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Review article: Synthesizing data assimilation for snow, glaciers, and permafrost

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Abstract. Terrestrial snow, glaciers, and permafrost are changing rapidly in response to anthropogenic global warming. Accurately quantifying their state trajectories on time scales ranging from seconds to millennia and on spatial scales from meters to continents is fundamentally hindered by our limited observational and modeling capacity. Data assimilation (DA) offers a principled Bayesian framework to combine uncertain models with noisy observations. In this review, we synthesize the main classes of DA methods and their applications across snow, permafrost, and glaciers, and identify the cross-disciplinary themes common to all three components. Despite domain-specific differences, cryospheric DA applications share common bottlenecks, including the sparsity and indirect nature of the observations, the lack of accurate high-resolution atmospheric forcing (especially in remote areas), the treatment of non-Gaussian bounded variables, and adequate spatio-temporal modeling of both forcing and observation errors in complex terrain. Finally, we outline a research agenda that considers the integration of machine learning into the DA workflow, the use of adaptive sampling, the potential for propagating information from sparse observations in time and space, and quantifying the information that current and future data streams can bring to cryospheric modeling systems. The shared traits throughout the cryosphere mean that advances in one domain can and should translate to others.

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1 Introduction

The terrestrial cryosphere, including snow, glaciers, and permafrost, shapes global and regional climate, water resources, and ecosystems, but is undergoing rapid change in the anthropogenically warming world (e.g., Barry, 1985; Huss et al., 2017; Thackeray et al., 2019; Barry and Gan, 2022). Seasonal snowpack and glaciers act as natural reservoirs that modulate streamflow, releasing meltwater that supports ecosystems, hydropower, agriculture, and drinking water supplies to billions of people in downstream regions (Barnett et al., 2005; Immerzeel et al., 2020). Beyond their hydrological roles as source and storage of freshwater, snow and ice both have higher reflectance than most other natural surfaces, such that their depletion decreases surface albedo and amplifies warming through the snow and ice-albedo feedback (Croll, 1864; Cess et al., 1991; Räisänen et al., 2017; Riihelä et al., 2021). Permafrost underlies roughly 11% of the exposed land surface globally (Obu et al., 2019; Obu, 2021); its thawing has both local and global impacts, e.g., changes to local land stability and the release of organic carbon stored in the frozen ground (Biskaborn et al., 2019; Turetsky et al., 2019; Nitzbon et al., 2024). In a warming climate, changes in the global cryosphere, including snow loss, glacier retreat, and permafrost thaw, are increasingly linked to natural hazards such as floods, debris flows, landslides, rock-ice avalanches, ground subsidence, and snow drought (Huggel et al., 2019; Adler et al., 2022; Constable et al., 2022; Marshall et al., 2026). Given their multifaceted roles, these components of the terrestrial cryosphere must be accurately estimated across large areas and time spans in order to support reliable forecasts and projections, including in operational decision-making contexts (Yao et al., 2022; Rawlins and Karmalkar, 2024). The information required to meet this need comes from two sources: observations of the system and models of the processes that govern it, each with distinct strengths and limitations.

To observe cryospheric processes (Fig. 1 panel A), we rely on instrumented stations (e.g., Serreze et al., 1999; Burgess et al., 2000; Sorteberg et al., 2001; Zemp et al., 2009; Schöne et al., 2013; Schwartz et al., 2026), field campaigns (e.g., Corripio and Purves, 2005; Wagnon et al., 2007; Vieira et al., 2017; Durand et al., 2018; Loeb and Kennedy, 2021), and remote sensing platforms (e.g., Kääb et al., 2005; Nolin, 2010; Berthier et al., 2023; Gascoin et al., 2024). Stations and field campaigns are essential to advance process understanding, model development, and location-specific operations, but they cannot cover the full spatio-temporal extent of the terrestrial cryosphere given its size, remoteness and multitemporal dynamics. Remote sensing has significantly expanded observational capabilities, ranging from optical and passive microwave sensors (Derksen et al., 2017; Pulliainen et al., 2020) to synthetic aperture radar (SAR; Lievens et al., 2019; Chen et al., 2020) and lidar altimetry from satellites (Fair et al., 2025) and airborne platforms (Painter et al., 2016). However, remote observations of cryospheric quantities remain temporally intermittent and often indirect, with many key quantities requiring complex retrieval algorithms to convert observed signals into cryosphere-relevant values (Gascoin et al., 2024). These limitations are exacerbated in regions with complex terrain (Taylor et al., 2021) and dense vegetation (e.g., Derksen, 2008).

Not all quantities of interest can be observed with adequate accuracy, resolution, or completeness. Cryospheric dynamical models (Fig. 1B) provide the quantitative foundation for monitoring and predicting the evolution in space and time of snow, glaciers, and permafrost. However, model structural uncertainty can be high, particularly in heterogeneous or topographically complex regions (Kouki et al., 2023). Model parameterizations are often empirical (Essery et al., 2025), tuned at heavily-

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instrumented sites (Vionnet et al., 2012; Lehning et al., 2002), or sensitive to difficult-to-constrain initial conditions (Westermann et al., 2023). In addition, model forcing data (primarily of atmospheric quantities, but including, for example, snow states for permafrost models) are among the largest sources of uncertainty for models of any complexity (Raleigh et al., 2015; Liu and Margulis, 2019; Günther et al., 2019; Pruessner et al., 2021; Tang et al., 2023), especially in complex terrain where orographic effects influence precipitation, radiative and heat fluxes at scales that cannot be captured by global and regional atmospheric reanalyses (Avanzi et al., 2020; Fang et al., 2023).

Data assimilation (DA) combines observational data with dynamical models to improve estimates of the true state of a physical system. DA estimates retain the spatial, temporal, and process completeness of the underlying model while remaining constrained by observations and additionally providing a quantitative estimate of the uncertainty of the outputs (Evensen et al., 2022). The process of DA originated in numerical weather prediction (NWP, Lorenc, 1986), where it was developed to provide accurate initial conditions for forecasts of chaotic atmospheric flows (Lorenz, 1963), and has since been adopted and further developed in other fields, including oceanography, land surface modeling, and hydrology (Kalnay et al., 2024). DA now underpins operational weather forecasting and is increasingly central to land surface and hydrological prediction (Carrassi et al., 2018). Its adoption in the terrestrial cryosphere, however, remains more recent and uneven, despite the strong need for more accurate estimates of cryospheric variables in many regions.

Applications of DA to the terrestrial cryosphere present a unique set of challenges. First, the physical processes governing their evolution span different time scales: annual for seasonal snow, decades to centuries for glaciers, and decades to millennia for permafrost. Slowly evolving systems are challenging for DA since the corrective effect of an update may not become apparent for a long time. Assimilation windows must be correspondingly long and initial conditions (e.g., deep ground temperature) can have uncertainties at similar orders of magnitude to the process. Second, many cryospheric models are naturally nonlinear and high-dimensional. Cryosphere state variables are frequently bounded (e.g., fractional snow-covered area between zero and one, ice thickness is non-negative), contain discontinuities from water phase changes, and contain a wealth of state variables that must be updated consistently. These features violate the linear, Gaussian, and moderate-dimensionality assumptions on which many standard DA schemes rely. Third, many quantities are not directly observed, requiring the assimilation of indirect or derived products based on radiance, backscatter, or surface elevation through complex observation operators that introduce additional uncertainty (e.g., Li et al., 2017a; Vionnet et al., 2025). Fourth, in-situ observations for validation are sparse in time and space, and often not representative of grid-averaged modeled states (Van Leeuwen, 2015). This is heightened in remote and complex terrain, high elevations or latitudes, and at depth in the subsurface. The errors in these observations are often large and poorly quantified. Because these limitations and features are intrinsic to the cryosphere rather than incidental, methods that succeed in the cryosphere must contend with all of them.

This synthesis paper therefore reviews the current state of DA approaches applied to snow, glaciers, and permafrost (hereafter referred to as the terrestrial cryosphere; Fig. 1). Other frozen components, notably lake and river ice and marine quantities (sea ice and subsea permafrost) are outside the current scope. We begin (Section 2) by introducing DA methods as approximate Bayesian inference techniques for geophysical models, aiming at explaining high level ideas to help understand the DA techniques used in the cryosphere. We then review the state of terrestrial cryospheric DA for the following domains: snow, glaciers,

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and permafrost (Section 3); before turning to cross-cutting themes that are common to all such domains (Section 4). Finally, we introduce emerging areas of research in terrestrial cryosphere DA (Section 5) and suggest an agenda for future work (Section 6).

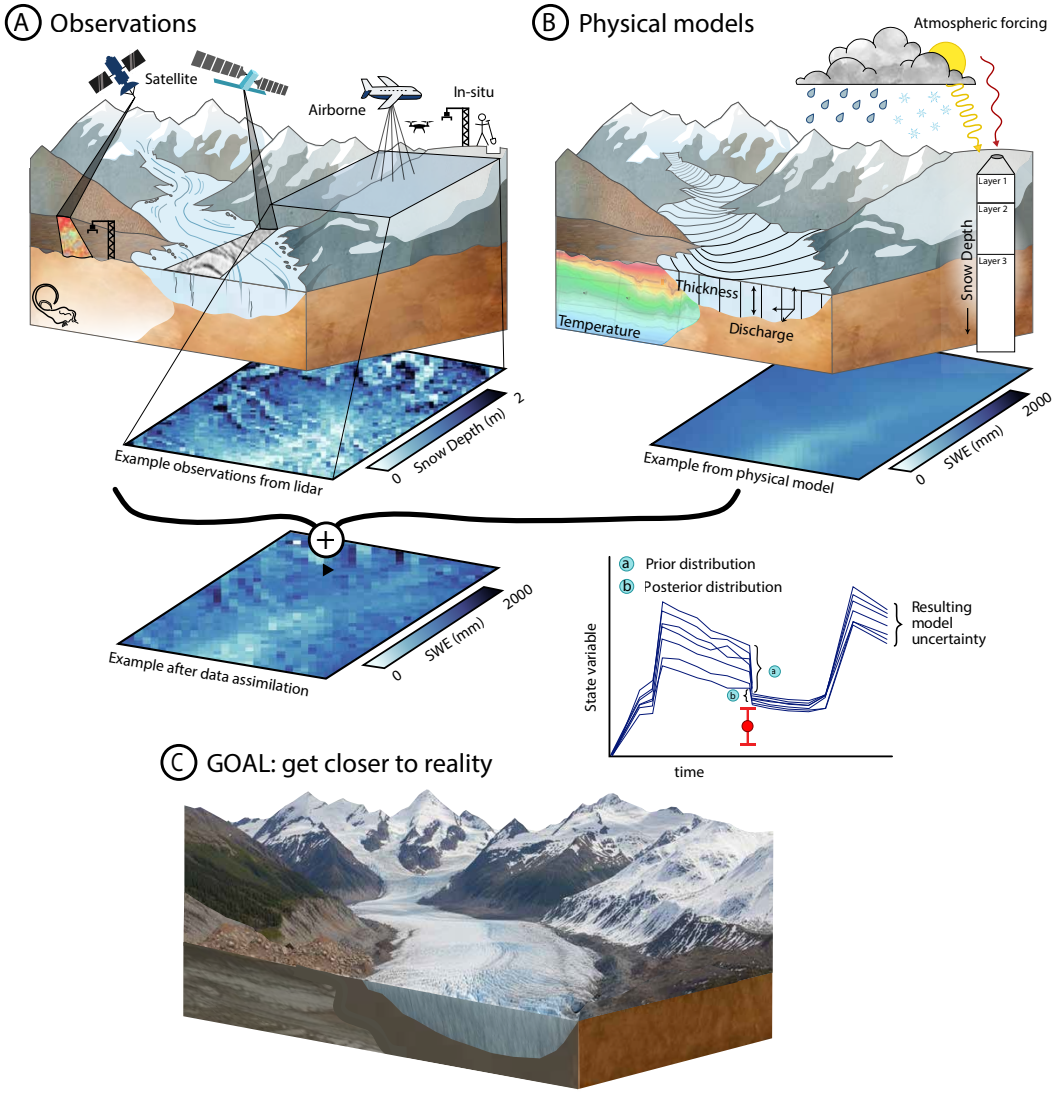

Figure 1. Schematic overview of cryospheric DA. Observations from satellite, airborne, uncrewed aerial systems (UAS), and in-situ platforms (A) are combined with prior knowledge from dynamical models that simulate snow, glacier, and permafrost processes under atmospheric forcing (B). Their combination via DA produces improved, spatially distributed state estimates with reduced uncertainty relative to either source alone, with the goal of bringing model simulations closer to the true state of the cryosphere (C). The map example shows how the assimilation of a one-time snow depth observation into a snow model can improve the spatial representation of the target quantity (or state variable). The inset time series presents forecasts and analyses within a cycling DA scheme, i.e. using a filter.

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2 Data assimilation theory

2.1 An introduction to data assimilation

The purpose of DA is to combine models with observational data to infer a probability distribution over uncertain variables representing a system of interest (e.g., snow depth, water equivalent, or ice thickness). This posterior distribution is the primary output, encapsulating knowledge of the modeled system *after* considering the data and its observational uncertainty (i.e., *a posteriori*).

Most modern DA approaches are built on Bayesian inference (Carrassi et al., 2018; van Leeuwen et al., 2019; Evensen et al., 2022) and aim to infer the posterior (also known as the analysis) probability distribution $p(\mathbf{x} \mid \mathbf{y}^o)$ of the state vector $\mathbf{x}$, containing the variables of interest, given the data in the observation vector $\mathbf{y}^o$, via Bayes' rule

$$p(\mathbf{x} \mid \mathbf{y}^o) = \frac{p(\mathbf{y}^o \mid \mathbf{x})p(\mathbf{x})}{p(\mathbf{y}^o)} \tag{1}$$

where $p(\mathbf{x})$ is the prior distribution (also known as the background or forecast), encoding background information about the state (and/or parameters) $\mathbf{x}$ before considering the observations, $p(\mathbf{y}^o \mid \mathbf{x})$ is the likelihood function which quantifies the goodness of fit between the data $\mathbf{y}^o$ and the model state vector $\mathbf{x}$, and $p(\mathbf{y}^o)$ is the model evidence or marginal likelihood which acts as a normalization factor ensuring that the posterior integrates to 1 over the space of possible model states. Formally, the likelihood function is a probability density evaluated at the fixed data $\mathbf{y}^o$ given a particular state vector $\mathbf{x}$. As such, it should be viewed as a goodness of fit function of the uncertain model state $\mathbf{x}$ for fixed $\mathbf{y}^o$ in line with the likelihood principle (Jaynes, 2003; MacKay, 2003). The so-called evidence term, $p(\mathbf{y}^o)$, is useful for higher levels of inference, such as model comparison (MacKay, 2003), but it can be challenging to estimate in practice so for most DA tasks it suffices to view the evidence as a normalizing constant.

We may thus rewrite Equation (1) as $p(\mathbf{x} \mid \mathbf{y}^o) \propto p(\mathbf{y}^o \mid \mathbf{x})p(\mathbf{x})$ where the normalizing constant $p(\mathbf{y}^o)$ is absorbed into the proportionality $\propto$. At least in theory, then, the DA problem consists of simply multiplying the prior (what is known from the dynamical model) with the likelihood (what the data tell) and normalizing to obtain the posterior (our new best estimate).

We treat the prior, likelihood and posterior as probability functions, consistently with the view that probability is a measure of uncertainty rather than of frequency. Crucially, such probability functions allows us to extract point estimates, credible intervals, and decision-relevant summaries can be derived depending on the loss or utility function adopted. (Robert, 2007; Särkkä and Svensson, 2023).

Generally, comparing noisy observations to the model state when evaluating the likelihood involves computing the corresponding noise-free predicted (modeled) observable $\widehat{\mathbf{y}}$ from the state via $\widehat{\mathbf{y}} = \mathcal{H}(\mathbf{x})$, where $\mathcal{H}(\cdot)$ is an observation operator. This operator maps from the hidden state (and/or parameter) space to the observation space, and can thus be seen as a forward model. The observation operator may be as simple as a binary matrix that picks out observed state variables from $\mathbf{x}$ or as complex as a nonlinear radiative transfer model driven by $\mathbf{x}$. As such, likelihood evaluations can involve running a complex observation operator $\mathcal{H}(\cdot)$ and, in most formulations (Section 2.3), also running a dynamical model $\mathcal{M}(\cdot)$ to advance the state in time, which makes these evaluations key bottlenecks. At the same time, the forward modeling view helps reveal a useful

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insight, namely that DA can be viewed as the application of Bayesian inverse modeling to dynamical systems (Sanz-Alonso et al., 2023). In this view, we consider that noisy observables, which are random (i.e., uncertain) variables, can be cast as being generated from the hidden state via

$$\mathbf{y} = \widehat{\mathbf{y}} + \boldsymbol{\epsilon} = \mathcal{H}(\mathbf{x}) + \boldsymbol{\epsilon}, \tag{2}$$

where the noise term $\boldsymbol{\epsilon}$ denotes the observation error that is typically assumed to be additive, and contains both the measurement error as well as the representation error, which typically arises due to scale mismatches (Van Leeuwen, 2015). The assimilation task can be seen as *inverting* the generally non-linear observation operator $\mathcal{H}(\cdot)$ to estimate the hidden state $\mathbf{x}$ given the *fixed* noisy observations $\mathbf{y}^o$ (conditioning on $\mathbf{y} = \mathbf{y}^o$) that we assimilate. That is, we can conceive of the observations $\mathbf{y}^o$ as a realization of the random variable $\mathbf{y}$ drawn through a noisy observation process (van Leeuwen, 2020).

Not clearly distinguishing between quantities in the observation space, especially the fixed observations $\mathbf{y}^o$ from nature and the modeled noise-free and noisy observables $\widehat{\mathbf{y}}$ and $\mathbf{y}$, where only the last two are random variables, can be a source of much confusion. For example, it has led to an inconsistent interpretation of the stochastic ensemble Kalman filter (Burgers et al., 1998), which was only recently resolved by van Leeuwen (2020) (Section 2.4.5). For an extended explanation of the full Bayesian inference notation we recommend the interested reader to see Appendix A.

The presence of unknown observation error $\boldsymbol{\epsilon}$ in (2) implies that this is a fundamentally ill-posed inverse problem where no unique solution exists, requiring a probabilistic turn and the use of Bayesian methods (Sanz-Alonso et al., 2023). As humorously and somewhat pedantically noted by Evensen et al. (2022), a Bayesian solution to this problem does not necessitate any explicit matrix or functional inversion of the model, however, as Bayes' rule (1) itself boils down to multiplying the prior and the likelihood. Still, viewing DA through the lens of Bayesian inverse modeling is conceptually helpful to grasp the essence of the problem while enabling a productive cross-pollination of methods between fields (Evensen et al., 2022; Sanz-Alonso et al., 2023). Despite the formal updating logic in Equation (1), the large dimensionality and nonlinearity of typical models and observations used in cryospheric science make direct analytical or grid-based applications of Bayes' rule intractable. Approximations to render this exercise computationally tractable therefore comprise the majority of cryospheric DA methods.

