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Climate Models as Guidance for the Design of Observing Systems: the Case of Polar Climate and Sea Ice Prediction

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Abstract

Purpose of review The Arctic and Antarctic are among the regions most exposed to climate change, but ironically, they are also the ones for which the least observations are available. Climate models have been instrumental in completing the big picture. It is generally accepted that observations feed the development of climate models: parameterizations are designed based on empirically observed relationships, climate model predictions are initialized using observational products, and numerical simulations are evaluated given matching observational datasets.

Recent findings Recent research suggests that the opposite also holds: climate models can feed the development of polar observational networks by indicating the type, location, frequency, and timing of measurements that would be most useful for answering a specific scientific question.

Summary Here, we review the foundations of this emerging notion with five cases borrowed from the field of polar prediction with a focus on sea ice (sub-seasonal to centennial time scales). We suggest that climate models, besides their usual purposes, can be used to objectively prioritize future observational needs – if, of course, the limitations of the realism of these models have been recognized. This idea, which has been already extensively exploited in the context of Numerical Weather Prediction, reinforces the notion that observations and models are two sides of the same coin rather than distinct conceptual entities.

Keywords polar regions · observing system design · climate modeling · environmental prediction · emergent constraints · data assimilation · observing system experiments · satellite simulators

Introduction

Numerical models of the climate system, referred collectively to as "climate models" from here on, are cornerstones of climate science because they allow answering questions that observations, or theory alone, cannot address. Climate models fulfill at least three primary purposes. First, they can be exploited to refine our understanding of how the climate system works: How are energy, water, and carbon cycled in the Earth system (1,2)? What are the main spatial and temporal modes of climate variability, from the deep ocean to the upper stratosphere (3)? Second, by offering the possibility to run counterfactual worlds, they can be used to quantify the influence that specific drivers may have on observed climatic events: What is the fraction of global warming attributable to human activities (4)? By how much has the likelihood of an observed extreme event increased due to background climate change (5)? Finally, by simulating the future of the climate system, climate models can be used as a support for adaptation and mitigation policies: Will a world with 2 °C warming above pre-industrial levels be fundamentally different from one with 1.5 °C warming (6)? Is geoengineering a viable solution for offsetting climate change (7)?

Here, we posit that climate models fulfill a fourth essential purpose besides the three listed above: they can help to explore hypotheses regarding the use of existing or potentially new observational data. More specifically, climate models can be used to optimize the design of future observing systems in order to address specific climate-related questions. To support this hypothesis, we take the case of Polar Regions, with the following background scientific question in mind: How can the current

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observing system be enhanced in order to improve polar predictions from months to centuries? Polar prediction is a "textbook example" for illustrating the idea that models can drive the development of observational systems. Indeed, at high latitudes, the observational network is sparse, the demand for environmental predictions is high, and the resources that can be allocated to the deployment of new observing platforms are limited. A rational strategy for the development of cost-effective observation systems is thus desirable, if not required. As will be illustrated in this article, much knowledge can be inherited from methods and concepts developed in Numerical Weather Prediction (NWP).

The current polar observing network provides a mixture of data that can broadly be categorized into two types: in-situ and remote sensing observations. In-situ observations have been collected for decades from automatic weather stations (8), drifting buoys (9,10), moorings (11), oceanographic vessels (12), radiosonde launches (13), aircraft-borne instruments (14,15), submarines (16), instruments onboard unmanned aerial (17) or underwater vehicles (18), among others. These point observations are particularly invaluable to study the interior of the ocean–sea ice system, which cannot be sensed remotely. In-situ observations are not free of errors, but their main limitation for climate applications is their lack of representativeness in time and space, owing to a lack of sufficient spatial coverage and inherent intermittency. On the other hand, remote sensing observations have been collected using passive infrared and microwave instruments onboard satellites (19–21) since the late 1970s, followed later by backscatter, laser (22,23) and radar altimetry (24) measurements since the 1990s. While the raw measurements (e.g., radiances) can be accurate as long as instruments are well-calibrated, the products derived from these measurements can be tainted with significant errors due to uncertainties in the transfer models.

Despite known spatiotemporal gaps and limitations, polar observations have been sufficient to formally detect high-latitude climate changes, e.g., tropospheric and stratospheric warming, Arctic sea ice retreat (25), Northern Hemisphere continental snow cover decline (26), and net mass loss from Greenland (27) and Antarctic (28) ice sheets. However, a question arises: If the observational network is adapted to detect changes that have already happened, is it necessarily adapted for feeding the climate models that will predict future changes?

