Advanced Sea Ice Modeling for Short-Term Forecasting for Alaska’s Coasts

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ABSTRACT: In Alaska’s coastal environment, accurate information of sea ice conditions is desired by operational forecasters, emergency managers, and responders. Complicated interactions among atmosphere, waves, ocean circulation, and sea ice collectively impact the ice conditions, intensity of storm surges, and flooding, making accurate predictions challenging. A collaborative work to build the Alaska Coastal Ocean Forecast System established an integrated storm surge, wave, and sea ice model system for the coasts of Alaska, where the verified model components are linked using the Earth System Modeling Framework and the National Unified Operational Prediction Capability. We present the verification of the sea ice model component based on the Los Alamos Sea Ice Model, version 6. The regional, high-resolution (3 km) configuration of the model was forced by operational atmospheric and ocean model outputs. Extensive numerical experiments were conducted from December 2018 to August 2020 to verify the model’s capability to represent detailed nearshore and offshore sea ice behavior, including landfast ice, ice thickness, and evolution of air–ice drag coefficient. Comparisons of the hindcast simulations with the observations of ice extent presented the model’s comparable performance with the Global Ocean Forecast System 3.1 (GOF33.1). The model’s skill in reproducing landfast ice area significantly outperformed GOF33.1. Comparison of the modeled sea ice freeboard with the Ice, Cloud, and Land Elevation Satellite-2 product showed a mean bias of −4.6 cm. Daily 5-day forecast simulations for October 2020–August 2021 presented the model’s promising performance for future implementation in the coupled model system.

SIGNIFICANCE STATEMENT: Accurate sea ice information along Alaska’s coasts is desired by the communities for preparedness of hazardous events, such as storm surges and flooding. However, such information, in particular predicted conditions, remains to be a gap. This study presents the verification of the state-of-art sea ice model for Alaska’s coasts for future use in the more comprehensive coupled model system where ocean circulation, wave, and sea ice models are integrated. The model demonstrates comparable performance with the existing operational ocean–ice coupled model product in reproducing overall sea ice extent and significantly outperformed it in reproducing landfast ice cover. Comparison with the novel satellite product presented the model’s ability to capture sea ice freeboard in the stable ice season.

KEYWORDS: Sea ice; Coastal meteorology; Ice thickness; Numerical analysis/modeling; Operational forecasting

1. Introduction

Storm surges and their associated flooding events are hazardous phenomena along Alaska’s western coasts. Regional forecasters and communities in this region have challenges to assess threats, to determine risk and the potential impacts of storms, or to evaluate safe evacuation routes and locations. In addition to complicated interactions among atmosphere, waves, and ocean circulation, the unique factor that brings further complexity to this region is sea ice. Sea ice alters the air–sea momentum transfer, accelerates/slowslows ocean currents, and dampens waves. All these processes collectively impact the intensity of storm surges and flooding. Such interactions and resulting hazardous total water levels (i.e., water surface elevation and waves) are difficult to predict accurately with a single numerical model that represents only one aspect of these processes.
Fundmed by the National Oceanic and Atmospheric Administration (NOAA) National Ocean Service's (NOS) U.S. Integrated Ocean Observing System (IOOS), a collaborative work built an integrated storm surge, wave, and sea ice model system for the coasts of western Alaska. The prototype system is deployed as the Alaska Coastal Ocean Forecast System (ALCOFS, https://gm-ling.github.io/ALCOFS-R/; Ling et al. 2023), which will be hosted by the Alaska Ocean Observing System (AOOS) to provide a real-time forecast guidance for forecasters and local communities. The model components of ALCOFS are the Advanced Circulation (ADCIRC) coastal ocean model (Luettich and Westerink 2018), the WAVEWATCH III (WW3) model (WW3DG 2019), the surface meteorology data component, and the Los Alamos Sea Ice Model (CICE; CICE Consortium 2021). The coupling of the model components is achieved using the National Unified Operational Prediction Capability (NUOPC) interoperability layer (Content Standards Committee Members 2023) and the Earth System Modeling Framework (ESMF; Balaji et al. 2022), which is a NUOPC application implemented following best practices of the Unified Forecast System (UFS, https://ufscommunity.org/) to couple coastal ocean models and other model components. Use of the ESMF/NUOPC infrastructure allows flexible, parallel, and efficient development of these model components. In other words, updates to the storm surge, wave, and sea ice models can occur simultaneously (often split by multiple developers) and seamlessly integrate into the coupled system. This streamlined development process, which would not be possible when the model components are internally coupled, allows efficient advancement of each model component. Many coastal model applications to predict total water level are based on storm surge, wave, and/or hydrological model components (e.g., Abdolali et al. 2020; Moghimi et al. 2020a, 2019, 2020b), which is a NUOPC application implemented following best practices of the Unified Forecast System (UFS, https://ufscommunity.org/) to couple coastal ocean models and other model components. Use of the ESMF/NUOPC infrastructure allows flexible, parallel, and efficient development of these model components. In other words, updates to the storm surge, wave, and sea ice models can occur simultaneously (often split by multiple developers) and seamlessly integrate into the coupled system. This streamlined development process, which would not be possible when the model components are internally coupled, allows efficient advancement of each model component. Many coastal model applications to predict total water level are based on storm surge, wave, and/or hydrological model components (e.g., Abdolali et al. 2020; Moghimi et al. 2020b; Funakoshi et al. 2013; Wang et al. 2021; Alves et al. 2023). The sea ice model component is less explored for total water level prediction despite its importance in such applications except for limited examples where empirical methods were used to represent sea ice in altering momentum transfer (e.g., Joyce et al. 2019). However, the needs for including a physics-based sea ice model in such systems are articulated by the navigation and coastal community (Seroka et al. 2022; van der Westhuysen et al. 2022; Huang et al. 2022). Previous studies that used coupled sea ice and ocean models for a domain covering Alaska’s coastal regions often focused on the overall circulations and thermal structure in the Bering and Chukchi Seas, as well as its seasonality and interannual variability (Durski and Kurapov 2019; Wang et al. 2009, 2014; Hu and Wang 2010). When the spatial scale of interest comes down to those of wave runup, overtopping, and coastal flooding, nearshore features of sea ice behavior need to be represented accurately. These include the form drag in partial ice cover that generally amplifies momentum transfer between the air and the ocean, landfast ice that acts as a damper of ocean surface currents, breakage of ice floes due to ocean surface waves, and resulting wave dampening. However, few sea ice model applications used sufficient spatial resolution to resolve these processes or verified them, particularly for coastal applications (Intrieri et al. 2023).

