Cold Regions Science and Technology 108 (2014) 1–9

Contents lists available at ScienceDirect

Cold Regions Science and Technology

journal homepage: www.elsevier.com/locate/coldregions

An ensemble forecast model of iceberg drift

K. Allison [a,1], G. Crocker [b,*], H. Tran [c], T. Carrieres [c]

[a] Faculty of Mathematics, University of Waterloo, Waterloo, N2L 3G1, Canada
[b] Ballicater Consulting Ltd., Kingston, K7L 4B4, Canada
[c] Canadian Ice Service, Environment Canada, Ottawa, K1A 0H3, Canada

ARTICLE INFO

Article history:
Received 19 December 2013
Accepted 22 August 2014
Available online 28 August 2014

Keywords:
Icebergs
Drift
Ensemble forecasting

ABSTRACT

A study of the application of ensemble techniques to iceberg forecasting has been performed using a numerical iceberg drift model. A simple 'Monte Carlo' approach was used in which variations for each key environmental parameter and iceberg property were sampled randomly to generate 250 ensemble members. The range of variations was estimated to represent the 95% confidence level in the parameter's value. A set of 216 iceberg tracks from the northern Grand Banks region, collected between 2002 and 2007, was used to assess the ensemble performance. While the ensemble mean drift forecast did not improve over the deterministic forecast, the ensemble model is shown to be consistent and the statistical properties of the ensemble provide useful information on the uncertainty inherent in the forecasts.

© 2014 Elsevier B.V. All rights reserved.

1. Introduction

The Canadian Ice Service (CIS) is the federal agency in Canada that is responsible for providing operational sea ice and iceberg information. The CIS prepares several products that inform marine interests of areas where ice hazards may be encountered and where they may be more severe. Iceberg products include charts depicting the number of icebergs within a 1° of latitude by 1° of longitude box while text products describe the spatial distribution of icebergs together with a delineation of the iceberg limit. These products are prepared by combining iceberg observations with iceberg drift and deterioration forecasts. Due to the high cost of conducting regular aerial reconnaissance over large geographical areas, a numerical model that simulates the drift and deterioration of icebergs is relied upon heavily to fill data gaps for the periods between observations.

For the CIS operational use, the iceberg model is run automatically every 6 h in order to keep the distribution of icebergs up to date. The original model was developed in the early 1980s (Anderson, 1983; Mountain, 1980) by the International Ice Patrol (IIP) and is referred to as the IIP iceberg model. More recently, a program of iceberg model research has been conducted at the CIS with the goals of improving the quality of forecasts and providing information on the uncertainty in iceberg forecasts. A newer model, referred to as the North American Ice Service (NAIS) iceberg model, has been developed by incorporating more complete parameterization and more reliable numerical methods.

An earlier version of the NAIS iceberg model has been described in detail by Kubat et al., (2005, 2007), but a brief overview of the main features is presented here.

The NAIS iceberg model estimates iceberg velocity using the equations for the balance of linear momentum,

$$m\left(\frac{d\mathbf{V}}{dt}+\mathbf{f}\times\mathbf{V}\right)=\mathbf{F}_a+\mathbf{F}_w+\mathbf{F}_r+\mathbf{F}_p+\mathbf{F}_{am}+\mathbf{F}_{si} \quad (1)$$

where m and $\mathbf{V}$ are the mass and velocity of the iceberg respectively, and $\mathbf{f}$ is the Coriolis parameter. The force terms of the right-hand side of the equation are air drag ($\mathbf{F}_a$), water drag ($\mathbf{F}_w$), wave radiation stress ($\mathbf{F}_r$), water pressure gradient ($\mathbf{F}_p$), added mass ($\mathbf{F}_{am}$), and sea ice force ($\mathbf{F}_{si}$). Parameterizations for the forces have been described in detail in Kubat et al. (2005). The implicit Euler method is used to solve the momentum balance equation, giving an estimate of the acceleration at each time step which is then used to update the iceberg velocity (Kubat et al., 2005). Meanwhile, the deterioration of icebergs is modeled using the approach originally developed by White et al. (1980) and updated by Kubat et al. (2007). The reduction in the size of icebergs is important because size affects the drift speed and direction, and because the icebergs must be removed from the system when they have completely deteriorated.

In this paper a preliminary study has been undertaken to assess the feasibility of applying ensemble forecasting techniques to iceberg drift. Ensemble forecasting is a relatively new approach to environmental modeling that uses two or more forecasts valid at the same time. The technique has been widely used in Numerical Weather Prediction (NWP) over the past decade, but has never been applied to operational iceberg drift forecasting. There have, however, been a few studies of iceberg drift forecasting that utilized some aspects of the ensemble method.

* Corresponding author.
E-mail address: ballicater@sympatico.ca (G. Crocker).
[1] Present Address: Rudolf Peierls Centre for Theoretical Physics, Oxford OX1 3NP, United Kingdom.

http://dx.doi.org/10.1016/j.coldregions.2014.08.007
0165-232X/© 2014 Elsevier B.V. All rights reserved.

These include Keghouche et al. (2009), who tuned iceberg mass and drag coefficients and found that the observed spread of position errors was of the same order as the forecast error. They suggest that this preliminary result is promising for the viability of an ensemble-based iceberg forecasting system. Keghouche (2010) used an Ensemble Kalman Filter to apply time varying corrections to iceberg position and to optimize model parameters. Lichey and Hellmer (2001) used an ensemble of icebergs to calibrate sea ice strength parameters in a study of Antarctic iceberg drift. Although full ensembles methods have not previously been used for forecasting iceberg drift, they have been applied to the drift of objects in the sea such as drifter buoys (Rixen et al., 2008), containers (Ailliot et al., 2007), pollutants, algae blooms (Vandenbulcke et al., 2009), and search and rescue targets (Breivik and Allen, 2008).

The work carried out on an ensemble forecast version of the NAIS iceberg model, which is presented here, includes the selection of an ensemble technique, the identification of the most important parameters affecting drift, the development of an ensemble model based on these key parameters, and an evaluation of model performance.

2. Ensemble forecasting methods

A history of ensemble forecasting is provided by Lewis (2005). The general approach to ensemble forecasting is as follows. In every ensemble forecast, a 'control forecast' is designated. This is the model prediction from the unperturbed or 'best estimate' initial conditions and is normally run at full (highest) resolution. It is used as a basis for comparison and evaluation of the ensemble forecast. Members of an ensemble forecast are then created by perturbing one or more of the following:

- the initial conditions,
- the model,
- the boundary conditions.

