Retrievals of Arctic sea ice melt pond depth and underlying ice thickness using optical data

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Abstract  Melt pond is a distinctive characteristic of the summer Arctic, which affects energy balance in the Arctic system. The Delta-Eddington model (BL) and Two-stream rAdiative transfer model (TEA) are employed to retrieving pond depth \( H_p \) and underlying ice thickness \( H_i \) according to the ratio \( X \) of the melt-pond albedo in two bands. Results showed that when \( \lambda_1 = 359 \) nm and \( \lambda_2 = 605 \) nm, the Pearson’s correlation coefficient \( r \) between \( X \) and \( H_p \) is 0.99 for the BL model. The result of TEA model was similar to the BL model. The retrievals of \( H_p \) for the two models agreed well with field observations. For \( H_i \), the highest \( r \) (0.99) was obtained when \( \lambda_1 = 447 \) nm and \( \lambda_2 = 470 \) nm for the BL model, \( \lambda_1 = 447 \) nm and \( \lambda_2 = 451 \) nm for the TEA model. Furthermore, the BL model was more suitable for the retrieval of thick ice \( (0 < H_i < 3.5 \) m, \( R^2 = 0.632) \), while the TEA model is on the contrary \( (H_i < 1 \) m, \( R^2 = 0.842) \). The present results provide a potential method for the remote sensing on melt pond and ice in the Arctic summer.

Keywords  Arctic, melt pond, sea ice, remote sensing, albedo


1  Introduction

Sea ice is the most important feature covering the ocean surface in the Arctic (Perovich et al., 2003). It can prevent direct heat exchange between the atmosphere and the ocean under sea ice by reflecting incident solar radiation, and plays an important role in regulating changes in the global climate and natural environment (Lenton, 2012; Qin et al., 2014).

In recent years, many studies have shown that Arctic summer sea ice is rapidly declining, not only in extent and area (Strove et al., 2007), but also in thickness. This is clear, especially in the later period of melting, which involves shrinking and thinning (Kwok and Rothrock, 2009). After Arctic sea ice begins to melt, melt-water from sea ice and snow accumulates in depressions of the sea-ice surface to form melt ponds. From June to September, the seasonal evolution of melt ponds can be observed to fall into five stages: pond formation, pond drainage, pond evolution, open water, and fall freeze-up. Before the pond refreezes, the pond depth increases gradually, and the underlying ice thickness decreases simultaneously (Polashenski et al., 2012; Lu et al., 2018a). This results in more solar radiation being absorbed by the sea ice and the underlying ocean due to the gradually decreasing broadband albedo, further promoting the melting of sea ice (Katlein et al., 2015; Perovich et al., 2002a).

Melt ponds play an increasingly important role in the melting of Arctic sea ice. Specifically, the depth of the melt pond is an important parameter. As melt pond depth increases, the surface broadband albedo of the melt pond decreases rapidly, especially in the initial stage of melt pond formation (Makashtas and Podgorny, 1996; Lu et al., 2016). Moreover, melt ponds have a significant energy absorption capacity, which greatly affects the partitioning of solar energy within the atmosphere, melt pond, underlying sea ice, and the ocean beneath the ice. As the depth of the melt pond

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increases, the energy absorbed by the melt pond becomes significantly greater than the energy absorbed by the underlying ice and ocean under the ice (Lu et al., 2018b). Melt ponds also affect the desalination process of sea ice. The coalesced brine channels due to the increasing porosities during melting give rise to downward flushing of surface meltwater into the ocean due to gravity and reduce the salinity of Arctic summer sea ice (Notz and Worster, 2009). In recent years, more and more numerical simulations have been incorporated into explicit melt pond models or parameterizations to consider the effects of melt ponds. Skillingstad et al. (2009) described the growing process of melt ponds on permeable sea ice in the Arctic and found that the melting rate of the sidewalls of the melt pond was greater than that of the underlying ice. The model of Popović and Abbot (2017) considered melt pond growth caused by vertical melting of the sea ice bottom. They found that the melt pond growth rate was more sensitive to changes in bare vertical melting of the sea ice bottom. They found that the surface albedo of a melt pond was mainly dependent on pond depth \( H_p \) and underlying ice thickness \( H_i \).

However, due to the severe weather conditions and marine environment in the Arctic region, existing observations of melt ponds mainly focus on the horizontal scale, such as coverage and size (Perovich et al., 2002b; Li et al., 2017; Wang et al., 2020). Whereas, few studies have recorded the depth evolution process of a melt pond (Scott and Feltham, 2010; Tsamados et al., 2015). The main reason for this is that melt ponds are relatively shallow, and their depth is difficult to determine by satellite remote sensing. In addition, changes in \( H_p \) are related to \( H_i \) (Holland et al., 2006), and the remote sensing data of the Arctic summer sea ice thickness has always been gap (Ji, 2015). The ICESat and Cryosat-2 satellites only provide sea ice thickness data in the period from October to April of the next year. The reason is closely related to the accuracy of leads identifying, the algorithm model parameters (snow thickness and density, sea ice and ocean density) and the uncertainty of microwave or laser penetration depth in the melting ice (Kwok and Cunningham, 2008; Ji et al., 2015). ICESat-2 is capable to distinguish between leads and ponds. Farrel et al. (2020) showed the potential of ICESat-2 for \( H_p \) retrieval.

