ice (i.e., stability depth of 0 m in Figure 1d). The central crater and most of  
154 the resolved smaller floor craters are too warm for stable surface ice. Note, however, that stable surface  
155 ice may exist in smaller cold traps unresolved by the DEM (Rubanenko et al. 2018).

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<sup>1</sup> <https://ssd.jpl.nasa.gov/horizons/>

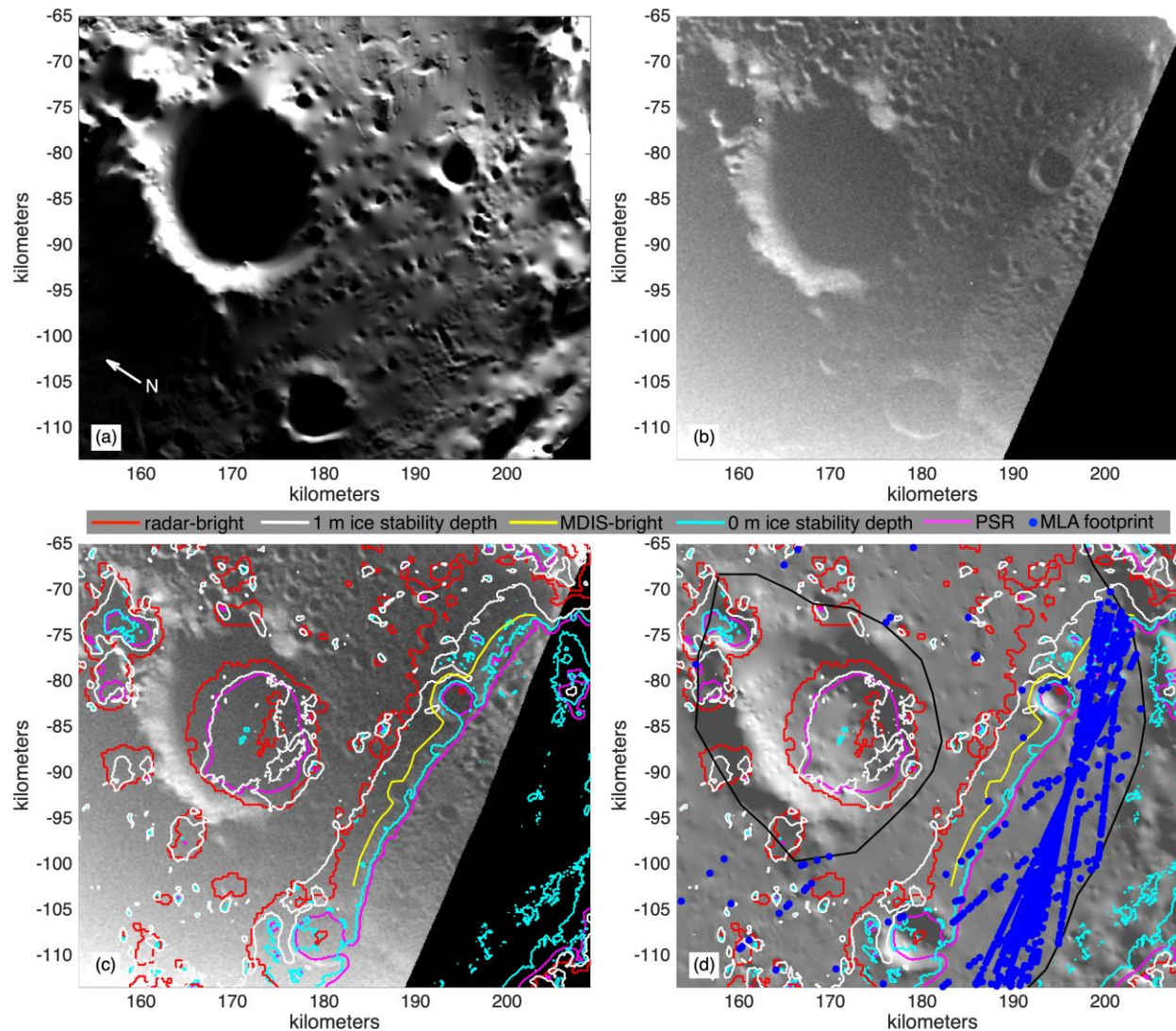


Figure 2 – Comparison between models ( $125 \text{ m pix}^{-1}$ ) and MDIS broadband image EW1020581108B ( $188 \text{ m pix}^{-1}$ ) in stereographic projection with the origin at the north pole and  $0^\circ$  longitude to the bottom. (a) Simulated image using the MLA+SfS DEM, (b) MDIS image, (c) MDIS image with contours: PSR (magenta), ice stability depth of 0 m (cyan), MDIS-bright boundary (yellow), ice stability depth of 1 m (white), and radar bright region (red), (d) hillshade of the MLA+SfS DEM with the same contours and black lines defining the inner and outer edge of the floor region used to select MLA reflectance footprints (blue points) for the mixture modeling in Section 3.

156 Figure 2a shows a simulated image that includes scattered light within the crater at the  
 157 acquisition time of the broadband MDIS image in Figure 2b when the sub-solar latitude and longitude  
 158 were  $0.008^\circ$  north and  $335.593^\circ$  east, respectively. A Lambertian surface was assumed although we also  
 159 tried a Hapke reflectance law tailored to Mercury (Domingue et al. 2016) which resulted in an insignificant

160 change. The simulation does not include instrumental stray light responsible for the large-scale gradient  
161 from bottom to top of the MDIS image as oriented in Figure 2b. A quantitative comparison between the  
162 acquired MDIS image and the simulated image is hampered by the lack of an absolute radiometric  
163 calibration for the WAC broadband filter (Denevi et al 2018). Nevertheless, the simulated image generally  
164 reproduces well the reflectance variations associated with topography particularly around the rim of the  
165 central peak. However, it does not exhibit the MDIS-bright region on the floor associated with the PSR.  
166 This confirms earlier lower resolution scattered light simulations based on the polar MLA DEM that could  
167 not reproduce this bright region (Chabot et al. 2014), and strongly supports that it is a real feature on the  
168 surface rather than a result of the natural topography and the diffuse lighting conditions.

169 The higher resolution and fidelity of the new models allow a more detailed examination of the  
170 PSR and MDIS-bright boundaries than previously possible. Figure 2c overlays on the MDIS image  
171 contours representing PSRs (magenta), 0 m ice stability depth (cyan), the MDIS-bright boundary (yellow),  
172 1 m ice stability depth (white), and radar brightness of  $4\sigma$  above the background (red) computed from a  
173 weighted sum of 13 Arecibo observations in the period 1999 – 2005 (Figure 3b of Harmon et al., 2011).