A measure of central tendency of the ensemble is used to produce an 'ensemble forecast' that is, ideally, more accurate than the control forecast. The statistical properties of the ensemble can also be used to identify uncertainties in the modeling process, estimate the decay of forecast skill with increasing forecast lead time, and estimate forecast accuracy.

When applied to iceberg drift/deterioration modeling, ensemble forecasting yields a collection of iceberg positions at a desired forecast period. Fig. 1 shows an example of such an ensemble forecast for iceberg HG03012d (a 55 hour drift track observed on the Grand Banks in April 2003) produced using the techniques described later in this paper. In this case, the deterministic (control) forecast performed reasonably well, but the ensemble forecast, computed as the mean position of the ensemble members, provided a better estimate of the true iceberg position. Moreover, a circle (or other enclosed shape) can be drawn around the position of the ensemble forecast that defines an area in which a certain proportion of the ensemble members lie. If the members of the ensemble forecast are generated appropriately, this contour can provide an estimate of the uncertainty in the forecast iceberg position.

Uncertainties in numerical predictions of iceberg drift, which are suitable for modeling with ensemble forecasting methods, can arise from three different sources. The first is the iceberg drift and deterioration model itself; primarily the model physics, the numerical methods used to simulate those physics, and the specification of initial conditions. The second, and perhaps more important source of uncertainty, is the specification of the environmental driving forces. Currents, winds and waves all play a role in determining where an iceberg drifts. To make a drift forecast, these environmental parameters must also be forecast (and then used to drive the iceberg drift model), and limitations to their accuracy and resolution limit the accuracy of the iceberg forecasts. Third are the uncertainties in the properties of the icebergs themselves. For the ensemble model considered in this paper, only perturbations related to iceberg initial conditions and environmental driving forces have been used to create members of the ensemble forecast.

Numerous perturbation strategies have been developed and many are currently used in ensemble models, both operationally and in scientific studies of meteorological phenomena. No single technique has been shown to be universally superior. The most widely used perturbation strategies are Monte Carlo methods, Lagged Average methods, Breeding of Growing Models methods, and EOF Based methods. Detailed descriptions of the various methods can be found in Leutbecher and Palmer (2008), Sivillo et al. (1997) and Toth and Kalnay (1993). Most of the techniques have been developed for NWP and several have been developed specifically to reduce the demand on computational resources, which can be very high in that application. In the case of iceberg forecasting, the model is relatively simple and requires only modest computational power to run. For our first attempt at ensemble forecasting of iceberg drift, we selected the Monte Carlo method because it can deal with large numbers of parameters (dependent or independent), and is simple to construct. It is, in a sense, a 'brute force' approach because the full model must be run for each ensemble member.

Monte Carlo modeling involves running many trials of a deterministic model with one or more of the model parameters (i.e. the initial iceberg properties and the environmental conditions) selected randomly from pre-defined probability distributions for each trial. The probability distributions are designed to simulate the uncertainty in each parameter. Since the iceberg observations used in this study are from the past, the model predictions are actually 'hindcasts'. However, the techniques are equally suited to real-time forecasts. To avoid repeated changes of the nomenclature, we use the term 'forecast' in both the discussion of ensemble methods and the analysis of the data, but it should be noted that the analyses were performed on past events.

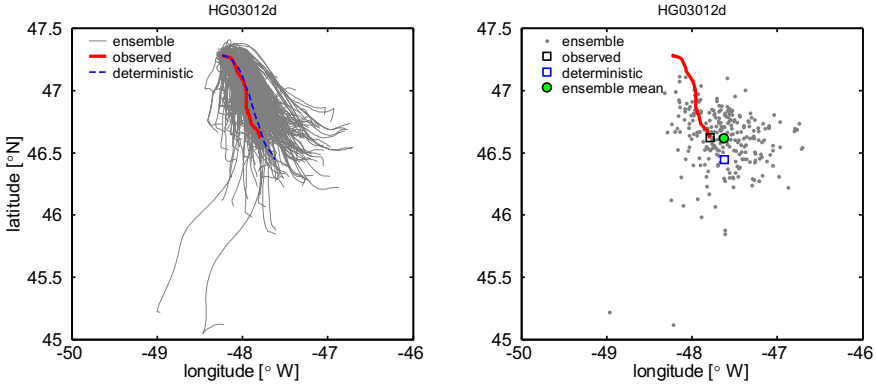

Fig. 1. An example of a 55 hour ensemble forecast for iceberg drift. *Left*: The forecast drift tracks for all ensemble members, together with the deterministic (control) forecast and the observed drift track. *Right*: The final forecast positions for all ensemble members, together with the ensemble mean position, the deterministic forecast position, and the observed position.

3. Model parameters and uncertainty

To determine which iceberg model parameters were included in the Monte Carlo ensemble model, a sensitivity study was conducted to determine the influence of the uncertainty in each parameter on the predicted iceberg drift. For simplicity, only those parameters whose uncertainty significantly affected the modeled iceberg drift were included in the Monte Carlo ensemble model.

In the sensitivity study, the drift of virtual icebergs with waterline lengths of 10 m, 37.5 m, 90 m, 160 m, and 350 m were modeled over a 72-hour period using base case ice and environmental parameter values that are typical of the Grand Banks region. For each model parameter, an estimate of the range of values large enough to encompass 95% of the parameter's uncertainty was made. That is, a range was selected around each base case parameter value that was thought to include the true value of that parameter approximately 19 times out of 20 (Table 1). These estimates were based on existing verification data when possible, but for several parameters no such data existed and the estimates were based on subjective judgment and experience. The iceberg drift was then re-modeled, varying one parameter at a time within its estimated range of uncertainty.

Summary results from the sensitivity analysis are given in Table 1. The average deviation is the average distance in kilometers between the base case forecast position and the positions predicted when the parameter was varied uniformly through the specified range of values; all after 72 h of simulated drift. The final column shows the importance of each parameter, with the parameters resulting in the greatest average deviation from the base case position given the highest ranks.

10 of these 19 parameters were found to account for most of the uncertainty in the drift predictions. For these parameters, a more detailed analysis of the range and distribution of the parameter uncertainty was performed. Appendix A provides a summary of the resulting probability distributions for the *errors* in the parameters. These were subsequently *subtracted* from the base parameter values in the Monte Carlo model. Note that several error distributions are truncated to ensure physically realistic parameters (e.g. a non-negative wind speed). In these cases, the distributions were re-normalized to ensure a cumulative probability of 1.

