SPECIAL PROJECT PROGRESS REPORT

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Progress Reports should be 2 to 10 pages in length, depending on importance of the project. All the following mandatory information needs to be provided.

Reporting year	2016
Project Title:	Potential sea-ice predictability with a high resolution Arctic sea ice-ocean model
Computer Project Account:	spdelosc
Principal Investigator(s):	Dr. Martin Losch
Affiliation:	Alfred Wegener Institute
Name of ECMWF scientist(s) collaborating to the project (if applicable)	………………………………………………………….…… ………………………………………………………….……
Start date of the project:	Jan 01, 2015
Expected end date:	Dec 31, 2017

Computer resources allocated/used for the current year and the previous one
(if applicable)
Please answer for all project resources

		Previous year		**Current year**	
		Allocated	Used	Allocated	Used
High Performance Computing Facility	(units)	14594000	15170408.68	13784000	1087425.18
Data storage capacity	(Gbytes)	5356	887.0	7312	813

Summary of project objectives

Predicting sea ice conditions such as sea ice thickness and concentration will become increasingly important for Arctic marine operations, but the predictability of sea ice conditions on very short spatial scale and temporal scales is still unclear. Thus, we aim to establish a rigorous comparison between observed fracture zones and leads in the Arctic with structures that emerge in high-resolution (grid spacing of 5 km and smaller) numerical sea-ice simulations. We will develop new methods for meaningful comparisons of the ice deformation between the model simulations and retrievals from radar images. Finally, the predictability of the deformation features at these scales will be explored with high-resolution numerical simulations. A prerequisite step towards developing the sea ice deformation prediction system is to investigate the intrinsic characteristic of the sea ice dynamics model that is used to produce the forecasts.

Summary of problems encountered (if any)

So far, we did not encounter any serious problems.

Summary of results of the current year (from July of previous year to June of current year)

The central aim of this phase of our project is to explore the intrinsic reproducibility of sea ice deformation forecasts i.e. potential predictability. Our study focuses on long and narrow geophysical features formed in high resolution deformation fields known as linear kinematic features (LKFs). Such structures are important since they emerge throughout the year in the Arctic pack ice and a large portion of sea ice deformation localized along them (see e.g. Kwok 2001). Investigating the potential predictability of LKFs does not inform about the realism of the LKFs. However, the results make an important contribution to development of a sea ice deformation prediction system.

This phase of the project includes three stages. First, we have performed several ensemble prediction scenarios. They set out to investigate the sensitivity of the potential predictability to sea ice initialisation and also growing uncertainties of the atmospheric forcing caused by the chaotic nature of the atmosphere. The second stage is devoted to development of a fast applicable detecting method. Although it is possible to use complex and modern object detecting algorithms, our experience shows that they are expensive and might be impractical. The results show that the final binary maps of LKFs depend on the deployed detecting parameters. Thus, it is also necessary to analyse their effects on potential predictability. In the third stage, we measure the spatial reproducibility of the sea ice deformation and the LKFs using different metrics including spatial correlation and Modified Hausdorff Distance (MHD).

Our results show that, on the 10-day-time scale, the model has lower predictive skill for LKFs and deformation than for sea-ice thickness and concentration. In addition, the atmospheric forcing uncertainties largely determine LKFs predictability. Furthermore, the potential predictability skills varies geographically such that the prediction skill of the pan Arctic deformation can be largely different from the skill of a regional potential prediction. We still need to analyse the sensitivity of potential predictability to the seasonal anomalies and the ensemble size of the prediction system. For this purpose, we have performed several ensemble forecasts for two seasons including six months and twelve starting dates. The size of the ensembles vary between 15 to 50 members.

We found that with an ensemble prediction system that uses one unique atmospheric forcing realisation and starts from perturbed initial condition for sea ice and ocean variables, that are physically consistent, the potential predictability increases with time. However, perturbing only sea ice thickness reduces potential predictability and has smaller effects on predictability than uncertainties associated with atmospheric forcing. Our analysis of sensitivity of sea ice thickness initialisation is categorised in three groups based on their perturbation correlation length. The results show that, we need to be careful in perturbing sea ice thickness because a very short perturbation correlation length, i.e. white noise, generates artificial LKFs.

Comparing different metrics shows that spatial correlation is a strong metric for comparing the similarity of deformation fields. However, it fails to show high correlation of two similar LKF structures when one of them is spatially shifted even only with a short distance. The MHD metric can improve the results, but its result can also be misleading if LKF density is artificially changed due to spurious initial perturbations. By further analysing the data obtained from this phase of study, we aim to apply new diagnosing methods to detect the characteristics of LKFs such as orientation, length, width and density. We will quantify the potential predictability as a variable that compares the LKFs forecast characteristics with their climatological saturation level. The attached scientific report explained in detail this phase of the project.

