SPECIAL PROJECT PROGRESS REPORT

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	2017
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)	13784000	13647538	13892000	4375837
Data storage capacity	(Gbytes)	7312	887	3656	3656

Summary of project objectives

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

So far, we did not encounter any serious problems.

Summary of results of the current year

We conduct the project in two separate phases. In the first phase, assuming a perfect numerical model, we explored the limits of sea ice predictability. To this end, we measured the deviations from a reference results ("truth") due to imperfect initial conditions of key sea-ice variables, and growth of uncertainties due to the chaotic behavior of the atmospheric forcings. In the second phase, we developed a method for meaningful comparisons between retrievals from radar images and model simulations.

The central aims of our project was to measure the potential predictability of sea ice deformation and Linear Kinematic Features (LKFs), to figure out how long they are potentially predictable, and whether the potential predictability of sea ice deformation is spatially and temporally variable on short time scales of up to ten days. We used a high-resolution sea ice-ocean model forced by an ensemble weather prediction system. Our analyses and simulations indicate that LKFs are less predictable than other sea ice parameters such as sea ice concentration anomalies, especially beyond the first two days of the forecast. From the outcome of our investigation it is possible to conclude that atmospheric uncertainty is more important in generating sea ice forecast error than initial sea ice uncertainty, especially for medium-range (3–10 day) predictions.

Fracture zones and leads represent challenges for numerical sea-ice models that generally rely on a quasi-continuity assumption and some form of viscous-plastic (VP) rheology. At coarse resolution, the solutions of velocity field and sea ice state are smooth and with very little detail. In contrast, at high resolution, numerical sea-ice models introduce sharp discontinuities in the ice movement that makes the comparison between model simulations and observations complex. Thus, we developed a verification method using a neighborhood approach and spatial verification metrics for detailed comparisons of deformation and LKFs observed in satellite radar images and the sea ice simulations. We found that our numerical model generates large scale continuous LKFs. In contrast, the detected LKFs from the observational data source are affected by both small and large scale sea ice movement. Furthermore, from the deterministic spatial verification that has been carried out, it is possible to conclude that the numerical model generates fewer LKFs, that is, the LKF density is lower. In addition, our sea ice model has higher skill, whenever the density of the numerical LKFs increases. The findings suggest that this approach is useful for sensitivity analyses used to identify the missing physical processes in the atmosphere/ocean/sea-ice models. The attached scientific report explains in detail this phase of the project.

List of publications/reports from the project with complete references

Conference -Poster
Mohammadi Aragh, M. , **Losch, M.** , **Goessling, H.** , **Hutter, N.** and **Jung, T.** (2017)
Predictability of Deformation Features in Arctic Sea Ice ,
Polar Prediction Workshop, Bremerhaven, 27 March 2017 - 30 March 2017 .
hdl:10013/epic.50670

Conference -Poster
Mohammadi-Aragh, M. , **Losch, M.** , **Goessling, H.** , **Hutter, N.** and **Jung, T.** (2016)
Potential Predictability of Arctic sea-ice linear kinematic features in high-resolution ensemble simulation ,
2016 FAMOS School and Meeting, Woods Hole Oceanographic Institution, 1 November 2016 - 4 October 2016 .
hdl:10013/epic.48940

Conference -Poster
Linow, S. , **Mohammadi Aragh, M.** , **Dierking, W.** and **Losch, M.** (2016)
Continuous discontinuities: comparing observed and modelled sea ice deformation features ,
ESA Living Planet Symposium, Prague, 9 May 2016 - 13 May 2016 .
doi:10.13140/RG.2.1.3706.2009 , hdl:10013/epic.47924

Summary of plans for the continuation of the project

Part of the project is analysing the effects of uncertainties in the forcing and of internal errors of the sea ice model on sea ice deformation predictability. Our currently available ensemble prediction system, which we used for testing and first predictability estimates, covers only a few months in the year 2005. Now, we need to provide more ensemble cases to investigate the seasonality effects. Furthermore, during our investigation it is became clear that the resolution of the atmospheric forcing may play a pivotal role in the predictability of the LKFs. Our deterministic analyses have shown the dominant effects of the atmosphere in the predictability, but to our mind our analysis can only be complete after we have investigated the mechanisms of transferring predictability from larger scale, which current low resolution atmospheric forcing are resolved, to the smaller scales. Thus, we need additional ensemble simulations with high resolution atmospheric forcing products. We plan to compare simulations with HRES forcing (http://www.ecmwf.int/en/forecasts/datasets/set-i#I-i-a) to our ensemble simulations with lower resolution forcing.