For several environmental parameters, most notably the current/wind speed and the swell/wind wave height, there is an important issue in subtracting the randomly sampled error from the base parameter value: these environmental parameters (and their error distributions) change over the forecast period, and so it is possible that an initially sampled error may not be valid at a later time in the forecast period. For instance, a wind speed error of +2 m/s is valid for an initial wind speed of 3 m/s but it is not valid when the wind speed drops to 1 m/s. To properly account for changes in the error distributions over the forecast period, the cumulative probability of the randomly sampled error (the uniformly distributed number between 0 and 1) was maintained throughout the forecast period, rather than a fixed error. For parameters that do not change over the forecast period, the error remains the same as the initially sampled value.

4. Ensemble iceberg model structure

The NAIS iceberg model generates a deterministic drift forecast for a set of initial iceberg properties (position and length) and forecast environmental conditions. The initial iceberg properties are estimated from aerial observations while the environmental conditions are provided by various forecast models as follows: ocean currents from the Canadian Ice Service implementation of CECOM (Tang et al., 2008), forecast atmospheric forcing from the Canadian Meteorological Centre (CMC) regional GEM (Côté et al., 1998) and wave forecasts from the CMC implementation of WAM (The WAMDI Group, 1988). The Monte Carlo ensemble drift model creates a set of random perturbations in these base model parameters, produces a deterministic drift forecast for each set of perturbations, and then combines these forecasts into a single ensemble forecast. Statistical properties of the ensemble are also used to estimate the uncertainty in the forecast. In this section, the specific methods used in the ensemble iceberg model for generating the ensemble forecast and the statistical information are described.

First, N sets of perturbations in the base model parameters are generated by randomly sampling values from the error distributions in Appendix A. As described in Section 3, these errors are subtracted from the base parameter values to obtain the perturbed parameters for the N ensemble members. Since iceberg drift forecasts may be run for many days or weeks, maintaining constant perturbation vales over the entire forecast may lead to unrealistic representations of the uncertainty. For example, it may be realistic to maintain a large variation in the wind speed for a day, but it may not be realistic to maintain that large variation in the wind speed for a week. To account for this, the ensemble model resamples the parameter perturbations after a fixed interval of forecast

Table 1
Summary of parameter variability and results from sensitivity analysis.

		Range	Base value	Units	Avg. Dev.	Rank
Iceberg properties						
	Length	±50%	37.5/90/160/350	m	8 km	12
	Added mass	0-1	0.5	–	<2 km	16
Driving forces						
Wind	Direction	±45°	225	° true	30 km	3
	Speed	±30%	10	m/s	10 km	8
	Drag coefficient	0.5–2.5	1.9	-	12 km	7
Current	Direction	±90°	135	° true	124 km	1
	Speed	0-0.8	0.4	m/s	67 km	2
	Drag coefficient	0.5–2.5	1.3	–	18 km	4
Wave stress	Significant wave height	±50%	1.5	m	9 km	9
	Wave stress coefficient[a]	0–0.3	0.15	–	14 km	6
	Wave period	±50%	6	s	<2 km	15
	Wave direction	±45°	225	° true	9 km	10
Swell stress	Significant swell height	±50%	1.5	m	15 km	5
	Swell stress coefficient[a]	0–0.3	0.15	–	14 km	6
	Swell period	±25%	8	s	2 km	13
	Swell direction	±30°	315	° true	8 km	11
Initial conditions						
	Initial position	±5 km	0	km	<2 km	14
	Initial speed	0-0.8	0.4	m/s	<2 km	17
	Initial direction	±45°	0	° true	<2 km	18

[a] The wind wave and swell stress coefficients were varied together so they have the same rank.

lead time. Since the most appropriate re-sampling interval was not known *a priori*, a value of 48 h was chosen to yield a consistent approach in the model calibration (see Section 6.1). Note that here and throughout this paper, the term 'consistent' has a specific meaning. In a consistent model, the ensemble spread of the forecast should represent the true variability (uncertainty) of the observations. This is discussed in more detail in Section 6.

After generating the perturbations in the N ensemble members, a collection of N deterministic drift forecasts is generated for a given forecast lead time. The ensemble forecast position is taken to be the mean position of all the ensemble members with each member given equal weighting. This choice seems appropriate for a preliminary investigation of ensemble iceberg drift forecasting in which the full NAIS iceberg model is run for each ensemble member.

The collection of forecast iceberg positions is then used to estimate the uncertainty in the mean position by generating contours that enclose a certain percentage of the ensemble members. The size of these contours provides an estimate of the uncertainty in the forecast while the shape provides additional probabilistic information that cannot be captured in a single forecast. The probability contours are created by first centering a circular normal distribution that is re-normalized to a cumulative probability of $1/N$,

$$f(r,\theta) = \frac{1}{2\pi\sigma^2 N}\exp\left[-\frac{r^2}{2\sigma^2}\right] \tag{2}$$

on each member's forecast position and adding the distributions together. Contours are then generated that enclose a certain percentage of the overall probability distribution.

The standard deviation σ must be chosen to reflect the characteristic scale of the ensemble spread; if σ is too small then the contours will be peaked very sharply at the ensemble member positions, and if σ is too large then the detail in the cluster will be lost. Following Anderson (1997), the average distance d_{avg} between each ensemble member's position and the ensemble mean position was used to measure spread so that

$$\sigma = c \cdot d_{avg} \tag{3}$$

where c is a tunable constant. Fig. 2 shows how the value of c affects the size and shape of the contours. The value $c = 0.5$ was chosen to yield a consistent model in the model calibration process (see Section 6.1) and to optimize the parameter perturbation re-sampling interval.

Note that the circular normal distribution was chosen for simplicity; other radially-symmetric distributions with a characteristic length scale could also have been used, and the resulting contours would be similar.

The ensemble iceberg drift model uses the deterministic forecasts of $N = 250$ members to generate an ensemble forecast. This was the smallest number of ensemble members that was found to produce a sufficiently dense and consistent spread of forecast positions. Larger ensemble sizes increased the model run time without significantly affecting the ensemble forecast (Allison, 2007).

5. Model evaluation

To evaluate the performance of the ensemble drift model, we used a set of 216 iceberg drift track observations that was collected primarily by Provincial Aerospace (PAL) in the Grand Banks region between 2002 and 2007 (Fig. 3). Typically, the icebergs were first spotted by aircraft that provided only infrequent estimates of location and approximate estimates of the iceberg size. If the icebergs drifted toward an offshore installation, their positions were tracked more regularly by radar and by supply vessels. In these cases, detailed measurements of iceberg drift and deterioration were made for up to several weeks.

A set of iceberg observations had to satisfy a few criteria in order to be used as a drift track. First, the observations must have extended over at least a 24-hour period so that the model could produce a forecast with a meaningful lead time. Second, there must have been several iceberg observations per day in order to be confident that the track came from a single iceberg. Finally, the iceberg must not have been grounded or under tow by a supply boat since the iceberg model only simulates the free drift of an iceberg.