174 Several key points are evident in Figure 2. First, the radar-bright boundary extends up to several  
175 km outside the PSR (and MDIS-bright region). This strongly favors the interpretation that this boundary  
176 offset is real and not an artifact of inaccuracies in the MLA-only or MLA+SfS DEMs or in the ability to  
177 register the radar and MESSENGER datasets and makes this region unique on Mercury for hosting a  
178 substantial radar-bright area outside a PSR. This transition zone from the edge of the PSR to the edge of  
179 the radar-bright region is unlikely to be a radar beam-smearing effect since the area is larger than the  
180 radar resolution of 1.5 km (Harmon et al. 2011). If radar clutter due to the high incidence angle was  
181 artificially boosting the signal in this region, then that would apply to radar-bright regions everywhere on  
182 Mercury, and every radar-bright region would extend well beyond the PSR. But in fact, we do not see that  
183 and only see it for this region in Prokofiev (Deutsch et al. 2016). Volume scattering off wavelength-scale  
184 rocks and bedrock fractures below the surface may be contributing to the apparent radar brightness.  
185 However, sub-surface ice appears to be a simpler explanation for the radar-bright unit outside the PSR  
186 because it is predicted by the thermal models, which are generally supported by the observational  
187 evidence for ice below and on the surface in Mercury's PSRs as summarized in Section 1. The ice  
188 stability depth in this transition zone reaches up to  $\sim 1 - 2$  m, suggesting that any sub-surface ice would  
189 have to be thick enough to appear as radar-bright through the radar-attenuating dry upper layer. The dry  
190 upper layer here may be less attenuating compared to the polar average or there may be ice closer to, or  
191 even exposed on, the surface inside small-scale cold traps unresolved by the models (Rubanenko et al.  
192 2018). However, any surface ice in this zone outside the MDIS-bright boundary must also be obscured  
193 from view or too faint to be visible in the MDIS image (the coldest surfaces most likely to host ice also  
194 receive less scattered light and therefore contribute fewer photons to passive imagers). Notably, the MLA  
195 reflectance inside this transition zone is anomalously bright and similar to that in the PSR region (see

196 Section 3), but most of the MLA footprints here lie in a small cluster between the PSR and MDIS-bright  
197 boundaries at map coordinates (200 km, -75 km) in Figure 2d. Therefore, we cannot say for certain if  
198 there is stable surface ice in small-scale cold traps beyond the MDIS-bright region.

199 Second, the MDIS-bright boundary in Figure 2 extends ~1.0 km farther than the stable surface ice  
200 boundary. This offset is about 3 times larger than the estimated registration accuracy based on manual  
201 feature matching between the MDIS and simulated images. If the MDIS-bright region hosts stable surface  
202 ice, then this discrepancy could be due to several factors, such as the ice not yet having reached  
203 equilibrium, topographic effects below the resolution of the DEM, or choices of parameters within the  
204 thermal model. This could imply some form of vertical migration of ice from the subsurface, such as  
205 impact gardening or thermal diffusion, that exceeds the rate of surface loss in these areas. Also, as  
206 previously mentioned, sub-resolution topographic roughness could make stable surface ice more likely to  
207 exist beyond where the current 125 m  $\text{pix}^{-1}$  thermal model predicts. This explanation may require further  
208 study, however, since the small-scale slopes would need to be oriented both to avoid all but the briefest  
209 periods of direct sunlight during the Mercury day and to be observable from the position of MESSENGER  
210 at the time of the MDIS image in Figure 2b. The small-scale slopes would also have to receive enough  
211 scattered radiation to be detectable by MDIS during the acquisition of the image in Figure 2b but not so  
212 much as to lead to maximum temperatures  $> 110$  K which would rapidly sublimate the ice. Additionally,  
213 the thermal model has several parameters that were tuned to lunar regolith which could be different for  
214 Mercury's regolith. Variations in certain parameters (e.g., thermal conductivity), which could be caused by  
215 the ice itself, could cause the model's stable surface ice boundary to be larger or smaller. Also, the model  
216 assumes that the maximum temperature ever experienced controls the ice loss rate. Ice might only  
217 experience that maximum temperature for a short period making the time-integrated loss rate more  
218 appropriate (Schorghofer & Williams 2020).

219 Finally, out of all the contoured regions, the PSR has the smallest area and surface ice is  
220 modeled to be stable slightly beyond the PSR. This is not altogether unexpected given the low  
221 conductivity assumed in the thermal model and it demonstrates that surface ice can withstand small  
222 amounts of sunlight. Indeed, the ~500 m wide gap between the PSR and surface ice stability contours  
223 experiences  $< 1\%$  solar illumination ( $< 100$   $\text{W m}^{-2}$ ) during a single period with duration  $< 1$  Earth day  
224 during every Mercury solar day (176 Earth days). H<sub>2</sub>O observed similar behavior in dark deposit craters  
225 where the dark surface volatile deposits can extend past the PSRs by as much as ~1 km, farther than ice  
226 here due to the higher inferred stability of the dark deposit compounds.

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### 3 Mixture Modeling

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230 To constrain the ice abundance, we use the MLA reflectance, or normal albedo, since it is  
231 observed at a phase angle of zero degrees and is thus free from the confounding effects of illumination

232 geometry and scattered light (Neumann et al. 2013). Nevertheless, the MLA reflectance<sup>2</sup> was a noisy  
 233 measurement with systematic instrumental errors necessitating manual selection of a reliable subset of  
 234 data. By examining the dependence of the MLA reflectance on various instrument-related parameters, we  
 235 found that including only pulse widths of 15 – 90 ns, ranges of 100 – 800 km, and emission angles < 20°  
 236 removed noisy measurements and outliers and yielded a reasonably consistent set of measurements  
 237 (Figure 3). The reason for the pulse width behavior in Figure 3 (left panel) is not entirely clear, but it may  
 238 be related to the fact that the MLA reflectance is based on the difference in pulse width measured at a  
 239 pair of thresholds. Noise, sub-optimal system response, non-ideal operating conditions, and degradation  
 240 of the transmitted pulse may cause errors in the pulse width estimation, thus impacting the derived  
 241 reflectance (Neumann et al. 2013; Sun & Neumann 2015). The secondary trend visible in light blue below  
 242 the main trend in Figure 3 (left panel) is due to the data with range < 100 km (seen in the middle panel).  
 243 The global mode of the MLA reflectance (~0.17) is within 20% of the 996 nm normal albedo predicted by  
 244 MDIS-based photometric models (Domingue et al. 2016), so we take 20% as the absolute uncertainty.  
 245 Also, the spread in MLA reflectance about the mean is about 25% globally in individual bins of size  
 246 0.1x0.1 degrees (~4x4 km at the equator). Given that some of that variance is geological, it is roughly  
 247 consistent with a 20% instrumental error.

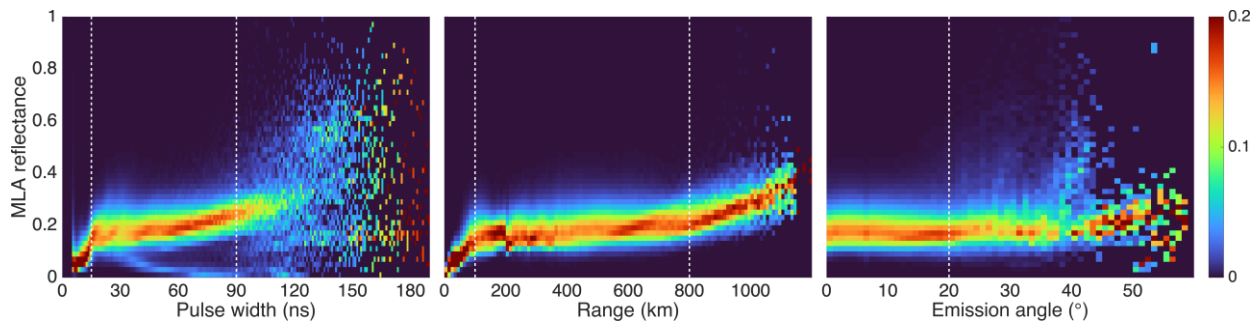


Figure 3 – 2-dimensional histograms of MLA reflectance as a function of pulse width (left), range (middle), and emission angle (right) for latitudes 55 – 83°. The color scale gives the fraction of the number of points in each column of each histogram. The y-axis bin size is 0.02 and the x-axis bin size is 1 ns, 10 km, and 1°. The dashed white lines show the adopted thresholds used for extracting good data: pulse width = 15 – 90 ns, range = 100 – 800 km, and emission angle < 20°. The middle and right panels have had the pulse width and pulse width + range cuts applied, respectively.