Skill assessment of the sea ice models to simulate the Linear Kinematic Features in Arctic sea ice

Mahdi Mohammadi-Aragh, Martin Losch and Helge Gößling

Abstract

Linear kinematic features (LKFs) in sea ice deformation field, potentially important for short-term forecasts and for climate simulations, emerge as viscous-plastic sea ice models are used at high resolution. The sea ice models tend to present smooth features with very little detail at coarse resolution. However, at high resolution, the numerical solutions include complex patterns of LKFs which are not straightforward to be verified. Thus, we developed a verification method using neighborhood approach and spatial verification metrics for detailed comparisons of LKFs observed in satellite radar images and obtained from model simulations. The proposed verification method assesses the skill of numerical sea ice models in generating of LKFs. We used a unified LKF detecting algorithm for both deformation fields. Such a definition is necessary for using the deterministic spatial verification metrics such as Modified Hausdorff Distance in a meaningful way. The findings suggest that the developed verification method can be used for diagnosing the role of physical processes and numerical schemes in enhancing the generation of LKFs.

1. Introduction

Increasing resolutions of viscous-plastic sea ice models results in extra useful information such as long and narrow geophysical features in sea ice deformation field, known as Linear Kinematic Features (LKFs). Their associate divergence and shear stresses generate strong converging or diverging zones that consequently form ridges and open area within the sea ice cover with elongated, curvilinear or piecewise linear features. Miles and Barry (1998) investigate the association between the large scale distribution of the leads and the sea ice key physical variables. They found that sea ice shear and divergence correspond the most to the lead parameters. Stern et al. (1995) show that sea ice shear stress amplifies the tendency of divergence in the production of leads. Thus, it is optimal to detect the LKFs observed in the deformation field as indicative of leads. Predicting such structures as the most important geophysical feature of the sea ice cover is important for example for navigation and marine operations.

One aim of this report is to deal with developing an applicable, unified LKF detecting algorithm for both numerical and observational sea ice deformation fields. Such unified method is necessary for performing deterministic spatial verification and also for the corresponding probabilistic skill assessments. In addition, we introduce a verification method that assess the skill of the sea ice model in generating LKFs.

2. Sea ice model and observation data sources

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 model (e.g., Losch et al. 2010). 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 grid with 50 vertical layers. We use atmospheric reanalysis fields (ERA-Interim) to force the sea ice-ocean model.

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We use the 3-day gridded dataset of RGPS (Radarsat Geophysical Processor System) sea ice divergence and shear products (available online at https://rkwok.jpl.nasa.gov/radarsat/3daygridded.html) for verification. The data values cover a 3-day period with grid spacing of 12.5 km. We compute the 3-day interval average of the numerical sea ice deformation field and interpolate it over the structured grid of RGPS for the verification.