The criteria used to evaluate the ensemble drift model are based on Anderson (1997), which describes four measures of a general ensemble forecast:

i. *Skill* — How accurate the ensemble forecast's mean value is to the verifying truth (i.e. the observed value). An ensemble forecast's skill is usually measured by the root mean square (RMS) error between the ensemble forecast's mean value and the verifying truth. A more skillful ensemble forecast is one with a lower RMS error over a large set of forecast cases.
ii. *Consistency* — How well the distribution of ensemble forecast members reflects the verifying truth. An ensemble forecast is said to be 'consistent' if the verifying truth is indistinguishable from a randomly selected ensemble member over a large set of forecast cases. Rank histograms or 'Talagrand diagrams' are often used to evaluate model consistency (Anderson, 1997; Hamill, 2001). This method involves partitioning the forecast range into bins using the ensemble members themselves and checking whether the verifying truth falls into those bins with uniform probability. Consistency is referred to by some authors as 'reliability'.

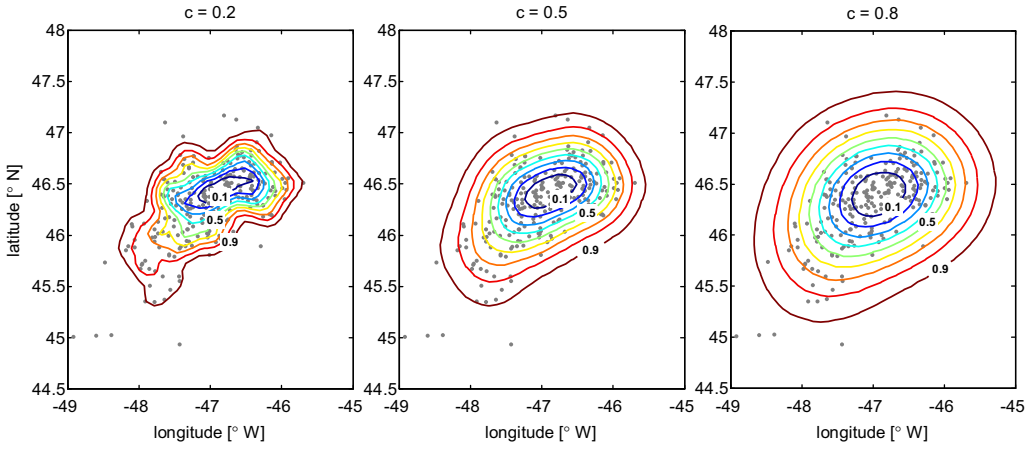

Fig. 2. The effect of the coefficient c on the size and shape of the probability contours generated for a typical forecast ensemble. Each contour labeled 0.1–0.9 contains a corresponding percentage of the ensemble members. *Left to right*: Coefficient values of $c = 0.2$, 0.5, and 0.8.

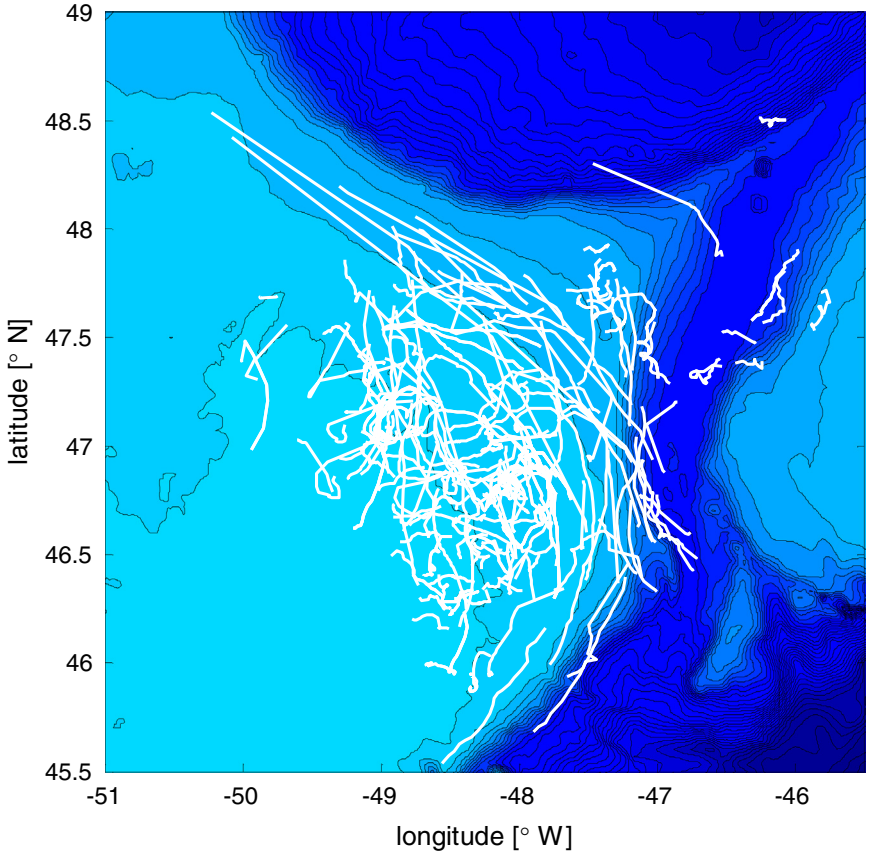

Fig. 3. The collection of 216 iceberg drift tracks used to evaluate the ensemble forecast model.

iii. *Spread vs. Skill* — How well a measure of the ensemble forecast's spread is able to predict the ensemble forecast's skill. The ability of an ensemble model to predict the skill of a forecast is typically determined by examining the correlation between the ensemble spread and the forecast error. However, it is also possible to examine the consistency of the ensemble predictions of forecast error and the verifying forecast error. Spread vs. skill is sometimes referred to as 'resolution'.

iv. *Inclusiveness* — How well the extreme outliers of the probability distribution are sampled. Due to the unstable nature of this statistic, there are many specialized techniques but no generally accepted technique for measuring the inclusiveness of an ensemble forecast.

The first two of these measures, skill and consistency, have been used to evaluate the performance of the ensemble drift model. Skill was measured by the RMS error distance between the iceberg's observed position and the ensemble forecast position. It was presented as a function of forecast lead time. Consistency was measured by comparing the percentage of iceberg observations that were contained within the probability contours generated from the ensemble forecast; a consistent model will have 20% of the observations contained in the 20% contour, 40% of the observations contained in the 40% contour, and so on. This technique for evaluating the model's consistency can be viewed as a two dimensional generalization of the binning technique used in rank histograms and Talagrand diagrams. Like skill, consistency has been presented as a function of forecast lead time.

