Reviewer 1

This is a well written manuscript addressing the topic of sea-ice thickness distribution configuration, which is important for those who use the NEMO-LIM ocean-sea-ice model. Therefore the paper is suitable to be published in the Nucleus for European Modelling of the Ocean - NEMO special issue. The manuscript provides useful results for NEMO-LIM modellers based on advanced statistical and visualisation methods that appear valid. To my opinion, these results sufficiently substantially advance in modelling science. In particular, the main result that no clear benefit is obtained from increasing the number of sea ice thickness categories beyond the current usual standard of 5 categories in NEMO3.6-LIM3 is useful so that a model user will not waste time in testing a range of number of sea-ice categories for better results.
We thank the Reviewer for the appreciation and the thoughtful comments. In the following we answer each specific point (in blue).

In Discussion the authors conclude that changes in the ice thickness distribution configuration need re-tuning parametrizations and parameter values. Would be useful for future approaches to list which parameters needed re-tuning. In the current version no specifics has been discussed.
We referred to the typical parameters of the sea ice models, which include, among others, snow thermal conductivity, bare sea-ice albedo, and compressive ice strength, P*. This is now discussed in the revised manuscript (Lines 383–389).

The other aspects for a reviewer to consider, seem adequately addressed too, but there are a few things that might be useful for the NEMO community if added or expanded the paper. There are also a small amount of corrections that the text requires. Due to these, a minor revision is required with the details following.

Detailed comments:
• line 14 ’coherence across’ would be more precise to say ’correlation across’
Corrected.

• line 16 Here ’atmospheric variability’ does not point to synoptic one, as one might guess when reading the abstract, but longer, large-scale atmospheric modes. This could be specified by rewriting ’long-term atmospheric variability’.

Clarified as suggested

• line 24 You could mention why there is ’overly large simulated sea-ice growth’. Is it due to the fact that thin ice grows faster?
Massonnet et al. [2019] show that this is because of a net increase in basal ice growth rate, which is indeed promoted when the relative area of thin ice is large. This is indicated in the revised manuscript now (Line 23)

• line 26 ’Antarctica’ comes sudden here as improvements there has not been mentioned before in the abstract. I suggest adding a sentence how Antarctic sea-ice was improved by better resolved thin ice after the sentence ending in line 21.
Done.

• line 33. ’... Antarctica. These modes drive ...’
The sentence has been clarified.

• line 40. ’... variability in modes such as the NAO ...’
Corrected.

• line 45. ’...determines its important physical processes, such as salt and ...’
We think the word properties, as in the original manuscript, is more precise than processes to describe quantities like heat capacity or resistance to deformation. The line therefore has not been modified.

• line 81. To me 167 mm/day is not weak but strong restoring. Drop word ’weak’ in line 80.
Done.

• line 81. ’concentratio’ -> ’concentration’
Corrected.

• line 127. ’... (namely Duda-Hart ...’
Corrected.

• line 142. '... the optimal number ...'
Corrected.

• line 153. '... clusters presented later ...'
Corrected.

• line 171. '... emerging from ..'
Corrected.

• line 244. '... configuration with single category ...'
Corrected.

• line 247. '... where the single category ...'
Corrected.

• line 252. 'In the Antarctic summer ...'
Corrected.

• line 257. '... increases especially with respect ...'
Corrected.

• line 287. '... repartition of detrended data ...'
Corrected.

• line 289. '... their third clusters ...'
Corrected.

• line 294. '... all the clusters in the S3 configurations ...'. In S2 max categories is 15, so it says nothing can be said about categories beyond 30.
Corrected.

• line 298. '... other configuration, the ...'
Corrected.

- line 303. '... suggests only marginal ...'

Added.

- line 308. Using the word 'trend' in this context is confusing because trend is commonly understood as a change in time. I suggest you replace 'trend' with e.g. linear fit or something else more suitable.

Corrected as suggested.

- line 315. Is enhanced bottom grow because thin ice grows faster? You should explain the physics behind the enhanced bottom grow.

This has been explained (Lines 339–342).

- line 319. '... more thick categories ...'

Added.

- line 320. '... in the Central Arctic that can potentially compensate for this decrease in terms of SIE ...'

Added.

- line 329. Explain what expression in parenthesis mean in OSI-SAF and NSIDC. Are they needed here? Data are already described in section 2.

This has been removed as that information is already given in Section 2.

- line 330. '... done by both including and excluding long-term trends.'

Corrected.

- line 336. '... such as the 2007 SIE minimum'.

Added.

- line 350. This is a one-sentence paragraph. Merge it with the earlier one.

All the Discussion section has been reformulated.

- line 360. '... are adjusted to reproduce ...'

Modified as suggested.

- line 364. '... computationally more efficient than configurations with more categories.'

Added.

- line 366. '... sea ice to changes in model parametrization.

Added.

- Fig 5. caption. 'anomalies in the range of ±15

Corrected.

Reviewer 2

Moreno-Chamarro et al.: Impact of the ice thickness distribution discretization on the sea ice concentration variability in the NEMO3.6-LIM3 global ocean–sea ice model. The authors investigate ice thickness distribution (ITD) categories in NEMO-LIM and how they impact sea ice concentration variability. They use k-means clustering as a technique in tandem with three observational based SIC datasets. The authors do not find an optimal configuration as results in the Arctic and Antarctic have opposite responses to ITD changes, so no clear benefit to NEMO-LIM is determined from changing ITD.

Overall, I believe this will be suitable for publication with a few major/moderate changes. I felt that the scientific significance and quality were good to fair, but could be improved with some expansion in the text. The Scientific Reproducibility is also fair, which again could be improved with further clarification in the text. The Presentation quality was excellent.
We thank the Reviewer for the appreciation and the thoughtful comments. In the following we answer each specific point (in blue).

Specific Comments:

- One of the biggest concerns I have about this paper is that it doesn't generalize to modeling in general beyond NEMO-LIM to provide insight about modeling in general. I realize that this is for the NEMO special issue, however, it currently feels a bit like a sensitivity experiment to determine optimal model configuration but not otherwise generally of interest to the community of sea ice modelers who may be setting up their own models using LIM or other sea ice models.

  This begins in the introduction where there should be a brief discussion of previous work about why 5 ITD categories have been chosen in the past due to volume studies (Lipscomb 2001, Remapping the thickness distribution in sea ice models, doi: 10.1029/2000JC000518; Bitz et al. 2001, Simulating the ice-thickness distribution in a coupled climate model, doi: 10.1029/1999JC000113). In fact, in Bitz 2001 one of the conclusions is "…the concentration of open water and thin ice, which is relatively insensitive to the number of categories beyond M=5," which is directly relevant for this paper. Why weren't these cited? If anything, studies using CICE that agree with these results should strengthen your results because they become more robust across models.

We thank the reviewer for the references. We opted for an Introduction briefly reviewing previous research on the impact of the ITD in climate models since a longer, more detailed one is provided in the companion paper Massonnet et al. (2019). This was also done because nearly all of the previous studies have focused on the mean climatological state of the sea ice (the focus in Massonnet et al., 2019) and not on its variability (our focus). Thus, whereas Bitz et al. (2001) was indeed cited in the Introduction as an example, Lipscomb (2001) was not. Both works are now cited in the revised manuscript. The Introduction has further been clarified on this point and extended following the Reviewer's suggestion (Lines 48–55).

In the discussion and conclusions section you should add more information about how these results might be directly relevant in coupled models. This is brought up briefly but could be fleshed out and suggestions for how to test this would be useful. Additionally, you mention that parameterizations and parameter values are tuned for 5 categories (line 359). Can you specify which of these might be directly affected or changed? Are similar parameterizations present in other sea ice models? How can this be generalized for the community?