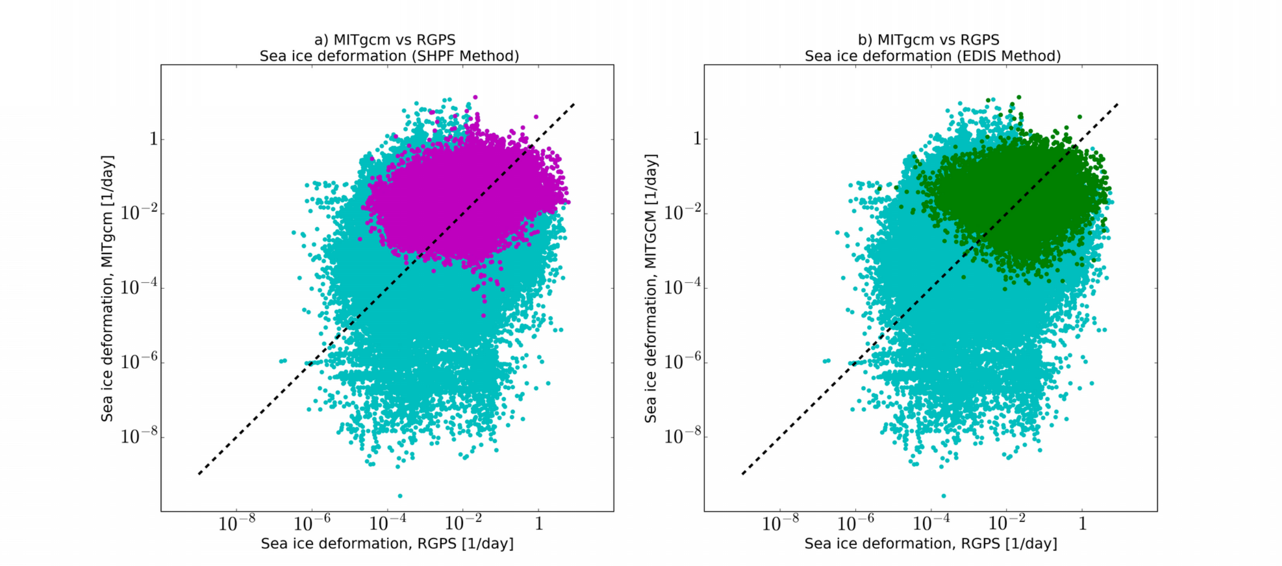

Fig 1. The scatter plots of sea ice deformation of RGPS products and MITgcm simulations for the winter 2003. The cyan, violet, and green colour cod represent the deformation in the entire region, the deformation of common LKFs in both fields using the SHPF Method, and the deformation of common LKFs in both fields using the EDIS Method.

3. Methodology

Our verification method necessitates an algorithm that diagnoses LKFs from sea ice deformation fields. Given that zones of shear as well as convergence and divergence of sea ice are concentrated along LKFs, we opt for a simple method that is based solely on the total deformation rate of sea ice. However, agreeing on a unified LKF detection algorithm from numerical results and observational data sources is the first task in our sea ice intercomparison project. First, we use a detection method that is able to extract all LKFs regardless of the magnitude of sea ice deformation (SHPF method, see section 3.1). In the second approach (EDIS method, see section 3.2), we define an LKF as the locus of points that have specific geomorphological features and also have a comparable distribution of total deformation in both numerical models and observational data source (see Fig. 1). Our primary visual comparisons show that the detected LKFs from both deformation fields using the SHPF method has many features in common. However, the EDIS method shows that the model has less skill to produce the same order of LKF density. In this section, we introduce both methods and their characteristics. The bias between the detected LKFs from numerical results using both algorithms is an indication of missing parameterisations and unresolved physical processes.

3.1 Spatial High Pass Filter (SHPF) method

We obtain the logarithmic deformation field because the order of deformation is more important for us than the deformation itself. Then, we use a Gaussian filter 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, grid cells are detected as belonging to an LKF if total deformation exceeds the background deformation. The result is a binary map. The values equal to 1 represent LKFs. The final binary map depends on the applied threshold and the Gaussian filter parameters. To extract all the LKFs seen in both data source with linear and thin characteristics of LKFs, we need to use different parameters for the observational and numerical deformation fields.