To make up for the lack of existing sea-ice remote-sensing products in summer and to provide strong data support for simulating and verifying rapid changes in melt ponds and sea ice, this paper explores the possibility of using the reflection characteristics of summer sea ice to retrieve \( H_p \) and \( H_i \) based on four methods (Legleiter et al., 2014; Lu et al., 2018a; Malinka et al., 2018; König and Oppelt, 2020). The four existing methods are introduced in Section 2. Improvement to the method proposed by Legleiter et al. (2014) and validation using field measurement are presented in Section 3. The influence of sky conditions is discussed in Section 4. Conclusions are finally drawn in Section 5.

## 2 Retrieval methods of \( H_p \) and \( H_i \)

### 2.1 Summary of previous retrieval methods

Table 1 summarizes the major methods proposed in recent years for retrieving \( H_p \) and \( H_i \) according to optical properties. Also shown are the main ideas and the calculation processes of each method.

<table>
<thead>
<tr>
<th>Reference</th>
<th>Ice type</th>
<th>Input parameters</th>
<th>Output parameters and the range used for verification</th>
<th>Accuracies</th>
<th>Advantage</th>
<th>Notes</th>
<th>Illumination condition</th>
<th>Instrument setups</th>
</tr>
</thead>
<tbody>
<tr>
<td>Legleiter et al., 2014</td>
<td>Glacier ice</td>
<td>Melt pond spectral reflectance ( H_p ) ( (H_p) ) ( 0.31-10.45 \text{ m} )</td>
<td>( R^2=0.93 ) ( c=0.65 \text{ m} ) ( (n=4398) )</td>
<td>This study demonstrated the feasibility of use WV2 to retrieve ( H_p ) on the Greenland ice sheet. The deeper the pond depth, the better the retrieval effect.</td>
<td>This method did not establish a general relation between ( H_p ) and reflectance</td>
<td>Good atmospheric conditions</td>
<td>Spectrometers</td>
<td></td>
</tr>
<tr>
<td>Lu et al., 2018a</td>
<td>Sea ice</td>
<td>Melt pond color (RGB or HSL intensity) ( H_i ) and ( H_p ) ( (H_i&lt;1 \text{ m}) )</td>
<td>( H_p R^2=0.671 ) ( c=0.156 \text{ m} ) ( (n=5) )</td>
<td>The color of melt ponds is easy to measure, the retrieval effect of thin ice is better ( (H_i&lt;1 \text{ m}) )</td>
<td>The relationship between simulated and measured ( H_p ) is not apparent.</td>
<td>Overcast sky condition</td>
<td>Digital camera</td>
<td></td>
</tr>
<tr>
<td>Malinka et al., 2018</td>
<td>Sea ice</td>
<td>Melt pond surface spectral albedo ( H_i ) and ( \sigma ) ( (H_i) ) ( 0-0.5 \text{ m}, ; H_i ) ( 0-3 \text{ m} )</td>
<td>( H_i R^2=0.56 ) ( c=0.215 \text{ m} ) ( (n=8) ) ( H_i R^2=0.62 ) ( c=0.582 \text{ m} ) ( (n=26) )</td>
<td>The model considers different illumination conditions. And the retrievals results of ( H_i ) are reasonable.</td>
<td>Retrievals results of ( H_p ) are more uncertain</td>
<td>Clear and overcast sky conditions</td>
<td>Spectrometers</td>
<td></td>
</tr>
<tr>
<td>König and Oppelt, 2020</td>
<td>Sea ice</td>
<td>The slope of the log-scaled spectrum at 710 nm and the solar zenith angle ( H_p ) ( (H_p) ) ( 0-0.3 \text{ m} )</td>
<td>( R^2=0.79 ) ( c=0.028 \text{ m} ) ( (n=48) )</td>
<td>Not affected by the characteristics of the underlying ice</td>
<td>The method is now only suitable for clear sky condition and cannot be used for ( H_i ) retrieving now</td>
<td>Clear sky condition</td>
<td>Spectrometers</td>
<td></td>
</tr>
</tbody>
</table>
2.1.1 Method of Legleiter et al.

Legleiter et al. (2014) retrieved Greenland glacier melt pond depth based on the ratio of the reflectance of different bands. Due to the instruments being placed over sub-kilometer distances, the differences in solar zenith angle between the sensors were negligible. The reflectance $R$ was obtained by multiplying the ratio of upwelling spectral radiance to downwelling spectral irradiance ($R_n$) by $\pi$, because a Lambertian bidirectional reflectance distribution function was assumed. Under these conditions, reflectance $R$ equals albedo.

The basic theory is that the total upwelling irradiance $F_\lambda$ on the surface of a melt pond is the sum of contributions from the bottom, the water column, the water surface, and the atmosphere ($F_\lambda^{atm}$). Among these components, only the irradiance reflected from the pond bottom, $F_\lambda^{b}$, is directly related to depth; it decreases exponentially with increasing $H_p$. Radiative transfer in the melt pond is mainly affected by the absorption coefficient $k$ of the water. The long-wave irradiance $F_\lambda^{l}(\lambda_2)$ attenuates faster than the short-wave irradiance $F_\lambda^{s}(\lambda_1)$ ($k_2 > k_1$), $\lambda_2$ and $\lambda_1$ represent different wavelengths. $F_\lambda^{l}(\lambda_2)/F_\lambda^{s}(\lambda_2)$ increases with greater $H_p$. Therefore, the upwelling irradiance ratio $X$ of different bands can be used to express the influence of melt pond water depth on radiation attenuation. For the same incident irradiance, the ratio of upwelling irradiance at different bands can also be simplified as the ratio of albedo. Under reasonably good atmospheric conditions where $H_p$ is tens of centimeters and the water is relatively clear, other irradiance components in the melt pond can be ignored (Legleiter et al. 2009). $F_\lambda^{s}(\lambda)$ mainly depends on $F_\lambda^{b}(\lambda)$. Furthermore, $X$ and $H_p$ are linearly related.

