Ecohydrologic modeling in deciduous boreal forest: Model evaluation for application in non-stationary climates

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Abstract

Soil moisture is an important driver of growth in boreal Alaska, but estimating soil hydraulic parameters can be challenging in this data-sparse region. To better identify soil hydraulic parameters and quantify energy and water balance and soil moisture dynamics, we applied the physically-based, one-dimensional ecohydrologic Simultaneous Heat and Water (SHAW) model, loosely coupled with the Geophysical Institute of Permafrost Laboratory (GIPL) model, to an upland deciduous forest stand in interior Alaska over a 13-year period. Using a Generalized Likelihood Uncertainty Estimation (GLUE) parameterization, SHAW reproduced interannual and vertical spatial variability of soil moisture during a five-year validation period quite well, with root mean squared error (RMSE) of volumetric water content at 0.5 m as low as 0.020. Many parameter sets reproduced reasonable soil moisture dynamics, suggesting considerable equifinality. Model performance generally declined in the eight-year validation period, indicating some overfitting and demonstrating the importance of interannual variability in model evaluation. We compared the performance of parameter sets selected based on traditional performance measures (RMSE) that minimize error in soil moisture simulation, with those that were designed to minimize the dependence of model performance on interannual climate variability. The latter case moderately decreases traditional model performance but is likely more suitable for climate change applications, for which it is important that model error is independent from climate variability. These findings illustrate (1) that the SHAW model, coupled with GIPL, can adequately simulate soil moisture dynamics in this boreal deciduous region, (2) the importance of interannual variability in model parameterization, and (3) a novel objective function for parameter selection to improve applicability in non-stationary climates.

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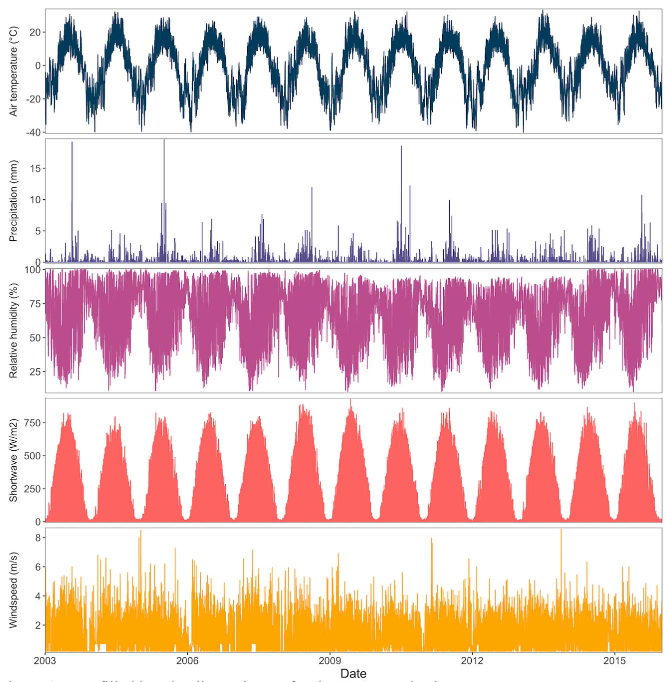

Figure 1. Gap-filled hourly climate inputs for the UP1A study site.

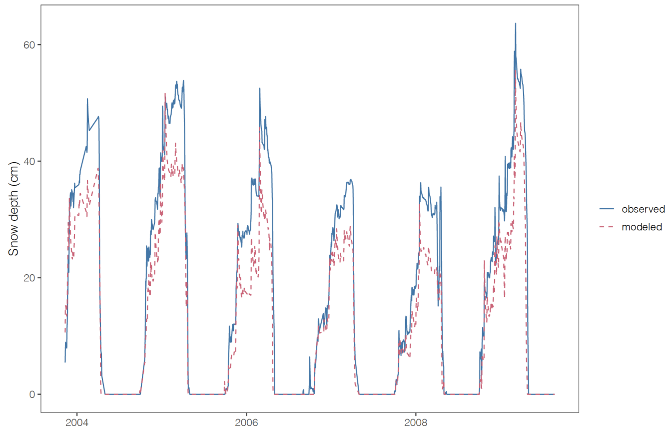

Figure 2. Uncalibrated modeled and observed snow depth at the nearby LTER1 site.