Polar prediction has received much attention in recent years, sparked by new opportunities but also inevitable risks associated with rapid climate shifts occurring at high-latitudes (29). Here, we refer to "polar prediction" in a broad sense as any tentative to predict the evolution of the atmosphere, the ocean, and the cryosphere on sub-seasonal to centennial time scales (thus as a result of internal climate variability, external forcing, or both), with climate models. In response to the increased interest in polar prediction, the scientific output on the topic has flourished in recent years (Fig. 1), with about 50% of the scientific contributions published since 2014. While prediction skill has overall improved in many components (atmosphere, sea ice, ocean), a key limitation is the lack of satisfactory observational data, whether it is for improving process-based models, for initializing predictions or for verifying them (30).

The goal of this article is not to provide actual recommendations regarding future polar observing systems, but instead to demonstrate that a wealth of conceptual tools, most of them directly inherited from NWP, can be used to improve current observing systems in order to eventually address climate-related questions in Polar Regions. We illustrate this idea with five concrete cases drawing from the recent literature on polar and sea ice prediction:

- Case 1 *Observing System (Simulation) Experiments and Quantitative Network Design*. Climate models can be used to test the influence that an existing type of observations, or a hypothetical new type of observations, has on prediction skill.
- Case 2 *Emulation of satellites and their retrieval algorithms*. Climate models can be used to explore how assumptions in satellite retrieval algorithms (choice of transfer model, values of geophysical parameters) affect the final observational product.
- Case 3 *Constraining long-term projections*. Climate models can be used to identify the observational gaps that, if filled, would allow reducing uncertainty in projected changes thanks to improved model evaluation and selection.
- Case 4 *Evaluation of observational products*. Climate models can be used to evaluate the reliability and quality of large-scale observational products (satellite data, reanalyses, re-gridded datasets).
- Case 5 *Strategic placement of* in-situ *sampling sites*. Climate models can be used to optimize the location of future in-situ observational sites that would best monitor the main modes of polar climate variability.

Integrating Climate Models in the Observational Process: Five Cases

Case 1. *Observing System (Simulation) Experiments and Quantitative Network Design*

Observing System Experiments (OSEs) refer to sensitivity experiments conducted with weather and, more recently, climate models. OSEs aim to estimate the influence that selected observations can have on forecast quality, thereby indicating the added value, or the lack thereof, of a particular observation type for prediction purposes (31). In practice, OSEs are conducted by adding, degrading, sub-sampling, or removing a specific set of observations that are usually assimilated in a

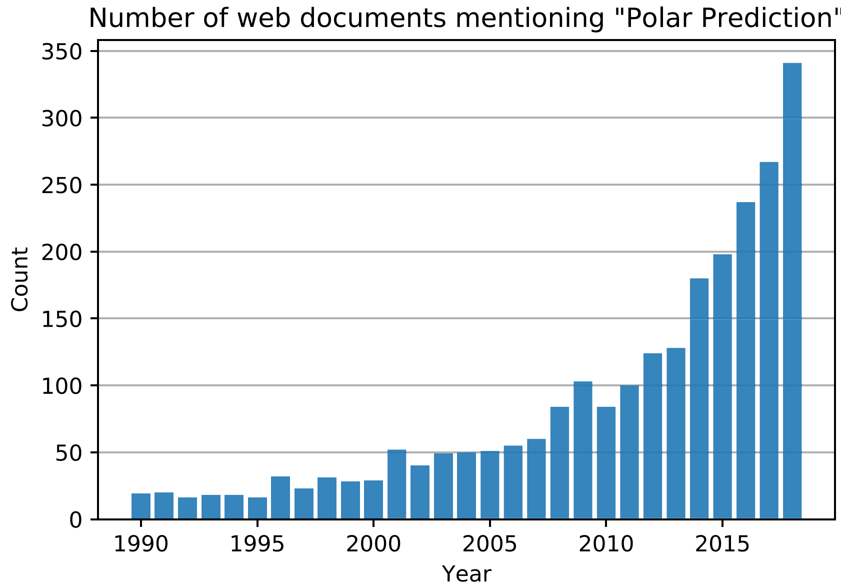

Fig. 1 Number of publications listed by Google Scholar (https://scholar.google.com) that include any of the following phrases: "Arctic … prediction", "Antarctic … prediction", "Southern Ocean … prediction" or "Polar … prediction" where "…" denotes up to any three words. The results comprise scientific papers, presentations, and conference abstracts