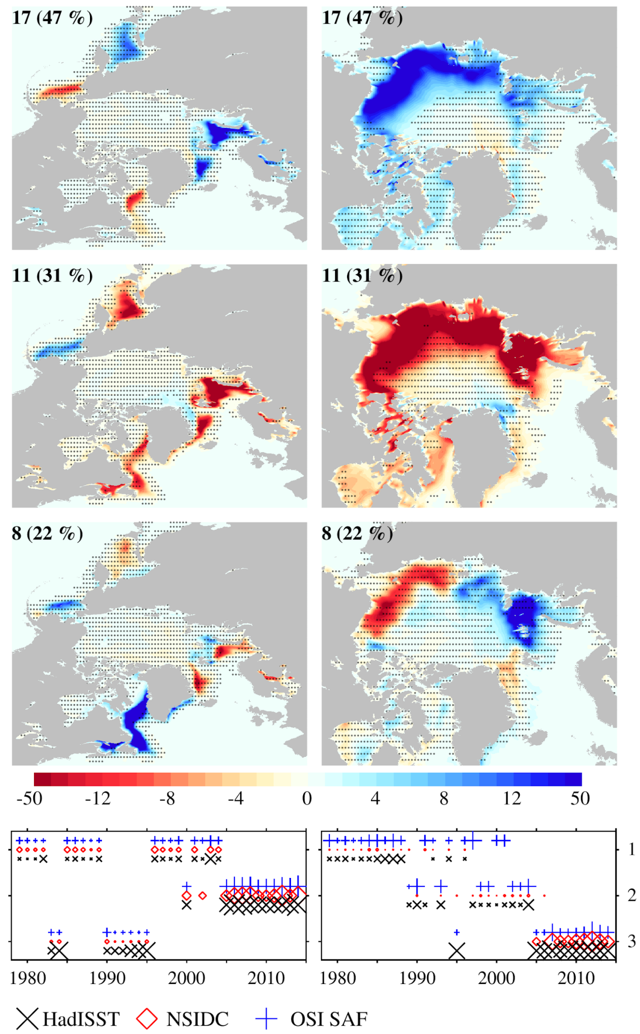
The Discussion section has been rewritten in full to accommodate these suggestions. Now dedicated parts discuss the tuning parameters that might need adjustment in the model (Lines 383–389), the potential relevance for other sea ice models beyond NEMO3.6-LIM3 (Lines 390–406) and for fully-coupled modes (Lines 407–415).

- The methods need clarification, particularly for replicability purposes. In particular, I found these sections to need to be expanded.

  1) At line 145/Figure 2 the Arctic "winter" cluster was defined but didn't include April. What threshold values for these groups were used? Are your results sensitive to including different months? These things should be tested.

  We opted for the standard definition of a season of three months. To define the winter (summer) season, we search for the largest correlation coefficient between the monthly clusters and the adjacent second largest value in the winter (summer) half year (correlations coefficients are plotted in Fig. 2). The two seasons must be and are consistent across the three observational datasets included in the analysis. This method renders two seasons in which monthly cluster agreement is consistently high: JFM and ASO, on which we then base the whole paper analysis. Although monthly clusters in April and in previous months show good agreement, agreement is smaller than across JFM. This method hence leaves April outside the winter season. We note our winter season agrees with the analysis in Close et al., 2017, where monthly Principal Components of the sea ice concentration show that January, February, and March have similar modes, different from those in November, December, or April. For these reasons, we have decided to keep our definition of a winter season without April. This point has nonetheless been clarified in the revised manuscript (Lines 156–160).

In addition, to show that including April in winter would actually have had little impact on the analysis, Response Figure 1 (below) shows the test where the clusters are extracted in the 4-month seasons January–April (as winter) and July–October (as summer) in the Arctic. The main difference with respect to the clusters in JFM and ASO (Fig. 5) is that the second and third clusters have switched positions. Cluster patterns and years of occurrence are however virtually identical as those in JFM and ASO (c.f. Fig. 5). The Response Figure 1 is not included in the received manuscript, but we do mention in the text that results are not sensitive to the specific season definitions.



Response Figure 1: As in Fig. 5 in the main text, but in JFMA (left) and JASO (right)

2) The % values in Fig.5/6 refer to occurrence, can you translate these values to number of months or something to better indicate what this means?

The value is the percent of years in the period 1979–2014 whose anomaly pattern is the closest to a particular cluster. The number of months is now shown together with the percent value in Figs. 5 and 6, and Supp. Figs. 2, 3, and 5.

3) Section 3.3.1 – are these correlation differences statistically significant from one another? Can you clarify what you mean by these are significant?

In the updated manuscript, statistical significance of the difference between correlation coefficients is tested using Fisher's z-transform assuming a two-tailed significance level of 0.05. Given the large number of coefficient pairs for which differences might be tested, we simplify this by comparing only the median values between an ITD discretization and the one immediately below within the same discretization type: for example, S1.50 is compared with S1.30, the latter with S1.10, and so on; S2.15 is compared with S2.11, and so on; S1.03, S2.03, and S3.05 are all compared with S1.01. The results of these significance tests are now included and discussed in the revised manuscript (see the new Figs. 7, 8 and 10, and Supp. Fig. 6).

4) Line 263 – how was the polynomial determined? Can you provide information about this?
Detrending is done by removing a spatially varying 2nd degree polynomial fit with respect to time using the 'Trend' function in the s2dverification R package [Manubens et al., 2018]. This is now indicated in the revised manuscript (Lines 145–146).

- If there is not a lot of information gleaned from the de-trended Arctic analysis, then why is it presented? Can this be condensed somehow since the variability analysis primarily shows the forced trend without being de-trended?
We would like to keep this section in the main text. The analysis of detrended data is actually critical to characterizing interannual variability in summer, a season which is dominated by the long-term melting trend in the Arctic. Without detrending, Arctic clusters mostly capture this trend (compare Figs. 5 and 9 in the main text). The analysis of detrended data further shows that ice thickness distributions with more than 30 categories can help improve model–data agreement in the Arctic, at a cost of making the simulations computationally more expensive.

- I think that if possible you should consider including Supplemental Figures 4 and 7 as regular figures since they are referred to in detail.
We would like to keep them in the Supplement. Both Figures are only briefly discussed in the manuscript and add little extra information to the discussion of the results. And although the number of figures is not a constraint for publication in GMD, we think 11 main Figures is already a high enough number.

Technical corrections:

Line 81: misspelled "concentration"
Corrected

Lines 269-275: It looks to me like patterns 2 and 3 are both dipoles but opposite patterns. Can you clarify where the quadrupole is?
We call quadrupole a cluster that shows four dominant poles in Arctic sea ice concentration, regardless of the sign. In the winter Arctic this usually means a pole in the Labrador, Barents-Greenland, Okhotsk, and Bering seas respectively. This follows the definition of the quadrupole in Close et al., 2017. Both clusters 2 and 3 in Fig. 9 would therefore fall in this definition. We note, however, small differences between the two. In cluster 2 the pole in the Labrador Sea dominates and dominates in years of strong positive winter NAO. We interpret this as the wind-driven signature of the NAO on the ice concentration [Bader et al., 2011]. Cluster 3 is instead closer to cluster 1 in not detrended data and dominates in similar years. They both further resemble the quadrupole pattern analyzed in Close et al., 2017. This point has been clarified in the revised manuscript.

Lines 296-298: sentence is confusing. "…suggesting that this configuration poorly captures the forced variability but does capture interannual variability as well as any other configuration."?
This has been clarified.

The stippling markers are used to indicate significance in Fig. 11 but insignificance in Fig.5. It would be nice if they were used consistently.
Both Fig. 11 and Supp. Fig. 7 have been modified as suggested.