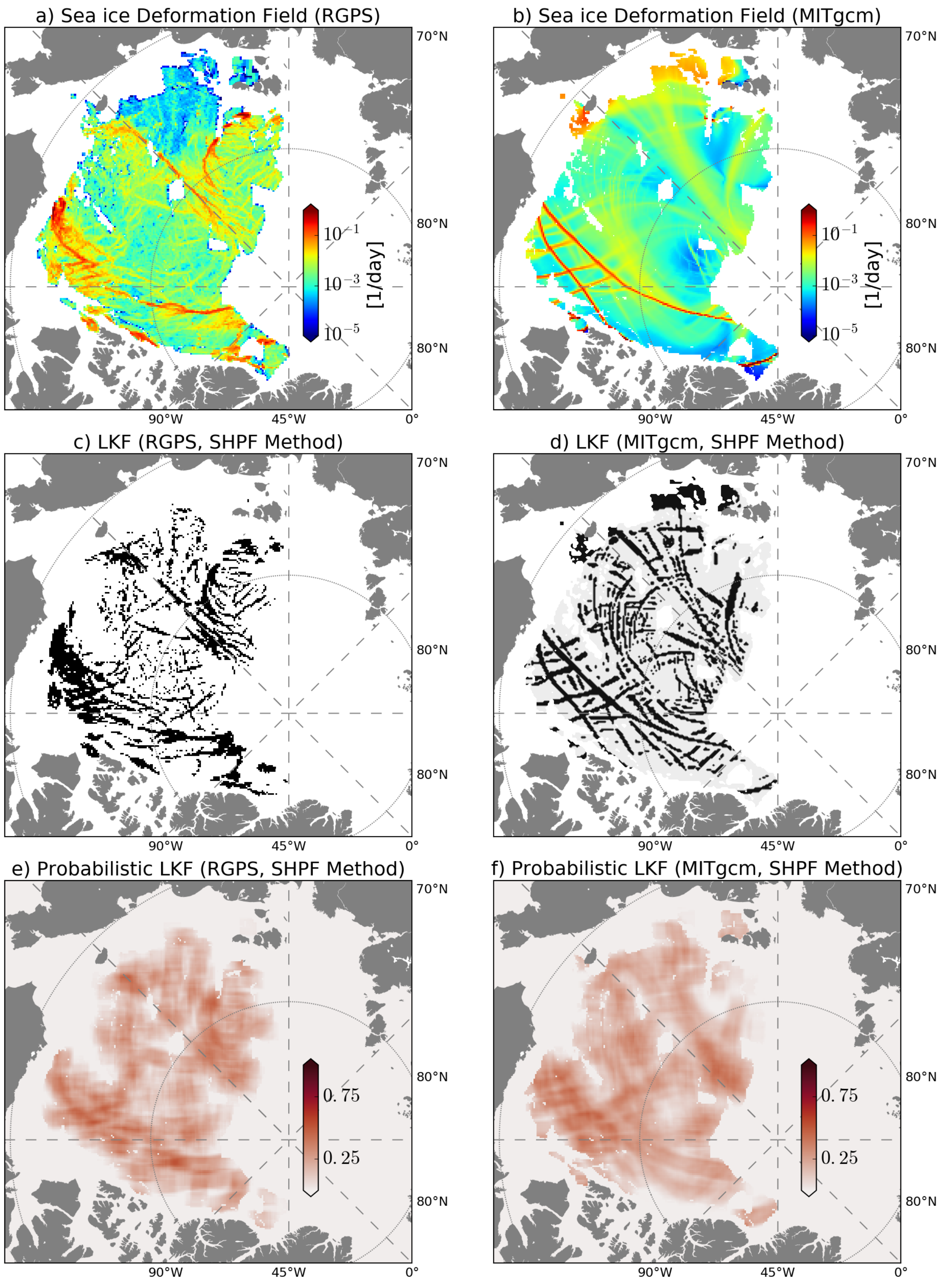

Fig. 2: The comparison of sea ice deformation fields of a) RGPS, b) MITgcm; Detected LKFs using the SHPF method SHPF method c) RGPS, d) MITGcm, Probabilistic LKF d) MITgcm, e) RGPS.

