Simultaneous Parameter Optimization of an Arctic Sea Ice–Ocean Model by a Genetic Algorithm

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ABSTRACT

Improvement and optimization of numerical sea ice models are of great relevance for understanding the role of sea ice in the climate system. They are also a prerequisite for meaningful prediction. To improve the simulated sea ice properties, we develop an objective parameter optimization system for a coupled sea ice–ocean model based on a genetic algorithm. To take the interrelation of dynamic and thermodynamic model parameters into account, the system is set up to optimize 15 model parameters simultaneously. The optimization is minimizing a cost function composed of the model–observation misfit of three sea ice quantities (concentration, drift, and thickness). The system is applied for a domain covering the entire Arctic and northern North Atlantic Ocean with an optimization window of about two decades (1990–2012). It successfully improves the simulated sea ice properties not only during the period of optimization but also in a validation period (2013–16). The similarity of the final values of the cost function and the resulting sea ice fields from a set of 11 independent optimizations suggest that the obtained sea ice fields are close to the best possible achievable by the current model setup, which allows us to identify limitations of the model formulation. The optimized parameters are applied for a simulation with a higher-resolution model to examine a portability of the parameters. The result shows good portability, while at the same time, it shows the importance of the oceanic conditions for the portability.

1. Introduction

Sea ice plays an important role in the Arctic climate system. It reflects larger amounts of solar radiation than the open ocean and it substantially modulates the exchange of heat, freshwater, and momentum between the

ocean and the atmosphere (e.g., Wadhams 2002; McPhee 2008; Thomas and Dieckmann 2009). Well-adjusted sea ice models are thus necessary for climate studies (Budikova 2009; Overland 2016), and for the further development of climate models (Notz 2015; Notz et al. 2016). Comprehensive large-scale sea ice models have been developed and applied to a variety of studies focusing on climate for more than three decades (Hunke et al. 2010). However, even state-of-the-art models differ substantially in the simulated ice properties and exhibit pronounced biases in comparison with observations (Rothrock et al. 2003; Rampal et al. 2011; Stroeve et al. 2007, 2012; Uotila et al. 2019). Ceaseless efforts are ongoing to improve parameterizations of dynamic and thermodynamic processes in sea ice models (e.g., Juricke et al. 2013;

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Tsamados et al. 2013; Ungermann et al. 2017), and to find optimal parameters for corresponding parameterizations and model configurations (e.g., Miller et al. 2006; Nguyen et al. 2011; Docquier et al. 2017).

An exploration of optimal parameters for a certain model configuration is a nontrivial and iterative task (Holland et al. 1993; Chapman et al. 1994; Kim et al. 2006). Miller et al. (2007) pointed out that the optimal sea ice model parameters are dependent on the atmospheric forcing, to compensate for deficiencies in the forcing data, for example, snow/ice albedo parameters have to compensate for biases in the radiative forcing (Eisenman et al. 2007). This means a re-exploration of the optimal parameters is necessary for every alteration/update of the atmospheric forcing. Also the implementation of new physical schemes requires the re-examination of all relevant parameters (e.g., Massonnet et al. 2011), since the optimality of individual parameters depends on the other parameters (i.e., optimal parameters are interrelated; Chapman et al. 1994; Posselt and Vukicevic 2010; McLay and Liu 2014). The introduction of new observational data products, in addition, offers opportunities for further validation/examination of the optimal parameters. For these reasons modelers need efficient and automated parameter optimization algorithms.

Studies exploring optimal parameters have been based initially on sensitivity experiments, in which an individual parameter is varied and the other parameters are kept constant (Shine and Henderson-Sellers 1985; Ledley 1991a,b; Holland et al. 1993), while later multivariate sensitivity experiments took into account the interdependence of the model parameters (Chapman et al. 1994; Harder and Fischer 1999; Miller et al. 2006). Although this is a suitable approach to examine the interrelation between a few parameters, it is not a feasible approach for larger numbers of tuning parameters n , because the number of necessary sensitivity experiments increases with the n th power. In recent years, more sophisticated approaches using automatic parameter optimization by data assimilation methods have been introduced (Nguyen et al. 2011; Sumata et al. 2013; Massonnet et al. 2014). Data assimilation synthesizes observed data and modeled physics based on statistical theory (Wunsch 2006, Blayo et al. 2015): a control vector composed of model parameters is optimized to minimize the model–observation misfit normalized by the observation uncertainty (cost function). Nguyen et al. (2011) applied the Green's function approach to optimize 13 model parameters, initial and surface boundary conditions simultaneously. They reported a large reduction of the value of the cost function, although stopped the process after only one iteration (i.e., did not receive an optimal set of parameters).

Massonnet et al. (2014) applied the ensemble Kalman filter (EnKF) method to optimize three dynamic sea ice model parameters, and reported a large reduction of the sea ice drift speed bias. Sumata et al. (2013) compared the efficiency of two different optimization methods; the gradient descent and genetic algorithm for seven parameters. The study showed that a stochastic approach (genetic algorithm) is more suitable to find the global minimum of a structurally complicated cost function than the gradient descent approach.

In the framework of data assimilation, a parameter optimization is regarded as a search problem of the global minimum of the cost function. Since even a single model parameter strongly influences the modeled sea ice properties, a combination of many parameters gives rise to a complicated structure of a cost function; for example, Hunke (2010) showed that multiple combinations of parameter values can produce the same mean ice thickness using the Los Alamos Sea ice Model. If a cost function has a complicated structure (e.g., many local minima and steep spikes), the exploration of the global minimum is a nontrivial task. A search algorithm based on gradient descent approaches is likely to get stuck at local minima. For explorations of complicated cost functions, stochastic approaches (e.g., simulated annealing, genetic algorithm) have generally clear advantages. Stochastic approaches have been widely applied for parameter optimizations in other research areas, such as biogeochemical modeling (e.g., Athias et al. 2000; Schartau and Oschlies 2003; Shigemitsu et al. 2012), whereas they have not been applied to parameter optimizations of general circulation models (GCMs), presumably due to their excessive demands on computational resources. Recently Sumata et al. (2013) applied a micro genetic algorithm (mGA), a small population version of the genetic algorithm, to a parameter optimization of a coupled sea ice–ocean model with a short (1 yr) optimization window. They reported that the mGA can be used for parameter optimizations of GCMs on modern parallel computing environments.

This study presents a method to improve simulated climatology, trend, and interannual variability of sea ice models based on the previous work of Sumata et al. (2013). The improvements are achieved by simultaneous optimization of 15 dynamic and thermodynamic model parameters. Three observed sea ice properties (concentration, drift, and thickness) covering the entire Arctic Ocean over more than two decades are used to define the cost function. The optimizations are performed by an mGA, and the uniqueness of the minima of the cost function is assessed by a series of independent experiments. To reduce the computational burden of the mGA method, we utilize a low-resolution model

FIG. 1. (a) Model domain including names of topographies mentioned in the main text. (b) The time line of the model integration window.

