Merging regional climate models and remote sensing datasets to estimate mountain snow water equivalent: Proof-of concept in the Tuolumne watershed

Michael T. Durand[1,2], Melissa L. Wrzesien[3], Jessica Lundquist[4], Laura Hinkelman[5], Karl Rittger[6], Jeff Dozier[7], Tamlin M. Pavelsky[3], Sarah B. Kapnick[8], Kristen Rasmussen[9]

[1]School of Earth Sciences, Ohio State University, Columbus, OH

[2]Byrd Polar and Climate Research Center, Ohio State University, Columbus, OH

[3]Department of Geological Sciences, University of North Carolina, Chapel Hill, NC

[4]Department of Civil and Environmental Engineering, University of Washington, Seattle, WA

[5]Joint Institute for the Study of the Atmosphere and Ocean, University of Washington, Seattle, WA

[6]Institute of Arctic and Alpine Research, University of Colorado, Boulder, CO

[7]Bren School of Environmental Science and Management, University of California, Santa Barbara, CA

[8]Geophysical Fluid Dynamics Laboratory, National Oceanic and Atmospheric Administration, Princeton, NJ

[9]Department of Atmospheric Science, Colorado State University, Fort Collins, CO

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Abstract

Large-scale high-resolution estimation of snow water equivalent (SWE) in mountainous areas is challenging. Two approaches currently deployable at continental scale are SWE reconstruction and regional climate model (RCM) simulation. Here, we present a method that produces a simultaneous estimate of daily mass and energy balances at 500 m resolution, including SWE timeseries, informed by RCMs and constrained by observations in a way similar to SWE reconstruction. We formulate this as a constrained optimization problem; we seek to minimize the difference between our estimates and observed MODIS snow-covered fraction (SCF) and CERES irradiance, as well as RCM SWE from 3-km Weather Research and Forecasting (WRF) model simulations, subject to mass and energy balances constraints. This problem is readily solved using off-the shelf software. We compute Tuolumne watershed SWE (where it flows into the Hetch Hetchy reservoir: 775 km^2 or 3,612 MODIS pixels) in the Sierra Nevada, USA for water year 2009, a year with average snow accumulation. We validate against snow pillows and snow course data. We find that the SCF and irradiance observations constrain the WRF estimates significantly, with final RMSE of 66 mm and 98 mm at two snow pillows within the watershed, about 15% of peak SWE. Across the watershed, the total SWE volume estimated by our algorithm (0.34 km^3) compared well to high-resolution (90 m) SWE reconstruction (0.38 km^3), while WRF alone was too high (0.45 km^3). Our method represents a compromise, leveraging the beneficial qualities of both RCMs and reconstruction, and producing a simultaneous estimate of mass and energy fluxes and storages applicable to mountain regions.

1 Introduction

Earth's mountains cover 30 million km^2, or 23% of global land (Fig. 1), and are water towers for major population centers (Viviroli et al., 2007). However, current estimates of water and energy balance suffer from poor representation of complex mountainous terrain. Existing global water and energy balance estimates typically do not accurately resolve mountain water and energy processes, leading to significant biases in some cases. For example, Wrzesien et al. (2018) estimated that long-term average peak snow water equivalent (SWE) integrated across North American mountains is nearly three times greater than estimates from available global datasets. Presuming such underestimation exists in global estimates, these errors will result in the following issues: runoff will come too early, too much solar irradiance will be absorbed, and sensible heat flux and convective precipitation will be overestimated.

RCMs such as WRF have demonstrated remarkable accuracy in simulating mountain precipitation and SWE (e.g. Hughes et al., 2017; Rasmussen et al. 2011), due in part to recent developments in snowflake hydrometeor shape for modeling snowfall (e.g. Thompson et al., 2008). A considerable number of studies have found that WRF simulations at spatial resolutions less than 10 km reliably estimate precipitation (Warrach-Sagi et al., 2013; Qian et al., 2010; Currier et al., 2017; Hughes et al. 2017; Rasmussen et al. 2017). WRF coupled with the Noah-MP hydrological model (Niu et al., 2011) also accurately estimates snow cover and SWE dynamics (Rasmussen et al., 2011; Pavelsky et al., 2011; Jin and Wen, 2012; Wrzesien et al., 2015). Wrzesien et al. (2017) demonstrated that WRF reproduced the total SWS over the entire Sierra Nevada mountain range with reasonable accuracy (Fig. 5). Thus, a consensus has begun to develop that RCMs show enough skill to reproduce reasonable patterns of SWE in mountain terrain (Ikeda et al., 2010; Jin and Wen, 2012; Minder et al., 2016).