2.2 Example: Inferring SWE from snow depth observations

Consider a scenario in which we wish to update a model of snow water equivalent (SWE) using observations of snow depth. In the model, we have two hidden state variables: SWE (m with units mass per unit area) and the bulk snow density (ρ with units mass per unit volume). These state variables are related to a (noise-free) snow depth observable $\widehat{d}$ via the non-linear forward model $\widehat{d} = m/\rho$. In a field campaign, snow depth is measured with a probe, resulting in a snow depth observations d^o, but no corresponding density sampling is performed. In this example, our prior beliefs about the SWE and depth (Figure 2 red distributions in a and b, respectively) are broad and centered away from the true values (Figure 2 black dash-dot lines). The goal is to use the snow depth observation (Figure 2b gray dotted line) to update the model's prior representation of the state variables m and ρ as well as the associated (noise-free) observable $\widehat{d}$, while accurately balancing our uncertainty in both the

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observation's accuracy and the model's representation of the true underlying state of the real-world snowpack. The DA process should move the resulting posterior distribution (Figure 2 blue distributions) closer to the truth.

Following Equation (2), we account for potential noise in the snow depth observation process via a data-generating model of the form $d = \widehat{d} + \epsilon$ where d denotes the noisy observable. We assume that the observation error ϵ is an additive Gaussian noise term with zero mean and a standard deviation of σ_d (Carrassi et al., 2018), allowing us to define the likelihood function (Figure 2, gray shaded lines). The noise-free snow depth observable $\widehat{d}$ (also referred to as the predicted observation or model-predicted measurement), is directly related to SWE and density via the forward model. Translating this model into the notation outlined previously in Section 2.1, the state vector is $\mathbf{x} = [m, \rho]$ and the observation operator is $\mathcal{H}(\mathbf{x}) = m/\rho$. Moreover, all quantities related to the observation happen to be scalars: the noise-free observable is $\widehat{\mathbf{y}} = \widehat{d}$, the noisy observable is $\mathbf{y} = d$, the observation is $\mathbf{y}^o = d^o$, and the noise is $\boldsymbol{\epsilon} = \epsilon$.

We generate a synthetic snow depth observation d^o (Figure 2b, gray dotted line) by assuming a true hidden state $[m^\star, \rho^\star]$, computing a corresponding true snow depth observable $d^\star = m^\star/\rho^\star$, and adding a sampled error realization $\epsilon^\star \sim \mathrm{N}(0, \sigma_d^2)$ so that $d^o = d^\star + \epsilon^\star$. The use of a synthetic experiment allows us to compare our results directly to the truth, which is generally not available in DA experiments assimilating real data. As is commonly done for testing DA methods, this example is a so-called synthetic (or twin) experiment in which the truth is known (Figure 2, black dash-dotted line). Gelman et al. (2026) highlights the importance of such experiments for the practitioner for understanding and testing in Bayesian workflow. It is important to note that the very same inference approach can be applied to assimilate real observations, as it does not require access to the truth.

Using the data-generating model $d = \widehat{d} + \epsilon$, we can infer the uncertain hidden state variables ρ and m via the forward model $\widehat{d} = m/\rho$ by conditioning on the noisy snow depth observation $d = d^o$. We have prior knowledge (corresponding to $p(\mathbf{x})$ in (1)) of the two state variables, as shown for m in Fig. 2. In practice, priors are typically constructed by perturbing forcings and/or parameters around nominal values (e.g., from reanalysis or forecast products, or a previously published value), with perturbation distributions informed by physical bounds, climatology or typical published ranges (some examples in Margulis et al., 2016; Aalstad et al., 2018; Rounce et al., 2020b). When these sources of information, a prior may be weakly informative (e.g. Groenke et al., 2023). In any given case, choice of a prior is problem-specific and pragmatic Banner et al. (2020). For simplicity, we have assumed Gaussian priors and a Gaussian likelihood, however, the nonlinearity of the forward model precludes an analytical solution. Here, density ρ acts as a nuisance variable (Jaynes, 2003). While SWE is our primary target, ρ is strictly required to relate the observed snow depth to SWE, effectively modulating the informativeness of the observation in terms of the quantity of interest m. Because a given snow depth can be consistent with a range of possible SWE values depending on the density, marginalizing over ρ broadens the resulting likelihood in the SWE space (Figure 2a) relative to the depth space (Figure 2b). Rather than assuming a fixed density, the Bayesian approach treats ρ as uncertain and infers it jointly with SWE using Bayes' rule (1). Marginalizing over this nuisance variable yields the final SWE posterior ($p(m \mid d^o)$)(Figure 2a, blue line), which automatically propagates uncertainty without relying on simplifying assumptions typical of standard error propagation.

The observation of snow depth (Fig. 2b, gray dotted line) is assumed to be unbiased and informative, i.e. its observation error is centered at 0 and its variance is of comparable size or smaller than the prior variance in observable (snow depth)

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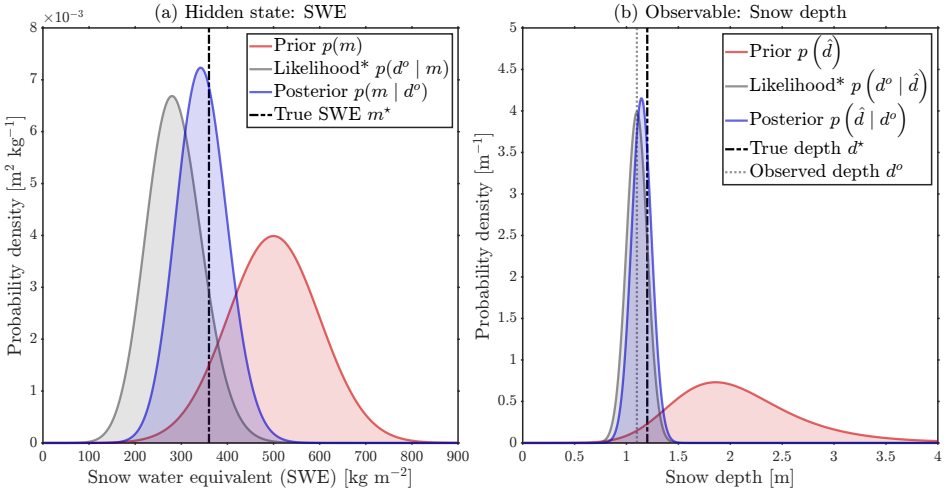

Figure 2. Applying a Bayesian approach to the common problem of inferring SWE (unknown) from a noisy snow depth observation (d^o, gray dotted line) while accounting for density (ρ) uncertainty. The synthetic truth is known and depicted with a black dash-dotted line. The two plots show the prior (red), (*scaled non-dimensional) likelihood (gray) and posterior (blue) in both the hidden SWE space (left) and the observation space (right).

space. If those conditions are met, together with that of an unbiased model, we expect such an observation to update the prior distribution (Fig. 2a, b red lines) to a posterior distribution (Fig. 2a, b blue lines) over values of $\widehat{d}$, m, and ρ that is more precise (smaller distribution standard deviation) and more accurate (closer to the truth), consistent with the narrower, better-centered posteriors we achieve in this example (Figure 2 blue distributions).

This Bayesian updating process involves a major practical challenge in cryospheric DA: inference in high-dimensional spaces. In the low-dimensional setting of the current example, we could obtain a solution to this Bayesian DA problem via a grid approximation (MacKay, 2003). However, due to the curse of dimensionality (Murphy, 2023), this brute force grid approach is generally prohibitively expensive for spatio-temporal ('4D') models with large numbers of states or parameters. The remainder of Section 2 describes the methods and strategies for efficiently solving this inverse problem in cryospheric applications.

2.3 State, parameter, and forcing estimation

Following Evensen et al. (2022), a DA application can update either the model's state directly (the *model-state formulation*), e.g., SWE as depicted in section 2.2, or the inputs that drive the model (the *forcing formulation*). Table 1 shows a non-exhaustive list of states and forcing that can be updated for the three main cryospheric domains. The distinction between state, parameter, and forcing updates is in practice model-dependent: a given quantity may be treated as a state in one model and as forcing in another, and parameters can be used to perturb forcing inputs.

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The state of a system is the vector of its dynamic variables (the state variables), such as SWE, snow depth, glacier velocity, or permafrost temperature at a specific time step and location. The model-state formulation updates these variables directly. This explicitly mitigates errors that arise from model structure, which are typically represented as stochastic process noise term (Sasaki, 1970), hence in this formulation the model (i.e., its structure) acts as a weak constraint to the system, as updates can violate the model's dynamics. Cryospheric examples include sequentially assimilating snow depth observations to directly update a snowpack model's SWE state (Brangers et al., 2024) as shown schematically in Figure 2, or using glacier albedo data to directly update the state of surface layer grains (Dumont et al., 2012). Despite its operational success, this formulation has disadvantages: state estimates may be dynamically inconsistent with the model and produce saw-shaped time series, violate physical conservation laws (Wunsch et al., 2023), or fall outside of physical bounds (Anderson et al., 2024).

In the forcing formulation, observations update the inputs controlling the behavior of the dynamical model rather than the states directly (Evensen et al., 2022). Note that the term 'forcing' in this context includes the time-varying external states and fluxes generally referred to as 'forcing data' but also includes static or slowly varying parameters (e.g. the albedo) and the initial conditions. A dynamically consistent model state trajectory is then recovered indirectly by rerunning the model, or in some cases by resampling existing trajectories. This formulation is often imposed by using the model (i.e. the model's structure) as a strong constraint whereby the model itself is assumed to be perfect, with all uncertainty attributed to the inputs. We still imply the modeled states are uncertain, but such uncertainty derives from the uncertain inputs (forcing, parameters and initial conditions). This assumption is both strong and strictly false. However, the underlying idea is pragmatic: all models are wrong, but not all aspects of all models are importantly wrong (Box, 1976). For cryospheric DA, the importantly wrong input is often the meteorological forcing (primarily precipitation) (Raleigh et al., 2015; Günther et al., 2019), making the forcing formulation appealing for its physical consistency and match to a dominant source of error (Alonso-González et al., 2022). Consequently, this approach is widespread both in cryospheric forecasting (Metref et al., 2023; Mott et al., 2023) and reanalysis (Margulis et al., 2016; Fiddes et al., 2019). A common cryospheric application is the snowfall factor in snow models, a multiplicative correction applied to precipitation; estimating this parameter rather than SWE directly improves the representation of seasonal accumulation (e.g., Girotto et al., 2024), typically via batch techniques (see Section 2.5). Forcing fields can also be updated directly, for example by adjusting precipitation toward observed accumulation or revising temperature lapse rates to match observed melt timing. The forcing formulation can be extended to a weak constraint by including model error in the uncertain input vector (Evensen et al., 2022), but this approach remains underexplored in cryospheric science.

2.4 Common assimilation methods

There is no universally optimal cryospheric DA scheme. Rather, the choice of which method to use for a given cryospheric problem is dictated by many intertwined factors. These include, but are not limited to: the computational cost, model complexity, assimilation dynamics (Section 2.5, where the difference between filters and smoothers is outlined), problem formulation (Section 2.3), prior specification (the assumed form of the prior $p(\mathbf{x})$, e.g., whether it must be Gaussian or can be bounded and non-Gaussian; see Section 2.1), likelihood specification (the assumed observation-error model $p(\mathbf{y}^o \mid \mathbf{x})$, including the form of the observation operator and error distribution; see Section 2.1), nonlinearity of the dynamical model, differentiability

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Table 1. Examples of possible key uncertain state variables, parameters, and forcing that can be updated via DA in typical seasonal snow, glacier, and permafrost models. Updating states directly corresponds to the model-state formulation while updating parameters and forcing directly (and the state indirectly) corresponds to the forcing formulation of DA. Key uncertain forcing variable symbols: Near surface air temperature T_a, precipitation P, incoming shortwave radiation $S^{\downarrow}$, and incoming longwave radiation $L^{\downarrow}$.

Model type	State	Internal Parameter	Forcing
Intermediate-complexity snow model (Essery et al., 2025)	Snow depth, SWE	Albedo decay rates	$T_a, P, S^{\downarrow}, L^{\downarrow}$
Temperature-index glacier model (Huss and Hock, 2015)	Surface mass balance	Melt factor	T_a, P
Permafrost model (Groenke et al., 2024)	Ground temperature	Thermal conductivity	Snow depth, T_a

(access to gradients), and the extent to which rigorous posterior uncertainty quantification is desired (Evensen et al., 2022). The synthesis proposed in this section aims to guide the reader in the method understanding and selection process, while Table 2 summarizes the Bayesian problem's approximations the classes of methods takes in each of its elements, the assumptions about the dynamical model, the ease of implementation and the computational cost.

2.4.1 Direct insertion

Direct insertion involves replacing model-generated values with the corresponding observational data in a sequential manner in a forward-in-time model run (e.g., Liston et al., 1999; National Operational Hydrologic Remote Sensing Center, 2004; Hedrick et al., 2018). Since this corresponds to assuming the observations are completely accurate and certain (an extreme version of the 'sure thing hypothesis,' Jaynes, 2003), direct insertion is not uncertainty-aware and is thus not a DA approach as it does not follow the Bayesian inference principles. Nonetheless, the strong assumption of perfect observations makes direct insertion simple to implement by avoiding the requirements of specifying a prior and likelihood along with the associated Bayesian computational machinery. For example, direct insertion is useful as a simple fix for correcting modeled snow cover errors of commission (predicting snow cover where it is absent), in that one can simply completely remove snow in the affected grid cells by using a snow free mask obtained from satellite data (Rodell and Houser, 2004). As such, despite its simplicity, direct insertion remains widely used in operational applications. However, direct insertion ignores both observational and model uncertainty and can create discontinuities. Furthermore, it cannot update coincident or antecedent unobserved model variables or be used in a forcing formulation. It can nonetheless be a viable and rapid approach in instances where one has dense observations of the variable of interest, say SWE, and where the role of the model is primarily to interpolate in time without considering uncertainty (Liston et al., 1999). Nudging is a softer version of direct insertion: it avoids discontinuities and pulls the model towards the data by augmenting the model equations with a Newtonian relaxation term (Kalnay et al., 2024). This is closer in spirit to more sophisticated Bayesian DA methods that seek a compromise between model and noisy observations, although unlike Bayesian methods nudging in itself is not probabilistic. Nudging methods have been used to great effect for regional snow reanalysis (Avanzi et al., 2023) and are worth considering as the next level of complexity beyond simple direct insertion.

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2.4.2 Variational data assimilation

Variational DA methods originated in objective analysis methods for DA in weather forecasting (Sasaki, 1958, 1970; Lewis and Lakshmivarahan, 2008) and estimate an optimal state (without uncertainty) by using gradients to minimize a cost function. The cost corresponds to a least squares functional that combines a model background term and observation term where both terms are based on Gaussian error models (Bannister, 2017). Through a Bayesian lens, the model background and observation terms correspond to the prior and likelihood, respectively, to which an additional model error term can be added in weak-constraint formulations (Sasaki, 1970; Bannister, 2017). To compute cost function gradients, variational DA has traditionally relied on carefully deriving hand coded adjoint equations. This derivation requires expertise and time even for relatively simple forward models. The need for an adjoint model has thus been a major obstacle to more widespread adoption of variational methods, even for models that are in principle differentiable. Recent developments in deep learning have made automatic differentiation methods more readily available for researchers (Sapienza et al., 2025), making the technical barrier-to-entry for variational DA considerably lower.

Variational methods inherently yield a single optimized solution and not an ensemble, which makes them less useful for decision making under uncertainty (Palmer, 2017). Nonetheless, these methods are widely used in practice for high-dimensional problems where gradient-based methods thrive, as evidenced both by the success of variational DA in operational meteorology and mathematically closely related gradient descent methods in deep learning (Geer, 2021). In fact, variational methods underpin schemes used for operational DA in numerical weather prediction (e.g., Hersbach et al., 2020). Moreover, hybrid approaches that combine variational and ensemble methods allow for so-called flow-dependent (i.e., dynamic) uncertainty quantification (Bannister, 2017).

The three dimensional variational (3D-Var) method (Lorenc, 1986) remains a widely used variational DA approach due to its computational tractability (Køltzow et al., 2022; Ridal et al., 2024). In 3D-Var, where the '3D' refers to the three spatial dimensions, all observations are assimilated as if they occurred at the same analysis (update) time, ignoring model dynamics across the assimilation window (see Section 2.5). The more sophisticated four dimensional variational (4D-Var) method (Le Dimet and Talagrand, 1986) was developed around the same time as 3D-Var, but is much more computationally intensive as it involves tracking the temporal dimension in addition to the three spatial dimensions. Specifically, 4D-Var compares the state trajectory from the dynamical model, either as a strong or weak constraint, and observations across the entire assimilation window to obtain the analysis (Bannister, 2017).

Because 3D-Var and 4D-Var methods in DA seek to optimize a cost function over states without inherent uncertainty quantification, they can at best be seen as a 'plug-in approximation' of Bayesian inference (Murphy, 2023). Variational Bayesian methods, on the other hand, are more Bayesian in spirit as they seek to optimize a functional with respect to a variational distribution to approximate the entire posterior distribution. As such, they can provide both point estimates and uncertainty quantification. This key distinction avoids conflating these disparate variational methods, especially since the more sophisticated and flexible variational Bayesian approach has received less attention to date for general DA applications compared to the traditional 3D-Var and 4D-Var methods which are both implicitly Gaussian and degenerate.

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In the cryosphere, variational methods have been used most extensively for ice sheet inverse problems, while 4D-Var and variational Bayes have only recently been adopted in mountain glacier modeling (see Section 3.2. Applications outside ice sheet and glacier flow modeling remain rare: notable exceptions include the variational assimilation of albedo into the Crocus snowpack model (Dumont et al., 2012) and an early use of variational methods to estimate soil thermal properties in a permafrost model (Nicolsky et al., 2007).

2.4.3 Linear Gaussian data assimilation: From Kriging to Kalman filtering

The linear Gaussian statistical approach to DA for numerical weather prediction emerged in parallel with variational methods (Kalnay et al., 2024), starting with the foundational work of Eliassen (1954) on the optimal interpolation (OI) technique that was formalized by Gandin (1965). This OI approach is mathematically identical to the Kriging methods developed independently in geostatistics (Krige, 1951; Matheron, 1963; Diggle and Ribeiro, 2007), such that the terms OI and Kriging can technically be used interchangeably. These methods typically operate in a strictly spatial setting, updating a background (prior) field with observations to obtain an analysis (posterior). They can be derived in a pragmatic bottom-up manner as the Best Linear Unbiased Estimator (BLUE) via generalized least squares based on 'classical' frequentist statistics (Cressie and Wikle, 2011; Kalnay et al., 2024). Taking a more theoretical top-down approach, these methods can also be obtained through an uncertainty-aware Bayesian route by applying Bayes' rule to linear Gaussian models (Jazwinski, 1970; Särkkä and Svensson, 2023; Murphy, 2023).

