SPATIAL ANALOG MODELS OF SNOW

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ABSTRACT

Empirical modeling of physical processes is essential to the advancement of our scientific understanding and to the improvement of more complex physically based and conceptual models. In the face of climate change, these models must not only be grounded in strong knowledge of the natural world; they must also be transferable to conditions not observed in the historical record. Here we develop empirical spatial analog models of April 1 SWE and Snow Residence Time at SNOTEL sites based on winter temperature and precipitation. We find that spatial analog models capture the nonlinear relationship between the independent and dependent variables, provide very strong fits to the data, and provide additional insight into physical mechanisms. A non-random cross-validation test indicates that the models transfer well to warmer conditions. Finally, we provide an example of how this simple empirical model can be leveraged to obtain information from more complex global climate models in a straightforward and computationally efficient manner. (KEYWORDS: model transferability, snow, spatial analog)

INTRODUCTION

Empirical models of physical processes can reveal insights about consistent behavior across space and time, helping to flesh out hydrologic theory (Clark et al., 2016). These insights support and enhance more complex physically based and conceptual models which are often used to answer the big questions facing science today. At the same time, simple empirical models have the potential to answer big questions on their own while avoiding issues of overparameterization and high computational cost.

For practical reasons most models (empirical, conceptual, etc.) are calibrated on limited geographic regions (e.g. a watershed) or time periods (e.g. a decade) and are expected to make predictions in different regions (e.g. global) or time periods (e.g. 2100), often requiring significant extrapolation. Applying models outside of calibration conditions has two potential pitfalls: 1. 'getting the right answer for the wrong reason' (Kirchner, 2006), and 2. getting the wrong answer. The first stems from an inadequate understanding of underlying theory and processes. In operational contexts the right answer may be sufficient, but it does not further our scientific understanding. The second may lead to misguided policy decisions that are at best not helpful and at worst detrimental to our goals. Avoiding these pitfalls requires evaluation of model transferability (Klemes, 1986; Wenger and Olden, 2012). The rigor of the transferability assessment should be commensurate with the predictive task to which the model will be applied (Klemes, 1986). Through sufficiently conservative tests models have the opportunity to fail, allowing us to improve scientific understanding, which will help us get the right answers in all conditions.

We apply the above concepts to the case of snow metrics in the western United States. Using precipitation and temperature data at Snowpack Telemetry (SNOTEL) sites, we create empirical spatial analog (SA) models of April 1 SWE (A1SWE) and snow residence time (SRT). SA models, also known as space-for-time models, evaluate the relationship between variables across space (SNOTEL sites), whereas more commonly used time models evaluate relationships over time (e.g. at watershed A from 1980-2010). We apply a rigorous transferability test to our models and demonstrate application of the model to global climate model (GCM) outputs.

DATA AND METHODS

Data

Daily precipitation and snow water equivalent (SWE) observations were obtained from 497 SNOTEL sites for water years 1991-2011. In light of SNOTEL temperature data quality concerns (Oyler et al., 2015), daily minimum and maximum temperature for SNOTEL sites from the TopoWx (Oyler et al., 2014) dataset for the same

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time period were used. TopoWx applies additional quality assurance checks beyond those applied by the Natural Resources Conservation Service (NRCS), including infilling and homogenization.

Historical (1975-2005) and projected future (2070-2090, RCP 8.5) temperature and precipitation data were obtained from the Multivariate Adaptive Constructed Analogs version 2 (MACAv2) dataset of Abatzoglou and Brown (2011) for the western United States. MACAv2 provides statistically downscaled 4km grid resolution outputs from GCMs in the Coupled Model Intercomparison Project 5 (CMIP5, Taylor et al., 2012) and uses the training dataset of Abatzoglou (2013).

Methods

Following Luce et al., (2014), annual values of winter (Nov-Mar) cumulative precipitation and average temperature were computed for each SNOTEL site and these were averaged to get a single climatological temperature value (mT) and precipitation value (mP) for each site. Similarly, mT and mP were computed for each MACA grid cell for historical and future and then averaged across all models to get ensemble mT and mP values for each period and grid cell. A1SWE was obtained directly from the SNOTEL records. SRT was computed as the center of timing of melt minus the center of timing of accumulation where accumulation was any positive increment in SWE over the year and melt was any negative increment in SWE over the year. They were calculated as:

$$CT_{acc} = \frac{\sum t_i acc_i}{\sum acc_i} \qquad \text{and} \qquad CT_{melt} = \frac{\sum t_i melt_i}{melt_i}$$

where t_i is the number of days since Oct 1, acc_i is the increase in SWE on day i and $melt_i$ is the decrease in SWE on day i.