248 Figure 4 compares the resulting MLA reflectance distribution for several different areas relevant  
 249 to our analysis: 1) Prokofiev’s floor outside both the MDIS-bright region and PSRs (“non-MDIS-bright,

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<sup>2</sup> RADR v4 data available at the NASA Planetary Geodesy Data Archive (<https://pgda.gsfc.nasa.gov>) at Goddard Space Flight Center

250 non-PSR”, orange line, 83 points total), 2) Prokofiev’s floor inside the MDIS-bright region but outside  
 251 PSRs (“MDIS-bright, non-PSR”, black line, 95 points), 3) Prokofiev’s floor PSRs (“PSR”, cyan line, 833  
 252 points), 4) a nearby control sample outside Prokofiev (“nearby Prokofiev”, red line, 4126 points), and 5)  
 253 PSRs of the 8 H2O dark deposit craters (“dark deposit”, blue line, 1662 points). The peak in the  
 254 reflectance distribution outside Prokofiev’s floor PSRs and MDIS-bright region (orange line) is consistent  
 255 with the nearby control sample (red line) and global value suggesting that the majority of Prokofiev’s sunlit  
 256 floor is representative of average Mercury regolith whereas the peak of ~0.4 for the distribution inside  
 257 floor PSRs (cyan line) is ~2x brighter as noted in previous work (Neumann et al. 2013, Chabot et al.  
 258 2014). Additionally, the MLA reflectance distribution in the narrow MDIS-bright region outside PSRs  
 259 (black line) is consistent with the one inside PSRs although, as noted in Section 2, the spatial sampling of  
 260 MLA reflectance in this region is limited (Figure 2d).

261 The fact that the PSR reflectance is much smaller than the expected value of ~1.0 for pure ice  
 262 suggests the presence of a darkening agent mixed with the ice. The abundance and form of the mixture  
 263 (e.g., areal or intimate) is unknown. Here, we assume a checkerboard areal mixture model in which each  
 264 photon interacts only with ice or the darker material and, hence, the observed reflectance is the linear  
 265 combination of the reflectance values of these end-members weighted by their fractional areal coverage  
 266 (Hapke 2012).

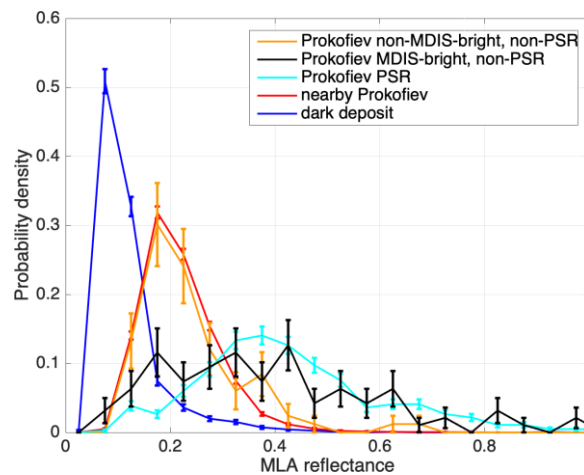


Figure 4 – Distribution of MLA reflectance for 1) Prokofiev’s floor outside both the MDIS-bright region and PSRs (“non-MDIS-bright, non-PSR”, orange), 2) Prokofiev’s floor inside the MDIS-bright region but outside PSRs (“MDIS-bright, non-PSR”, black), 3) Prokofiev’s floor PSRs (“PSR”, cyan), 4) a nearby control sample outside Prokofiev (“nearby Prokofiev”, red), and 5) the 8 H2O dark deposit PSRs (“dark deposit”, blue). Each histogram has a bin size of 0.05 and is normalized by its total number of points. The error bars are Poisson errors.

267 Initially, we assume all of the MLA footprints (each ~30 – 40 m in diameter) contain this mixture  
 268 and that the dark and icy end-member reflectances are simple delta-functions. This allows a first-pass  
 269 estimate of the sub-footprint ice areal fraction,  $f_i$ . We set the ice reflectance,  $r_i$ , to 0.8, the optimal value

270 Fisher et al. (2017) derived by fitting the Lunar Orbiter Laser Altimeter (LOLA) reflectance data of the  
271 Moon's south polar PSRs. Two different choices for the dark end-member reflectance are likely to  
272 encompass the range of possible values: 1) Prokofiev's non-MLA-bright and non-PSR floor reflectance  
273 ( $\sim 0.17$ ) and 2) the dark deposit PSR reflectance of the H20 craters ( $\sim 0.08$ ). The darker the non-ice end-  
274 member is, the more ice that is required to match the observed PSR reflectance. Given Prokofiev's typical  
275 PSR reflectance of  $\sim 0.4$ , the resulting sub-footprint ice areal fraction,  $f_i$ , is 0.36 (case 1) and 0.44 (case 2).  
276 Increasing (decreasing)  $r_i$  by 0.2 decreases (increases)  $f_i$  by  $\sim 0.1$  ( $\sim 0.2$ ).

277 Next, we take a more detailed approach by relaxing the assumptions that all MLA footprints  
278 contain the mixture and that the end-member reflectances are delta-functions. We fit the PSR reflectance  
279 distribution (cyan line in Figure 4) as a linear mixture of 1) "dry" regolith with reflectance distribution given  
280 by that outside the MDIS-bright region and PSR (orange line in Figure 5) and 2) pure ice with a Gaussian  
281 reflectance distribution with mean  $r_i$  and standard deviation  $\sigma_i$  to which a 20% measurement error is  
282 added. To keep the ice reflectance distribution symmetric and positive, we restrict it to the range 0.0 to  $2r_i$ .  
283 A fraction  $F_i$  of MLA footprints contains the mixture each with a sub-footprint areal ice fraction  $f_i$ , while the  
284 remaining fraction  $(1-F_i)$  of footprints have only the darker non-ice material. Figure 5 shows the effects of  
285 varying these model parameters. A wide range of  $f_i$  and  $r_i$  produce acceptable fits since they are highly  
286 correlated. Thus, we fix  $r_i$  at 0.8 as in the first-pass estimates above. The model is fitted to the data using  
287 a  $\chi^2$  cost function minimized over a grid in the parameters with step sizes of 0.01/0.02/0.025 for  $F_i/f_i/\sigma_i$ .