Whereas OI and Kriging are inherently spatial methods, their temporal linear Gaussian model analog is the Kalman filter (Kalman, 1960), which was key to the Apollo program and GPS, among other applications (Grewal and Andrews, 2010). Just like OI and Kriging, the Kalman filter was originally derived using the BLUE approach but was later formalized as a Bayesian filter (Jazwinski, 1970; Särkkä and Svensson, 2023) as defined in Section 2.5. All of these spatial and temporal statistical DA methods are based on the closed form (i.e., analytical) solutions for the posterior distribution of linear Gaussian models in space and/or time via Bayes' rule for Gaussians (Murphy, 2023). In fact, these are all special cases of a more general method known as Gaussian process (GP) regression (Rasmussen and Williams, 2005; Sarkka et al., 2013), with an equally rich history (Lauritzen, 1981), that is widely used in spatio-temporal statistics (Cressie and Wikle, 2011) and machine learning (ML) (Murphy, 2023). We stress how remarkable the availability of an analytical Bayesian solution is for linear Gaussian models: it makes exact Bayesian inference computationally tractable even for relatively high dimensional problems with thousands of state variables and observations. As such, not only does inference become exact, but it breaks the curse of dimensionality that plagues brute force grid approximations. At the same time, these exact methods do not scale to arbitrarily 'big data' beyond $\mathcal{O}(10^4)$ observations due to costly matrix inversion (Rasmussen and Williams, 2005). The development of more scalable approximations remains an active and promising area of research (Heaton et al., 2019). An example is the integrated nested Laplace approximation (INLA; Rue et al., 2009), which exploits sparse representations of latent Gaussian models and accommodates predictors that are nonlinear in their parameters (inlabru; Lindgren et al., 2024). However, for now, a more fundamental issue with these statistical methods is the requirement of a linear model.

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While there are classical nonlinear extensions to these methods, such as the extended Kalman filter based on linearization (Jazwinski, 1970; Särkkä and Svensson, 2023) or, analogously, the iterative linearization of INLA approach (Anderka et al., 2024), these require gradients and may quickly become intractable in high dimensional DA as they require inverting, updating, and storing large covariance matrices (Evensen et al., 2022). Overcoming such bottlenecks to incorporate statistical approximations in DA is an active line of research (Key et al., 2025). Still, both exact statistical DA methods and their classical nonlinear extensions remain suitable for linear or differentiable weakly nonlinear DA problems with tractable dimensionality.

Linear Gaussian DA schemes have a long history of applications in the terrestrial cryosphere. For example, Carroll and Cressie (1996) used point-scale data from a basin in Idaho to improve the Kriging approaches to spatial SWE estimates used in streamflow forecasts in the US. In a glaciological application, Hock and Jensen (1999) showed how Kriging can be used to spatially interpolate point data and estimate glacier-wide mass balance. Around the same time, Brasnett (1999) developed an optimal interpolation scheme to provide a global spatial analysis of snow depth that remains the foundation for snow DA in many operational numerical weather prediction systems (de Rosnay et al., 2014; Gichamo and Draper, 2022). These methods remain popular and are used operationally at the national scale, such as in the University of Arizona SWE product over the USA (Zeng et al., 2018), the SeNorge snow product covering Norway (Lussana et al., 2018), and the S2M meteorological and snow cover reanalysis over the French mountains (Vernay et al., 2021). Recall that mathematically the Kriging schemes explored for snow hydrology (Carroll and Cressie, 1996) and glaciology (Hock and Jensen, 1999) are not fundamentally different from the OI scheme of Brasnett (1999), and the terminology is largely based in field-specific tradition. While many of these products are presented as purely data-driven, unlike model-based reanalysis (e.g., Margulis et al., 2016; Hersbach et al., 2020), we stress that these actually involve purely statistical modeling with few or no geophysical constraints (Parker, 2016).

2.4.4 Ensemble-based methods

Direct insertion (Section 2.4.1) and variational (Section 2.4.2) DA methods can be applied to nonlinear dynamical models, but do not provide uncertainty quantification. On the other hand, linear statistical DA (Section 2.4.3) offers rigorous uncertainty quantification, but cannot propagate uncertainty through a nonlinear dynamical model. Ideally, we would aspire to use Bayesian methods that are at the same time uncertainty-aware *and* applicable to nonlinear dynamical models. While Bayesian extensions to variational methods (Brinkerhoff, 2022) and the nonlinear extended Kalman filter (Sun et al., 2004) offer promising avenues, these require gradients that are challenging to obtain or even approximate without specialized software and may scale poorly to high dimensions. Ensemble-based methods, particularly ensemble Kalman and particle methods, are a widely-used solution to these limitations. Here, we use the term ensemble-based broadly to refer to Monte Carlo methods relying on (pseudo) random sampling, encompassing ensemble Kalman, particle as well as Markov Chain Monte Carlo methods. These methods should thus be seen in the broader context of the Monte Carlo revolution of Bayesian computational statistics in the early 1990s (Robert and Casella, 2011) that continues to this day (Gelman et al., 2013; Murphy, 2023). In geophysics, both for DA (Evensen et al., 2022) and forecasting (Palmer, 2017), the statistical physics term *ensemble* is used to refer to a collection of Monte Carlo samples whereas individual realizations are referred to as ensemble members or particles. Most ensemble-based

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methods are also highly parallelizable, making the implementation of hundred-to-thousand-member ensembles comparable in wall-time to variational methods.

2.4.5 Ensemble Kalman methods

Ensemble Kalman methods retain the Gaussian and linear assumptions of the Kalman filter and Kriging/OI, but they have the key advantage of still being applicable to nonlinear models without the need for gradients (Evensen et al., 2022). This is done by replacing the exact statistics, namely the means and covariances, that appear in Bayes' rule (1) for Gaussians with their ensemble-based (sample) counterparts obtained from an ensemble of dynamical model simulations. This ensemble is, in turn, generated by sampling perturbations of the model states, parameters, and/or forcing via pseudo-random number generators that are then passed through the dynamical model. As such, ensemble Kalman methods have 'flow dependent' (dynamic) statistics, in the form of ensemble means and covariances, that evolve implicitly via the ensemble without the need for storing or updating large covariance matrices (Carrassi et al., 2018). This is in contrast to traditional variational DA (Bannister, 2017), where the background covariance needs to be prescribed, and the extended Kalman filter, where the model covariance matrix needs to be both updated and stored (Särkkä and Svensson, 2023). The benefits of ensemble Kalman methods are clear: they are nonlinear and avoid the need to explicitly handle massive covariance matrices without the need for gradient calculations. To put the second in perspective, the state space in global-scale models can have billions of degrees of freedom ($\sim \mathcal{O}(10^9)$; Kalnay et al., 2024), which would require storing an $\mathcal{O}(10^{18})$-entry covariance matrix, making the linear algebra of complexity $\mathcal{O}(n^3)$ intractable. With ensemble Kalman methods, the model covariance matrix can instead evolve implicitly via an ensemble of size 100 or less, as evidenced in large scale applications from Arctic ocean and sea ice modeling (Othmani et al., 2026) to global numerical weather prediction (Buehner et al., 2025). Such small ensemble size is possible because the dynamical model acts as tight coupling mechanism for the state vector space, effectively reducing the degrees of freedom (and the search space) of the DA method. Ensemble Kalman methods are therefore well-suited to nonlinear high-dimensional DA problems but with the added benefit of uncertainty quantification.

The current widely used ensemble Kalman method is the stochastic ensemble Kalman filter (EnKF) proposed by Evensen (1994), refined by Burgers et al. (1998) to include perturbed observations, and recently improved by van Leeuwen (2020) to instead perturb the predicted observations from the model. Several deterministic variants of the EnKF (e.g., Sakov and Oke, 2008) have since been proposed to reduce sampling errors for small ensembles (Katzfuss et al., 2016; Evensen et al., 2022). The EnKF was also rapidly adapted to a batch smoother formulation known as the ensemble smoother (ES) by van Leeuwen and Evensen (1996) as well as myriad more general ensemble Kalman smoothers (EnKS) (Cosme et al., 2012; Girotto et al., 2014, see Section 2.5).

The core update equations for ensemble Kalman methods stem from Bayes' rule for Gaussians (Murphy, 2023) and are thus equivalent to those for Kalman filters, Kriging/OI, and GPs more generally, with the key addition being the use of flow-dependent ensemble-based statistics from a dynamical model. In the linear Gaussian case, an ensemble Kalman update will converge to the same solution as the classical Kalman update in the theoretical limit of an infinite ensemble size and in practice often with just ~ 100 ensemble members. Crucially, however, unlike the Kalman filter, ensemble Kalman methods do not

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strictly require a linear observation operator or a linear dynamical model and are thus widely applicable to general nonlinear DA problems. Nonetheless, since linearity is assumed in the ensemble Kalman update equation, the method remains a biased approximation of the Bayesian posterior in nonlinear problems. It turns out that this approximation is often remarkably good in practice, especially for weakly nonlinear models (Evensen et al., 2022). Furthermore, the development of iterative ensemble Kalman methods that implicitly temper the likelihood (i.e., assimilate the same observations several times with inflated error, Murphy, 2023) via 'multiple DA' (MDA; Emerick and Reynolds, 2013) have extended the applicability of ensemble Kalman methods to highly nonlinear problems including deep learning (e.g., Kovachki and Stuart, 2019). Such developments exploit the fact that local linearity is a feature of most of the nonlinear problems, provided that the search space and its nonlinearities are explored gradually enough. Gaussianity turns out to be key to the scalability of ensemble Kalman methods, not only because it allows for the use of the Kalman update equations, but since it naturally accommodates spatial localization techniques (Sakov and Bertino, 2011) that split high dimensional problems into manageable local subproblems (Evensen et al., 2022). Section 4.1 elaborates more on the limitations and mitigation strategies that arise from having Gaussianity as a central assumption in such methods.

The wide applicability of ensemble Kalman methods and their relative ease of implementation facilitates their widespread use in cryospheric DA, particularly for snow DA (see Section 3 for details). Further, the Gaussian assumption inherent in ensemble Kalman methods can also be relaxed to accommodate bounded variables (like snow and ice cover) through the use of transformation techniques known as Gaussian anamorphosis from geostatistics (Bertino et al., 2003; Carrassi et al., 2018) that are analogous to link functions in statistics (Gelman et al., 2013). Early applications of the EnKF for snow DA include the work of Andreadis and Lettenmaier (2006), Durand and Margulis (2006) and Slater and Clark (2006) on assimilating respectively remotely sensed snow cover extent, passive radiometric, and in-situ observations into conceptual hydrological models. Subsequent work developed the use of the ES in a Bayesian snow reanalysis framework (Durand et al., 2008) and applied this to real satellite data (Girotto et al., 2014). The field then advanced from purely temporal '1D' filtering with independent grid cells to '4D' spatio-temporal schemes that propagate information spatially (De Lannoy et al., 2010, 2012). Iterative ensemble Kalman methods, notably the ES-MDA (Aalstad et al., 2018) and EnKF-MDA (Alonso-González et al., 2022), subsequently improved performance by tempering the effects of nonlinearity. Beyond snow, these methods have recently been extended to glaciers through synthetic twin experiments (Herrmann et al., 2025; Cao et al., 2025) and to permafrost, where they have improved soil temperature estimates from satellite data (Zwieback et al., 2019) and inferred thermal state from borehole observations (Groenke et al., 2023).

2.4.6 Particle methods

Particle methods are general Bayesian inference algorithms that impose no assumptions on Gaussianity or linearity. As such, they have emerged as a promising approach to geophysical DA since the turn of the century (van Leeuwen, 2009; van Leeuwen et al., 2019). These methods can approximately represent a general posterior distribution through a weighted ensemble of discrete point masses known as 'particles' (Särkkä and Svensson, 2023). This is analogous to how the ensemble Kalman methods use an equally weighted ensemble to represent the statistics of a Gaussian approximation to the posterior distribution

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(Katzfuss et al., 2016). In fact, the terms ensemble member and particle can be used interchangeably (van Leeuwen, 2009), where particle is more concise and may imply some form of weighting. Particle methods enjoy the same implicitly 'flow dependent' uncertainty quantification as the ensemble Kalman approach by virtue of propagating the particle ensemble through the dynamical model. The key departure from the ensemble Kalman approach is that the particle methods do not inherit the linear Gaussian assumption, making them, at least in theory, even more widely applicable to non-Gaussian and strongly nonlinear problems.

The key algorithmic steps underlying particle methods, namely the combination of importance sampling and resampling, have a long history in Bayesian statistics (see Smith and Gelfand, 1992, and references therein) and computation more generally (Hammersley and Morton, 1954). Importance sampling is an extension of direct Monte Carlo integration for estimating expectations with respect to a distribution, such as the Bayesian posterior, which is generally intractable, based on sampling from a *tractable* simpler distribution known as the proposal (MacKay, 2003; Robert, 2007). The discrepancy between the target distribution and the proposal distribution is accounted for via importance weights for each particle (sample) based on a ratio between the target and proposal probability density (Murphy, 2023). As such, particles with higher (lower) probability density from the target and/or lower (higher) probability density from the proposal are given higher (lower) weight. In practice, this means we can estimate the integrals that arise in cryosphere DA, such as estimating the posterior mean, via simple sums without invoking Gaussian assumptions. After importance weighting, the particles are typically resampled with replacement such that high-weight particles are copied and low weight particles are removed (van Leeuwen, 2009). This helps remove superfluous particles and simplifies calculations as the resulting resampled particles have equal weight.

Building on this importance sampling foundation, particle filtering and smoothing methods for dynamical problems were independently proposed around the same time by Gordon et al. (1993) for filtering and Kitagawa (1996) for filtering and smoothing. Nearly identical methods in the form of the original Generalized Likelihood Uncertainty Estimation (GLUE) method with a formal likelihood (Beven and Binley, 1992) and the 'direct ensemble method' (van Leeuwen and Evensen, 1996) were simultaneously (re)discovered in hydrology and geophysical DA, respectively. Particle degeneracy (i.e. ensemble collapse) is a common problem particle methods face, and it happens when all weight is received by a single particle in high-dimensional problems as well as the rapid posterior contraction in cases with 'big' and/or very precise data (Snyder et al., 2008). Modern particle approaches combat degeneracy by using likelihood tempering and data tempering in Sequential Monte Carlo (Chopin and Papaspiliopoulos, 2020; Murphy, 2023) and adaptive importance sampling methods that refine the proposal distribution (Bugallo et al., 2017). In these cases, collapse occurs because the variance of the importance sampling estimator is related to the divergence between the proposal and the posterior (the optimal proposal), an effect that is amplified in challenging problems where variance explodes (MacKay, 2003). So, while the ensemble Kalman methods provide a biased yet low (sampling) variance posterior approximation in nonlinear settings, particle methods provide an unbiased yet higher sampling variance approximation, a bias-variance trade-off explored by Frei and Künsch (2013). Lastly, we note that although the aforementioned resampling step is sometimes heralded as resolving the degeneracy problem, this only solves the weight degeneracy problem and not the more fundamental path degeneracy problem (Murphy, 2023).

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The obstacle of particle degeneracy has slowed the broad application of particle methods to high dimensional spatio-temporal problems (van Leeuwen et al., 2019). While ensemble Kalman methods rely heavily on localization methods to help scale them up to very high dimensional problems, these have been more challenging to apply to particle methods (Farchi and Bocquet, 2018). On the one hand, if the ensemble is updated globally across all grid cells, degeneracy is likely. On the other hand, with the natural solution of restricting particle DA to local spatial windows, it is unclear how to consistently re-stitch the particle ensemble back together across the spatial domain. Nonetheless, the considerable and still ongoing research effort on scaling up particle methods ensures that progress is steadily being made (Farchi and Bocquet, 2018; van Leeuwen et al., 2019). For example, Potthast et al. (2019) showed how a localized adaptive particle filter could be applied in an operational global numerical weather prediction framework. Furthermore, building on his previous work, Poterjoy (2022) recently demonstrated how regularization, likelihood tempering, and hybridization can improve the performance of local particle filters.

The move away from primarily using ensemble Kalman methods for cryospheric DA began with Leisenring and Moradkhani (2011), who showed that, at least with a large ensemble, a particle filter could outperform the EnKF when assimilating SWE observations in a simple snow model; while Charrois et al. (2016) extended the particle filter adoption to a detailed snow model. Magnusson et al. (2017) further demonstrated the promising performance of the particle filter for snow DA across multiple sites in the Alps, laying the foundations for subsequent operational developments (Winstral et al., 2019; Oberrauch et al., 2026). Promising workflows to leverage the particle filter for glacier surface mass balance estimation have also been developed (Landmann et al., 2021). The widely applicable particle batch smoother (PBS) was introduced by Margulis et al. (2015) for snow DA to further improve ensemble-based snow reanalysis (Durand et al., 2008; Girotto et al., 2014). Recent work by Aalstad et al. (2026a) introduced an adaptive PBS (AdaPBS) and showed how iteratively adapting the proposal, beyond the often implicit prior proposal, can further enhance the performance of the PBS for snow DA; this method has subsequently been implemented for glacier (Yang et al., 2026) and coupled snow-permafrost models (Willmes et al., 2025).

2.4.7 Toy example comparing ensemble Kalman and particle methods

This section applies the two most common classes of cryospheric DA methods to the non-linear Bayesian example introduced in Section 2.2. In Figure 2, we showed a numerical solution to the classic cryospheric problem of inferring SWE after having obtained a noisy measurement of snow depth with means of a snow probe, while accounting for a prior uncertainty of the density. Figure 3 compares the posterior estimates of the EnKF and the particle filter by means of the ensemble distribution with the solution obtained with numerical grid-based integration as explained in Section 2.2. On the one hand, the results of the EnKF ensemble members have an updated position in panel (b), as the effect of the Kalman update is to move the ensemble by comparing the observation to the prior predictions. However, it is clear that the result is biased (i.e., the average of the posterior members does not correspond to that of the numerical grid-based solution), because the forward model $d = m/\rho$ is not linear while the Kalman update assumes model linearity. Nonetheless, the approximate posterior obtained from the ensemble Kalman method retains a distribution that allows us to conservatively estimate the uncertainty of the posterior estimate. On the other hand, the particle filter can handle the non-linearity of the model and hence the posterior appears less biased than the EnKF solution. However, since the prior proposal distribution was sampled with only 30 ensemble members, the particle posterior

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obtained by weighting and resampling has collapsed onto the single particle (turquoise square in panel (b) corresponding to the red circle closest to the star in panel (a)) contained in the true posterior. We hence produce highly overconfident (i.e., degenerate) uncertainty quantification from this particle approximation of the posterior. Sections 2.4.5 and 2.4.6 discuss several strategies to mitigate the problems that can arise with basic implementations of ensemble Kalman and particle methods for challenging problems.

