Sea Ice Deformation in Fram Strait — Comparison of CICE Simulations with Analysis and Classification of Airborne Remote-Sensing Data

Ute C. Herzfeld,^{1,2,3} Elizabeth C. Hunke⁴, Brian McDonald⁵ and Bruce Wallin⁵

¹*Department of Electrical, Computer and Energy Engineering, University of Colorado Boulder, Boulder, Colorado*

80309-0425, USA, phone: +1-303-492-9066, e-mail: ute.herzfeld@colorado.edu, e-mail2: uch5678@gmail.com

²*Cooperative Institute for Research in Environmental Sciences, University of Colorado Boulder, Colorado, USA*

³*Department of Applied Mathematics, University of Colorado Boulder, Colorado, USA*

⁴*T-3 Fluid Dynamics and Solid Mechanics Group, Los Alamos National Laboratory, Los Alamos, New Mexico, USA*

⁵*Department of Electrical, Computer and Energy Engineering, University of Colorado Boulder, USA*

ABSTRACT.

Complex surface topography is a characteristic especially of older sea ice, and an observed loss of older or multi-year sea ice in the Arctic indicates an imminent transition of the Arctic ice cover from perennial to seasonal. Prediction of this transition in the Arctic system is one of today's "big science" questions. The objective of this paper is to compare model output and data analysis, toward addressing a key problem in sea-ice modeling, the correct representation of ridges and other spatial features that result from deformation. Morphologically complex, ridged ice exists in Fram Strait. High-resolution airborne remote sensing data, including image data and altimeter data showing ridging, collected from unmanned aircraft over Fram Strait during the Characterization of Arctic Sea Ice Experiment (CASIE) in 2009, are analyzed using geostatistical classification. This approach results in parameters that capture deformation characteristics and facilitates comparison to model results. Ridging and other forms of deformation are implemented in the Los Alamos sea-ice model CICE. The main parameters that are compared are freeboard as a proxy of ice thickness and per-

centages of level versus ridged ice from modeling and laser altimeter data analysis. Results from freeboard analysis indicate that except for the elevation class 0.1m-0.2m, models and observations match very well. For concentration of deformed ice, results from CICE using the standard parameter configuration are within 20% of deformed ice area concentration compared to results from altimeter data analysis. Variation of several physical parameters indicates the sensitivity of model results to ridging parameters and provides results that are within 7% of data analysis results in each grid cell, with the parameter that yields the best match depending on geographic location and morphologic province. In general our approach demonstrates an avenue for parameterization on both the data analysis side and the modeling side that allows a direct comparison of results from sea-ice models and data analysis and hence an evaluation of numerical sea-ice models.

KEYWORDS

model-data comparison; Arctic sea ice; sea-ice complexity; laser altimetry, sea-ice classification; sensitivity experiments

1. INTRODUCTION

The rapid decline of the Arctic sea ice cover is one of the most apparent signs of climatic change, and one that has threatening consequences for weather, climate, ecosystems and human livelihood in the northern hemisphere (Solomon et al., 2007; Pachauri and Reisinger, 2007; Stroeve et al., 2005, 2007; Maslanik et al., 2007; Drobot et al., 2008). In turn, sea ice is also a driver of climate change, as it functions as an insulator and modulates heat, moisture and momentum transfers between atmosphere, ice and ocean. Record lows in sea-ice extent in two consecutive years followed by a recovery in 2008 indicate large fluctuations in sea-ice coverage, while the trend of long-term decrease remains.

More alarming than the reduction in geographic extent is the observation that the ratio of multiyear ice to relatively thin first-year ice is decreasing (Maslanik et al., 2007) indicating a trend toward a seasonal rather than a perennial ice cover in the Arctic. Older, thicker ice is typically morphologically more complex and less susceptible to melting. Ice deformation resulting in ridges and leads is the most prominent expression of morphogenetic complexity of sea ice. Hence it is important to represent ridging correctly in a model that is used to predict the future of the sea-ice cover. The term “ridging” in connection with sea-ice models is used to describe deformation processes that affect ice thickness and ice thickness distribution, which

drive and constrain sea ice growth and melt rates. Notably, sea-ice extent can be modeled using an ice thickness distribution, and areas of zero ice thickness represent open ocean.

Mechanical deformation of sea ice is currently modeled using complex parameterizations developed in the 1970s (Thorndike et al., 1975a; Hibler, 1980; Rothrock, 1975). Due to lack of appropriate observations, evaluation or validation of these parameterizations has been lagging behind theoretical modeling for decades. Evaluation of model parameterizations using observations is clearly necessary to correctly represent the cryosphere and is the objective of this paper.

Data collected during the Characterization of Arctic Sea Ice Experiment (CASIE) include high-resolution laser altimetry, microASAR, imagery, and GPS coordinates and hence provide an opportunity to undertake such evaluations. The CASIE experiment was conducted over Fram Strait in July/August 2009 from a base in Ny Alesund, Svalbard, using the NASA SIERRA unmanned aircraft. CASIE data consist of up to 1000km long tracks per flight, which extend from Svalbard about three quarters of the way to the eastern coast of Greenland, with altimeter data recorded every 7-10 cm over sea ice (Crocker et al., 2011; Zaugg et al., 2010).

Complexity of sea ice, thickness distribution and redistribution as well as ridging and rafting of ice, are represented in the Los Alamos Sea Ice Model, CICE (Hunke et al., 2013). As part of the Community Climate System Model (CCSM3, 4), CICE was one of the models that most correctly represented sea-ice cover when the average of models used in the fourth assessment of the International Panel on Climate Change (IPCC) underestimated the current sea-ice decline (Solomon et al., 2007; Pachauri and Reisinger, 2007). CICE uses a thickness distribution with values in five categories to capture the effects of thermodynamics and dynamic deformation, helping to overcome the problem that these processes occur at scales smaller than the grid size (Lipscomb et al., 2007a; Hunke and Lipscomb, 2010). The effect of the ridging parameterizations used in CICE on large-scale sea ice motion and concentration has been investigated in Vancoppenolle et al. (2009) and Hunke (2010). The current version models the total volume and spatial pattern of sea ice well, but the thickness distribution exhibits discrepancies with data (Jahn et al., 2011; Jahn, 2011).

The detailed implementation of the ridging parameterization in CICE has not been validated in stand-alone CICE runs nor in climate models that use CICE, beyond the overall behavior of the ice thickness distribution. A comparison of modeled ridged and level ice fractions with observed spatial characteristics has not been carried out. The objective of this paper is a comparison of CICE simulated ice ridges with analyses of CASIE altimeter data. This will serve to evaluate physical concepts of sea-ice deformation and further facilitate a spatial comparison of sea-ice thickness, extent, and areas of level and deformed ice.

2. SUMMARY OF THE APPROACH TO MODEL – DATA COMPARISON

Comparison of CICE model simulations with analysis of CASIE data requires a derivation of parameters from the data analysis that lend themselves to comparison with model output. On the model side, sensitivity studies dependent on changes in the parameterization of physical processes are necessary.