(~ 55 km) for the optimization and apply the optimized parameter sets later to a medium-resolution model (~ 28 km). Note, that this study is not intended to perform a state estimation, but to examine to what extent models can be improved just by optimizing its parameters. Inspections of the residual model–observation misfit and deviation of the optimized parameter values from physical reasonable values will guide the identification of the limits of the current model set up (e.g., boundary conditions, physical processes formulation) and further model development. We show 1) that the approach successfully improves the modeled climatology, trend and interannual variability, and 2) that the optimized parameters can be transferred to a higher-resolution model. The optimality of the solution will be discussed by invoking results from additional optimization experiments. The paper is organized as follows: section 2 describes the methodology and experimental design, section 3 describes the results of the optimizations, section 4 contains a discussion, and the paper ends with the conclusions (section 5).

2. Experiment design

a. Coupled sea ice–ocean model

We apply a regional sea ice–ocean model of the Arctic and northern North Atlantic Ocean [North Atlantic/Arctic Ocean Sea Ice Model (NAOSIM)] developed at the Alfred Wegener Institute (Gerdes et al. 2003; Kauker et al. 2005; Karcher et al. 2007, 2011). The sea ice part of the model uses the viscous plastic (VP) rheology (Hibler 1979; Harder 1996). The thermodynamics of sea ice and snow is given by the so-called zero-layer

formulation (Semtner 1976) and the implementation is based on Owens and Lemke (1990) with some modifications [e.g., implementation of ridging like in Flato and Hibler (1991); a subgrid-scale parameterization of ice thickness following Castro-Morales et al. (2014)]. A complete set of the dynamic and thermodynamic equations for the sea ice model is provided in the online supplemental material. The ocean part of the model is based on the Modular Ocean Model, version 2 (MOM-2), developed at the Geophysical Fluid Dynamics Laboratory (Pacanowski 1995), and is coupled to the sea ice following the formulation of Hibler and Bryan (1987). The model is formulated on a spherical rotated grid covering the whole Arctic and the North Atlantic Ocean north of approximately 50°N (Fig. 1a). The geographical North Pole is shifted to 60°E on the equator to realize nearly equidistant grid cells over the model domain. For the current study, we employ a low- and a medium-resolution version of NAOSIM. The low-resolution version (hereafter LR, horizontal resolution of $55\text{ km} \times 55\text{ km}$ and 20 levels in the vertical; Kauker et al. 2009; Sumata et al. 2013) is applied for the parameter optimization experiments, while the medium-resolution version (hereafter MR, $28\text{ km} \times 28\text{ km}$ with 30 levels; Gerdes et al. 2003; Karcher et al. 2012) is used to assess the portability of the optimized parameters to different model resolutions.

For the LR model, an open boundary condition has been implemented along the Atlantic sector of the model boundary following Stevens (1991), while in the Pacific sector the Bering Strait is treated as a closed wall. Temperature and salinity at inflow points of the Atlantic sector are restored toward the Polar Science Center Hydrographic Climatology (PHC; Steele et al. 2001), and barotropic velocities normal to the boundary are

TABLE 1. Dynamic and thermodynamic model parameters applied for the optimization.

Name	Short description	Lower bound	Upper bound	Increment	CTRL run
h_0	Demarcation thickness between thin and thick ice for ice compactness equation (m)	0.1	1.0	8.798×10^{-4}	0.5
P^*	Ice compressive strength constant (N m^{-2})	1.0×10^4	5.0×10^4	3.91×10	2.5×10^4
C_{dwin}	Wind drag coefficient	0.5×10^{-3}	2.5×10^{-3}	1.955×10^{-6}	1.1×10^{-3}
C_{dwat}	Water drag coefficient	3.5×10^{-3}	8.5×10^{-3}	4.888×10^{-6}	5.5×10^{-3}
C_{lat}	Latent heat transfer coefficient	1.0×10^{-3}	2.5×10^{-3}	1.466×10^{-6}	1.75×10^{-3}
C_{sens}	Sensible heat transfer coefficient	1.25×10^{-3}	2.5×10^{-3}	1.222×10^{-6}	1.75×10^{-3}
α_s	Snow albedo	0.65	0.95	2.933×10^{-4}	0.8
α_{sm}	Albedo of melting snow	0.65	0.95	2.933×10^{-4}	0.77
α_i	Ice albedo	0.65	0.95	2.933×10^{-4}	0.65
α_{im}	Albedo of melting ice	0.65	0.95	2.933×10^{-4}	0.68
C^*	Ice strength decay constant	5.0	20.0	1.466×10^{-2}	10.0
C_{melt}	Area melting constant for ice compactness equation	0.1	1.0	8.798×10^{-4}	0.5
α_w	Albedo of seawater	0.05	0.45	3.91×10^{-4}	0.1
κ_H	Oceanic vertical diffusion coefficient ($\text{cm}^2 \text{s}^{-1}$)	0.0	1.0	9.775×10^{-4}	0.0
e	Eccentricity of the yield curve describing the viscous-plastic rheology	1.5	2.3	7.82×10^{-4}	2.0

specified from a model version covering the entire Arctic and Atlantic Ocean north of 20°S (Köberle and Gerdes 2003). The MR model employs the same open boundary condition along the Atlantic sector, while in the Pacific sector Bering Strait is treated as an open boundary (monthly climatological influx, temperature and salinity). Other than a finer topography (especially in the Canadian Archipelago) and the open Bering Strait, the MR model differs from the LR model by the implementation of a biharmonic diffusion of momentum to better represent the ocean circulation (Karcher et al. 2003). The sea ice part of the model is identical to that of the LR model with respect to process formulations and parameter values.

The initial condition (year 1980) of the current optimization experiments is given by a 32-yr integration (1948–80) with NCEP–NCAR reanalysis forcing (Kalnay et al. 1996) starting from temperature and salinity fields given by the PHC climatology and 100% sea ice concentration with 2 m thickness in regions where the sea surface temperature lies below the freezing point temperature of seawater. The model is driven by daily forcing of 2-m air temperature, 2-m specific humidity, downward long- and shortwave radiation, 10-m surface wind, and total precipitation from the NCEP Climate Forecast System Reanalysis (NCEP-CFSR; Saha et al. 2010) for 1980 to 2010 and from the NCEP Climate Forecast System, version 2 (NCEP-CFSv2; Saha et al. 2014), for 2011–16.

b. Model parameters selected for optimization

We selected 15 sea ice and ocean model parameters for the optimization (Table 1), which have been identified in advance by our sensitivity experiments to have a

considerable impact on the sea ice properties. The selected dynamic parameters of the sea ice model are: ice compressive strength constant P^* ; ice strength decay constant C^* ; eccentricity of the yield curve describing the VP-rheology e ; wind and water drag coefficients, C_{dwin} and C_{dwat} . The ice strength constant P^* and the drag coefficients (C_{dwin} and C_{dwat}) are considered as key tuning parameters to obtain a realistic horizontal sea ice distribution, and optimal values have been investigated in many studies (Chapman et al. 1994; Harder and Fischer 1999; Massonnet et al. 2014). The ice strength decay constant C^* defines the exponential decay of the ice strength with decreasing sea ice concentration. Since C^* parameterizes the subgrid-scale interaction between ice strength and concentration, it is considered as a tuning parameter (Holland et al. 1993; Dumont et al. 2009). The eccentricity of the yield curve (e) defines the ratio between compressive strength and shear strength of sea ice. Miller et al. (2005) reported that reducing the eccentricity from the value proposed by Hibler (1979) improved the ice thickness contrast between Beaufort Sea and North Pole in the Los Alamos Sea Ice Model. In addition Bouchat and Tremblay (2017) showed that reducing the eccentricity gives a better agreement of modeled shear and divergence distributions with those derived from the RadarSat Geophysical Processor System.