Using field observations to verify this theory, it was determined that when $\lambda_1 = 584$ nm, $\lambda_2 = 599$ nm, the correlation between $X$ and $H_p$ was the highest ($R^2 = 0.94$). And the correlation coefficient matrix also indicated that many other band combinations had $R^2$ values that were almost as high. Legleiter et al. (2014) convolved the field spectra to match the spectral response functions of the WorldView2 (WV2) satellite and found that the correlation was still high. Finally, to verify the feasibility of using satellite data to retrieve $H_p$, a correlation analysis was conducted between a randomly selected subset (50%) of $H_p$ measured in the field and $X$ obtained from WV2 satellite images, and the largest correlation coefficient between $X$ and $H_p$ was $R^2 = 0.92$. Using the other half of the observed data for verification, the correlation coefficient between the retrieved and the measured $H_p$ was $R^2 = 0.93$ and $\epsilon = 0.65$ m, which proved that this method could be used for the satellite to retrieve $H_p$.

2.1.2 Method of Lu et al.

Lu et al. (2018a) established a quantitative relationship between the color $C$ of melt pond and both $H_o$ and $H_i$. Color is an apparent optical property that is easy to observe. Physically, there is no distinct difference between color and albedo because both are quantities describing the reflected radiation by a surface. However, mathematically, color here refers to the values measured by a digital camera in the visible band. The value of a color consists of three intensity values in different bands: red, green, and blue.

In the Arctic summer, even on the same ice floe, the color of melt ponds varies greatly, depending largely on the nature of the water body and the underlying ice. The TEA model is used to calculate the albedo of the melt pond, by utilizing the colorimetric method that converts the reflection spectrum into the three RGB primary colors. Then, the relationship between $H_o$, $H_p$, and the color $C$ can be established.

Melt pond color $C$ is affected by pond depth, underlying ice thickness, the incident solar radiation level and optical properties of ice. The influences of $H_i$ and $H_p$ are the most important. So, pond color can be expressed as $C = f(H_i, H_p)$, where $C$ is a vector composed of the intensities of red, green, and blue in the RGB color space or of hue, saturation, and brightness in the HSL (hue-saturation-luminance) color space. The $C$ calculated by this model was consistent well with measured results ($R^2 = 0.676$), which proved the feasibility of the proposed method. This indicated the possibility of retrieving $H_i$ and $H_p$ from melt pond color, i.e., $(H_i, H_p) = f^{-1}(C)$. The retrievals $H_i$ and $H_p$ of the inverse function were compared with the measured data. The relationship between simulated and measured $H_i$ was not clear. So did for $H_p$. But a good agreement can be found for thin ice with $H_i < 1$ m ($R^2 = 0.671$ and $\epsilon = 0.156$ m).

2.1.3 Method of Malinka et al.

Malinka et al. (2018) showed that pond reflectance is mainly determined by the albedo of the underlying ice. The basic idea is based on radiation transfer theory. If the absorption and transport scattering coefficients of the underlying ice are known, then a two-stream approximation can be used to calculate the melt pond bottom albedo $a_b$ ($a_b = f(a_i, H_i)$), where $a_i$ is the transport scattering coefficient of under-pond ice, and the absorption coefficient of sea ice is equal to that of pure ice. The melt pond surface albedo $a$ can be further calculated using $a_b$ and $H_p$. Therefore, $a$ is mainly determined by three parameters: $H_p$, $a_i$, and $H_i$. For the illumination conditions, Malinka et al. (2018) considered both the direct and diffuse incident solar radiation. Clear sky conditions were influenced by the solar zenith angle, while for overcast conditions diffuse radiance was assumed. For a mixture of direct and diffuse incidence, Malinka et al. (2018) confirmed the effect of the background was negligible, so the results of the melt pond albedo measurements can be processed without a prior knowledge of the albedo of the surrounding background. Melt ponds have a smaller and constant albedo contrast to white ice and snow for wavelengths longer than 0.9 $\mu$m.
Because snow and ice have a local maximum at about 1.1 μm. Thus, this slight peak can be considered as a criterion for determining if a spectrum is taken entirely from an open pond or partially from snow/ice surface. In the Arctic, most sky conditions were overcast in summer, so only a few measurements were taken at clear sky conditions. In the cases of overcast sky, the measured albedo was interpreted as the white-sky one. In the clear-sky cases, the Rayleigh atmosphere with the Arctic background aerosol was assumed. In this case the solar incidence angle was determined from the pond reflection in the infrared range (IR): at intervals of 1.25–1.3 μm (ideal) or 0.85–0.9 μm.

These three parameters, \( H_\alpha, H_\iota, \) and \( \sigma \), make up a 3-D vector, which was varied according to the Newton-Raphson method to provide the best fit (in the sense of least squares) of the measured and modeled spectra. Malinka et al. (2018) verified this model with different field observation data sets. The retrievals results of \( H_\iota \) were found to be essentially consistent with the measured value \( (R^2 = 0.56 \) and \( \epsilon = 0.215 \) m). Due to the pond reflectance depends poorly on its water depth, the retrieval of the \( H_\iota \) is uncertain: its value can differ up to 2 times from the measured one \( (R^2 = 0.62 \) and \( \epsilon = 0.582 \) m).