The model, CICE, is run for the time frame and region of the observations from the CASIE Experiment. Physical parameters that control the ridging process are varied in several model runs, to examine the effect of parameterizations on resultant ice distribution and morphology. Parameters that will be evaluated include areas of level ice, deformed ice, open ocean, freeboard, mean ice thickness and sail height (see section 3.).

On the data analysis side, parameters descriptive of ice morphology need to be derived. Here we take the approach of geostatistical classification (Herzfeld, 2008; Herzfeld et al., 2006), which allows calculation of spatial parameters that relate to spacing and morphological significance of ridges and other characteristics of sea-ice morphogenesis, and more generally, utilizes a mathematical formation of generalized surface roughness (section 4).

Our work is aimed at answering two types of questions: (1) Are the parameterizations of sea-ice processes relating to extent, thickness and complexity correct, or do they need to be improved? and specifically (2) Is the sea-ice thickness redistribution function correct?

The analysis can have two possible outcomes: (1) a validation of the existing parameterization of ridging and ice-thickness distributions in the model (which has not been done before), or (2) a derivation of a new parameterization of the ridging scheme and a different ice-thickness distribution. This paper seeks to validate the current ridging parameterization in CICE and tests a simple change to the ice strength that affects the spatial distribution and amount of deformed sea ice.

Relationship to previous work. The work in this paper is aimed at directly relating deformation as manifested in sea-ice ridging in modeling (specifically, in CICE) to observations of sea-ice micro-topography, using the mathematical vehicle of general surface roughness. Going back to Bagnold (1941), the influence of surface roughness on wind speed has been studied (Oke, 1987; Stull, 1988) in boundary layer meteorology, centering around the notion of aerodynamic roughness length z_0 , which is usually determined experimentally. Ice surface roughness plays a role in energy exchange and momentum between different media. Herzfeld et al. (2004a) quantified the importance of surface roughness over snow and ice surfaces in energy exchange models, using surface roughness measurements collected in Arctic and alpine environments (on land). Overland (1985) used an effective roughness length in connection with heat flux between atmosphere, sea ice and ocean. Relationships between drag, decomposed into form drag and skin drag, momentum and heat flux and aerodynamic roughness length were investigated in Mai et al. (1996).

Steiner et al. (1999) modeled ice roughness and its effects in an Arctic sea ice model by implementing roughness as an additional prognostic variable representing the accumulated work of internal forces acting on the ice (with roughness as a scalar variable derived from integration of work during deformation over time). They found that including sea ice roughness improves simulated boundary layer processes in climate models. Shoutilin et al. (2005) describe a simpler approach, where ridging is formulated as a response to horizontal transport of sea ice into a grid cell that would result in more than 100% coverage. Both studies compare the number of ridges per unit area with observations, finding general agreement in the pattern of ridge production and buildup (ice thickness). Martin (2006) compares different ridge formation models with laser profiling observations, not including the more sophisticated ridging scheme used in CICE.

Sea-ice thickness distribution in the Arctic Ocean, derived from sub-marine data, has been analyzed in Bourke and Garrett (1987). A morphological approach to analysis of sea-ice ridges was taken by Mock et al. (1972); Timco and Burden (1997); Strub-Klein and Sudom (2012). A review of material properties of sea ice is given in Timco and Weeks (2010).

Surface roughness has been defined in different ways, using root-mean-square roughness (standard deviation with respect to a least-squares fit over some distance), Hurst coefficients, aerodynamic roughness length, and relationships between small-scale surface geometry and statistics (e.g. Lettau (1969) for land surfaces, Arya (1973) for partly ice-covered ocean, Arya (1975, 1988); Joffe (1983)). Relationships between some of these definitions are established in Herzfeld et al. (2004a). All of the above use one-dimensional roughness measures. The analysis in this paper employs a generalized concept of spatial surface roughness (Herzfeld, 2008), which facilitates a direct comparison of deformation effects in models and observations.

Following the theoretical work of Thorndike et al. (1975a); Rothrock (1975) and Hibler (1980), research on the sea-ice distribution function has seen both simplifications and theoretical advancements and accordingly different implementations. The earlier developments are described in Gray and Killworth (1996) and recent work is included in summary in Savage (2008). Gray and Morland (1994) used a mixture model applied to two classes, undeformed level ice and deformed (ridged) ice. Flato and Hibler (1995a) used the two classes of ridged and unridged ice, but each with a specific thickness distribution function. CICE uses one thickness distribution function with 5 thickness classes. Schulkes (1995) derived a simplified alternative to the model used in (Gray and Morland, 1994). Bitz et al. (2001) introduced a formulation of the ice thickness distribution function that is Lagrangian in thickness space to improve the role of the thermodynamics of sea ice and employed this in a coupled climate model. Shinohara (1990) related the redistribution function to the stress associated with deformation rate fields, while others limit the considered deformation types to convergent and divergent flow, neglecting shear (e.g. Gray and Morland (1994)). Haapala (2000) further refined ice classes (open water, undeformed level ice, undeformed lead ice, rafted ice, ridged ice, rubble ice) with specific evolution functions and a redistribution function that shifts material among the ice classes. The classification allows separation of thermally and mechanically produced ice. Modeled ice types and ice thicknesses

were compared to observations in the Baltic Sea with a focus of ice deformation during storm events, which indicates a high temporal resolution of the model. The model of Harder and Lemke (1994) also resolves seasonal evolution of level and deformed ice, for the Weddell Sea. Savage (2008) implemented a two-component sea-ice redistribution model for undeformed level ice and deformed (ridged) ice, which is based on the mixture model of Gray and Morland (1994) and formulated for general deformation fields (including shear). As part of the Canadian Ice Service’s ice forecasting model, the thickness redistribution after Savage (2008) is coded using an advection method that is based on a particle-in-cell approach and avoids discrete thickness classes (Kubat et al., 2010); the model has then been evaluated in several studies in the Canadian Arctic, for the Gulf of St. Lawrence using 2004 field observations of ridges (Prinsenberget al., 2006), for Frobisher Bay using observations of besetting events that occurred in 2012, and for Strait of Belle Isle (Kubat et al., 2010, 2011, 2012, 2013). Forecasting of ridging events is important because pressure ridges cause a threat to shipping lines in the Arctic.

3. MODELING APPROACH: RIDGES AND OTHER FORMS OF MECHANICAL DEFORMATION IN THE SEA-ICE MODEL CICE

A basic goal of sea ice models is to predict the area and thickness of sea ice in time and space. Sea ice growth and melt rates are highly sensitive to ice thickness, particularly for thin ice (less than about 1 m thick), but grid cells are large in global climate models and may contain a wide range of ice thicknesses. To better resolve the growth and melt rates in each grid cell, the ice in the cell is described using an ice thickness distribution (ITD). In practice only a few thickness categories are used, typically five, but with more of the categories assigned to thinner ice to better resolve growth rates. In mathematical terms, the ice thickness distribution is the fractional area covered by ice in a given thickness range at a particular time and location. The equation describing evolution of the ITD is fundamental in the sea ice model, because it ties together all of the various processes affecting sea ice. One of these processes is the mechanical redistribution of the ITD as the sea ice deforms. In CICE, we refer to the mechanical redistribution processes collectively as “ridging” although they also include other deformational events such as rafting (one floe rides up on top of another one without breaking) and crushing of floes. Sea ice ridges are piles of ice blocks that have broken from the edges of ice floes under convergent and/or shear forces.