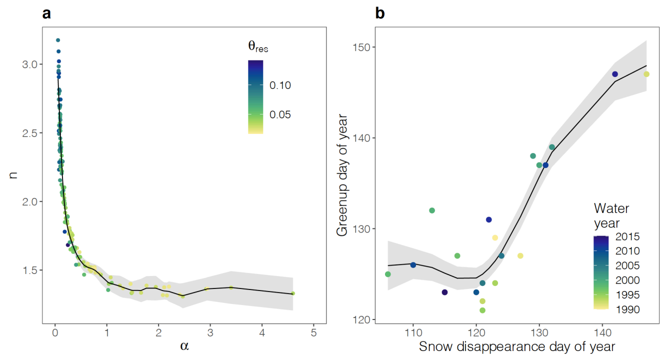

Figure 3. (a) relationship between van Genuchten α and n from the NCSS database, with generalized additive model (GAM) fit (n = 158, $R^2 = 0.943$). (b) relationship between snow disappearance date and green-up (GAM n = 21, $R^2 = 0.841$).

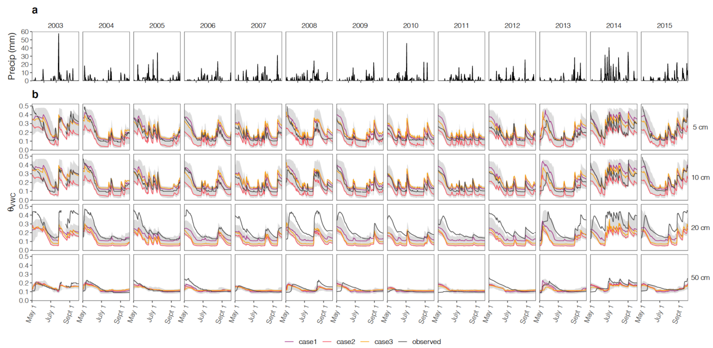

Figure 4. Modeled and observed soil moisture at four depths in May-September. Gray area delineates bounds of predictions by parameter sets with RMSE < 0.03 and NSE > 0.5 in the calibration period (3192 sets). Calibration period is 2003-2007; validation is 2008-2015.

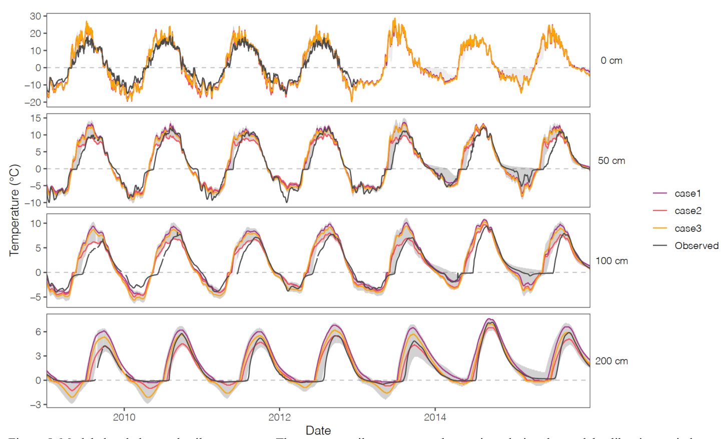

Figure 5. Modeled and observed soil temperature. There are no soil temperature observations during the model calibration period.

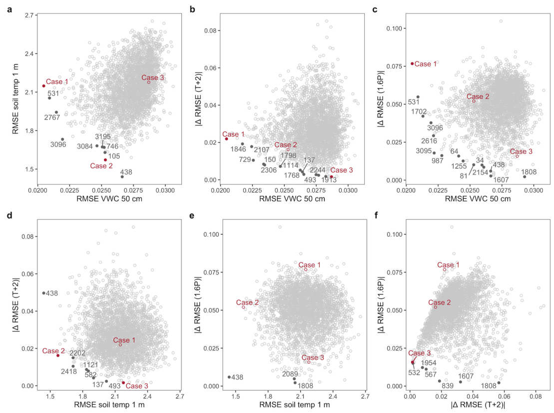

Figure 6. Pareto fronts for each possible combination of four objective criteria. Pareto-optimal points are in dark grey and are labeled for ease of comparison between plots. Each case is identified in each plot; points for these cases are filled when they are included in the Pareto front and open otherwise.