### 2.1.4 Method of König and Oppelt

The method proposed by König and Oppelt (2020) uses the spectral data of bare ice surfaces to simulate melt pond spectra for model development and validate the model with in situ melt pond measurements. The specific steps are to define a water column without absorption and scattering water constituents on bare ice and to calculate the reflectance of the water surface. The depth of the water column and the type of underlying ice can both vary, and finally a reflection spectrum library containing five different types of underlying ice and different melt pond depths between 0 and 100 cm can be generated. Based on this spectral library, the correlation between \( H_\iota \) and the slope of the log-scaled spectrum, \( \gamma(\lambda) \), was studied. It was found that the \( r \) between \( H_\iota \) and \( \gamma \) was −1 when \( \lambda \) was in the range of 700–750 nm. Analysis of field observation data confirmed this conclusion, with the \( r \) of about −0.9 for field measurements of \( H_\iota \) and \( \gamma \) in the vicinity of the \( \lambda=700 \) nm band. And the slope of the log-scaled spectrum at 710 nm was widely independent of the bottom albedo. Based on this correlation, the slope of the log-scaled spectrum at 710 nm of the pond surface can be used to establish a linear model: \( H_\iota = f(\gamma(710 \text{ nm})) \). The slope and intercept of the linear model is influenced by the solar zenith angle. Therefore, the inputs for this model were the slope of the log-scaled spectrum and solar zenith angle. The theoretical depth range of the retrieval was 0–100 cm. And the model is only suitable for clear sky conditions. A strong linear correlation \( (R^2 = 0.74 \) and \( \epsilon = 0.028 \) m) is shown in the comparing between the simulated \( H_\iota \) and measured \( H_\iota \) with solar zenith angles varies from 58.9° to 61°.

### 2.2 Evaluation for the four methods

To achieve the retrieval of \( H_\iota \) and to take summer sea-ice thickness into account at the same time, the four methods described above must be improved based on a comprehensive assessment. Method of Legleiter et al. (2014) demonstrated the feasibility of retrieving \( H_\iota \) through melt pond surface albedo in a specific band. The results could be matched with the observation band of the remote-sensing satellite to achieve large-scale observations and retrievals. Although the Arctic summer \( H_\iota \) and \( H_\iota \) were both less than those of glaciers, which increased the uncertainty and difficulty of retrieving \( H_\iota \) and \( H_\iota \). However, the changes in the underlying ice caused changes in the surface reflection characteristics (Lu et al., 2016). So, this method is hoped to show changes in \( H_\iota \) and \( H_\iota \) by varying albedo.

Method of Lu et al. (2018a) show a good agreement when retrieving thin ice \( (H_\iota < 1 \text{ m}) \) \( (R^2 = 0.671 \) and \( \epsilon = 0.156 \) m), and a clear relationship between simulated and measured \( H_\iota \) is not shown. The retrieval \( H_\iota \) from method of Malinka et al. (2018) was reasonable \( (R^2 = 0.56 \) and \( \epsilon = 0.215 \) m). But the \( H_\iota \) retrieval was uncertain \( (R^2 = 0.62 \) and \( \epsilon = 0.582 \) m) and no improvement can be achieved unless additional information was used other than spectral reflectance in the visible range. The retrieval \( H_\iota \) from method of König and Oppelt (2020) requires a spectrum library based on field observation data, and the model is suitable for clear sky conditions. And cannot be used for retrieving \( H_\iota \) at its present state. The model is theoretically valid for the depth range of 0–100 cm and is influenced by solar zenith angle. In Figure 11 of König and Oppelt (2020), validations using field observations were conducted only within the depth range of 0–30 cm with sun zenith angles between 58.9° and 61°. To enlarge its validity range, more field data covering different weather and illumination conditions are necessary.

To sum up, we take the spectral albedo (350–1000 nm) into consideration and try to find two optimal bands for retrieving \( H_\iota \) and \( H_\iota \) according to Method of Legleiter et al. (2014). With more field data and more consideration of uncertain factors, e.g., the inherent optical properties (IOPs) of sea ice, the method could further reduce the uncertainty in retrievals. Therefore, it is theoretically feasible to separate the effects of \( H_\iota \) and \( H_\iota \) from the reflection characteristics.

### 2.3 Improvement and application of method

To find a general relationship between \( H_\iota \) and surface spectral albedo, two radiative transfer models are employed to implement the retrieval method of Legleiter et al. (2014). The estimated results of two models were used to build the retrieval method, then the field measurement data were used to verify the method. The TEA is a two-stream radiative transfer model which is under the assumptions of diffuse incident solar radiation and isotropic scattering. Assuming the continuity of radiation fluxes at the air-pond, pond-ice,
and ice-ocean interfaces, the irradiance in both directions in each layer can be calculated as well as the melt-pond albedo \(a_p\). The model is governed by two coupled first-order differential equations (Lu et al., 2016):

\[
\begin{align*}
\frac{dF^+(z,\lambda)}{dz} &= -k_i F^+(z,\lambda)dz - \sigma_i F^+(z,\lambda)dz + \sigma_0 F^+(z,\lambda)dz \\
\frac{dF^-(z,\lambda)}{dz} &= -k_i F^-(z,\lambda)dz + \sigma_i F^-(z,\lambda)dz - \sigma_0 F^-(z,\lambda)dz
\end{align*}
\]

where \(\sigma_0\) is the wavelength-dependent scattering coefficient, and \(k_i\) is the absorbing coefficient. \(00(z, \lambda)\) are the upwelling and downwelling irradiances respectively. The BL model sub-divides the melt pond into two layers and the IOPs of each layer are constant.

