ASSIMILATING SUBSAMPLED AIRBORNE LIDAR: HOW MUCH LIDAR IS ENOUGH?

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ABSTRACT

Airborne lidar snow depth retrievals are vital for water resource management in basins with limited snow observations. However, airborne lidar remains impractical to collect frequently over large domains due to the high economic cost. In this study, we investigated the extent to which lidar coverage improved modeled snow evolution using a distributed model and assimilation scheme. Full-coverage Airborne Snow Observatory snow depth data in Tuolumne, California and the Olympic Mountains of Northwest Washington State were used as a baseline in which to test the improvement in modeled snow water resources when optimizing flight frequency, timing, and spatial coverage. Collections over multiple seasons in Tuolumne were also used to investigate the impact when assimilating observed snow patterns. Our results indicate that errors in distributed models make snow depth difficult to determine at fine spatial resolutions. However, patterns from lidar in previous seasons are informative enough to train modeled accumulation in following years, therefore reducing the need for repeated, full lidar collections. (KEYWORDS: lidar, assimilation, distributed modeling, snow patterns, tradespace)

INTRODUCTION

Distributed snow modeling is notoriously difficult in high mountainous regions where spatially-heterogeneous processes of accumulation and melt impact the snowscape to varying degrees. We therefore set up a controlled experiment with a) high-confidence, calibrated snow simulations, b) simulations with manually-perturbed precipitation errors, and c) simulations with data assimilation using varying degrees of airborne lidar coverage. This process allowed us to observe the amount and type of snow depth observations that posed the best ability to correct simulations with typical precipitation errors (Raleigh et al., 2015; Wayand et al., 2017). We argue that comparisons of assimilation accuracy and economic cost can therefore be used to optimize lidar operations and improve our ability to derive snow evolution over larger domains in every snow season.

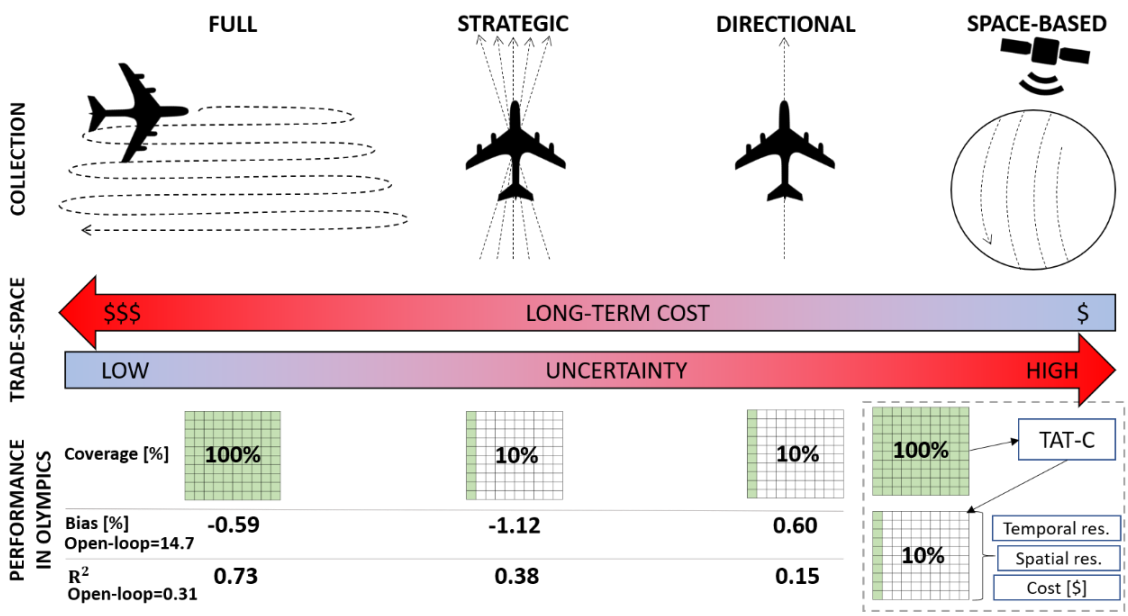

Figure 1. Cost-uncertainty trade-space and statistics for the Olympic Mountain domain (Figure 2) are shown for each collection strategy. While not currently investigated, space-based determination of snow depth will be simulated using NASA's TAT-C platform (Le Moigne et al., 2017) and full lidar collections.

