Implementation of a 1-D Thermodynamic Model for Simulating the Winter-Time Evolvement of Physical Properties of Snow and Ice Over the Arctic Ocean

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Abstract This paper presents a sea ice prognostic model involving a one-dimensional thermodynamic diffusion model, nudging satellite-derived snow/ice temperatures, and two-dimensional Lagrangian ice tracking. The aim of the model is to produce the evolvement of the physical properties of the snow and ice over the Arctic Ocean during the winter season. While the one-dimensional column process solves the solution at a specific time and location, the evolvement of physical properties of the same ice target can be continuously simulated along the trajectory of ice movement determined by the Lagrangian tracking method. The main inputs were reanalysis-based atmospheric forcings, thermal conditions constrained through nudging of snow skin temperature and snow-ice interface temperature, and satellite-derived ice motion vectors. The simulation results showed that the model can successfully reproduce well-known regional features and geographical distributions of snow depth and ice thickness. The model-simulated variables (i.e., snow depth, total freeboard, ice freeboard, ice thickness, and temperature) showed high correlations with the in situ or satellite measurements. In particular, the simulated temperatures were in excellent agreement with drifting buoy measurements. Since the nudging of the satellite-derived temperature data into the model improved the thermal structure considerably, these data appear to be a key element for the successful simulation of other variables as well.

Plain Language Summary The forecast skill in the polar region is still much lower than for other regions in the globe. One of the main reasons is the poor surface characterization including the surface emissivity, which determines the degree of radiation emission at the surface. Aiming at providing necessary emissivity data over the Arctic Ocean, we developed a one-dimensional thermodynamic vertical heat transfer model for simulating physical states of snow and ice (e.g., their distributions and depths, thermal states, grain sizes) during the winter. The comparison against in situ observations and satellite measurements indicates that the model can simulate well-known regional characteristics and geographical distributions of the snow and ice, which can be utilized for improving the surface characterization of the snow and sea ice over the Arctic during the winter.

1. Introduction

The rapidly changing climate over the Arctic (Graversen et al., 2008; Johannessen, 2004; Serreze et al., 2009) also influences the mid-latitude weather system (Cohen et al., 2014; Francis & Vavrus, 2012, 2015). Thus, better forecasts over the Arctic region may improve weather forecasting in the low- and mid-latitudes as well, as demonstrated by modeling and data assimilation experiments (e.g., Jung et al., 2014; Lawrence et al., 2019; Sato et al., 2017). In fact, the demand for better weather forecasts over the Arctic has been increasing (World Meteorological Organization’s Polar Prediction Project Steering Group, 2013). However, compared to the dramatically improved global forecast skills over the past 3 decades through advances in data assimilation, model physics, and ensemble modeling (Bauer et al., 2015), forecast skills over the Arctic region continue to lag (Bauer et al., 2016; Jung & Matsueda, 2016).
Poor data assimilation over the Arctic has been recognized as one main reason for the lagging forecasting performance of this region compared to other regions (Jung et al., 2016). Data assimilation provides more accurate initial conditions for forecasting, as it optimally combines conventional observations and satellite radiance measurements with model backgrounds (Talagrand, 1997). Due to the extreme weather conditions in the Arctic, conventional observations such as radiosonde measurements are very rare, and thus, the data assimilation for this region typically involves satellite-based observations. In fact, abundant satellite data are available over the Arctic region due to the more frequent visits of polar-orbiting satellites compared to those for the lower-latitude regions. In particular, amongst the various satellite measurements, microwave measurements are in high demand because they are less affected by clouds and exert significant impacts on forecasts (Lawrence et al., 2019). However, the use of microwave satellite sounding channel measurements (especially low-tropospheric sounding channels) is limited in data assimilation because of uncertainties in the calculation of the upwelling radiance over the snow-covered sea ice (English, 2008).

For data assimilation using microwave measurements, the surface brightness temperature, which is used as the input to the forward radiative transfer model, is defined as the product of the surface emissivity with the physical skin temperature, and it is assumed that the surface medium is homogeneous and isothermal (Phalippou, 1993; Ulaby & Long, 2014). However, given that microwaves can penetrate snow and ice layers, this assumption is not valid. Instead, the surface emissivity and emitting layer temperature should be estimated using the radiative transfer calculation within the snow-ice layers (Tonboe, 2010). Accordingly, detailed physical states of the snow and ice layers, such as temperature and grain size profiles, should be known. However, retrievals of such physical properties for the Arctic Ocean via any means of observation pose a formidable challenge.

Efforts have been made to estimate the surface emissivity and emitting layer temperature with model-calculated physical properties of the snow/ice over the Arctic (Tonboe, 2010; Tonboe et al., 2011). The surface emissivity and emitting layer temperature at the microwave window and sounding channels were calculated using a radiative transfer model for the multilayered snow and ice and model-produced physical properties as inputs. The model used to produce the physical properties of the snow and ice was a one-dimensional (1-D) thermodynamic model for sea ice growth (Tonboe, 2005). Despite the successful estimation of the surface emissivity and emitting layer temperature, the model was limited to 1-D column applications. To assimilate satellite-based microwave measurements over the Arctic, such a 1-D column application should be extended to a two-dimensional (2-D) spatial domain at least.

In this study, we produce the physical properties of the snow and ice over the Arctic Ocean in winter by improving Tonboe’s 1-D column approach and extending the 1-D model for obtaining surface-leaving radiance in the space-time domain. The produced outputs are used as inputs to the radiative transfer model for calculating the surface emissivity and emitting layer temperature over the snow-covered sea ice. To this end, we first implement the 1-D thermodynamic model for sea ice based on Maykut and Untersteiner (1971) and Tonboe (2005). In particular, our improvement introduces satellite-derived snow skin temperature and snow-ice interface temperature via a nudging technique to regulate the vertical temperature structure of the snow-sea ice system in the model. For the 2-D extension, the 1-D thermodynamic model runs at all ice targets over the Arctic Ocean at the initial time and then follows trajectories of moving ice targets that are determined from satellite-derived ice motion vector fields. The model-produced surface emissivity and emitting layer temperature over the Arctic Ocean during winter can be used to assimilate microwave measurements and improve weather forecasting over the Arctic.

### 2. Set-Up for the 2-D Prognostic Model

#### 2.1. Implementation of the 1-D Model and Solving Method

The columnar snow-sea ice system over the Arctic Ocean employed in this study consists of snow and ice layers. The snow layer is separated from the air above and from the ice below by the respective interfaces, as is the ice layer from the snow above and from the ocean water below (Figure 1). The snow layer above the ice exchanges heat with the air through the upper boundary (between the air and snow interface), while the ice layer exchanges the heat through the lower boundary (between the ice and ocean interface). Any heat
exchange through these interfaces induces heat transfer within the heterogeneous snow-sea ice system, which can be described by the thermodynamic heat transfer equation given below.

\[
\rho c_p \left( \frac{\partial T}{\partial t} \right) = k \frac{\partial^2 T}{\partial z^2}
\]

(1)

where \( T \) is the temperature, \( c_p \) is the specific heat capacity, \( \rho \) is the density, \( k \) is the thermal conductivity of sea ice or snow, and \( z \) represents the vertical coordinate.

Heat exchange components at the upper boundary consist of the net shortwave radiation flux (\( F_{sw}^{net} \)), net longwave radiation flux (\( F_{lw}^{net} \)), sensible heat flux (\( F_s \)), conductive heat flux (\( F_c \)), and latent heat fluxes for vaporization and melting (\( F_l \) and \( F_m \), respectively). The energy balance between these components is expressed as follows:

\[
F_{sw}^{net} + F_{lw}^{net} + F_s + F_c + F_l + F_m = 0
\]

(2)

Since we attempt to apply the 1-D thermodynamic model to diagnose the thermal and physical states of the snow-sea ice system during the winter over the Arctic Ocean, the skin temperature is considered to be lower than the freezing point (i.e., \( F_m = 0 \), Maykut & Untersteiner, 1971). Thus, Equation 2 becomes

\[
F_{sw}^{net} + F_{lw}^{net} + F_s + F_c + F_l = 0
\]

(3)

At the lower boundary, the sea ice grows (or melts) depending on the net energy flux between the conductive heat flux (\( F_c \)) and oceanic heat flux (\( F_{ow} \)), as expressed below.

\[
F_c - F_{ow} = \rho_i H \left( \frac{dH}{dt} \right)
\]

(4)

where \( \rho_i \), \( H \), and \( L_f \) are the sea ice density, sea ice thickness, and latent heat of sea ice, respectively. Note that the temperature within the snow and ice changes in response to the heat fluxes imposed at the upper and lower boundaries, which in turn changes the sea ice thickness accordingly.