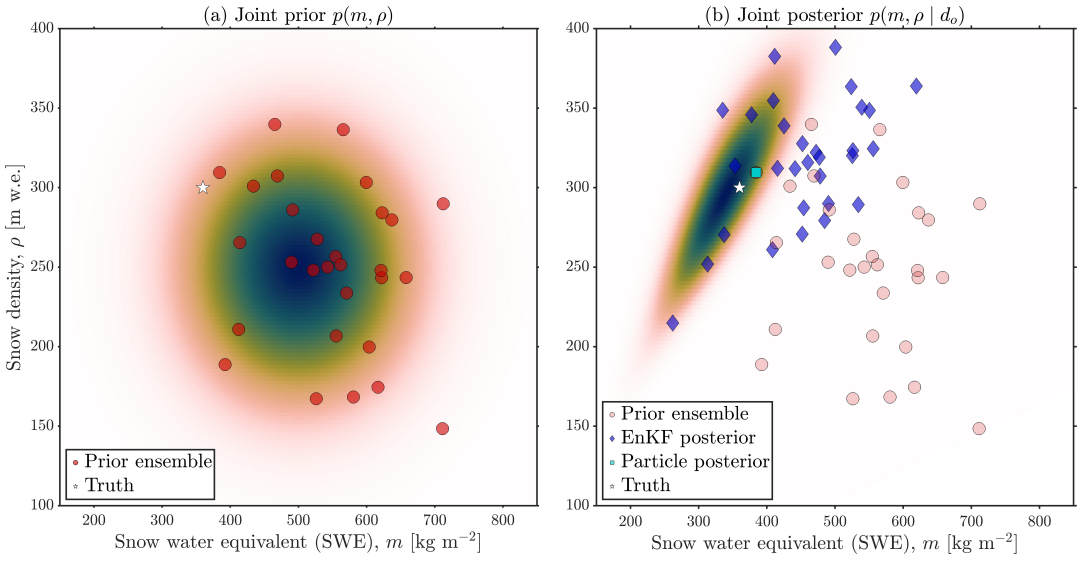

Figure 3. The non-linear problem of inferring SWE by assimilating a noisy snow depth observation presented in Figure 2 is solved using two different approximations: an EnKF and a particle filter, both with 30 members. The prior distribution is shown in the panel (a) and the prior ensemble (red circles) is the same for both the methods. The posterior distribution is in the right panel and is approximated with an ensemble distribution with blue diamonds for the EnKF and with an turquoise square for the particle filter (all particles converged to a single posterior). The truth is depicted with a white star, and the exact pdfs (obtained through numerical integration, normalized independently for the prior and posterior) are shown by background color.

2.4.8 Markov Chain Monte Carlo

Markov Chain Monte Carlo (MCMC) methods are widely considered the gold-standard computational tool for performing approximate Bayesian inference in practical statistics (Gelman et al., 2013; Robert, 2007; Murphy, 2023), although they can be so costly as to be intractable for many DA problems (Cleary et al., 2021). As described in Robert and Casella (2011), MCMC stems from the physics paper of Metropolis et al. (1953), first translated to statistical inference by Hastings (1970), outlining the Random Walk Metropolis (RWM) algorithm that still serves as a kernel for current state-of-the-art MCMC schemes such as gradient-based Hamiltonian Monte Carlo (MacKay, 2003; Neal, 2011). All MCMC schemes construct Markov chains that take sequential steps through state and/or parameter space to asymptotically sample from the target posterior distribution. Typically, this involves accepting or rejecting proposed steps by comparing the proposed posterior density to that of the current step. When

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this procedure is repeated for enough sequential steps, typically tens or hundreds of thousands, after discarding an initial warm up phase, the resulting Markov chain can be used to form a good approximation of the posterior. This explains why, outside of valuable theoretical case studies (Apte et al., 2007), MCMC is often not computationally feasible for most problems: having to run a dynamical model sequentially (i.e., not in parallel) hundreds of thousands of times for each assimilation window is completely intractable (Cleary et al., 2021). Nonetheless, MCMC can still serve as an invaluable 'gold standard' benchmark to evaluate the performance of more tractable DA algorithms, such as ensemble Kalman and particle methods, in scaled down targeted experiments (Law and Stuart, 2012; Aalstad et al., 2026b).

The asymptotic (i.e., in the long run) performance guarantees make intensive MCMC sampling an attractive option in settings when it remains computationally feasible. In cryospheric DA, the high cost means that MCMC has mostly been applied to problems with simple and fast dynamical models, limited spatial extents, and/or static problems. For example, the snow DA work of Kolberg and Gottschalk (2006) assimilated Landsat-based fractional snow-covered area (FSCA) data into a temperature-index model with a depletion curve via an MCMC sampler to improve SWE and runoff estimates. Garnello et al. (2021) used MCMC to calibrate static thermodynamic parameters in a permafrost model by assimilating ground temperature data from a single site and subsequently performed site-level projections of permafrost thaw under various scenarios. In glaciology, MCMC has been used to great effect to constrain static parameters in temperature index models to simulate mass balance at both the regional (Rounce et al., 2020a) and, via emulators, global scale (Rounce et al., 2023). Most studies using MCMC in cryospheric DA, including the examples above, to date have relied on variations of the basic RWM algorithm. Thus, there lies much untapped potential in exploring more sophisticated MCMC samplers (e.g., Neal, 2011) in the cryospheric domain. The rise of emulators for accelerating MCMC (Cleary et al., 2021; Rounce et al., 2023; Keetz et al., 2025) is also greatly broadening the viable domain of applicability of these algorithms.

To synthesize the dense information about each class of DA methods treated in this synthesis paper, Table 2 proposes a summary of the approximations of the Bayesian problem in each of its elements, the assumptions about the dynamical model, the ease of implementation and the computational cost.

2.5 Filtering and smoothing

The DA methods discussed in Section 2.4 can handle the update either through a filtering or smoothing type approach (Cosme et al., 2012), which differ fundamentally in how they ingest observations in the time dimension (Särkkä and Svensson, 2023). Filters update the system state (and/or parameters) $\mathbf{x}_k = \mathbf{x}(t_k)$ at the current time t_k sequentially using all observations available up to that time $\mathbf{y}^o_{1:k} = \{\mathbf{y}^o_1, \ldots, \mathbf{y}^o_k\}$, where $k \geq 0$ indexes time, by targeting the filtering distribution $p(\mathbf{x}_k|\mathbf{y}^o_{1:k})$. This makes filters suitable for real-time forecasting and other sequential applications (Carrassi et al., 2018). The time-domain is usually split into assimilation windows denoted by the vertical lines in Figure 4, and the filtering exercise is a sequential process, where Bayes' rule (Equation (1)) is applied recursively using the posterior inferred in the previous window to help form the prior for the next window (Särkkä and Svensson, 2023). The upper panel of Figure 4 shows the ensemble collapse that occurs as more observations are assimilated due to path degeneracy over multiple windows when using a simple variant of the particle filter (Gordon et al., 1993) in which the posterior distribution of each assimilation window is used to generate

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Table 2. Overview of the DA methods presented in Section 2.4 stating their assumptions, requirements, level of Bayesian uncertainty quantification (UQ, where asymptotic means exact with infinite particles), difficulty of implementation, and computational cost. The implementation difficulty and cost levels depend on the variant of the method used, e.g. a 1D stochastic EnKF (easy) vs. a spatio-temporal ES-MDA (medium to hard). These levels can be seen as an average in terms of cryospheric DA applications that are subject to change with more advanced variants. *: Approximate with EnVar and Variational Bayes, *: Easier with automatic differentiation, †: Exact inference only scales up to $\simeq 10^4$ observations, $^\circ$: Harder to localize for spatio-temporal problems, ‡: Very high to avoid degeneracy in higher-dimensional problems.

DA method	Section	Assumptions	Requires	Bayesian UQ	Implementation	Cost
Direct insertion	2.4.1	Perfect data	Hard overwrite	No	Very easy	Low
Variational	2.4.2	Gaussian	Cost minimization	Limited*	Hard*	Low-to-moderate
Kalman, OI/Kriging	2.4.3	Linear Gaussian	Linear model	Exact	Easy	Low†
Ensemble Kalman	2.4.5	Linear Gaussian	Ensemble	Approximate	Medium	Moderate
Particle	2.4.6	Minimal	Ensemble	Asymptotic	Easy$^\circ$	High‡
MCMC	2.4.8	Minimal	Markov chain	Asymptotic	Medium	Very high

the prior for the next window. While resampling can superficially help with weight degeneracy, it does not address this more fundamental path degeneracy issue (Murphy, 2023), which instead requires measures ranging from heuristics like jitter to more advanced particle methods (van Leeuwen et al., 2019)

Smoothers, in contrast, can infer past states by incorporating all the observations in the assimilation window, both before and after the time of interest, by targeting the smoothing distribution $p(\mathbf{x}_k \mid \mathbf{y}^o_{1:\ell})$ where $\ell \geq k$. As such, unlike forecasting problems that rely primarily on filtering, smoothers have the benefit of hindsight making them ideally suited for problems such as reanalysis. Among the many variants of smoothers (Cosme et al., 2012; Särkkä and Svensson, 2023), a fixed-interval variant known as a batch smoother, where ℓ is fixed and set to correspond to the length of the assimilation window, is the most widely used approach in cryospheric DA. The filtering and smoothing formulations happen to coincide in the special case where an assimilation window is the period between two subsequent observations (top panel in Figure 4). In the more general case, however, with multiple observation times within a window (bottom panel in Figure 4), the batch smoother will benefit from hindsight within the window and attempt to fit the entire trajectory of observations therein. As such, when multiple windows are chained together it is entirely possible to perform smoothing within a window but filtering across windows. The bottom panel of Figure 4 shows how a PBS (Margulis et al., 2015) handles the same data as the aforementioned simple particle filter by assimilating them all at once in a single batch in a long assimilation window containing all observations in the water year. Such batch smoother methods yield dynamically consistent state estimates that satisfy the model physics over the entire assimilation window at the cost of requiring offline, retrospective processing rather than online sequential filtering (Carrassi et al., 2018; Kalnay et al., 2024). Together with hindsight, this dynamical consistency explains why smoothers are particularly powerful in the context of reanalysis (e.g., Margulis et al., 2016; Hersbach et al., 2020).

The comparison in Figure 4 provides an illustrative example of the mechanisms driving filters (top) and smoothers (bottom). In the beginning of the snow season, only a few observations have been assimilated by the particle filter, so the filtering posterior

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is able to match the SWE measurements closely. For this part of the time series, it happens to provide a more accurate estimate compared to the particle batch smoother. On the other hand, as this basic particle filter progresses over multiple windows the particle paths become degenerate and collapse onto only a single path by the fifth window despite using 10^4 particles. A simple solution to prevent this behavior is to add carefully tailored jitter (i.e., noise) to the particles to increase their diversity. In contrast, the smoother shows a much better performance towards the end of the snow season where it remains non-degenerate. This batch smoother is able to consider all information at all times which allows it to find a compromise across its entire large single DA window, yielding better performance on average than the filter. In both cases, these particle schemes were used to directly update forcing-related parameters in a temperature index model that are held constant within each DA window. As such, the state is updated indirectly while satisfying the underlying temperature index model physics through the forcing formulation (see Section 2.3), using the model as a strong constraint (Evensen et al., 2022). The fact that the batch smoother SWE posterior is not able to encompass the observations everywhere is evidence of the approximation made by assuming a single set of uncertain forcing parameters for a water year in a temperature index model.

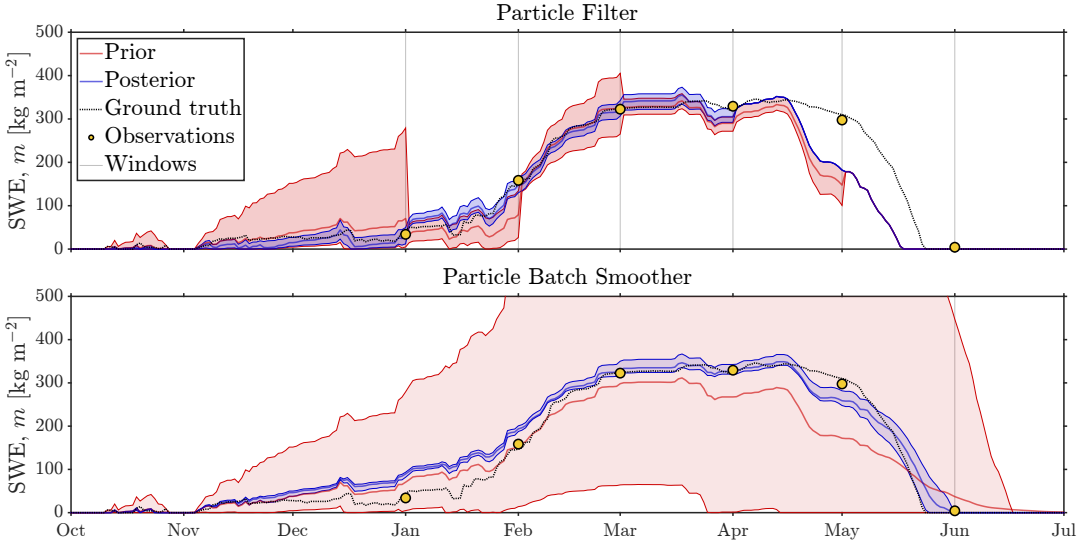

Figure 4. Comparison between filtering and smoothing with particle methods in a temperature index model forced by ERA5 reanalysis data. The ground truth (dotted black line) shows real SWE measurements from the Filefjell station (950 m asl), in Western Norway (Stranden et al., 2024). The observations (yellow points) are obtained by sampling the SWE data every month and adding a noise term to mimic observation error from a satellite retrieval. The prior distribution (in red) is rendered with an ensemble of 10000 particles for both the methods. The posterior (in blue) is obtained by assimilating the observations sequentially across 6 assimilation windows (gray vertical lines) for the Particle Filter (upper panel) while all the observations are considered at the same time in a single window for the Particle Batch Smoother (lower panel).

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2.6 Sources of uncertainty and complexity

The DA methods outlined in Section 2.4 operate either implicitly or explicitly on uncertain quantities. In Bayesian DA, we quantify uncertainty through probability density functions for the prior and posterior (Section 2.1), representing the *epistemic* (knowledge-related) uncertainty before and after conditioning on data. We also rely on the likelihood function to encode irreducible *aleatoric* ('random') uncertainty to model unresolved noise and representation error in the data (Van Leeuwen, 2015). Without entering philosophy (see e.g., Nearing et al., 2016), we are primarily concerned with epistemic uncertainty that is, at least in principle, reducible through information gained from data, whose uncertainty also must be included (see Section 4.2 and 4.4). Strictly speaking, aleatoric uncertainty is part of our model specification and is thus itself subject to epistemic uncertainty (Heße et al., 2019) at least in higher levels of inference (MacKay, 2003). Multiple kinds of epistemic uncertainty enter the analysis in Earth system science (Mansfield and Christensen, 2026). The first is the *input uncertainty* surrounding the variables typically targeted by the inference in the strong constraint forcing formulation (Section 2.3), such as parameters and forcing. The second is *model uncertainty* (sometimes called *structural uncertainty*), which is the uncertainty related to model error (also known as model discrepancy), i.e., how well the dynamical model represents the target physical processes (Berliner et al., 2023). This model uncertainty can be incorporated by including model error terms in the model-state formulation (Särkkä and Svensson, 2023) and the weak constraint forcing formulation (Evensen et al., 2022) as discussed in more detail in Section 2.3.

Dynamical models represent physical processes with varying degrees of detail, which we refer to as the *complexity* of the model. Simple models often use fewer parameters: a degree-day model uses two uncertain parameters, the degree day factor and temperature bias, to represent snow or ice ablation as a function of mean daily temperature alone (e.g., Hock, 1999). More complex models tend to employ many parameters: a multilayer snowpack model with an energy balance models ablation by resolving snow temperature, density, albedo, and grain shape and size at every layer, using a large number of uncertain parameters (examples with increasing complexity are Essery, 2015; Vionnet et al., 2012). Computational cost typically increases with complexity, while performance does not necessarily (Magnusson et al., 2015).

Adopting a more complex model reduces structural error by resolving more processes, but at the cost of additional parameters that must be estimated, effectively trading model uncertainty for greater uncertainty in the inference targets (Günther et al., 2019). The ideal model is therefore as simple as possible, following the principle of parsimony known as Occam's razor (MacKay, 2003), but as complex as necessary to capture the outputs of interest. This accuracy-complexity tradeoff persists even without computational constraints: a model with more parameters is more sensitive to errors in those parameters, which can degrade its outputs (Günther et al., 2019; Magnusson et al., 2015).

Resolving this tradeoff can be achieved via DA (Carrassi et al., 2017), and approximate Bayesian inference in general (Llorente et al., 2023), by estimating the *model evidence* (marginal likelihood, Section 2.1) which is the expectation of the likelihood with respect to the prior (Llorente et al., 2023). A complex model can fit a wide range of possible observations, but in doing so it dilutes its predictive density and assigns only a small probability to the actual observations, reducing its model evidence. On the other hand a parsimonious model concentrates its predictive density on a narrower range of possible

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observations, but it is rewarded only once actual observation fall within it. This can be used as a 'Bayesian Occam's razor' to select between (or average across) competing model structures and constrain model uncertainty via higher levels of inference (MacKay, 2003). Computational cost enters this comparison implicitly: only models tractable for the problem at hand can be evaluated. Practical model choice also involves subjective considerations such as interpretability and physical realism, which become increasingly relevant as machine-learning components are introduced into the modeling chain (Section 5.7). Priors play a complementary role. By introducing theoretical or empirical constraints on parameter values, a model with many nominally free parameters can be made effectively simpler, both improving tractability and enabling the use of limited or noisy data.

3 Domain-specific approaches

DA in different cryospheric domains is at different stages of development, with snow DA being more mature compared to glacier and especially permafrost applications. This discrepancy reflects the greater availability of observations for snow, modeling frameworks that are more mature and better suited to DA, and stronger operational demand for forecasts than has historically existed for glacier and permafrost applications. Here, we present an exploration of DA applications for the terrestrial cryospheric realms of snow, glaciers and permafrost, and consider how improved constraints on cryospheric states may propagate through coupled Earth system processes and affect other states and fluxes.

3.1 Snow

DA was adopted in snow science for two main objectives: reanalysis and forecasting. In a reanalysis setting, DA is used to reconstruct the seasonal evolution of the snowpack using all observations available over the period of interest to produce the best possible retrospective analysis (reanalysis for short) of snow states and fluxes. In a forecasting setting, the objective is to update the model before the prediction period begins in order to provide accurate initial conditions for the future evolution of the snowpack. This distinction is central because reanalysis can leverage hindsight by exploiting information that becomes available only later in the season, whereas forecasting requires sequential methods and near-real-time observation availability.