The first two paragraphs of the discussion were clear and concise. The next three are a bit confusing and all over the place. I'd suggest you rearrange in the following order: 1. One category has worst results necessitating multi-category sea ice models like LIM3 or CICE; 2. The standard configuration is 5 ITD levels; 3. Adding more thin categories decreases agreement; 4. Having 30+ categories can improve some but is significantly more expensive at double the cost, which is clearly significant for coupled models
Both the Discussion and Abstract have been rewritten following the Reviewer's recommendation.

Impact of the ice thickness distribution discretization on the sea ice concentration variability in the NEMO3.6-LIM3 global ocean–sea ice model

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Abstract. This study assesses the impact of different sea ice thickness distribution (ITD) ~~configurations~~discretizations on the sea ice concentration (SIC) variability in ocean-standalone NEMO3.6-LIM3 simulations. Three ITD ~~configurations~~discretizations with different numbers of sea ice thickness categories and boundaries are evaluated against three different satellite products (hereafter referred to as "data"). Typical model and data interannual SIC variability is characterized by ~~k~~K-means clustering both in the Arctic and Antarctica between 1979 and 2014 ~~in~~. We focus on two seasons, winter (January–March) and summer (August–October), ~~when coherence~~in which correlation coefficients across clusters in individual months ~~is~~are largest. ~~Analysis in~~In the Arctic ~~is done~~, clusters are computed before and after detrending the series with a 2nd degree polynomial to separate interannual from longer-term variability.

~~Before~~ The analysis shows that, before detrending, winter clusters ~~capture~~reflect the SIC response to large-scale atmospheric variability at both poles ~~and summer cluster a positive and negative trend in the~~, while summer clusters capture the negative and positive trends in Arctic and Antarctic SIC respectively. After detrending, Arctic clusters reflect the SIC response to interannual atmospheric variability predominantly. ~~Model–data cluster comparison suggests that no specific ITD configuration or category number increases realism of the simulated Arctic and Antarctic SIC variability in winter. In the Arctic summer, more thin-ice categories decrease model–data agreement without detrending but increase agreement after detrending. Overall, a single-category configuration agrees the worst with data.~~
~~Direct model–data comparison of SIC anomaly fields shows that more thick-ice categories improve winter SIC variability realism in Central Arctic regions with very thick ice. By contrast, more thin-ice categories reduce model–data agreement in the Central Arctic in summer, due to~~The cluster analysis is complemented with a model–data comparison of the sea ice extent and SIC anomaly patterns.

The single-category discretization shows the worst model–data agreement in the Arctic summer before detrending, related to a misrepresentation of the long-term melting trend. Similarly, increasing the number of thin categories reduces

model–data agreement in the Arctic, due to a poor representation of the summer melting trend, and an overly large ~~simulated~~winter sea ice volume~~.~~

In summary, whereas better resolving thin ice in NEMO3.6-LIM3 can hamper model realism in the Arctic but improve it associated with a net increase in basal ice growth. In contrast, more thin categories improve model realism in Antarctica, and more thick~~ ice categories increase realism in the Arctic winter. And although the single-category configuration performs the worst overall, no optimal configuration is identified~~ ones improve it in Central Arctic regions with very thick ice. In all the analyses we nonetheless identify no optimal discretization. Our results thus suggest that no clear benefit in the representation of SIC variability is obtained from increasing the number of sea ice thickness categories beyond the current ~~usual~~ standard ~~of~~with 5 categories in NEMO3.6-LIM3.

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1 Introduction

~~Analyses~~Analysis of recent observations ~~have~~has allowed identifying different drivers of sea ice variability. ~~For example, interannual sea ice variability has primarily been related to~~Interannual sea ice variability, for example, has been associated primarily with changes in atmospheric and oceanic circulation: atmospheric variability~~, which can directly be~~ related to large-scale atmospheric modes, such as the North Atlantic Oscillation (NAO) or Siberian High in the Northern Hemisphere~~,~~ and the Southern Annular Mode over Antarctica, can drive changes in the sea ice both dynamically and thermodynamically [e.g., Rigor et al., 2002; Rigor and Wallace, 2004; Ogi et al., 2007; Yuan and Li, 2008; Wang et al., 2009; Hobbs and Raphael, 2010; Holland and Kwok, 2011; Renwick et al., 2012; Kohyama and Hartmann, 2016; Lynch et al., 2016; Close et al., 2017; Blackport et al., 2019; Olonscheck et al., 2019]. Similarly, interannual changes in ocean heat transport to high latitude can contribute to anomalous episodes of Arctic sea ice melting in both the Atlantic and Pacific sectors [e.g., Hibler, 1986; Venegas and Mysak, 2000; Ingvaldsen et al., 2004a; 2004b; Woodgate et al., 2010; Schlichtholz, 2011]. On longer time scales, the accelerating thinning in Arctic sea ice [Comiso et al., 2008; Serreze and Stroeve, 2015] might be modulated by lower-frequency variability in modes ~~like~~such as the NAO [e.g., Delworth et al., 2016] or Atlantic Multidecadal Variability [e.g., Day et al., 2012; Drinkwater et al., 2014; Miles et al., 2014]. Accurately capturing ~~this~~the complex range of variability in sea ice, together with ~~its~~the potential impacts on the lower latitude climate [e.g., Screen, 2013], demands for a realistic representation of ~~the~~ sea ice in climate models.

One among the many crucial features of sea ice to ensure its realistic representation is its thickness ~~complexity~~heterogeneity, which determines other important physical properties, such as ice's salt and heat content, resistance to deformation and fracture, and melting and growth rates. State-of-the-art sea ice models typically use an ice thickness distribution (ITD) [Thorndike et al., 1975] to account for subgrid-scale variability of ice properties. In most cases, through an ITD the different ice thicknesses are sorted into a fixed number of categories in a configuration ~~which~~with usually ~~presents~~ the finest resolution in the thinnest ice range. Several studies have explored the advantages of including an ITD to simulate the mean state and seasonality ~~in~~of the sea ice accurately, as well as the number of categories that would render ~~the~~its most realistic ~~ice representation [e.g.~~representation, albeit with mixed results [among others, Bitz et al., 2001; Lipscomb, 2001; Holland et al., 2006; Massonnet et al., 2011; Uotila et al., 2017; Ungermann et al., 2017~~;~~, and Massonnet et al., 2019]. ~~These studies, however, have partly overlooked~~Although 5 to 7 categories were initially found sufficient to simulate large-scale sea ice realistically [Bitz et al., 2001; Lipscomb, 2001], the later study by Hunke [2014] concluded that such numbers might lead to an inaccurate representation of the observed sea ice thickness and a model misrepresentation of mechanical sea ice processes controlling its volume. The optimal number of categories and discretization are therefore still debated (a more detailed review is given in the companion paper, Massonnet et al., 2019). Interestingly, we note that these previous studies partly overlook the impact of the ITD discretization on the simulated sea ice variability. To our knowledge, only Massonnet et al. [2011] reported a more realistic interannual variability in the Arctic sea ice extent (SIE) in the LIM3 sea-ice model than in ~~its~~the previous model version, LIM2 (although this improvement cannot exclusively be attributed to the addition of an explicit 5-category ITD in LIM3 but to all the refinements in sea ice parametrizations absent in LIM2). Thus the question of whether a particular ITD ~~configuration~~discretization or number of categories ensures a more realistic sea ice variability and long-term trend remains unanswered.