The results have been presented in the Polar predictability workshop 2016 at Lamont-Doherry earth observatory and a manuscript is being prepared.

List of publications/reports from the project with complete references

Conference -Poster
Mohammadi-Aragh, M. , Losch, M. , Goessling, H. F. and Hutter, N. (2016)
Predictability of Arctic sea-ice linear kinematic features in high-resolution ensemble simulations ,
Polar predictability workshop, Palisades, New York, USA, 4 May 2016 - 6 May 2016 .
hdl:10013/epic.47969

Summary of plans for the continuation of the project

(10 lines max)

The next phase of the project is devoted to investigating the realism of LKFs and measuring the actual forecast skill. We aim to perform a new series of regional sea ice-oceanic simulations with finer horizontal grid size up to 1 km to explore the realism of the quasi-linear structures even in shorter scales. The new configuration includes either the entire Arctic region or an isolated Arctic region with rich observation data. The new configuration will be designed based on our primary evaluation of current numerical model results and the analysed radar images. If the detected LKFs compare favorably with observations we will perform a new series of ensemble forecasts to measure the actual prediction skill.

References

Kwok R. 2001. Deformation of the Arctic ocean sea ice cover between November 1996 and April 1997: a qualitative survey. In: IUTAM symposium on scaling laws in ice mechanics and ice dynamics. Springer, pp. 315–322.

June 2016

Appendix

Potential predictability of Arctic sea-ice linear kinematic features in high-resolution ensemble simulations

Mahdi Mohammadi Aragh, Martin Losch and Helge Gößling

Abstract

Linear kinematic features (LKFs) in sea ice, potentially important for short-term forecasts and for climate simulations, emerge as viscous-plastic sea ice models are used at high resolution (~ 4.5 km). Here we analyze the short-range (up to 10 days) potential predictability of LKFs in Arctic sea ice using an ocean/sea-ice model with a grid point separation of 4.5 km. We analyze the sensitivity of predictability to idealized initial perturbations, mimicking the uncertainties in sea ice analyses, and to growing uncertainty of the atmospheric forcing caused by the chaotic nature of the atmosphere. For the latter we use different members of ECMWF ensemble forecasts to drive ocean/sea-ice forecasts. For our analysis, we diagnose LKFs occurrence and investigate different sea ice characteristics. On the 10-day-time scale, the forcing uncertainty (due to limited atmospheric predictability) largely determines LKF predictability. We found that perturbing sea ice thickness using white noise generates artificial LKFs. Although spatial correlation is a strong metric for measuring the reproducibility of deformation fields of ensemble forecasts, it fails to describe the similarity between two very similar pattern of LKFs that are only slightly shifted in space. The Modified Hausdorff Distance (MHD) appears to be a more appropriate metric, but it can also be misleading if the LKF density is very high, for example because of spurious initial condition.

1. Introduction

Modern computational resources of the forecast services make high resolution short range forecasts of sea ice deformation (∼ 5 km) that may have a pivotal role in Arctic navigation in the near future. It has been shown that the large portion of sea ice deformation in high resolution deformation fields are localized along with narrow geophysical features linear kinematic features (LKFs; for example Wang and Wang, 2009 and Kwok, 2001). The central aim of this phase of our project is to explore the potential predictability of LKFs as the most important geophysical feature of the sea ice deformation field. This part of the project does not investigate the realism of the simulated LKFs. Still, the findings are expected to be an important contribution to the development of a skillful sea ice deformation prediction system.

In addition, this phase sets out to investigate the sensitivity of the potential predictability to uncertainties due to the initial conditions and also growing uncertainty of the atmospheric forcing caused by the chaotic nature of the atmosphere. This report has been divided into four sections. The first section deals with the Arctic sea ice setup, the applied ensemble prediction system and the sea ice state initialization. The second section explains a fast detection method of LKFs from the sea ice deformation field. The greatest challenge of this phase is to assess the spatio-temporal reproducibility of the deformation fields and the LKFs. Therefore, in the third section, we explain the metrics that we have applied so far. The remaining parts of the report present the results and conclusion.

2. Sea ice model, initialisation and sea ice ensemble prediction system

In this section, we explain the main features of the developed ensemble prediction system including the sea ice model, forcing and sea ice state initialisation. Different scenarios are designed to assess the role of uncertainties due to the initial conditions and growing uncertainties of the atmospheric forcing.

2.1. Sea Ice Model

We use an Arctic-wide setup for 2006 at a spatial resolution of approximately 4.5 km. We use the Massachusetts Institute of Technology general circulation model (MITgcm) with the MITgcm sea ice-ocean model (Losch et al. 2010, e.g.). We use a viscous-plastic high resolution configuration of the viscous-plastic Arctic regional setup of Losch et al. (2010) including monthly open boundaries in both the Pacific and Atlantic sections extracted from a global configuration (Menemenlis et al. 2008). The Arctic ocean and sea ice model are simulated using an orthogonal structured horizontal domain grid with 50 vertical layers.