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METHODS

Snow simulations were performed in areas with high snow depth heterogeneity using the SnowModel snow evolution framework (Liston and Elder, 2006). Simulations were forced with WRF forcing data used by Currier et al. (2017) and Hughes et al. (2017) in the Olympic Mountains of Washington State, and Tuolumne, CA, respectively. Assimilation was performed with the SnowAssim framework (Liston and Hiemstra, 2008) where errors in modeled snow water equivalent (SWE) were corrected by precipitation or melt weights that were spatially distributed using the Barnes interpolation scheme (Barnes, 1964). Since only snow depth observations were assimilated in this experiment, the SnowAssim routine was adapted to ingest these observations. When perturbing precipitation forcing with $\pm 200\%$ error (constant in time) with $\pm 25\%$ Gaussian noise (random in time), simulations assimilating snow depth observations reduced model errors by 95% and were 52% better than those assimilating SWE observations at the same periods.

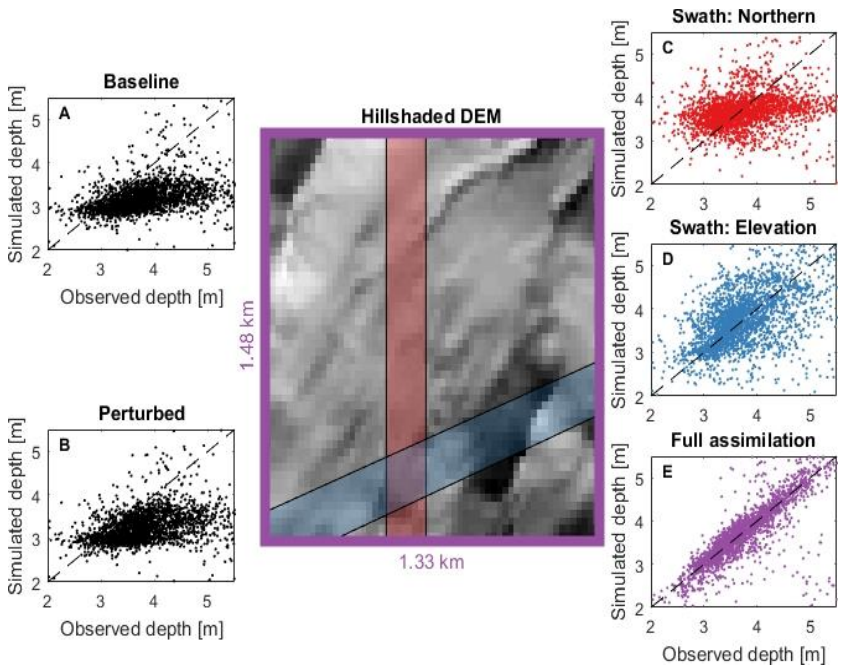

Figure 2. Model performance versus airborne lidar observations for 20m simulations (A) and simulations perturbing precipitation with 15% gaussian noise (random in time, uniform in space) and 30% bias (uniform in time and space) (B) in the Olympic Mountain domain. Modeled snow depth improvements are shown when assimilating observed depth at every gridcell (E), a northbound lidar swath (C), and an elevation-oriented lidar swath (D).

Simulations with perturbed precipitation were assimilated with subsampled lidar data representing full airborne lidar collections, cardinally-oriented flight swaths, and flight swaths oriented in the gradient of highest topographic variability (Figure 1 and Figure 2). In the Tuolumne, where over 40 full lidar collections are available over 4 years, snow depth patterns were quantified using standardized depth values (SDV) (Sturm and Wagner, 2010)

$$SDV_i = (d_i - \mu)/\sigma,$$

where d_i is the snow depth observed at point i, μ is the mean snow depth of the scene, and σ is the standard deviation (Figure 3).

RESULTS

Simulated snow depth in the Olympic Mountains and Tuolumne watershed resulted was too homogeneous as compared to observations (Figure 2 and Figure 3). This was true even when allowing redistribution by wind and avalanching and was unable to be corrected when calibrating parameters responsible for deposition and scour. However, precipitation adjustments derived from full airborne lidar collections were able to correct simulations

(Figure 2, purple, bottom right). When assimilating a northbound swath accounting for ~10% of the scene, modeled snow depth bias was corrected (Figure 2, red, top right). However, orienting the swath in the direction of high topographic variability improved both snow depth bias and heterogeneity (Figure 2, Blue, middle right). This indicates that at least part of the snow depth variability is driven by gradients in elevation and that observations oriented to changes in the topography are more informative to the Barnes interpolation scheme.