In contrast with TEA, the BL model is also employed here. It also divides the underlying ice into one “drained layer (DL)” and four “interior layers (INT)”. The thickness of the DL and first INT is 1/4 of layer (DL)” and four “interior layers (INT)”. The thickness here. It also divides the underlying ice into one “drained layer (DL)” and four “interior layers (INT)”. Therefore, both models used the OBRA method, and the retrieval method for \(H_p\) was similar. The two radiative transfer models were used to conduct theoretical calculations, to enable comparisons, and to increase the reliability of the results.

### 3 Results

#### 3.1 Pond depth-spectral albedo relations

In this study, \(H_p\) was assumed to vary between 0 and 0.5 m, and \(H_f\) vary between 0.1 and 5 m. The range of ice thickness was slightly larger than the current state in the Arctic summer (Lang et al., 2017; Lu et al., 2018a). However, it was still beneficial to record the outcome of the proposed model under limited conditions. The improved OBRA method was used to calculate \(r\) between \(X = (\lambda_1, \lambda_2)\) and \(H_p\). Figure 1 shows the results. The selected waveband range was between 350 and 1000 nm, the main reasons are the strong interaction with water, ice, and snow, with 70%-80% of the solar energy reaching the Earth’s surface contained in this waveband (Liou 2002; Lu et al., 2016).

In respect to the results of the BL model, Fig. 1 shows that there were two situations in which \(X\) was strongly correlated with \(H_p\). In the first situation, \(\lambda_1\) was between 350 and 600 nm and \(\lambda_2\) was between 600 and 800 nm; in the second situation, \(\lambda_1\) was between 750 and 850 nm and \(\lambda_2\) was between 850 and 1000 nm. The maximum \(r\) of 0.99 occurred when \(\lambda_1 = 359\) nm and \(\lambda_2 = 611\) nm. Therefore, in the two models, when \(\lambda_1\) and \(\lambda_2\) were both small or both large, or when \(\lambda_1\) was small and \(\lambda_2\) was large, the correlation between \(X\) and \(H_p\) was weak.

These results are due to the different IOPs of sea ice and pond water in the different bands. When \(\lambda_1\) and \(\lambda_2\) were small, the absorption capacity of sea ice and pond water was so weak that the solar radiation in this band passed through the melt pond, underlying ice, and reached the ocean easily. When both \(\lambda_1\) and \(\lambda_2\) were large, the incident radiance was easily absorbed by pond water. When \(\lambda_1\) was small and \(\lambda_2\) was large, the increase in \(H_p\) will result in a small change in the albedo of the shorter wavelength, but a large decrease in albedo at the longer wavelength due to strong absorption by melt pond water (Lu et al., 2018b). Whether the solar radiation passed through or was absorbed by the melt pond, it had a large effect on the upwelling irradiance reflected by the underlying ice, which in turn affects the upwelling irradiance on the surface of the melt pond. Therefore, the retrieval of \(H_p\) using the albedo of this band was not effective.
3.2 Verification of OBRA

Theoretical calculations revealed a strong correlation between \( X \) and \( H_p \) in a specific band. Table 2 summarizes the five different datasets of in situ field measurements that were used for the evaluation of the improved OBRA.

In these field data, part of the melt pond was covered by snow, which led to some points being deleted during the comparison due to the large difference between the actual conditions and the model. The other part of the melt pond was covered with ice, but when the ice lid was thin (2–3 cm), it had little impact on the albedo and transmittance of the melt pond (Lu et al., 2018c), and therefore the data could still be used for model verification. Perovich et al. (2002) carried out observations of a dual pond, and we compared the results with the findings of Malinka et al. (2018). This particular pond had a portion with a light bottom and a portion with a dark bottom. The water depth was the same in both sections, but the properties of the underlying ice differed. The ice in the lighter section had many more air bubbles than the ice in the darker section.

<table>
<thead>
<tr>
<th>Reference</th>
<th>Location</th>
<th>Time</th>
<th>( H_p )</th>
<th>( H_i )</th>
<th>Sky condition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cao et al. (2020)</td>
<td>Arctic</td>
<td>2018.7–2018.10</td>
<td>0–0.3 m</td>
<td>1–1.5 m</td>
<td>Overcast sky</td>
</tr>
<tr>
<td>Wang et al. (2018)</td>
<td>Arctic</td>
<td>2016.7–2016.10</td>
<td>0–0.3 m</td>
<td>0.5–1.0 m</td>
<td>Overcast sky</td>
</tr>
<tr>
<td>Istomina et al. (2016)</td>
<td>Arctic</td>
<td>2012.8–2012.10</td>
<td>0–0.5 m</td>
<td>0.4–3.0 m</td>
<td>Clear and overcast sky</td>
</tr>
<tr>
<td>Polashenski et al. (2012)</td>
<td>Barrow</td>
<td>2008–2009</td>
<td>0–0.3 m</td>
<td>–</td>
<td>Clear and overcast sky</td>
</tr>
<tr>
<td>Perovich et al. (2002a)</td>
<td>Beaufort Sea</td>
<td>1998.7–1998.8</td>
<td>–</td>
<td>0–1.2 m</td>
<td>Overcast sky</td>
</tr>
</tbody>
</table>

A comparison between \( H_p \) retrieved by the model and field-measured values under overcast sky conditions (Figure 2) showed that the range of \( H_p \) retrieved by the model was 0–0.4 m, which was consistent with the observed range. The correlation coefficient of the retrieval results from the BL model was \( R^2 = 0.421 \), at the significance level \( P = 0.05 \), the root-mean-squared error was \( \varepsilon = 0.067 \) m, and the average of the relative error \( < \zeta > = 138 \% \). The retrieval results of TEA had corresponding values of \( R^2 = 0.426 \), \( P = 0.027 \), \( \varepsilon = 0.084 \) m, and \( < \zeta > = 228 \% \). Most of the retrieval results of the BL and TEA models were within the range of \( \pm 2\varepsilon \), namely the 95% confidence interval.