3.1.1 Snow reanalysis

Snow reanalyses have arguably emerged as the canonical large-scale application of DA for the terrestrial cryosphere (Barrett, 2003; Margulis et al., 2016; Alonso-González et al., 2021). Such snow reanalyses have primarily relied on the use of FSCA retrievals, as these are widely available at varying resolutions from multiple satellites (e.g., Aalstad et al., 2020) and the seasonal evolution of FSCA provides strong constraints on both accumulation and melt dynamics (Margulis et al., 2015). This idea can be traced back to the deterministic snow reconstruction approach, first suggested by Martinec and Rango (1981) and later elaborated by Cline et al. (1998), where peak SWE is estimated by building up the snowpack in reverse from the melt-out date by combining remotely sensed FSCA with modeled snowmelt rates. While deterministic snow reconstructions are still being used to great effect in regional products (e.g., Bair et al., 2023), this approach is essentially a direct insertion that ignores uncertainty in the model, forcing, and observations (Slater et al., 2013).

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By instead using an uncertainty-aware ES scheme, the synthetic experiments in Durand et al. (2008) presented a highly tractable and promising approach to Bayesian snow reanalysis. Extending this, Girotto et al. (2014) used real FSCA satellite data from Landsat in a small California Sierra Nevada watershed to show how the Bayesian snow reanalysis method of Durand et al. (2008) was a more robust probabilistic generalization of deterministic snow reconstruction. Taking this a step further, Margulis et al. (2016) performed a snow reanalysis for the entire Sierra Nevada spanning the Landsat-era at 100 m resolution using a novel PBS scheme (Margulis et al., 2015), later expanded to the Andes (Cortés and Margulis, 2017) and the full western US (Fang et al., 2022). Aalstad et al. (2018) tested the snow reanalysis framework in the high Arctic archipelago of Svalbard by using both MODIS and Sentinel-2 data as well as a novel iterative ensemble Kalman scheme in the form of the ES-MDA (Emerick and Reynolds, 2013). Fiddes et al. (2019) adapted the PBS snow reanalysis method to assimilate MODIS data at hydrological hyper-resolution (30 m) in the Swiss Alps using spatial clustering techniques. Subsequently, Liu et al. (2021) showed how MODIS and Landsat data could be jointly assimilated to generate a 2000-2017 snow reanalysis for High Mountain Asia at 500 m resolution. Alonso-González et al. (2021) embedded the PBS in a quasi-dynamical meteorological downscaling workflow to perform a 1 km MODIS-era snow reanalysis for the Lebanese mountains. Independent SWE product evaluation studies consistently identified the snow reanalysis of Fang et al. (2022) among the best-performing products (Ritchie et al., 2025; Lundquist et al., 2026). As a further step towards global snow reanalysis, Sun et al. (2025) applied the same framework to the MODIS Snow_cci and found that accuracy varied with the number and viewing geometry of the relevant retrievals.

Beyond FSCA, several recent studies have explored the potential added value of other remotely sensed observations in smoothing-based snow reanalysis frameworks. Gravimetric terrestrial water storage (TWS) anomalies retrieved from GRACE have been used to constrain snow mass at coarse resolutions, particularly in high-latitude, snow-dominated basins where the seasonal TWS signal is dominated by snow accumulation and melt (Zaitchik et al., 2008; Forman et al., 2012). Passive-microwave SWE retrievals have likewise been assimilated, in combination with ground-based snow depth observations, in the coarse-resolution GlobSnow product, an assimilation-based dataset estimating hemispheric SWE in the areas outside the mountains(Luojus et al., 2021). Margulis et al. (2019) demonstrated the considerable potential of assimilating a single airborne lidar-based snow depth image with the PBS; with a single observation time, the PBS reduces to a filter, but the same image can be assimilated jointly with another quantity within the seasonal batch smoother framework. Although airborne lidar snow depth retrievals are not widely available except for a few basins around the world, satellite retrievals of snow depth are becoming available (Lievens et al., 2019; Fair et al., 2025). Girotto et al. (2024) showed how C-band snow depth retrievals from Sentinel-1 from Lievens et al. (2019) could be assimilated using the PBS to correct snowfall biases in a simple snow model. To contend with the fact that snow depth data is often spatially sparse, Alonso-González et al. (2023a) developed a method for spatio-temporal snow DA with a localized iterative ensemble Kalman smoother scheme (DES-MDA) for snow reanalysis. Alonso-González et al. (2026) recently applied this method to assimilate airborne lidar data at hyper-resolution, showing how snow depth data in forest gaps can be used to correct the snowpack under the canopy. Furthermore, Mazzolini et al. (2025) extended this method propagating in space the snow depth retrievals along profiles from the satellite altimeter ICESat-2, meaningfully updating the prior results, especially when FSCA retrievals from Sentinel-2 are assimilated jointly. Figure 5 shows how assimilating multiple complementary observations improves posterior estimates.

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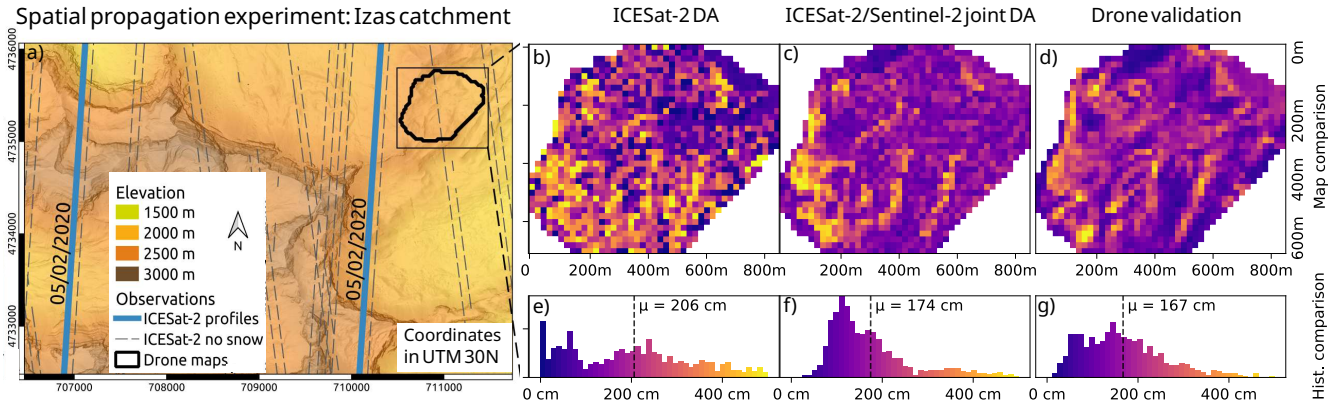

Figure 5. A high-resolution (20 m) joint assimilation retrospective experiment in the Izas experimental catchment in the Spanish Pyrenees. Sparse ICESat-2 snow depth observed along the blue profiles are assimilated independently and jointly with FSCA retrievals from Sentinel-2. The posterior simulated snow depth maps are shown respectively in panels b) and c). Information from the snow depth profiles is propagated in space using the spatial structure encoded in the prior covariance matrix. The spatial distribution of snow depth at peak-SWE from an independent UAS acquisition is used as validation and is shown in d). The histograms in e) and f) correspond to the respective posterior simulations shown in b) and c) can be compared to the corresponding histogram from the UAS map shown in g). Figure adapted from Mazzolini et al. (2025)

All of these snow reanalysis applications leverage batch smoothing with the entire water year as an assimilation window. As such, especially when using FSCA, this approach must wait for the snow cover to melt-out before it can be applied to generate retrospective snowpack estimates. This apparently makes snow reanalysis of limited direct value compared to forecasting systems for real time decision making. At the same time, several studies have shown that such snow reanalyses can help identify spatial patterns that are consistent across years (Kolberg and Gottschalk, 2010; Fiddes et al., 2019; von Kaenel and Margulis, 2025). This consistency remains largely untapped in snow hydrological forecasting applications, despite the rich trove of information provided by reanalyses. So, while an operational particle filter forecasting program has been used to generate new snow reanalysis products (Oberrauch et al., 2026), using smoothing-based snow reanalyses to inform snow hydrological forecasts remains underexplored.

3.1.2 Snow forecasting

In forecasting applications, DA typically operates sequentially through filtering and updates the model as observations become available in near real time. Early studies used direct insertion (Liston et al., 1999) or optimal interpolation (Brasnett, 1999) to update snow states, either in dedicated snow models or the land surface model in numerical weather prediction (de Rosnay et al., 2014), by assimilating distributed snow depth measurements, snow cover maps, and/or SWE observations (Fletcher et al., 2012; Avanzi et al., 2023). A key step forward to enable flow-dependent uncertainty quantification was the adoption of

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ensemble-based filtering methods, especially the EnKF. The pioneering studies of Andreadis and Lettenmaier (2006), Slater and Clark (2006), and Clark et al. (2006) were motivated by using EnKF-based DA to improve the initial SWE states and thus benefit downstream streamflow forecasts. Later work by Huang et al. (2017) explored the same theme across several basins in the western US, highlighting the potential of EnKF-based SWE DA for improving streamflow predictions in poorly calibrated basins. Building on De Lannoy et al. (2010, 2012), Magnusson et al. (2014) developed a spatio-temporal ensemble Kalman filter for snow station observation assimilation through what can be seen as a dynamic extension of optimal interpolation (Brown et al., 2003). This enabled the assimilation process to spatially propagate information, thereby potentially improving model states even at points without measurements (Magnusson et al., 2014) and elegantly assimilating multiscale data including coarser retrievals than the model grid (De Lannoy et al., 2012). Beyond direct state estimation, the work of Stigter et al. (2017) on a Himalayan catchment demonstrated how snow DA with the EnKF can also be used to calibrate snow model parameters. More recently, Dunmire et al. (2026) demonstrated the value of incorporating dynamic observation uncertainty when assimilating Sentinel-1 snow depth retrievals with the EnKF.

Despite the early success and popularity of the EnKF in operational snow forecasting applications, particle filters have become far more widespread over the last decade. Thirel et al. (2013) was early to explore the potential of assimilating satellite-based FSCA retrievals from MODIS with a particle filter in a hydrological model. The study of Charrois et al. (2016) showed how a particle filter could be applied to complex multi-layer snowpack models, in this case Crocus, by assimilating synthetic reflectances (via radiative transfer modeling) and in-situ snow depth data in twin experiments at a single site in the Alps. Magnusson et al. (2017) further demonstrated the promising performance of the particle filter by assimilating snow depth data into an intermediate complexity snow model across multiple sites in the Alps. Piazzi et al. (2018) tested the performance of the particle filter for multivariate snow DA by jointly assimilating multiple ground-based observations at three alpine test sites, emphasizing the need for perturbing both parameters and forcing to avoid degeneracy. Targeting a catchment in the High Atlas range, Baba et al. (2018) was the first study to test the added value of assimilating Sentinel-2 FSCA data into a distributed snowpack model via a particle filter. The studies of Smyth et al. (2019, 2020) investigated the use of particle filters to assimilate snow depth so as to improve estimates of SWE by exploring the role of forcing and compaction parametrization uncertainty (Smyth et al., 2019) as well as the effects of observation timing and uncertainty (Smyth et al., 2020).

Beyond purely temporal (1D) applications, Cantet et al. (2019) showed how to perform spatio-temporal snow DA on snow survey data with a particle filter across a region in Canada by using correlated forcing perturbations and spatially interpolating the local particle weights. Odry et al. (2022) extended the framework of Cantet et al. (2019) to also assimilate station data while exploring particle reordering strategies to better maintain spatial consistency. As an alternative to this somewhat heuristic approach, Cluzet et al. (2021) suggested a promising method to localize particle filters for spatio-temporal snow DA through synthetic experiments in a semi-distributed domain in a single massif in the Alps. In a follow up study, Cluzet et al. (2022) extended this approach to real experiments across multiple massifs in the Alps and Pyrenees. Recent applications of the particle filter for spatio-temporal snow DA, such as the large scale and operationally motivated work of Oberrauch et al. (2024, 2025), have reverted to the spatial interpolation approach. Still, there remains untapped potential in further exploring localized particle filters for spatio-temporal snow DA suggested by Cluzet et al. (2021), as shown in theoretical DA research by Poterjoy (2022).

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3.1.3 Meteorological applications

In meteorological applications, snow DA is primarily used to provide realistic initial snow conditions for NWP, from short-range hazard forecasting to medium- and long-range weather forecasts (de Rosnay et al., 2014). Better initialization of snow states can improve not only snow variables themselves, but also forecasts of surface fluxes and lower-atmospheric conditions (Orsolini et al., 2013; Jeong et al., 2013; Thomas et al., 2016; Li et al., 2019, 2022); as well as circulation features in regions with strong snow–atmosphere coupling (e.g., East Asia; Senan et al., 2016; Lin et al., 2020; Komatsu et al., 2023). For this reason, operational prediction centers are increasingly moving toward coupled land–atmosphere DA systems that seek a more consistent initialization of snow, surface, and lower-atmospheric variables (de Rosnay et al., 2022). While these NWP systems have traditionally relied on static schemes such as optimal interpolation for snow DA (de Rosnay et al., 2014), recent work has demonstrated the value of flow-dynamic schemes such as the EnKF (Bakketun et al., 2026). Operational meteorological snow DA usually relies on synoptic in-situ snow depth measurements together with satellite observations of snow cover in the optical and/or passive microwave domain. Widely used in operational NWP is the IMS multi-instrument snow cover product (Helfrich et al., 2007), which has recently become available at a resolution as high as 1 km. A major priority is to assimilate a broader range of satellite products jointly, provided that biases, latency, and other technical constraints are properly handled. Promising directions include the greater use of lidar and active microwave products (Lievens et al., 2019), as well as observations from geostationary satellites, which offer high temporal resolution. These tradeoffs are especially acute in mountainous regions, where snow heterogeneity is large and where near-real-time snow analysis for NWP remains less mature (Dozier et al., 2016; Wrzesien et al., 2019; Orsolini et al., 2019; Daloz et al., 2020; Liu et al., 2022; Mudryk et al., 2025). More broadly, meteorological applications must balance gains in snow analysis quality against operational constraints such as data availability, timeliness, computational efficiency, and the need to avoid degrading forecast skill.

3.1.4 Hydrological applications

In hydrological applications, snow DA is used to improve reanalyses, near real time estimates, and forecasts of snowmelt, runoff, streamflow, flood risk, and hydropower inflow in snow-dominated basins. Here, the value of snow DA lies in constraining the accumulation and melt processes that govern water storage and release, especially in catchments where precipitation uncertainty is large (Tang et al., 2023; Fang et al., 2023) and in-situ observations are sparse. Snow DA schemes developed for numerical weather prediction are useful in this context, but they are not always optimal for hydrological applications because the required spatial resolution is generally higher (Fan et al., 2019) and because basin-scale water balance is often the primary concern (Zsoter et al., 2019). Assimilating snow products into hydrological models can enhance runoff forecast performance in snow-dominated catchments (Girotto et al., 2020; Garnaud et al., 2021; Brangers et al., 2024; De Lannoy et al., 2024), particularly where in situ observations are sparse. Assimilation of FSCA (Clark et al., 2006; Andreadis and Lettenmaier, 2006; Nagler et al., 2008; Kolberg and Gottschalk, 2010; Thirel et al., 2013), snow depth (Girotto et al., 2024), SWE (Magnusson et al., 2014), or combinations of these variables (Oberrauch et al., 2025) is now being developed in operational snow hydrology (Micheletty et al., 2022; Mott et al., 2023), hydropower inflow forecasting (Magnusson et al., 2020; Metref

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et al., 2023), and flood prediction (Saloranta, 2016). However, studies report both clear improvements and marginal or even negative effects on snowmelt runoff prediction, depending on the model, catchment, and observational product (Thirel et al., 2013; Magnusson et al., 2020; Clark et al., 2006; Beaton et al., 2024). In operational settings, performance is further shaped by data availability, latency, and regional differences in observation quality. While these applications mostly focus on using snow DA to improve streamflow forecasts, the recent inverse modeling work of Wiersma et al. (2026) shows the value of streamflow data in constraining snow mass, highlighting the largely untapped potential of fully coupled snow-hydrological DA.

3.2 Glaciers

Glacier evolution models depend on quantities that remain sparsely or indirectly constrained, including ice thickness, rheological parameters, bed geometry, and basal traction, even as remote sensing and in situ measurements increasingly constrain observable aspects of glacier geometry and dynamics, such as glacier area, surface velocity, and surface-elevation change. Within glaciology, variational approaches are among the most widely adopted DA methods and have been developed most extensively in ice-sheet modeling. An early influential application used an adjoint-based inverse formulation to estimate basal friction and ice viscosity from remotely sensed surface velocity (MacAyeal, 1992), analogous to static variational DA (Section 2.4.2). These approaches were subsequently extended to higher-order ice-flow models and a broader range of observations, including altimetry (Granzow, 2014; Morlighem et al., 2013). Bayesian approaches have been applied directly to this problem; Werder et al. (2020) combined surface velocity and elevation observations with a mass-conserving flow model in an MCMC framework to infer ice thickness across many glaciers. More recently, automatic differentiation has simplified gradient evaluation and reduced reliance on manually derived adjoints, facilitating the assimilation of time-dependent observations in glacier models (e.g., Goldberg and Heimbach, 2013; Recinos et al., 2023), analogous to 4D-var.

Since variational inversions yield optimal estimates without uncertainty, subsequent work has focused on quantifying the uncertainty in the inverted fields and propagating it into transient simulations (Koziol et al., 2021; Recinos et al., 2023). Ensemble Kalman methods have been demonstrated to be a valid adjoint-free alternative with built-in uncertainty quantification (see Section 2.4.5): twin experiments have shown that a deterministic and square-root implementation of EnKF can jointly estimate ice thickness and basal sliding in a flowline model (Bonan et al., 2014). Moreover, Gillet-Chaulet (2020) used a similar variation of the EnKF with synthetic surface elevation and velocity observations to jointly constrain basal friction and bedrock topography in a transient ice-sheet model.

The systematic adoption of DA in glacier modeling lagged behind that in ice-sheet modeling but has accelerated with the expanding spatial and temporal coverage of remote-sensing observations (e.g., Taylor et al., 2021; Hugonnet et al., 2021; Berthier et al., 2023; The GlaMBIE Team, 2025). Unlike ice sheets, mountain glaciers comprise a large, heterogeneous population of relatively small and physically distinct ice bodies, giving rise to two complementary modeling and assimilation regimes. At the individual-glacier scale,spatially distributed models of mass balance and ice flow pose assimilation problems broadly similar to those encountered in ice-sheet modeling, with comparable state variables, control variables, and inversion methods (e.g., Choi et al., 2023; Brinkerhoff et al., 2025). At regional to global scales, by contrast, models must represent large glacier inventories at tractable computational cost. For most land-terminating glaciers, glacier mass change is driven primarily by surface

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processes, chiefly snow accumulation and the melt of snow and ice (Cuffey and Paterson, 2010; Zekollari et al., 2022). Accordingly, large-scale models emphasize surface mass balance, commonly using computationally efficient temperature-index formulations, while representing glacier geometry and ice dynamics in simplified form (e.g., Huss and Hock, 2015; Maussion et al., 2019; Malles and Marzeion, 2021; Sjursen et al., 2023). Models of marine- and lake-terminating glaciers additionally require representations of frontal ablation and the associated dynamic response. The relatively low computational cost per glacier of these formulations makes large ensembles tractable, enabling Bayesian calibration and ensemble-based DA across large glacier inventories.