2.3. Forcing data

We use atmospheric reanalysis fields (ERA-Interim) and ensemble forecasts of the European Center for Medium-Range Weather Forecasts (ECMWF) to force the sea ice-ocean model. Different atmospheric forcing members are used to estimate the effect of growing uncertainties by the chaotic nature of the atmosphere on the predictability of LKFs and sea ice deformation. We use also ERA-interim forcing data in combination with different initial conditions for sea ice thickness to explore the effects of the initially small differences on the potential predictability of sea ice deformation. We constrain the selection of ensemble forcing to year 2006 where the atmospheric ensemble prediction system is in some aspects very similar to ERA-interim. Therefor, instead of conducting ensemble forecasts for several years, we performed the simulations in two winter and summer seasons each includes three months and each month has two starting date.

2.2. Sea ice thickness initialization

We systematically investigate the sensitivity of potential predictability to the initialization using stochastically perturbation of sea ice state. In addition, we want to know whether improving the initialization can improve the potential predictability or not. We use three categories of perturbed sea ice thickness based on the spatial correlation length and the intensity of the perturbation. Figure 2 illustrates the difference between three categories using different correlation length.

2.3. Sea ice ensemble prediction system and experiment design

To have a clear-cut understanding of the effects of initialization and also growing uncertainties of atmospheric forcing on reproducibility of the sea ice deformation, we analyze those factors separately in cases A and B as below:

Case A: A unique initial sea ice condition with different members of the ECMWF ensemble prediction system;
Case B: Different initial sea ice conditions with the same forcing for all members.

We also analyze the reproducibility of the LKFs with perturbed initial conditions using a series of physically consistent perturbed initial sea ice and ocean conditions in a series BA. This series of forecasts uses the final sea ice and oceanic state of the case A together with the forcing of case B. In another series of forecasts CA, we use also the final sea ice and ocean state of the case A together with the the forcing of case A. Table 1. summarizes our ensemble forecasting system. There are two starting dates for the 10-day simulations on 1st and 15th of each month. For some cases, 50 members of forecasts are conducted. However, all cases we evaluate only 15 ensemble members for each series in our analysis.