forecasting system, in order to isolate the impact that such a change could have on prediction error. OSEs have been used since decades in the NWP context (32,33) and have been instrumental in demonstrating, for example, the added value of assimilating radiance data on geopotential height forecasts (34). More recently, OSEs have been applied in the context of Arctic weather forecasting (35,36) and a study based on OSEs recently suggested (37) that better use could be made of existing data to improve Arctic weather predictions. Another recent study, although using a simplified setup (38), showed dramatic increases in prediction skill of potentially impactful synoptic events like Arctic cyclones if data acquired from 6-h radiosonde launches was assimilated instead of data acquired from 12- or 24-h launches only. In this case, the OSE makes a strong case for sustaining 6-hourly radiosonde launches.

Observing System Simulation Experiments (OSSEs (39)) are a natural extension of OSEs. OSSEs follow the same principles as OSEs, except that the sensitivity study is conducted in the model world: model output is assimilated instead of real observations, and forecast skill is evaluated against simulation output and not real observations. Thus, OSSEs allow testing the influence that a hypothetical new observation type would have on prediction skill. The idea of OSSEs for high-latitude weather forecasting is progressing (40) but has not yielded concrete recommendations yet for the design of Arctic observations.

Quantitative Network Design (QND) is a technique that has deep methodological connections with OSSEs. Like OSSEs, QND is based on data assimilation theory but had initially emerged from the area of seismology (instead of NWP). The goal was then to develop an optimal network of seismographs that could best estimate the process of earthquake faulting, based on aftershocks measurements (41). In QND, one seeks to optimize a measurement strategy through the minimization of a cost function based on a specific forecast target (42). QND allows estimating the contributions of various sources of uncertainty (observational, model, parameter, initial-condition) to forecast error through a rigorous mathematical framework and, as such, can be applied to study the benefit of assimilating new hypothetical observations in terms of forecast skill.

The use of OSEs, OSSEs and QND for high latitudes has been relatively limited beyond weather time scales, and in particular for polar climate prediction. One reason is that these approaches require a full data assimilation system, which is not present in most climate models. Alternative approaches have been followed. For example, in a seasonal Arctic sea ice prediction study, Day and colleagues (43) showed that the neglection of sea ice thickness information in July degrades predictive skill of late-summer sea ice concentration and thickness but also impacts near-surface temperature up to following early fall. These results confirmed earlier predictability studies (44,45) that had shown the critical role of sea ice thickness distribution preconditioning on seasonal sea ice concentration skill. However, sea ice thickness and its distribution are not easily observed from space and are subject to significant errors (see Case 2). Proper OSSEs can be salutary in that respect by providing hints on alternative geophysical variables to assimilate. For example, Zhang and colleagues (46) showed that the joint assimilation of total and multi-year sea ice concentration (two relatively well-observed geophysical variables) could reduce the forecast error or Arctic sea ice volume error by 50% compared to no assimilation at all. The use of QND also bears promise to better isolate the measurements that could lead to enhanced forecast skill. In a re-forecast of the September 2007 Arctic sea ice minimum, Kaminski and colleagues (47) found that additional sea ice thickness and wind stress measurements would have been beneficial to increase forecast skill in the Chukchi Sea region at short (10 days) and long (90 days) time scales, respectively. A later study using the same approach (48) confirmed the importance of joint snow and sea ice freeboard observations for summer sea ice volume predictions along the Northern Sea Route.

Research on OSEs, OSSEs and QND is currently significantly Arctic biased. The observing system of the Antarctic is sparser than the Arctic one, especially over sea ice and in the Southern Ocean. Thus, the potential impact of new observations there, even a few ones, can be enormous for polar prediction. This reality should encourage more systematic use of climate models to quantify this potential of new Antarctic observations, in order to inform the future development of major observing initiatives like the Southern Ocean Observing System (SOOS, (49)).