To solve the heat transfer equation for a snow-sea ice system whose boundaries are allowed to exchange heat, the system is divided into \( N \) layers, with individual layer depths starting at 2 cm (Figure 1).
number of layers $N$ changes with time, due to the varying ice thickness and snow depth, and $N$ is determined by dividing the snow and ice layers with a 2 cm interval, that is, $N = \text{(snow depth in cm + ice thickness in cm)}/2$. The following forward first-order finite differential equation is used to obtain the numerical solution:

$$T_j^{n+1} = T_j^n + \frac{\Delta t}{(\rho c_p)} \left[ k_j \frac{T_{j+1}^n - 2T_j^n + T_{j-1}^n}{\Delta z_j} \right]$$

(5)

where $\Delta t$ and $\Delta z$ are the integral time and space distance, respectively, superscripts $n$ and $n + 1$ are the $n$th and $(n + 1)$th integration time steps, respectively, and subscript $j$ represents the $j$th layer among $N$ layers (i.e., $j = 1, \ldots, N$).

The numerical errors caused by the first-order approximation are closely associated with the numerical stability and thus must be small enough to yield the final convergence. To ensure stability, the Courant number $(\sigma)$, defined in Equation 6, must be less than 0.5 (Kalnay, 2003).

$$\sigma_j = \frac{k_j}{(\rho c_p)} \frac{\Delta t}{\Delta z_j}$$

(6)

Considering the overall computational efficiency with this criterion, the integral time for both the snow and ice layers is set as 60 s.

The vertical heat transfer within the snow-sea ice system is expressed by the vertical heat diffusion in Equation 5, which includes the term $k/\Delta z$. Throughout the integration, $k$ varies with the changing morphologies of the snow and ice, and $\Delta z$ varies with the changing depths of the snow and ice layers. Thus, the heat exchange between two adjacent layers (e.g., $j$ and $j + 1$) can be better explained by introducing the following thermal transfer coefficient ($R_{j,j+1}$ in units of W K$^{-1}$ m$^{-2}$):

$$\frac{0.5\Delta z_{j+1}}{k_j} + \frac{0.5\Delta z_{j}}{k_{j+1}} = \frac{1}{2} \left( \frac{\Delta z_j k_{j+1} + \Delta z_{j+1} k_j}{k_j k_{j+1}} \right) = \frac{1}{R_{j,j+1}}$$

(7)

As displayed in Figure 1, Equation 7 describes the quantity of $\Delta z/k$ in the middle of two adjacent layers. The conductivities ($k$) for snow and sea ice vary for each layer and are calculated using the heterogeneous thermal conductivity model of Schwerdtfeger (1963a), (1963b).

Then, the heat diffusion equation expressed by the first-order finite differential method with the absorbed incoming shortwave radiation flux at layer $j$ ($I_j$ in units of W m$^{-2}$) is given as follows:

$$T_j^{n+1} = T_j^n + \frac{\Delta t}{(\rho c_p)} \Delta z_j \left[ R_{j,j+1} \left( T_{j+1}^n - T_j^n \right) - R_{j-1,j} \left( T_j^n - T_{j-1}^n \right) + I_j \right]$$

(8)

Further, the heat transfer within $N$ snow/ice layers can be simplified in the matrix form, as seen below.

$$
\begin{bmatrix}
T_1^{n+1} \\
T_2^{n+1} \\
\vdots \\
T_N^{n+1}
\end{bmatrix} =
\begin{bmatrix}
B_1 & C_1 & \cdots & 0 \\
A_2 & B_2 & C_2 & \vdots \\
\vdots & \ddots & \ddots & \vdots \\
A_N & B_N & C_N & 0
\end{bmatrix} \begin{bmatrix}
T_1^n \\
T_2^n \\
\vdots \\
T_N^n
\end{bmatrix} +
\begin{bmatrix}
\xi_1 I_1^n \\
0 \\
\vdots \\
\xi_N I_N^n
\end{bmatrix}
$$

(9)

where $A$, $B$, and $C$ are defined as follows:

$$A_j = \frac{\Delta t}{(\rho c_p)} \frac{\Delta z_j}{R_{j-1,j}}$$

(10)
In Equation 9, the multiplication of the first two matrices on the right-hand side denotes the internal heat transport from the given temperature profile at the nth time step ($T_n$). The second column matrix denotes the upper and lower boundary conditions expressed by the skin temperature ($T_s$) and the ocean temperature ($T_o$), respectively. In this regard, given the atmospheric forcing at the upper boundary, the skin temperature satisfying the energy balance in Equation 3 is diagnosed with the minimum residual method at each time step (see Appendix A for the calculation of the fluxes from atmospheric forcing variables). It should be noted that the melting processes are not included in the heat diffusion model. Thus, the model integration stops if the diagnosed skin temperature is higher than the freezing point. At the lower boundary, the ocean temperature beneath the ice ($T_o$) is fixed to 271.35 K (i.e., the freezing point of seawater at a typical salinity of ~34 psu). The last column matrix denotes the transmitted shortwave radiation as an additional heat source (see Appendix B for the calculation of the transmitted shortwave radiation).

In the heat transfer model, the snow depth is treated as a predictable variable although it is diagnosed with precipitation provided in atmospheric forcing. It is because the snow depth significantly influences the vertical distribution of temperature and heat transfer. The provided precipitation is considered to be newly formed snow, and it accumulates over the preexisting snow. The newly formed snow is then converted into the snow depth using the snow density parameterization proposed by Jordan et al. (1999). With time, the accumulated snow undergoes metamorphism and compaction processes, inducing changes in the snow’s physical states (Anderson, 1976; Jordan et al., 1991; Kojima, 1967). Moreover, the corresponding change in snow grain size is calculated by an empirical model (Marbouty, 1980). If the accumulated snowpack becomes heavy and is submerged beneath the waterline, seawater infiltrates into the submerged snowpack through ice cracks or floe edges, forming wet saline snow before it refreezes to snow ice. This snow ice formation is assumed to be wet saline snow refreezing immediately into snow ice and this process performs under all negative freeboard cases based on the hydrostatic equilibrium condition (Fichefet & Maqueda, 1999). Here, the reference density of newly formed snow ice is given as 880 kg m$^{-3}$ (Leppäranta, 1983), and the salinity is determined by the weighted average of salinity between snow (= 0 psu) and seawater (= 34 psu).

We intend to solve the 1-D thermodynamic model at any analysis time using the given top and bottom boundary conditions. Here, the atmospheric forcing required for the top boundary is obtained from three hourly ERA-Interim (ERA-I) reanalysis data in a 0.125 x 0.125° latitude-longitude grid format, which is produced by European Center for Medium-Range Weather Forecasting (ECMWF, Berrisford et al., 2011). The used atmospheric forcing variables are wind speed at 10 m, dew point temperature at 2 m, air temperature at 2 m, surface pressure, precipitation, and downward longwave and shortwave fluxes. Another required forcing is the oceanic heat flux from the underlying ocean to the ice column. We adopt the right side of the bell-shaped curve, which falls from five to 0.2 W m$^{-2}$ with an average of 2 W m$^{-2}$ (Ebert & Curry, 1993), to specify the oceanic heat flux during the simulation period. Thus, the thermal and physical structures of the snow-sea ice system in this heat transfer model are mainly forced by the top boundary condition.

### 2.2. Nudging Satellite-Derived Temperatures into the Model

In addition to the atmospheric forcing, the satellite-derived temperatures are used to constrain the temperature structure of the snow-sea ice system through the nudging scheme. These nudged temperatures induce
to produce the more realistic snow-sea ice system regarding temperature structure and ice growth. The model states are adjusted toward the satellite observation states by adding a nonphysical nudging term to the model equation (Jeuken et al., 1996; Lei et al., 2015; Telford et al., 2008). The nudging term \( Q \) in Kelvin can be expressed as the product of the integration time, nudging coefficient, and innovation, as seen below.

\[
Q = \Delta t \, G \left( \eta T_{\text{obs}}^n - T_j^n \right)
\]  

(14)

where \( G \) is the nudging coefficient (in s\(^{-1}\)) that quantifies the strength of the nudging term, and \( T_{\text{obs}}^n \) and \( T_j^n \) indicate the observation and model states at the \( n \)th time step, respectively. \( \eta \) refers to the observation scale factor associated with the intersatellite calibration. Thus, the nudging term is now added to the temperature prediction equation (Equation 8), which is revised as follows:

\[
T_{j}^{n+1} = F_m \left( T_j^n \right) + W Q
\]

(15)

where \( W \) denotes the weighting function that determines the vertical distribution of the nudging weight, and \( F_m \) denotes the model equation on the right-hand side of Equation 8.

To apply the nudging technique to constrain the model state, we use the infrared-based skin temperature and microwave-based snow-ice interface temperature (hereafter referred to as SIIT) as the nudging variables. The skin temperature is sourced from Advanced Very High-Resolution Radiometer (AVHRR) and Visible/Infrared Imager Radiometer Suite (VIIRS) measurements using a split window method. Its algorithm and data processing have been reported in detail by Dybkjær et al. (2018). A bias of \( \sim -4 \) K and a root mean square difference (RMSD) of less than 5 K were reported on a monthly time scale against match-up drifting buoy-measured temperature. The Level 2 path products in spatial resolution of 750 m are available since 2016 from the repository of the Ocean and Sea Ice Satellite Application Facility (OSI SAF) High Latitude Processing Center, and the three-hourly data set in 0.125 \( \times \) 0.125° latitude-longitude grid format between 1983 and 2015 is available from the Danish Meteorological Institute.