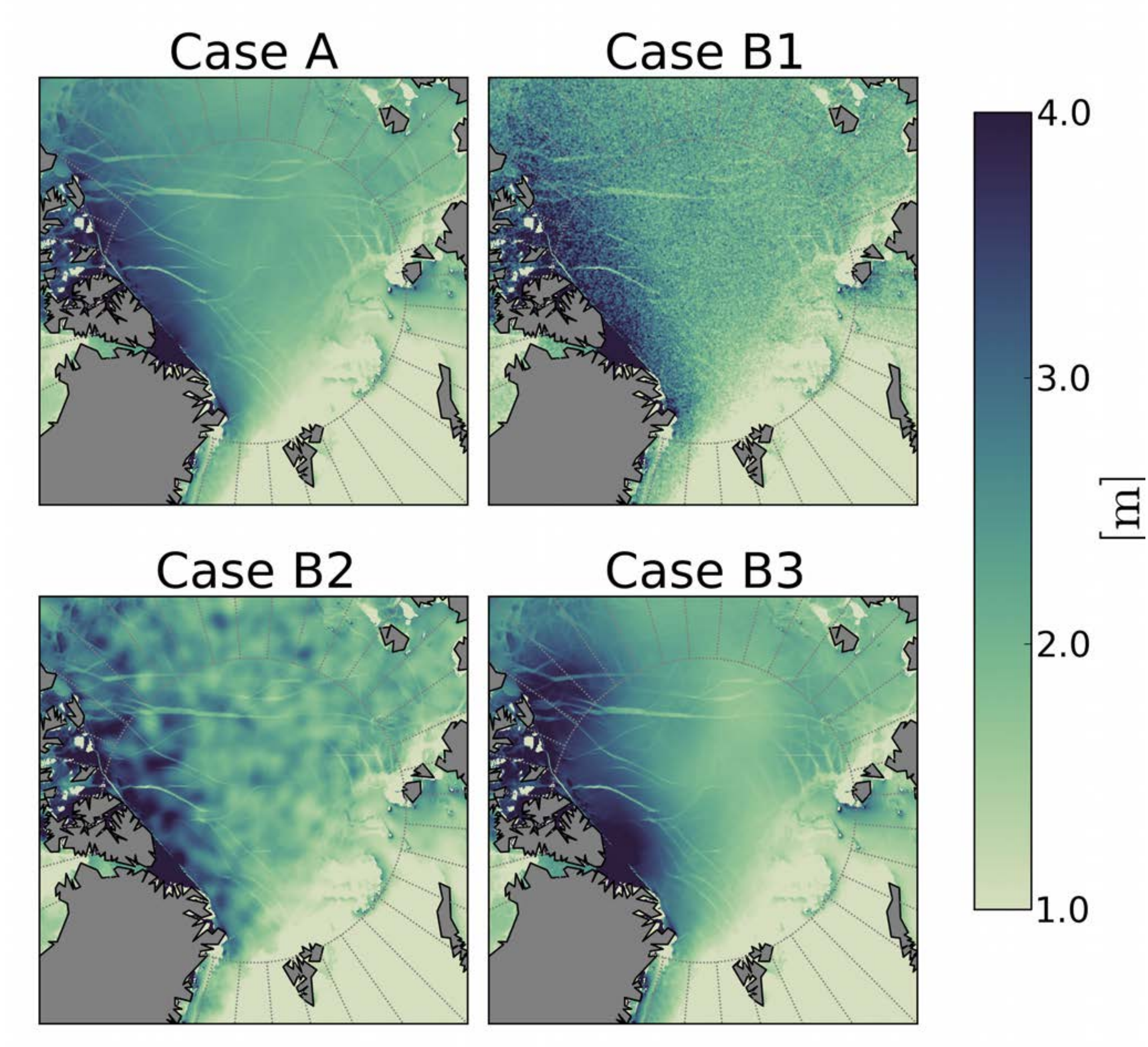

Figure 1. Initial perturbed sea ice thickness.

3. Methodology

This section is devoted to the algorithm that we used to detect LKFs and also the metrics that measure the distances between different LKFs structures. We use the most straightforward LKF detecting algorithm. Sensitivity analysis of the potential predictability to different detecting methods is part of our future work. Using modern algorithms such as object detecting methods might help us to develop detecting LKFs methods. However, based on our experience such algorithms are complex and expensive.

Table 1. List of experimental setup.

Name	Initial perturbation	Forcing
A	None	ECMWF Ensemble
B1	Gaussian σ = 0.1 km	Unique forcing
B2	Gaussian σ = 10 km	Unique forcing
B3	Gaussian σ = 50 km	Unique forcing
BA	Final ocean and sea ice state of A	Unique forcing
CA	Final ocean and sea ice state of A	ECMWF Ensemble

3.1. Detecting LKFs

We first obtain the logarithmic deformation field (see Figure 2.) because the order of deformation is more important for us than the deformation itself. Then, using a Gaussian filter, we smooth the logarithmic deformation field to find the logarithmic background deformation field. The deformation anomaly is then computed from the difference between the logarithmic deformation field and its background. Finally, we apply a threshold on the deformation anomaly field to separate LKFs from the background deformation field. The result is a binary map. Values of 1 represent LKFs. The final binary map depends on the applied threshold and the Gaussian filter parameters. Figure 2 illustrates the four-step-LKF detecting algorithm.

3.2 Metrics: Spatial correlation and Modified Hausdorf Distance (MHD)

Spatial correlation is a strong tool used to measure the spatial similarity between the fields (deformation, sea ice concentration, etc) of two arbitrary ensemble members. However, spatial correlation can only provide one-one comparisons. A small shift between two very similar patterns of LKFs, binary maps, fails to reflex the high geometry similarity. Therefore, we use Modified Hausdorf Distance (MHD) to measure the matching degree of the geometric shapes. For more detail, see for example the work of Gößling et. al. (2016) .

4. Results and discussion

For our primary analysis, we have focused on early February.

4.1. Overlay of LKFs in two ensemble members

Figures 3 and 4 show overlaid LKFs of two arbitrary ensemble forecasts for all six experiments at the initial state and after 10 days. For the case A (same initial conditions with ensemble forcing), all LKFs are the same between two forecasts, but after 10 days the there are hardly any common LKFs left. The comparison of case B1, B2 and B3 (same forcing, different initial conditions) show that initially they also have many common LKFs. Although in these cases a unique forcing is applied for all members, the initial perturbation could affect the final LKFs in Figure 4. The structures of LKFs are very similar in the two ensemble members but the are shifted by a few grid cells. The minimum distance between the parallel LKFs is found for case B1 (minimum spatial perturbation correlation length in sea ice thickness). The results of case B1 show that white noise perturbation can generate artificial LKFs. In contrast to the cases A and B, the cases BA and CA have very few common LKFs initially. The LKFs of case BA evolve to a common LKF feature. It shows that the atmospheric forcing is governing the structures of LKF more than initial perturbation. The results of case CA confirms our findings as the difference in the atmospheric forcing (i.e. proxy for uncertainty) increases the differences between LKF distributions.