CICE distinguishes between level and deformed ice for some purposes such as melt pond evolution (Hunke et al., 2012). The level ice area and volume variables are carried as tracers on the ice area fraction and volume; that is,

$$\begin{aligned}\frac{\partial}{\partial t} [a_n T_{an}] + \nabla \cdot [a_n T_{an} \mathbf{u}] &= S_a, \\ \frac{\partial}{\partial t} [v_n T_{vn}] + \nabla \cdot [v_n T_{vn} \mathbf{u}] &= S_v,\end{aligned}$$

where $a_i(n)$ is the fractional ice area in category n , v is volume, T is the tracer, and S represents sources or sinks of the tracers.

The total ice area in the grid cell is $a_i = \sum_n a_n$, and the ice volume is $v_i = \sum_n v_n = \sum_n h_n a_n$. This volume represents the *mean* thickness over the grid cell area (its unit is volume per unit area, m^3/m^2), including open water. The *actual* thickness over the ice area within the grid cell is v_i/a_i . Likewise, the level-ice quantities output by the model are averages over the grid cell:

$$\begin{aligned} a_{lvl} &= \sum_n a_n T_{an} \\ v_{lvl} &= \sum_n v_n T_{vn}. \end{aligned}$$

The ridged ice quantities are computed such that $a_{lvl} + a_{rdg} = a_i$ and $v_{lvl} + v_{rdg} = v_i$:

$$\begin{aligned} a_{rdg} &= \sum_n a_n (1 - T_{an}) \\ v_{rdg} &= \sum_n v_n (1 - T_{vn}). \end{aligned}$$

162 Mechanical redistribution of the modeled sea ice occurs in two steps (Thorndike et al., 1975b). First, a participation function
163 defines which portion of the ice thickness distribution participates in ridging. The second piece is a redistribution function,
164 which describes how the ice participating in ridging is redistributed among other thickness categories, based on the initial
165 thickness and the desired height-to-area ratio of the ridge. Various ridge profiles have been suggested for models (Thorndike
166 et al., 1975b; Hibler, 1980; Amundrud et al., 2004). CICE assumes an exponential distribution of ridge thicknesses, consistent
167 with observations of thick ice.

The participation function is the thickness distribution of the ice participating in ridging. A weighting function b assigns relative weights to the ice thickness categories, so that thinner categories tend to contribute more of their area to ridge formation (Lipscomb et al., 2007b):

$$b(h_n) = \frac{\exp[-G(h_n)/a^*]}{a^*[1 - \exp(-1/a^*)]} \quad (1)$$

168 where the cumulative ice thickness distribution $G(h)$ is the fractional area covered by ice thinner than h . From (1), the mean
169 value of G for ice participating in ridging is a^* .

The redistribution function deforms ice of thickness h_n into a ridged ice thickness distribution, g_n , with a negative exponential tail (Lipscomb et al., 2007b):

$$g_n(h) = \begin{cases} \frac{h_n}{(h_{\min} + \lambda)\lambda} \exp\left(-\frac{h - h_{\min}}{\lambda}\right) & \text{if } h \geq h_{\min}, \\ 0 & \text{if } h < h_{\min}. \end{cases} \quad (2)$$

170 Here, μ_{rdg} is a tunable parameter in units $\text{m}^{1/2}$ that controls the e -folding scale, $\lambda = \mu_{rdg} h_n^{1/2}$. The minimum ridge thickness
171 is $h_{\min} = \min(2h_n, h_n + h_{\text{raft}})$ where $h_{\text{raft}} = 1$ m is the thickest ice allowed to raft, yielding a mean ridge thickness of $h_{\min} + \lambda$.

Varying the parameter μ_{rdg} can produce ridges with a range in heights typical of first-year through multi-year ice, similarly to the role played by H^* in the original redistribution function of Thorndike et al. (1975b).

Following Rothrock (1975), sea ice strength is assumed proportional to the change in ice potential energy per unit area of compressive deformation. C_f is a factor in the proportionality constant that accounts for frictional energy dissipation; it is the ratio of rate of work done to the rate of change in potential energy during ridging. Hopkins (1994) estimates $C_f \sim 10$ for 1m thick sea ice. Following Flato and Hibler (1995a), C_s with $0 \leq C_s \leq 1$ determines the fraction of the shear component of mechanical energy that contributes to ridging, with the remainder of the mechanical energy in a balance equation being dissipated in sliding of ice over water.

In our sensitivity tests, we vary the parameters a^* , μ_{rdg} , h_{raft} , C_f and C_s . In addition, we test a simple parameterization of C_f that varies with ice thickness.

4. DATA ANALYSIS APPROACH: ROUGHNESS, RIDGING, COMPLEXITY - SPATIAL SEA-ICE PROPERTIES AND MATHEMATICAL ANALYSIS CONCEPTS

The approach used here for systematic analysis of remote-sensing data integrates principles from continuum mechanics, structural geology (deformation processes), spatial statistics and signal processing. The kinematics of moving sea ice causes breaking and collision of sea-ice plates, which in turn cause lead formation, re-closure of leads, formation of ridges, faulting and upward thrusts (examples are seen in Steffen (1986)). Structural geologic principles provide links between dynamics, kinematics and deformation, which can be physically formalized and quantified using continuum mechanics (Ramsay and Lisle, 2000; Means, 1976; Liu, 2002; Greve, 2003; Suppe, 1985; Twiss and Moore, 1992). Sea ice ridging is a form of brittle deformation that occurs when local forces exceed a threshold.

Characterization of generalized spatial surface roughness is a mathematical approach that utilizes parameters derived from spatial statistical functions to capture spatial properties of a surface (Herzfeld, 2008). This applies to deformed sea ice as well as to level, undeformed sea ice. Combining structural geology and mathematical roughness analysis allows derivation of deformation characteristics in sea ice and mapping of deformation provinces (see Herzfeld et al. (2006)); links between structural geology, deformation, continuum mechanics and the classification approach are discussed in Herzfeld et al. (2004b) for glaciers. A deformation province is an area that is homogeneous with respect to deformation characteristics and that is maximal with this property.

4.1. Mathematical background: Geostatistical classification

In the interest of brevity, we limit the mathematical description to the parameters that are applied in this study. The theoretical background is described in detail in Herzfeld (2008), where more types of geostatistical classification parameters are introduced.

The analysis is based on vario functions, which are spatial functions defined in a discrete mathematics framework that capture spatial variability similar to probabilistic variograms. Vario functions generalize to higher order functions that work more robustly in situations of poor signal-to-noise ratios. Inspired by signal processing methods, we define families of parameters that summarize spatial properties at several scales (Herzfeld, 2002).