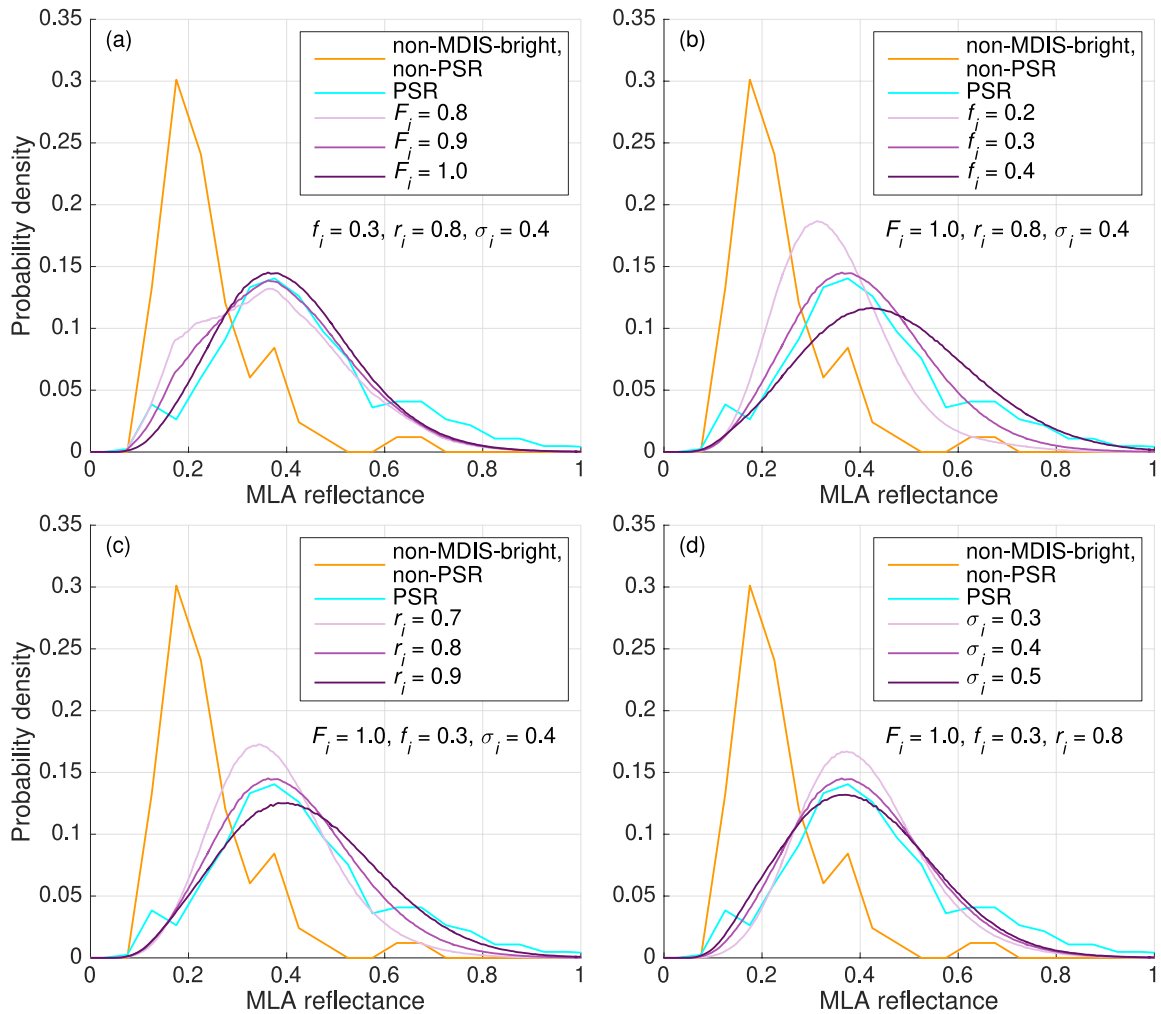


Figure 5 – Effect of varying the mixture model parameters, a) ice-bearing footprint fraction  $F_i$ , b) sub-footprint ice fraction  $f_i$ , c) mean ice reflectance  $r_i$ , and d) ice reflectance spread  $\sigma_i$ . These models use the non-MDIS-bright, non-PSR distribution (orange line) as the dark, non-icy end-member for fitting the PSR distribution (cyan line).

288 The resulting best-fit model (Figure 6) has  $F_i = 1.00$ ,  $f_i = 0.33$ , and  $\sigma_i = 0.40$ . Reasonable fits can  
 289 be obtained with  $F_i$  in the range  $\sim 0.83 - 1.00$  ( $1\sigma$ ),  $f_i \sim 0.24 - 0.42$ , and  $\sigma_i \gtrsim 0.15$ . A high ice-bearing  
 290 fraction  $F_i$  agrees with the broadband MDIS image (Figure 2b) which shows a relatively uniform and  
 291 continuous ice distribution in the MDIS-bright region at the pixel scale of the image ( $188 \text{ m pix}^{-1}$ ).

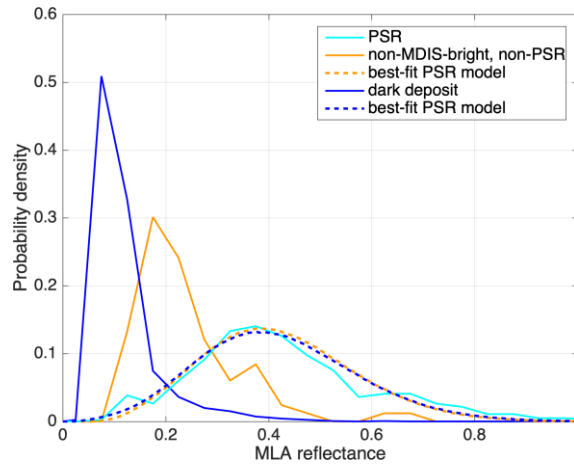


Figure 6 – Best-fit linear mixture models (dashed lines) using (1) the non-MDIS-bright, non-PSR distribution (orange) and (2) dark deposit (blue) as the non-icy end-member to fit the observed PSR distribution (cyan). In both best-fit models, all MLA footprints are ice-bearing ( $F_i = 1.00$ ) while the sub-footprint ice fraction is (1)  $f_i = 0.33$  and (2)  $f_i = 0.44$ .

292            Rather than average non-PSR regolith, the dark material may consist of the same material that  
 293 forms the polar dark deposits, hypothesized to be complex organics. To investigate this scenario, we  
 294 adopt the average PSR reflectance distribution of the 8 H<sub>2</sub>O craters as the dark end-member. This  
 295 distribution (Figure 6) has a peak at ~ 0.08 that is narrower than the dry distribution of the previous model.  
 296 The resulting best-fit looks nearly identical to the previous model and the preferred ice-bearing footprint  
 297 fraction is  $F_i = 0.97 - 1.0$  with sub-footprint ice fraction  $f_i = 0.37 - 0.53$  and ice reflectance spread  $\sigma_i =$   
 298  $0.19 - 0.40$ .

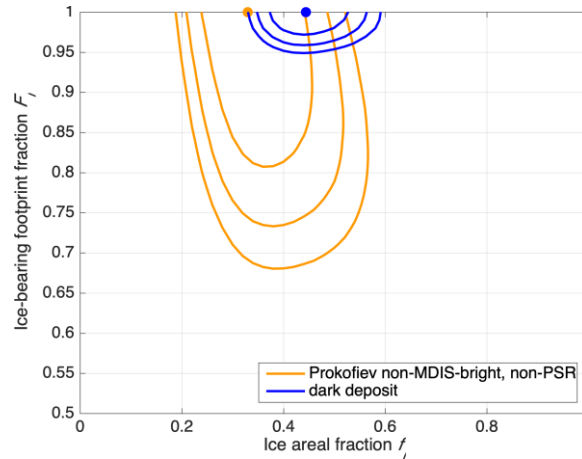


Figure 7 – Best-fit values (solid dots) for the ice-bearing footprint fraction,  $F_i$ , and sub-footprint ice areal fraction,  $f_i$ , with their respective 1, 2, and 3 $\sigma$  uncertainty contours (innermost to outermost). Two models are shown assuming that the dark end-member’s reflectance distribution is the same as that of 1) Prokofiev’s floor outside the MDIS-bright region and PSRs (“Prokofiev non-MDIS-bright, non-PSR”; orange lines), or 2) the 8 H<sub>2</sub>O dark deposits hypothesized to be sublimation lags of complex organics (“dark deposit”; blue lines). In both models,  $f_i < 1$  at high confidence meaning pure ice is strongly disfavored.

299           The results of fitting with the full reflectance distributions are consistent with the first-pass  
 300 estimates based on delta-functions, but allow a fuller treatment of natural variations in the reflectances  
 301 and patchiness of the end-members. Taken together, these models suggest that the majority, and likely  
 302 all, of the MLA footprints in the PSR contain some ice with a sub-footprint areal coverage of at least ~25%  
 303 and possibly as high as ~50% (Figure 7). The models are inconsistent with  $f_i = 1.0$  meaning that pure ice  
 304 is strongly disfavored. In addition, although we assume nothing about the sizes of the patches in this  
 305 checkerboard mixing model, we note that  $F_i \approx 1.0$  implies that the patches are smaller than the typical  
 306 MLA footprint size of ~30 – 40 m, which may also explain why the optically bright deposit looks fairly  
 307 uniform in the MDIS image.