RCMs are far from infallible: we here highlight two challenges. First is spatial resolution: Wrzesien et al. (2018) produced estimates across North American mountains at 9 km, because runs at 3 km were too resource-intensive. Secondly, WRF developers have focused on precipitation accuracy more than on energy balance. Lapo et al. (2017) found satellite observations consistently outperform WRF estimates of incoming solar irradiance in California. Among future efforts suggested in a recent survey of WRF development are improvements in energy cycle representation (Powers et al., 2017).

In this paper, we constrain WRF with two types of remote sensing observations: MODIS snow covered-fraction (SCF) and CERES Syn radiation in order to estimate snow water equivalent (SWE). We refer to this method, not previously presented, as mass-and-energy constrained optimization (MECO). We test MECO SWE estimates by validating them against in situ data along with the Sierra Nevada Snow Reanalysis (SNSR) of Margulis et al. (2016). We demonstrate that this method is deployable at scale, and could thus be used to produce a new estimate of water and energy balance in global mountains.

2 Datasets used

- WRFv3.6 with Noah-MP model simulations: 3 km resolution, forced by NARR at boundary conditions. Datasets from Wrzesien et al. (2017).

- SCF: MODIS Snow Covered Area and Grain Size (MODSCAG: Painter et al., 2009).
- $R_s^{\downarrow}$ and $R_l^{\downarrow}$: CERES Synoptic: hourly, 1° resolution: Rutan et al. (2015).
- In situ data: the CA DWR snow surveys and snow pillows, after QA/QC, as described by Lundquist et al. (2016).
- 90 m SWE estimates from UCLA Margulis group Sierra Nevada Snow Reanalysis (SNSR): Margulis et al. (2016).

3 Methods

We use the HPC language Julia (Bezanon et al., 2017) to solve the following mass-and-energy constrained optimization problem:

$$\min_x \sum \left(\frac{x_i - \bar{x}_i}{\sigma_i}\right)^2 \tag{1}$$

$$\text{subject to: } \frac{dSWE}{dt} = P - M \tag{2}$$

$$M = \left[R_s^{\downarrow}(1-\alpha) + R_l^{\downarrow} - R_l^{\uparrow} - H - LE\right]SCF$$

where $R_s^{\downarrow}$, $R_l^{\downarrow}$, and $R_l^{\uparrow}$ are the (surface) downwelling shortwave, upwelling longwave and downwelling longwave respectively, α is albedo, ρ is water density, L is latent heat of vaporization, LE is latent heat flux, H is sensible heat flux, P is precipitation, and Q is runoff; the vector x represents the MECO estimate of SWE, SCF, P, $R_l^{\uparrow}$, H, and E, σ represents uncertainty, and the overline denotes either WRF or observed estimate, respectively. CERES $R_s^{\downarrow}$ and $R_l^{\downarrow}$ and WRF α are taken as given. Forest impacts will be considered in future versions.

We use Julia, a new open source language for scientific computing designed for high performance computing (Bezanson et al., 2017). The "ForwardDiff" (Revels et al., 2016) and Julia for Mathematical Optimization (JuMP) (Lubin and Dunning, 2015), and the interior point line-search algorithm "Ipopt" (Biegler and Zavala, 2009) packages are used to provide automated differentiation tools and fast solvers to compute optimal estimates.

We analyze each pixel independently, so analysis can take maximum advantage of multiple computing cores. MECO is computed on the ~500 m MODIS grid, to which all algorithm inputs are scaled, including CERES Syn. We include SCF as a variable and relate it to SWE using the Noah-MP snow depletion curve.

4 Results

Fig. 1 shows results from a simplified version of the algorithm and a subset of the proposed observations: MODSCAG snow cover (Fig 1c) and CERES Syn $R_s^{\downarrow}$ and $R_l^{\downarrow}$. We tested with WRF 3 km model runs of Wrzesien et al. (2017) for the Tuolomne watershed where it flows into Hetch-Hetchy (775 km^2; 3,612 MODIS pixels) and compared to in situ validation data of Lundquist et al. (2016). Constrained by CERES $R_s^{\downarrow}$ and $R_l^{\downarrow}$, algorithm estimates of net radiative flux are lower than WRF (Fig 10d). At both TUM and DAN, the algorithm accurately estimates

SWE (RMSE of 66 mm and 98 mm, respectively) despite significant WRF overestimation at TUM.