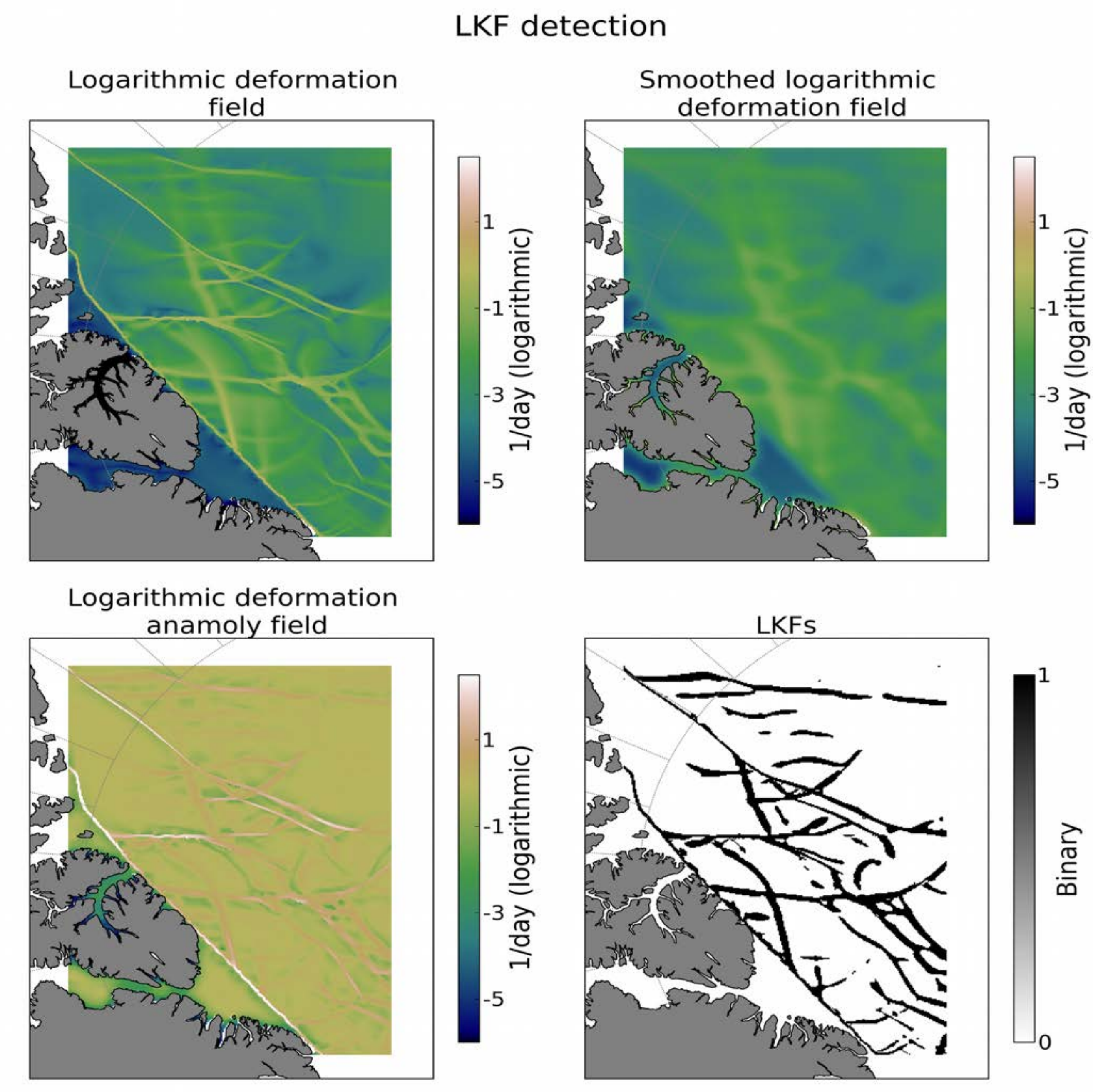

Figure 2. LKF-detecting method.