To mathematically summarize spatial surface roughness in a given area, first-order vario functions and residual vario functions are used, which are motivated and defined as follows. In order to characterize the surface structure in a given area, the actual value at each location is not as relevant as the parameters that describe the morphology more generally for the whole study area. Therefore, differences of measurement values are formed and averaged over all points that have the same common distance (or distance and direction), creating *vario functions*.

$$v_1(h) = \frac{1}{2n} \sum_{i=1}^n [z(x_i) - z(x_i + h)]^2 \quad (3)$$

for pairs of points $(x_i, z(x_i)), (x_i + h, z(x_i + h)) \in \mathcal{D}$, where $\mathcal{D}$ is a region in $\mathcal{R}^2$ (case of survey profiles) or $\mathcal{R}^3$ (case of survey areas) and n is the number of pairs separated by h ; the distance value h is also termed “lag”. The function $v_1(h)$ is called the *first-order vario function*. This function exists always and has a finite value.

The residual vario function is often more useful to analyze roughness in situations where a regional trend or a local drift underlies the data. Using

$$m(h) = \frac{1}{n} \sum_{i=1}^n [z(x_i) - z(x_i + h)], \quad (4)$$

the residual vario function is defined as:

$$res_1(h) = v_1(h) - \frac{1}{2}m(h)^2. \quad (5)$$

Geostatisticians note that the first-order vario function is formally equivalent to the variogram, however, the variogram is defined for a data set that may be considered a realization of a spatial random function satisfying the intrinsic hypothesis (see Matheron (1963, 1973)). A discussion of the theoretical and practical differences between vario functions and variograms is given in Herzfeld (2008). Vario functions are more robust analysis tools than the covariance function and the power spectrum (power spectral density) and exist under conditions where those functions do not exist, making them particularly useful in geoscience applications. In the geostatistical classification method, the vario function is used akin to the spectrum, but in contrast to the spectrum, it is not easily perturbed by disturbances over small scales, which is an important aspect in the study of roughness characteristics. We employ vario functions for characterization and classification of sea-ice provinces, and for extraction of characteristic parameters that lend themselves to comparison with parameters used in sea-ice models.

4.2. The *pond* parameter and its relationship to aerodynamic roughness length

The *pond* parameter is defined as the maximal value of the vario function:

$$pond = \max\{v_1(h_i) | i = 1, \dots, n\} \quad (6)$$

where $h_i = i h_{unit}$, h_{unit} is the unit lag (here: 1 m), and n is the number of steps. The maximal lag value is then $n h_{unit}$, where the number of steps is selected to exhaust 80% of the along-track data window (here 500 m). [Note that the unit lag is a bin-value used in a numerical implementation while h is a variable.]

The *pond* parameter is directly related to aerodynamic roughness length z_0 , as employed in boundary layer meteorology (Oke, 1987). Here we use a relationship of roughness length *arl* to the *pond* parameter developed for snow surfaces in Herzfeld et al. (2004a):

$$arl = \frac{1}{2} \sqrt{2 pond_{var}}. \quad (7)$$

The terms *pond_{var}* and *pond_{res}* designate *pond* determined from the first-order vario function and the residual vario function, respectively. For surfaces that are level on a large scale (a scale much larger than roughness), the *pond_{var}* parameter should be used. For rough, sloping surfaces, the *pond_{res}* parameter should be substituted in equation (7). Because sea ice has a zero trending surface elevation, the residual vario function and the vario function are expected to have the same value, and hence the *pond_{res}* and the *pond_{var}* parameters are expected to coincide. The analysis here uses *pond_{var}*.

4.3. Other parameters

The *mindist* parameter is defined as the lag of the first minimum after the first maximum in the vario function and gives the spacing of parallel ridges. Significance parameters *p1* and *p2* are calculated as

$$p1 = \frac{\gamma_{max_1} - \gamma_{min_1}}{h_{min_1} - h_{max_1}} \quad (8)$$

$$p2 = \frac{\gamma_{max_1} - \gamma_{min_1}}{\gamma_{max_1}}. \quad (9)$$

p1 is the slope parameter and *p2* the relative significance of the first minimum *min₁* after the first maximum *max₁*, and h_x and γ_x denote lag and vario-function value of x .

For laser altimeter data, the parameters are calculated in an along-track moving window. For image data, the parameters are derived for two-dimensional moving windows and a resulting parameter map is created.

The main parameters that we compare are the areas of deformed ice, level ice and open water, derived from model runs undertaken with various model parameters and from classification parameters derived from data analyses. Analyses are carried out for all laser data along the CASIE track; results are averaged for data falling into the grid cells used by CICE and compared

to model results. Classification of image data will illustrate the complexity of deformed ice and through that, the complexity of the problem treated in this paper.

5. DATA

The analysis in this paper utilizes high-resolution laser altimeter data and image data from CASIE, an experiment conducted with the NASA Systems Integration Evaluation Remote Research Aircraft (SIERRA), an unmanned aircraft system (UAS) of NASA AMES Research Center from a base in Nye Alesund, Svalbard, over Fram Strait in July and August 2009. The CASIE experiment was led by J. Maslanik, U. Herzfeld, D. Long, R. Kwok, R. I. Crocker and M. Fladeland (airborne operations). The SIERRA has about a 7-m wingspan and an endurance of 10 hours. The use of UAS is a relatively new method for conducting polar geophysical research. During CASIE, 10 flights of up to 1000km were conducted. The data sets are of very high quality, with altimeter data spaced approximately 7cm apart over 1000-km long flight tracks with simultaneously recorded microASAR data, video and still image data, and aircraft location, attitude and altitude data. Here, we use data from a flight (flight 9, July 25, 2009) that crosses about three fourths of Fram Strait between Svalbard and Northern Greenland (see Figure 1). During this flight, all instruments worked perfectly and collected data during the entire 10-hour flight. For calibration, a short dog-leg was flown to collect microASAR data and laser altimeter data of the same sea ice floes (the microASAR looks to the side, whereas the laser measures at approximately nadir). The experiment is described in Crocker et al. (2011).

The CU LIDAR Profilometer and Imaging System (CULPIS) is designed for integration into small UAS and to provide fine-resolution surface topography and imagery in polar environments. The CULPIS sensor suite consists of a profiling, single-beam nadir-pointing LIDAR altimeter (Laser Technology, Inc., Universal Laser System (ULS)) that is used to measure the distance from the aircraft to the ground surface, a NovAtel, Inc., SuperStar II GPS module that provides aircraft location, a Microstrain, Inc., 3DM-GX1 inertial measurement unit (IMU) that provides aircraft attitude information to correct for off-nadir pointing of the LIDAR, and a barometric pressure sensor which serves as an independent measure of vertical position, supplementary to the GPS. The imaging system consists of an Aiptek A-HD+ 1080P high definition video camera and a Canon PowerShot G10 still camera, which are used to provide imagery that is coincident with the profilometer data and can serve as a visual reference for the topography measurements (Crocker et al., 2011).