Sea ice concentration (SIC) and thickness are the main quantities used to characterize ~~its~~ice cover variability. Most of the previous studies have focused on the impact of an ITD on the sea ice thickness, especially in the Arctic [e.g., Holland et al., 2006; Hunke, 2014; Ungermann et al., 2017]. By contrast, SIC has received less attention, perhaps motivated by the relatively minor or only indirect effect that the ITD appears to have on the representation of ~~its~~the mean state [e.g., Massonnet et al., 2011; Uotila et al., 2017; Massonnet et al., 2019]. However, while SIC has continuously been measured by satellites since 1978 [Cavalieri et al., 1996; EUMETSAT, 2015], equivalent measurements of thickness have only become available in the past decade [e.g., Laxon et al., 2013]. Literature exploring the observed SIC variability is therefore much richer than that on sea ice thickness and offers a more exhaustive account of its key features and drivers (see most of the references above). This study therefore represents a step forward with respect to previous ones, as it presents ~~the~~, to our knowledge, ~~the~~ first detailed assessment of the impact of the ITD discretization on the SIC variability at both poles since 1978, using the state-of-the-art coupled ocean–sea ice model NEMO3.6-LIM3. This study is a companion paper to Massonnet et al. [2019], in which the response of the modelled sea ice ~~climatology~~mean state to an ITD discretization is investigated.

The paper is structured as follows: Section 2 describes the model and experimental design, ~~–~~ Section 3 follows with the main results of the model–data comparison, and Sections 4 finishes with the discussion of the results and main conclusions.

2 Model and experimental setup

2.1 Model description

We use the dynamic-thermodynamic sea ice model LIM3.6 (Louvain-la-Neuve sea Ice Model) [Rousset et al., 2015] coupled to a finite-difference, hydrostatic, free-surface-primitive-equation ocean model within the version 3.6 of the NEMO framework (Nucleus for European Modelling of the Ocean) [Madec, 2008]. Only a short description of the model is provided in the following; for more details we refer to Barthélemy et al. [2018] and Massonnet et al. [2019]. Both the ocean and sea ice models are run on the global eORCA1 grid with a~~–~~ 1° nominal zonal resolution. The ocean has 75 vertical levels which increase non-uniformly from 1 m at the surface to 10 m at 100 m depth and 200 m at the bottom. To avoid spurious model drift, a ~~weak~~ restoring toward the World Ocean Atlas 2013 surface salinity climatology [Zweng et al., 2013] is applied with a strength of 167 mm/day. The restoring is damped under the sea ice (multiplied by one minus its ~~concentratio~~concentration), where observations are less reliable, to avoid altering ocean–ice interactions.

2.2 Experimental setup: atmospheric forcing

The model is run over the period 1979–2014. The atmospheric forcing is provided by the DRAKKAR Forcing Set version 5.2 (DFS5.2) [Brodeau et al., 2010; Dussin et al., 2016]. This global forcing set is derived from the ERA-Interim reanalysis over the period 1979–2015. It has a spatial resolution close to 0.7°, or 80 km, and it is used within the CORE forcing formulation of NEMO, which uses bulk ~~formulas~~formulae developed by Large and Yeager [2004]. Continental freshwater inputs include river runoff rates from the climatological dataset of Dai and Trenberth [2002] north of 60°S, prescribed meltwater fluxes from ice shelves along the ~~coastline of Antarctica~~Antarctic coastline [Depoorter et al., 2013], and climatological freshwater fluxes from iceberg melting at the ~~surface of the~~ Southern Ocean surface [Merino et al., 2016]. Forcing the NEMO3.6-LIM3 model with observation-based atmospheric variability ensures that simulated SIC variability follows observations to a large extent, in particular the atmospheric-driven changes; this allows us to compare model and observations (hereafter also referred as to data) and evaluate the impact of the different ITD ~~configurations~~discretizations.

2.3 Experimental setup: ITD ~~configurations~~discretizations

LIM3.6 employs an ITD to represent the subgrid-scale distribution of the sea ice thickness, enthalpy, and salinity [Thorndike et al., 1975], discretized into a fixed number of categories. An ITD discretization is characterized by both the number of categories and the position of their boundaries. We run three different sets of sensitivity experiments to evaluate the impact of the ITD on the SIC variability (Fig. 1). In the first set (hereafter, S1), the categories are set by the default ITD discretization of LIM, which varies both the position and the resolution of the thickness categories according to the number of categories~~, setting~~ following a predefined formula that sets the finest resolution to the thinnest ice (Eq. 2 in Massonnet et al., 2019). In the second set (S2), new thickness categories are successively appended without changing the existing category boundaries, which allows assessing the impact of ~~the~~ thick ice categories. In the third set ~~of experiments~~, the lower boundary of the thickest category is set as 4 m ~~depth~~thick, and the ITD resolution is increased or reduced by merging or splitting ~~the~~ existing categories. The upper limit ~~of~~at 4 m thick corresponds to the maximum thickness that thermodynamic ice growth can sustain in the Arctic [Maykut and Untersteiner, 1971] and therefore allows the thickest category to host the deformed ice produced in the model. For more details of the ITD and these experiments we refer to Massonnet et al. [2019].

2.4 Reference observations

Arctic and Antarctic SIC variability in the model simulations is compared with that from three satellite observational products for the period 1979–2014: OSI SAF (OSI-409/OSI-409-a) [EUMETSAT, 2015], NSIDC-0051 [Cavalieri et al., 1996], and HadISST v2.2 [Titchner and Rayner, 2014]. Both OSI SAF and NSIDC provide monthly mean SIC since October, 1978; NSIDC, however, lacks a circular sector centered over the North Pole ("pole hole"), where SIC is set as 1. HadISST blends historical sources, such as sea ice charts, with OSI SAF passive microwave data to provide monthly SIC since January 1850, with concentration values between 0 and 0.15 reset as 0 (open water).

2.5 K-means clustering

K-means clustering as included in the s2dverification R package [Manubens et al., 2018] is used to characterize interannual SIC variability in model simulations and observations. K-means clustering aims at simultaneously minimizing the Euclidean distance between members of a given cluster and maximizing the distance between centroids of ~~the~~ different clusters [Wilks, 2011]. It is an alternative method of dimension reduction to other, more commonly used, such as principal component analysis. With respect to those, K-means clustering is more robust in a physical sense, it can account for potential nonlinearities in a climate field [Andeberg, 2014; Hastie et al., 2009], and it does not assume orthogonality or linearity between dominant modes. K-means clustering has successfully been employed to extract atmospheric weather regimes over the North Pacific and North Atlantic [e.g., Michelangeli et al., 1995, Rossow et al., 2005, Coggins et al., 2014], dynamically similar regions of the global ocean circulation [Sonnewald et al., 2019], or variability clusters from the pan-Arctic sea ice thickness [Fučkar et al., 2015, 2018]. In ~~our case~~this study, each cluster is characterized by a pattern of SIC anomalies (cluster centroids) and a discrete time series of occurrence. Both the spatial features of the patterns and their occurrence in time vary with the computed total number of clusters, K. Cluster validity, characterised by the most robust choice of K, is determined using 10 indices ~~(namely,~~that assess both intra-cluster similarity and inter-cluster dissimilarity. The indices are Duda–Hart, Ratkowsky–Lance, Ball–Hall, SD, cubic clustering criterion, traceCovW, Rubin, Beale, Scott, and Marriot~~)~~, ~~which forms~~and they form a selection of the 10 computationally fastest ones out of the 30 included in the NbClust R package. [Charrad et al., 2014]~~; these indices assess both intra-cluster similarity and inter-cluster dissimilarity~~. We test K values between 2 and 5 and evaluate the results of K-means clustering with those validity indices. Since this is a very computationally demanding analysis, we previously reduce the number of degrees of freedom by interpolating the SIC field from satellite observations onto a 3° horizontal regular grid. For all seasons and observational datasets the optimal K (i.e., the most frequent value for the 10 validity indices) thus evaluated is 3. Therefore we hereafter apply K-means clustering with K value set as 3 to the SIC fields on a 1° horizontal regular grid from both model and observational data. ~~All the calculations are done over the period 1979–2014.~~ Our results are insensitive to the initial seed used to calculate clusters (not shown). All the calculations are done over the period 1979–2014. Clusters are computed from the original time series and after detrending by removing a spatially varying 2nd degree polynomial fit with respect to time using the 'Trend' function in the s2dverification R package [Manubens et al., 2018]