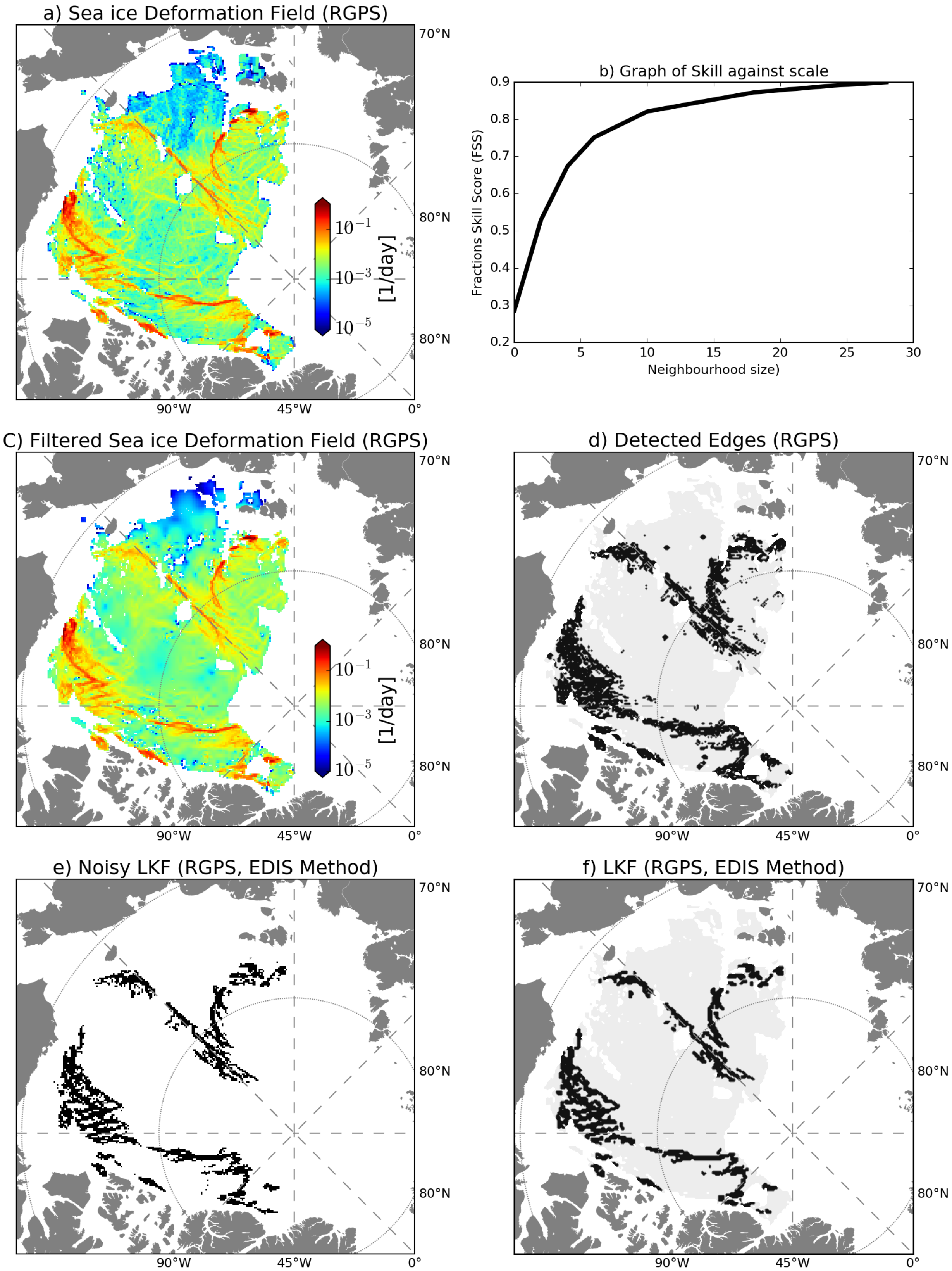

Fig. 3: EDIS detection LKF method. a) Deformation field of RGPS product, b) The seasonal Fractional skill score (winter 2003) versus neighbourhood size, c) Smoothed sea ice deformation field, d) LKF detected edges, e) Noisy detected LKFs, f) Separated LKFs from the noisy LKFs in e).

3.2 Edge Detection and Image Separation method (EDIS)

The second method is based on detecting edges of LKFs. The primary edge detecting approaches detect the points with high magnitude of spatial deformation gradient. However, applying such methods might lead to detect large wide regions from the smooth numerical deformation field. Such spatial features are far from the geomorphological characteristics of LKFs. We found that applying the two dimensional Hildreth-Marr edge detecting theory is more effective. Thus, the edges of the LKFs are the points where the second spatial derivative of deformation crosses zero and also where the spatial deformation gradient is larger. Then, we detect the points in the neighbourhood of the edges with higher sea ice deformation. The diagnosed regions consist of the features with point- and curvelike parts. Thus, we deployed an image separating method (G, Kutyniok, and L, Wang-Q. 2010) for extracting the curvelike parts by employing a combined dictionary consisting of wavelets and compactly supported shearlets.