In this study, we present the development of the standalone sea ice model based on the CICE version 6 (CICE6) as a concurrent effort with the storm surge (ADCIRC) and wave (WW3) model developments within the larger collaborative framework to develop ALCOFS (Ling et al. 2023). We configure CICE6 for Alaska’s coast, conduct hindcast simulations forced by operational atmospheric and oceanic analyses datasets, and conduct extensive sensitivity experiments for the air–ice drag parameterization and basal stress parameterization. We also present the skill assessment results of 5-day forecast simulations using CICE6 for the 2020/21 period. Section 2 describes the model configuration, forcing datasets, and observational datasets used for comparison with the model results. Section 3 discusses the results from the hindcast simulations, the sensitivity experiments, and the skill assessment of the 5-day forecast simulations. Section 4 summarizes and concludes the study.

2. Methodology

a. Sea ice model configuration

We use CICE (CICE Consortium 2021) as the standalone sea ice model. The sea ice model domain has roughly 3-km spatial resolution and covers the Gulf of Alaska, Bering, Chukchi, Beaufort, and East Siberian Seas (Fig. 1). The ice internal stress parameterization is based on the elastic–viscous–plastic rheology (Hunke and Dukowicz 1997). Five ice thickness categories are used with upper bounds of 0.64, 1.39, 2.47, 4.57, and 9.33 m. The ice strength parameterization is based on the CICE version 6 (CICE6) as employed (Semtner 1976), and the slab model for the ocean mixed layer is activated.

We conduct a series of numerical experiments for the air–ice drag coefficient $C_{D_{\text{air}}}$, the basal stress parameterization, and the tensile stress parameterization (Table 1). We examine the constant air–ice drag coefficient $C_{D_{\text{air}}} = 1.63 \times 10^{-3}$, as well as the parameterization that accounts for the form drag due to ice ridges (Lüpkes et al. 2012; Tsamados et al. 2014). The basal stress parameterization by Lemieux et al. (2015, 2016) is used to represent the grounding of ice in shallow waters and resulting impacts on the modeled landfast ice. Lemieux et al. (2015) defined the basal stress $\tau_b = (\tau_{b_0}, \tau_{b_1})$ for incorporation into the momentum equation of ice:

\begin{equation}
\tau_b = \begin{cases}
0 & \text{if } h > h_c \\
\frac{u}{|u| + \eta_0}(h - h_c)e^{-(h-h_c)^2}, & \text{if } h \leq h_c
\end{cases},
\end{equation}