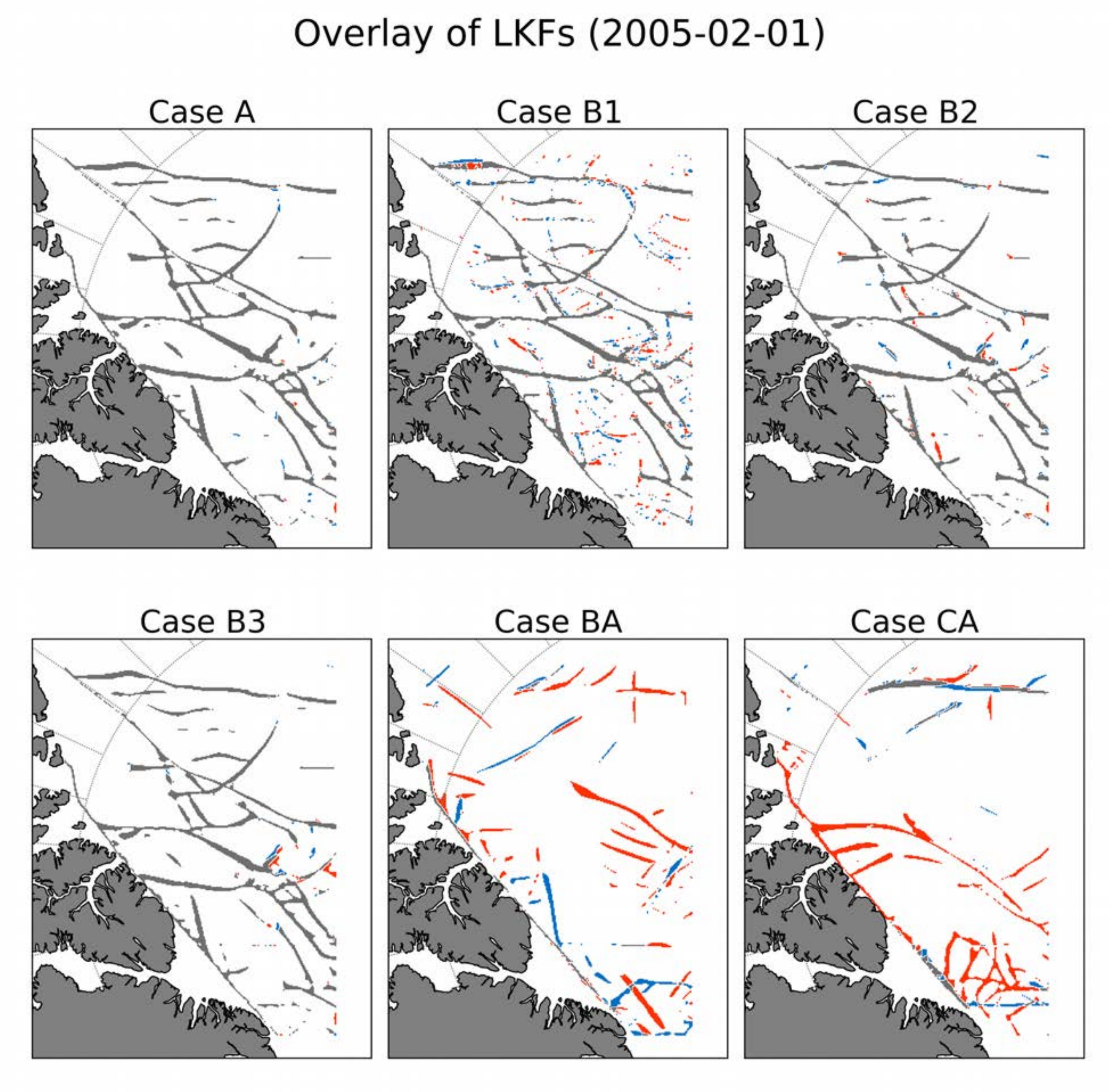

Figure 3. The overlay of LKFs in initial state. The gray color illustrates the LKFs that are common in the binary map of both arbitrary forecasts. The blue and red colors indicate each the LKFs which are belonged to only one LKF.

4.2. Evolution of different distance metrics over 10 days

Figure 5.a compares the ensemble mean of spatial correlation of pan-Arctic sea ice deformation forecast pairs. The correlation of Case A and Case CA is slightly decreased after 10 days. The LKFs of case B and Case BA are highly correlated until the end of simulations. The LKFs of case CA and BA are initially less correlated than the other cases, because their initial sea ice velocity fields are different. Figure 5.b illustrates local pairwise spatial correlation of deformation field for the selected region in Figure 3. In contrast to the pan-Arctic correlation, the correlation of cases B and CA is decreased after 10 days. The correlation of case A is less than cases B in the final state. These results show that the uncertainties in the atmospheric forcing affect the potential predictability more than the uncertainties due to the initialization. The increasing correlation of case BA and the reduction in the spatial correlation of the case CA are in good agreement with the results of Figure 4. However, the spatial correlation could not represent the similarities between the arbitrary forecasts in the cases B because the LKFs are shifted by a few computational grid points and the spatial correlation

fails to capture the observed similarities seen in the Figure 4. Thus, we used he Modified Hausdorff Distance (MHD) to measure the difference between two LKFs. Figure 5.d shows that the MHD increases with for cases A and B. Case A increases faster confirming the previews finding that the atmospheric forcing uncertainties have the largest effect