Another temperature used as a nudging variable is the proxy temperature at the interface between the snow and ice layer. Lee and Sohn (2015) developed a retrieval algorithm for determining the emitting temperature from the Advanced Microwave Scanning Radiometer for EOS (AMSR-E) 6.9 GHz brightness temperatures in conjunction with the combined Fresnel equation (Sohn & Lee, 2013). The details of the physics and algorithms involved in the retrieval are reported by Lee and Sohn (2015) and the references therein. The determined emitting temperature at 6.9 GHz was found to be the physical temperature around the ice top, leading to it being called the SIIT. The bias and RMSD of SIIT are reportedly smaller than 1 K and 2 K, respectively, against collocated drifting buoy-measured temperatures. The SIIT used in this study is retrieved from the Level 3 AMSR-2 6.9 GHz brightness temperature. The Level 3 daily products in the polar stereographic resolution of 25 km from 2011 are available from the Japan Aerospace Exploration Agency’s G-portal system.

For the nudging coefficients \( G \), empirically determined values of \( 4.28 \times 10^{-3} \) and \( 9.26 \times 10^{-5} \) are used for the skin temperature and SIIT, respectively. The weighting function of the snow skin temperature is given only at the top first layer since the infrared emission originates from the surface film layer. On the other hand, the weighting function for the SIIT is given as a bell-type curve with a peak at 12 cm below the snow-ice interface.

### 2.3. Lagrangian Approach to Simulate the 1-D Model along the Ice Trajectory

Thus far, the model has been set up for the snow-sea ice column process for a specific location, and here, we attempt to apply the model for the entire Arctic Ocean. We do so by applying the 1-D model following the movement of the sea ice target (referred to as the “moving target”), which can be determined from satellite-derived ice motion vectors by applying the Lagrangian tracking scheme. Unlike the Eulerian approach, this Lagrangian approach should have advantages for such as ice targets to keep their identities as a material element for long period and the simpler 1-D calculation. The 1-D model is implemented to follow
each moving target over the entire Arctic Ocean. If we apply this 1-D model run at all ice targets at an initial
time and at the new positions that follow, the 1-D modeling can be effectively expanded to the space-time
domain.

We assume that any moving targets (sized $\sim 25 \times 25$ km$^2$) within a spatial resolution ($\sim 62.5 \times 62.5$ km$^2$)
of the satellite-derived ice motion vector have the same motion. The provided motion vector will carry the
moving target to a new position where the 1-D model is run again. This sequence of processes is repeated
over the simulation period. During the course of ice drift, moving targets can diverge from each other, pos-
sibly yielding ice-free areas between the moving targets. If the number of moving targets is smaller than
five within 100 km of a radius centered at any specific location, then the location is filled with a new ice.
On the other hand, no overlapping is allowed even if moving targets converge, assuming that they behave
independently of each other.

To obtain the drift motion of the moving target, we use the OSI SAF satellite-derived ice motion vector in
the spatial resolution of $62.5 \times 62.5$ km$^2$ and a temporal resolution of 48 h. The procedure is based on the
optimized pattern matching algorithm, which uses sequential satellite images of a passive microwave radi-
ometer and an active microwave scatterometer (Lavergne et al., 2010). The drift motion data available from
2006 are obtained from the repository of the OSI SAF High Latitude Processing Center.

3. Data Sets Used for the Initialization and Assessment of the Simulation
Results

The required data for the model initialization are snow depth, ice thickness, snow and ice density profiles,

ice salinity profile, and sea ice type. The snow depth and snow density climatology are sourced from War-
ren et al. (1999); hereafter referred to as ”W-99”. The ice density and ice salinity profiles are obtained from
Campbell et al. (1978); hereafter referred to as ”C-78”. Ice thickness data are sourced from the CryoSat-2
(CS2) altimeter-based retrieval results. Details about the CS2 sensor and data processing have been report-
ed by Kurtz and Harbeck (2017). To evaluate the model performance, the model-simulated results of the
predicted variables are compared with climatology, in situ, airborne, and satellite estimates. The following
subsections describe the data used for the initialization and validation.

3.1. Snow Depth and Snow Density from W-99

W-99 reports monthly snow depth and snow density climatologies over the Arctic Ocean, which were pa-
rameterized by a 2-D quadratic function of locations based on in situ snow observations at Soviet drifting
stations. At each station, the snow depth and snow density were measured every 10 days at a 10 or 100 m
interval along a 500 or 1,000 m line, respectively. The data set was created with data from one or two stations
on the multiyear ice zone for 37 years (from 1954–1991). In W-99 climatology, the snow depth is character-
ized by the steep accumulation in autumn and slow accumulation in winter, during which time the snow
density increases steadily. Given the limited spatial coverage by stations, these climatologies are one of few
data sets available for the Arctic Ocean.

3.2. Ice Density and Ice Salinity Profiles from C-78

C-78 includes measurements of extensive sea ice physical, dielectric, and radiative properties over the Arc-
tic Ocean over a one-year period (from April 1975–May 1976) which were collected as part of the Arctic Ice
Dynamics Joint Experiment campaign. The variables used in this study are the ice density and ice salinity
profiles for the first-year (FY) and multiyear (MY) ice based on in situ observations over the north of Alaska.
The density of FY ice is between 900 and 920 kg m$^{-3}$ and is nearly invariable throughout the ice layer. How-
ever, in the top layer, the MY ice density becomes much smaller when the brine is replaced by air pockets
in the freeboard. The salinity profile of the FY ice is $\sim 12$ psu at the ice top and decreases rapidly with in-
creasing ice depth. In contrast, the salinity at the top of the MY ice is one order lower than that at the top of
the FY ice due to desalination in summer, but it ranges from 1–2 psu throughout the ice layer. On the other
hand, for the newly formed sea ice at the bottom of the ice, the salinity is specified using the equation given
in Nakawo and Sinha (1981) and the density is specified as 910 kg·m$^{-3}$. 
3.3. Ice Freeboard and Ice Thickness from CS2

The CS2 satellite, active since April of 2010, detects the backscattering layer as an ice surface using an aperture radar altimeter at Ku-band (13.575 GHz) and estimates the ice freeboard from the local sea level. During this procedure, two adjustment terms (i.e., radar penetration depth and radar penetration speed) are considered to correct errors arising from the radar penetration into the snowpack. The first term is to adjust the displaced scattering surface above the snow-ice interface due to the volume scattering in the snowpack, and the second term is the ratio of light speed between the snow and air adjusting the reduced penetration speed in the snowpack. Then, assuming isostatic equilibrium, the CS2 ice freeboard can be converted into ice thickness by solving the hydrostatic equation with the prescribed bulk densities of ocean water, snow, and sea ice and the modified W-99 snow depth. The CS2 ice thickness is retrieved when the sea ice concentration exceeds 70%. The Level 4 CS2 monthly composite of ice freeboard and ice thickness in the polar stereographic resolution of 25 km from 2011, for the September–April period, are downloadable from the repository of the National Snow and Ice Data Center (NSIDC).

3.4. Snow Depth, Total Freeboard, and Ice Thickness from Operation IceBridge

NASA's Operation IceBridge (OIB) airborne campaign has been collecting various snow and ice variables over the Arctic since 2009 (Kurtz et al., 2015). The used OIB data are snow depth, total freeboard, and ice thickness collected over the Arctic Ocean during March and April. The snow depth is measured by differentiating the height between the air-snow and snow-ice interfaces from the OIB snow radar, which has a footprint of 5–11 m. The OIB laser altimeter at 532 nm, which has a footprint of about 40 m, measures the topography of the air-snow interface. The total freeboard is then estimated by calculating the difference between the air-snow interface and the local sea level. The OIB snow depth and total freeboard are used to estimate the ice thickness based on the isostatic equilibrium assumption. The OIB “Quick Look” product for snow depth, total freeboard, and ice thickness for each OIB flight path from the 2012 campaign is downloadable at the repository of NSIDC.

3.5. Temperature and Trajectories from the CRREL Ice Mass Balance Buoy

The Cold Regions Research and Engineering Laboratory (CRREL) Ice Mass Balance Buoy (IMB) measurements are designed to monitor the vertical temperature profiles, snow and ice depth, and other variables of the sea ice and overlying surface atmospheric layer where instruments are installed (Perovich et al., 2019). A limited number of drifting buoys were deployed in optimized positions to strategically observe sea ice changes and trends. The temperature profiles within the snow and ice and the geographical buoy positions for the 2000–2015 period are available from the CRREL-Dartmouth Mass Balance Buoy Program.

3.6. Sea Ice Type from OSI SAF

The daily surface type over the Arctic area can be open water, FY ice, and MY ice. The OSI SAF produces the surface types by examining the radiative characteristics from satellite measurements of the passive microwave radiometer and active microwave scatterometer (Aaboe et al., 2018). The OSI SAF-produced surface types over the Arctic in the polar stereographic resolution of 10 km are available on a daily time scale for the October–May period since 2005, and these products are downloadable from the repository of OSI SAF High Latitude Processing Center.

