THE ROLE OF MICROSTRUCTURE IN FORWARD MODELING AND DATA ASSIMILATION SCHEMES: A CASE STUDY IN THE KERN RIVER, SIERRA NEVADA, USA

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Photo: Danielle Perrot
OBJECTIVE AND OUTLINE

How accurately can SWE be estimated from passive microwave with a data assimilation scheme?

• Why we think this might work
• Describe prototype modeling setup and highlight grain size treatment
• Show preliminary assimilation results
IN SITU ASSIMILATION SUCCESS AT CLPX - COLORADO 2003

Prior (first guess)
Posterior (estimate)
Observations

Durand et al., GRL, 2009
A Case Study of Using a Multilayered Thermodynamical Snow Model for Radiance Assimilation

Ally M. Toure, Kalifa Goïta, Alain Royer, Edward J. Kim, Michael Durand, Steven A. Margulis, and Huizhong Lu


Coupling the snow thermodynamic model SNOWPACK with the microwave emission model of layered snowpacks for subarctic and arctic snow water equivalent retrievals

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Radiance data assimilation for operational snow and streamflow forecasting

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Despite dramatic variability in snow depth and snow grain size, simulations indicate that mean brightness temperature ($T_b$) is still sensitive to mean snow depth.

Vander Jagt et al., TGRS, 2013
STUDY AREA:
KERN RIVER BASIN, SIERRA NEVADA, CALIFORNIA

- Area: 511 km²
- Minimal vegetation
- Large SWE accumulation
- Accumulation due to a few storms
STRATEGY

• Downscale NLDAS-2 meteorological data to 90 m

• Run snow physics model (SAST) at 90 m to get first guess SWE and grain size et al.

• Run MEMLS to estimate $T_b$ at 90 m

• Use models + data assimilation to downscale information about SWE from AMSR-E to 90 m scale
SATELLITE OBSERVATIONS

- AMSR-E L2A $T_b$ observations at 36.5 GHz, v-pol
- Elliptical footprints with long dimensions of 8.2 x 14 km
- Footprint area is 88 km$^2$, 7x smaller than EASE grid
DOWNSCALING FORCING

- NLDAS-2 (with PRISM) forcing data used
- Topographic shading for solar radiation correction
- Longwave radiation biases removed

Girotto et al., 2013
SNOW PHYSICS MODELS

- SAST snow physics model (Sun et al., 1999)

- Grain growth following Jordan (1991):

  \[
  \frac{dD}{dt} = \alpha_1 \frac{U_v}{D}
  \]

- We calibrated \( \alpha_1 \) to match the rate of decrease of \( T_b \) as from AMSR-E: used value of 3E-7 m^4/kg
MICROWAVE MODELS

• MEMLS (Wiesmann & Mätzler, 1999) with Improved Born Approximation (Mätzler & Wiesmann (1999))

• Used relationship for relating correlation length and grain size (Wiesmann et al., 2000):

\[ L = 0.16D \]


• We calibrated one soil parameter to match AMSR-E during snow-free season
A NEW WAY TO HANDLE LAYER COMBINATIONS DURING SNOWFALL

The Problem:

The Solution: after each snowfall, automatically set bottom-layer grain size to be that which gives 4-layer $T_b$

Li et al., in review
Modeling study

Choose precipitation to give correct SWE at snow courses (2004-2006)

Calibrate grain growth rate using between-snowfall drops in $T_b$ (2004-2006)

Test how well this new fix allows for simulation of $T_b$ (2003, 2007, 2008)
IMPORTANCE OF RESAMPLING FIX

Li et al., in review

Note: large snowfalls lead to increase in $T_b$!
Model responding to elevational gradients, aspect, etc.

But is it correct?

Li et al., in review
We scale 90 m model up to observation resolution

Li et al., in review
Overall pre-March RMSE is 3.3 K

We cannot simulate well after March, when snow becomes wet
SATURATION

Modeled results at a single pixel (UTY snow pillow) for WY2005 (maximum accumulation)
MODELING SUMMARY

• Made modifications to modeling scheme to allow 90 m runs for three-layer model

• One parameter for grain growth rate calibrated

• Achieve 3.3 K RMSE during validation years

• Can such a system be used in an assimilation scheme to estimate SWE?
ASSIMILATION SCHEME IDEA

\[ y_{\text{posterior}} = y_{\text{prior}} - K[z_{\text{predicted}} - (z + v)] \]

Durand & Margulis, 2007; Durand et al. 2009
ASSIMILATION SCHEME DETAILS

• **Ensemble batch smoother**: all obs. used to update SWE at all times

• No observations used after March

• Uncertainty added to precipitation, soil roughness, grain growth rate

• No localization done: we use model spatial and temporal autocorrelations as simulated

• Temporal correlation in observation error considered to account for non-clear sky

• Assimilate October 1 - March 1 $T_b$ observations, but update total WY SWE
MARCH 1 2005 ASSIMILATION IMPACT

Prior

Posterior

AMSR-E downscaled via model-based dynamic Tb-SWE correlations
SNOW COURSE EVALUATION

- Half the bias in the prior estimate corrected in the posterior
- Shape of the depletion after March due to model issues
- Melt-out time wrong: could be corrected with visible + NIR snow cover fraction

Legend:
- Posterior estimate
- Prior estimate
- Snow course
SIX YEAR APRIL 1 SWE EVALUATION AT THREE SNOW COURSES

Prior (red):
Bias: -0.19m, RMSE: 0.22m

Posterior (blue):
Bias: -0.01m, RMSE: 0.11m
HOW DO THE “APPLIED” MICROSTRUCTURE QUESTIONS RELATE TO THE THEORETICAL?

- Can variations in $T_b$ be accurately linked by models to variations in SWE for deep mountain snow?
- What grain size models need to be used? Is physical really better?
- What microwave models should be used? Can we get away with empirical scattering instead of improved Born in this context?
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EXTRA SLIDES
Li et al. *RSE*, 2012.