SA models were constructed for A1SWE and SRT using the locfit package (Loader, 1999) in R. Locfit fits a polynomial equation of degree 2 to each data point to create a regression surface. The models were specified in R as, for example: *locfit(swe ~ lp(mT, mP, nn=0.8, scale=T)* where mT and mP are independent variables predicting swe (A1SWE or SRT). Locfit does not require a priori assumptions about the form of the equation, allowing the data to direct the model. Sensitivities of A1SWE and SRT to changes in temperature and precipitation were assessed using the partial derivatives of temperature and precipitation from the locfit model. The relative importance of mP and mT in the models was calculated as:

$$\frac{pd(mT) \times sd(mT)}{pd(mP) \times sd(mP)}$$

where *pd* is the partial derivative and *sd* is the standard deviation.

To assess the transferability of the models we applied a non-random cross-validation test. The test was designed to evaluate the models' ability to predict under conditions outside of calibration conditions by creating distinct (non-randomly selected) calibration and validation samples which mimicked the difference between historical conditions and future conditions under which the model may be applied. We chose to use a conservative 2-fold cross-validation because the task of predicting future snow metrics is formidable. We did this by selecting the four years with the coldest west-wide temperatures at SNOTEL sites and using temperature and precipitation averaged over these years for model calibration. The models were then validated using temperature and precipitation in the four warmest west-wide years. The mean temperature difference between the calibration sample (cold years) and the validation sample (warm years) was approximately 2°C. Results were assessed using the Nash-Sutcliffe coefficient (NSE), the Pearson correlation (Cor) and the root mean square error (RMSE).

mT and mP from the MACA ensemble for historical and future periods were fed to the SA models to predict historical and future A1SWE and SRT at the MACA grid level.

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The SA model for A1SWE was strong (NSE=0.87, Cor=0.87, RMSE=104mm, Figure 1a) and captured the nonlinear relationship between the dependent and independent variables. The temperature sensitivity of the SA model was largely a function of precipitation, while the precipitation sensitivity was largely a function of temperature. The highest temperature sensitivity was found at warm and wet sites whereas the highest precipitation sensitivity was found at cold and dry sites. In general, precipitation had a much stronger influence on A1SWE than temperature did (Figure 2).

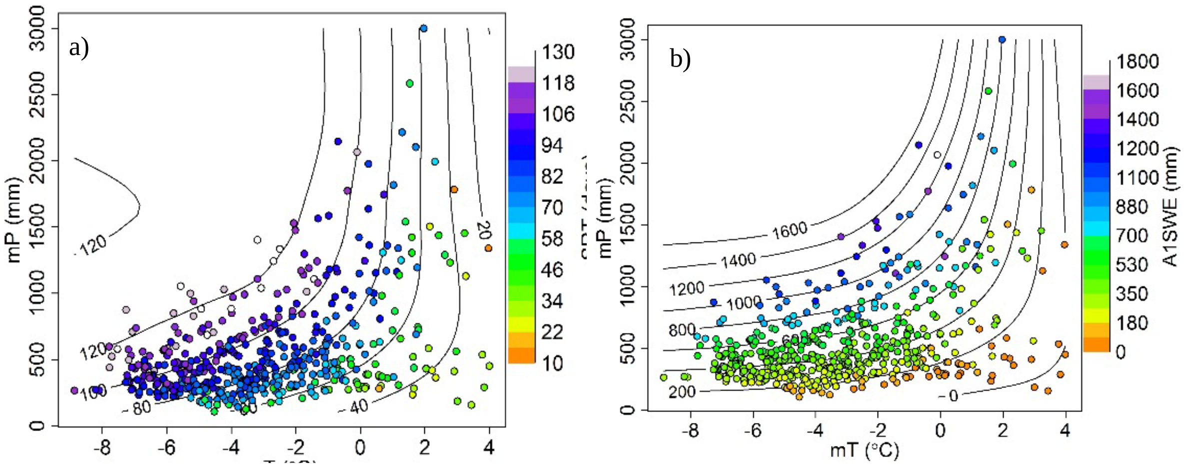

Figure 1. SA models of a) A1SWE and b) SRT.

Table 1. Results of non-random cross-validation.