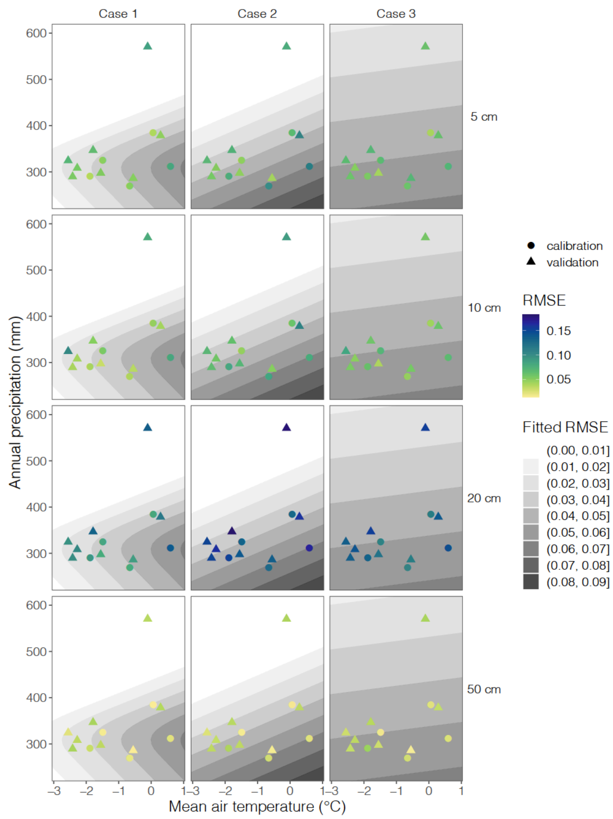

Figure 7. Interannual variability in model performance at each depth as a function of mean annual air temperature and precipitation. Points represent individual water years, and contours represent GAMMs fitted to the data for the respective parameter sets. Plots include the climate space encompassed by all water years, but GAMMs were fit on only the calibration data.

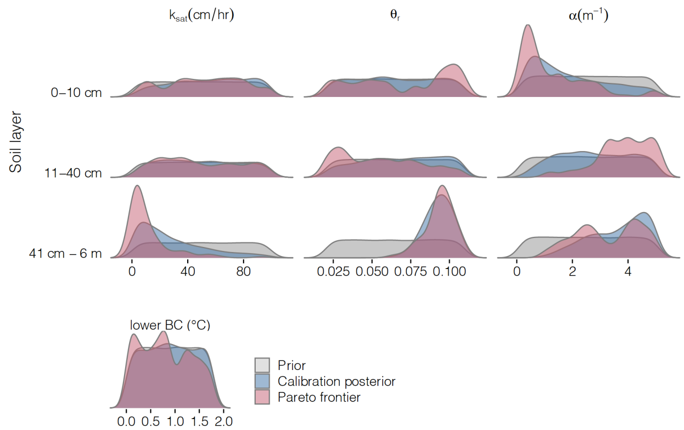

Figure 8. GLUE distributions of prior parameter, behavioral parameters in the calibration period (VWC RMSE at 50 cm < 0.03; NSE > 0.5), and parameter sets included in the four-objective Pareto frontier.

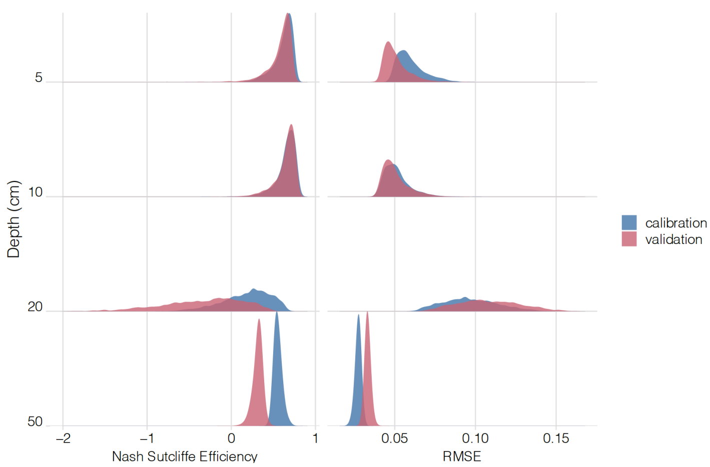

Figure 9. Model fit statistics of all accepted parameter sets during the calibration and validation period at multiple depths.

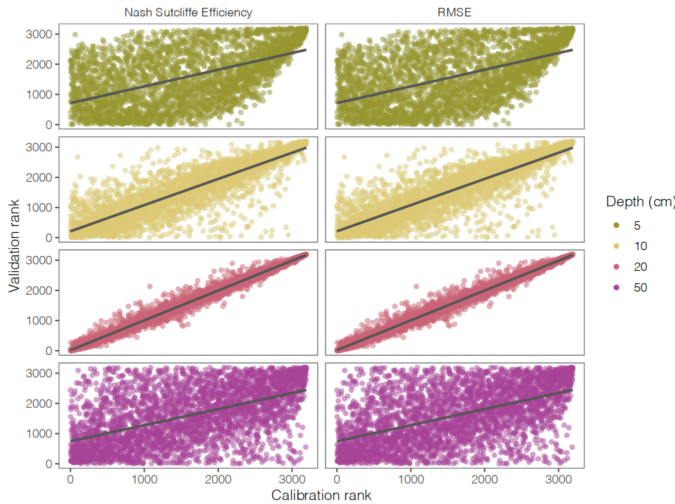

Figure 10. Rank of accepted parameter sets based on NSE or RMSE on calibration versus validation data. At all depths, linear regression $p < 0.0001$. R^2 is 0.31 at 5 cm, 0.75 at 10 cm, 0.98 at 20 cm, and 0.29 at 50 cm.