308           If we relax the assumption that the mean ice reflectance  $r_i = 0.8$ , then values of  $f_i$  between ~0.02  
 309 and 1.0 can produce acceptable fits, but they require  $r_i$  to be as high as 7.0 and as low as 0.4,  
 310 respectively. Are such values of ice reflectance reasonable? The single-scattering albedo of pure ice in  
 311 the near-infrared is likely to be very close to unity (Warren & Brandt 2008). However, the normal albedo  
 312 can depend on a variety of factors besides the single-scattering albedo, such as the ice grain size, the  
 313 ice’s macroscopic surface roughness and porosity, the opposition effect amplitude, and the ice grain  
 314 scattering behavior (e.g., the ratio of forward-to-backward scattering in the single particle phase function).  
 315 Little is known about these properties for space-weathered ice at the relevant environmental conditions.  
 316 Hence, our assumption of  $r_i = 0.8$  seems reasonable at this time. This assumption also facilitates

317 comparisons between the Moon and Mercury, a point which we discuss in Section 5.

318 The best-fit models also prefer an ice reflectance spread  $\sigma_i \sim 0.2 - 0.4$  implying a non-negligible  
319 contribution from values much lower and higher than  $r_i$ . An ice reflectance spread may result from natural  
320 variations in the ice properties previously mentioned, some of which may be controlled by spatially  
321 varying environmental conditions, such as temperature. Alternatively, the sub-footprint ice fraction may  
322 vary spatially, mimicking the effect of  $\sigma_i$  with a spread of values for  $f_i$  instead.

323 To investigate the effect of adopting a non-Gaussian reflectance distribution for the pure-ice end-  
324 member, we tried a Chi distribution by fixing its reflectance peak at 0.8 and varying its degrees of  
325 freedom,  $k$ , with the mixture parameters,  $f_i$  and  $F_i$ . This yielded only a marginally better fit with preferred  
326 values of  $k$  in the range 2 – 4 ( $k = 2$  for a Rayleigh distribution) and  $f_i = 0.26$  and  $0.40$ , i.e., within  $1\sigma$  of the  
327 best-fit values obtained with a Gaussian ( $F_i$  was unchanged). This test shows that the precise shape of  
328 the pure-ice reflectance distribution is unlikely to significantly affect the main parameters of interest,  $f_i$  and  
329  $F_i$ .

330 One final important caveat is that other types of mixture models, such as intimate mixing and  
331 intraparticle mixing (Lucey & Riner 2011), may yield different estimates for the ice abundance than the  
332 linear models presented here. Intimate mixing, for example, can hide significantly more ice with a  
333 relatively small abundance of dark grains (Hapke 2012; Yoldi et al. 2015). These models contain more  
334 free parameters than we can constrain with just one wavelength. Multi-spectral data, such as what will be  
335 collected by the Visible and near-Infrared Hyperspectral Imager (VIHI) instrument on the BepiColombo  
336 mission, may allow disentangling these other parameters and distinguishing between different types of  
337 mixtures (Filacchione et al. 2020), if such measurements of PSR surfaces are possible.

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#### 339 4 Topography of the Volatile Deposit

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341 Next, we look at the elevation trends across Prokofiev's floor to identify signatures of the volatile  
342 deposit. We use only the bundle-adjusted MLA altimetry as this provides a consistent set of data both  
343 inside and outside the PSRs. First, Mercury's geoid height was subtracted from the altimetry. This  
344 amounts to a  $\sim 30$  m trend across the whole DEM in the up-down direction (plan view, as in Figure 1).  
345 The resulting mean elevation of the  $\sim 4500$  MLA footprints outside radar-bright regions within a crater-  
346 centric radius of 20 – 38 km is  $-4107 \pm 104$  m and the mean elevation of the  $\sim 2200$  footprints inside radar-  
347 bright regions over the same radial range is  $-4170 \pm 67$  m. This results in a mean elevation difference of -  
348  $67 \pm 124$  m between radar-bright and non-radar-bright regions. Here we consider only crater-centric radii  
349 of 20 – 38 km to avoid the central peak ring area and crater walls. We also exclude the two large craters  
350 at coordinates (194 km, 179 km) and (-81 km, -108 km) as presented in Figure 1a.

351 Subtracting a radially-averaged elevation profile reveals a long-wavelength tilt amounting to a  
352  $\sim 200$  m height decrease across the crater in the direction of roughly 2 o'clock (plan view, Figure 1). This

353 appears unrelated to the volatile deposit as it is not aligned with the radar-bright region, and it is also  
354 present in the sunlit, non-PSR left half (plan view, Figure 1) of the crater. We, therefore, fit a plane to the  
355 floor elevation data allowing the crater centroid to vary while minimizing the residuals around the radially  
356 averaged profile. Accounting for the long-wavelength tilt and allowing the centroid to move improves the  
357 residuals across the entire floor and crater walls.

358 After subtracting the best-fit plane, the radial profile (Figure 8) shows a small trend of increasing  
359 elevation with crater-centric radius which was also evident in the initial profile. The crater centroid moved  
360 to (162.976 km, -82.345 km), roughly 2.5 km from its initial location at the central peak (160.464 km, -  
361 82.043 km), but closer to the center of the peak ring. The post-fit elevation residuals (Figure 9) are ~2 – 3  
362 times smaller compared to pre-fit and are well-centered on zero with a mean of  $0 \pm 53$  m outside radar-

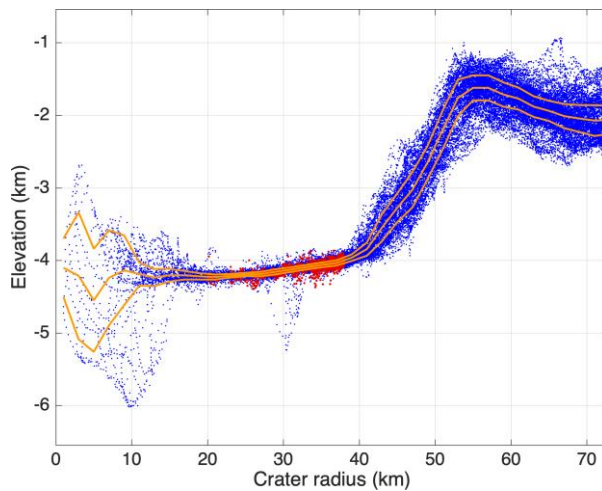


Figure 8 – MLA altimetry (blue points) and best-fit median radial profile and inter-quartile range (orange lines). The red points are the radar-bright MLA footprints.