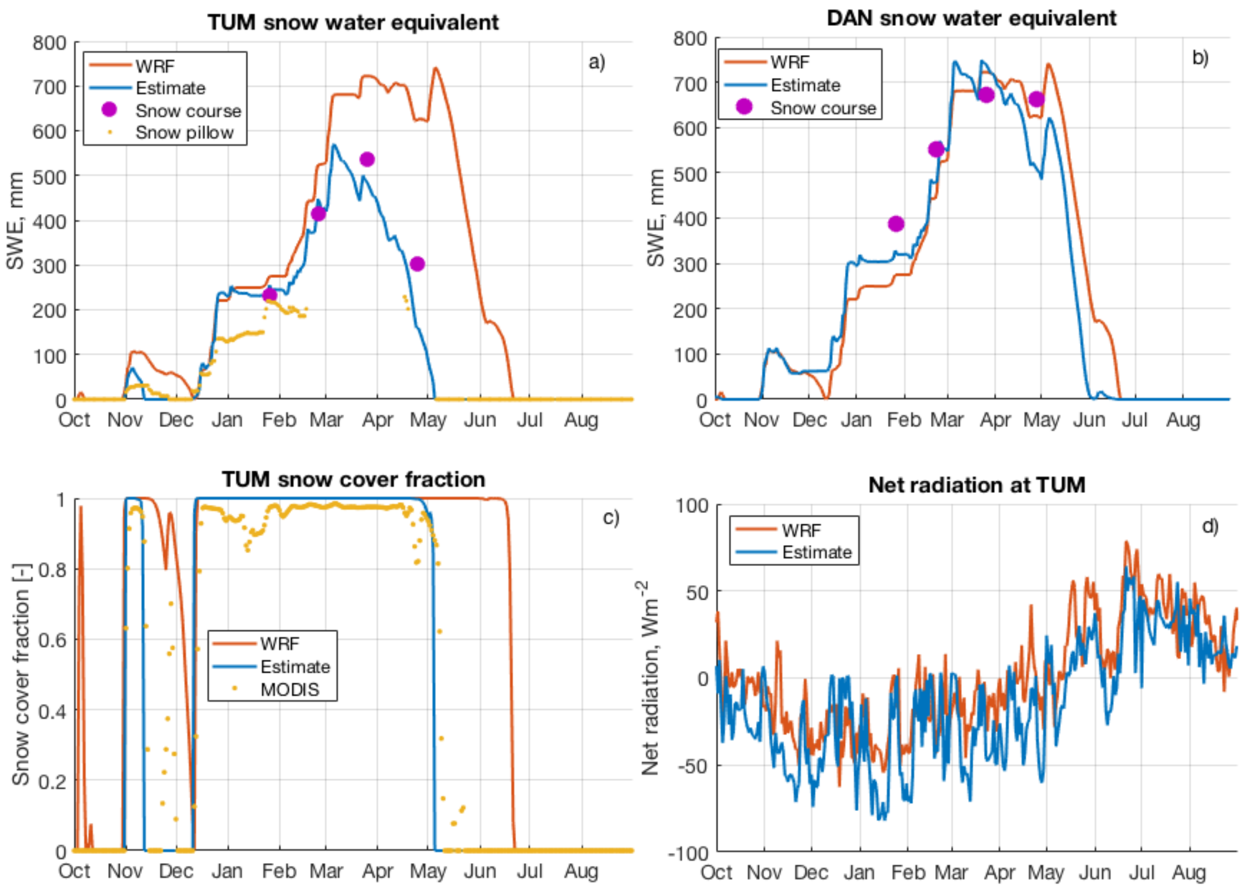

Figure 1. Example results from the proposed data merger algorithm: MODIS snow cover (c) and CERES (d) constrain SWE timeseries for two MODIS pixels (a and b) in the Tuolomne watershed.

We also compared spatial results (Fig. 2) to the independent SNSR SWE (Margulis et al., 2016) on March 1, 2009. The merged estimate matches SNSR total SWS and spatial pattern (note that SNSR is ~100 m resolution) better than does WRF.