3.3 The influence of band selection

The above results showed that the spectral albedo of a specific wavelength can be used to retrieve \( H_p \), and Figure 1 also shows that broader wavelength bands, rather than an essentially continuous spectrum, would be sufficient for \( H_p \) retrieval. To verify the feasibility of retrieving \( H_p \) over a wide band, satellite remote-sensing bands were further used to retrieve the depth of the Arctic melt pond. Different satellites had different bands and each type of satellite corresponds to a special situation was taken into consideration. As technology develops, more satellites and different satellite bands may become available. To obtain the general relationship, the wavelength width of the various bands of the MODIS and WV2 satellites was considered to be about 50 nm. The spectral albedo calculated previously was convolved with a step length of 50 nm, and the relationship between the ratio \( X^* \) of the
convolved albedo and $H_p$ was recalculated. Figure 3 shows the results. Also supplied in the supporting material are results a step of 20 nm.

Figure 3 is similar to Figure 1, and further demonstrates the feasibility of using satellite-related wavebands to retrieve $H_p$. In the BL model results, the maximum correlation coefficient was found at a convolved albedo of $\lambda^*_1 = 355-404$ nm, $\lambda^*_2 = 564-613$ nm, which included the band with the largest correlation in the retrieval of spectral albedo. The TEA results resembled those of the BL model. Moreover, the two specific bands ($\lambda^*_1, \lambda^*_2$) of $X^*$ calculated by the two models and the general relationships between $X^*$ and $H_p$ were similar, indicating that the field environment had a similar effect on the model when using the convolved albedo to retrieve $H_p$.

The theoretical calculations indicated a strong correlation between $H_p$ and $X^*$. The field data for overcast sky conditions were convolved to verify the relationship; the results shown in Figure 4. The results retrieved from the BL and TEA models showed that the correlation coefficients between $X^*$ and $H_p$ were similar with the results between $X$ and $H_p$, but $\varepsilon$ and $<\zeta>$ are larger than that. Moreover, the retrieved $H_p$ was greater than the measured. This phenomenon was much like the one that occurred when Legleiter et al. (2014) used the convolved spectrum to retrieve $H_p$ and it could be explained in terms of adjacency effects. The reflectance of satellite remote sensing is located within a certain band and the step length of the convolved spectrum was close to the wavelength of the different satellite bands. This result was therefore beneficial for the use of satellite remote sensing to retrieve the depth of Arctic melt ponds. Regardless of whether the spectral albedo or convolved albedo was used to retrieve $H_p$, the corresponding wavelength band at the maximum correlation was within the visible light range. In the visible range of the MODIS satellite, the red band is 50 nm (620–670 nm), and the green (545–565 nm) and blue (459–479 nm) bands are both 20 nm. To further explore the feasibility of retrieving $H_p$ by satellite remote sensing, the spectral albedo was convolved with a step length of 20 nm, and the relationship

![Figure 2](image2.png)

**Figure 2** Comparison between the on-site measured $H_p$ and the estimated values from the BL model (a), and the TEA model (b).

![Figure 3](image3.png)

**Figure 3** Correlation coefficient $r$ between $X^*(\lambda^*_1, \lambda^*_2)$ of the convolved albedo and $H_p$ based on the BL model (a) and the TEA model (b). Also listed in the left corner are the information of best relations.
between the ratio of convolved albedo $X'$ and $H_p$ was estimated (see the attached material for the results). The $\varepsilon$ and $R^2$ between the measured $H_p$ and the simulated $H_p$ resembled the results obtained from the convolved albedo with the 50-nm step. Under the maximum correlation coefficient, the corresponding band of the BL model was $\lambda_1' = 357–376$ nm, $\lambda_2' = 591–610$ nm, and that of TEA was $\lambda_1'' = 350–369$ nm, $\lambda_2'' = 595–614$ nm. The specific wavebands corresponding to the maximum correlation coefficients calculated by the two models were all within the range of $\lambda_1'$ and $\lambda_2'$ corresponding to the maximum correlation coefficient integrated by the 50-nm step. These results further proved the feasibility of the improved OBRA method for retrieving $H_p$ using satellite remote sensing.

Figure 4  Comparison between the on-site measured $H_p$ and the estimated values from the BL model (a), and the TEA model (b).

3.4 Underlying ice thickness-spectral albedo relations

The improved OBRA method can also be used to retrieve $H_i$. Figure 5 shows the correlation between $X(\lambda_1, \lambda_2)$ and $H_i$. Figure 5 shows that the correlation between $H_i$ and $X$ was good only when $\lambda_1$ and $\lambda_2$ were both small (350–450 nm). This was because only the 350–450 nm solar irradiance band was likely to penetrate the melt pond and the sea ice to reach the subglacial ocean (Lu et al., 2018b), and then the characteristics of the underlying ice will affect the upwelling irradiance of this band on the surface of the melt pond. When retrieving $H_i$, the convolved albedo shown in Figure 3 was not used. This was because the uncertainty of retrieving $H_i$ was great, and $\lambda_1$ and $\lambda_2$ were both small and relatively close at this time, resulting in the retrieval bands overlapping after convolution. On-site measured data for overcast sky conditions were further used to verify this relationship, the results of which were shown in Figure 6.