4. Simulations and Assessment

We run the model over the Arctic Ocean for the period from October 1 to the following March 31, 2012–2018 period except for the October 2015 to March 2016 period in which snow skin temperature measurements have a gap. Thus, the total simulations span five winter years of 2012–2013, 2013–2014, 2014–2015, 2016–2017, and 2017–2018. Amongst these five years, 2012–2013, 2016–2017, 2017–2018 are considered to be thinner sea ice winters while 2013–2014, 2014–2015 are considered to be thicker winter years (Kwok, 2018). In this experiment, the first two months (October and November) of the simulations
are considered to be a spin-up time. This is because a couple of months are needed until the prescribed isothermal condition, snow depth, and ice thickness for thick ice fully respond to given forcings at the snow top and ice bottom. The analysis is conducted with the following four months (December–March) of simulations.

Each moving target represents a spatial resolution of $25 \times 25$ km$^2$ and outputs are produced with a three-hourly interval. Since the satellite-derived motion vector has a spatial resolution of $62.5 \times 62.5$ km$^2$, any moving targets within the motion vector grid are assumed to have the same drift motion (as described in Section 2.3). For the comparison, the OIB-measured and model-simulated products in different resolutions are converted into the same $25 \times 25$ km$^2$ equal-area grid, based on the use of the 25 km grids cell in the NSIDC Sea Ice Polar Stereographic North (https://nsidc.org/data/polar-stereo/ps_grids.html).

### 4.1. Initialization

In this simulation, inputs of temperature profiles for snow and ice layers, snow and ice density profiles, ice salinity profile, snow depth, ice thickness, and grain sizes of snow and ice are needed as the initial conditions. Table 1 summarizes the values and sources of the input variables.

The model is run from October 1, because the temperature profile around this date is well characterized as being close to the isothermal condition, as shown by the monthly mean temperature profiles during September over the Soviet North Pole station (e.g., Weeks, 2010). To determine the initial isothermal condition for the ice on October 1, we analyzed temperature profiles taken from 26 CRREL IMBs deployed during the Septembers of 2006–2015. The results of the analysis indicate that the vertical temperature profile is close to isothermal ($\sim 271$ K), and thus, 271 K is used as an initial temperature for the entire ice layer for both the FY and MY ice. Since the initial data depend on ice types, we need the ice type of each moving target. The ice extent and type on October 1 are provided by the OSI SAF satellite-derived ice type data, and the associated initial states of ice density and ice salinity profile are sourced from in situ observations of C-78. The initial state of the snow density profile is sourced from the bulk density of the W-99 monthly climatology, and snow salinity is set to zero. However, since the W-99 snow depth may be too deep for the FY ice (Kurtz & Farrell, 2011), half values of the W-99 snow depth climatology are used for the FY sea ice (Laxon et al., 2013). These half values of the W-99 snow depth climatology are called the modified W-99 snow depth and are referred to as MW-99. The initial distribution of ice thickness is provided from the monthly composite of the CS2 ice thickness in October.

For the simulation after October 1, we examine whether ice-free areas are caused by divergence of moving ice targets and whether new ice is present. When new ice is present, the initial states of snow depth and ice thickness are set to 4 cm and 30 cm, respectively, and the conditions used for the initial states of FY ice are also used for the density, salinity, and temperature profiles. The initial states of all grain sizes of MY, FY, and newly formed ice are set to 0.2 mm for snow and 0.5 mm for ice.

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| Table 1: Initial Conditions or Data Source for Defining the Status of the Variables |
|---------------------------------|-----------------|-----------------|
| Multiyear sea ice               |               | First-year sea ice |               | Newly formed sea ice |               |
| Snow                            | Ice            | Snow             | Ice            | Snow             | Ice            |
| Temperature (K)                 | Isothermal profile of 271 K | Isothermal profile of 271 K | Isothermal profile of 271 K |
| Density (kg m$^{-3}$)           | W-99           | C-78             | W-99           | C-78             | W-99           | C-78             |
| Salinity (psu)                  | 0              | C-78             | 0              | C-78             | 0              | C-78             |
| Thickness (m)                   | MW-99          | CS2              | MW-99          | CS2              | 0.04           | 0.3              |
| Grain size (mm)                 | 0.2            | 0.5              | 0.2            | 0.5              | 0.2            | 0.5              |

C-78: In situ observation of ice density and ice salinity profile from Campbell et al. (1978). CS2: Monthly composite of ice thickness from CryoSat-2 radar altimeter. W-99: Monthly climatology of snow depth and snow density from Warren et al. (1999). MW-99: Modified W-99.
4.2. Trajectories of Sea Ice Drift

To assess the accuracy of the target trajectories based on the use of OSI SAF satellite-derived ice motion data, we compare the obtained results against 10 reference trajectories taken from CRREL IMB GPS locations over October–March of 2012–2015. Table 2 summarizes detailed information about the CRREL IMB measurements. The moving targets collocated with 10 buoy positions in October were traced using the OSI SAF ice motion vector with the 2-D Lagrangian technique described in Section 2. Figure 2 compares the estimated Lagrangian trajectories with the IMB reference trajectories. It is shown that the estimated trajectories show a good agreement with IMB buoy trajectories in all 10 comparison cases. The daily difference in location between the estimated Lagrangian and reference trajectories is calculated as a quantitative measure. Daily differences for 10 cases are provided with the Julian days and the mean difference in Figure 3. The trajectory errors should be accumulated over the integration period. Although the trajectories of two cases (2014F and 2014G) show differences greater than 60 km, which is particularly notable immediately after the middle of October, the mean difference remains smaller than 40 km over the October–March period. Considering that the spatial resolution of the OSI SAF sea ice motion vector used in this study is 62.5 km, the overall difference apparently equals an order of one grid size, allowing us to resolve even the meandering features shown in the reference trajectories (Figure 2).

Despite the good agreement between the two trajectories shown in Figures 2 and 3, it may be necessary to confirm that the 2-D Lagrangian technique with the OSI SAF ice motion vector can be applied to produce reliable trajectories even over the entire Arctic Ocean domain. Since ice drift measurements other than

![Figure 2. Comparison of estimated trajectories (blue) with CRREL IBM’s trajectories (red) in the October–March periods of (a) 2012–2013, (b) 2013–2014, and (c) 2014–2015. Black and red/blue dots represent the starting and ending points, respectively.](image-url)
those provided by the drifting buoys are not available, we examine this aspect indirectly by comparing the Lagrangian-based trajectories with well-known features related to the ice drifts over the Arctic Ocean. It has been reported that an ice drift is primarily caused by wind on a time scale of days to weeks, and a near-linear relation can be established between the wind speed and ice drift speed (Thorndike & Colony, 1982). Thus, we may expect a close relationship between the calculated ice displacement and wind speed if the Lagrangian technique using the OSI SAF ice motion vector is applicable. To examine such an expectation, we compare the 15-d displacements of ice trajectories with the 15-d mean distribution of ERA-I wind speed at a height of 10 m in the period January 1–15, 2013 over the Arctic Ocean domain (see Figure 4a for the comparison results provided for a grid-scale measuring 62.5 × 62.5 km²). A general agreement is noted between the magnitude of the ice displacement and wind speed; areas showing larger movement correspond to those with stronger wind speed. These two fields are calculated every 15 d over the analysis period and compared (Figure 4b). The scatterplot reveals a correlation coefficient of 0.62, indicating close agreement between the two variables. Thus, we suggest that if the surface wind speed exceeds ∼3 m·s⁻¹, the ice movement tends

![Figure 3. Time series of the geographical distance of calculated Lagrangian trajectories from the CRREL IBM’s trajectories given in Figure 2. The thin colored line indicates the difference in the individual trajectory, while the thick black line denotes the average of the differences.](image)

![Figure 4. (a) Comparison of estimated ice displacements by the 2-D Lagrangian approach (black arrow) with mean near-surface wind speed from ERA-I reanalysis (color) for 15 d of January (January 1–15) 2013. (b) Scatterplot of ice displacements versus near-surface wind speed over the Arctic Ocean domain averaged over each 15 d period for 2012–2013, 2013–2014, and 2014–2015. 2-D, two-dimensional.](image)
Figure 5. Difference in temperature profile (a) between “with nudging” and “without nudging”, (b) between buoy measurement and model simulation with nudging, and (c) between buoy measurement and model simulation without nudging along the buoy measurements of CRREL IMB 2012G from December 1 to March 31 of 2012–2013 period. The black solid line at 0 cm height represents the snow–ice interface.
to increase linearly with the increasing wind speed. This result agrees with that of a similar analysis using the HIRHAM–NAOSIM model (Yu et al., 2020). These comparisons confirm that the Lagrangian approach with the OSI SAF ice motion vector can facilitate the running of the 1-D thermodynamic model on the 2-D regional scale covering the Arctic Ocean.