The selected thermodynamic parameters are snow and ice albedo for freezing and melting conditions (α_s , α_{sm} , α_i , α_{im}); latent and sensible heat transfer coefficients, C_{lat} and C_{sens} ; demarcation thickness between thin and thick ice h_0 ; and area melting constant for ice compactness equation C_{melt} . The sea ice and snow

albedo are the key parameters to regulate the heat budget of the sea ice model, and the optimal values for various formulation have been extensively examined (e.g., Kim et al. 2006; Miller et al. 2006, 2007; Uotila et al. 2012). The latent and sensible heat transfer coefficients are important parameters regulating the thermodynamic equations. We select these parameters since the optimal values of these parameters for a specific year largely differ from our control values (Sumata et al. 2013). The demarcation thickness between thin and thick ice, h_0 , first introduced by Hibler (1979), appears in the ice compactness equation to define the thickness of newly formed ice under freezing condition. It is considered as a tuning parameter, since it represents the unresolved sea ice formation processes in the model (e.g., Nguyen et al. 2011). The area melting constant for the ice compactness equation, C_{melt} , is introduced for the ice thickness distribution parameterization of Castro-Morales et al. (2014). In that parameterization a spatially and temporally fixed distribution with 15 ice classes based on EM (electromagnetic induction sounding) sea ice thickness observation (Haas et al. 2010) is used. The area melting constant C_{melt} is related to the occupation of the lowest ice class. Since EM measurements have difficulties to distinguish between very thin ice [$O(10)$ cm] and open water, the occupation of the lowest ice class is very uncertain. Therefore C_{melt} is used as a tuning parameter. It is a unitless parameter to relate ice volume reduction to ice concentration reduction [see also Eq. (A20) in the supplemental material]. For the 7 equally distributed ice classes of Hibler (1979), C_{melt} is determined to be 0.5 by geometrical reasons.

Two ocean parameters are taken into account as well: the albedo of seawater α_w and the oceanic vertical diffusion coefficient κ_H . The albedo of seawater has a large effect on the sea ice albedo feedback and the vertical diffusion coefficient κ_H regulates the heat exchange between the mixed layer and the deeper stratified ocean.

c. Observational data

We implement basin-wide observations of three sea ice variables into the cost function of the optimization: concentration, thickness, and drift.

1) SEA ICE CONCENTRATION

The concentration dataset employed is the low-resolution product OSI-409/OSI-409a (version 1.2; Eastwood et al. 2017) provided by the European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT) Ocean and Sea Ice Satellite Application Facility (OSI SAF). The concentration is derived from brightness temperatures obtained from various satellite sensors

[Scanning Multichannel Microwave Radiometer (SMMR), Special Sensor Microwave Imager (SSM/I), Special Sensor Microwave Imager/Sounder (SSMIS)] with corrections for wind roughening and water vapor effect. The dataset contains daily mean concentration and associated error estimates on a polar stereographic grid with a horizontal resolution of 10 km and covers the entire Arctic Ocean. The data cover the time period from October 1978 to April 2015. We process the daily data to monthly mean data on the model grid to facilitate the cost function calculation described in section 2d. Since we have no information on the temporal error covariance, we define the error of the monthly mean ice concentration by the average of error of the daily data as a tentative approach. Spatially we assume no error covariance (i.e., we assume that the error is spatially independent). The monthly mean ice concentration and associated errors for 23 years (1990–2012) are used to define the cost function.

2) SEA ICE DRIFT

The drift data are taken from three different products covering the Arctic basin: OSI-405 (Laverne et al. 2010), the sea ice motion estimates by Kimura et al. (2013), and the Polar Pathfinder Daily 25 km EASE-Grid Sea Ice Motion Vectors, version 2 (hereafter referred to as NSIDCv2) (Tschudi et al. 2010; Fowler et al. 2013). OSI-405 is a combination of a single-sensor product derived from the Advanced Microwave Scanning Radiometer of the Earth Observation System (AMSR-E) for the period 2002–06 and a multisensor product derived from passive microwave sensors (e.g., SSM/I, AMSR-E) and Advanced Scatterometer for the period after 2006. The sea ice motion estimates by Kimura et al. (2013) is derived from brightness temperature maps of AMSR-E 89 GHz H/V polarization channels for winter seasons, whereas the summer ice drift (from May to November) is obtained from those of 18.7 GHz channels. NSIDCv2's drift data are deduced from a variety of satellite-borne sensors [Advanced Very High Resolution Radiometer (AVHRR), SMMR, SSM/I, and AMSR-E, in situ observations from the International Arctic Buoy Program (IABP; Colony and Thorndike 1984)] and takes wind effects on the ice motion into account (Thorndike and Colony 1982). Sumata et al. (2014) compared these products and discussed its advantages and weaknesses: OSI-405 has the smallest uncertainty among the products, while the spatial coverage is also the smallest. Ice drift in summer was not available from OSI SAF for the study (but will be delivered in the near future; T. Laverne, Met Norway, 2018, personal communication), and the temporal coverage is limited (the dataset does not cover the period before November 2002). The ice motion estimates

FIG. 2. Schematic flow diagram of the genetic algorithm optimization system; $\vec{p}_m^n$ denotes the genotype (parameter set) of the m th individual at n th generation. See main text for description.

by Kimura et al. (2013) gives a larger spatial coverage than OSI-405 and provides ice drift for summer seasons with smaller uncertainty than NSIDCv2 (Sumata et al. 2015a). NSIDCv2 exhibits the largest uncertainty among the three products (Sumata et al. 2015b) and exhibits patchy ice drift fields associated with merging of buoy-based and satellite-based ice motions (Szanyi et al. 2016). Regardless of such shortcomings, NSIDCv2 is the only product which covers the entire period of satellite operation (from 1978). We combine the three products to take their full advantage: The combined ice drift dataset employs OSI-405 if data are

available, uses drift by Kimura et al. (2013) for the summer months, and NSIDCv2 is utilized for the times uncovered by the other two products (before 2002 and summer ice drift for 2011–12). Sumata et al. (2015b) reported biases of the drift from these products, which we take into account. We calculate monthly mean drift from the combined dataset and implement the cost function for 1990–2012.

3) SEA ICE THICKNESS

The thickness observation is taken from the basin wide ice thickness estimate by Lindsay and Schweiger (2015).

FIG. 3. (a) Seasonal cycle and (b) temporal variation of sea ice extent from CTRL, OPT, and observation. The sea ice extent is defined by 15% sea ice cover on monthly basis. In (a), interquartile range of the individual years is shown as shading.