5.1. CUPLIS Laser Data

Laser altimeter data are geolocated using GPS data (not IMU data), as described in Crocker (2012). Several studies were carried out to determine the accuracy of the CULPIS data. The manufacturer (LaserTech Inc., Denver) specifies a ± 2 cm range error of the ULS. Edwards (2008) determines a CULPIS data precision (error standard deviation) of 1.34 cm when the sensor is operated at 500 Hz without averaging over several pulses. However, operation at 400Hz averaged from 4000 Hz

internal ULS frequency during CASIE reduced the range error. The IMU may introduce an additional ± 1 cm range error for typical flight conditions of the unmanned aircraft (Smith, 2007). (Crocker, 2012) determined a maximal range error of ± 5 cm with a precision (residual error standard deviation) of 0.6 cm for CUPLIS operation and observed that nearly all range errors were within ± 2 cm. Hence ± 2 cm is taken as the error in the analysis here. Notably, largest errors in absolute surface elevation are due to GPS data corrections (Crocker, 2012), but since the GPS errors occur over a larger spatial scale, they do not affect the roughness analysis that is carried out in this paper. The GPS correction yields sea-ice freeboard values in a physically correct range, which demonstrates that large-scale long-wave errors have been removed correctly. An example of aerodynamic roughness length (arl) derived from CULPIS laser altimeter data and matched with co-geolocated microASAR data demonstrates the unprecedented high spatial accuracy of the CASIE data and at the same time indicates that the approach using geostatistical roughness parameters is well suited to analyze complexity in Arctic sea ice (see Figure 2).

The laser altimeter data themselves can be employed to locate the boundary between open water and sea ice, as is seen in Figure 3, because the different reflectivities of water and ice lead to different numbers of received laser signals per distance unit (actually, per transmitted shot). Within the study area, the ice area is identified, then data from only the ice area are selected for further analysis and comparison with CICE model simulations. The study area corresponds to 35 grid cells in CICE, of which 25 cells are identified as ice-covered (Figure 4). As the ice-ocean boundary is not a well-defined edge but a wide region of ice of increasing density in coverage, we used a histogram-based criterion to determine the ice edge (see Figure 3), this was verified using imagery. The criterion for identifying sea ice is that laser counts in 10-m bins have to consistently exceed 400.

5.2. CULPIS Image Data

Images are of high quality and show the types of sea ice encountered during July 2009 in Fram Strait. The sea ice is very complex as illustrated in Figure 5a. Heavily-deformed ice with closely-spaced ridges is seen in the right third of the image. Melt ponds appear on the middle third and are interspersed by a few widely-spaced ridges. A large melt-pond or open water area (of dark appearance) is seen in the left third.

6. DATA ANALYSIS: LASER ALTIMETRY

6.1. Freeboard

Freeboard is defined as the sea-ice-surface elevation minus the elevation of the ocean surface in a lead. For the corrected CASIE ULS data, freeboard is determined as sea-ice elevation minus the minimum value in a 400-m moving window. This calculation assumes (with Crocker (2012)) that the minimal elevation is that of the ocean surface in a lead or between ice floes and that there is at least one lead in each 400-m section of data. By visual inspection of CASIE ULS data, this assumption holds for

the CASIE data. In this context, it should be noted that the ice surface at the foot of a large ridge may be depressed below sea level, which may introduce a small error that is neglected here.

Sail height is defined as the height of a ridge above the normal-level ice height. Notably, this is not the same as the maximal sea-ice freeboard.

6.2. Parameters *pond* and *arl*

The centerpiece of the laser-altimeter data analysis is the calculation of the *pond* (*pond_{var}*) parameter and aerodynamic roughness length *arl*, as defined in section (4.2). To facilitate the CASIE-CICE data-model comparison, the study area, as defined by the coverage from the CASIE flight-9 ground track, is matched to the grid used by the sea-ice model CICE (see Figure 4). CASIE data exist for 35 grid cells, of which 25 contain ice and 10 are open water, as determined in section (5.1).

The analysis that uses geostatistical classification parameters is carried out for corrected CASIE laser altimeter data (not for freeboard values, because the freeboard determination uses an additional assumption about the existence of leads). Since vario functions are calculated in difference space, absolute height above the sea surface does not need to be known. Vario function values are calculated for the entire flight track, using 1m unit lags (in equation (3)) and 100 m windows; then the parameters *pond* and *arl* are determined for each window, as defined in equation (6) and equation (7). Figure 4 shows sea-ice surface roughness using *pond* and *arl* along the flight track.

To scale the results based on high-resolution laser altimeter data up to the grid-scale used by the model, we calculate the percent of level ice in a grid cell versus the percent of ridged ice in a grid cell, which is also available from the model. To derive this set of parameters, a definition of “level” and “ridged” ice is needed. Table (1) gives the percent of level versus ridged ice for several threshold values of *pond* and *arl*.

The analysis in later sections of this paper uses $pond=0.08m^2$ as the threshold for level versus deformed ice. This value was selected based on a semi-heuristic analysis of ULS data. A large number of examples of segments of CASIE data was investigated in altimeter and image data. With this threshold, ice with a feature height of less than 0.2 m is considered level ice. The spatial distribution of ridged and level ice in the study area in Fram Strait is shown in Figure 4 (for the $pond=0.08m^2$ threshold value). Table 1 indicates the sensitivity of the analysis to the threshold value for the entire study area. Figure 6a represents the sensitivity of the value of the deformed ice area for each individual model grid cell, using *pond*-threshold values of 0.04^2 , $0.08m^2$ and $0.12m^2$, as well as several model parameters.

The CICE model does not use a height criterion to distinguish level and ridged ice; instead, it tracks the area and volume of level ice using the functions and tracers described in section 3, diagnosing ridged ice area and volume from the level ice quantities. In the model-data comparison, the underlying problem of the definition of deformed ice is much more complicated than previously assumed, as will be discussed in the section on the definition of deformed ice.

7. DATA ANALYSIS: IMAGE CLASSIFICATION

As a second method to determine the area of level ice versus deformed or ridged ice, sea-ice imagery from CASIE flight 9 was analyzed. The geostatistical classification parameters provide several means to formalize and map deformation characteristics, as demonstrated in Figure 5. The *pond* parameter (Figure 5b) works as an edge-detector, which serves to locate edges of large melt ponds and leads, as well as ridge lines. Parameter *mindist* measures average spacing of dominant features and therefore can be used to separate ridged areas from areas with infrequent or no ridges (Figure 5c). Parameter *p2* shows the significance of the features - the densely spaced ridges in the right third of the image are less significant than the widely-spaced features in the left two thirds (Figure 5d).

In this paper, image analysis is employed to show the complexity of the sea ice in Fram Strait and to cast light on the question of the definition of deformed ice. The model includes deformed ice in a generalized way, as described in section 3. The complexity of the sea ice, as revealed by the CASIE data, motivates to revisit the basic question: “What is deformed ice?”.