3 Results

3.1 Defining the winter and summer seasons

We intend to focus the comparison between simulated and observed SIC variability in two seasons centered around winter and summer, when maximum and minimum sea ice areas occur respectively. To avoid any a priori assumption about which months define these seasons, we first assess agreement across monthly clusters and aggregate months with similar variability. Following the steps described in Section 2.3 for each observational product separately, we first calculate 3 (~~as~~the optimal number) clusters in each individual month in the Arctic and Antarctica. At each pole, we then compute the spatial correlation coefficients between all the clusters in any two months. We retain the maximum positive value from the resultant distribution, which sets the uppermost-limit of cluster agreement between those two months. Results in OSI SAF are shown in Fig. 2 (results of NSIDC and HadISST are very similar and therefore not shown). ~~Two periods stand out at both poles, when~~The winter and summer seasons are then defined by finding the three months which have the largest and the immediately second largest correlation coefficients in the winter and summer half year (November–April and May–October respectively). The two seasons must be and are consistent across the three observational datasets included in the analysis. This method renders two seasons in which monthly cluster agreement is ~~largest,~~consistently high: January through March (JFM), and August through October (ASO). The use of JFM as the winter season is consistent with the Principal Component analysis in Close et al. (2017), in which monthly modes were best correlated in JFM as well. We find no major differences if the clusters are calculated in winter including April (JFMA) and summer including July (JASO). All the subsequent analyses focus on ~~these~~the two seasons JFM and ASO, which we refer to as winter and summer (even though they include climatological spring and fall months).

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3.2 Sea ice extent

Before comparing SIC clusters, we explore the impact of the ITD ~~configuration~~discretization on the temporal evolution of the Arctic and Antarctic sea ice extent (SIE) over the period 1979–2014 (Fig. 3). This analysis will help interpret results from the clusters ~~below~~presented later. Note that impacts on the simulated climatological mean state and seasonal cycle over this period have previously been described by Massonnet et al. [2019]. In the model, seasonal SIE is calculated from monthly SIC on the original model grid; in observations, seasonal SIE is calculated from the monthly SIE directly provided by the different products. The impact of different ITD ~~configurations~~discretizations on the Arctic SIE in both seasons and Antarctic SIE in winter is marginal, and all the simulations show values that are within observational uncertainty (which we assume to be defined by the envelope of the different observational products; Fig. 3). The largest differences across simulations are for the summer Antarctic SIE. Increasing the number of categories from 1 to 50 in the S1 ~~configurations~~discretizations reduces the Antarctic SIE by about $4 \cdot 10^6$ km^2, although the largest decrease, of about $2 \cdot 10^6$ km^2, is ~~from S1.01 to~~between S1.01 and S1.03. This renders the simulated SIE values in the S1 ~~runs~~cases closer to those in OSI SAF and NSIDC but more different to ~~those in~~ HadISST. HadISST SIE values are consistently above those in OSI SAF and NSIDC in the Arctic and Antarctica in both seasons, as also noted by Titchner and Rayner [2014]. Increasing the number of categories in the S2 and S3 ~~configurations~~discretizations has a comparatively smaller impact, reducing and increasing the summer Antarctic SIE by about $1 \cdot 10^6$ km^2 respectively~~; these results are~~, yet still within observational uncertainty. The simulated SIE trend is slightly underestimated in the winter Arctic, although it is well captured in summer, as well as in Antarctica in both seasons. In terms of interannual variability, the simulations disagree the most with the observations in Antarctica, especially in summer, when the simulations show large interannual variations that are not found in observations (for example, around 2000). By contrast, the simulated Arctic SIE variability for all ITD ~~configurations~~discretizations is very close to the observations in both seasons.

To characterize differences between simulated and observed SIC, we calculate the integrated ice edge error (IIEE) as the total area where model and observations disagree on SIC values above 15% [Goessling et al., 2016]. In general terms, the largest IIEE is in the Arctic and Antarctica in ~~JFM~~winter, with the smallest values ~~emerging for the comparison~~when compared with NSIDC (Supp. Fig. 1). For all the simulations, the IIEE remains relatively constant over the period 1979–2014 at both poles and seasons, and the impact of a different ~~ITDs~~ITD discretization on the IIEE is marginal in the Arctic in both seasons and in Antarctica in winter. The situation is different in the Antarctic summer (JFM), when differences in IIEE due to the ITD are the largest (Fig. 4). IIEE between ~~the~~ simulations and observations is overall larger than across observations for all the ITD ~~configurations~~discretizations. The single-category ~~ITD configuration~~discretization exhibits the largest IIEE with respect to all ~~the~~ observations. Increasing the number of categories in the S1 and S3 ~~configurations~~cases tends to reduce the IIEE by about $1 \cdot 10^6$ km^2 between the coarsest and finest ~~resolution~~resolutions. Changes in categories ~~in the S2~~

~~configuration~~across S2 discretizations have a smaller impact on the IIEE, with no clear improvement or worsening for a finer or coarser ITD. These results suggest that a finer resolution of the thinner ice and not of the thicker sea ice to some degree improves the representation of the simulated Antarctic SIC in ~~ASO~~winter in our model with respect to observations. This might be related to an improved response of the thin ice (the easiest to melt, grow, and advect) to the atmospheric forcing.

3.3 SIC cluster analysis

In the following, we describe the three clusters of SIC variability in the observations. Clusters in OSI SAF are shown in Figs. 5 and 6 in the Arctic and Antarctica respectively (since clusters in NSIDC and HadISST are very similar, they are shown in Supp. Figs. 2 and 3 respectively). In the Arctic winter, the first cluster shows four poles of dominant variability, with more ice in the Barents, Greenland, and Okhotsk seas and less ice in the Labrador and Bering seas (Fig. 5); this pattern agrees with the quadrupole mode described ~~by~~in previous literature associated with variations in the strength of the Siberian High [e.g., Ukita et al., 2007; Close et al., 2017]. The second cluster presents similar centers of action to the first one, but SIC anomalies are negative in the Labrador, Barents and Okhotsk seas and positive in the Bering Sea. The third cluster shows strong anomalies of opposite ~~sign~~signs in the Labrador (strongly positive) and Nordic seas (negative)~~ which~~, a pattern that resembles the typical fingerprint of a positive NAO phase on the SIC [Bader et al., 2011]. In fact, this cluster dominates between 1990 and 1996, when the winter NAO was persistently positive [Hurrell and Deser, 2010]. Overall, the first and third clusters alternate until 2004 approximately, after which the second cluster dominates. In the last decade, the root mean square distance between the clusters and the anomaly fields (indicated by the symbol size in Fig. 5) increases to its largest values over the whole period in OSI SAF, but not in NSIDC and HadISST. These results suggest that the winter SIC variability might fundamentally have changed after 2004, in agreement with the observed acceleration in the SIC melting trend [e.g., Comiso et al., 2008; Serreze and Stroeve, 2015].

In the Arctic summer, both the cluster patterns and relative occurrences reflect a long-term melting trend (Fig. 5). The first and third clusters are very similar~~, which respectively~~: both exhibit widespread positive and negative anomalies in the central Arctic and dominate over the initial period (ca. 1979–1988) and last one (ca. 2005–2014) respectively. The second cluster, by contrast, dominates in the middle decades (ca. 1989–2005) and presents a dipole of positive and negative anomalies between the central Arctic and the surroundings. Such partitioning in decades of alternating dominance suggests that the long-term melting trend in sea ice (as seen in the SIE; Fig. 3b) controls the clustering; previously detrending the data might therefore be necessary for a more robust characterization of the interannual variability (see below).