The construction of their estimate is based on a least squares multiple regression model [Ice Thickness Regression Procedure (ITRP; Rothrock et al. 2008)]. The original data used for the regression model are obtained from upward-looking sonars mounted on submarines or moorings, electromagnetic sensors on helicopters or aircraft, lidar or radar altimeters on airplanes or satellites. Based on these data Lindsay and Schweiger (2015) provided a comprehensive ice thickness estimate covering the Arctic basin for the period 2000–12 all year-round with associated errors of the regression. However, because only lower-order polynomials in space and time are statistically significant, the ice thickness from the ITRP is spatially smoothed (detectable for instance north of the Fram Strait) and does not contain interannual variability except for a nonlinear trend. Nevertheless, the thickness from the ITRP is assumed to be the most reliable long-term Arctic Ocean wide dataset for the time being. We calculate monthly mean ice thickness and associated errors on each model grid cells based on the regression model. An ice area mask based on the ICESat ice thickness product (Kwok et al. 2009) is applied to exclude the area without any input data for the regression model (e.g., south of the Fram Strait, the Barents Sea). Before the data are applied we examined the seasonal cycle of the ITRP thickness and found that the maximum thickness occurs in June, presumably an artifact coming from the regression procedure with only few input data in summer. To avoid constraining the model by erroneous thickness data in summer, we exclude these months and use the thickness estimates only from October to May.

d. Cost function

As a metric of the model–observation misfit, we introduce the cost function:

$$J = \frac{1}{2} [\mathbf{d} - \mathbf{b} - H(\mathbf{p})]^T \mathbf{R}^{-1} [\mathbf{d} - \mathbf{b} - H(\mathbf{p})], \quad (1)$$

where $\mathbf{d} = [d_1, d_2, \dots, d_N]^T$ is the observation vector composed of monthly mean value of concentration, thickness, and drift at each model grid point in each month covered by observations; $\mathbf{b} = [b_1, b_2, \dots, b_N]^T$ is the bias vector (defined for drift only); $\mathbf{p} = [p_1, p_2, \dots, p_{15}]^T$ is the control vector composed of the 15 model parameters (section 2b); H is the observation operator, which maps the control vector to modeled monthly mean sea ice quantities (i.e., running the full nonlinear model described in section 2a with a parameter set $\mathbf{p}$ and calculating counterparts to the observed data); and $\mathbf{R}$ is the uncertainty covariance matrix of the observations. Since spatial and temporal correlation of the observational errors are not known, we assume the errors to be uncorrelated (i.e., we take into account only the diagonal elements of the matrix $\mathbf{R}$). To realize equal contributions from the three sea ice quantities to the cost function (otherwise the concentration would dominate the cost function because it has the lowest relative uncertainty), we normalize the contributions from the respective quantities by those calculated from a reference experiment (control run; described in section 2f), that is, the total cost for the reference experiment is 3.0 (each component is normalized). This definition makes it easy to compare the reduction of the cost with regard to the respective sea ice quantities, although we have to admit that we are losing objectivity. The minimum value of the cost function is examined by the method described in section 2e.

Different from the cost function used for state estimation, the cost defined here takes neither a prior term nor model errors into account. The exclusion of the prior term allows us to explore the entire parameter space (with some restrictions explained later) without preferring “physical”

Winter mean sea ice concentration (Feb., Mar., Apr.), 1990-2012

Summer mean sea ice concentration (Aug., Sep., Oct.), 1990-2012

FIG. 4. (a)–(c) Winter and (d)–(f) summer mean sea ice concentration from (left) CTRL, (middle) OPT, and (right) observation.

or empirical values. Together with the omission of the model errors, every shortcoming of the modeling system (the model and the boundary conditions) will thus be reflected in the optimal parameters. In the aftermath the inspection of the optimal parameters can provide us information on missing physical processes and/or forcing biases.

e. Genetic algorithm

We apply a microgenetic algorithm (mGA) to minimize the cost function. Genetic algorithms (GAs) are global optimization algorithms based on the natural selection of living things (Holland 1975; Goldberg 1989) and mGA is a small-population version of the GAs (e.g., Athias et al. 2000). GAs are suitable for extrema search of ill-shaped or multimodal functions, and the mGA is particularly suitable for object functions requiring huge

computational resources (Krishnakumar 1989; Kim et al. 2002). The mGA minimizes the cost function by the following procedure (Fig. 2): 1) A prescribed number of individuals are prepared. A genotype of each individual represents a single set of parameters, which is realized by encoding the real numbers of the control vector into a binary bit string. 2) An assessment of fitness of each individual is performed by model simulations and subsequent cost function evaluation. 3) A selection is performed by retaining the fittest individual (i.e., the individual with the lowest cost function) and dismissing the other. 4) A new generation is prepared from the fittest individual and some other individual from the previous generation. In this process, the bit strings representing the genotypes of the two individuals are randomly merged. Since the fittest individual from the previous generation always enters this process, it

FIG. 5. Sea ice extent of CTRL, OPT, and observation in September (top) from 1990 to 2000 (every 5 years) and (bottom) the record minimum in 2007 and 2012. The sea ice extent is defined by 15% sea ice cover on monthly basis.

influences the direction of the evolution. 5) The convergence of the genotype of the new generation is assessed by evaluating the differences in the cost functions and if it is smaller than a prescribed threshold, 6) a re-initialization is performed. The fittest automatically survives and enter the next generation. If the difference in the cost functions is larger than the threshold, the process steps 2–4 are repeated. A more comprehensive explanation of the mGA and its implementation for parameter optimization of a coupled sea ice–ocean model are described in Sumata et al. (2013).

For the application of the mGA, we prescribe possible ranges of the respective parameters by upper and lower bounds (Table 1). The spanned range is deliberately defined very large to allow the algorithm to explore a vast parameter space, while some “weak” constraints are applied (e.g., negative values are not allowed for all parameters, albedos should not exceed 1). The parameter ranges are discretized with 512 values, that is, a parameter value is represented by a 9-bit genotype

($2^9 = 512$). The increments for the respective parameters are shown as well in Table 1. Altogether the mGA explores a parameter space composed of 15 parameters with 512 possible values for each (approximately 4.36×10^{40} possible values in total). We use a population size of 6 (the number of individuals in each generation) motivated by our earlier study (Sumata et al. 2013). The number of generations (number of iterations) is 1000, which is more than 2 times larger than in our previous study.

f. Optimization experiment

An optimization experiment is performed using the LR model. The MR model is used to test the portability of the optimal parameters obtained from the LR model. The model integration length is 37 years (1980–2016, Fig. 1b) where the first 10 years (1980–89) are used as spinup time to allow the sea ice and upper ocean to adjust to the new parameters (certainly the deeper ocean is not adjusted after 10 years but that is tolerated because we are mainly interested in the sea ice and

Ice concentration in September, 1995

Ice concentration in September, 2007

Ice concentration in September, 2012

FIG. 6. Examples of monthly mean sea ice concentration from (left) CTRL, (middle) OPT, and (right) observation in September from the mid-1990s (1995) and the record minimum in 2007 and 2012.