Algorithm run-times benchmarked on the Owens Ohio Supercomputer (OSC) cluster took ~45 seconds each on a single processor. No effort was yet made to optimize Julia code performance in any way; e.g. we have only tried a single algorithm, and have not yet consulted with computing experts. Given the additional speedup expected, and the need to solve for additional variables, we expect the runs to take approximately 1 minute per pixel. For global mountains, for three years each range, we estimate a total computational cost of 6 million core hours, aside from WRF run time.

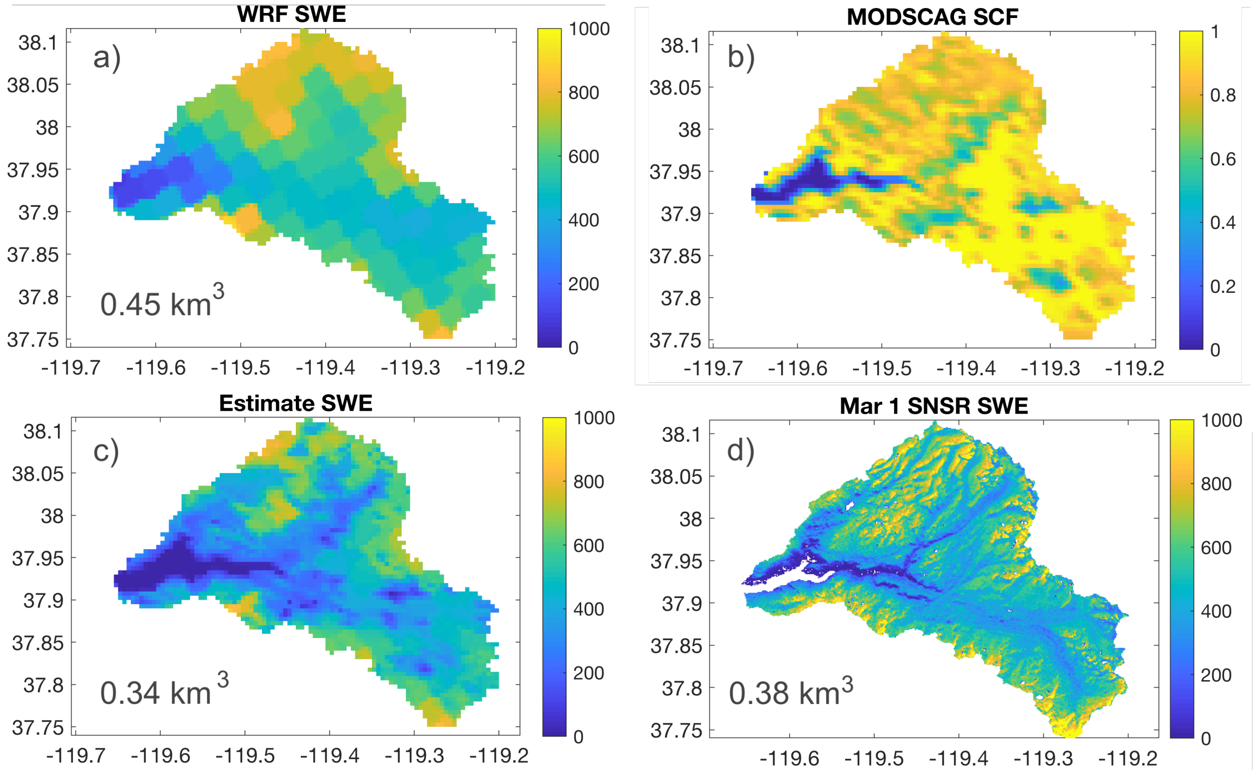

Figure 2. Example algorithm results for Tuolomne watershed: Algorithm inputs include WRF SWE (a) and MODIS SCF (b). Merged SWE (c) compares well to SNSR SWE (d). Total SWS (km^3) is shown in a, c, d.

5 Conclusions

We here demonstrate MECO, a new method for estimating SWE based on WRF, MODIS, and CERES Syn data. It compares well with in situ SWE estimates, as well as to a high-resolution reanalysis. It is 500 m spatial resolution, while the WRF output it drew from was at 3 km. It is scalable, and could be depolyed globally to better constrain global SWE estimates.

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