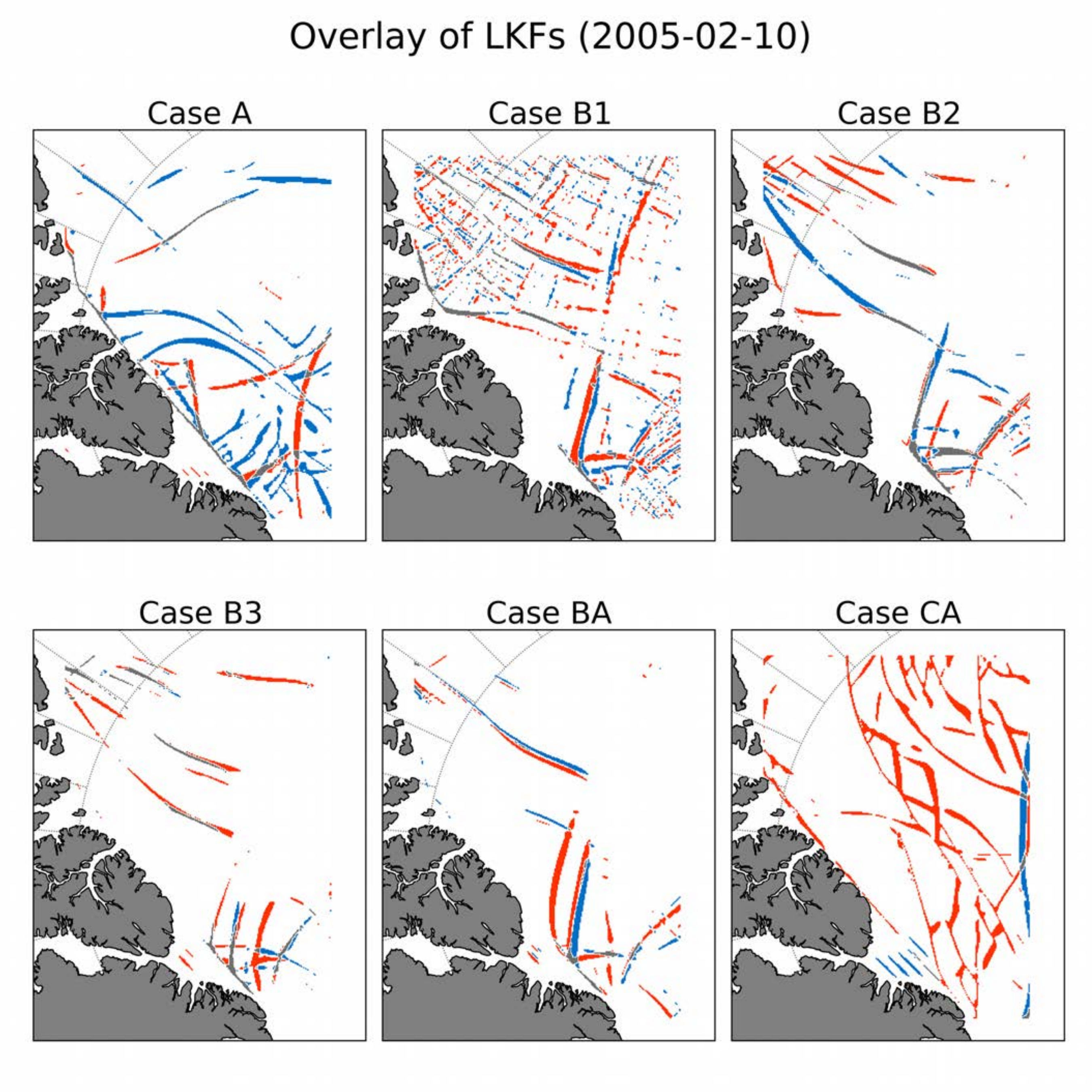

Figure 4. The overlay of LKFs after 10 days. The gray color illustrates the LKFs that are common in the binary map of both arbitrary forecasts. The blue and red colors indicate each the LKFs which are belonged to only one LKF.

on potential predictability. The MHDs of case BA and CA start from a large distance but the MHD of case BA is decreased because all ensemble members are forcing by the atmospheric fields. In contrast to case BA, the chaotic characteristics of atmosphere increases the distance of the lKFs of case CA.