Despite its attractive aspects, the approach has several limitations. The error statistics that are prescribed in synthetic observations used in OSSEs and QND might not match the error statistics of real observations (50). An adverse consequence is that one could erroneously overstate the importance of a new type of observation while it would, in reality, have little impact on prediction skill. It could also be that climate models have predictability mechanisms that are not present in the real world. In that case, the choice to observe a new variable based on model experiments could lead to no or unsignificant improvement in prediction skill.

Case 2. *Emulation of satellites and their retrieval algorithms*

The advent of satellite information, first from passive (since the late 1970s) and then active (since the 1990s) sensors, has been a leap forward in the study of polar regions and in particular by providing near real-time monitoring of sea ice concentration and thickness. In theory, the combined measurements of sea ice concentration and thickness would allow reconstructing the global mass balance of sea ice, a diagnostic of interest from a climate point of view. In practice, both retrievals of concentration and thickness are uncertain. The deduced volume estimates are thus even more uncertain (51,52). This uncertainty, combined with the presence of substantial interannual variability, complicates the evaluation of climate models (53,54). A natural question arises: can observational uncertainty be better quantified and how can it be reduced?

Satellites do not directly measure physical variables like sea ice concentration or thickness but instead rely on indirect measurements (e.g., emitted radiance by a surface, distance traveled by an electromagnetic signal). These measurements are then converted into model-like variables such as concentration or thickness using an appropriate transfer model, or "retrieval algorithm." Because these algorithms are imperfect, uncertainty is introduced in the final product. For example, the Synthetic aperture Interferometric Radar Altimeter (SIRAL) onboard the CryoSat-2 satellite sends electromagnetic pulses that allow locating the snow-ice interface within stated precision. Sea ice freeboard, the height of the emerged part of the sea ice floe, is then deduced from the surface elevation measurement and neighboring measurements of sea surface height. Finally, freeboard is converted to thickness using hydrostatic equilibrium assumption. However, solving for thickness requires among others to know about the depth of the snow layer on top of the sea ice floe. In the Arctic, it is most often assumed that snow depth takes climatological values based on late twentieth century measurements (55) on multi-year ice and half the values on first-year ice. Sea ice, snow and seawater densities are assumed constant. The reader is redirected to reference (56) for further details on the methodology.

Retrieval algorithms thus rely on several choices (a functional form for the transfer model, values of geophysical parameters, geometrical assumptions). These choices explain why some spread can be seen in the various available products of sea ice concentration (57–59) or sea ice thickness (60,61). Producers of satellite-based climate data are aware of this spread and typically face two questions:

(a) How sensitive are the estimates of the retrieved variables to assumptions in the transfer model?
(b) What is the ideal level of post-processing for optimal use of the observational product by modelers?

A possible solution to address these observational questions is to ask them from the standpoint of climate models, in what is commonly referred to as "satellite simulation" (62) (a common practice in NWP data assimilation). The idea of satellite simulation is to project the climate model state (while it is running or after the simulation using available output) on the observational space using an appropriate operator, thereby facilitating the model-observation comparison. Loosely speaking, the idea behind satellite simulation is to diagnose what a satellite would "see" if it was flying over the model's Earth. In a recent study (52), Bunzel and colleagues used an ocean-sea ice model to explore how retrieved sea ice thickness would differ from the known model thickness if various assumptions were varied in the Cryo-Sat2 algorithm described above and applied to their model. Uncertainties in the snow depth were found to dominate to retrieved sea ice thickness uncertainty, followed by freeboard measurement error. Uncertainty in density parameters was found to play a smaller role. Such a study is valuable in that it confirmed snow depth as the current bottleneck of sea ice thickness retrieval from radar altimetry (51), thereby bringing an answer to question (a) and prioritizing future observational needs.

The satellite simulation approach for polar climate research has initially been pioneered by the cloud community (63–66), allowing a consistent evaluation of cloud biases in climate models and addressing the question (b). More recently, some work in that direction has been devoted to sea ice. Roberts and colleagues (67) proposed that freeboard should be calculated in the model based on the model's own values of snow density, and subgrid-scale ice thickness distribution, before being matched to freeboard in observations (thus moving away from the classical thickness-thickness evaluation). Another example involves sea ice dynamics: the evaluation of velocity fields in sea ice models is now done by deploying virtual buoys/tracers in the model and comparing their trajectories to observed ones (68) (see also the Sea Ice Drift Forecast Experiment, https://rdrr.io/github/helgegoessling/SIDFEx/, for similar evaluation procedures).