8. MODEL RESULTS

For the model simulations shown here, we applied a beta version of CICE v5.0 (revision 575), configured and forced as in Hunke et al. (2012). In particular, we use the “level-ice” melt pond scheme presented in Hunke et al. (2012), with the delta-Eddington radiation parameterization (Briegleb and Light, 2007; Holland et al., 2012). As in Hunke (2010) and Hunke et al. (2012), our simulations are forced with a combination of climatological ocean model output (12 months of surface salinity and slope, currents, and deep heat flux convergence), taken from the CCSM3 1990 control run b30.009 (Collins et al., 2006) and averaged over 20 years into an annual climatology of monthly values; radiation fields as specified by the Arctic Ocean Model Intercomparison Project (Hunke and Holland, 2007); and a modified version of the Common Ocean Reference Experiments (CORE, Griffies et al., 2009) atmospheric forcing fields for wind components, 10-m air temperature, humidity (all 6-hourly) and monthly climatological precipitation. The control simulation ran for the years 1958–2009. Sensitivity tests were branched from the control run on 1 Jan 2000 and run for 2000–2009.

Table 2 lists the default parameters used for the control run, the values tested in sensitivity runs, and the resulting deformed ice concentrations averaged for the Northern Hemisphere and for the 25 grid cells corresponding to the CASIE track. For the sensitivity tests, we changed only one parameter at a time. In addition to the constant parameter values, we also tested C_f defined as a simple function of the mean ice thickness, such that it is constant for thicknesses less than 1 m ($C_{f\min}$) and for thicknesses greater than 3 m ($C_{f\max} = 30$), and linearly increasing for thicknesses between 1 m and 3 m.

The maximum ice thickness allowed to raft, h_{raft} , makes very little difference to the simulation. We find that μ_{rdg} and C_f produce the largest excursions of mean deformed ice area from the control, with $\mu_{rdg} = 5$ yielding the smallest fractions and

$C_f = 10$ the largest. As discussed in Hunke (2010), μ_{rdg} controls the ratio of ridge area to height; increasing μ_{rdg} decreases that ratio, forming thicker ridges that cover less area. Thus, μ_{rdg} can be used to tune the simulated ice thickness distribution (Hunke, 2010).

The parameter C_f controls the ratio of rate of work done while forming ridges to the gravitational potential energy production rate, and represents frictional dissipation of energy during the ridging process. Decreasing C_f allows more energy to be used to form ridges, effectively increasing the amount of ridging that occurs. The increased ridge volume is distributed through both increased ridge area (Fig. 7) and greater ridge thicknesses (Fig. 8). Likewise, increasing C_s causes more ice deformation, greater areas of ridged ice, and an older ice pack (not shown).

Hopkins (1994), using direct numerical simulations of the piling-up of ice blocks, provides some guidance for parameterizing C_f in terms of the large-scale model variables, especially ice thickness. He found that for ice thinner than 0.5 m, a value of C_f on the order of 10 is appropriate. Fitting his data using least squares regression, he found that C_f increases with ice volume. We allow C_f to increase linearly for mean ice thickness from 1 to 3 m to a value of 30, with the minimum value set at 17 (default) or 10 for ice thinner than 1 m. Decreasing C_f uniformly to 10 creates much greater sail heights, thicker and older ice. Conversely, increasing $C_{f \max}$ leads to younger, thinner ice. Not surprisingly, the changes vary from region to region due to differences in ice thickness.

In these simulations we adjust only one parameter at a time. A thorough parameter tuning study is beyond the scope of this paper, but based on our results, adjustment of μ_{rdg} and C_f together appears to be a reasonable path for improving the simulation of sea ice mechanical redistribution.

9. MODEL-DATA COMPARISON AND DISCUSSION

9.1. Freeboard as proxy of thickness distribution

The objective of this initial model-data comparison step is to investigate the ice thickness distribution. Figure 9 shows the comparison of model and data freeboard distributions as a histogram for the entire CASIE region. The CASIE flight tracks correspond to 35 cells of the $gx1$ grid used for our CICE runs (1° resolution), of which 25 cells contained sea ice in the observational data. Except for the elevation class of 0.1-0.2m, model and observations match very well. In general, the model has too little ice with freeboards of 0.1–0.2 m and too little thicker ice.

Freeboard measurements are used to avoid the introduction of an additional error inherent to the derivation of thickness from freeboard observations. Data histograms are produced from freeboard data as described in section (6.1). When calculating model thickness distribution histograms, we first compute the actual thickness over the ice area for binning purposes, convert to freeboard when desired by multiplying by $(1 - \rho_i)/\rho_w$ where $\rho_i = 917kg/m^3$ and $\rho_w = 1026kg/m^3$, and sum up the areas

(m^2) of ice in each of the bins. We then divide by the total ice area (m^2) and multiply by 100 to get the percentage of ice area, plotted in the histograms. Any snow in the model simulation is ignored here.

9.2. Area of deformed ice

The main parameter that we compare is the area of deformed ice in model runs and in data analysis. Comparing deformed ice areas in Figure 7 we see that the overall pattern is similar, with a lower percentage of deformed ice on the eastern side of Fram Strait, more deformed ice to the west, and open water near Svalbard. For the CICE control run and the $\text{pond}=0.08\text{m}^2$ ($\text{arl} = 0.2\text{m}$) roughness threshold, percentages in the model are in the same range as in the data with less than 20% differences in area of deformed ice. Highest percentages of ridged ice of 40–50% occur near the westernmost portion of the ULS track.

As already noted by Weeks (2010) for general identification of ridges, the fraction of level and ridged ice in the observed data is sensitive to the threshold chosen for the parameters. To further examine the match between model results and observations, we undertook sensitivity studies varying roughness thresholds as well as model parameters (see Table 2). Results are shown in Figure 6 and indicate that values for model and data-analysis-derived percentages of deformed ice area now match with differences less than 7%, with the model parameterization that yields the best match depending on geographic location. Best matches are achieved for the roughness threshold of $\text{pond}=0.08\text{m}^2$ ($\text{arl} = 0.2\text{m}$) and (1) experiments using model parameters $h_{\text{raft}} = 0.17\text{m}$, i.e. a smaller maximum rafting thickness than the control $h_{\text{raft}} = 1\text{m}$, (2) experiments with a thickness-dependent parameter C_f used instead of the constant that accounts for frictional energy dissipation and (3) experiments using $C_s = 0.5$ (instead of $C_s = 0.25$ as in the control run) for the proportion of shear energy that contributes to ridging, especially for central locations (Figure 6b). Of the five model parameters that directly impact the amount of ridging in the model, μ_{rdg} and C_f generally give the extremes for level and ridged ice areas. Since the winning model parameterization depends somewhat on geographic area, a combination of changing parameter values for h_{raft} , C_s and using a function for C_f may be expected to be most promising to capture ridging in different sea-ice morphological provinces. However, Figure 6 also shows that the natural variability of the area of deformed ice is much higher than that of the modeled results.