where $k_2$ is a free parameter (N m$^{-3}$), $u = (u_x, u_y)$ is the ice velocity vector, $|u|$ is the speed of drifting ice, $\eta_0$ is a small velocity parameter for a smooth transition between the static and kinetic friction regimes, $h$ is the mean ice thickness in a
grid cell, $h_c = Ah_w/k_1$ is the critical mean thickness, $h_w$ is the water depth, and $A$ is the ice concentration ($0-1$). The term $k_1$ is the first free parameter and is also called the critical thickness parameter, and the term $k_2$ is called the maximum basal stress parameter (Lemieux et al. 2015). The maximum basal stress sustained by the grounded ridge depends on the weight of the ridge in excess of hydrostatic balance. As shown in Table 1, $k_1$ and $k_2$ are perturbed to examine the impacts on the modeled landfast ice. Note that the newest version of CICE6, which was released at the time of writing this manuscript, includes a basal stress parameterization based on the probability of contact between the ice and the seabed (Dupont et al. 2022), whose testing in coastal applications like this study is deferred to a future work.

CICE6 includes the isotropic tensile strength parameterization by updating the bulk viscous coefficient $\zeta$ in the governing equations for ice internal stress to the following:

$$\zeta = P_p(1 + k_t)/2\Delta^*, \quad (2)$$

where $P_p$ is the compressive ice strength (Lipscomb et al. 2007) and $\Delta^* = (\Delta + \Delta_{min})$, where $\Delta$ is a function of ice divergence, the horizontal tension rate, the shearing strain rate, and the ratio of major and minor axes of the elliptical yield curve. The term $\Delta_{min}$ is a small value added to avoid a singularity with $\zeta$. The term $k_t$ is the isotropic tensile strength parameter and characterizes the amount of tensile strength as a function of the ice strength in compression ($k_tP_p$), and $P = P_p\Delta/\Delta^*$ is a replacement pressure to ensure the internal stresses are zero when the strain rates are zero. Details on the governing equations for ice internal stress, implementation of the isotropic tensile strength parameter, and its impacts on elliptical yield curves are detailed in Lemieux et al. (2016) and are thus omitted in this paper. They examined $k_t = 0, 0.1, 0.2, 0.3,$ and $0.4$ for their application to the Arctic Ocean and found that $k_t$ should be between $0.1$ and $0.2$ to obtain the most realistic results. In the North American Great Lakes application by Lin et al. (2022), they found that the landfast ice

<table>
<thead>
<tr>
<th>Process</th>
<th>Parameterization</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Air–ice drag coefficient $C_{D_{air}}$</td>
<td>Constant</td>
<td>$1.63 \times 10^{-3}$</td>
</tr>
<tr>
<td></td>
<td>Dynamic (Tsamados et al. 2014)</td>
<td>Dynamically calculated. Consists of skin drag $C_{D_{air,skin}}$ and form drag $C_{D_{air,form}}$ from ridge, floe edge, and melt pond</td>
</tr>
<tr>
<td>Landfast ice</td>
<td>Tensile stress (Lemieux et al. 2016)</td>
<td>In Eq. (1), $k_1 = 4$, $10$, $16$, $k_2 = 7.5$, $15$ are tested</td>
</tr>
<tr>
<td></td>
<td>Basal stress (Lemieux et al. 2016)</td>
<td>No tensile stress or basal stress</td>
</tr>
</tbody>
</table>

Fig. 1. The domain used for the CICE6 simulations is indicated by the color shaded area. The color denotes the defined mixed layer depth, which is the water depth for areas of 50-m depth or shallower and a constant of 50 m for areas deeper than 50 m. For reference, the isobaths of 50, 200, and 1000 m are shown as white contour lines. The red box indicates the western Alaska domain where most analyses were conducted. The light pink box indicates the domain where ice extent time series were calculated.
area was relatively insensitive to varying \( k_t \) from 0 to 0.4 in their high-resolution configuration using the unstructured mesh hydrodynamic-ice model. In this study, we examine \( k_t = 0, 0.2, \) and 0.4.

Numerical experiments were conducted for the hindcast simulation period from 1 October 2018 to 30 September 2020. In addition, using the control experiment (Table 1), daily 5-day forecast simulations are conducted for the period from 1 October 2020 to 31 August 2021. A schematic of 5-day forecast simulations is shown in Fig. 2. The sea ice model is forced by the surface meteorology data and surface ocean data from the operational model outputs. The surface meteorology data are obtained from the operational analysis of the NOAA’s Climate Forecast System version 2 (CFSv2; Saha et al. 2014).