Figure 5  Correlation coefficient $r$ between $X(\lambda_1, \lambda_2)$ of the spectral albedo and $H_i$ based on the BL model (a) and the TEA model (b). Also listed in the left corner are the information of best relations
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Figure 6  Comparison between the on-site measured $H_i$ and the estimated values from the BL model (a), and the TEA model (b).

Comparison of $H_i$ retrieved by the models and the on-site measured values revealed that $H_i$ retrieved by the models was in the 0–3.5 m range, which was consistent with the observed range. The correlation coefficient between the measured and simulated $H_i$ using the BL model was $R^2 = 0.604$, $\varepsilon = 0.632$ m, and $<\zeta> = 46\%$; while the overall relationship between simulated and measured $H_i$ is not apparent for TEA ($R^2 = 0.047$, $\varepsilon = 0.954$ m and $<\zeta> = 53\%$).

But a good agreement can be found for thin ice with $H_i < 1$ m for TEA. The correlation coefficient of the TEA between measured and simulated $H_i$ was $R^2 = 0.842$, $\varepsilon = 0.232$ m and $<\zeta> = 28\%$. While the relationship from the BL model was not clear in the range of $H_i < 1$ m ($R^2 = 0.089$, $\varepsilon = 0.348$ m and $<\zeta> = 41\%$). This indicated that the present retrieval method for TEA was more suitable for thin ice than thick ice.

Nevertheless, the results were still encouraging. Affected by global warming, the Arctic sea ice is undergoing a rapid melting process, and the sea ice is continuously thinning. Lindsay and Schweiger (2015) found that the declining trend in annual mean ice thickness over the Arctic Basin was $-0.58 \pm 0.07$ m·decade$^{-1}$ over the period of 1975–2012, with the annual mean ice thickness decreasing from 3.59 m in 1975 to 1.25 m in 2012. Namely, the range of $H_i < 1$ m will be critical for Arctic summer sea ice retrievals. The results provided support for a possible new method of determining ice thickness, which would complement our understanding of summer sea-ice thickness.

4  Discussion

To assess the validity of the method under clear sky conditions, we used the BL model to calculate the spectral albedo of a melt pond under different illumination conditions by adjusting the ratio of direct ($r_{dir}$) and diffuse incident irradiance ($r_{dif}$) ($r_{dir} = 100\%$, $r_{dif} = 0\%$; $r_{dir} = 75\%$, $r_{dif} = 25\%$; ...; $r_{dir} = 0\%$, $r_{dif} = 100\%$) at solar zenith angle of 60°. Following Lu et al. (2016), $H_p = 0.3$ m and $H_i = 1.0$ m were used, corresponding to a clear water pond on a typical Arctic FYI. The results are shown in Figure 7.

Figure 7  The influence of different sky conditions on albedo.

The differences among these spectral albedos were dependent on the ratio of $r_{dir}$ and $r_{dif}$. As can be seen in Figure 7, the effects of sky conditions on the model can be neglected, and only small differences were seen. We applied the pond data under clear sky conditions to verify the relationship between $H_p$ and $X$.

Figure 8  Comparison between the on-site measured $H_p$ in clear sky and the estimated values from the BL model.

A clearer relationship was presented under clear sky condition than under overcast sky conditions. The
correlation coefficient of the retrieval results of the BL model was $R^2 = 0.744$, $P = 0.01$, $\varepsilon = 0.0756$ m, and $\zeta^2 = 37\%$. The main reason is that the OBRA method had a smaller $F_p(\lambda)$ under clear sky condition than under overcast sky conditions (Legleiter et al., 2009). The smaller the $F_p(\lambda)$ is, the smaller the model error is when it is ignored. At present, only limited data are available on Arctic sea ice under melt ponds during summer. More validations from field observations are required to verify the model under clear sky condition.

Besides, the original method was used for glaciers, which have an infinite optical depth and quite stable optical properties, while sea ice is much thinner and has much less air bubbles, causing strong uncertainty in its albedo. At the same time, the inherent optical properties of first- or multi-year ice can be different. But there is not much research that can be referred to, so we set the IOPs of ice as constant. This may be a factor limiting the accuracy of the model. To improve the accuracy, more field data and studies of sea ice IOPs are necessary.

5 Conclusions

This paper summarized the four methods of retrieving $H_p$ and $H_i$ proposed in recent years. Based on an improvement of the method from Legleiter et al. (2014), we established a general relationship between pond depth, underlying ice thickness, and spectral albedo using BL and TEA models, and provided a feasible method to retrieve $H_p$ and $H_i$ at the same time.

Five key results were obtained. (1) There was a strong correlation ($r = 0.99$) between $X$ and $H_p$ as well as that between $X$ and $H_i$. (2) When retrieving $H_p$ using the convolved spectrum, the correlation coefficient ($R^2 = 0.354$ for the BL model) was lower than that obtained using the continuous spectrum ($R^2 = 0.421$ for the BL model) due to the adjacency effect. The same was observed for the TEA model. (3) Different illumination conditions had a large influence on the performance of the improved OBRA. Clear sky conditions reduced the irradiance reflected by the atmosphere and improved the accuracy ($R^2 = 0.744$). (4) Due to the differences in model settings and field conditions, the application of the BL and TEA models had a certain influence on the retrieval results, which could also be used to compare with and verify each other. When the spectral albedo and convolved albedo were used to retrieve $H_p$, the results of the two models were quite similar. When retrieving $H_i$ using the spectral albedo, the results for the BL model were suitable for the overall relationship ($0 < H_i < 3.5$ m, $R^2 = 0.632$), while the TEA model was only applicable for thin ice retrieval ($H_i < 1$ m, $R^2 = 0.842$). (5) The BL model was more complex than TEA and it satisfied the anisotropy assumption. TEA satisfied the isotropy assumption, was easier to calculate, had an analytical solution and could do more analysis. When the differences between the two models were not large, we can use a brief model.