Figure 6. Top panels: Time series of (a) snow depths and (b) ice thicknesses simulated with MW-99 (blue) and SnowModel-LG (red) snow depths as initial conditions. Data were averaged over the Central Arctic Ocean (MY ice area) from the 2012–2013 simulation. The thick line and shaded area indicate the regional mean and associated variation (i.e., one standard deviation) on a daily scale, respectively. Bottom panel: (c) Mean difference in ice temperature profile from two sets of snow initial thickness (SnowModel-LG minus MW-99). The black solid line at 0 cm indicates the ice top.
Impact of Nudging and Sensitivity to Initial Snow Depth

In this study, satellite-derived snow skin temperature and SIIT are used to constrain the thermal structure of the snow-ice system. Thus, it is important to examine how the nudging of satellite-derived temperatures gives the impact on the temperature profile of the snow-sea ice system. In doing so, the model was performed with and without nudging for the ice target along the trajectory of the CRREL IMB 2012G, and simulation results are compared with buoy observations. The temperature profiles of buoy measurement and model simulations with and without nudging can be found in the Supporting Information. Figure 5 shows the difference in the temperature profile between “with nudging” and “without nudging” for the period from December 1 to March 31 of 2012–2013, along the buoy trajectory. It is shown that the nudging brought in the warmer snow-ice structure and thinner sea ice. It is interesting to note that the nudging tends to force the snow surface layer colder than that from “without nudging”, throughout the analysis period. Such adjustment to colder surface appears to correct the warm bias of the surface air temperature of ECMWF analysis (Batrak & Müller, 2019). Although this model does not update the atmospheric forcing (or surface heat budget) with the adjusted temperature profile, the nudging tends to keep correcting the ECMWF warm bias at each time step, effectively introducing updated heat budget at the surface.

It is clearly shown that the nudging impact reaches deep into the bottom ice layer, resulting in a much closer thermal structure than without nudging, in comparison to the buoy observations (Figure 5b). The result suggests that the thermal structure of the whole snow-ice column can be constrained by the use of satellite-derived surface layer temperature information, although the adjustment is more pronounced in the upper ice layers. In the snow layer, the temperature appears to be colder than the buoy-observed temperature, likely due to the thinner snow depth of “with nudging”. Much larger thermal contrast between the snow layer and ice layer is clear in “without nudging” temperature profiles (Figure 5c). Overall, this experiment demonstrates that the nudging of the satellite-derived temperature into the model helps to shape...
the thermal structure closer to the observations, thus resulting in more reasonable snow and ice physical properties in the simulations.

It is of importance to examine how the results are sensitive to the given initial snow depth since the snow is a good insulator so that any depth difference in the beginning will affect the thermal structure and ice growth. In order to examine the sensitivity, the simulation was done with the snow depth data from Snow Model-LG (Liston et al., 2020) as an initial snow depth on October 1, 2012 for 2012–2013, instead of use of MW-99 snow data. Results are presented for the Central Arctic Ocean region (defined as CAO in Figure 9) only because the initial snow depth is fixed to be 4 cm for the new ice formed after October 1.

Figure 6 shows the evolutions of the simulated snow depth and ice thickness and the resultant temperature difference between from two snow depth inputs. The mean Snow Model-LG snow depth at CAO on October 1, 2012 was about a half of MW-99 value, but the difference tends to be substantially reduced during

Figure 8. Same as in Figure 7 for (a) model-simulated ice freeboard, (b) model-derived ice thickness (after applying the CS2 retrieval method), (c) CS2-measured ice freeboard, and (d) CS2-estimated ice thickness. Note that the model-simulated ice freeboard in Figure 7(b) is presented in (a) here again, for better comparison.
the course of the simulation, from 10.3 cm on October 1 to 5.3 cm on March 31. More importantly, the influences of snow difference on the sea ice growth appear to be rather minor, probably due to the nudging effect. Compared to less significant difference in the ice depth, the ice temperature is colder for the case with the use of Snow Model-LG data, obviously due to the smaller insulating effect by thinner snow. Nevertheless, the temperature difference appears small within 1 K only over the top ice layers, and only at occasional periods in which unusual cold spells are thought to be prevalent. These rather smaller influences should be due to the continuous nudging of the satellite-derived temperatures.

4.4. General Features of Snow and Sea Ice Properties

Here we examine the general features of simulated snow and ice physical properties. In doing so, five-year December–March mean snow depth, ice freeboard, ice thickness, snow grain size, snow density, and ice density are given in Figure 7. Geographical distribution of simulated snow depth (Figure 7a) shows that the thickest snow area is located north of the Canadian Archipelago where the thickest ice area is located (Figure 7c). Relatively thinner snow areas are located over the Beaufort to Chukchi Sea region and over the Kara to Barents Sea region, where FY ice is dominant. Such features showing the contrast between the deep and shallow snow depths or between the thick and thin ice freeboards and ice thicknesses are found to be in good agreement with the geographical contrast between the MY and FY ice areas. The general agreement in the pattern suggests that the current 1-D thermodynamic model approach is capable of successfully producing snow-sea ice growth over the Arctic Ocean. It is probable that the imposed atmospheric forcing, the employed Lagrangian technique for the moving target, and the use of the satellite-derived thermal states for regulating the model-simulated thermal structure resulted in reasonable distributions of snow depth and ice thickness over the period of December–March.

The simulated snow mean grain size (Figure 7d) shows the distributions that are in near mirror image of the snow depth, that is, smaller grains over the thick MY ice area and larger size over FY ice area. This is because the settlement process leading to the growth of grain size occurs only in upper layers if snow is already thick, but over most of layers if the snow is thin. Thus, the model seems to reproduce known features regarding the growth of grain size of the snow. The snow mean density (Figure 7e), on the other hand, shows relatively heavier snow over the MY ice region, compared to the snow over the FY ice region. The ice mean density shows relatively smaller value over the MY ice region, compared to the density over the FY ice region (Figure 7f). Such distributions can be expected since, in the current model, the ice density profile is initially provided with fixed values and kept invariable throughout the simulation period, except for the newly formed ice at the bottom of ice. Since the newly formed ice is heavier due to higher salinity, ice density over the FY ice area is found to be larger.

For more quantitative examination of the simulations, we compare the five-year mean simulated ice freeboard and derived ice thickness with CS2 estimates (Figure 8). Because the ice thickness retrieval from freeboard measurements depends on the input of snow depth, we use the same MW-99 snow climatology as used for the CS2 retrieval to derive the ice thickness from the simulated ice freeboard. It is shown that the geographical distribution of the simulated ice freeboard is in good agreement with CS2 measured ice freeboard, except for the thick MY ice region north of the Canadian Archipelago where the underestimate by simulated freeboard is clear. Because of that, the underestimate of ice thickness by the model is also clear over the thick MY ice region, which appears to be a caveat of this thermodynamic approach.

Sea ice grows thermodynamically as well as dynamically. The dynamical processes include divergence/convergence, ridging, and advection of sea ice floes. But, in this model, dynamic processes are not included as a sea ice growing mechanism, likely giving limitations to the simulation of the thick sea ice, because the sea

![Figure 9. Three regions of the Arctic Ocean used for examining general features of snow and ice distributions: Central Arctic Ocean (CAO), Beaufort Sea and Chukchi Sea (BC), and East Siberian Sea and Laptev Sea (ESL).](image-url)
ice deeper than 2.5 m grows dynamically rather than thermodynamically (Chevallier & Salas-Mélia, 2012; Flato, 1995). Such limitation may be improved by adjusting the model’s snow skin temperature and SiIT, at each data available time, to those estimated from satellite measurements. It is done by adding the nonphysical nudging term into the heat diffusion equation. But, even if model-produced temperatures are adjusted to the satellite-estimated temperatures, this thermodynamic approach may not properly reflect the impact of dynamically induced depth change over a short period of time because of the slow response of thick ice to a given forcing. By contrast, for the thin ice, because of the fast response to the thermal forcing, the use of satellite data can force the model to produce realistic ice thickness features, being less dependent on the dynamical processes. Furthermore, the good agreement of the thermal structure in the upper ice layers with observations suggests that model outputs can be used for the surface emissivity calculation. It is because the emission weighting functions for the microwave channels are largely located in the upper ice layers (Lee et al., 2017).

We further examine the general features using the time series of regionally averaged variables. Here it is presented how the model-simulated snow and sea ice physical properties have evolved over four months (December–March) of five simulation years. Amongst five years, 2012–2013 and 2016–2018 are considered...
to be thinner sea ice years while 2013–2015 are thicker ice years. As regions in interest, we focus on three characteristic regions, namely the Central Arctic Ocean (CAO), Beaufort Sea and Chukchi Sea (BC), and East Siberian Sea and Laptev Sea (ESL), which are outlined in Figure 9. The CAO, BC, and ESL regions are well characterized with MY ice prevalence throughout the year, MY ice transport from the CAO region, and newly formed FY ice in the fall–winter season, respectively.