9.3. On the definition of deformed ice

One approach for narrowing the data-based estimates may be to use the imagery to calibrate the vario parameter ranges for several cases, then apply that to all of the data. Such a calibration, however, requires us to revisit the question “what is deformed ice?” Out in the field, the bigger ridges are obvious because they are tall, and these features stand out in the images as well. However, some ice deforms by rafting, when a flat piece of ice slides on top of another flat piece of ice; the resulting “deformed” ice is relatively smooth. Also many very small deformations do not build big ridges, but they deform the ice around the floe edges. Laser altimeter observations register small spatial changes in elevation over tilted sea-ice pieces and

hence provide a more reliable source of geophysical information than imagery. Therefore laser altimetry is used as the primary data in this analysis. Because of the outstanding problems, systematic image analysis is deferred to a future paper.

In CICE, the “ridging” parameterization is used for all ice deformation, including rafting of thin ice, and “ridged ice” refers to all deformed ice in the model. In the model, we track the amount of level ice; as soon as the ice deforms, it’s not considered level anymore and we remove that amount from the level-ice tracer. The only source for level ice is freezing of new ice; therefore tracking level ice is straight-forward. All ice that is not level is classified as deformed in the model. This means that the model will have a lot more deformed ice than is visible in the images, because its ridged ice includes rafting and small deformations too. We need to rectify the definitions of deformed ice to be comparable between the model and the data. Various authors have applied a range of cutoff values for identifying ridges in observational data, typically between 0.5 and 1.0 m for laser profiling data (Weeks, 2010). Tin and Jeffries (2003) used a smaller value of 0.3 m for a Southern Ocean study, still considerably larger than the 0.1 m value used here. A minimum sail height parameter could be used during the post-processing stage for diagnosing ridged ice area, but it would have to be applied to the mean freeboard and sail height in each grid cell and thus would not be comparable to the measurements. Moreover, this approach would add yet another parameter with which the model output could be tuned to match the data without gaining any additional understanding of how or why the model results differ from the observations; therefore we have chosen to use the unaltered model output.

9.4. Model sensitivity to parameters

The simulated deformed ice area is more sensitive to μ_{rdg} and C_f than to the other parameters, in the ranges tested. It is possible that μ_{rdg} might be determined from observations, since it controls the ratio of ridge area to height. Volkov et al. (2002) summarize studies of hummock and ridge parameters, including width-to-height ratios, but translation to the parameter μ_{rdg} is difficult. C_f , on the other hand, represents the energy lost through frictional dissipation during ridging, which Hopkins (1994) considered.

Here we examine the implications of making C_f a function of sea ice thickness. We have tested a simple parameterization of C_f that varies linearly from a minimum value for thicknesses less than 1 m to a maximum value for thicknesses more than 3 m. When the maximum value is increased, the fraction of ridged ice decreases; more energy is consumed by frictional dissipation, resulting in smaller ridges. However, when the minimum value of C_f is decreased, enough energy may remain in the system that the resulting ridges become thicker, moderating the decrease in ice strength such that the ice moves more slowly.

The sensitivity experiments indicated that a much smaller value for the maximum thickness of ice allowed to raft, h_{raft} , produces a better match with observations, and given that the ice in the study area was thin in July 2009, a dependence of h_{raft} on thickness may be indicated. The ice in Fram strait was of a complex nature with large percentages of deformed ice,

as imagery and altimetry showed, in this context it makes sense that an increased percentage of mechanical energy dissipation is attributed to ridging (using a higher value for C_s).

10. SUMMARY AND CONCLUSIONS

The approach developed in this paper demonstrates an avenue for derivation of parameters from altimeter and image data and for adjusting model parameters that improve sea-ice model-data comparison.

The study in this paper compares modeling results carried out with the Los Alamos sea-ice model, CICE, and data analysis results from very high-resolution observations, collected during the Characterization of Arctic Sea Ice Experiment (CASIE) over Fram Strait. The experiment demonstrated the capability of conducting a low-flying unmanned aircraft mission over the sea ice, with tracks of 1000 km length. In consequence, the CASIE experiment has yielded data of unprecedented quality and resolution, which enable this validation study from the data analysis side. A new data analysis approach has been derived that results in spatial parameters that capture ridging from laser altimetry and imagery and that also can be scaled upward to the modeling scale of approximately one degree. The sea-ice model CICE can be run for exactly the time domain and area of the flight experiments (July 2009, Fram Strait), which facilitates a direct comparison of numerical simulation results and data analysis results.

The comparison includes results from laser-altimeter data analysis and from modeling. The main parameters that were compared are percentages of level versus ridged ice and distribution of freeboard as a proxy of ice thickness. Results from laser altimetry yield ranges of percentage of ridged ice that fall in the same ranges as results from the CICE experiments with differences of less than 20% deformed ice area. Sensitivity studies are carried out on both the data analysis side, varying ice-surface roughness thresholds, and on the modeling side, varying several model parameters including those controlling the ridge profile and ice strength. Varying model parameters yields a match to data-derived deformed ice area concentration to within 7% in each grid cell. The closest match is generally achieved for changes in three parameters: h_{raft} , the maximal thickness of ice that can raft; C_s , the fraction of shear that contributes to ridging; and employing a function rather than a constant for C_f , the energy lost through frictional dissipation during ridging. Our results also show some dependence on geographic region or morphologic province. Spatial variability is higher in observations than in modeled results.

In conclusion, the present analysis indicates that it may be possible to achieve a convergence of data analysis and modeling by varying parameters in the model, keeping the current model physics, when accepting a spatial smoothing effect. However, a form drag parameterization has recently been implemented in a newer version of CICE by Tsamados et al. (2013), that provides variable air and ocean drag coefficients as the ice roughness varies due to ridges, floe edges and melt ponds. This parameterization will be included in future model-data comparisons.

Outlook. The analysis in this paper uses the notion of level versus deformed ice in an heuristic fashion, which has led to a numerical implementation in the sea-ice model, CICE. In the analysis here, we have followed a practical approach to determination of threshold values to facilitate a first comparison between observations and numerical simulations. At several points in the analysis, however, it becomes apparent that we need to revisit the definitions of “ridged” or “deformed” versus “level” ice. This will necessitate a renewed investigation of the types of deformation that are included in the model. The current definition includes rafted ice. As well, detailed validation of the definitions will have to include measurements and analysis of ridge heights in image and laser altimeter data for specific types of ice.

In this paper, we have established a framework for model-data comparison, facilitated by the high quality and accuracy of the CASIE data set. The data set is, however, limited in coverage. Airborne observations of the Arctic sea ice are being undertaken as part of NASA’s Operation IceBridge (OIB), an airborne mission that was originally designed as an altimeter gap-filling mission between NASA’s ICESat (Ice, Cloud, and land Elevation Satellite), which operated between 2003 and 2009, and ICESat-2, which is planned to be launched in 2017. OIB conducts several flights in the Arctic and Antarctic each summer season, starting in 2009. Laser altimeter data from OIB are of lower resolution than those of CASIE; imagery is collected as well. ICESat-2 will carry a next-generation laser altimeter that is expected to collect data with a spacing of 0.7m along-track. These data may provide a source for additional model-data comparisons following the approach developed in this paper.