Cyclonic sea ice motion in summer: August, 2006

Anticyclonic sea ice motion in summer: June, 2007

FIG. 7. Examples of (top) cyclonic and (bottom) anticyclonic sea ice motion field in summer from (left) CTRL, (middle) OPT, and (right) observation. The cyclonic (anticyclonic) fields come from monthly mean sea ice motion in August 2006 (June 2007). For a comparison purpose, the same area mask taken from observational data is applied for the modeled ice drift fields.

upper ocean here). All-year-round observed sea ice concentration and sea ice drift (section 2c) are assimilated in the following 23 years (1990–2012), while sea ice thickness is assimilated in the last 13 years of the window (2000–12) in the winter months [October–April; see section 2c(3)]. The last 4 years of the simulations (2013–16) are used as independent validation data. We also conduct a reference experiment (a control run), for which the standard parameter values for the model (Sumata et al. 2013) are used (see Table 1). The cost function calculated from the control run is used as a reference to assess the reduction of the cost function by the optimizations. Hereafter the optimized model run is referred as OPT, while the control run is referred as CTRL.

In addition to the above experiments, we conduct a set of 10 independent optimization experiments with the

LR model to test the optimality of the solution (asymptotic reduction of the cost toward a unique minimum). Each optimization starts from randomly chosen parameter sets by using different seeds for the creation of the random numbers, that is, each optimization carries out a search of the minimum cost from a different starting point along a different search path. The result from the additional 10 optimization experiments is used to assess the optimality of the solution.

3. Result

a. Optimized sea ice variables

The optimization experiment successfully reduces the total cost function and the costs of the respective ice

Cyclonic sea ice motion in winter: January, 2009

Anticyclonic sea ice motion in winter: February, 2010

FIG. 8. As in Fig. 7, but for winter ice drift field. The cyclonic (anticyclonic) fields come from monthly mean sea ice motion in January 2009 (February 2010).

properties simultaneously. Large reduction of the cost occurs in the first 50 generations and the reduction rate decreases with the progressing number of generations. The reduction of the cost after the 200th generation is very small. Since a further reduction of the cost hardly occurs after the 600th generation, we stop the optimization at the 1000th generation. General features of the reduction of the cost will be discussed in conjunction with the optimality of the solution in section 4a. The sea ice fields obtained from the 1000th generation is used for the following analyses.

1) SEA ICE CONCENTRATION AND SEA ICE EXTENT

The optimization reduces the sea ice concentration cost function by approximately 40% in comparison to the cost function of CTRL. CTRL shows a too excessive mean seasonal cycle of the sea ice extent compared to

the seasonal cycle of the extent deduced from the observations; it overestimates by approximately 10% in winter and underestimates by about 30% in summer (Fig. 3a). In the 1990–2012 mean, the winter extent is too large east of Greenland and in the eastern part of the Barents Sea (Fig. 4a) and in summer ice extent and concentration are underestimated in the western Canadian basin and the Eurasian basin in comparison to observations (Fig. 4d). OPT reduces all spatial biases (Figs. 4b,e) and the bias of the mean seasonal cycle (Fig. 3a). The spread of its interannual variations (interquartile range of the individual years is shown as shading in Fig. 3a) encloses that of the observations (Fig. 3a). In particular, the summer sea ice extent of OPT shows remarkably good agreement with the observations from 2000 onward (Fig. 3b). This might be attributed to the quality of the atmospheric forcing, as

since about 2000 much more atmospheric data streams are assimilated in the reanalysis. The improvement is also evident in the spatial patterns of the extent and concentration in individual years (Figs. 5, 6). The optimized simulation captures the observed spatial patterns of the extent much better than CTRL, although biases remain as for example in 2012 (Fig. 5). Regardless of the overall improvement of spatial pattern of sea ice concentration, the model still fails to reproduce the sharp gradient of ice concentration near the ice edge in summer (Fig. 6). Note, that the improvements are not limited to the optimization window (1990–2012), but extend over the entire integration period (1980–2016) (Fig. 3b). This shows that the optimized parameter set that is “learned” in the optimization window has improved the representation of the physical sea ice system in a more universal sense.

2) SEA ICE DRIFT

The drift cost function reduces approximately by 10%, which is relatively small compared to the reduction of other cost functions (ice concentration: 40%, ice thickness: 20%). Figure 7 shows examples of cyclonic and anticyclonic drift in summer 2006 and 2007, respectively. In both states, CTRL fails to reproduce the fast sea ice motion ($>8 \text{ cm s}^{-1}$) observed in some areas, while OPT successfully reproduces such fast sea ice motions. In two examples for winter ice drift fields in 2009 and 2010, respectively, we find a general improvement for OPT, while it fails to reproduce fast ice motions as observed those years (Fig. 8). We partly attribute this limitation of the optimization to inconsistencies of the observed sea ice drift. The mean ice drift speed derived from the observational data shows a remarkable speed-up in 2002 (Fig. 9a, black line), which is due to a change in the observational product used. Before 2002, we applied the sea ice drift from NSIDCv2 for the cost function calculation. NSIDCv2 has the largest error and the slowest drift speed among the three drift products employed (Sumata et al. 2014, 2015b), which explains the rapid transition of the mean drift speed occurring in 2002 at the time of the drift product replacement (a drop of drift speed occurs also in 2011–12 as a consequence of the partial use of NSIDCv2; Fig. 9a). Since we constrain the modeled drift by using the respective uncertainties of the observational products in the cost function (Sumata et al. 2015b), the optimization adjusts the model parameters to achieve a better agreement with observations for the period covered by lower-uncertainty products (i.e., after 2002). This is clearly seen in Fig. 9a—the optimization makes the model–observation misfit worse in 1990–2002, while it improves the misfit after 2002 where lower-uncertainty

FIG. 9. Temporal variation of pan-Arctic mean ice drift speed: (a) Interannual variation of annual mean ice drift speed, and (b) seasonal cycle of ice drift speed calculated from 1990 to 2012 and (c) that calculated from 2002 to 2012 period. The seasonal cycles in (b) and (c) are shown by median. The area mask taken from observed ice drift field is applied to the modeled ice drift field for a comparison purpose.

products are employed. The deterioration of the misfit in OPT for 1990–2012 (Fig. 9b) in contrast to an improvement of the misfit after 2002 (Fig. 9c) is also apparent in the mean seasonal cycle. After 2012 the observations show a pronounced speed-up which is not

Winter mean ice thickness (Feb., Mar., Apr.), 1990-2012

Summer mean ice thickness (Aug., Sep., Oct.), 1990-2012

FIG. 10. (top) Winter and (bottom) summer mean sea ice thickness from (left) CTRL, (middle) OPT, and (right) observation.

captured by OPT. There is a discussion ongoing in the science community whether this speed-up is real or an artifact due to the use of different products and/or changes in the motion detection procedure (N. Kimura, NIPR, 2018, personal communication).