4. Verification

High resolution simulations of sea ice provide useful information of LKFs. However, often the LKFs are located in the wrong places. Thus, the traditional point-by-point verification approaches may entail significant loss of information in such complex structures. We use a probabilistic evaluation to find the smallest neighbourhood size (smallest spatial scale) at which the LKFs in the numerical results and observational data source are comparable. After filtering the features smaller than the diagnosed spatial scale, we apply spatially verification metrics.

4.1 Fuzzy verification

Fuzzy verification, a neighbourhood approach, is applied to provide LKFs fractions from binary fields. The neighbourhood approach we deployed provides probabilistic LKF that can be interoperated as probabilities of occurrence of LKF over spatial scales larger than the grid-scale. Then, we compare two sets of fraction fields using a Fractions Skill Score (FSS) to determine the spatial scales at which the LKFs of both fields meet certain accuracy requirements. We compute FSS similar to Roberts and Lean (2007). FSS ranges from 0 to 1. A perfect agreement between observational and numerical probabilistic LKF has a score of 1; a score of 0 means no agreement.

4.2 Spatial verification methods

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

5. Results

It is convenient to start the discussion of the verification by comparing the detected LKFs using the SHPF method. Fig. 2.a and Fig. 2.b compare the observational and numerical sea ice deformation fields, respectively. The spatial pattern of the deformation fields are visually very similar. However, the time series of the spatial correlation (Fig. 4.a) shows low skill. In addition, the mean sea ice deformation of the MITgcm (Fig. 4.b) is obviously smaller than the mean sea ice deformation of the RGPS product during winter 2003.

Although the results show that the deformation fields are not in good agreement, we are interested in determining the skill of the model in simulating LKFs. Thus, we used the SHPF method (Fig. 2.c and Fig. 2.d) and tuned the algorithm using different parameters to detect features with similar geomorphological features. The first method detects almost all visible linear features regardless of