In ~~Antarctica~~the Antarctic summer (JFM), the three clusters exhibit poles of dominant variability close to the continental coast, especially in the Weddell and Ross seas (Fig. 6). The first and second clusters show similar patterns but of opposite sign, with an overall decrease or increase respectively but in the Amundsen and Bellinghausen seas. The third cluster shows a dipole ~~of~~with negative anomalies in the Weddell Sea and positive ones in the Amundsen Sea. Summer SIC variability is dominated by the first cluster (58%), especially during the first decades. Although the second and especially the third clusters are much less frequent (31% and 11% respectively), the second one tends to dominate in the last decade (ca. 2005–2014). This might be due to a slight positive trend, as seen in the SIE (Fig. 3d).

In the Antarctica ASO (winter), the ~~Antarctic~~ first and second clusters show opposite-sign poles in the Weddell, Bellinghausen, and Amundsen seas, with smaller contributions from ~~other seas~~the others (Fig. 6). These two modes resemble SIC variability driven by Rossby wave activity across the Drake Passage described ~~by~~in previous literature [e.g., Yuan and Li, 2008; Hobbs and Raphael, 2010; Renwick et al., 2012; Kohyama and Hartmann, 2016]. In fact, the first cluster resembles the pattern of Antarctic SIC response to an El Niño [e.g., Ding et al., 2011] and dominates in years of strong ones, such as 1984, 1998, and 2010. The third cluster shows negative SIC anomalies along all the Antarctic ~~perimeter~~coast but in the Bellingshausen and Amundsen seas, where anomalies are positive; this is however the least persistent cluster (11%), and SIC variability is clearly dominated by the first two (47% and 42% respectively). Cluster occurrences and patterns in NSIDC are slightly different from those in OSI SAF and HadISTT (Supp. Figs. 2 and 3), suggesting that observational uncertainty ~~can impact~~impacts the dominant Antarctic SIC modes of variability.

3.3.1 Impact of ITD discretization on the SIC clusters

For each cluster of SIC variability, observations and simulations are compared mainly through their spatial correlation (Fig. 7). Statistical significance of the difference between correlation coefficients is tested using the Fisher's z-transform, assuming a two-tailed significance level of 0.05 [Storch and Zwiers, 1999]. Given the large number of coefficient pairs whose differences can potentially be tested, we simplify the test by comparing only the median values between an ITD discretization and the one immediately below within the same discretization type: for example, S1.50 is compared with S1.30, the latter with S1.10, and so on; S2.15 is compared with S2.11, and so on; and S1.03, S2.03, and S3.05 are all compared with S1.01. As a measure of the observational uncertainty, we also calculate the spatial correlation coefficients between the three observational datasets. We further calculate the root mean square error (RMSE) across observed and simulated clusters to provide an additional assessment. Results of the RMSE analysis are shown in the Arctic only (Supp. Fig. 4) and are commented when they complement or disagree with results from the spatial correlation coefficients.

In the Arctic winter, correlation coefficients between observed and simulated clusters slightly decrease as the number of categories increases in ~~all three configurations~~ the three discretization types, and only very few pairs show coefficients that are significantly different (Fig. 7)~~; by~~. By contrast, including more categories slightly reduces the RMSE (which suggests a slightly better agreement with the observations) in the third cluster in the S1 and S3 ~~configurations~~cases and increases it in the S2 one (Supp. Fig. 4). Overall, nonetheless, changing the ITD ~~configurations have~~discretization has a small impact on ~~the~~ model–data agreement, and no ~~configuration~~discretization or number of categories ~~appear~~appears to be consistently the best.

In the Arctic summer, spread in model–data agreement is much larger than in winter (Fig. 7 and Supp. Fig. 4). The RMSE is barely impacted by the ITD ~~configuration~~discretization (Supp. Fig. 4) and shows similar changes to ~~those in~~ the correlation coefficients. The lowest model–data correlation coefficients are for the second cluster across all ~~configurations~~discretizations. This is likely because of its characteristic spatial pattern of small, mostly statistically non-significant anomalies (Fig. 5). Such noisy features are indeed difficult to be captured by the model accurately, thus resulting in comparatively small spatial correlation coefficients. By contrast, anomalies in the first and second clusters take larger values over a larger area and are successfully reproduced by the simulations. Model–data spatial correlation coefficients are little influenced by the ITD ~~configuration~~discretization for the first and third clusters but show a statistically significant decrease with a ~~large~~ number of thin ice categories beyond 30 for the second cluster in the S1 and S3 ~~configurations~~cases. Although increasing the number of thick categories in the S2 ~~configuration~~discretization has no major impact on model–data correlation coefficients, the S2.07 case shows a statistically significant drop in correlation values in all the clusters. This suggests that variability is slightly differently distributed across the clusters ~~in this configuration. The configuration with one~~. The discretization with a single category, S1.01, shows the lowest correlation coefficients (Fig. 7; with statistically significant differences with the coefficients of the S1.03, S2.03, and S3.05 discretizations) and highest RMSE values (Supp. Fig. 4) ~~overall~~. These results suggest that an ITD with one category or a large number of thin categories ~~can potentially~~ hamper representation of SIC variability in the Arctic. This contrasts with and complements results in Massonnet et al. [2019], where the ~~one-category configuration~~single-category discretization was found performing as good as or even better than multi-category ~~configurations~~ones in terms of sea~~–~~-ice mean ~~climatology~~state. Comparison of mass budget across ~~configurations~~discretizations showed that ~~this configuration~~the single-category case compensates basal ice growth deficit (relative to multi-category cases) through a larger dynamic ice production from fall to winter (and, thus, ~~potentially~~ right for the wrong reasons) [Massonnet et al., 2019].

In the ~~Antarctica~~Antarctic summer, model–data agreement is lower than in the Arctic in terms of both the spatial correlation (Fig. 8) and RMSE (not shown). Almost all the correlation coefficients are statistically non-significant for the second and third cluster (Fig. 8), with only some ITD ~~configurations~~discretizations with 3 or 5 categories showing significant correlations for all clusters. For the first cluster, however, more than 5 categories ~~seem to improve~~show a statistically significant improvement in the agreement with ~~the~~ observations, in particular for the S1 ~~configuration.~~ cases.

In the Antarctic winter, model–data agreement increases with respect to summer, ~~especially~~ and correlation coefficients tend to be statistically significant for the first and especially the second cluster (Fig. 8). However, the impact of the ITD distribution is small and there is no robust response to any ~~configuration~~discretization.

3.3.2 Arctic SIC clusters after detrending

For a sound characterization of the modes of interannual variability over the period 1979–2014, the long-term, accelerating melting trend in the Arctic SIC is now filtered out. This trend is well captured by both the SIE (Fig. 3) and clusters (Fig. 5). Arctic SIC clusters are now calculated after detrending by removing a spatially varying 2nd degree polynomial fit with respect to time (~~Fig. 9~~see Section 2). Clusters calculated after detrending with a 1st degree polynomial (linear detrend) are still affected by the melting trend and are not discussed here further. We do not consider higher order degree polynomials either, since they have shown no improvement to characterize clusters of sea ice thickness over the period 1958–2013 [Fučkar et al., 2015]. No similar analysis has been performed for Antarctic SIC as the clusters suggest a rather weak positive trend in summer (Fig. 6).

In OSI SAF, detrended SIC variability in winter is evenly distributed into the three clusters (Fig. 9; 36%, 33%, and 31% of occurrence frequency). The first cluster shows a dominant pole of negative anomalies in the Labrador Sea (Fig. 9). The second and third clusters show a similar quadrupole pattern with opposite signs. The second cluster shows two poles of variability of positive and negative anomalies in the Labrador and Nordic seas respectively. This cluster is very similar to the third one in not detrended data, and both dominate in similar years~~, in particular during periods of~~ with a positive NAO ~~phases~~phase. This suggests that they capture the fingerprint of a positive winter NAO on the Arctic SIC. The third cluster ~~shows a clear quadrupole structure, like~~ is instead similar to the first cluster in ~~not detrended~~the raw data~~,~~ and ~~dominates~~both dominate in similar years. They both further resemble the quadrupole pattern analyzed in Close et al. [2017]. Clusters in HadISST and NSIDC are very similar and shown in Supp. Figs. 4 and 5 respectively.