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**Fig. 2.** A schematic diagram showing the flow of 5-day forecast simulations. No initialization or nudging of ice conditions was applied.

**Fig. 3.** Time series of sea ice extent \( (\times 10^6 \text{ km}^2) \) for the light pink domain in Fig. 1. The analysis (black line) is from the National Ice Center. The color lines are from the CICE6 hindcast simulations. (top) The time series of sea ice extent from the simulation results with perturbed \( k_1 \) and \( k_2 \) (basal stress parameters) and fixed \( k_t = 0 \) (tensile stress parameter). (bottom) As in the top panel, but with fixed \( k_1 = 10 \) and \( k_2 = 15 \) and perturbed \( k_t \).
for the hindcast simulations and from the NOAA’s Global Forecast System (GFS) for the forecast simulations (0–120-h forecasts at 1200 UTC cycles, only cloud cover and downward shortwave radiations are from 5–126-h forecasts at 0600 UTC cycles). The ocean data of sea surface temperature, sea surface salinity, and sea surface current are obtained from the Global Ocean Forecast System 3.1 (GOFS3.1).

b. Datasets for model verification and skill assessment metrics

The sea ice extent analysis from the National Ice Center (https://usicecenter.gov/Products/ArcticData) is obtained for comparison of the time series of sea ice extent over the inner domain excluding near-boundary regions (light pink box in Fig. 1). The Alaska Sea Ice Program (ASIP, https://www.weather.gov/afc/ice) issues daily ice analyses in visual charts and the shapefile format that provides detailed regional ice information, including ice concentration, landfast ice area, and ice stage. We use the landfast ice area from the ASIP product. In the model results, we define landfast ice as ice covered cells when ice concentration exceeds 99% and ice velocity does not exceed 1.0 ms⁻¹. We used tighter criteria than Lemieux et al. (2015, 2016, 2018) to represent the immobile characteristics of landfast ice better in a time scale of days. The evaluation of modeled landfast ice area is conducted only for Alaska’s coasts but not for the Russian coasts (the western Alaska domain in Fig. 1). For reference, the sea ice model outputs from GOFS3.1 are included in the landfast ice area comparison. The hindcast and forecast simulation results are evaluated based on the root-mean-square errors (RMSEs) and mean errors (MEs). The Multisensor Analyzed Sea Ice Extent (MASIE)–AMSR2 (MASAM2) daily 4-km sea ice concentration product was used for the evaluation of ice edge location.

<table>
<thead>
<tr>
<th>Basal stress–free parameters</th>
<th>$k_1 = 4$, $k_2 = 15$</th>
<th>$k_1 = 10$, $k_2 = 15$</th>
<th>$k_1 = 16$, $k_2 = 15$</th>
<th>$k_1 = 4$, $k_2 = 7.5$</th>
<th>No basal stress</th>
<th>$k_1 = 10$, $k_2 = 15$</th>
<th>$k_1 = 10$, $k_2 = 7.5$</th>
<th>$k_1 = 10$, $k_2 = 15$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drag coefficient parameterization</td>
<td>Tsamados et al. (2014)</td>
<td>Constant</td>
<td>Tsamados et al. (2014)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tensile stress parameter $k_1$</td>
<td>0</td>
<td>0.2</td>
<td>0.4</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RMSE</td>
<td>0.059</td>
<td>0.056</td>
<td>0.061</td>
<td>0.059</td>
<td>0.060</td>
<td>0.060</td>
<td>0.063</td>
<td>0.078</td>
</tr>
<tr>
<td>ME</td>
<td>-0.032</td>
<td>-0.026</td>
<td>-0.011</td>
<td>-0.032</td>
<td>-0.034</td>
<td>-0.015</td>
<td>-0.033</td>
<td>-0.045</td>
</tr>
</tbody>
</table>

Table 2. RMSEs and MEs of the time series of ice extent. Units are 10⁶ km². The control case is indicated by bold font.