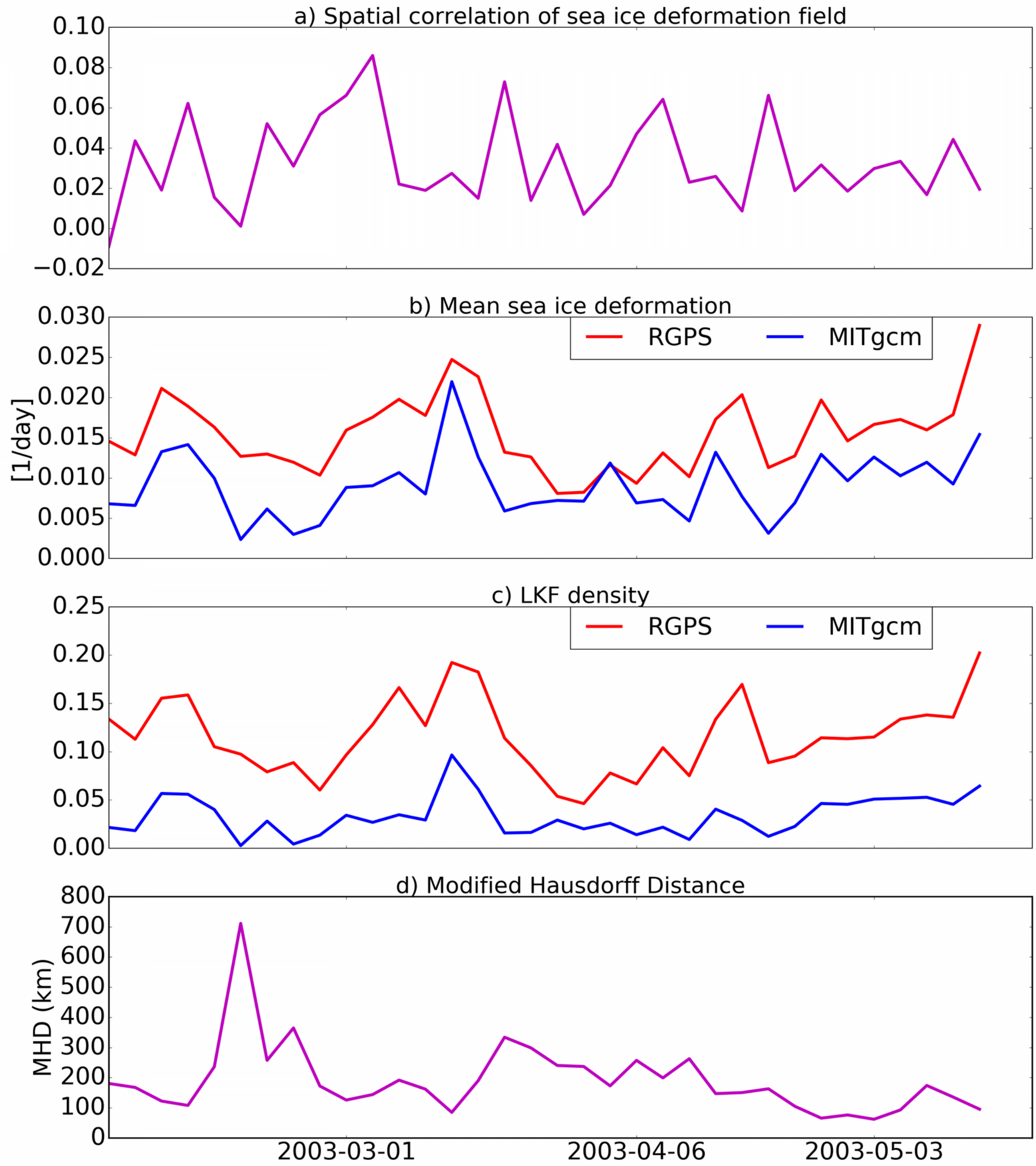

Fig. 4: Deterministic verifications using EDIS method: a) spatial correlation of sea ice deformation field; b) time series of mean sea ice deformation; c) time series of LKF density; e) time series of Modified Hausdorff Distance.

the smoothness of the deformation field. The resultant LKFs fields are very complex and rich in term of curve- and point like features. Using Fuzzy verification, we determine the spatial scales that the probability of LKFs of both fields are in good agreement. We compute the fractional LKFs with increasing the neighbourhood size from 1 grid point to 30 grid points (see Fig.2.d and Fig. 2.e). Fig. 3.b shows the mean FSS over the winter 2003 versus the neighbourhood size. The result indicates that FSS is not increased significantly from the neighbourhood size of 5 grid points.

The LKFs detected from RGPS products include small scale features that are not resolved by our sea ice model configuration. In addition, the spatial verification metrics are very sensitive to the points that represent different events. Thus, to truly verify the skill of the model in generating the LKFs, we need to use the EDIS method from the smooth deformation fields. Thus, we filter the features that are smaller than the diagnosed spatial scale (5 grid points) in the RGPS deformation field using a wavelet low-pass filter (See Fig. 3.c). The second method detects the LKFs in both fields with a unified definition of LKFs. Figures 3.d, 3.e, and 3.f show the edges of LKFs, the noisy detected LKFs, and the LKFs separated from the noisy features, respectively. The comparison of the time series of the global LKF density of both LKF field (Fig 4.c) using the second method show that our numerical configuration generates fewer LKFs than there are in the RGPS products. Furthermore, the time series of the Modified Hausdorf Distance (Fig. 4.d), present higher distance when the numerical global density of LKFs is minimum.

6. Discussions and conclusions

The RGPS products include spatial features smaller than 20 km that our sea ice numerical configuration with approximately 4.5 km horizontal resolution cannot resolve. In addition, visually comparing the detected LKF fields shows that the numerical model generate large scale continuous LKFs. In contrast, the LKFs detected from RGPs products show both small and large scale LKFs. Furthermore, the results of the modified Hausdorf Distance and the time series of the LKFs densities show when the numerical model generate higher level of LKFs (applying the second method), the skill of the model increases.

We conclude that a combination of both detecting methods should be used for identifying the missing physical processes and numerical schemes that can enhance the generation of LKFs and increase the skill of model. We hypothesis that the main reasons of the bias are the imperfect atmospheric reanalysis, low resolution atmospheric forcing and the missing essential parameterisations, in the sea ice model that cannot transfer the insert momentum in sea ice model from larger scales to smaller scales.

7. References

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