There are other variables that we can compare, such as sail height. The ice draft is the portion of the ice that is underneath the ocean surface; the sail height is the height of ridges above the top of level ice, and the laser altimeter data, combined with photos to determine open water areas, can be used to measure this. The CASIE track did not quite reach the more interesting ridged area near Greenland. The large-scale Arctic circulation tends to pile sea ice up against northern Greenland and the Canadian archipelago, and hence this area is of special interest for a model-data comparison.

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Fig. 1. Flight tracks of the CASIE Experiment July/August 2009. Data used here stem from flight 9 (marked blue).

Fig. 2. Aerodynamic roughness length (arl) of sea ice in Fram Strait derived from CULPIS laser altimeter data [top], matched with co-geolocated microASAR data [bottom] from July 2009 CASIE (Segment 1 (msar104), Flight 9, 2009-07-25, CASIE 2009). MicroASAR data in bottom panel color-coded by intensity; units along image axes in meters; location of altimeter data ground track indicated by red line. Data are from the dogleg section of the flight, to position altimeter footprint over area surveyed with microASAR.

Fig. 3. Differences in laser reflectance and surface roughness length between open water (left) and sea ice (right). Laser reflectance of (a) open water and (b) sea ice. Histograms of surface roughness length from CASIE ULS data over (c) open water and (d) sea ice. Histograms of returns in 10-m bins for (e) water and (f) sea ice, used to determine the ice edge.

Fig. 4. Derivation of percent deformed ice, based on July 25, 2009 laser altimetry data analysis from CASIE flight 9. See also Table (1).

(a) *pond* parameter, calculated along-track. (b) Aerodynamic roughness length. (c) Percent deformed ice per CICE model grid cell. A threshold value of *pond*= 0.08m^2 , corresponding to *arl* = 0.2m , is used. (d) Cell index, employed to match with Figure 6, organized east to west (and south to north).

Fig. 5. Geostatistical classification parameters applied to CASIE image showing complex ice areas with ridged ice, level ice and melt ponds (image 20090725-15.36.22-IMG-9080.jpeg). Parameter *pond* shows areas of highest spatial variability and enhances edges and ridges (units relate to grey scale of image and only relative values matter). Parameter *mindist* measures average spacing of dominant features (units relate to numbers of pixels). Parameter *p2* indicates the significance of features ($0 \leq p2 \leq 1$).

Fig. 6. Sensitivity of the percent value for the area of deformed ice, for CASIE and for CICE parameters. Geographic reference for model grid cells is given in Figure 4d. (a) Sensitivity of altimetry-based percentages to the threshold used for *pond* shown by vertical bars. Center of each bar: threshold $pond=0.08m^2$ ($arl = 0.2m$), bottom: threshold $pond=0.12m^2$ ($arl = 0.244m$), top: threshold $pond=0.04m^2$ ($arl = 0.141m$), from CASIE data, 25 July 2009. See also Table (1). Sensitivity of model-based percentages to changes in parameters used in CICE, as indicated in legend, for parameter values see Table (2). (b) Residuals of percent deformed ice with respect to percent deformed ice from altimeter data for $pond = 0.08m^2$ threshold (calculated as $\{\text{percent deformed ice area in cell } i \text{ from altimeter data}\} - \{\text{percent deformed ice area in cell } i \text{ for sensitivity run } j\}$, for all cell $i=1,\dots,25$ and for all experiments j). Blue lines are at 7%.

Fig. 7. Fraction of grid cell area covered with ridged ice for the control and three sensitivity runs, averaged for July 2009 (legends relate values of fractional ice cover to the color scheme). Svalbard is an island group in the northern central Atlantic, located north of the Scandinavian Peninsula and east of northeastern Greenland. Insets: The region of the surveys over Fram Strait is shown in the zooms in the upper left-hand corner of each figure panel. The zooms show Svalbard in the right, northwestern Greenland in the left and use the same color scheme as the main figure panels. Track of CASIE flight 9 marked in white in the control run zoom.

Fig. 8. Sea ice sail height for the control and three sensitivity runs, averaged for July 2009 (legends relate sail height in meters to color scheme). Svalbard is an island group in the northern central Atlantic, located north of the Scandinavian Peninsula and east of northeastern Greenland. Insets: The region of the surveys over Fram Strait is shown in the zooms in the upper left-hand corner of each figure panel. The zooms show Svalbard in the right, northwestern Greenland in the left and use the same color scheme as the main figure panels. Track of CASIE flight 9 marked in white in the control run zoom.

Fig. 9. Comparison of freeboard histograms from CASIE ULS data analysis and CICE model results for the July 2009 run, in both cases evaluated for the area of the 25 grid nodes of the CICE-CASIE comparison over sea ice.

pond [m^2]	arl [m]	% ridged	% level
0.020	0.100	64.8	35.2
0.040	0.141	46.9	53.1
0.060	0.173	37.1	62.9
0.080	0.200	30.6	69.4
0.100	0.224	25.2	74.8
0.120	0.244	21.3	78.7
0.140	0.265	18.6	81.4

Table 1. Aerodynamic roughness length (arl), level and ridged ice percentages for the entire study area from CASIE flight 9 (July 2009) laser altimeter data analysis for several values of *pond*. The analysis in later sections of this paper uses $pond=0.08m^2$ and $arl = 0.2m$ as the threshold for level versus deformed ice, based on ULS data analysis. Spatial distribution for the $pond=0.08m^2$ threshold value is shown in Figure 4.

Parameter	Description	Default	Tests	NH	CASIE Mask
		control		31.1634	38.1931
a^*	mean values of the cumulative ice thickness distribution participating in ridging	0.05 ^a			
			0.03	32.4175	45.5128
			0.07	30.9051	39.2194
h_{raft}	thickest ice allowed to raft	1 m			
			0.17 m ^b	33.0950	41.8181
			2 m ^c	30.7335	37.6406
μ_{rdg}	controls the e-folding scale of the ridge ice thickness distribution	3 m ^{1/2} ^a			
			4 m ^{1/2} ^{a,e}	24.6877	27.6685
			5 m ^{1/2}	20.2645	21.2877
C_f	ratio of the rate of work done to the rate of potential energy change during ridging	17 ^d			
			10 ^f	41.5542	63.9714
$C_{f \text{ min,max}}$			10, 30	29.9066	37.4987
			17, 30	27.0120	33.8172
C_s	fraction of the shear component of mechanical energy that contributes to ridging	0.25			
			0.5 ^d	36.6809	50.2486

Table 2. CICE parameters and resulting deformed ice area fraction (%) in July 2009 for the Northern Hemisphere and the CASIE mask (25 nodes). Parameters are denied in section 3. ^aLipscomb et al. (2007b), ^bParmerter and Coon (1975) and Weeks and Kovacs (1970), ^cKovacs (1970), ^dFlato and Hibler (1995b), ^eHunke (2010), ^fHopkins (1994).