363 bright regions and  $-8 \pm 50$  m inside radar-bright regions yielding a mean elevation difference of  $-8 \pm 73$  m.  
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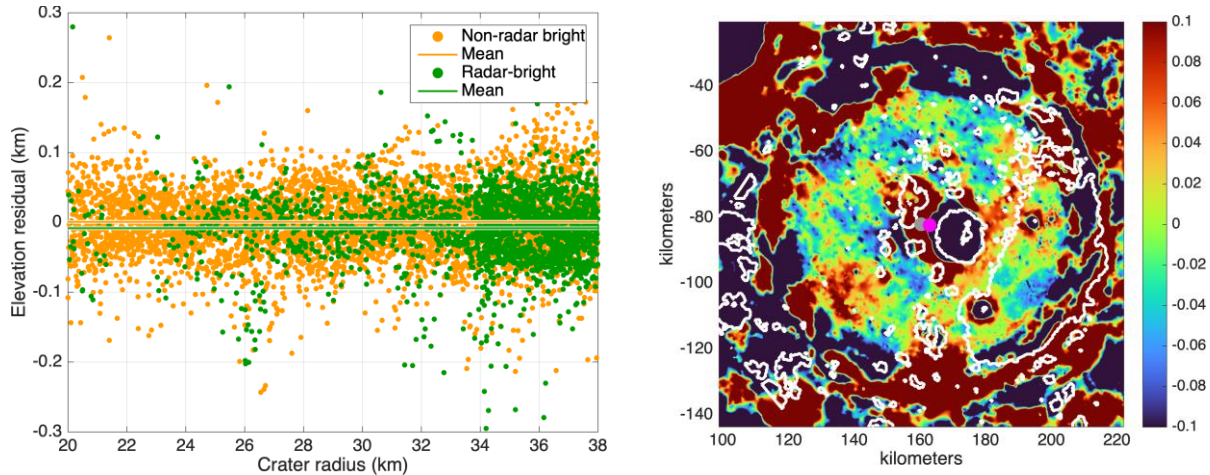


Figure 9 – Left: Elevation residuals of MLA altimetry in radar-bright (green) and non-radar-bright areas (orange) relative to the best-fit radial profile in Figure 8. Right: Elevation residuals (in km) with radar-bright regions overlaid (white lines). The solid gray and magenta circles denote the initial and best-fit crater centroid, respectively.

365 To place an upper limit on the thickness of the volatile deposit, we wish to test the null hypothesis  
 366 that the mean elevation residuals are the same inside and outside the radar bright regions. If the null  
 367 hypothesis is rejected, then that would implicate the ice deposit as the reason for the difference.  
 368 However, natural topographic variations could also lead to a rejection of the null hypothesis. These  
 369 variations are spatially correlated over many length scales because the power spectrum of topography on  
 370 Mercury, and other terrestrial bodies, is not flat as it is for white noise, but rather increases with scale  
 371 (Shepard et al. 2001; Rosenburg et al. 2011; Susorney et al. 2017). This characteristic is responsible for  
 372 the similarly-colored contiguous regions (hills and depressions) up to ~10 km in size on the crater floor in  
 373 Figure 9b. Those patterns could lead us to reject the null hypothesis even without an ice deposit present.  
 374 If the topographic residuals were uncorrelated (i.e., white noise with a flat power spectrum), then there  
 375 would be no such spatial patterns. Thus, we need a control sample with similar topographic variations to  
 376 act as a reference for judging differences between the radar-bright and non-radar-bright regions.  
 377 Computing bundle-adjusted MLA altimetry for a sample of control craters in the same way as done for  
 378 Prokofiev is a task beyond the scope of this work. Instead, to account for the extra uncertainty introduced  
 379 by natural topographic variations, we computed bootstrapped errors by rotating the radar map through  
 380 360 degrees in 1000 equally spaced increments and computing the mean elevation residuals for each  
 381 rotation. The resulting 95<sup>th</sup> percentile of the difference in mean elevation residual between radar-bright  
 382 and non-radar-bright regions was 26 m, which we adopt as an upper limit on the thickness of Prokofiev's  
 383 volatile deposit.

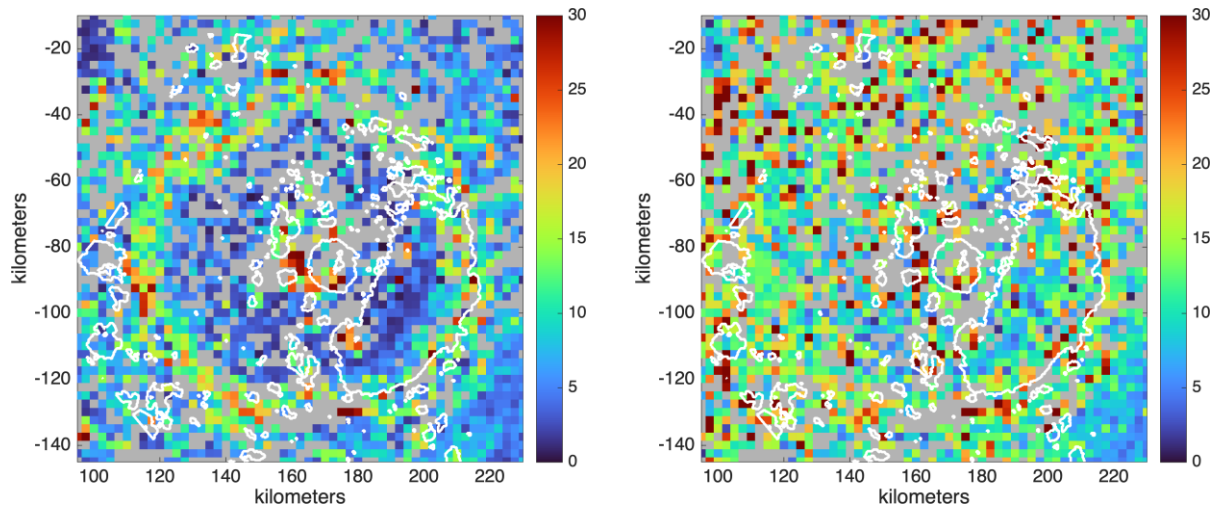


Figure 10 – Left: Slope (in degrees) of plane fits to MLA footprints over a maximum baseline of 1 km. Right: Roughness (in meters) computed as the corresponding slope-detrended standard deviation. Gray pixels contain too few (< 5) MLA footprints for the analysis.

384 We also searched for signatures of ice in the slope and roughness characteristics of Prokofiev’s  
 385 floor. Here again we use the MLA footprints directly since interpolated pixels in the MLA-only DEM could  
 386 lead to biases in slope and roughness. We calculated slope and roughness by stepping through a grid  
 387 with increments of 375 m, and at each grid point fitting a plane to 5 MLA footprints within 500 m. Figure  
 388 10 shows maps of the slope of the plane fit and roughness (detrended standard deviation, i.e., residuals  
 389 of the plane fit) binned at 2.5 km resolution. Characterizing roughness with the detrended standard  
 390 deviation has the advantage of removing most of the correlation between slope and roughness that could  
 391 otherwise confound interpretation of other roughness measures such as the terrain ruggedness index and  
 392 the standard deviation of elevation.

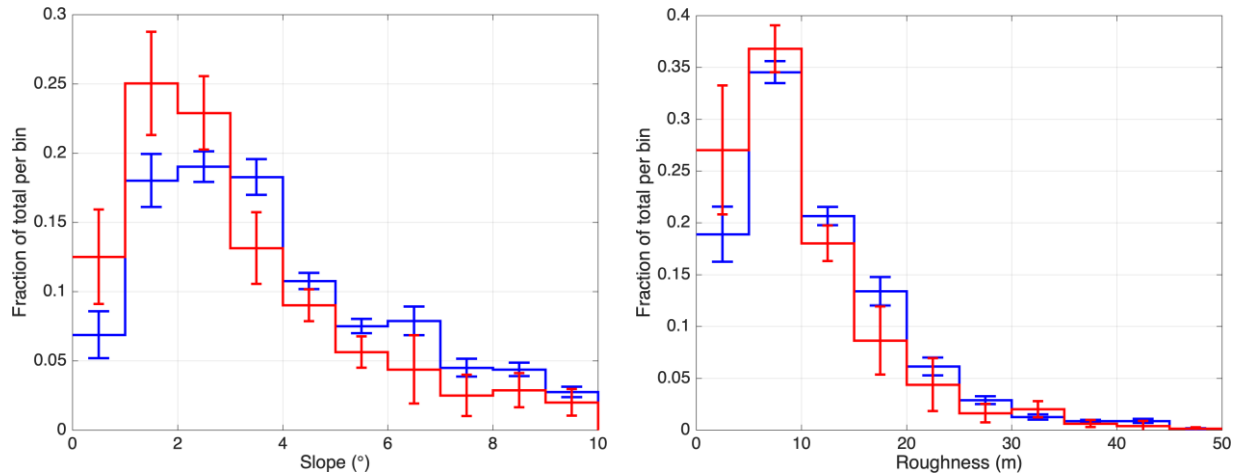


Figure 11 – Histograms of slope (left) and roughness (right) over baselines  $\leq 1$  km inside (red) and outside (blue) radar-bright regions within a crater-centric radius of 20 – 38 km. Error bars represent the standard deviation of a bootstrap sample size of 1000 (see text for details). Roughness is computed only for slopes  $< 10^\circ$ .