Fig. 4. Spatial pattern of daily averaged ice concentration from the model results with the control configuration (color shading). The 10% and 90% of ice concentration contours from the MASAM satellite measurements are shown in black and gray lines, respectively.
and the calculation of the anomaly correlation coefficient (ACC; ECMWF 2024). MASAM2 is a blend of the MASIE product and ice concentration from the Advanced Microwave Scanning Radiometer 2 (AMSR2). In the 5-day forecast simulations, the GOFS3.1 reanalysis product was also used for comparison of ice extent modeled by CICE6. ACC was calculated for forecast days 1–5 based on anomalies of ice concentration from the 2012–19 mean of MASAM2. Typically, ACC around 0.5 indicates that the model has forecast skill comparable with climatology-based forecasts, and ACC > 0.6 typically indicates that the model forecast has value in capturing synoptic patterns.

The sea ice freeboard data are obtained from the ATL10 dataset (Kwok and Markus 2018) of the Advanced Topographic Laser Altimeter System (ATLAS) instrument on board the Ice, Cloud, and Land Elevation Satellite-2 (ICESat-2) observatory. The modeled sea ice freeboard was compared with the ATL10 dataset for select tracks that crossed the model domain. This comparison is limited to January, February, and March, when ice extent over the region reaches maximum to avoid the sea state bias issues in partial ice cover. The comparison is limited to January, February, and March, when ice extent over the region reaches maximum to avoid the sea state bias issues in partial ice cover. The comparison with the ICESat-2 data points was made only when the modeled ice concentration at the closest pixel is above 90%. As a result, a total of 3496 data points were obtained for comparison with the CICE6 simulations for the western Alaska domain during January, February, and March of 2019 and 2020.

3. Results and discussion

a. Hindcast simulation results—Overall conditions

Figure 3 shows the time series of ice extent from the CICE6 hindcast simulations and the National Ice Center analysis. Overall, the model captures the observed seasonality of ice extent. Fluctuations over a few weeks are also captured well (e.g., late February–early March in 2019). The ice extent from the model presents minimal sensitivity to the basal stress parameterization (Fig. 3, top). This is expected as the basal stress parameterization is designed to take effect only in shallow, nearshore regions. The sensitivity to the tensile stress parameterization is also weak, except for the melting periods in summer (Fig. 3, bottom). In both summers, the modeled ice extent decays slightly earlier as $k_t$ becomes larger from 0 to 0.4. Table 2 shows the RMSE and ME values for the modeled ice extents. RMSE is minimal in the control case, while the ME is not the best.

The spatial patterns of ice concentration are shown in Fig. 4 for select dates in the season of 2018/19. The ice edge locations from the model agree well with the analyses from the MASAM satellite measurement in each month, suggesting that the model captures seasonal evolution of ice edge reasonably. Figure 5 shows the modeled, daily averaged ice thickness and ice velocity vector. Near the ice edge, ice thickness is mostly within the range of 0–40 cm. On the other hand, along
the Russian coast, it tends to reach nearly 4 m in February–May. This seems to be in the higher range compared with that shown by Kwok and Cunningham (2015), whose estimates based on the CryoSat-2 for the winters of 2010/11–2013/14 tended to be less than 3 m for the area in February–May. The difference might be due to the interannual variability (our simulation period does not overlap with Kwok and Cunningham 2015) or the simple continuous boundary condition used in the model (i.e., ice inflow from the northern and western boundaries does not reflect those in actual years). However, such high ice thickness does not appear in most of the regions of western Alaska’s coast, which is the focus of this paper. Detailed examination of sensitivity of modeled ice thickness as well as modeled ice freeboard for the western Alaska domain will be provided in section 3c. The daily ice velocity vector field shows overall northward flow along the Bering Strait (Fig. 5), consistent with the northward volume transport across the Strait documented in many previous studies (e.g., Woodgate 2010; Peralta-Ferriz and Woodgate 2017; Woodgate et al. 2005, 2006; Woodgate 2018; Woodgate et al. 2015), with occasional flow reversal due to wind directions. The southerly ice flow on 15 December 2018 across the Strait (Fig. 5) might be such an example.

b. Landfast ice

The modeled landfast ice area presents stronger sensitivity to the basal stress and tensile stress parameterizations (Fig. 6). In the basal stress parameterization, the modeled landfast ice area increases as $k_1$ increases from 4, 10, to 16, while it barely changes with $k_2$ (Fig. 6, top). This is also evident in the RMSE and ME values in Table 3. As in Eq. (1), $k_1$ determines the critical ice thickness $h_c$ and $k_2$ determines the intensity of basal stress once ice thickness goes above $h_c$. Within the tested ranges of $k_1$ and $k_2$, the results indicate that modeled landfast