One of the main obstacles to climate model evaluation is the lack of definition- and scale-awareness in model-data comparisons (65). Climate model evaluation should be carried out at some mid-point between the raw model output and the raw measurements collected by observational devices, in such a way that the resulting metrics of evaluation are the least uncertain. Where this mid-point lies is case-dependent but a few answers can be obtained by the use of satellite simulators implemented in climate models (69), which can then orient the development of transfer models processed by developers of observational products. One of the lessons learned from recent workshops on model-data comparison in polar regions is that the developers of observational products should not necessarily process their products down to model space (70) as this has been most often the case until now. In that respect, recent results obtained from model-based studies could be exploited to inform space agencies and satellite product developers about the optimal level of processing required for modelers.

Case 3. ***Constraining high-latitude climate projections***

While state-of-the-art climate models generally agree on the essential traits of future Arctic climate changes (reduced Arctic sea ice (71), polar amplification with larger increases in temperature in winter than in other seasons (72), intensification of the Arctic hydrological cycle (73,74)), the magnitude of these changes varies considerably from model to model and remains consequently uncertain. How to evaluate climate models with past observations in order to narrow uncertainty in future changes is a critical question that applies not just to the Arctic (75). Nonetheless, the Arctic bears remarkable properties. Indeed, in many cases, future simulated changes are tightly related to present-day characteristics in models. For example, changes in modeled wintertime surface air temperature along the Arctic ice edge are significantly anti-correlated to the baseline mean temperature (76); September Arctic sea ice extent change over 2021–2040 is well correlated to historical (1979–2007) trends (77,78), and the timing of a summer ice free Arctic is correlated to the baseline model state (79); models with larger fall (September–October-November) sea ice concentration over the present-day experience larger reductions in near-surface air temperature variability in the future (80); models with larger annual mean Arctic sea ice volume over the present-day display more pronounced volume losses for a given scenario (54,81,82).

In the Antarctic, where climate projections are notoriously more uncertain, strong relationships were still identified between projected changes in annual mean sea ice area, precipitation and temperature, and the baseline annual mean sea ice area in state-of-the-art climate models (83); moreover, the spread in projected changes in the latitudinal position of the austral jet was traced to the climatological position of the jet in models.

All the relationships mentioned above emerge spontaneously in multi-model ensembles. These relationships take the general form Y (projected change) is related to X (present-day state). If these relationships are not spurious but instead based on physically explainable mechanisms, they offer the potential to orient the design of future observing systems. Indeed, under the assumption that the real world obeys the same relationships as those found in the models (i.e., that observations align with the models), evaluating models based on X in observations would allow better constraining the real projected change Y. However, the successful application of these "emergent constraints" (75,84) is conditioned on the existence of matching observational datasets for X. In that sense, the identification of emergent constraints can be seen as an objective reason to prioritize a particular type of observation. For example, CMIP3 model results indicate that future Arctic warming is positively correlated to historical northward ocean heat transport (85). Observational data of oceanic heat transport are scarce, however, which would justify enhancing the observations of that variable. As another example, the long-term model sensitivity of Northern Hemisphere continental surface albedo to temperature change is closely related to the equivalent quantity computed seasonally (86). However, the corresponding observational estimate is uncertain, and improved retrievals of surface albedo would help better constraining its sensitivity to future temperature changes.

This approach can only lead to robust insights if the model relationships are themselves robust. In particular, there is a risk that spurious present-future relationships emerge if the ensemble is composed of highly inter-dependent models or if the models share common structural biases. Thus, precautions must be taken to ensure that the choice of observing a new variable is rooted in a solid understanding of physical processes underlying the identified emergent constraints.

Case 4. ***Evaluation of observational products***

Because the in-situ polar observing system is inherently sparse, climate models are most frequently evaluated against gridded datasets such as remote sensing products, reanalyses or re-gridded products. However, each of these gridded verification datasets is subject to errors. Determining their intrinsic quality is challenging because well-sampled in-situ data are not always available to evaluate the datasets independently.

Recent findings from the field of seasonal forecasting could bring an elegant solution to the problem of estimating the quality of gridded observational datasets. The idea is to use climate models as a third-party source of information to infer the statistics of observational errors. The rationale behind this argument is simple: standard skill scores used in forecast verification (e.g., correlation, root mean square error, Brier score) are sensitive to errors in both the forecast and the verification data (87,88). If one particular observational verification product is corrupted with larger errors than other products, this observational product should systematically stand out compared to others, when inspecting the forecast skill scores of model predictions.