393 The slope and roughness distributions inside radar-bright regions appear skewed to smaller  
 394 values than outside radar-bright regions (Figure 11). The mean slope is  $3.8/3.1^\circ$  and the mean roughness  
 395 for slopes  $< 10^\circ$  is  $11.6/10.0$  m in the non-radar-bright/radar-bright regions representing differences of  
 396  $0.7^\circ$  and  $1.6$  m, respectively. To estimate the significance of these differences, we use the bootstrap  
 397 sampling previously described. The observed difference in mean slope and roughness correspond to the  
 398 81<sup>st</sup> and 74<sup>th</sup> percentiles of the bootstrap sample. For comparison, the 95<sup>th</sup> percentiles of the bootstrap  
 399 sample were  $0.9^\circ$  and  $2.2$  m, both larger than the observed values.

400 An Anderson-Darling (AD) test can also be used to assess whether the radar-bright and non-  
 401 radar-bright distributions arise from the same underlying distribution. The AD test is similar to, but more  
 402 powerful than, the Kolmogorov-Smirnov test (Engmann & Cousineau, 2011). If the AD test statistic is  
 403 greater than the critical value for a chosen significance level, then the null hypothesis that the two  
 404 distributions are drawn from the same population is rejected. Here, too, we use the bootstrap sample to  
 405 estimate significance since the natural undulations in topography could lead to erroneous rejection of the  
 406 null hypothesis. For the bootstrap sample, the 95<sup>th</sup> percentile AD test statistics are  $32.4$  and  $25.4$  for slope  
 407 and roughness, respectively, whereas the observed values are  $24.9$  and  $13.1$ , corresponding to the 82<sup>nd</sup>  
 408 and 58<sup>th</sup> percentiles of the bootstrap sample.

409 Altogether, these tests demonstrate that, while the slope and roughness values within the radar-  
 410 bright regions tend to have lower values than outside those regions, these differences do not rise to a  
 411 significance threshold of 95% (p-value of 0.05) when considering the natural topographic variations  
 412 throughout the entire crater floor. Table 1 lists the morphometric parameters derived in this section.

413

	Non-radar-bright	Radar-bright
Mean elevation (m)	-4107 ± 104	-4170 ± 67
Mean elevation residual (m)	0 ± 53	-8 ± 50
Mean slope (°)	3.8 ± 2.3	3.1 ± 2.2
Mean roughness (m)	11.6 ± 8.3	10.0 ± 7.8
Ice deposit thickness upper limit (m)	N/A	26

Table 1 – Main morphometric parameters for Prokofiev derived in this study. Errors are one standard deviation.

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## 5 Discussion

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The new illumination and thermal models presented here confirm earlier indications that the largest radar-bright region of Prokofiev extends past its PSR by up to several km. This transition region is unique on Mercury for hosting a significant radar-bright area outside permanent shadow. Our thermal models indicate that the radar-bright signal in this zone is likely due to sub-surface ice within the top ~1 – 2 m. The high crater density on Prokofiev’s floor suggests that it may host small-scale, sub-resolution cold traps that allow ice to exist even closer to the surface (Rubanenko et al. 2018).

Does Prokofiev’s floor contain a dark deposit like what is seen in the H20 craters? Prokofiev’s  $T_{\max}$  distribution (Figure 12) is shifted to lower values relative to the H20 craters and it has a significant area with  $T_{\max} < 300$  K, the approximate stability temperature of the dark deposit material hypothesized by H20 ( $300 \pm 50$  K). Therefore, we might expect Prokofiev to host a widespread dark deposit; yet visual inspection of the MDIS images does not reveal any clear signatures of one and the MLA reflectance of Prokofiev’s non-radar-bright floor does not resemble that of the dark deposits (Figure 4).

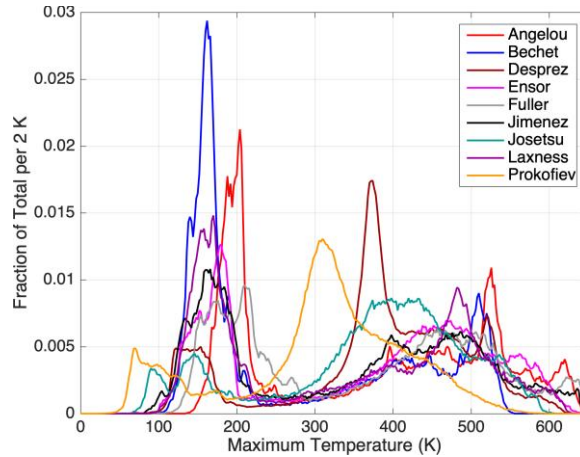


Figure 12 – Distribution of  $T_{\max}$  for Prokofiev compared to that of the smaller, lower-latitude dark deposit craters studied in H20. Prokofiev’s non-radar-bright floor exhibits a peak at  $T_{\max} \sim 310$  K.

430 Broadly speaking, each crater’s  $T_{\max}$  distribution in Figure 12 is bimodal with a cold peak at  $T_{\max} <$   
 431 250 K on its southern half and a hot peak at  $T_{\max} > 250$  K on its northern half. The generally higher  $T_{\max}$   
 432 peak of the other craters compared to that of Prokofiev is consistent with expectations from thermal  
 433 models that PSR temperatures generally increase toward lower latitudes and that small bowl-shaped  
 434 craters tend to be hotter than larger, flat-floored craters (Vasavada et al. 1999). Given the lack of an  
 435 obvious widespread dark deposit in Prokofiev and the fact that most of its floor has  $T_{\max} > 250$  K, the  
 436 stability temperature of the dark deposit material may be closer to 250 K than 300 K. Alternatively, the  
 437 lack of a dark deposit on Prokofiev’s relatively warm floor compared to other craters (Figure 12) may  
 438 suggest that the dark deposits are only present in areas where ice was at least temporarily stable or sub-  
 439 surface ice is stable, suggesting such conditions may be needed if the dark deposit material is due to the  
 440 formation of a lag deposit over stable water ice.

441 The MLA reflectance distribution within Prokofiev’s largest PSR suggests the presence of a  
 442 darker-than-ice surface material. What is this material? Two possibilities are silicates and/or organics  
 443 delivered simultaneously with the ice or through subsequent impacts. If the ice is as young and as thick  
 444 as hypothesized, then it seems unlikely that there has been enough time for impact gardening to bring  
 445 significant quantities of silicates to the surface from below the ice (Costello et al. 2020). Chemical  
 446 processing of organics by high energy radiation from Mercury’s magnetosphere may also act to  
 447 continuously increase the near-surface abundance of dark material (Crites et al. 2013; Delitsky et al.  
 448 2019). Ice loss through non-thermal processes, such as impact vaporization and ejection (Farrell et al.  
 449 2019) and desorption by Ly- $\alpha$  radiation (Morgan & Shemansky 1991) may increase the relative proportion  
 450 of the dark material, as well.