The evolutions of snow depth, ice freeboard, and ice thickness in these three regions over the four months of the analysis period are given in terms of daily mean and one standard deviation (Figure 10). The time series of the snow depth shows that it increased over four months from 25 to 32 cm in the CAO region, from 13 to 23 cm in the BC region, and from 14 to 23 cm in the ESL region over the simulation period. The snow accumulation rate corresponds to \( \sim 2 \) cm per month, which is found to be broadly consistent with the rates noted in the monthly climatology of MW-99, the NASA Eulerian Snow on Sea Ice Model (NESOSIM) analysis of Petty et al. (2018), and the Lagrangian snow evolution model (Snow Model-LG) analysis of Stroeve et al. (2020).

The time series of ice freeboard shows that it slowly increased over four months from 10 to 14 cm in the BC region and from 8 to 11 cm in the ESL region over the five-year period, with a growth rate of \( \sim 1 \) cm per month. On the other hand, the simulated ice freeboards in the CAO region show different trends of increase
and decrease from year to year in the range of 15–25 cm. These results well describe the regional features for higher ice freeboard in the CAO region (MY ice zone) and lower ice freeboard in the ESL region (FY ice zone), reported by Kurtz et al. (2014). Similar to the ice freeboard, the thickest ice is found in the CAO region, and the shallowest in the ESL region. The ice growth rate in this heat transfer model is mainly driven by atmospheric forcing. However, it is also affected by the ice thickness itself. The growth rate of the thin sea ice (in the ESL region), which is prone to energy loss to the atmosphere, is found to be faster than that in the thick sea ice area (at CAO). The time series of the ice thickness also indicate the sea ice growth ranges of 2.15–2.48 m at the CAO region (MY ice zone), 1.1–1.84 m at the BC region (mixing zone), and 0.95–1.6 m at the ESL region (FY ice zone). The ranges of ice growth in the FY and MY ice zones are broadly consistent with those reported by Kwok and Cunningham (2015), who used the two-density algorithm (i.e., FY ice density = 917 kg m$^{-3}$ and MY ice density = 882 kg m$^{-3}$).

Although five years of simulations may be too short to examine the interannual variations of ice thickness, the current model simulations at least suggest that the model appears to capture features of interannual variations of ice thickness; years of 2012–2013, 2016–2017, and 2017–2018 find relatively thinner ice...
The evolvement of snow mean grain size, snow mean density, and ice mean density at these three regions over the four-month period are shown in Figure 11. The time series of mean grain size in the snow layer indicate general size ranges; 0.32–0.36 mm in the CAO region, 0.41–0.46 mm in the BC and ESL regions. The ranges of snow mean grain size over four months are similar to the values for the densified snow and hard snow types reported by Mäzler (2002). More fluctuating patterns of the grain size may be considered (in particular associated with first-year/mixed ice at BC and ESL) while years of 2013–2014 and 2014–2015 relatively thicker ice (associated with thicker ice at CAO in 2013–2014 and with thicker ice at BC in 2014–2015).
one of characteristics of the grain size growth, and the occasional sharp decrease is probably due to the accumulation of the newly formed snow with smaller grain sizes associated with heavy precipitation event. Note that, in the current version of this model, the ice grain sizes initially provided are kept invariable throughout the simulation.

The time series of mean snow density shows that the density gradually increases with time, with ranges of 378–422 kg m\(^{-3}\) in the CAO region, 320–406 kg m\(^{-3}\) in the BC region, and 319–387 kg m\(^{-3}\) in the ESL region and \(~15\) kg m\(^{-3}\) per month growth rate. These results are broadly consistent with values from some past expeditions and model analysis. From the Norwegian young sea ICE (N-ICE2015) expedition, the average snow layer density was 300 ± 54 kg m\(^{-3}\) over FY ice and 381 ± 237 kg m\(^{-3}\) over MY ice in the Atlantic side of the Arctic Ocean (Merkouriadi et al., 2017). From the Multidisciplinary drifting Observatory for the Study of the Arctic Climate (MOSAiC) expedition, the snow density was found to be in 218–500 kg m\(^{-3}\) over the fall–winter period (Stroeve et al., 2020). The Snow Model-LG analysis showed that the snow density increases from around 300–350 kg m\(^{-3}\) in November to a maximum of 450 kg m\(^{-3}\) in May over the Arctic Ocean.

Figure 14. Top panel: (a) cross-section of model-simulated, model-derived, and OIB-estimated ice thicknesses along 24 OIB flight paths in March of 2013, 2014, and 2015. Bottom panels: scatterplots of (b) simulated ice thicknesses versus OIB ice thicknesses, and (c) derived ice thicknesses versus OIB ice thicknesses.
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In the time series of the mean ice density, the relatively light sea ice is found over the CAO region (MY ice zone) while the relatively heavy sea ice in the ESL region (FY ice zone). It shows that it slightly increases with growing ice over the four-month period, with the range of 884–889 kg m$^{-3}$ in the CAO region, 891–895 kg m$^{-3}$ in the BC region, and 894–900 kg m$^{-3}$ in the ESL region. The growth rates correspond to 1–2 kg m$^{-3}$ per month. These values are found to be reasonable, in comparison to in situ observations. Timco and Frederking (1996) summarized that the reported ice densities range from low values of around 720 kg m$^{-3}$ up to values around 940 kg m$^{-3}$.

4.5. Snow Depth

Simulated snow depths are compared with the OIB measurements. During the analysis period, the OIB measured the snow depth along its 24 flight paths, mainly over the CAO and BC regions (i.e., six flight paths from March 21–27, 2013, 11 flight paths from March 12–31, 2014, and seven flight paths from March 19–30, 2015). Moreover, the snow depth climatology of MW-99 is included for the comparison.

Figure 15. Top panel: (a) cross-section of model-simulated, model-derived, and CS2-estimated ice thicknesses along 24 OIB flight paths in March of 2013, 2014, and 2015. Bottom panels: scatterplots of (b) simulated ice thicknesses versus CS2 ice thicknesses, and (c) derived ice thicknesses versus CS2 ice thicknesses.
Figure 12a shows the cross-section of model-simulated, OIB-measured, and MW-99 climatology snow depths along the 24 flight paths. While the general variations in the simulated snow depth along the OIB flight paths appear to be reasonably well correlated with the OIB variations, they are slightly overestimated. By contrast, the comparison against MW-99 clearly indicates that MW-99 tends to alternate two snow depth values between the FY and MY ice types. The scatterplot of simulated snow depth versus OIB snow depth shows a correlation coefficient of 0.73, bias of ~6.6 cm, and RMSD of ~9 cm against the OIB estimates for the simulated snow depth (Figure 12b). The comparison against the MW-99 snow depth reveals a correlation coefficient of 0.67, bias of ~−1.5 cm, and RMSD of ~6.0 cm (Figure 12c). In this study, results are compared against the OIB measurements to assess the simulation accuracy of the snow depth.

4.6. Total and Ice Freeboards

The model produces total freeboard as well as ice freeboard. The model-simulated total freeboard is compared against the OIB-measured total freeboard along the same 24 flight paths used for the snow depth comparison. To compare the ice freeboard, we add the CS2-measured ice freeboard collocated along the same OIB flight paths. Figure 13 shows the cross-sectional total freeboard and ice freeboard along the OIB’s 24 flight paths (Figure 13a), and the scatterplots of the simulated total freeboard versus the OIB total freeboard (Figure 13b) and the simulated ice freeboard versus the CS2 ice freeboard (Figure 13c). The simulated cross-sectional total freeboard shows good agreement with the OIB freeboard, as indicated by the correlation coefficient of 0.76, bias of 3.6 cm, and RMSD of 12.6 cm. However, the values appear to fluctuate less than the OIB estimates. Similarly, the simulated ice freeboard shows good agreement with the CS2 ice freeboard, with a correlation coefficient of 0.70, a bias of ~−3 cm, and an RMSD of 6.9 cm. Note that RMSD of CS2 ice freeboard was reported to be 7.4–11 cm against OIB measurements (Kurtz et al., 2014). It is worth noting that the CS2 ice freeboards higher than 30 cm (Figures 13a–13c) are mostly located in the Canadian Archipelago and north of the Greenland region, where snow depths are rather deeper than 30 cm (as shown in Figure 12a).

4.7. Ice Thickness

In this section, we compare the model-simulated ice thickness with the OIB-estimated ice thickness from the total freeboard as well as the CS2-estimated ice thickness from the ice freeboard. Nonetheless, even if the model simulates a freeboard and snow depth that exactly match with the OIB and CS2 values, it does not necessarily mean that they are in perfect agreement. This is because the bulk parameters used for estimating the ice thickness from the freeboard measurements in the hydrostatic equation are different from those used in the model. Thus, for a fair comparison, we also calculate the ice thickness from the model-simulated freeboards and snow depth by applying the same procedures used for the OIB and CS2 methods. These values differ from the “model-simulated ice thickness” and are referred to as “model-derived ice thickness.”

Using the uncertainty level provided with the OIB data, some retrievals are found to be unreasonably thick ice (with a high level of uncertainty). Thus, quality control is necessary before these values can be used. Here, we remove the OIB data if their uncertainty level exceeds 1.3 m. Although the criterion of 1.3 m for the OIB data removal is subjective, 1.3 m of ice thickness corresponds to the modal value of the OIB samples. Approximately 23% of the total 1,210 samples are excluded after applying this uncertainty criterion.