To our knowledge, Mutz et al. (2015) provided the earliest application of Bayesian methods to mountain glaciers, using a statistical surrogate to generate probabilistic projections of glacier mass change. Subsequently, Rounce et al. (2020a, b) used MCMC to directly calibrate the climatic mass balance component of a large-scale glacier evolution model for individual glaciers across High Mountain Asia, constrained by glacier-wide remotely-sensed geodetic mass balance estimates. Related studies by Sjursen et al. (2023) and Sjursen et al. (2025) combined observations from remote sensing and in situ measurements to infer temperature-index model parameters and produce probabilistic hindcasts of glacier mass changes from 1960 to 2020. Extending Bayesian calibration beyond climatic mass balance, Yang et al. (2026) applied the particle method AdaPBS to jointly calibrate parameters governing climatic mass-balance and frontal-ablation in a coupled glacier model for marine-terminating glaciers in Svalbard. For each glacier, the framework assimilated 10-year mean glacier-wide geodetic mass balance together with annual terminus position changes, expressed as length changes along the central flowline. Figure 6 illustrates the resulting hindcast for 2000–2019: observations through 2009 were assimilated during calibration, whereas those from 2010 to 2019 were withheld for independent validation.

Whereas earlier studies inferred time-invariant parameters over fixed study periods, parallel work has developed sequential filtering and batch smoothing approaches to exploit time-resolved observations and multiple data types. Landmann et al. (2021) applied a particle filter to assimilate near-real-time in-situ glacier mass balance measurements while dynamically weighting an ensemble comprising temperature index models and a simplified energy balance model. Herrmann et al. (2025, 2026) used an iterative EnKF to infer surface mass balance parameters and equilibrium line altitudes by assimilating glacier elevation changes from remote sensing (Hugonnet et al., 2021). Cao et al. (2025) conducted a suite of twin experiments using large ensembles to compare the performance of a PBS and an ES smoother in assimilating both synthetic snow depth and albedo observations for a glacier on Svalbard. On the Greenland ice sheet, analogous approaches were used to constrain surface mass balance by assimilating synthetically generated ice surface temperature with the ES (Navari et al., 2016), and MODIS albedo with the PBS (Navari et al., 2018). Hierarchical extensions of particle methods share information across space and time: Guillet et al. (2026) jointly infer glacier-specific parameters and regional hyperparameters for outlet glaciers of the Jostedalsbreen ice cap, allowing information from observed glaciers to improve modeling of unobserved ones, while Aalstad et al. (2026a) jointly infer annual parameters and climatological hyperparameters to produce data-constrained glacier reanalyses even in data-sparse time periods. Variational and related gradient-based methods are also emerging in glacier DA, mostly to constrain ice flow, with applications to parameter inference (Brinkerhoff, 2022), probabilistic forecasting (Brinkerhoff et al., 2025) and time-dependent assimilation inspired by 4D-Var in the Open Global Glacier Model (Schmitt et al., 2026).

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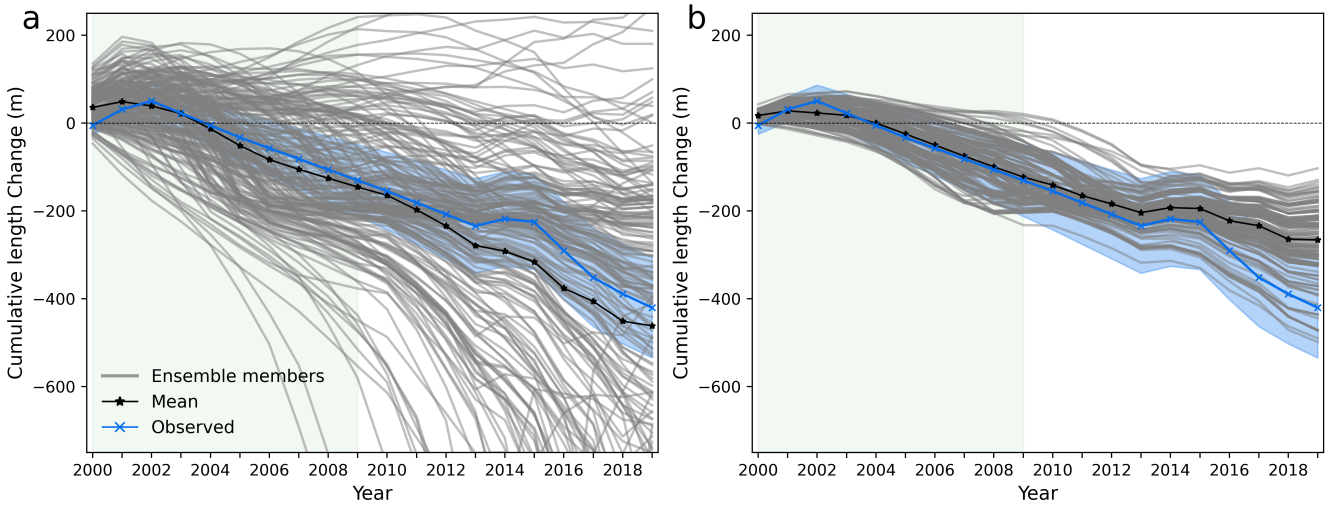

Figure 6. Cumulative length-change time series for Sabinebreen, a marine-terminating glacier in Svalbard. Observations through 2009 (time-span indicated by the light green shading) were assimilated during Bayesian calibration, while observations from 2010 to 2019 serve as validation. Panel a shows the prior ensemble, while panel b shows the posterior ensemble compared to the observed length change. Adapted from Yang et al. (2026).

Overall, glacier DA is advancing from glacier-specific calibration toward scalable assimilation of multiple observation types and joint state parameter inference. Key challenges include coupling mass balance and ice dynamics, representing observational errors and parameter non-stationarity, and sharing information across glaciers and time without obscuring genuine spatial and temporal variability. Addressing these challenges is essential for robust reanalyses and projections across scales.

3.3 Permafrost

Permafrost process models simulate exchanges of heat, water, and (potentially) carbon between the atmosphere and the land surface, along with the thermal and hydrological dynamics of the subsurface. These dynamical simulations rely on parameterizations of the ground material (e.g., soil properties) as well as features of the land surface (e.g., snow and vegetation) which are often poorly constrained even at the site scale, let alone entire catchments or regions. Despite improvements in global permafrost monitoring networks (e.g., CALM and GTN-P; Brown et al., 2000; Burgess et al., 2000; Biskaborn et al., 2015), observational data coverage of the hydrological and thermal state of permafrost remains sparse. This is in part due to the fact that permafrost is fundamentally a subsurface phenomenon, obfuscating direct observation via remote sensing (Trofaier et al., 2017). Thus, the potential of DA within the context of permafrost modeling is to reduce uncertainty surrounding the state of permafrost by assimilating permafrost-related observations. The two primary sources of data for permafrost DA are large scale remote sensing data for surface-level variables (e.g., surface temperature and moisture, vegetation and snow cover, or

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subsidence measurements) and sparse, *in situ*, long-term observation data from borehole temperature measurements and soil and meteorological data from long-term observation sites (Boike et al., 2018).

Despite the clear and ever more urgent need for DA to help constrain these sources of uncertainty in understanding the changing thermal state of permafrost, applications of DA to permafrost models remain relatively underexplored, with some notable exceptions. Nicolsky et al. (2007) demonstrate the use of variational DA to estimate soil moisture and thermal properties from in situ temperature measurements with a permafrost model. Similarly, Harp et al. (2016) analyzed the effects of uncertainties in soil properties on simulated permafrost thaw by applying a calibration-constrained Monte Carlo method to 3D simulations of subsurface heat and water flow in the Advanced Terrestrial Simulator (Coon et al., 2019). Other studies have used fully Bayesian inverse modeling via MCMC methods to estimate thermal properties (Brunetti et al., 2022) as well as to constrain future projections of permafrost thaw (Garnello et al., 2021). As an alternative to MCMC approaches, Zwieback et al. (2019) used EnKF to assimilate high-resolution remotely sensed soil moisture into the CryoGrid permafrost model. The recent study of Willmes et al. (2025) demonstrates the value of assimilating snow cover data retrieved from Sentinel-2 to constrain the permafrost thermal regime. The results are shown in Figure 7, where the prior and posterior ground surface temperature (GST) are compared to *in-situ* measurements obtained with temperature loggers for both a wind-exposed as well as a snow-drift location. The assimilation is carried out with the CryoGrid model using the AdaPBS.

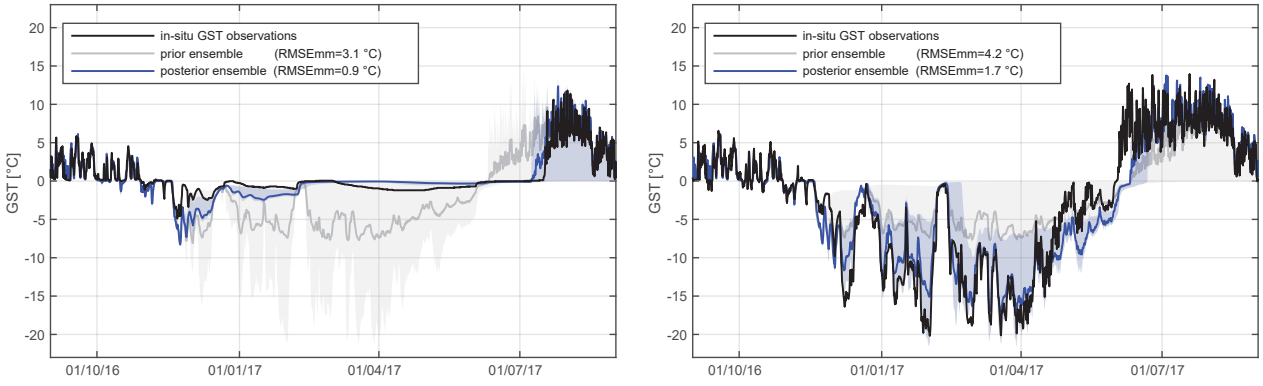

Figure 7. Assimilation of snow cover data to improve ground surface temperatures (GST) in the CryoGrid permafrost model with the AdaPBS method. Snow cover is retrieved from Sentinel-2 for a snow drift location (left panel) and a wind-exposed ridge (right panel) in the Bayelva permafrost site located in the arctic Svalbard archipelago. Snow cover isolates the ground from cold air influence (left). Figure adapted from Willmes et al. (2025).

As with other application areas of DA, however, applying these methods to transient permafrost simulations over long time frames (years to decades) has a high computational cost. This is in part because of the problem of spin-up (Lamontagne-Hallé et al., 2020; Ross et al., 2022), i.e., the need to find suitable initial conditions for slowly evolving land processes such as deep soil temperature, groundwater levels, and carbon stocks. This clearly distinguishes permafrost DA from applications in seasonal snow cover or catchment-scale hydrology where assimilation windows can typically be limited to a single seasonal cycle. To

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mitigate this high computational cost, highly parallelizable ensemble-based approaches such as ensemble Kalman samplers (Garbuno-Inigo et al., 2020) have been explored both for estimating soil and surface parameters (Groenke et al., 2023) as well as for other types of inverse problems such as surface temperature reconstruction (Groenke et al., 2024). A further option is to sidestep the cost of the dynamical model altogether by replacing it with a computationally cheap surrogate and then carrying out the inference on that surrogate instead (Zhou et al., 2024).

3.4 Cryospheric data assimilation to constrain other Earth system states and fluxes

As seasonal snowpack evolution, glacier mass balance, and permafrost thermal state integrate the atmospheric forcing they are subject to (i.e. the air temperature, precipitation, and surface energy fluxes), assimilating cryospheric observations can help reduce uncertainty and indirectly constrain sparsely observed non-cryospheric variables across the Earth system. In DA, this information propagates through the covariances and model process couplings, so that assimilating snow, glacier, or permafrost observations can update states and fluxes of other unobserved quantities. For example, snow dynamics directly affect surface albedo, thermal insulation, and the partitioning of received precipitation between storage and runoff, which in turn modifies surface radiation, turbulent fluxes, and water transfer to the soil. Therefore, assimilating snow cover, snow depth, or related observations can influence the estimates of surface albedo, soil insulation, and snow–atmosphere exchanges (e.g., Sun et al., 2004; Kumar et al., 2008; Wang et al., 2015; De Lannoy et al., 2022; Xue et al., 2022); constraining glacier mass balance propagates to meltwater and downstream hydrology (see Section 3.2); and constraining the permafrost thermal state affects soil heat and water storage, freeze-thaw fluxes, and carbon exchange (MacBean et al., 2022; Raoult et al., 2025). Which information propagates and how far depends on the model structure and should be interpreted as the consequence of this propagation through the coupled model, rather than a direct constraint.

Most cryospheric DA applications in the present review use offline models in which standalone snow, glacier, permafrost, hydrology, or land surface models are driven by atmospheric forcing information from observations, reanalyses, or external model outputs. In such an uncoupled setup, there is no dynamic feedback to the atmosphere or other Earth system components. These offline models offer important advantages for understanding cryospheric processes, investigating sources of uncertainty and performing computationally efficient assimilation experiments. They can also help inform developments in coupled land surface models by providing detailed process representations of the cryospheric processes, particularly for snow and, in some cases, glaciers and permafrost (see Matthes et al., 2025, and references therein).

In contrast, coupled DA allows information to be exchanged between the analyses of the different model components (de Rosnay et al., 2022; Evensen et al., 2024). Moving to such coupled framework in land surface and Earth System Models (ESM) reduces the forcing uncertainty found in offline models and allows the same cryospheric observations to provide constraints on a broader coupled state space (e.g., Geer, 2021; Kumar et al., 2022; De Lannoy et al., 2022; Eyring et al., 2024; Raoult et al., 2025). However, additional challenges arise. ESMs must conserve mass and energy, whereas the model-state formulation of DA (see Section 2.3) is likely to violate conservation laws (Wunsch et al., 2023). The forcing formulation appears then as a natural alternative, even though uncertainties in model structure and parameters must be represented consistently across the model components. Spatial and temporal scale mismatches between observations and model states are also

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important because they result in uncertainty structures that can vary considerably across different Earth system components. DA methods can compensate for errors in atmospheric forcing, parameterization, and model structure; however, systematically correcting missing model physics remains a challenge (Berliner et al., 2023). Terrestrial cryosphere DA should therefore be viewed not only as a means of updating offline models of the cryosphere itself, but also as a path toward constraining coupled water, energy, and carbon cycles of the Earth system, over seasonal to decadal timescales (De Lannoy et al., 2022; Kumar et al., 2022; Raoult et al., 2025).

4 Cross-cutting challenges

The three cryospheric domains differ from one another in ways that shape the specific challenges of DA in each. Snow evolves on relatively short time scales that justify frequent updates, whereas permafrost and glacier dynamics operate over much longer time scales, which can require assimilation windows that span years to decades. Snow and permafrost exhibit high spatial heterogeneity that is often poorly captured by models or observations, while glacier evolution models tend to treat elevation as the dominant driver of within-glacier mass balance variability (Rounce et al., 2023), somewhat simplifying the spatial distribution problem. Finally, the three domains are at different stages of methodological maturity: snow DA is the most developed, with established operational implementations, while glacier and especially permafrost DA remain comparatively fragmented, with fewer standardized approaches and more limited observational constraints. Despite these differences, many challenges recur across the terrestrial cryosphere (Fig. 8) and can have common solutions. The key recurring challenges are summarized next.

4.1 Model and forcing uncertainty

A central premise of DA is that both the model and its forcing are inevitably imperfect. DA aims not to ignore these errors but to represent them explicitly, with each method relying on different approximations of their structure (see Section 2.4).

Ensemble perturbation of model parameters, initial states, and forcing fields is the standard approach to representing model and forcing uncertainty (Carrassi et al., 2018), but computational constraints limit ensemble size and therefore the fidelity of the uncertainty representation (Section 2.6). Advances in ML emulation offer a route to larger ensembles within computational budgets (Section 5.7 and Figure 8c). Many cryospheric variables are non-negative and bounded from below at zero (e.g., SWE) or even double bounded (e.g., FSCA) making Gaussian error assumptions inappropriate (8b) even with additional transformations. While particle methods can address this issue in theory, they are almost universally applied with Gaussian priors and likelihoods in practical cryospheric applications (e.g., Aalstad et al., 2026b, and references therein). Ensemble Kalman methods are restricted to Gaussian assumptions, but can still be desirable for larger scale spatio-temporal cryospheric problems due to their lower computational cost, ease of implementation, and maturity of applications (Section 2.4). More research is needed to better accommodate non-Gaussian error models in cryospheric applications (Anderson et al., 2024), with transformations often serving as a promising first step.

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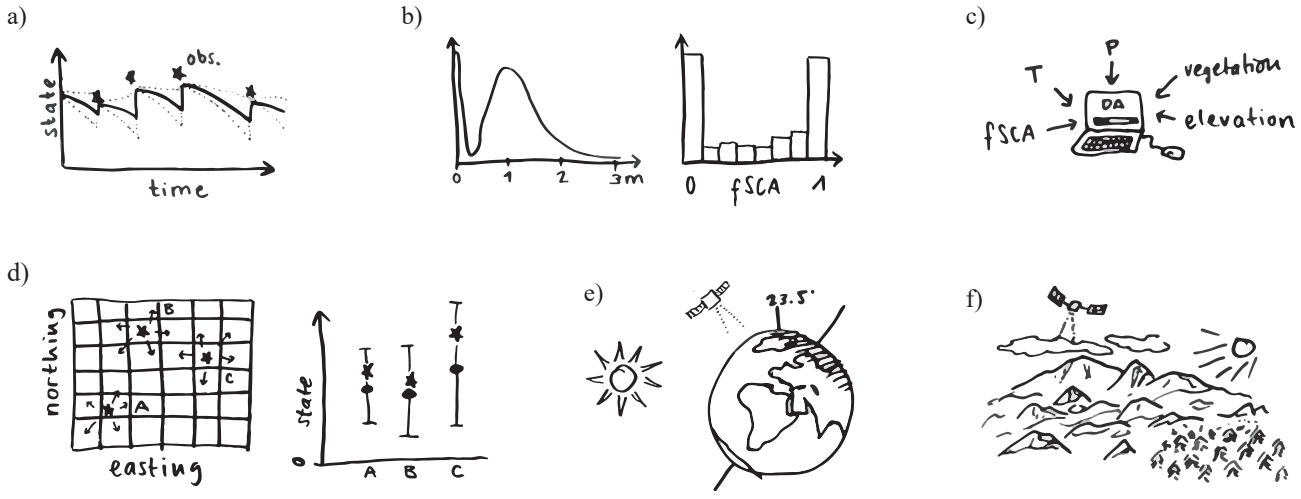

Figure 8. Cryospheric DA typically faces challenges such as (a) measurement gaps in time (observations here displayed as stars) or inconsistent bias over time, and model drift resulting in a sawtooth pattern in the case of sequential updates (solid line), (b) bounded and zero-inflated variables that often have non-Gaussian distributions, such as snow depth or fSCA, (c) indirect observations and forcing uncertainty, (d) sparse observations with varying information content, often a scale mismatch, and uncertainty including biases and heteroskedasticity, (e) data gaps in remotely sensed data, e.g. due to fixed satellite orbits causing suboptimal coverage, or lack of optical data during polar night and cloud cover, (f) heterogeneity of the area of interest, for example varying topography or land cover, which causes representation error in measurements and complicates spatial propagation of information.