Recent results support the notion that forecast skill depends on the observation used for verification. In a recent study (89), it was found that the skill of the MPI-ESM climate model in predicting Arctic sea ice area from May to October was impacted by the choice of the observational product used for verification. A better agreement was found between the model and the Boostrap algorithm for sea ice concentration retrieval than the NASA Team algorithm. The authors hypothesized that the correction for melt pond issues applied in the Bootstrap product (but not in the NASA Team product) could be the reason. These results were confirmed independently in another study using a multi-model ensemble of seasonal forecasts (90) with four observational products. Finally, two studies conducted with the CanSIPS seasonal forecast system on the prediction of snow-water equivalent (SWE) content (91,92) highlighted that this prediction system reached higher skill scores (as measured by the anomaly coefficient correlation) for the average of four reference products than for any individual product. Furthermore, it was found that the worst scores were reached when ERA-Interim and MERRA-Land reanalysis products were used for SWE content forecast verification (92), confirming a posteriori known issues in those products identified in an earlier study using in-situ observations (93).

The polar prediction community is moving, slowly but surely, toward the systematic use of ensembles of observational products for model evaluation and forecast verification. A number of fascinating properties emerge from the above-mentioned studies: (i) model forecasts tend to score better against more advanced observational products, (ii) the difference in skill can be understood on the basis of the products quality and (iii) the average of several observational products yields better score to models than any of the products alone. From that point of view, observational ensembles seem to obey the same rules as the multi-model climate model ensembles. Moreover, climate models seem suited to support objective observational dataset evaluation and selection.

The principal limitation to this approach is the possibility that climate models have been tuned or calibrated to match one of the observational references under investigation, in which case the conclusions could be flawed.

Case 5. ***Strategic placement of* in-situ *sampling sites***

Several sea ice, ocean and atmosphere variables exhibit significant covariance in space, in time, and with one another. As far as these dependencies are assumed to be linear and the covariances to be stationary, it is not required to monitor all these variables at all times and everywhere: a minimal number of well-chosen stations targeting key variables could, in principle, reveal the dominant modes of high-latitude climate variability in the real world. This problem is undoubtedly exciting from a purely academic point of view. Formally, it is equivalent to solving an optimization problem under constraints, i.e., that of explaining the maximum of the real-world polar climate variability using a minimum number of measurements. The problem is also highly relevant from a practical and operational point of view. The deployment of an observing system is subject to constraints (financial and logistical) that impose a prioritization of the location, time of the year, and type of instrument to be deployed.

This problem of optimization is not new and has been formalized some 30 years ago when it was already attempted to determine the optimal placement of point gauges that would best reconstruct the global mean temperature (94,95) or the global CO_2 budget (96). The problem is arguably even more challenging in polar environments and in particular for sea ice, which is in addition a drifting material. The selection of best in-situ sampling sites is only possible if spatiotemporal variability is well characterized. From that point of view, the large-scale observations provided by passive and active remote sensing sources are of limited use: the observational record is rather short, forced trends interfere with the internal variability and the retrievals are uncertain (see Case 2). Climate models, by contrast, can output any variable at all locations and seasons. While climate models cannot substitute for observations, they do provide the level of spatiotemporal sampling required for helping to answer the initial question.

To our knowledge, the question of optimal sampling in polar regions has only been tackled for two cases: optimal sampling of the Arctic Ocean heat content variability and optimal sampling of the Arctic sea ice volume variability. In a model study, Lique and Steele (97) found that enhancing the oceanic mooring network in the Eurasian Basin would be beneficial for estimating the Arctic oceanic heat content variability, as the spatial anomalies display large-scale coherence in this basin (unlike the freshwater content anomalies which are rather confined in the Canadian Basin and the Beaufort Gyre). Similarly, well-placed moored upward-looking sonars could help estimating sea ice volume variability. In climate models and reanalyses, Arctic sea ice thickness anomalies exhibit persistence from 3 to 20 months, depending on the location, season, and source investigated (98–100). At the same time, these anomalies display spatial coherence with a typical decorrelation length scale in the range 300–1000 km. These estimates, even if uncertain, can provide a lower bound on the number of independent fixed point measurement sites that would be required to capture most of the Arctic sea ice volume variability. With an ice-ocean model, a study (101) found that the judicious placement of just three sampling sites would already explain 57% of the spatial and temporal variability of annual mean sea ice thickness. Recent results obtained from four different climate models suggest that sampling monthly mean thickness at four sites could explain more than 70% of the temporal variability of Arctic sea ice volume anomalies (102). No equivalent study has been conducted for Antarctic sea ice, despite the need.