3) SEA ICE THICKNESS

OPT successfully reproduces the observed thick sea ice along the northern coast of Greenland and the Canadian Archipelago, both in summer and in winter, which is not captured by CTRL (Fig. 10). In contrast to the distribution of the thick sea ice, OPT does not succeed to reproduce thin sea ice (<1.5 m) over the Siberian shelf in winter. However, it should be noted that the ITRP thickness over the east Siberian shelf is deduced from remote sensing data without any validation by in situ measurements (Lindsay and Schweiger 2015), and needs to be reexamined in future when in situ data in

these regions might be available. A comparison of the model results with monthly mean snapshots of sea ice thickness estimates based on the independent *CryoSat-2* altimeter dataset (Ricker et al. 2014) shows an overall consistency of the thickness distribution with the observations (Fig. 11), although the model still shows a weak negative bias for the thick sea ice (>3 m) around the North Pole. The simulated overestimation of the sea ice thickness on the East Siberian Shelves in OPT, as compared to ITRP, leads to a deterioration of the simulated sea ice volume, particularly in winter (Fig. 12a). We note, however, that the better correspondence to the observations in winter in the case of CTRL occurs as a consequence of the compensation effects of biases of thick versus thin sea ice regions described above. Although the modeled thickness in the melting season (from June to September) is not constrained by observed data, OPT gives thickness

Ice thickness spatial pattern, November, 2010

Ice thickness spatial pattern, March, 2011

FIG. 11. Monthly mean snapshot of ice thickness distribution from (left) CTRL, (middle) OPT, and (right) *CryoSat-2* observation (Ricker et al. 2014) in (top) November 2010 and (bottom) March 2011.

more consistent with the observation from autumn to early winter (October–November) (Fig. 12a). This is also mirrored in the interannual development of the ice volume (Fig. 12b). CTRL and OPT roughly capture the observationally based trend of ice volume loss both in winter and in summer for the thickness optimization window (2000–12). The large underestimation of the summer sea ice volume in CTRL is improved in OPT (still 18% lower than the observational estimate on average), but at the cost of a slight increase of overestimation of OPT in winter (14% higher than the observational estimate).

b. Optimized model parameters

Table 2 lists the optimized model parameters together with their values in CTRL. Some parameters are drastically changed by the optimization (e.g., wind drag

coefficient C_{dwin} , and albedo of seawater α_w), while some are not (e.g., demarcation thickness h_0 , albedo of melting ice α_{im}). The optimization couples the sea ice dynamically stronger to the atmosphere and ocean (larger wind and water drag coefficients; C_{dwin} and C_{dwat}) and makes the sea ice more incompressible and more shear stress resistant (larger P^* and smaller e). Since the values of these optimized dynamic parameters reside within the range suggested by observations (e.g., Overland 1985; Lu et al. 2011), the dynamical processes simulated by the current model setup (process formulations and surface forcing) may capture the essence of those embedded in the observation.

Some of the optimized thermodynamic parameters, on the other hand, give counterintuitive (“unphysical”) values: the albedo of snow under freezing condition (α_s) is slightly smaller than under melting condition (α_{sm})

FIG. 12. (a) Seasonal cycle and (b) temporal variation of mean sea ice thickness from CTRL, OPT, and the observational estimate based on ITRP (Lindsay and Schweiger, 2015). An area mask taken from the ICESat ice thickness product (Kwok et al. 2009) is applied to the mean thickness calculation for a comparison purpose.

and even smaller than the albedo of sea ice under freezing (α_i) and melting (α_{im}) conditions. In the utilized model set up, the four snow and sea ice albedos are supposed to parameterize the observed seasonal cycle of the surface albedo (e.g., Perovich et al. 2002). The optimization, however, leads to optimized values of the four albedos that are unphysical. This result, although unwelcome, help us to identify problems embedded in the current model experiment: the increase of the albedos for melting condition implies either a weakness in the model's process formulation (e.g., a shortcoming associated with the simple zero-layer thermodynamic formulation) or biases in the atmospheric forcing.

The drastic increase of the albedo of seawater (α_w) points also to a missing parameterization. The current model employs a constant for the albedo of seawater, while many studies have suggested variable ocean albedo as a function of zenith angle of solar radiation (e.g., Briegleb et al. 1986), wind speed (e.g., Hansen et al. 1983), and optical depth of the atmosphere (e.g., Jin et al. 2004). Since the albedo of seawater used in CTRL represents that for the mid-latitude ocean, the optimization gives 4 times larger albedo to compensate the effect of the sharp increase of albedo in the high-latitude ocean. The optimized albedo of seawater, on the other hand, imposes an unrealistically large albedo over the southernmost

TABLE 2. Control and optimized model parameters.

Name	Short description	CTRL	OPT
h_0	Demarcation thickness between thin and thick ice for ice compactness equation (m)	0.5	0.5227
P^*	Ice compressive strength constant (N m^{-2})	2.5×10^4	3.019×10^4
C_{dwin}	Wind drag coefficient	1.1×10^{-3}	2.136×10^{-3}
C_{dwt}	Water drag coefficient	5.5×10^{-3}	8.471×10^{-3}
C_{lat}	Latent heat transfer coefficient	1.75×10^{-3}	1.150×10^{-3}
C_{sens}	Sensible heat transfer coefficient	1.75×10^{-3}	1.365×10^{-3}
α_s	Snow albedo	0.8	0.6576
α_{sm}	Albedo of melting snow	0.77	0.6659
α_i	Ice albedo	0.65	0.6870
α_{im}	Albedo of melting ice	0.68	0.6805
C^*	Ice strength decay constant	10.0	9.1390
C_{melt}	Area melting constant for ice compactness equation	0.5	0.3254
α_w	Albedo of seawater	0.1	0.3983
κ_H	Oceanic vertical diffusion coefficient ($\text{cm}^2 \text{s}^{-1}$)	0.0	0.0176
e	Eccentricity of the yield curve describing the viscous-plastic rheology	2.0	1.5016

Winter mean sea ice concentration (Feb., Mar., Apr.), 1990–2012

Summer mean sea ice concentration (Aug., Sep., Oct.), 1990–2012

FIG. 13. As in Fig. 4, but for medium-resolution models.

part of the model domain, indicating sophisticated parameterizations for ocean surface albedo (e.g., those mentioned above) are necessary for models extending over mid- to high-latitude ocean. The appropriateness of the optimized parameters will be further discussed in conjunction with the optimality of the solution in section 4.

c. Application to the medium-resolution model

To examine the portability of the optimized parameters gained from the LR model experiments we test their use in the medium-resolution version of the model (Gerdes et al. 2003; Karcher et al. 2012). Two model runs are carried out; one is the reference run, in which the standard parameter set (CTRL) is used, while for the other run the optimal parameter set (OPT) is applied (hereafter referred to as CTRL-M and OPT-M).