The third measure, spread vs. skill, provides information on the case-to-case changes in skill. It has not been used in the present analysis, but some indication that the model does capture case-to-case variations is provided (below) by the comparison of the ensemble RMSE versus that produced by the drift climatology.

The fourth measure, inclusiveness, was not used to evaluate the performance of the model because it is not critically important for iceberg drift forecasting. Although inclusiveness may be an important property of an ensemble model attempting to predict extreme weather conditions, it is more important for the ensemble drift model to predict iceberg drift accurately on average than in exceptional cases.

We first examined the consistency of the ensemble model since this measure was used to calibrate the model on half the data set. We then considered the skill of the ensemble forecast and compared it with the skill of the deterministic (control) forecast.

6. Results and discussion

6.1. Model consistency

Consistency is one of the most important measures in assessing the validity of the ensemble model as forecast tool; if the probability contours of the ensemble forecast are consistent, then the size and shape of the contours can give accurate information about the uncertainty in the drift forecast. To establish the consistency of the ensemble model, it must be tested on a large set of forecast cases. There are two free parameters related to the generation of probability contours that directly affect their size and shape, and hence the ensemble model's consistency: the parameter perturbation re-sampling interval and the coefficient c that controls the standard deviation of the circular normal distributions. The parameter perturbation re-sampling interval affects how quickly the size of the contours grows with forecast lead time (a longer re-sampling interval maintains large perturbations for longer and hence produces larger contours) while the coefficient c affects the size and shape of the contours independently of forecast lead time. It was therefore necessary to calibrate these two parameters on a subset of the drift tracks before evaluating the consistency of the ensemble model.

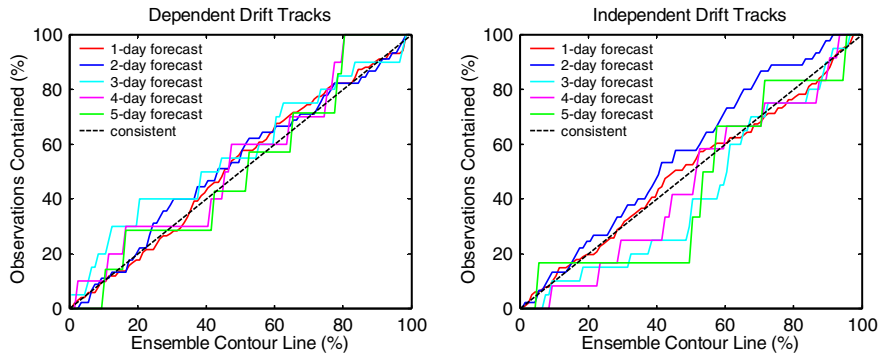

Fig. 4. Evaluation of the consistency of the ensemble drift model. The model is considered consistent if each contour line contains its percentage of the observed iceberg positions. *Left*: The calibration of the model's consistency on the dependent set of drift tracks. *Right*: The test of the model's consistency on an independent set of drift tracks. In both plots, there are approximately 108, 46, 20, 15, and 7 drift tracks that extend up to 1, 2, 3, 4, and 5-day forecast lead times, respectively.

The parameter perturbation re-sampling interval and the coefficient c were adjusted to maximize the ensemble model consistency on a randomly selected subset of half of the available 216 observed drift tracks, leaving the other half as an independent set to verify the consistency of the model. In the calibration, it was found that a parameter re-sampling interval of 48 h and a coefficient $c = 0.5$ made the model most consistent on the dependent set of drift tracks. Fig. 4 shows the consistency of the ensemble model for the dependent and independent sets of drift tracks. Note that there are approximately 108, 46, 20, 15, and 7 drift tracks that extend up to 1, 2, 3, 4, and 5-day forecast lead times, respectively. Overall, the ensemble model was fairly consistent for the independent set of drift tracks for 1 and 2-day forecast lead times. For forecast lead times greater than 2 days, however, the ensemble model exhibited some inconsistency in the 20–60% contours. This inconsistency may be due to having too few drift tracks to calibrate and/or evaluate the ensemble model beyond 2 days. In this case, calibrating and evaluating the model with a larger set of drift tracks should correct the problem. On the other hand, the inconsistency may indicate a more fundamental problem with the method used to generate parameter perturbations in this ensemble model. A major challenge in the development of a Monte Carlo-based drift model that uses a single forecast for the environmental parameters is the construction of realistic perturbations in these parameters over a period of several days. The technique used in this paper of re-sampling all parameter perturbations after the same, fixed interval may be inadequate for modeling environmental parameter perturbations for forecast lead times greater than 2 days. If this is the case, alternative methods for generating extended environmental parameter perturbations should be investigated. Note that limiting the re-sampling interval also has the effect of allowing for changes in the dynamic regime in which the icebergs are drifting. For example, after 48 h an iceberg could move from the relatively passive current regime on the Grand Banks to the region strong flow in the Flemish Pass.

As a further test of the consistency of the model, it is interesting to examine the average area enclosed by the 5%, 20%, 40%, 60%, 80%, and 95% contours as a function of forecast lead time for the dependent and independent sets of drift tracks. Fig. 5 shows that, for all contours and at all forecast lead times, the ensemble spread was approximately 20% smaller for the *independent* set of drift tracks than for the *dependent* set. When combined with the fact that the ensemble drift model is reasonably consistent for the independent set, this result tends to validate the ensemble drift model as a forecast tool; the ensemble model can correctly predict which drift track forecasts are relatively certain by having a smaller ensemble spread for those forecasts. This information may be more accurate and informative than the rough estimate of 5 nm/day for the model forecast error growth that is currently used for operational iceberg products prepared by the International Ice Patrol and the CIS.

6.2. Model skill

The skill of the ensemble drift model was measured by the RMS error distance between the iceberg's observed position and the mean position of the ensemble member forecasts. It is presented in Fig. 6 as a function of forecast lead time. Note that the dependent and independent sets of drift tracks are presented separately because the calibration of the ensemble model using the dependent set can, in principle, have an effect on the model's skill. However, the model calibration does not attempt to improve the forecast skill and, in practice, the effect is small.