The cross-sections of the model-simulated and model-derived ice thicknesses along the 24 OIB Flight paths are evaluated against the OIB-estimated values (Figure 14a), and the associated scatterplots are given in Figures 14b and 14c. The cross-sectional model-simulated ice thickness shows good agreement with the OIB ice thickness, as indicated by the correlation coefficient of 0.71, bias of ~−24 cm, and RMSD of 78 cm (Figures 14a and 14b). The cross-sectional model-derived ice thickness also shows good agreement with the OIB ice thickness, given that the correlation coefficient, bias, and RMSD are 0.69, 4 cm, and 72 cm, respectively (Figures 14a and 14c). In particular, the bias is substantially reduced from ~−24 to 4 cm when the simulated total freeboards and snow depths are converted using the same technique employed in the OIB algorithm.
Figure 15 shows the cross-sections of the model-simulated and model-derived ice thicknesses as well as the CS2-estimated ice thickness along the 24 flight paths (Figure 15a). Their respective scatterplots appear in Figures 15b and 15c. The cross-section shows that the model-simulated ice thickness is also consistent with the CS2 ice thickness, as indicated by the correlation coefficient, bias, and RMSD of 0.81, −60 cm, and 84 cm, respectively. On the other hand, the bias and RMSD reduce to −28 cm and 65 cm, respectively, while the correlation coefficient hardly changes (0.78) when the derived ice thicknesses are compared against the CS2 values. Note that RMSD of CS2 ice thickness was reported to be 70–100 cm against OIB measurements (Kurtz et al., 2014). Similar to the comparison result against the OIB estimates, the bias reduces substantially when the simulated ice freeboard is converted using the CS2 algorithm. This comparison also shows a large bias if the CS2 ice thickness is deeper than 3.5 m. Once again, these underestimations are mostly observed for the Canadian Archipelago and to the north of Greenland, probably due to missing dynamical processes for the sea ice growth. Overall, we show that the RMSD of the model-derived ice thickness using the same retrieval conditions as those in the OIB and CS2 estimates is ∼70 cm against the lidar-based OIB ice thickness as well as the radar-based CS2 ice thickness.

Since the CS2 measurements cover the Arctic Ocean domain, it is interesting to examine how the model-simulated ice freeboard and ice thickness and the model-derived ice thickness may be compared against the CS2 measurements over the Arctic Ocean. We accomplish this using the last day of each year’s simulation (March 31 of 2013, 2014, and 2015). The results appear in Figure 16. Both the ice freeboard and ice thickness are consistent with the CS2 results along the OIB paths. The correlation coefficients for ice thickness (0.75 and 0.76) are higher than that for the ice freeboard (0.59). It should be noted that the model-derived ice thicknesses are lower than the CS2 estimates, particularly if the CS2 ice thickness is deeper than 3.5 m, which is primarily the case for the high ice freeboard areas of the Canadian Archipelago and to the north of Greenland.

Figure 16. Scatterplots of (a) model-simulated ice freeboards, (b) model-simulated ice thicknesses, and (c) model-derived ice thicknesses against the corresponding CS2 products over the Arctic Ocean domain on March 31 in 2013, 2014, and 2015.

Figure 17. Scatterplots of model-simulated daily mean temperatures at the (a) skin, (b) snow layer, and (c) ice layer (i.e., first top 30 cm of ice) against collocated drifting buoy temperatures during the analysis periods of 2012–2013, 2013–2014, and 2014–2015.
4.8. Snow and Ice Temperature

Model-simulated snow and ice temperatures are evaluated against collocated CRREL IMB measurements. The collocation requirements are as follows: (1) Buoys were deployed from August–October, and (2) all the variables are available throughout the simulation periods without substantial omissions. Five buoys satisfying these requirements are selected (i.e., 2012G, 2012H, 2013G, 2014F, and 2014I). The simulated snow skin temperature, snow-layer mean temperature, and mean temperature of the top 30 cm of the ice layer are compared with the corresponding buoy temperatures on a daily time scale (Figure 17).

The good agreement shown in Figure 17 is thought to be due to the nudging of the satellite-derived snow skin temperature and SIIT. A bias of ∼1 K and an RMSD of less than 3 K with high correlation coefficients for all three variables against the match-up drifting buoy-measured temperature are observed. To examine the nudging impact, we also run the model without nudging and compare the results with those of nudging (Recall that the comparison of the simulation results thus far involved nudging). Table 3 summarizes how the nudging improves the temperature simulations for the snow and ice layers. The comparison clearly shows that introducing the nudging of the satellite-derived temperature information caused considerable improvement. This improvement may be attributed to the nudging constraining the model's snow-sea ice system toward the imposed satellite-derived information on the snow skin temperature and SIIT. Thus, we infer that this enhancement of the temperature structure in the snow-sea ice system could bring about model improvements in the various processes associated with temperature.

5. Conclusions and Discussion

In this study, we implemented the 1-D thermodynamic diffusion model to investigate sea ice growth. To diagnose the physical properties of the snow and ice layers, the vertical heat transfer in the 1-D thermodynamic model was solved for given ERA-I atmospheric heat fluxes at the snow surface. Furthermore, to tightly constrain the thermal structure of the snow-ice system, satellite-derived snow skin temperature and SIIT were imposed through a nudging technique. The resulting 1-D model system was then extended to the space-time domain, covering the Arctic Ocean by counting satellite-derived ice motion vectors.

Table 3
Statistical Comparison of Model-Simulated and Buoy-Measured Temperatures Between Two Simulation Experiments (“Without Nudging” and “With Nudging”)

|                  | Skin temperature | Snow layer temperature | Ice layer temperature |
|------------------|------------------|------------------------|----------------------|
|                  | Without nudging  | With nudging           | Without nudging      | With nudging          | Without nudging | With nudging |
| R                | 0.93             | 0.96                   | 0.78                 | 0.85                  | 0.74           | 0.82         |
| Bias [K]         | 2.4              | 0.8                    | −0.7                 | −0.4                  | −2.3           | 0.4          |
| RMSD [K]         | 3.5              | 2.0                    | 3.2                  | 2.3                   | 3.7            | 1.7          |

Note. The bias refers to the model simulation minus buoy observation.

Table 4
Accuracy Levels of Simulated Snow Depth, Total and Ice Freeboard, Ice Thickness, and Temperature in Terms of Correlation Coefficient (r), Bias, and RMSD

|                  | Snow depth (cm) | Freeboard (cm) | Ice thickness (m) (derived ice thickness) | Temperature (K) |
|------------------|-----------------|----------------|------------------------------------------|-----------------|
|                  | versus OIB      | versus MW-99 along OIB path | versus CS2 along OIB path | versus CS2 over Arctic | versus OIB | versus CS2 along OIB path | versus CS2 over Arctic | versus CRREL IMB |
| r                | 0.73            | 0.67            | 0.76                                     | 0.70            | 0.60            | 0.71 (0.69)               | 0.81 (0.78)               | 0.75 (0.76)            | 0.96           | 0.85 | 0.82 |
| Bias             | 6.6             | −1.5            | 3.6                                      | −3.0            | −3.4            | −0.24 (0.04)              | −0.60 (−0.28)             | −0.43 (−0.32)          | 0.8             | −0.4 | 0.4  |
| RMSD             | 9.1             | 6.0             | 12.6                                     | 6.9             | 6.5            | 0.78 (0.72)               | 0.84 (0.65)               | 0.69 (0.61)            | 2.0             | 2.3  | 1.7  |
Snow-sea ice growth and the associated thermal and physical properties were simulated for the October–March period of 2012–2013, 2013–2014, 2014–2015, 2016–2017, and 2017–2018 over the Arctic Ocean. Analysis of various variables over the December–March period revealed that the model was able to successfully reproduce well-known features and geographical distributions of the snow and sea ice over the Arctic Ocean. The estimated trajectories of drifting ice showed an uncertainty level lower than 40 km. For the assessment of various model-simulated variables, we compared the outputs with available in situ observations or satellite retrievals. We noted that the model-produced snow depth, total freeboard, ice freeboard, and ice thickness were in reasonable agreement with the reference values (as summarized in Table 4). In particular, the snow and ice temperatures showed good agreement with the in situ measurements, suggesting that the nudging of satellite-derived temperatures must have forced the thermal conditions close to the observations. Since the vertical structure of the temperature within the snow-ice column should be closely linked to the ice thickness, the nudging likely contributed to the good agreement for the other variables as well.

Overall, we conclude that the modeling strategies employed in this study helped to successfully implement the 1-D based thermodynamic model for the 2-D application, producing reasonable physical properties of the snow and ice. This study may be an example of showing how satellite observations give an impact on the sea ice modeling. As demonstrated in this study, in spite of only the thermodynamic part employed, the successful simulation can be largely attributed to the introduction of satellite-derived skin temperature and SIIT to shape the thermal structure of the snow-ice system. This type of approach using satellite information can also be taken for climate simulations. Active integration of snow and ice observations from satellites or other means into the model system would bring in better climate simulations.