The overall reduction of the cost function (OPT-M relative to CTRL-M) is 29% (ice concentration 43%; ice drift 10%; ice thickness 31%), which is almost the same reduction that has been achieved for the low-resolution model. Similar to the low-resolution case, CTRL-M overestimates the sea ice extent in winter and underestimates it in summer. The overestimation occurs in the Nordic Sea and in the Barents Sea (Fig. 13a), while an underestimation occurs in the Canadian basin and on the entire Eurasian side of the Arctic (Fig. 13d). These biases are clearly cut back in OPT-M, in a similar fashion as that were cut in OPT, although the sea ice concentration in the central Nordic Sea (the so-called Is Odden) remains slightly overestimated (Figs. 13b,e). The ice margin in the Barents Sea in OPT-M (but also in CTRL-M) fits much better to the observations, a fact which we attribute to the better representation of the oceanic heat transport into the Barents Sea (melting more ice at the

Winter mean ice thickness (Feb., Mar., Apr.), 1990-2012

Summer mean ice thickness (Aug., Sep., Oct.), 1990-2012

FIG. 14. As in Fig. 10, but for medium-resolution models.

ice edge) in the medium-resolution model. Spatial patterns of the horizontal sea ice thickness distribution also exhibit clear improvements in winter and in summer (Fig. 14) best seen in the increase of the sea ice thickness along the northern coast of Greenland and the Canadian Archipelago. The overestimation of ice thickness over the Siberian shelf in winter, however, is not reduced in OPT-M. Improvements of the sea ice extent and the ice thickness on the pan-Arctic scale are also evident in their seasonal cycle and interannual variations (Fig. 15); in OPT-M the seasonal cycle of the sea ice extent is much closer to the observations, while OPT-M still shows slightly less sea ice extent in the summer months (Fig. 15a). The interannual variability and trends of the sea ice extent also are closer to the observation (Fig. 15b). Improvements of the seasonal cycle and the interannual variations of the pan-Arctic mean ice drift speed are limited to the period

2002–12 (Figs. 15c,d) for the same reasons as discussed in section 3a(2). An improvement of the seasonal cycle and the interannual variability of the pan-Arctic mean sea ice thickness can be shown for OPT-M (Figs. 15e,f), even though the sea ice thickness is still about 0.5 m thinner than observed in summer (Fig. 15f). In contrast to the overall improvement of the spatial pattern of the summer sea ice extent in OPT (Fig. 5), OPT-M shows only limited improvements in the 1990s (Fig. 16) as a consequence of the too small thickness in summer (see also discussion in section 4d).

4. Discussion

a. Optimality of the solution

Although optimizations using the mGA are less prone to end up in local minima compared to gradient descent approaches (Sumata et al. 2013), the optimality

FIG. 15. (left) Seasonal cycle and (right) interannual variation of (top) sea ice extent, (middle) pan-Arctic mean ice drift speed, and (bottom) mean ice thickness from medium-resolution model experiments.

of the solution is not guaranteed—one cannot obtain the ultimate global minimum of the cost function without testing all possible combinations of the parameter values (4.36×10^{40} model runs would be necessary, which is obviously not doable). In practice, however, one must resort to test the convergence of the cost function and associated sea ice variables by a set of optimization experiments starting from different initial parameter values. For this effort we carried out 10 additional optimization experiments as described in section 2e. The

initial parameter values for the experiments are not sampled using a space-filling strategy (e.g., Latin hypercube sampling), but are purely randomly sampled. Figure 17 shows the evolution of the cost functions and their spread for the 11 optimization experiments (the original experiment plus the additional 10 experiments). The spread is defined by the range of the maximum of the value of the cost function and its minimum in the set of the 11 optimizations in each generation. All experiments show an asymptotic reduction

FIG. 16. As in Fig. 5, but for medium-resolution model.

of the values of the cost function toward (almost) the same value, and none of the optimizations ends up in a local minimum, showing the usefulness of the mGA for the parameter optimization problem of general circulation models. The sea ice variables of the 11 optimizations exhibit strikingly similar climatology, trend, and interannual variability (low to very low spread, see Fig. 18), which underlines the robustness of the results. However, despite the very similar costs and simulated sea ice variables, some of the optimized parameter values largely differ between the different optimizations, suggesting covariability and compensating effects—a feature of sea ice–ocean models that has been shown earlier in other studies (e.g., Miller et al. 2006; Hunke 2010). This issue will be looked at more closely in our follow-up paper.

b. Applicability of the mGA approach

For each iteration (generation) of the optimization algorithm the system requires computational resources

2–3 times larger than a 4DVar system, which is doable by exploiting a modern parallel computing environment. The advantage of this approach compared to the adjoint is the use of the full nonlinear original physical model system, that is, no requirement of building an adjoint code, which linearizes the physical model and might lead to exponentially growing perturbations. Adjoint of sea ice–ocean models has been successfully applied only for a few years assimilation window yet and is very unlikely that the adjoint can be applied for multidecadal windows because the adjoint gets unstable. In comparison with the parameter optimizations using the EnKF approach (e.g., Annan et al. 2005; Massonnet et al. 2014), the mGA approach again requires larger computational resources (approximately one order of magnitude larger than EnKF). Nevertheless, the mGA approach has an advantage when the model shows a strongly nonlinear relation between model state and parameters, for which the EnKF approach requires larger number of ensembles or even has difficulties to

FIG. 17. Evolution of (a) total cost function and costs from (b) ice concentration, (c) ice drift, and (d) ice thickness for the 11 optimization experiments. The dashed line denotes the reference cost from CTRL run. The gray shade denotes spread (the range of maximum – minimum cost) of 11 optimizations.

provide an appropriate solution (Posselt and Bishop 2012). Note that the mGA approach is not directly applicable to optimization problems with a large-size control vector (e.g., optimization of initial and/or boundary conditions or optimization of spatially and/or temporally varying model parameters). For these applications, the mGA approach requires a drastic simplification and/or contraction of the control vector (e.g., by applying an EOF analysis), and therefore other advanced data assimilation approaches (e.g., adjoint or EnKF smoother) have clear advantages.

It is worth noting that the mGA optimizations reached nearly the same value of the cost function after several hundreds of generations, although the current optimization would require $O(10^{40})$ model runs for the full inspection of the parameter space. We argue that such an efficient convergence of the solution is largely due to the nature of the cost function. The number of necessary combinations to achieve a convergence is largely dependent on the shape of the cost function, particularly the smoothness of the local structure of the cost function. Although the cost function used in our study supposedly has a complicated structure on the global scale, the local shape of the cost function is seemingly smooth, at least with respect to the small

changes of just few parameters. This can be seen by the differences of the cost functions at every reinitialization, at which the variation of the genotypes (i.e., variation of the parameter values) is very small and the difference of the corresponding costs is also very small (i.e., a smaller dp gives a smaller dJ ; J is the cost function and p refers to parameters). The smoothness of the cost function at the local scale reduces the number of necessary combinations to be tested, since the algorithm can concentrate to find the “global scale” minima in the parameter space. The efficiency of the mGA approach indicates that the scale of the variation of the cost function in the parameter space is much larger than the discretization step used for each parameter.

c. Limitations of the model setup

Since the final values of the cost function from the independent optimizations are very close to each other, we claim that for practical purpose the sea ice variables shown in section 3 are almost as good as it gets for the given model system [consisting of the model formulation, the surface boundary values and the initial state used at the start of the optimization (1 January 1980)]. The limited improvement of the sea ice drift is partly due to inconsistencies between the three different drift