While attractive in its principle, the application of this idea has several practical limitations. First, point measurements of sea ice thickness in the real world exhibit variability over a broader frequency spectrum than climate models output at their current nominal resolution. Second, there is evidence that thickness variability is not stationary (100) but does depend on the mean state (103). Namely, the persistence time scale of thickness and volume anomalies decreases as the ice thins (54), which means that a higher number of stations will be required as the Arctic sea ice transitions toward a seasonally ice-free regime. Third, it is likely that the optimal number of stations would depend on the models' effective resolution (a limiting case would be that of a model with four grid cells over the entire Arctic, which would provide unrealistically long decorrelation scales). Finally, there is simply no guarantee that models display the right modes of variability. Even in reanalyses, which are supposed to be the most constrained gridded estimates of sea ice thickness, the optimal location of stations is reanalysis-dependent (102).

Conclusions

Since four decades, the number of polar observations has soared thanks to the coordination of national and international programs (e.g., space missions, in-situ campaigns, initiatives like the International Polar Year or the Year of Polar Prediction). Concurrently, the need for reliable polar predictions has become more and more pressing, fueled by rapid changes that took many by surprise. Does the supply of observations meet the demand for polar prediction and do we make the best possible use of existing data? The question is still open, as polar prediction has not reached its age of maturity yet. However, given the rapidly changing seasonality of the Arctic system (104), the stationarity of predictor-predictand relationships might not hold in the future (105), which would mean that the observations of yesterday would not necessarily be fit for evaluating or initializing the predictions of tomorrow. What are the conceptual tools at hand to design such an observing system, then?

In a review published in this journal three years ago, Kay and colleagues (69) advocated a "two-way street" paradigm for Arctic cloud research, whereby lessons learned from observations should feed climate model development and vice-versa. The "vice-versa" part of the statement is arguably the least obvious, as one would a priori assume that climate model development is following, not preceding, the development of observing systems. The case of polar prediction and more particularly sea ice prediction crystallizes the idea that the future development of cost-effective observing systems will have to rely, at least in part, on the intelligent use of climate models. We illustrated this idea with five cases taken from the recent literature on polar prediction, with most examples from sea ice. Our five cases illustrate that there is no best observing system in an absolute sense, but rather good observing systems that can help to answer specific scientific questions. We note that these five cases are transposable to non-polar regions. A recent study (106) made a strong case of using climate OSSEs such as those described in Case 1, to test the added value of new possible observations on answering climate questions.

A recurring idea behind the use of climate models for observational purposes is to rely on "Nature Runs" (39,40), i.e., numerical climate model simulations that emulate the real world and for which the impact of a specific observational choice can be quantitatively tested. The validity of this approach can be questioned (50). One issue is that climate models have biases, so they might not perfectly emulate what one is trying to observe. Another issue is that the climate models might have been extensively tuned toward a particular type of observations, which would flaw the reasoning and give rise to circular arguments. Nevertheless, in many of the cases highlighted here, climate models bring first-order answers to questions that would otherwise not be answered, such as: What is the ideal level of post-processing for consistent climate model evaluation? What is the impact of assumptions in satellite retrieval algorithms on the final product? Where should sampling sites be deployed during coordinated intensive campaigns like the Special Observing Periods of the Year of Polar Prediction? Are wintertime observations more important than summertime ones for a specific question?

It has been argued (107) that one way to improve weather and climate predictions will be to follow a seamless approach, whereby the same numerical models are used in both weather and climate contexts. Our review goes a step further by highlighting that many concepts and methodologies already routinely applied in the NWP models (such as OSEs/OSSEs and satellite simulation) should systematically be transposed to climate models to inform on the optimal design of observing systems for climate science, especially in remote polar regions where observations are most needed.

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Compliance with Ethical Standards

Conflict of Interest The corresponding author states that there is no conflict of interest.

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