It is anticipated that, using the improved method, spectral albedo can be used to retrieve $H_p$ and $H_i$. And this method is not only can be used in field observations but also in remote sensing. Information about changes in melt pond depth and underlying ice thickness is helpful to improve our understanding of the entire melting process of Arctic melt ponds and their impacts on climate change.

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Supplementary Material

This is an auxiliary note for “Retrievals of Arctic sea ice melt pond depth and underlying ice thickness using optical data”.

To further explore the feasibility of retrieving melt pond depth by satellite remote sensing, the estimated spectral albedo was convolved with a step length of 20 nm, and the relationship between the ratio of convolved albedo $X'$ and $H_p$ was shown in Supplementary Figure A.

**Supplementary Figure A** Correlation coefficient $r$ between $X'_{1,2}$ and $H_p$ based on the BL model (a) and the TEA model (b). Also listed in the left corner are the information of best relations.

In the estimated results of the BL model, the maximum correlation coefficient was found at a convolved albedo of $\lambda'_1=357–376$ nm, $\lambda'_2=591–610$ nm, which covered the band with the largest correlation in the retrieval of spectral albedo.

The $\lambda'_1$ and $\lambda'_2$ corresponding to the maximum $r$ calculated by the two models were all within the range of $\lambda'_1$ and $\lambda'_2$. The estimated results of TEA were much like those of the BL model.

**Supplementary Figure B** Comparison between the on-site measured $H_p$ and the estimated values from the BL model (a), and the TEA model (b).

The calculations showed a strong correlation between $H_p$ and $X''$ in a specific convolved band. The field data under overcast sky conditions was convolved to verify the relationship. The results shown in Supplementary Figure B were quite similar to that of convolved albedo with 50 nm.
## Supplementary Table A  Abbreviations

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Full name</th>
</tr>
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<tbody>
<tr>
<td>BL model</td>
<td>Delta-Eddington model</td>
</tr>
<tr>
<td>C</td>
<td>Melt pond color</td>
</tr>
<tr>
<td>DL</td>
<td>Drained layer for the BL model</td>
</tr>
<tr>
<td>$F_\lambda$</td>
<td>Incident solar irradiance</td>
</tr>
<tr>
<td>$F_{\text{up}}$</td>
<td>The total upwelling irradiance on the surface of a melt pond</td>
</tr>
<tr>
<td>$F_{\text{down}}$</td>
<td>Path irradiance from the atmosphere</td>
</tr>
<tr>
<td>$F_{\text{b}}$</td>
<td>Bottom-reflected irradiance</td>
</tr>
<tr>
<td>$F_\lambda(z, \lambda)$</td>
<td>The upwelling and downwelling irradiance</td>
</tr>
<tr>
<td>HSL</td>
<td>Hue, Saturation, Lumination</td>
</tr>
<tr>
<td>INT</td>
<td>Interior layer for the BL model</td>
</tr>
<tr>
<td>$k$</td>
<td>The absorption coefficient of pond water</td>
</tr>
<tr>
<td>$n$</td>
<td>The number of samples used for verification</td>
</tr>
<tr>
<td>$P$</td>
<td>The significance level</td>
</tr>
<tr>
<td>$r$</td>
<td>The Pearson’s correlation coefficient</td>
</tr>
<tr>
<td>$R^2$</td>
<td>Correlation coefficient</td>
</tr>
<tr>
<td>RGB</td>
<td>Red, Green, Blue</td>
</tr>
<tr>
<td>$S=S(\Omega\Omega')$</td>
<td>Scattering phase function</td>
</tr>
<tr>
<td>$X$</td>
<td>The ratio of spectral melt-pond albedo in two bands</td>
</tr>
<tr>
<td>$X^*$</td>
<td>The ratio of convolved albedo in 50-nm</td>
</tr>
<tr>
<td>$X''$</td>
<td>The ratio of convolved albedo in 20-nm</td>
</tr>
<tr>
<td>$y(\lambda)$</td>
<td>The slope of the log-scaled spectrum</td>
</tr>
<tr>
<td>$z$</td>
<td>The layer thickness</td>
</tr>
<tr>
<td>$\sigma_\lambda$</td>
<td>The spectral albedo of the melt pond</td>
</tr>
<tr>
<td>$\sigma_\text{b}(\lambda)$</td>
<td>The albedo of the bottom of the melt pond</td>
</tr>
<tr>
<td>$\sigma_t$</td>
<td>The scattering coefficient of under-pond ice</td>
</tr>
<tr>
<td>$\mu=\cos \theta$</td>
<td>Cosine the zenith angle</td>
</tr>
<tr>
<td>$\tau$</td>
<td>The optical depth</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>The scattering coefficient</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>Wavelength</td>
</tr>
<tr>
<td>$&lt;\zeta&gt;$</td>
<td>The average of the relative error</td>
</tr>
<tr>
<td>$\varepsilon$</td>
<td>Root mean square error</td>
</tr>
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</table>