A large improvement in the ensemble forecast skill compared to the deterministic (control) forecast would be an important reason to adopt an ensemble drift model. Fig. 7 compares the forecast skill of the two

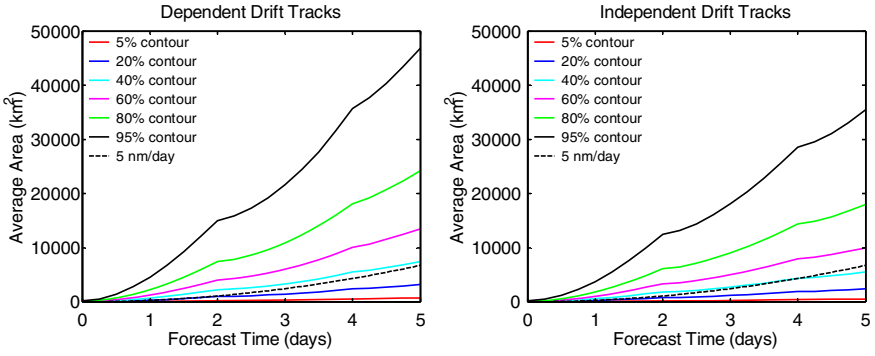

Fig. 5. The spread of the area enclosed by the probability contours for the ensemble drift model for the dependent (left) and independent (right) sets of drift tracks as a function of forecast lead time. In both plots, there are approximately 108, 46, 20, 15, and 7 drift tracks that extend up to 1, 2, 3, 4, and 5-day forecast lead times, respectively.

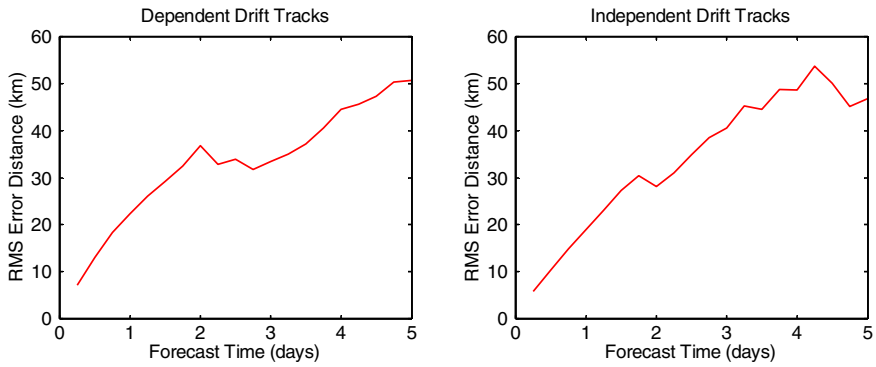

Fig. 6. The skill of the ensemble drift model for the independent (left) and dependent (right) sets of drift tracks as a function of forecast lead time. In both plots, there are approximately 108, 46, 20, 15, and 7 drift tracks that extend up to 1, 2, 3, 4, and 5-day forecast lead times, respectively.

models using the full set of 216 drift tracks since, as discussed, the model calibration has only a small effect on the forecast. Approximately 216, 92, 40, 29, and 14 drift tracks extend to forecast lead times of 1, 2, 3, 4, and 5 days, respectively. The results showed that the skill of the ensemble forecast was very similar to the skill of the deterministic forecast. Although there was some indication that the deterministic model performed better for forecast lead times of up to 3 days while the ensemble model performed better for longer forecast lead times, a paired t-test of the RMS error values indicated that the difference was not significant at the 95% confidence level. A simple explanation for this result, which seems to be confirmed by the parameter sensitivity study, is that iceberg drift model is essentially linear in its most influential environmental parameters (i.e. the ocean currents and wind). The ensemble forecast position, which is the mean position of ensemble member forecasts with parameter perturbations distributed roughly evenly about the control value, is therefore very close to the deterministic forecast position.

To evaluate the model's ability to capture case-to-case variations in skill, the RMSE of the independent sample was compared to the RMSE produced by the observed drift climatology. The comparison was performed for 24 hour forecasts. The climatology was derived from the probability distributions of the u and v components of the observed drift tracks over the first 24 h of observation for each of the 216 icebergs. The u and v components were sampled independently (the correlation coefficient r was -0.07) and applied to the start position to produce a 24 hour 'climatology ensemble' for each independent drift track. The average RMSE error for the climatology was 32 km, versus about 19 km for the ensemble model, which is an indication that the model is more accurately predicting the variations in skill.

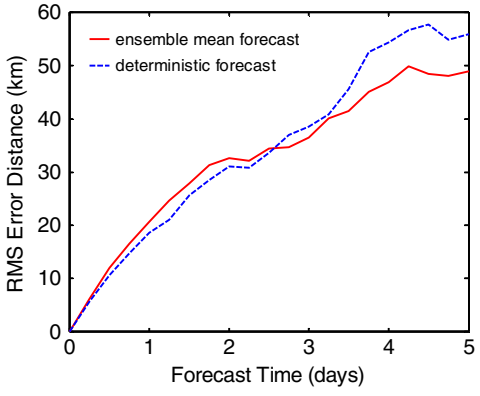

Fig. 7. The overall skill of the deterministic drift model (red) and the ensemble drift model (blue) as a function of forecast lead time. There are approximately 216, 92, 40, 29, and 14 drift tracks that extend up to 1, 2, 3, 4, and 5-day forecast lead times, respectively.

7. Conclusions

A simple ensemble forecasting model for iceberg drift has been developed for operational use by the CIS. It is based on a Monte Carlo approach with 250 ensemble members in which key iceberg and environmental parameters are randomly perturbed to reflect the estimated uncertainty in their values. A set of 216 iceberg tracks from the northern Grand Banks region, collected between 2002 and 2007, was used to assess the ensemble performance. It is shown that the skill of this particular ensemble model did not improve over the deterministic forecast — a result that is likely due to the linear behavior of the underlying iceberg drift model. However, the ensemble model is shown to be reasonably consistent on an independent set of drift tracks. Most importantly, the ensemble model can provide quantitative information on the uncertainty inherent in the iceberg forecasts and is therefore a useful analysis tool. It has been previously assumed that forecast errors grow by about 5 nm/day. Our analyses indicate that the 5 nm/day estimate grows in area approximately as the contour containing 40% of the ensemble members. We believe that more accurate and informative estimates of uncertainty can be achieved by replacing the 5 nm/day rule with contours that contain the ensemble spread at prescribed probability values.

A sensitivity analysis indicated that the most important parameters to be perturbed in the ensemble are, in order of importance: current direction, current speed, wind direction, and the water drag coefficient. This highlights the importance of ocean currents to iceberg drift forecasting, and indicates that better estimates of ocean current perturbations should be derived; ideally based on direct comparisons between currents forecasts and physical measurements. It also supports the idea that significant improvements in the accuracy of deterministic or ensemble iceberg forecasts will be achieved only when better ocean models are available.

The next step in ensemble iceberg forecasting at the CIS will be to replace the Monte Carlo technique with more explicit representations of uncertainty in the wind and ocean forecasts. This will be achieved by using ocean current forecasts from a variety of ocean models and using an ensemble weather prediction system. It is anticipated that these ensemble forecasts will better capture the true variability in the atmosphere and ocean, possibly resulting in more skillful ensemble forecasts. Moreover, it may be possible to gain insight into the bias of the environmental parameter forecasts by examining ensemble members whose parameter perturbations produce drift tracks closest to the observed drift track.