On the other hand, we admit limitations of this approach such as underestimate of the sea ice thickness over the thick ice regions, likely due to missing dynamically induced ice growing processes. For the better simulations, dynamic components should be included, probably using the convergence information from obtained sea ice drift motions. Another caveat would be the winter-time only capability. In order to extend this approach to the summer melting season, melting processes including the wet snow metamorphism and redistribution processes of solar radiation linked to wet snow and melt ponds should be included. Furthermore, more refined algorithm to retrieve the SIIT during the summer is needed to provide essential inputs to the model for the summer application. It is because the microwave remote sensing for the SIIT is more susceptible to uncertainty during the melting season, due to the difficulty of understanding of surface emissivity in case of surfaces covered with wet snow and melt ponds.

Nevertheless, in future studies, the microwave surface emissivity and emitting layer temperature will be diagnosed from simulated physical properties, so that the surface upwelling radiance can be calculated for the microwave data assimilation over the Arctic Ocean during the winter. Considering that satellite-derived input data (i.e., OSI SAF snow skin temperature, AMSR-derived SIIT, and OSI SAF sea ice drift motion) are all currently available with a delay of one day, the use of this approach for the operational weather forecasting is feasible with at least a one-day time lag. Concerning the time delay, however, because the sea ice emissivity should not change substantially at the given area over a short period (e.g., in the order of days), the impact of delayed input data should be minimal.

### Appendix A

The net longwave radiation flux at the upper boundary expresses the energy budget between the incoming longwave radiation flux ($F_{LW}^\downarrow$) from atmospheric forcing and outgoing longwave radiation flux ($F_{LW}^\uparrow$) from the Stefan–Boltzmann law. The net longwave radiation flux can be described as follows:

$$F_{LW}^{net} = F_{LW}^\downarrow - F_{LW}^\uparrow = F_{LW}^\downarrow - \varepsilon_{LW} C_{SB} T_s^4$$  \hspace{1cm} (A1)

where $\varepsilon_{LW}$ and $C_{SB}$ are the longwave emissivity (assumed to be 0.99) and the Stefan–Boltzmann constant, respectively.

The net shortwave radiation flux at the upper boundary is determined by the reflection and absorption of the incoming shortwave radiation ($F_{SW}^\downarrow$) from atmospheric forcing, as shown in the following equation:
where the $\varphi$ and $\alpha$ indicate the absorptivity and albedo of the upper boundary, respectively. The absorptivity is set to 62% (Untersteiner, 1961), and the albedo is parameterized for the snow or bare ice surface. The snow albedo ($\alpha_{\text{snow}}$) is estimated by a multilinear function of snow density and total cloud cover ($tcc$) following Greuell and Konzelmann (1994), and the bare sea ice albedo ($\alpha_{\text{ice}}$) is estimated by a logarithmic fitting function of ice thickness ($H_{\text{ice}}$) as per Weller (1972). $\alpha_{\text{snow}}$ and $\alpha_{\text{ice}}$ are defined as follows:

\[
\alpha_{\text{snow}} = 0.58 - 4.42623 \times 10^{-4} \left( \rho_s - 910 \right) + 0.05 \left( tcc - 0.5 \right) \left( h_{\text{snow}} > 0 \right)
\]

\[
\alpha_{\text{ice}} = 0.4723 + 0.0674 \ln \left( H_{\text{ice}} \right) \left( h_{\text{snow}} = 0 \right)
\]

The net longwave radiation flux is a significant term that governs the heat budget at the upper boundary in the winter season, whereas while the net shortwave radiation flux is not so significant in the winter season, it is important in inducing the temperature rise in early spring and the onset of melting in late spring.

The sensible and latent heat fluxes are expressed as bulk parameterizations, as shown in Equations A4 and A5. The sensible heat representing heat exchange due to the temperature deviation between the surface and near-surface air ($\sim 2 \text{ m}$) is described as follows:

\[
F_s = \rho_{\text{air}} c_{p,\text{air}} C_s U_{10m} \left( T_{2m} - T_s \right)
\]

where $\rho_{\text{air}}$ is the density of dry air, $c_{p,\text{air}}$ is the specific heat capacity of dry air, $U_{10m}$ is the wind speed at 10 m, $T_{2m}$ is the air temperature at 2 m, and $C_s$ is the bulk transfer coefficient of sensible heat.

The latent heat flux representing the vapor flux exchange owing to vaporization between the surface and near-surface air is described as follows:

\[
F_l = \rho_{\text{air}} L_v C_l U_{10m} \frac{0.622}{P_s} \left( RH_{\text{air}} \cdot e_{\text{air}} - RH_s \cdot e_s \right)
\]

where $P_s$ is the surface pressure, $L_v$ is the latent heat of vaporization, $RH_{\text{air}}$ and $RH_s$ are the relative humidity of the near-surface air and surface, respectively, and $C_l$ is the bulk transfer coefficient of latent heat. We assume the relative humidity at the surface as 100% (i.e., $RH_s = 1$). Since the atmospheric boundary above the sea ice is known to be under the saturation or supersaturation condition in the winter season (Andreas et al., 2002), the latent heat flux takes up a relatively small amount in the energy budget in winter.

As mentioned earlier, the conductive heat exchange becomes

\[
F_c = \frac{0.5 \Delta_{z1}}{k_1} \left( T_i - T_s \right)
\]

Thus, given the atmospheric forcings and snow-sea ice conditions, all the flux terms in Equation 3 can be expressed as a function of the skin temperature. Then, we can diagnose the skin temperature satisfying Equation 3 at each time step using the minimum residual method.

**Appendix B**

Using the result of Equation A2 in Appendix A, the incoming shortwave flux that penetrates the upper boundary ($I_0$) can be defined as follows:

\[
I_0 = \left( 1 - \varphi \right) \left( 1 - \alpha \right) F_{sw}^+ \tag{B1}
\]

To solve the radiative transfer equation within the snow-sea ice system, the shortwave radiation flux absorbed by each $j$th layer ($j = 1, \ldots, N$) ($I_j$) is expressed by Beer’s law, as follows:
\[ I_j = I_0 \left( Y_{j-1} - Y_j \right) = I_0 \left[ e^{-\tau_{\beta_{\text{ice}, j}}(\beta_e)} - e^{-\tau_{\beta_{\text{snow}, j}}(\beta_e)} \right] = I_0 \left[ \int_{\rho_0}^{\rho_j} \left( \beta_e \right)_{\text{ice}} d\rho - \int_{\rho_0}^{\rho_j} \left( \beta_e \right)_{\text{snow}} d\rho \right] \]  

where \( Y_j \) refers to the accumulated transmittance from the first to the \( j \)th layer. In this regard, the transmittance is defined as the exponential function of the accumulated optical depth (\( \tau \)), and the accumulated optical depth of the \( j \)th layer is expressed as the integral of the bulk extinction coefficient (\( \beta_e \), in units of m\(^{-1}\)) from the first to the \( j \)th layer. Hence, the shortwave radiation flux reaching each layer falls off exponentially for the accumulated optical depth. The bulk extinction coefficient for the snow and sea ice at the \( j \)th layer is defined as follows:

\[ \left( \beta_e \right)_{\text{snow}} = 0.12 \frac{\rho_j}{d_j} \]  

\[ \left( \beta_e \right)_{\text{sea ice}} = 1.3 \]  

where \( \beta_e \) for snow is parameterized by a function of snow density (\( \rho \)) and grain size (\( d \)) as per Bohren and Barkstrom (1974), while \( \beta_e \) for sea ice is set to 1.3 following Perovich (1996).

**Data Availability Statement**

The ERA-I reanalysis data is downloadable from the ERA-Interim full-resolution database (https://apps.ecmwf.int/datasets/data/interim-full-daily/levtype=sfc). The Level 3 AMSR2 brightness temperature data is downloadable from Japan Aerospace Exploration Agency’s G-portal system (https://gportal.jaxa.jp). The OSI SAF high latitude ice surface temperature data, OSI SAF low-resolution sea ice drift data, OSI SAF global sea ice type data are available from the repository of the OSI SAF High Latitude Processing Center (http://osisaf.met.no/p/ice). The three-hourly, January 1, 2012 through December 31, 2015, OSI SAF high latitude ice surface temperature data were provided by G. DybkjÆR working for the Danish Meteorological Institute (http://ocean.dmi.dk). The Level 4 CryoSat-2 monthly composite ice freeboard and thickness data and the Operation IceBridge snow and ice depth, total freeboard, and ice thickness Quick Look data are available from the repository of National Snow and Ice Data Center (https://nsidc.org/data/RDEFT4) and (https://nsidc.org/data/NSIDC-0708/versions/1), respectively. The CRREL IMB data are available from the website of the CRREL-Dartmouth Mass Balance Buoy Program (http://imb-crrel-dartmouth.org/archived-data). Other simulated data used for analysis and generating figures in this manuscripts are available at https://doi.org/10.5281/zenodo.4500137.

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