Snow deposition across a scene tends to persist and creates repeatable patterns from one year to the next (Sturm and Wagner, 2010). At Tuolumne, these patterns were even present across a windswept region. In fact, when calculating SDV patterns in midseason and late-season lidar observations, the SDV variance between collections was less than 4% of the typical SDV range across the domain. In other words, the snow distribution pattern (Figure 3) was present regardless of the period in which it was collected. It was even present for abnormal snow seasons like low-snow water-year 2015 and high-snow water-year 2017. Since snow patterns near peak-SWE in typical snow seasons are often most persistent (Schirmer et al., 2011), a mean SDV map was generated from distributed lidar observations on 29 April, 2013 and 7 April, 2014. Subsampled lidar and the observed SDV mean were then used in in a 3-step assimilation approach where: 1) the subsampled lidar observations were assimilated to correct the model bias and calculate μ and σ, 2) a distributed snow depth field was back-calculated using the SDV map, and 3) the new distributed field was assimilated at a pixel-by-pixel basis to adjust distributed precipitation. The resulting 3-step assimilation percent bias was 25% better than the default model simulation and increased the coefficient of correlation from 0.25 (default) to 0.95 (assimilated). This accuracy was accomplished using only the northbound swath depicted in Figure 3 and was insensitive to the area in which the swath was located.

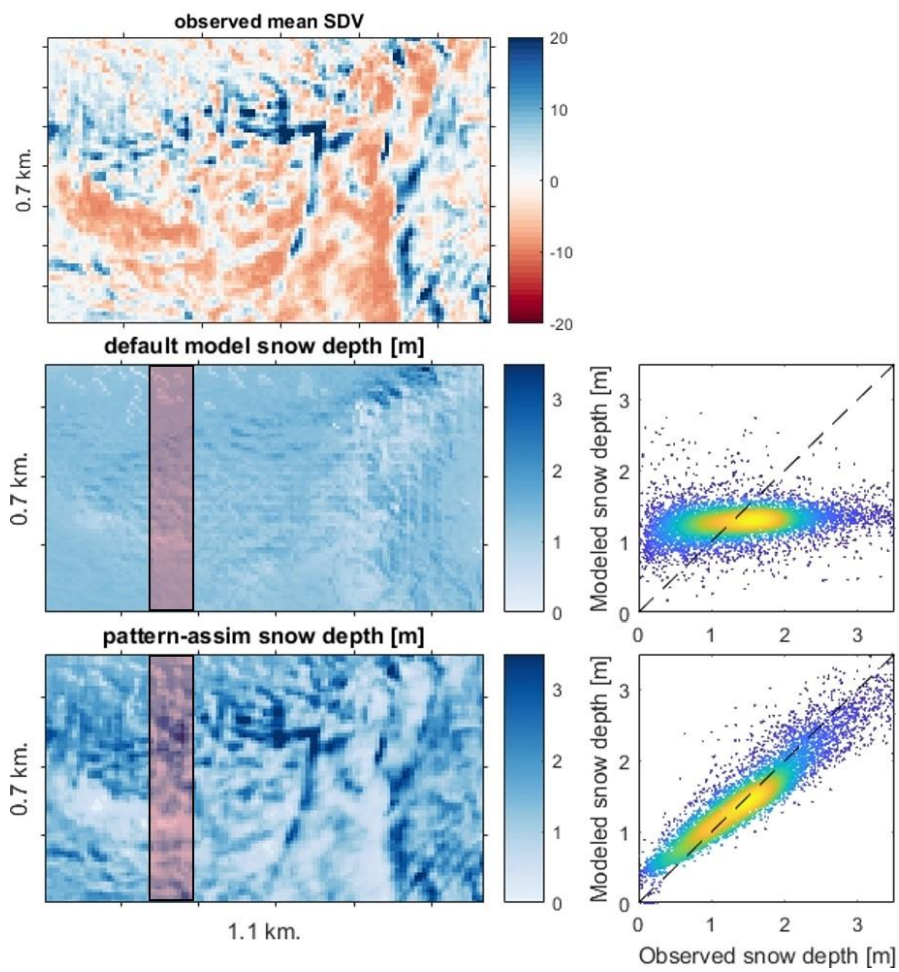

Figure 3. Mean-observed SDV map (top) used to transform the default modeled snow depth (middle) to a pattern-assimilated snow depth (bottom) using the lidar swath oriented in the shaded red region. Gridcell comparisons of modeled and observed depth are shown in the scatter plots with shading representing point density.

SUMMARY

Snow depth determination across large domains using lidar is increasingly in demand for both water-management and scientific purposes. However, models can be more efficiently combined with lidar observations to optimize our use of these expensive resources. Specifically, more domains can be covered at reduced cost by employing a strategic combination of full and reduced lidar coverage. Our results indicated that single airborne swaths were able to derive mean snow depth across large domains. However, snow distribution was better represented when strategically selecting the path of the swath. If full lidar collections are economically feasible, snow distribution patterns could be leveraged for future snow seasons, therefore reducing the need for multiple full-coverage collections. In Tuolumne, snow depth patterns were persistent for all lidar collections, but varied most when observed in the accumulation season, or at times with zero snow depth. Future work will expand this analysis to include different climates, land-cover types, and terrain features. Future work will also consider the implementation of coarse, satellite-based altimetry given snow depth patterns given by lidar observations.

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