In summer, detrending the data leads to clusters with more marked regional contrasts (compare Figs. 5 and 9). The first cluster in OSI SAF, which dominates in two thirds of the years, shows a dipole of positive SIC anomalies in the Kara, Barents, and Greenland seas and negative ones in the East Siberian and Laptev seas (Fig. 9). The second cluster mirrors the first one but with opposite-sign and larger anomalies (Fig. 9). These two clusters respectively resemble the fingerprint of a positive (in 1995, 1999, 2002, and 2005) and negative (in 1996, and 2004) Arctic dipole on the summer SIC [Wang et al., 2009]. Occurrence of these two clusters, however, does not systematically coincide with strong Arctic dipole anomalies (for example, in 1998 or 2003; Wang et al., 2009). The Arctic oscillation has also been proposed as a driver of similar SIC anomaly patterns [Rigor et al., 2002; Rigor and Wallace, 2004; Wang et al., 2009]. Lastly, the third cluster shows a monopole of strong negative anomalies confined to the Beaufort gyre. This pattern dominates only in 4 years ~~such as~~, including 2007, when the Arctic sea ice extent was the lowest over the period 1979–2014. ~~Such extreme~~Extreme melting events such that have been associated with ~~an~~ exceptional ~~episode~~episodes of atmospheric [Graversen et al., 2010] and oceanic [Woodgate et al., 2010] warm flow into polar latitudes and summer storm activity [Screen et al., 2011]. Note that cluster repartition of detrended data is not exactly the same as in HadISST and NSIDC in summer (Supp. Fig. 5): their first ~~ones~~clusters are similar to the first one in OSI SAF but with ~~a~~ different local expressions; their thirds clusters resemble the second one in OSI SAF but with weaker anomalies near the Alaskan coast.

~~Regarding their sensitivity to the ITD configuration after detrending, the winter clusters show a rather consistent model–data agreement~~With respect to the sensitivity of the model clusters to the ITD discretization, we find that the winter clusters rather consistently agree with the observed ones both in terms of the spatial correlation coefficients (Fig. 10) and RMSE (not shown) and are little impacted by the discretization. In summer, increasing the number of categories beyond 30 ~~improves the~~leads to a statistically significant improvement in model–data correlation coefficients (Fig. 10) ~~and reduces~~, while reducing the RMSE (not shown) for all the clusters in the S1 and S3 ~~configurations (while no robust response is found in the S2 configuration)~~discretizations. This implies that, overall, a large number of ~~—~~ thin categories ~~can~~ help improve the representation of SIC interannual variability in summer. In contrast to what happens ~~with~~in not detrended data, the ~~one-category configuration~~single-category discretization agrees with the observations as well as any other ~~configurations, suggesting that this configuration poorly captures the forced variability~~. This suggests that one category poorly captures the forced variability (this is, the long-term melting trend) but is as ~~well~~good as any other ~~one the~~ discretization at capturing interannual variability.

3.4 Anomaly-based analyses

Two extra analyses are discussed in the following to complement previous ones and explore their robustness. In the first analysis, spatial correlation coefficients are computed directly, in each year, between the simulated and observed SIC anomalies in both seasons and hemispheres. In each case, a distribution of correlation coefficients is generated by combining the values in all the years and in the three observational products. This analysis suggests only marginal sensitivity to the number of sea ice categories or its ~~configuration~~discretization in the Arctic before (Supp. Fig. 6) and after detrending (not shown) and in Antarctica (not shown).

The second analysis ~~is to provide~~provides a spatial perspective to the impacts of the ITD ~~configurations~~discretizations on SIC. For this, temporal correlation coefficients at the grid point level are first computed between simulated and observed SIC anomalies in both seasons. ~~The trend~~A linear fit in such correlation coefficients with respect to the number of categories is then calculated across simulations of a given ~~configuration~~discretization. The result is a map which provides a measure of the regions where changing the number of categories most impacts agreement with observations. Since results are similar across the observational products, an average between the three cases is computed for the Arctic (Fig. 11) and Antarctica (Supp. Fig. 7).

Increasing the number of categories tends to decrease model–data agreement (blue colors in Fig. 11) in the S1 and S3 ~~configurations~~discretizations in both seasons (but most clearly in the S3 one in summer) in the Central Arctic, near the region where the largest increase in sea ice thickness is simulated for an increase in the number of categories [Massonnet et al., 2019]. In ~~that~~this region, a ~~higher sea ice volume due to enhanced bottom growth rate results in a less realistic~~larger bottom growth rate increases the sea ice volume for finer ITD resolutions. This is because conductive heat flux through ice, which is inversely proportional to ice thickness, increases (facilitates ice growth) on average on a grid cell when the thickest ice accumulates on a few categories and thereby leaves more grid space for faster-growing thin ice [Massonnet et al., 2019]. In the Central Arctic, therefore, higher sea ice volume makes the simulated sea ice less realistic. In the S2 ~~configuration~~discretizations, model–data agreement particularly improves with the number of categories in winter north off Greenland and the Queen Elizabeth Islands, regions where the thickest ice is simulated (Fig. 11, contours). Although the overall Arctic sea ice volume increases with the number of categories [Massonnet et al., 2019], the improvement in that particular region suggests that ~~more~~a discretization including more thick categories ~~help~~helps capture variability in thick ice. In summer, a decrease in model–data agreement occurs in the same region, although there are improvements elsewhere in the central Arctic that ~~can potentially~~might compensate for this decrease (Fig. 11). In Antarctica, only the S2 ~~configuration~~discretization in summer (JFM) shows some clear trends in model–data agreement near the Ross Sea (Supp. Fig. 7). However, these results appear spurious as sea ice is very thin and presents a concentration below 15% in the area (contours in Supp. Fig. 7).

4 Discussion and conclusions

This article explores the impact of different ITD ~~configurations~~discretizations on the simulated SIC variability in the Arctic and Antarctica. Using ocean–sea ice stand-alone simulations with the NEMO3.6–LIM3 model, we assess three different ITD ~~configurations~~discretizations in which both the number and boundaries of the sea ice thickness categories are changed. SIC variability is characterized via K-means clustering analysis over the period 1979–2014; the simulated clusters are compared with those from three satellite observational products, OSI SAF ~~(OSI-409/OSI-409-a), NSIDC (0051)~~, NSIDC, and HadISST v2.2. We focus on two seasons, JFM (winter) and ASO (summer), across which monthly clusters are found most spatially coherent. In the Arctic, cluster comparison is done ~~both~~by including and excluding the long-term ~~trends, this~~trend, the latter by detrending with a spatially varying 2nd degree polynomial. We complement the cluster analysis by comparing sea ice extent and anomaly fields between model and observations.

Overall, winter clusters reflect the imprint of atmospheric variability such as NAO and Siberian High on the Arctic SIC, and of ENSO on the Antarctic SIC. Summer clusters reflect the dominant trends in SIC, slightly positive in Antarctica and prominently negative in the Arctic. After detrending, Arctic summer clusters allow isolating the SIC response to atmospheric variability associated with the Arctic Dipole and Arctic Oscillation, as well as identifying outstanding events such as the 2007 ~~minimum.~~

~~Comparison between simulated and observed clusters indicates that no particular ITD configuration and number of categories systematically helps to improve the representation of model SIC variability at both poles in winter, both before~~

~~and after detrending. In summer, more thin-ice categories decrease model–data agreement at both poles before detrending, due to a poorer representation of the long-term trends; more categories, however, do improve model–data agreement in the Arctic after detrending. Nonetheless, such an improvement is found~~sea ice extent minimum.