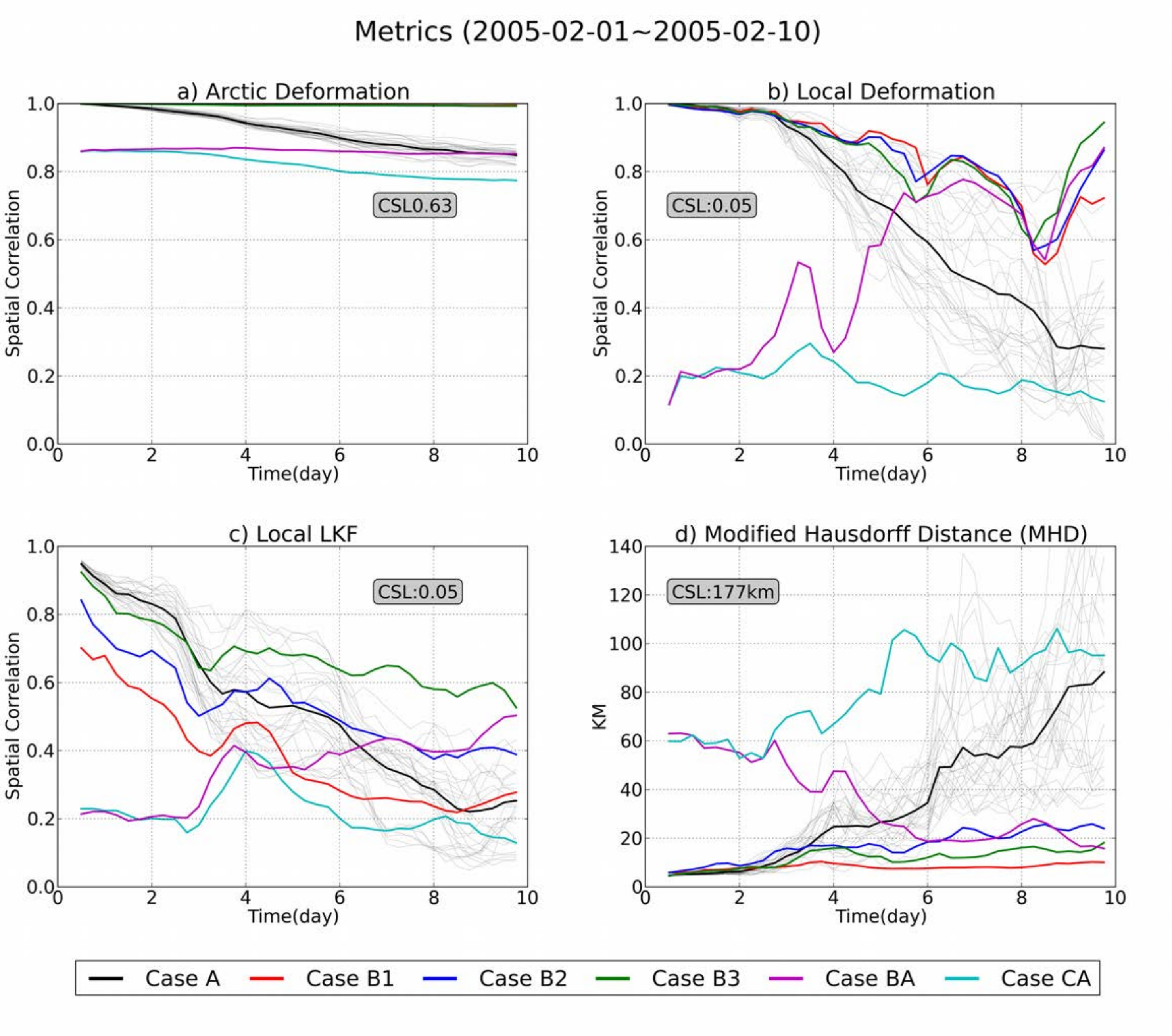

Figure 5. Time evolution of spatial correlation of deformation and MHD.

5. Conclusion

We found that the initial sea ice thickness perturbation needs to be selected carefully because they might generate artificial LKFs in the deformation field. However, the LKFs predictability is largely determined by atmospheric forcing uncertainties. Our analysis suggests that spatial correlation of deformation is not an appropriate metric because it fails to represent the similarity between two very similar LKF features that are slightly shifted. The Modifiied Hausdorff Distance, as an alternative metric, generates more plausible results, however, in some case it can also be misleading if LKF density is artificially changed for example due to spurious initial perturbations.

6. References

Gößling HF, Tietsche S, Day JJ, Hawkins E, Jung T. 2016. Predictability of the arctic sea-ice edge. Geophysical Research Letters.

Kwok R. 2001. Deformation of the arctic ocean sea ice cover between November 1996 and April 1997: a qualitative survey. In: IUTAM symposium on scaling laws in ice mechanics and ice dynamics. Springer, pp. 315–322.

Losch M, Menemenlis D, Campin JM, Heimbach P, Hill C. 2010. On the formulation of sea-ice models. part 1: Effects of different solver implementations and parameterizations. Ocean Modelling 33(1): 129–144.

Menemenlis D, Campin JM, Heimbach P, Hill C, Lee T, Nguyen A, Schodlok M, Zhang H. 2008. Ecco2: High resolution global ocean and sea ice data synthesis. Mercator Ocean Quarterly Newsletter 31: 13–21.

Wang K, Wang C. 2009. Modeling linear kinematic features in pack ice. Journal of Geophysical Research: Oceans 114(C12).