When these uncertainty representations fail to capture unresolved or misrepresented processes, the residual systematic model and forcing biases can cause model drift, which then produces sawtooth-like state updates in filtering applications (Figure 8a). This may also cause physically unrealistic flux adjustments in related variables such as precipitation to account for unresolved wind redistribution as is typical in snow DA (Alonso-González et al., 2023a).

Forcing data (Figure 8c), particularly atmospheric inputs like precipitation and temperature (Günther et al., 2019; Fang et al., 2023; Tang et al., 2023), represent a dominant and systematic source of uncertainty for all three cryospheric DA domains (snow, glacier, and permafrost; see Section 3). Atmospheric reanalysis and forecasts at high elevations tend to be biased and in general worse compared to non-cryospheric applications as there is a clear gap in meteorological in-situ observational data for nearly all the world's high-mountain regions (e.g., Matiu et al., 2021). Because these meteorological forcing errors are shaped by mesoscale to local patterns, they are correlated in both space and time rather than being independent. Consequently, cryospheric DA cannot fully correct for these errors through state or parameter updates alone but must explicitly address forcing uncertainty. While this can be naturally incorporated through the forcing formulation of the DA problem (Evensen et al., 2022), it can be difficult to disentangle forcing errors from inherent parametric or structural model errors (Raleigh et al., 2015; Liu and Margulis, 2019).

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The dominant source of atmospheric forcing error varies by domain. For seasonal snow DA, the primary culprit is precipitation (Smyth et al., 2020; Girotto et al., 2024); for glacier DA, it also includes temperature and surface energy fluxes, and for permafrost DA, errors often stem from misrepresentation of snow amounts and duration (Pruessner et al., 2021; Willmes et al., 2025). Rather than applying a static single seasonal bias correction, treating these forcing errors as spatially and temporally varying yet highly correlated inference targets continues to offer a promising path forward (see Section 5).

4.2 Observation error characterization

The likelihood, which is at the heart of any DA scheme (see Section 2.1), is defined by an observation error model. All such DA schemes (see Section 2.4) share the assumption of having a zero-mean observation error (i.e. it is *unbiased*); while most ensemble Kalman (Section 2.4.5) and variational methods (Section 2.4.2) also assume that the random part of the error is Gaussian (i.e. the error can be fully described with a covariance parameter) (Evensen et al., 2022). Particle methods are theoretically better suited to handling non-Gaussian and bounded distributions (Section 2.4.6).

When an observation carries a systematic *bias*, it is not corrected by the analysis but aliased directly into the state and parameter estimates, and such systematic errors are common in cryospheric remote sensing. Laser altimeters operating in the visible part of the spectrum penetrate the upper few centimetres of the snowpack and thus return surfaces biased below the true air–snow interface (e.g., ICESat-2, Deschamps-Berger et al., 2023); passive-microwave SWE retrievals saturate in deep snow, biasing estimates low (Derksen, 2008); gravimetric terrestrial water storage from GRACE is biased by signal leakage and attenuation across basin boundaries (Girotto et al., 2017); and land surface temperatures from satellite radiometers are negatively biased in winter for the Arctic (e.g., MODIS, Westermann et al., 2012). Such biases are most damaging when they drift over time, for instance due to changes in sensor, retrieval algorithm, or observation frequency, as assimilating these observations can imprint spurious trends on the DA output that are difficult to distinguish from real physical signals. This poses serious risks for the multi-decadal reanalyses increasingly targeted by cryospheric DA (e.g., the snow component of ERA5; Hersbach et al., 2020). Although bias-aware schemes that estimate and remove such biases online are standard in operational NWP (de Rosnay et al., 2022), they remain largely unexploited in cryospheric DA.

The random part of the error is rarely as simple as assumed and should theoretically be decomposed into an instrument component and a representation component (Van Leeuwen, 2015). In practice the instrument component is usually specified crudely: error covariances are typically static, which is a significant oversimplification given that many cryospheric observed variables have heteroskedastic errors that vary as a function of the observable in both space and time, as recently explored for snow DA in Dunmire et al. (2026). For example, FSCA retrieved from multispectral satellites often has higher and less-symmetric uncertainty at intermediate values than near the extremes of 0 and 1 (i.e., easy to detect no snow or completely snow covered ground than the values in between) as shown by Aalstad et al. (2020). Moreover, the observation error is often considered purely uncorrelated (i.e. with a diagonal error covariance matrix), further embedding subjective assumptions and complicating error characterization. However, spatially and temporally correlated errors are a well-known issue in NWP and are relevant for dense retrievals such as lidar elevation measurement (e.g., Mirza et al., 2025), as well as land surface temperature

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retrievals from radiometers (Ghent et al., 2019) and FSCA (Cluzet et al., 2021). Finally, observations of different kind could be correlated *together*, such as land surface temperature and FSCA during spring snow melt.

On the other hand, representation errors, often ignored, arise when the observed quantity and the modeled quantity represent different spatio-temporal scales (Figure 8d and Van Leeuwen 2015) and are thus related to the change-of-support problem (Cressie and Wikle, 2011). These errors are pervasive in cryosphere DA, and include point station measurements constraining distributed gridded models (Cluzet et al., 2022), flux tower footprints with temporally variable extent assimilated into spatially fixed grids (Keetz et al., 2025), and coarse-resolution satellite retrievals informing high-resolution simulations (De Lannoy et al., 2012). In practice, representation error is routinely absorbed into an inflated observation error term (Van Leeuwen, 2015), while treating them explicitly would allow for better characterization and differentiation with respect to the observation error.

4.3 Observation sparsity

Cryospheric observations are sparse in space and time (Figure 8a,d), and often irregularly available (Sections 3.1–3.3). At high latitudes, polar night and orbital geometry reduce satellite coverage (Figure 8e); while shading, geolocation errors, and frequent cloud cover limit retrieval quality elsewhere, especially in complex terrain (depicted in Figure 8f; Largeron et al., 2020; Gascoin et al., 2024). In both cases, logistical challenges hinder the collection of in-situ observations and contribute to heterogeneity of the quantity of interest, resulting in spatially sparse and potentially non-representative (see 4.2) datasets (Clark et al., 2011; Van Leeuwen, 2015). The representativity issue for flat snow measurement sites is especially relevant during the key period of the ablation season (Grünewald and Lehning, 2015). Temporal gaps in the observational record present a related challenge, particularly for processes where the model is sensitive to conditions that are only rarely observed (e.g., sporadic melt and refreeze events). When observations are absent during critical periods, such as the onset of snowmelt (Aalstad et al., 2018) or the summer thaw of the active layer (Willmes et al., 2025), the model can drift substantially between updates, and a short DA cycle may be insufficient to prevent step-like behavior in the output.

Two complementary responses to the temporal and spatial sparsity of observations are promising. First, spatio-temporal DA frameworks can explicitly propagate information from observed to unobserved locations (see Section 5.3). While this problem has been typically tackled to assimilate in a fully-distributed model observations obtained from snow observation networks (Magnusson et al., 2014; Cluzet et al., 2022), applications of such approach have also been shown to be able to assimilate sparse satellite retrievals (Mazzolini et al., 2025). See Figure 5 where snow depth retrievals from a satellite laser altimeter obtained along profiles have been assimilated to a distributed model showing an example in which sparse observation contribute to improved basin-wide snow amount estimates. Second, adaptive sampling strategies use uncertainty quantification to guide where and when new observations are collected (Section 5.4). Such approaches can both be trained offline, to guide the location where sampling of new observations are relevant based on prior information about the spatial distribution of the relevant processes, as well as online, when the DA system updates knowledge and guides the measurement system in real-time. Both approaches benefit from further development in DA infrastructure and closer coordination between modeling and observational communities.

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4.4 Indirect observations

Many cryospheric observations are not direct measurements of the model state variables of interest, but rather indirect proxies that require either a complex observation operator or pre-processing via a retrieval algorithm to connect them to model quantities (Van Leeuwen, 2015). Examples of this concept include linking satellite-derived surface subsidence to permafrost active layer thickness (Sadeghi Chorsi et al., 2024; Li et al., 2017b), elevated atmospheric methane concentrations to flux hotspots (van Hove et al., 2026), and elevation change to glacier mass change (Hugonnet et al., 2021). Another example is the relation between reflectance and snow cover observations, where the usual approach is to assimilate FSCA retrievals. However, the direct assimilation of snow reflectance data, with both synthetic (Charrois et al., 2016) and real (Cluzet et al., 2020) reflectance data, if properly calibrated and their error characterized, may contain much richer information on snow metamorphism than what is contained in higher level FSCA data.

There exists a choice in such cases where the scientist should decide where the DA system stops and the retrieval algorithm starts. An example in which there are several points where this boundary can be drawn is the use of SAR backscatter data to estimate SWE. One option is to delegate the connection between backscattered intensity and SWE to a retrieval algorithm (e.g., Lievens et al., 2019) and assimilate the resulting high-level product (Girotto et al., 2024). The alternative is to assimilate the backscatter directly, using a snow microwave radiative transfer model as the observation operator, so that the information the low-level signal carries about other parts of the system, such as snow properties, is retained (Leroux et al., 2026). When such complex observation operator is used, sensor uncertainty arguably translates in a more nuanced way to the dynamical variable uncertainty, at the cost of larger computational expense.

The choice between observation operators or retrieval algorithms hence introduces additional uncertainty and, when they are themselves a complex model, could propagate systematic model biases into the assimilation. ML approaches (Section 5.7) can be leveraged to help overcome these limitations (e.g., Kolassa et al., 2018); by training more accurate yet still affordable retrieval algorithms to map directly to model space, the ML component can reduce biases and partly eliminate the need to specify complex observation error models (Hou et al., 2021). Alternatively, lower level observations could be assimilated directly by using a high fidelity radiative transfer model (or a rapid emulator thereof) as an observation operator.

5 Research agenda

5.1 Theoretical information quantification

The relationship between observations, both remotely sensed and *in situ*, and DA is bidirectional: observations are required for DA and DA amplifies the impact of often expensive and time-consuming data collection work and can inform mission planning. However, not all observations are equally valuable to a DA system. In a DA context, information content is not simply a property of an observation in isolation; it depends on the observation's spatio-temporal correlation with model uncertainty, the quality of observation's error characterization, and the model structure (Fowler et al., 2018). Several observations with poorly characterized errors can degrade a DA analysis relative to a single well-characterized one.

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Methods for quantifying observation value fall into two categories: diagnostic and experiment-based approaches. Diagnostic approaches are computed from an existing DA system and can be applied to an existing simulation without additional counterfactual comparison simulations. These include information theory measures such as degrees of freedom and Shannon information content (Rodgers, 2000), observation-impact and forecast sensitivity quantification from numerical weather prediction (Langland and Baker, 2004), analysis of ensemble spread reduction, information gain, and, for ML emulations, SHAP-style sensitivity analysis (Lundberg and Lee, 2017). Experiment-based approaches instead use direct comparisons of assimilating and non-assimilating model runs. For example, Observing System Experiments (OSEs) withhold real observations in order to isolate the contribution of the withheld information in an assimilation context. A similar method, Observing System Simulation Experiments (OSSEs), extends this to apply to hypothetical observations and can prospectively evaluate a proposed satellite mission or campaign design before it exists (Arnold Jr and Dey, 1986). Such OSSEs are standard in numerical weather prediction but remain relatively rare in cryospheric DA (Cho et al., 2023; Margulis et al., 2026). This same experiment structure can be used to evaluate the information contained within a potential novel observation in the context of a specific model framework and is also used to evaluate the value of the assimilation strategy itself.

Given the expense of satellite missions and field campaigns, continued investment in OSSEs and variance-based approaches for proposed cryosphere observation efforts, both remote sensing and in the field, should be a community priority. At the same time, the cryospheric DA community should resist the temptation to assimilate all available data simply because it exists. Principled cost-benefit assessments of what each data stream actually adds, in the context of a specific DA system, is necessary for the field to mature and will allow both observation generation and DA to work more efficiently.

5.2 Novel remote sensing observations

Both remote sensing and DA stand to benefit from an increase in the volume and type of remote sensing data in upcoming years, but must be leveraged intentionally to maximize their mutual value. Upcoming missions offer not just more observations, but more diverse observation types, expanding the set of physical quantities that DA systems can directly constrain. Different observation types can carry complementary information. For example, active microwave retrievals are sensitive to snow mass in dry conditions (Tarricone et al., 2023; Margulis et al., 2026), passive microwave to freeze-thaw state (Farhadi et al., 2015), thermal infrared to surface energy balance (Alonso-González et al., 2023b), gravimetry to vertically integrated water mass (Girotto et al., 2017), and lidar altimetry to surface elevation change (Fair et al., 2025).

Recent and upcoming advances in remote sensing of snow, primarily in active microwave radar technologies (Hale et al., 2025), have the potential to expand the geographic extent and temporal frequency of observations, partially closing the observation gaps discussed in Section 4.3. For example, the NISAR mission (NASA-ISRO SAR; Rosen et al., 2025) was launched in July 2025; pre-launch assimilation experiments using airborne SAR quantified the value of the intended observations to reduce bias in snow depth and SWE in terms of both quantity and spatial patterns (Shrestha and Barros, 2025). An experiment using fully synthetic SAR observations in assimilation framework further quantified the value of a hypothetical active microwave sensing across terrain types and seasons (Cho et al., 2023), showing assimilation-driven model improvements even in mountainous, forested, and wet-snow conditions. Complementing these efforts, Margulis et al. (2026) demonstrated the

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power of a Bayesian framework to assimilate multi-band microwave (C-, L-, and P-band) interferometry (phase) data. Their synthetic experiments highlighted how a DA approach successfully overcomes the classic challenge and ambiguity associated with standard deterministic retrievals. The DA approach relies on Bayesian estimation which leverages prior model information to maintain highly accurate total SWE and snow accumulation estimates. The Terrestrial Snow Mass Mission (TSMM; Derksen et al., 2019), expected to be launched in the early 2030s, used an OSSE during the mission design phase to quantify the value gained by decreasing the revisit to one day (Garnaud et al., 2019) . The Earth Dynamics Geodetic Explorer (EDGE Fricker et al., 2025), planned for launch in 2031, will extend swath lidar altimetry capabilities to better spatial resolution and coverage well beyond its predecessor ICESat-2, offering dense snow depth and glacier mass balance observations of a type that spatio-temporal DA frameworks (Section 5.3) are specifically designed to exploit. The ESA EarthExplorer 10 mission Harmony, a bistatic SAR companion mission to the Sentinel-1 satellites, is scheduled for launch in ca. 2030. It will provide measurements of surface elevation changes such as ice volume change and permafrost thaw slumps, 3D surface motion, and the multiple lines of sight and bistatic backscatter may enable characterization of snow properties or estimation of dry snow water equivalent (Kääb et al., 2024).

For permafrost, one fundamental DA challenge is that the quantities of greatest interest (active layer thickness, ground ice content, deeper soil temperature) are subsurface and only indirectly observable from space. However, recently-planned future missions spanning passive microwave (CIMR; Donlon et al., 2023), thermal infrared (Sentinel-8 and NASA EAGLE; Bernard et al., 2023; Thompson et al., 2026), interferometric SAR (NISAR and ROSE-L; Rosen et al., 2025; Pierdicca et al., 2019), gravimetry (MAGIC; Haagmans and Tsaoussi, 2020) will collectively expand the indirect observational constraints available to all the cryosphere components, including permafrost. Moreover, upcoming column-averaged atmospheric CH_4 and CO_2 retrievals (CO2M; Rusli et al., 2021) have the potential to constrain the timing of soil thaw and the onset of methanogenesis through atmospheric inversion (Jacob et al., 2016).

For nearly all of these upcoming data streams, the specific value they would contribute through assimilation into cryospheric models and how this varies with mission design choices has not yet been comprehensively quantified. Conducting information quantification (see Section 5.1) in parallel with mission development, as was done for TSMM (Garnaud et al., 2019), should be a standard expectation rather than an exception.

5.3 Hierarchical spatio-temporal data assimilation

A known limitation in cryospheric DA is that information is often propagated within a short assimilation window, but rarely across space or long time horizons. In snow applications, with a few exceptions (e.g., De Lannoy et al., 2012; Magnusson et al., 2014; Cluzet et al., 2021; Alonso-González et al., 2023a), spatio-temporal DA has received much less attention than its purely temporal counterpart, in which each spatial unit is treated independently and observations only update the local model trajectory rather than affecting neighboring cells. This becomes problematic whenever observations are sparse and/or differ from the model resolution, as is common for many cryospheric applications in which large parts of the domain remain unobserved unless information is explicitly transferred from observed to unobserved locations (Reichle and Koster, 2003; De Lannoy et al., 2022). A related issue in the temporal dimension appears especially in glacier applications, where DA

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formulations face a trade-off. Some treat each mass-balance year as an independent assimilation window using the same prior but different yearly observations. This approach fails to carry information across years even though glacier evolution is strongly persistent in time (e.g., Cao et al., 2025). Other approaches use instead the entire time domain as a single assimilation window, requiring forcing-related parameters to be assumed constant in time (Rounce et al., 2020b).

A relevant statistical framework to address these limitations in DA is hierarchical Bayesian spatio-temporal modeling (Cressie and Wikle, 2011; Katzfuss et al., 2020). Such hierarchical spatio-temporal models provide a natural way to represent parameters and states at multiple levels (Wikle and Berliner, 2007), while accounting for how information should be shared across space and time, rather than assuming every grid cell or water year is independent (Gelfand, 2012). Therein, the prior distribution for the parameters and/or states depends on higher-level 'hyperparameters' that are in turn drawn from a hyperprior distribution, allowing uncertainty and information sharing across groups.

For DA, the key consequence is that the hyperparameters are themselves updated by observations, so the prior for each location or DA window is informed by the others rather than fixed in advance. Across space, observations can then constrain parameters at unobserved locations, as in regional glacier reanalysis (Guillet et al., 2026); across time, information carries over between DA windows, so that data-sparse years (including the past and the future) fall back on a calibrated parameter climatology rather than a vague prior (Aalstad et al. 2026a, see Section 3.2). These hierarchical decompositions are particularly useful in spatio-temporal settings, where dependence structures are high-dimensional, multiscale, and often strongly constrained by process understanding (Cressie and Wikle, 2011).

