Snowpacks are a primary source of water in the western United States, with runoff from snowmelt often supplying over half of the annual water consumption. For this reason, water resource planners invest considerable effort in estimating the water stored in mountain snowpacks in order to predict the spring snowmelt. For instance, planners for the city of Los Angeles conduct annual snow surveys at selected locations, compare the measured snow depth to years of historical measurements, and make predictions based on observed streamflow from past years with similar snow depths. Across the West, important managerial decisions affecting reservoir management, hydroelectricity generation, and irrigation policies rely on such streamflow predictions. Unfortunately, point-scale observations often are not representative of basin-wide snow characteristics, and the empirical relationships used to make predictions are subject to large errors, especially under the prospect of climate change.
Measurement and Modeling of Snow

Snow water equivalent (SWE) is the equivalent depth of liquid water stored in a snowpack. The need to obtain more accurate and robust estimates of SWE in mountainous watersheds has motivated research for over fifty years and prompted the development of in-situ measurement techniques, physical and empirical models of snow accumulation and ablation, and the use of remote sensing instruments for retrieval of snow parameters.

In-situ SWE Measurements:
The National Resources Conservation Service maintains a snow telemetry (SNOTEL) network of approximately 600 in-situ sensors that automatically measure SWE. These data provide very accurate observations, but at a very limited number of locations in the United States. While SNOTEL gauges provide a valuable data product used for forecasting and water resources management, the limitations of the method have led researchers to develop other methods for SWE estimation.

SWE Models:
Attempts have been made to model snowpack evolution using numerical models of varying complexity. These models require several meteorological forcing variables as inputs, including precipitation and air temperature. Measurement of input data, especially snowfall in mountainous regions, is notoriously difficult; gauge undercatch of 50 percent is not uncommon. Furthermore, the model structure and parameterizations are subject to uncertainty. While modeled SWE estimates generally are less accurate than in-situ measurements at a point, they are valuable because they can better capture the spatial variability of snow when appropriate ancillary inputs such as topography and meteorological data are available.

SWE Retrieval from Satellite Observations:
Remote sensing data have been used for over thirty years to estimate both snow-covered area (SCA) and snow water equivalent (SWE). Remote sensing estimates are generally less accurate than in-situ measurements at a point, such as a SNOTEL sensor, but they are valuable because they can better capture the spatial variability of snow when appropriate ancillary inputs such as topography and meteorological data are available.
and SWE. While SCA estimates are fairly accurate due to the strong reflectivity of visible radiation by snow, these frequencies contain virtually no information about snow depth or SWE. Researchers have therefore utilized observations of the surface emission of radiation at microwave wavelengths (which are sensitive to snowpack properties) for SWE estimation. These observations are characterized by their frequency and are often reported in terms of brightness temperature, which is directly proportional to the radiance. Because the earth emits low levels of radiation at these longer wavelengths, passive microwave observations are spatially coarse. Nevertheless, these observations are invaluable, as the combination of the satellite-borne SSM/I and AMSR-E sensors has provided passive microwave observations containing information about the global SWE distribution since 1987.

For the past twenty years, relationships between SWE and passive microwave observations have been examined through linear regressions on ground-truth SWE and satellite measurements of brightness temperature. In addition, radiative transfer models have been developed to predict the brightness temperature associated with different quantities of SWE. The SWE estimate is generally derived from linear combinations of two passive microwave frequencies. With these remote sensing algorithms, snow depth and SWE can be estimated across the entire globe without the need for ancillary data, a significant achievement. The problem with these retrieval approaches is that the dependence of the observed brightness temperatures on SWE is a time-dependent, many-to-one relationship, leading to large errors. Further, these retrieval methods generally are inapplicable for snowpacks greater than about one meter in depth.

**Merging Remote Sensing and Modeling to Estimate SWE**

Data assimilation, the science of merging observations with a model, provides a robust and flexible framework for optimally estimating hydrologically relevant parameters like SWE. The Ensemble Kalman Filter (EnKF) is a data assimilation framework that shows great promise for SWE estimation. It allows for the assimilation of multifrequency passive microwave brightness temperatures without the need for empirical retrieval algorithms. Further, important meteorological inputs and parameters related to snowpack evolution in time and space can be included in the framework. These inputs are treated as uncertain random variables and used along with a snow model to generate an ensemble of model realizations. The ability to propagate input uncertainty is especially important for SWE estimation where the primary input (snowfall) is known to contain both large systematic and random errors. Whenever an observation becomes available (as during a satellite overpass), the ensemble of estimates is optimally updated, based on the relative uncertainty in predicted model states and remote sensing observations. By tracking the evolution of the snowpack with a dynamic snow model, the update is based on the changing relationship between SWE and microwave radiobrightness at multiple frequencies. Finally, the EnKF framework allows maximum extraction of information from remote sensing observations via the assimilation of all available multifrequency observations, instead of only two or three, as is typical with retrieval algorithms.

Radiometric data assimilation using the EnKF, though widely used in other hydrologic applications, is still in the developmental phase for SWE estimation. Preliminary synthetic tests using meteorological data from Mammoth Mountain have been performed in order to test the feasibility of the methodology and compare its performance to model-based estimates and those from retrieval algorithms. These feasibility tests use a hydrologic and radiative transfer model to create a set of synthetic (“true”) snowpack states and corresponding microwave remote sensing observations. The data assimilation methodology then is applied using the synthetic remote sensing observations and erroneous model inputs (typical of snow modeling in mountainous watersheds) to evaluate the ability of the algorithm to recover the true SWE.

Results of this feasibility study are very promising. The upper chart on page 21 compares the EnKF estimate to a commonly used retrieval method, both using synthetic observations at SSM/I frequencies as inputs during early winter 1993/94 for snow depth less than one meter. The EnKF accurately recovers the truth while the retrieved SWE is unable to capture the accumulation trend. A snow model SWE estimate is also compared to the EnKF SWE estimate based on all available AMSR-E frequencies for the entire winter. In the lower chart, it is clear that assimilation of the AMSR-E observations is able to overcome a 50 percent bias in the precipitation input and reasonably estimate the accumulation of SWE throughout the season.

**The Future of SWE Estimation**

The next phase of this research will involve estimating SWE maps over an entire basin. While not shown here, the data assimilation framework is capable of downscaling coarse microwave observations through use of auxiliary information such as topography and meteorology at finer scales. The results of the downscaling procedure will include maps of SWE estimates at a spatial resolution finer than the actual observations. The use of active microwave (radar) observations (which are generally at finer resolution) is also a promising area for research. In summary, data assimilation approaches like the EnKF provide new technological capabilities for merging all available data along with the potential to provide accurate large-scale SWE estimates.

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