451 According to the linear mixture models derived here, the total ice areal fraction on the surface is  
 452  $\sim 25 - 50\%$ , suggesting that highly pure surface ice is not producing the optically-bright PSR seen in MDIS

453 images and MLA data. Strictly speaking, this result only applies to the MLA sensing depth, which is  
454 unknown precisely, but likely to be very small ( $\approx 1$  mm). Hence, the ice abundance just below the surface  
455 may be larger than this estimate. We also note again that other mixing modalities, such as intimate  
456 mixing, may hide significantly more surface ice than inferred from these linear models (Hapke 2012; Yoldi  
457 et al. 2015). However, a “dirty” surficial ice layer covering Prokofiev’s largest PSR is qualitatively  
458 consistent with the dirty ice inferred from radar-scattering models (Rivera-Valentín et al. 2022) suggesting  
459 a correlation between the surface and sub-surface impurities. Previous comparisons between S-band and  
460 X-band observations of Prokofiev were reported in Harmon et al. (2011). The differences were minor for  
461 Prokofiev but suggested to possibly be due to pure surface ice not exposed directly at the surface but  
462 covered by some amount of regolith.

463 A major unresolved question is why the surface ice stability regions in the Moon’s PSRs do not  
464 show bright reflectance features like that observed in Prokofiev (Koeber et al. 2014). In their study of the  
465 LOLA 1064 nm normal albedo in lunar south polar PSRs, Fisher et al. (2017) estimated a total ice-bearing  
466 footprint fraction of 75% and sub-footprint areal ice coverage of 7%. Assuming the same near-IR ice  
467 normal albedo ( $r_i = 0.8$ ), we have found in Prokofiev an ice-bearing footprint fraction  $\sim 80 - 100\%$  and sub-  
468 footprint areal ice coverage  $\sim 30 - 50\%$ . This suggests that surface ice in Prokofiev is at least  $\sim 4 - 10$   
469 times more abundant than at the Moon’s south pole. More generally, these results may provide an  
470 approximate minimum threshold of ice coverage for detectability by optical scattered-light imaging as  
471 done with MDIS (Chabot et al. 2014) and the Lunar Reconnaissance Orbiter Narrow Angle Camera  
472 (Koeber et al. 2014). Upcoming ShadowCam imagery from the Korean Pathfinder Lunar Orbiter  
473 spacecraft may help confirm such small areal coverages on the Moon (Robinson et al. 2018). One  
474 explanation for the presence of much more extensive ice in Mercury’s polar PSRs in comparison to the  
475 Moon is that Mercury’s ice is relatively young, perhaps delivered by a recent impactor, such as the one  
476 which made the rayed crater Hokusai (Ernst et al., 2018). In this scenario, as regolith gardening continues  
477 on Mercury, Mercury’s volatile polar deposits may evolve to resemble those of the Moon.

478 Finally, we investigated three different possible topographic expressions of Prokofiev’s volatile  
479 deposit, namely, average height, slope, and roughness. None of these showed a clear difference  
480 between radar-bright and non-radar-bright floor regions. Any differences that do exist are likely to be  
481 comparable to, or smaller than, the unrelated natural topographic undulations present on the crater floor.  
482 The radar-bright deposit had an overall lower elevation ( $-8 \pm 73$  m) compared to the non-radar-bright floor  
483 even after removing a long-wavelength trend. Using 5 hand-edited individual MLA tracks in Prokofiev,  
484 Susorney et al. (2019) estimated a mean elevation difference of  $36 \pm 60$  m between radar-bright and non-  
485 radar-bright regions. We attribute the difference between their estimate and ours to the limited spatial  
486 sampling of 5 MLA tracks and the natural elevation variability on Prokofiev’s floor. By combining similar  
487 measurements in 3 other radar-bright craters and comparing them to a control sample of 8 non-radar-  
488 bright craters, Susorney et al. (2019) derived an overall upper limit on the average ice deposit thickness

489 of 15 m. This is smaller than our upper limit of 26 m for Prokofiev, but formally it applies to the average  
490 thickness in several craters whereas the thickness in any one crater could be larger. While our limit is  
491 higher, it is more directly applicable to Prokofiev alone and it utilizes all the available MLA altimetry with  
492 reduced geolocation errors.

493         Regarding slope and roughness, Prokofiev's radar-bright floor tends to have lower values than its  
494 non-radar-bright floor. This is qualitatively consistent with other detections of reduced roughness in some  
495 PSRs on the Moon and Mercury (Deutsch et al. 2021a; 2021b). Those studies hypothesized this behavior  
496 may be due, on the Moon, to ice subduing surface topography and, on Mercury, to the young ages of the  
497 deposits and material property differences between ice and regolith. However, as in Prokofiev, there was  
498 considerable overlap in the roughness distributions inside and outside those PSRs due to natural  
499 topographic variations. Denser sampling of topography throughout the polar regions of both the Moon and  
500 Mercury would allow tighter constraints on the subtle surface expression of ice.

501

502

## 6 Conclusions

503

504         Using MDIS images and refined MLA altimetry, we derived a new high-resolution DEM of  
505 Prokofiev, which we then used to compute illumination and thermal models for this crater. The new  
506 models confirmed previous results that the largest radar-bright region in Prokofiev extends up to several  
507 kilometers past its PSR making this region unique on Mercury for hosting a significant radar-bright area  
508 outside a PSR, likely due to sub-surface ice.

509         The near-infrared normal albedo distribution of Prokofiev's PSR suggests the presence of a  
510 darkening agent mixed with the surface ice. Linear mixture models predict that at least roughly half of the  
511 surface area is covered with the dark material suggesting that highly pure surface ice is not producing the  
512 optically-bright deposit. The dark material may be composed of silicates or hydrocarbons  
513 contemporaneously delivered with the ice or through subsequent impacts. Chemical processing of  
514 organics by high-energy radiation and ice loss through non-thermal processes may also increase the dark  
515 material's relative abundance. This is the first estimate of the dark material's abundance specifically in  
516 Prokofiev which may be used to place limits on the age of the ice.

517         Using all the improved MLA altimetry available in Prokofiev, we placed an upper limit of 26 m on  
518 its ice deposit thickness. The topographic slope and roughness of the ice deposit on baselines < 1 km are  
519 lower than they are outside the deposit although the difference is not statistically significant when  
520 compared to the entire floor's topographic variations.

521         These results place new constraints on the nature of Prokofiev's volatile deposit that will inform  
522 future missions, such as BepiColombo. Higher-resolution topography combined with diffuse-light spectral  
523 imaging will be critical to better understand the role of small-scale cold traps and the amount of water in  
524 Prokofiev's icy upper layers.

525 Data Availability

526 The data used here can be downloaded from the NASA Planetary Data System ([https://pds-](https://pds-geosciences.wustl.edu/)  
527 [geosciences.wustl.edu/](https://pds-geosciences.wustl.edu/)), Planetary Geodesy Data Archive (<https://pgda.gsfc.nasa.gov/>) and the Johns  
528 Hopkins Applied Physics Laboratory Data Archive ([https://lib.jhuapl.edu/papers/new-constraints-on-the-](https://lib.jhuapl.edu/papers/new-constraints-on-the-volatile-deposit-in-mercury/)  
529 [volatile-deposit-in-mercury/](https://lib.jhuapl.edu/papers/new-constraints-on-the-volatile-deposit-in-mercury/)).

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