Although the results of all the model–data comparison present mixed conclusions, depending on the analysis, we extract a few take-home messages:

i) The single-category discretization shows the worst results overall, particularly in the Arctic summer without detrending due to a misrepresentation of the long-term melting trend. This result reinforces the recommendation of using multi-category sea ice models. In the companion study, Massonnet et al. [2019], the single-category discretization is found producing realistic mean states of sea ice extent; it was however hypothesized that this might be for the wrong reasons, thanks to error compensation in the simulated mass balance terms. The finding of the present study, focusing on variability, supports that the single-category framework is in fact not appropriate for investigating the cause of large-scale sea ice changes.

ii) Discretizations with more than 10 sea ice thickness categories can degrade model ability to simulate realistic Arctic SIC variability. In particular, better resolving thin ice in the Arctic hampers SIC representation, likely related to an unrealistic sea ice volume increase in the central Arctic [Massonnet et al., 2019] and a poorer representation of the long-term melting trend in summer (this study). In contrast, a finer resolution in thin sea ice increases realism of the simulated SIC in Antarctica; this improvement, nonetheless, most clearly arises for more than 30 thin categories, for which computational costs ~~substantially increases~~increase substantially (from 30 ~~to 60~~ minutes per simulated year ~~from~~for the standard 5-category ~~case~~discretization to 60 minutes for the 30-category one; Massonnet et al., 2019). ~~The one-category configuration tends to show the worst results overall, particularly in the Arctic summer before detrending. This reinforces the recommendation of using multi-category sea-ice models, such as LIM3.~~

~~Direct comparison of the SIC anomaly fields between observations and simulations suggests that increasing the number of thick categories can improve the representation of the very thick ice variability north of Greenland in winter. By contrast, including more thin categories can reduce model–data agreement in summer in the central Arctic, related to an overly large sea ice volume in the area [Massonnet et al., 2019].~~

~~Finally, comparison of SIE in simulations and observations suggests that a finer resolution of the thin ice and not of the thick ice increases realism of the simulated Antarctic summer SIE in our model.~~

~~Although the results of all these comparisons present mixed conclusions, depending on the analysis used, we can extract a few take-home messages. First, better resolving the thin ice in the Arctic can hamper SIC representation in the model, potentially related to an unrealistic sea ice volume increase, although it can improve its representation in Antarctica. Second, more thick categories can improve the very thick ice variability in winter in the Arctic, without noticeably compromising the performance in other regions or seasons. Thus, although no clear conclusion is drawn about an optimal number of sea ice~~

~~categories, our analysis does establish that configurations with more than 10 sea ice categories can degrade the realism of the simulated Arctic SIC variability. This appears counter-intuitive, as a finer resolution will allow the sea ice model to reproduce actual sea ice conditions better. Note, however, that NEMO3.6–LIM3 uses parametrizations and parameter values that are developed to reproduce actual sea ice conditions for a 5-category configuration. Changes in the ITD configuration may therefore need re-tuning those parametrizations and parameter values. This is however beyond our scope, as improvements in model SIC variability would hence reflect the new model configurations and not solely the use of a different ITD configuration. In light of our results, we recommend using the standard (S1.05) or similar configuration in NEMO3.6–LIM3, which is, in addition, computationally more efficient.~~

~~Our study and its companion, Massonnet et al. [2019], present an advance with respect to previous efforts, since they jointly address the response of the mean climatological state and variability of the sea ice to a model parametrization. The two studies use ocean stand-alone simulations in their analysis, as to~~With respect to including more thick categories, our analysis shows that it improves variability in very thick sea ice north of Greenland in winter without noticeably compromising the performance in other regions or in summer.

That multiple-category discretizations can degrade model realism appears counter-intuitive, since a finer resolution should allow the sea ice model to reproduce actual sub-grid scale variability in sea ice better. We note, however, that NEMO3.6–LIM3 uses parametrizations and parameter values which are adjusted for the 5-category discretization. Adjustments in the ITD may therefore need retuning those parametrizations and parameter values, which in LIM3 include, among others, the snow thermal conductivity, the bare sea-ice albedo, and the compressive ice strength, P*. Such model retuning is however beyond our scope, as improvements in SIC variability would hence result from the new model setup and not from each different ITD discretization.

Since no robust conclusion about the optimal number of sea ice categories can be drawn based on our analyses, we recommend using the standard (S1.05) or a similar discretization in NEMO3.6–LIM3, which is, in addition, computationally more efficient than others with more categories. This is in line with previous studies finding that discretizations with 5–7 categories represent sea ice characteristics realistically enough [Bitz et al., 2001; Lipscomb, 2001; Massonnet et al., 2019]. As noted by Hunke [2014], however, in the Los Alamos Sea Ice Model CICE "5 ice thickness categories are not enough to accurately represent observed thickness data nor to properly model mechanical sea ice processes that control ice volume."

A growing number of climate model now include a sea ice model with an ITD, such as LIM3, the Los Alamos Sea Ice Model CICE [Hunke et al., 2013], and the GFDL's SIS2.0 [Adcroft et al., 2019], and the prospect is that more will do so in the future. Although including an ITD has been proven to be beneficial for simulating more realistic sea ice characteristics [e.g., Bitz et al., 2001; Holland et al., 2006; Massonnet et al., 2011; Ungermann et al., 2017; Uotila et al., 2017], it introduces potential new tuning options, such as the number of categories, their boundaries, and the assumed shape function, which might need further validation against observations. A very fine ITD also makes simulation computationally very expensive, a factor that is particularly limiting in fully coupled models. Similar analyses to the one presented here would therefore be necessary to assess the impact of using a specific ITD discretization in a particular climate model. The extent to which our particular recommendation for NEMO3.6–LIM3 can be extended to other sea ice models is difficult to assess, however, considering that new tuning might be necessary for each ITD discretization, and that different sea ice models might have different tuning parameters and sensitivity to their values.

A potential caveat of our study is the use of ocean stand-alone simulations. These are aimed to reduce potential ~~sources of uncertainty~~uncertainty sources in SIC variability ~~given by~~associated with stochastic atmospheric noise, which might mask comparison with observations and the search for improvements in model realism. An open question for future studies is ~~therefore~~then whether our conclusions would hold in coupled model configurations, where ice-atmosphere feedbacks ~~may play a role in modulating the impact of the different ITD configurations. Despite the potential caveats, our joint approach can set~~might modulate the influence of ITD discretization. We propose an analysis focused on the impacts on sea ice and surface energy flux seasonal cycles, variability modes, and long-term trends, similar to this study and its companion paper, Massonnet et al. [2019]. The cost and benefits of such an analysis in coupled setups should however be weighted carefully beforehand, considering the limited impacts we find in ocean stand-alone simulations and the increase in computational costs for ITD discretizations with large numbers of categories.

This study and its companion, Massonnet et al. [2019], present an advance with respect to previous efforts since they jointly address the response of the mean climatological state and variability of sea ice to changes in a model parametrization. This approach sets an example for future assessments of the impact of model parametrizations on the representation of the sea ice or other climatic variables. Unfortunately, observational data are still too short for many climate components, ~~and~~making this sort of analysis ~~is therefore~~particularly challenging at most.

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Code/Data availability. The model source code is available at https://doi.org/10.5281/zenodo.3345604. Data and code to reproduce the authors' work can be obtained from https://doi.org/10.5281/zenodo.3540756.

Author contributions. EMC and PO conceived the study. FM provided the model data. EMC analysed the model and observational data and wrote the manuscript with contributions from all authors. All authors contributed to interpreting the results.

Competing interests. The authors declare that they have no competing interests.

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