Acknowledgments

Funding for this work was provided by the Natural Resources Canada Program on Energy Research and Development through the *Improved Iceberg Forecasts* and *Sea Ice and Ice Hazard Analyses and Forecasts* projects (B32.001). Most of the 216 iceberg drift tracks used in the analysis were provided by Provincial Aerospace (PAL).

Appendix A. Error distributions used in the Monte Carlo model

A.1. Iceberg length error

Distribution:	Uniform
Mean:	37.5 / 90 / 160 / 350 m (depending on length bin)
Standard deviation:	n/a
Range:	See below
Renormalization:	No

Comments: Iceberg lengths are provided as falling into one of the standard size bins (15–60 m, 61–120 m, 121–200 m, and >200 m, assumed to include the range 200–500 m). The deterministic drift model uses the mid-point of the bin as the starting length. In the Monte Carlo model the initial length value was sampled from a uniform distribution inside the indicated length bin.

A.2. Wind direction error

Distribution:	Normal
Mean:	0°
Standard deviation:	45°/1.96 = 22.96°
Range:	±180°
Renormalization:	CDF was then re-normalized so that the cumulative probability between the truncation points is 1.0.

Comments: No verification data were available so the error estimate has been based on judgment.

A.3. Wind speed error

Distribution:	Normal
Mean:	1.66 m/s
Standard deviation:	2.99 m/s
Range:	Left-truncated at −1 times the forecast wind speed and right-truncated at the forecast wind speed value.
Renormalization:	CDF was then re-normalized so that the cumulative probability between the truncation points is 1.0.

Comments: Khandekar and Lalbeharry (1996) compared surface level wind speed forecasts from the operational weather prediction models at CMC with wind speeds observed by buoys in the northwest Atlantic and northeast Pacific. Their mean bias value of 1.66 m/s and RMS error of 2.99 m/s were assumed to be representative.

A.4. Wind drag error

Distribution:	Error in parameter $\sqrt{A}/L$ sampled from normal distribution
Mean:	0.000
Standard deviation:	0.072
Range:	−∞ to +∞
Renormalization:	No

Comments: In the Monte Carlo model variability in the wind drag force was introduced by adding variability in cross sectional area of the sail. A proprietary analysis of a data set containing iceberg sail cross-sectional area (A) and corresponding iceberg length indicates that there is a slight trend in the relationship between the ratio of the square root of iceberg sail area to iceberg length $\left(\sqrt{A}/L\right)$ as a function of length (L). Deviations of $\left(\sqrt{A}/L\right)$ from the trend line are normally distributed with a mean of 0.0 and standard deviation of 0.0717.

A.5. Water drag coefficient error

Distribution:	Error in parameter D/L sampled from normal distribution
Mean:	0.000
Standard deviation:	0.194
Range:	−∞ to +∞
Renormalization:	No

Comments: The deterministic drift model uses a fixed water drag coefficient in a form that is not easily varied. Therefore the effects of variations in water drag have been modeled by allowing random variability in the draft of the icebergs. A proprietary analysis of measured length and draft data indicates that the ratio of draft to length (D/L) is a function of length (L). The deviations of D/L from the trend line are normally distributed with mean of 0.0 and standard deviation of 0.1914.

A.6. Current speed error

Distribution:	Scaled error sampled from generalized logistic distribution
Mean:	~0.17 m/s
Standard deviation:	~0.58 m/s
Range:	−∞ to right truncation at +1.0
Renormalization:	CDF was then re-normalized so that the cumulative probability between the truncation points is 1.0.

Comments: Lacking ocean model verification data needed to create representative error distributions, it was decided that relationships between the 24-hour forecast drift and the observed drift track would be used to generate current error distributions. A current speed 'error' data set was derived by calculating the difference between the observed and forecast drift after 24 h. The method employed a scaled current speed error of the form,

$$scaled\ \ error\ \ (\varepsilon_s) = \frac{(forecast\ \ speed - observed\ \ speed)}{observed\ \ speed}. \tag{A1}$$

The scaled error was found to be well represented by the generalized logistic distribution. The best fit distribution parameters were,

$$k = -0.24577$$
$$\sigma = 0.27055$$
$$\mu = 0.23580.$$

The current speed for a given ensemble member is calculated by multiplying the forecast speed by $(1 - \varepsilon_s)$. The scaled error can range from −∞ to +1. While it is possible to get very small values of scaled error from this distribution, and therefore very large current speeds, the probability of doing so is very small and the resulting distribution of current speeds was found to be reasonable. The variability was applied to each depth layer separately.

A.7. Current direction error

Distribution:	Normal
Mean:	−8°
Standard deviation:	$5°\ /(v_{avg}^2 + 0.05)$
Range:	±180°
Renormalization:	CDF was then re-normalized so that the cumulative probability between the truncation points is 1.0.

Comments: The error distribution was derived from comparison of observed and forecast drift tracks using the same approach as the current speed error described in A.6. The magnitude of the error was found to decrease as the average current speed (v_{avg}) increased. This

is accounted for by calculating the error standard deviation as function of the inverse of the square of the average current speed.

A.8. Swell and wind wave height error

Distribution:	H_s error sampled from normal distribution
Mean:	−0.21 m
Standard deviation:	0.52 m
Range:	left truncation at $-H_s$ to $+\infty$
Renormalization:	CDF re-normalized so that the cumulative probability from the truncation point to infinity is 1.0

Comments: Lalbeharry (2002) compared wave buoy observations to MCM regional WAM4 model predictions in the North Atlantic region to generate forecast error statistics. He found average RMS values of (0.52 m) and bias values of (−0.21 m).

It was assumed that the errors are normally distributed. Since H_s values cannot be negative, a left-truncated normal distribution was used, with the left truncation point equal to $-H_s$. Lalbeharry's analysis is for significant wave height. In the NAIS iceberg model the wave forces are always calculated separately for wind waves and swell waves. The relationship between significant wave height (H_s), wind wave height (H_w) and swell wave height (H_{sw}) is,

$$H_s = \sqrt{H_w^2 + H_{sw}^2}. \tag{A2}$$

Variability was applied to the wind wave and swell wave components in proportion to their magnitude, that is,

$$\varphi \cdot H_s = \sqrt{(\varphi \cdot H_w)^2 + (\varphi \cdot H_{sw})^2}. \tag{A3}$$

The multiplier (φ) was calculated from the input value of H_s and the random error term (ε) by,

$$\varphi = \frac{H_s + \varepsilon}{H_s} \quad H_s > 0, \quad H_s + \varepsilon \geq 0\,. \tag{A4}$$

Both H_w and H_{sw} are multiplied by φ to give the values to be used for the ensemble member. This distributes the random term equally between the wind waves and the swell waves.