<table>
<thead>
<tr>
<th>Basal stress–free parameters</th>
<th>$k_1 = 4, k_1 = 10, k_1 = 16$</th>
<th>$k_1 = 4, k_1 = 10, k_1 = 16$</th>
<th>$k_1 = 10, k_2 = 15$</th>
<th>$k_1 = 10, k_2 = 15$</th>
<th>$k_1 = 10, k_2 = 15$</th>
<th>GOFS3.1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drag coefficient parameterization</td>
<td>$k_2 = 15$</td>
<td>$k_2 = 15$</td>
<td>$k_2 = 15$</td>
<td>$k_2 = 15$</td>
<td>$k_2 = 15$</td>
<td>$k_2 = 15$</td>
</tr>
<tr>
<td>Tensile stress parameter</td>
<td>Tsamados et al. (2014)</td>
<td>Constant</td>
<td>Tsamados et al. (2014)</td>
<td>$k_t = 0$</td>
<td>$k_t = 0.2$</td>
<td>$k_t = 0.4$</td>
</tr>
<tr>
<td>RMSE</td>
<td>2.59</td>
<td>0.83</td>
<td>2.32</td>
<td>2.61</td>
<td>3.53</td>
<td>1.14</td>
</tr>
<tr>
<td>ME</td>
<td>−2.15</td>
<td>−0.34</td>
<td>1.51</td>
<td>−2.17</td>
<td>−3.00</td>
<td>0.48</td>
</tr>
</tbody>
</table>
ice area is more sensitive to the critical ice thickness, i.e., how easily basal stress is triggered. The sensitivity to the tensile stress parameter $k_t$ is not as evident, but the larger $k_t$ resulted in more landfast ice area (Fig. 6, bottom). These are overall consistent with Lemieux et al. (2015, 2016), who tested the sensitivity of modeled landfast ice area to $k_1$, $k_2$, and $k_t$ in the East Siberian, Laptev, Kara, and Beaufort Seas. It is also notable that landfast ice area is significantly underestimated in GOFS3.1, which does not take account of the basal stress and tensile stress parameterization (Metzger et al. 2014). The spatial patterns of modeled and observed landfast ice area are shown in Fig. 7. While modeled landfast ice underestimates in some areas (e.g., the northern coast of Alaska, Kotzebue Sound), overall patterns are captured by the model. The RMSE was minimal for the control configuration (i.e., $k_1 = 10$, $k_2 = 15$, and $k_t = 0$, with the form drag parameterization; see Table 3), while the ME was slightly lower with $k_t = 0.4$.

In the no-form drag experiment, both overall ice extent and landfast ice area are larger than the control, particularly in the melting season for ice extent (Fig. 3, bottom, red line) and throughout the seasons for landfast ice area (Fig. 6, bottom, red line). These resulted in larger RMSE and ME for the no-form drag experiment (Table 3). This is likely due to higher ice thickness simulated in the no-form drag experiment (Fig. 8, discussed in detail in the following section).

c. Ice thickness, drag coefficient, and freeboard

Unlike the spatial patterns of ice coverage, the accurate estimation of ice volume or thickness over the large spatial domain is not available. Thus, here, we discuss the sensitivity of simulated ice thickness to the parameterizations of basal stress, tensile stress, and air–ice drag parameterization, with a supplementary comparison with sea ice freeboard measurements from the ICESat-2 ATL10 along-track product. Figure 8 shows the evolution of mean ice thickness over the ice area. Overall, the sensitivity is small for the perturbed $k_1$ or $k_2$, yet the mean ice thickness is slightly larger in the melting phase as $k_1$ increases (i.e., higher critical thickness $h_c$). This makes sense as the remaining ice later in the season tended to be coastal ice and therefore had a more fraction of landfast ice, whose thickness is sensitive to $k_1$. The increase in mean ice thickness with $k_1$ is not quite simple. For example, the mean ice thickness with $k_1 = 16$ in May 2019 and for the rest of the season stands out. This is not seen in the 2019/20 season. As the tensile stress parameter $k_t$ becomes large, the mean ice thickness slightly decreased (Fig. 8, bottom). This tendency is less apparent in the 2019/20 season, and again, the sensitivity appears to be not simple. The most robust response was the increased mean ice thickness when the constant air–ice drag coefficient $C_{Dat}$ was used (Fig. 8, bottom, “no form drag”) instead of the dynamic $C_{Dat}$ (Tsamados et al. 2014).
is likely because the constant $C_{Dai}$ was larger than dynamic $C_{Dai}$ in most of the freezing and stable periods (i.e., October–March, Fig. 9); this resulted in stronger wind convergence and therefore higher ice thickness. In the melting phase (May–August), the dynamic $C_{Dai}$ goes above the constant $C_{Dai}$, which is contributed by the form drag components from the lateral side of floe and ridges. Sea ice freeboard comparison over the western Alaska domain (Fig. 10) shows a reasonable agreement between the control simulation and ICESat-2 ATL10, with the correlation coefficient of 0.69 at the 99% confidence level. The control simulation was negatively biased by 4.62 cm. Spatial comparison of sea ice freeboard (Fig. 11) shows that the overall spatial and temporal gradients are captured well. On the other hand,