FIG. 18. Spread of (left) seasonal and (right) interannual variations of (a),(b) sea ice extent and (c),(d) total ice volume obtained from the 11 optimizations. The spread is defined by the range of the maximum – minimum value in the 11 optimizations.

products used but could also be caused by the current drag formulation. More comprehensive formulations of the drag forces for both the atmosphere–sea ice and the sea ice–ocean interfaces might help (e.g., [Lüpkes and Gryanik 2015](#)). The observed thick sea ice (>3 m) around the North Pole is not well reproduced by the optimized simulation. Since thick sea ice is a consequence of accumulated thermodynamic and dynamic effects on the ice, further sophistication of relevant processes is necessary. Unacceptable or unphysical parameter values resulting from the optimization help us to identify the processes which need further improvement. The unphysical combination of the ice and snow albedo values, for example, indicates the necessity of further refinement of thermodynamic processes of the model and/or a more in depth validation of the incoming radiation from the atmospheric reanalysis. The large ocean albedo indicates a requirement of latitudinally variable albedo formulation for realistic heat uptake of the polar ocean. Note, that a refinement of this parameterization (as holds for all changes in the parameterizations) requires to rerun a simultaneous optimization of all relevant sea ice and ocean model parameters. The

automatic mGA parameter optimization system facilitates such an iterative model development effort.

d. Portability of the optimal parameters

The differences of the simulated sea ice properties between LR and MR indicates an important role of the lower boundary condition of the sea ice, namely, the upper ocean state. The most prominent difference between LR and MR occurs in the simulated mean sea ice thickness. The MR model simulates 0.2–0.4-m-thinner sea ice than the LR model over the entire Arctic Ocean in all seasons ([Fig. 19](#)), while the amplitude of the seasonal cycle of ice growth and melt is nearly the same ($<0.1 \text{ m yr}^{-1}$, except in seasonally ice covered area; [Fig. 20](#)). The difference of the equilibrium mean thickness comes from difference of oceanic heat supply to the ice (i.e., the lower boundary condition for the ice). In MR simulations, warmer inflows from the Bering Strait and the Barents and Kara Seas supply more heat to the interior Arctic Basins ([Fig. 21](#)). The warmer inflows provide a warmer lower-boundary condition for the thermodynamic system composed of sea ice and ocean mixed layer. The portability of sea ice model

Difference of sea ice thickness between LR and MR, 1990–2012

FIG. 19. (a),(b) Difference of simulated ice thickness between low-resolution model (LR) and medium-resolution model (MR) in the control runs (CTRL-M - CTRL) and (c),(d) in the optimized runs (OPT-M - OPT). (left) Differences of winter-mean thickness (February–April), and (right) differences of summer-mean thickness (August–October). The solid thin lines denote 0.2, 0.3, and 0.4 contour lines.

parameters is thus limited by the differences in the simulated ocean conditions at shallow-water levels.

5. Conclusions

We introduced an objective parameter optimization system for a coupled sea ice–ocean model to improve the simulated climatology and interannual variability of the sea ice. This is, as far as we know, the first application of a stochastic approach for simultaneous optimization of process parameters of a general circulation model using a multidecadal optimization window. The system performs a simultaneous optimization of 15 dynamic and thermodynamic model parameters to take into account interdependencies of the parameters. A genetic algorithm is applied for the optimization to minimize a

model–observation misfit (cost function) composed of three sea ice properties covering more than two decades. The optimality of the solution is tested by a set of independent optimization experiments, which enables us to confirm an asymptotic reduction of the values of the cost function toward an apparent global minimum. A rapid reduction of the cost occurs in the first 50 generations (iterations), with only little further reduction of the cost function after the 200th generation. We have shown that parameter sets found by the optimization procedure sufficiently improve sea ice simulations, if the model parameters previously are not very well tuned by a systematic approach.

The optimized model parameters improve the three sea ice properties entering the cost function simultaneously. The spatial patterns of simulated sea ice

Difference of dynamic and thermodynamic sea ice melt/growth (OPT-M - OPT), 1990–2012

FIG. 20. Difference of annual (top) thermodynamic and (bottom) dynamic (left) sea ice reduction, (middle) growth, and (right) total growth between MR (OPT-M) and LR (OPT) for 1990–2012 period. In the left column, positive value indicates smaller ice melt/retreat in MR, whereas in the middle and right columns, positive value indicates larger ice growth in MR. The contours denote difference of $\pm 0.1 \text{ m yr}^{-1}$.

concentration, sea ice extent and sea ice thickness improve significantly not only in their climatology but also in their interannual variability. Although the value of the cost function for ice drift reduces, the system could not successfully reproduce fast ice drift speed ($> 8 \text{ cm s}^{-1}$ on monthly basis) in some areas observed in winter, presumably due to inconsistencies of the observed ice drift products or limitations coming from the formulation used in the model.

One notable outcome of our approach is that the system successfully improves the simulated sea ice variables outside the optimization window as well as inside the window. This indicates a potential utility of the optimized parameters for an extended simulation, the time period of which is not covered by validation data. The resulting optimal parameter set is therefore beneficial for further applications such as sea ice outlooks or forecasts (e.g., [Hamilton and Stroeve 2016](#); [Blanchard-Whigglesworth et al. 2017](#)).

The optimal parameters estimated from the low-resolution (LR) model were applied to a medium-resolution model to examine the portability of the parameter sets. Regardless of the different spatial resolution, which for example, imposes different topographic features and ocean boundary conditions, the optimal parameter set estimated from the LR model successfully improves the sea ice properties simulated in the medium-resolution (MR) model run, in a way very similar to that achieved in the LR model. The result indicates that the main sea ice features simulated by the current dynamic and thermodynamic formulations are not very sensitive to the spatial resolution of the model, in the resolution range applied here. However, we also showed that differing oceanic conditions in the two used resolutions had an impact on the response to the optimized parameter sets and thus for the portability of sea ice model parameters.

The present study shows that even a relatively simple sea ice–ocean model (VP rheology with zero-layer

FIG. 21. Difference of mean ocean temperature for 1990–2012 period (0–60-m average) between MR and LR (left) in the control runs (CTRL-M – CTRL) and (right) in the optimized runs (OPT-M – OPT). The vector fields show mean ocean current (1990–2012 period, 0–60-m average) from MR runs. Sea ice mask taken from winter-mean ice concentration for 1990–2012 in the MR runs (concentration >15%) is applied for visibility.

thermodynamics), which has been used for more than two decades, can provide realistic spatial patterns of climatology, trends and interannual variability when the process parameters are optimized in a simultaneous fashion. On the other hand, our results elucidate limitations of the formulations used here. Since the final value of the cost functions obtained by the independent optimizations are very close to each other, we assume that further drastic reduction will not occur and that the optimized ice fields are almost the best that can be achieved by the current model set up (i.e., the present formulation of the ocean and sea ice physics and the employed surface boundary conditions). For further improvement of the simulated fields, refinement of relevant processes and elaboration of forcing fields are necessary (see e.g., Lindsay et al. 2014; Chaudhuri et al. 2014 for discussions on the differences between forcing fields from different reanalysis product).

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