A.9. Wave stress coefficient (C_w) error

Distribution:	Wave stress coefficient error sampled from normal distribution
Mean:	Deterministic value for C_w
Standard deviation:	0.10
Range:	Left truncated at 0 to + ∞
Renormalization:	CDF re-normalized so that the cumulative probability from the truncation point to infinity is 1.0

Comments: The wave stress coefficient is primarily dependent on the shape of the iceberg (of which we know very little in operational forecasting) and the ratio of the iceberg length to the wave length, that is, $C_w \propto L/\lambda$ (Isaacson, 1988). It is not known how much the coefficient varies for the wide range of real iceberg shapes. It is also not known how the variations are distributed about the mean or typical value. In the absence of more information, the approach to introducing variability into the wave radiation stress coefficient was to calculate an average C_w value from the Isaacson (1988) functions for the appropriate L/λ ratio, then sample a random value from a normal distribution with mean equal to the control value C_w and standard deviation of 0.1. This random value was then added to the average value to yield the parameter value used for the ensemble member. The standard deviation of 0.1 was selected based on the variability between Issacson's curves for different iceberg shapes. The process was the same for both wind waves and swell, but the variability for each was sampled separately.

A.10. Iceberg initial position error

Distribution:	North and east direction errors sampled from normal distributions
Mean:	0.00 km
Standard deviation:	5 km/1.96 = 2.6 km
Range:	−∞ to +∞
Renormalization:	No

Comments: Based on judgment.

References

Ailliot, P., Frénod, E., Monbet, V., 2007. Long term object drift forecast in the ocean with tide and wind. Multiscale Model. Simul. 5 (2), 514–531.

Allison, K., 2007. An Ensemble Iceberg Drift Forecasting Model for the Canadian Ice Service. University of Waterloo, Faculty of Mathematics, (Work Term Report prepared for the Canadian Ice Service).

Anderson, I., 1983. Iceberg Deterioration Model. Appendix C in Report of the International Ice Patrol in the North Atlantic (Season of 1983). , (Bull. No. 69).

Anderson, J., 1997. The impact of dynamical constraints on the selection of initial conditions for ensemble predictions: low-order perfect model results. Mon. Weather Rev. 125, 2969–2983.

Breivik, Ø., Allen, A., 2008. An operational search and rescue model for the Norwegian Sea and North Sea. J. Mar. Syst. 69, 99–113.

Côté, J., Gravel, S., Méthot, A., Patoine, A., Roch, M., Staniforth, A., 1998. The Operational CMC–MRB Global Environmental Multiscale (GEM) Model. Part I: Design Considerations and Formulation. Mon. Weather Rev. 126, 1373–1395.

Hamill, T., 2001. Interpretation of rank histograms for verifying ensemble forecasts. Mon. Weather Rev. 129, 550–560.

Isaacson, M., 1988. Influence of wave drift force on ice mass motions. 7th International Conference on Offshore Mechanics and Arctic Engineering, Houston, Feb. 7–12, pp. 125–130.

Keghouche, I., 2010. Modeling the dynamics and drift of icebergs in the Barents Sea(PhD Thesis) University of Bergen.

Keghouche, I., Bertino, L., Lisæter, K., 2009. Parameterization of an iceberg drift model in the Barents Sea. J. Atmos. Ocean. Technol. 26, 2216–2227.

Khandekar, M., Lalbeharry, R., 1996. An evaluation of Environment Canada's operational ocean wave model based on moored buoy data. Weather Forecast. 11 (2), 137–152.

Kubat, I., Sayed, M., Savage, S., Carrieres, T., 2005. An operational model of iceberg drift. Int. J. Offshore Polar Eng. 5 (2), 125–131.

Kubat, I., Sayed, M., Savage, S., Carrieres, T., Crocker, G., 2007. An operational iceberg deterioration model. Proceedings of the 16th International Offshore and Polar Engineering Conference, Lisbon, Portugal, July 1—6, 2007, pp. 652–657.

Lalbeharry, R., 2002. Evaluation of the CMC regional wave forecasting system against buoy data. Atmos. Ocean 40 (1), 1–20.

Leutbecher, M., Palmer, T., 2008. Ensemble forecasting. J. Comput. Phys. 227, 3515–3539.

Lewis, J., 2005. Roots of ensemble forecasting. Mon. Weather Rev. 133, 1865–1885.

Lichey, C., Hellmer, H., 2001. Modeling giant-iceberg drift under the influence of sea ice in the Weddell Sea, Antarctica. J. Glaciol. 47 (158), 452–460.

Mountain, D.G., 1980. On predicting iceberg drift. Cold Reg. Sci. Technol. 1, 273–282.

Rixen, M., Ferreira-Coelho, E., Signell, R., 2008. Surface drift prediction in the Adriatic Sea using hyper-ensemble statistics on atmosphere ocean and wave models: uncertainties and probability distributions. J. Mar. Syst. 69, 86–98.

Sivillo, J., Ahlquist, J., Toth, Z., 1997. An ensemble forecasting primer. Weather Forecast. 12 (4), 809–818.

Tang, C., Yao, T., Perrie, W., Detracey, B., Toulany, B., Dunlap, E., Wu, Y., 2008. BIO ice-ocean and wave forecasting models and systems for Eastern Canadian waters. Can. Tech. Rep. Hydrogr. Ocean Sci. 261, 1–61 (i-iv).

The Wamdi Group, 1988. The WAM model—a third generation ocean wave prediction model. J. Phys. Oceanogr. 18, 1775–1810.

Toth, Z., Kalnay, E., 1993. Ensemble forecasting at NMC: the generation of perturbations. Bull. Am. Meteorol. Soc. 74 (12), 2317–2330.

Vandenbulcke, L., Beckers, J.-M., Lenartz, F., Barth, A., Poulain, P.-M., Meyrat, J., Ardhuin, F., Tonani, M., Fratianni, C., Torrisi, L., Pallela, D., Chiggiato, J., Tudor, M., Book, J., Martin, P., Peggion, G., Rixen, M., 2009. Super-ensemble techniques: application to surface drift prediction. Prog. Oceanogr. 82, 149–167.

White, F., Spaulding, M., Gominho, L., 1980. Theoretical estimates of the various mechanisms involved in iceberg deterioration in the open ocean, Report CG-D-62-80. U.S. Coast Guard Res. and Dev Center.