![Fig. 8. Time series of mean ice thickness over the ice area. The domain is around the western Alaska domain (red box in Fig. 1).](image)

![Fig. 9. (top) Evolution of air–ice drag coefficient $C_{Dai}$ from the control simulation (solid line) and the no-form drag experiment (dashed line) and (bottom) breakdowns of $C_{Dai}$ in the control simulation using the form-drag parameterization by Tsamados et al. (2014). The values are averages over the ice area for the western Alaska domain (see Fig. 1).](image)
some detailed features, such as high sea ice freeboard in the north of Bering Strait on 14 February 2019, are missed by the control simulation. The model tends to include spatial offset for these detailed features (e.g., modeled ridge locations) due to uncertainties from the forcing datasets, as well as model parameters. Therefore, such discrepancies at detailed scales are expected.

d. 5-day forecast simulation results

Figure 12 shows the time series of ice extent and landfast ice area from the daily 5-day forecast simulations conducted from October 2020 to August 2021. To isolate the model skill from the benefit from data assimilation, these daily 5-day forecast simulations started off from restart files from previous days (i.e., no initialization using the observed ice data or other data assimilation). Therefore, errors from the previous forecast cycles were inherited. The overall skills (Table 4) are comparable with the hindcast results, while the errors are slightly larger in the forecasting applications (Tables 2 and 3). RMSEs in the forecast simulations were 0.093 × 10^6 and 0.84 × 10^4 km² for ice extent and landfast ice area, respectively, while RMSEs in the hindcast simulations were 0.056 × 10^6 and 0.83 × 10^3 km² for ice extent and landfast ice area, respectively. Similarly, MEs in the forecast simulations were −0.090 × 10^6 and −0.734 × 10^3 km² for ice extent and landfast ice area, respectively, while RMSEs in the hindcast simulations were −0.026 × 10^6 and −0.34 × 10^4 km² for ice extent and landfast ice area, respectively. The slightly larger errors in the forecasting applications are expected due to larger uncertainties in the forcing datasets (i.e., the GFS and GOFS3.1 forecast products) than those in the operational analyses, which was used for the hindcast simulations.

Notable degradation of the model skills occurred in the melting period, with a negative bias both in ice extent and landfast ice area. This could be due to uncertainties of forcing datasets, or the simple treatment of the boundary conditions for ice conditions, which might miss realistic ice inflow from the Arctic Ocean to the domain in the melting season. While this could be an area of improvement, in actual forecasting applications, simple initialization using observed ice cover would mitigate this issue. The mean ACC values for the whole forecast period (October 2020–August 2021) were 0.51, 0.51, 0.50, 0.50, and 0.49 for forecast days 1, 2, 3, 4, and 5, respectively. If we remove the melting period (May–August), the mean ACC values were 0.64, 0.63, 0.63, 0.62, and 0.62 for forecast days 1, 2, 3, 4, and 5, respectively. The values were relatively low even in the shortest lead time as these forecast simulations did not use initialization with sea ice observational data. However, we did not see major degradation in time, and the ACC values indicate that the model still maintains forecast skill slightly above the climatology-based forecasts.

It is also notable that the GOFS3.1 reanalysis also presents underestimation against the ASIP analysis not only in the melting period but also in the other periods. The negative bias in the stable period is larger than that of CICE6. Overall, the RMSE and ME of CICE6 are similar to those of the GOFS3.1 reanalysis, indicating the comparable performance of CICE6, despite the simplicity of the configuration (e.g., no data assimilation or nowcast cycles).

The daily 5-day forecast simulations did not present significant divergence in time (i.e., the daily 5-day lines mostly overlap with each other in Fig. 12). While divergence can be larger in the coupled system where the storm-surge, wave, and ice model components interact with each other, it is likely that divergence would largely originate from the uncertainties in the forcing datasets (i.e., surface meteorology, ocean surface temperature, salinity, and current).