Spatio-temporal propagation of information in DA can also arise even in non-hierachical models by allowing the prior to encode dependence in space between locations (Alonso-González et al., 2023a) as well as in time through assimilation windows (Magnusson et al., 2017). In the temporal context, this allows for encoding memory, for example, by allowing the posterior in one window to influence the prior in the next, as in classical Bayesian filtering (Särkkä and Svensson, 2023). In the spatial context, this enables the use of point-scale information, such as that obtained by automatic sensors in weather towers, and spatially incomplete observations generated by persistent cloud cover or by complex sun-sensor-terrain geometries in the case of orbital sensors to update states across the partly observed simulation domain. Within ensemble Kalman methods, the covariance structure can be either estimated as the sample covariance of the ensemble (e.g., Magnusson et al., 2014) or prescribed through the spatial structure of the prior (as in Alonso-González et al., 2023a). Because of these methods' robustness, there is great potential in developing spatio-temporal data assimilation experiments (Magnusson et al., 2014) where a single or even multiple observation types are assimilated in a joint assimilation exercises, opening up a wide range of possibilities.

In contrast, Section 2.4.6 outlines how particle method's weakness to degeneracy in high-dimensional states hinders their adoption in high spatio-temporal applications. Making spatio-temporal particle methods efficient in higher dimensional cryospheric DA problems thus necessitates improved particle localization strategies (Poterjoy, 2022; Cluzet et al., 2022) as well as strategies involving tempering (Chopin and Papaspiliopoulos, 2020) and modified proposal distributions (van Leeuwen et al., 2019; Aalstad et al., 2026b).

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Despite its potential, hierarchical and/or spatio-temporal DA in cryospheric applications presents challenges specific to the field. Many such methods have been developed with other applications in mind, such as numerical weather prediction (Potthast et al., 2019) or geostatistics (Diggle and Ribeiro, 2007; Cressie and Wikle, 2011). The models used in cryospheric sciences have particular characteristics that require adaptation of the methods typically used in the wider and more domain-agnostic literature (Farchi and Bocquet, 2018; Katzfuss et al., 2020).

5.4 Adaptive sampling and targeted assimilation

Adaptive sampling is the practice of sequentially adapting the data collection process (i.e., the spatial location, timing, or sensor used) based on the current posterior inference, and maximizing the expected information gain (Rainforth et al., 2024). It can also be used to explore parameter space efficiently when calibrating climate models (Reichelt et al., 2026). On the one hand, the sparseness of observational data in terrestrial cryospheric systems can motivate such sequential collection of observational data based on the uncertainty of model parameters or predictions. On the other hand, the vast amount of potentially redundant and mostly indirect data from Earth observing satellites also necessitates targeted and adaptive retrieval and assimilation strategies. As DA methods can quantify uncertainty reduction by an observation, they can be used to predict where and when new observations would be most informative, helping to design experiments (Rainforth et al., 2024) such as field campaigns, satellite acquisitions, or even targeted computer simulations. This process can be computationally demanding as a sufficiently large space of possible experimental designs need to be assessed within a DA cycle.

Each update to the sampling strategy requires a new DA cycle, so using adaptive sampling strategies in practice may require near-real-time DA. For field applications this includes data communication pipelines, automated quality control of new observations, and fast inference and prediction. Advances in hardware engineering, such as remote internet connectivity or compact embedded computing modules, can be combined with fast DA, such as emulator-based methods (Keetz et al., 2025) or amortized posterior estimation (Rainforth et al., 2024), to move experimental approaches toward operational utility.

While the operationalization of adaptive sampling strategies for cryospheric applications are still in their infancy, a few recent studies have taken promising steps in this direction. Pallandt et al. (2024) assessed the design and optimization of the network of high-latitude eddy covariance stations measuring surface energy and carbon exchange. van Hove et al. (2026) present a framework for intelligent path planning for drone-based surface flux estimation and applied it to estimate a methane hotspot in the high-arctic tundra on Svalbard.

5.5 Assimilating multiple observations

A methodological priority is to develop DA frameworks that can assimilate multi-resolution, multi-sensor, and multi-modal observations in a stable manner. As discussed in Section 5.2, upcoming satellite missions will provide an increasing number of observations of the terrestrial cryosphere. However, most of the existing and upcoming remote sensing products provide observations that do not capture the full complexity of the modeled phenomenon and are limited by both sensor and retrieval uncertainties as well as their sampling characteristics both in time and space. These disparate observations can, however, be used in integrated DA systems that are able to benefit from the complementarity of several observation types. Both observations

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that can be more directly mapped to a target state variable (e.g., Margulis et al., 2019; Rounce et al., 2020b; Alonso-González et al., 2023a) and those that are only indirectly related to the primary modeled phenomena of interest (Figure 7) can update models by providing their own distinct information content. There is thus demonstrated untapped potential in the joint assimilation of multiple complementary observation systems that is yet to be fully explored (e.g., Kumar et al., 2022; Oberrauch et al., 2025).

Carrassi et al. (2018) underlines that the rapid expansion of observational capabilities represents both an opportunity to better monitor and forecast the relevant processes as well as a methodological burden. The challenge is no longer just how to assimilate one single product well, but how to use several products together while respecting each product's innovation in the modeled system despite disparate spatial scales, precision, and connection with the modeled variables. These questions interact with the choice of DA algorithm. For example, ensemble Kalman methods remain attractive because they propagate the prior through evolving covariance structures and therefore provide robust framework under Gaussian assumptions (Carrassi et al., 2018). Considerable progress has also been made with the iterative variants of these methods, which dampen the issues Kalman methods suffer in case of strong non-linearity in the dynamical model (Emerick and Reynolds, 2013; Garbuno-Inigo et al., 2020; Evensen et al., 2022). However, such methods have yet to enjoy widespread adoption in cryospheric DA despite several recent studies demonstrating their performance across the terrestrial cryosphere (e.g., Alonso-González et al., 2022; Groenke et al., 2023; Herrmann et al., 2025). This suggests that ensemble iterative Kalman methods may be the most robust route in the near term for high dimensional multivariate cryospheric DA, mirroring the status in the broader field of DA (Evensen et al., 2022). Nonetheless, further research is needed when several variables are observed at different scales and are assimilated together in a scheme that also propagates information to unobserved locations and across assimilation windows.

As discussed in Section 2.4.6, particle filters are vulnerable to degeneracy in high-dimensional systems and as the number of informative observations increases. This poses fundamental questions as to how to deal with collapsed distributions when information needs to be propagated to unobserved locations and a distribution where accurate uncertainty quantification is key. For example, the operational workflow of Oberrauch et al. (2025) avoids a fully spatialized particle update by inferring forcing perturbations from a completely local particle-filter analyses and then mapping those parameters across the domain. This makes distributed assimilation feasible while reducing the particle-collapse problems that would arise if all observations were assimilated simultaneously in one high-dimensional filter. However, work by Cluzet et al. (2021, 2022) in snow DA, as well as Potthast et al. (2019) in NWP, indicates that localized particle methods can nonetheless become feasible in larger scale cryospheric DA settings, retaining the desirable ability to quantify uncertainty that is lost when particle-collapse happens. Moreover, the study of Aalstad et al. (2026b) suggests that particle degeneracy issues in cryospheric DA also have the potential to be resolved by adapting the proposal distribution within an assimilation window. As such, more research is required to unlock the full potential of nonlinear non-Gaussian particle methods in cryospheric DA, building off promising developments in DA research (van Leeuwen et al., 2019; Poterjoy, 2022).

Three research needs follow. The first is a systematic comparison of ensemble Kalman, particle, and hybrid approaches (see Section 5.6) on common multivariate problems, assessing both accuracy and computational cost, so that the choice of algorithm can be made on evidence rather than convention. The second is to establish when filtering and when batch smoothing

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is appropriate for observations of different variables, particularly in spatial DA problems where only some of the observations are propagated in space. The third is to identify which mitigation strategies are most robust, and in which implementations: localization, tempering, and ensemble rejuvenation all serve to maintain ensemble diversity, but their relative effectiveness in cryospheric settings, and their consequences for uncertainty quantification as well as accuracy, remain untested.

5.6 Progress in Bayesian data assimilation leveraging hybrid approaches

As described in Section 2.4, the different DA approaches (variational, ensemble Kalman, particle, and MCMC methods) all have their advantages and disadvantages, making it tempting to combine them to amplify their merits. Traditional variational methods (Bannister, 2017) often utilize prescribed Gaussian uncertainty statistics and are based on gradient-based optimization, ensemble Kalman methods (Evensen et al., 2022) are gradient free and rely on prior Gaussian uncertainty that can evolve through a massively parallelizable ensemble with the non-linear system, particle methods (van Leeuwen et al., 2019) share all the benefits of ensemble Kalman methods without the need for Gaussian linear assumptions albeit the risk of degeneracy, and MCMC methods (Apte et al., 2007) provide a highly accurate albeit computationally costly gold-standard approximate Bayesian inference benchmark (Law and Stuart, 2012). One promising synergy is to include ensemble information into variational methods via hybrid ensemble-variational (EnVar) methods that help to improve uncertainty quantification by adding dynamics to the prior error covariance matrix (Bannister, 2017). Adopting uncertainty-aware variational Bayesian methods (Blei et al., 2017) remains, with a few exceptions (Brinkerhoff, 2022), a largely unexplored research avenue in cryospheric science that has become increasingly feasible with automatic differentiation (Sapienza et al., 2025) and can be readily combined with particle methods (Murphy, 2023). Furthermore, there is great potential in combining ensemble Kalman and particle methods to resolve the inherent bias-variance tradeoffs (Stordal et al., 2011; Frei and Künsch, 2013) via hybrid methods (van Leeuwen et al., 2019). Cryospheric DA would also benefit from moving beyond basic particle methods by leveraging recent developments (Bugallo et al., 2017; van Leeuwen et al., 2019; Chopin and Papaspiliopoulos, 2020) for example through adaptive proposals (Aalstad et al., 2026b), MCMC diversification (van Hove et al., 2026), and tempering (Poterjoy, 2022).

5.7 Machine learning

Machine learning and DA are conceptually aligned: both use inference and/or optimization, aim to combine models and observations, and must explicitly or implicitly account for uncertainty (Geer, 2021; Bach et al., 2025). In cryospheric applications, ML has contributed across the full DA workflow (Sun et al., 2022). ML methods can help improve observation quality and spatial completeness prior to assimilation (Uslular et al., 2024; Dunmire et al., 2024; Honda and Yamazaki, 2024; Svoboda et al., 2025) with demonstrated improvements in outputs (Dunmire et al., 2026). DA outputs have further been used to aid parameter calibration and ML model training (Keetz et al., 2025; Brajard et al., 2021). The most computationally impactful contribution to date, however, has been emulation of expensive process models, which reduces runtimes substantially and makes larger ensemble sizes feasible within fixed resources (Guidicelli et al., 2024; Keetz et al., 2025). For example, work on glacier flow dynamics demonstrates that ML emulators can simultaneously improve runtime and physical realism while enabling broader geographic application (Jouvet, 2023; Cook et al., 2023). Furthermore, DA techniques can also be used to

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make cryospheric ML workflows uncertainty-aware, for example by leveraging approximate Bayesian neural networks trained by ensemble Kalman methods (Pirk et al., 2024).

An emerging frontier is the integration of ML within the assimilation step itself. Learned observation-error and model-error covariances could improve DA accuracy with fewer ensemble members, and end-to-end learned DA systems, including diffusion-model and transformer-based frameworks, are beginning to be explored as a subset of probabilistic DA (Bach et al., 2025). Furthermore, observation operators in cryospheric DA can be implemented in a purely data-driven fashion via ML without the need for explicit mechanistic modeling (Hou et al., 2021). The entire DA process itself can also be emulated via deep learning (Blandini et al., 2025), which can cut computational cost considerably by completely circumventing the need for an ensemble after training. A persistent challenge is physical consistency, as ML emulators of snow and ice processes can violate conservation laws or produce implausible states. Data scarcity compounds the difficulty as both ML and DA are data-hungry and the cryosphere offers limited real training data precisely where improved prediction matters most (Gauch et al., 2025). Realizing the potential of ML-DA integration for the cryosphere will require careful benchmarking against process-based baselines, systematic evaluation of where learned components genuinely add skill, and keeping up with rapid developments at the intersection of these fields (Bach et al., 2025; Arcucci et al., 2026). While these integration challenges are particularly acute in the data-scarce cryosphere, they reflect a broader paradigm shift occurring across the environmental sciences.

6 Conclusions

The terrestrial cryosphere is changing rapidly, yet our ability to accurately monitor these dynamics remains limited by large model and forcing uncertainties, a narrow observation base, and insufficient use of the available indirect observations. DA offers a principled path forward to improve estimates of the state of cryospheric systems, merging the complementary strengths of models and observations while explicitly representing uncertainty. The ongoing expansion of in-situ and remote sensing observations, together with the growth of computing resources, creates a clear opportunity to advance both the methods and applications of cryospheric DA. Snow, glacier, and permafrost applications share substantial methodological common ground such that the field benefits from combined consideration; we encourage cross-domain exchange of methods and benchmarks to be treated as a priority in its own right rather than as a byproduct of parallel progress.

Building on this common ground, we propose several concrete steps that can move the field forward. On the modeling side, forcing errors are a dominant error source, and they should be considered spatially and temporally correlated and estimated during inference to ensure physical consistency (Section 4.1). Observations error models should account for biases, heteroskedasticity, correlations, and representation error (Section 4.2). Since many cryospheric observations are sparse, spatio-temporal and hierarchical DA are promising frameworks for propagating information from observations in space and across assimilation windows (Section 5.3). Moreover, because many observations are inherently indirect, there is an increasing need for the joint assimilation of multiple data streams. However, we recommend that the information provided by each observation type is rigorously quantified (Sections 5.1, 5.5), including when evaluating future mission and campaign design (Section 5.2).

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As several classes of assimilation methods have desirable features, systematic comparisons are needed to assess the performance of ensemble Kalman, particle, and hybrid methods (Section 5.6), and frameworks where ML is integrated in DA (Section 5.7). Finally, since generic DA implementations often require substantial adaptation to the cryosphere, accessible frameworks, citable tutorials, analysis-ready observations with well-calibrated uncertainties, and closer collaboration between operational users and cryospheric DA specialists can lower the barrier to adoption.

Together, these steps point toward a longer-term objective: observationally constrained, uncertainty-aware estimates of snow, glaciers, and permafrost from catchment to global scales, covering the past (reanalysis), the present (monitoring), and the future (forecasts and projections). At present, the domains stand at different stages relative to this goal, with distinct strengths and obstacles. Snow DA benefits from frequent, extensive observations and has produced regional to hemispheric reanalyses (e.g., Fang et al., 2022; Luojus et al., 2021), but SWE remains poorly observed in complex terrain and models remain sensitive to forcing errors. Glacier DA continues to draw on and complement inventories and geodetic mass balance records, and Bayesian calibration of glacier models has reached the global scale (Rounce et al., 2023), but ice thickness and flow remain sparsely observed, and the naturally long response time of glaciers pushes the field toward inferring model parameters. Permafrost DA benefits from the long memory of the ground thermal regime, which means that high-quality borehole and active layer observations are informative for long time periods, but most relevant observables are sub-surface, which has largely constrained applications to the site scale. The integration of these products in future generations of reanalysis (and climate projections) is of high scientific and societal interest, given the substantial known disagreement in current global reanalyses and snow products (e.g., Liu and Margulis, 2019; Orsolini et al., 2019; Wrzesien et al., 2019; Kouki et al., 2023; Mudryk et al., 2025). Reaching this goal need not be the result of a single effort; we invite research groups specializing in cryospheric science, DA, and applied mathematics, together with space, governmental, and operational agencies, to take up complementary aspects of it while sharing benchmarks, interoperable frameworks, and open data. Even partial progress would support water management and climate impact assessment and adaptation.

Appendix A: Clarifying variables in the observation space

Some confusion regarding the interpretation of variables may arise partly due to a widely used shorthand notation in Bayesian inference (Gelman et al., 2013; Särkkä and Svensson, 2023), including DA (Evensen et al., 2022), where the distinction between random variables and realizations is implicit for the sake of economy. We adopt this implicit notation, avoiding the capitalization of random variables throughout, though we do distinguish quantities in the observation space. As mentioned in Section 2.1, this economic shorthand blurs the distinction between the fixed observations $\mathbf{y}^o$ and the noisy (noise-free) predicted/modeled observables $\mathbf{y}$ ($\hat{\mathbf{y}}$), where the latter are random variables while the observations are realizations from nature. This contributed to a long-standing misinterpretation of the stochastic EnKF, involving the perturbation of observations rather than the noise-free predicted observables (van Leeuwen, 2020). For the stochastic EnKF, this was not consequential because of the symmetric nature of the Gaussian curve, but such mix ups are more detrimental with non-Gaussian likelihoods (Anderson et al., 2024). Here, we provide some more specific definitions to help clarify notation.

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To elucidate the nature of variables in observation space, it is helpful (though not strictly necessary for inference) to assume that the noisy observations $\mathbf{y}^o$ are a corrupted version of the true observables $\mathbf{y}^\star$ related to a true underlying state $\mathbf{x}^\star$ via

$$\mathbf{y}^o = \mathbf{y}^\star + \boldsymbol{\epsilon}^\star = \mathcal{H}^\star(\mathbf{x}^\star) + \boldsymbol{\epsilon}^\star, \tag{A1}$$

where $\mathcal{H}^\star$ is a perfect observation operator such that $\boldsymbol{\epsilon}^\star$ is simply the measurement error. In contrast, $\boldsymbol{\epsilon}$ in Equation (2) may also contain representation error, which typically arises due to scale mismatches between the discretized model state and observables not accounted for by the observation operator (Van Leeuwen, 2015). Apart from the absence of representation error, the idealized truth-based inverse problem in Equation (A1) is thus analogous to Equation (2), which is used in practice. However, with real data, the true observables $\mathbf{y}^\star$ and true state $\mathbf{x}^\star$ are generally unknown, so inference is instead performed for the noise-free predicted observables $\widehat{\mathbf{y}}$ (that should be perturbed in the stochastic EnKF) and the hidden state $\mathbf{x}$ (which are uncertain and modeled as random variables). Estimating the (unknown) truth remains our target, but it does not appear in Bayes' rule and, fortunately, does not need to be specified to pose the problem.

Code and data availability. The code and data needed to generate all figures created for this synthesis (Figs. 2–4), except the conceptual schematics (Figs. 1 and 8), are available through https://doi.org/10.5281/zenodo.23046542 (Aalstad et al., 2026c). Figures reproduced or adapted from previous publications (Figs. 5–7) are credited in their captions.

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