The performance in the forecast applications demonstrates the readiness of the model for integration into the coupled storm surge, wave, and sea ice model forecast system to add value to the suite of the existing operational short-term forecast products, such as GFS and GOFS3.1. In particular, improved representation of landfast ice by the model fills gaps in these operational products and provides a critical piece for nearshore physics modeling associated with storm surges and high waves.

4. Summary and conclusions

Using the state-of-art sea ice dynamic and thermodynamic model, we demonstrated the capability of the regionally configured CICE6 model as a valid model component of the storm-surge, wave, and sea ice coupled system for Alaska’s coasts. Hindcast simulations during 2018–2020 and daily 5-day forecast simulations during 2020–21 showed the model’s promising performance in reproducing sea ice conditions for the western Alaska domain. In particular, modeling of landfast ice is significantly improved in comparison with GOFS3.1. This is important for the future coupled model system as immobile landfast ice alters air-sea momentum flux along the
FIG. 11. Sea ice freeboard from the CICE control simulation (shading) and the ICESat-2 ATL10 along-track product (circle marker). Examples of 29 Jan 2019, 14 Feb 2019, 19 Mar 2019, 10 Jan 2020, 9 Feb 2020, and 8 Mar 2020. For visualization purposes, every other data point is shown for the ICESat-2 ATL10 product.
coastline by acting as a damper of wind stress and waves and therefore intensity of surges and flood extent. Existing operational models have not incorporated or verified landfast ice simulations. In addition, this study provides one of the first uses of the ICESat-2 product for sea ice freeboard verification for coastal applications. The rigorous verification for the model results and evaluation of the numerical experiments endorse the next step where the sea ice model is being integrated into the Alaska Coastal Ocean Forecast System (ALCOFS) where the storm surge (ADCIRC), wave (WW3), and sea ice (CICE6) models interact via ESMF/NUOPC.

Among future areas of further development, the use of an unstructured mesh dynamical core for the sea ice model is a priority for the coastal applications, which require a detailed representation of coastlines, bathymetry, and spatial resolution. Sea ice satellite products or atmosphere–ice–ocean models that do not have sufficient spatial resolution could lead to the inaccurate representation of detailed coastal processes (e.g., heat flux; Müller et al. 2023). This can be problematic for prediction applications such as those for navigation, storm surge, flooding, and inundation. Sea ice models for coastal applications using unstructured meshes can be achieved by use

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<th>TABLE 4. RMSEs and MEs of 5-day forecast simulations.</th>
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<td>CICE6 ice extent (10^6 km^2)</td>
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<td>GOFS3.1 reanalysis ice extent (10^6 km^2)</td>
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<td>Landfast ice area (10^4 km^2)</td>
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Fig. 12. Time series of (top) ice extent and (bottom) landfast ice area for the 2020/21 winter season. Black dots are the National Ice Center analysis for ice extent and the Alaska Sea Ice Program for landfast ice area. Red lines are daily 5-day forecast simulations using the CICE6 control configuration. The green line in the top panel is from GOFS3.1 reanalysis. Note that red lines are collection of daily results spanning for 5-day durations.
of the existing unstructured mesh sea ice model (e.g., Gao et al. 2011; Zhang et al. 2023; Mehlmann and Korn 2021), implementing ICEPACK (the state-of-art column ice physics model used in this study; Hunke et al. 2022) into a suitable unstructured mesh dynamical core, or waiting on the readiness of the MPAS-Seacie (a sea ice model that uses the MPAS framework; Turner et al. 2022) for coastal applications that target short-term predictions.

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Data availability statement. The source codes of CICE version 6 can be obtained at the GitHub repository of the CICE consortium (https://github.com/CICE-Consortium/CICE). MASAM2 daily 4-km ice concentration data are available at the National Snow and Ice Data Center (https://nsidc.org/data/gi10005). The National Ice Center ice shapefiles are available from the Arctic Ice Products (https://usicecenter.gov/Products/ArcticHome). The ice analysis shapefiles for Alaska’s coastal region can be obtained by requesting the Alaska Sea Ice Program (https://www.weather.gov/afc/ice). CFSv2 operational analyses and GFS operational forecasts can be obtained at the National Center for Atmospheric Research (NCAR)’s Research Data Archive website (https://rda.ucar.edu/datasets/ds094.0, https://rda.ucar.edu/datasets/ds084.1, respectively). GOFS3.1 data can be obtained at the HYCOM consortium website (https://www.hycom.org/dataserver/gofs-3pt1/analysis).

REFERENCES