	Calibration			Validation		
	NSE	Cor	RMSE	NSE	Cor	RMSE
A1SWE	0.87	0.87	93 mm	0.61	0.70	150 mm
SRT	0.80	0.76	12 days	0.53	0.72	14 days

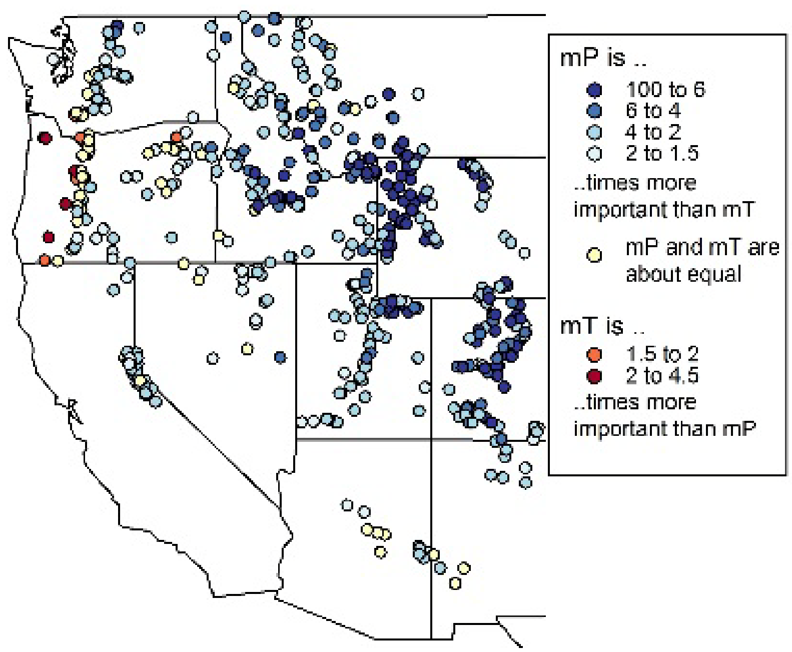

Figure 2. Relative importance of mP and mT to A1SWE.

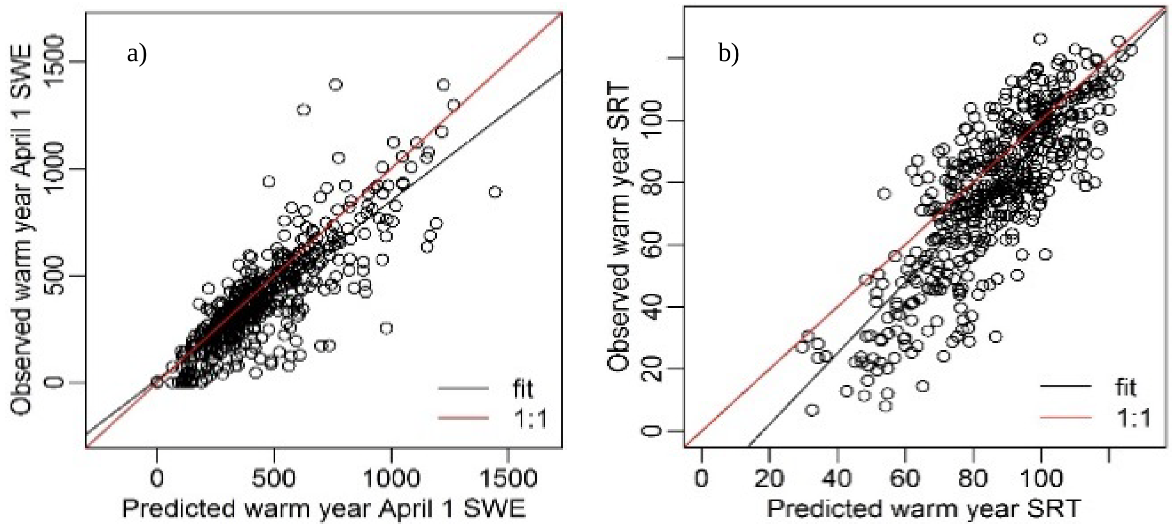

Figure 3. Predicted vs observed warm year a) A1SWE and b) SRT.

The SA model fit for SRT was nearly as strong as for A1SWE (NSE=0.82, Cor=0.82, RMSE= 9.8 days, Figure 1b). As with A1SWE, the contours for SRT indicated interacting effects of temperature and precipitation, however the SRT model had considerably less precipitation dependency. Temperature sensitivity ranged from -2.7 to -27.4 days/^{o}C whereas precipitation sensitivity ranged from -0.01 to 0.1 days/mm, indicating the relatively minor effect of changes in precipitation. Both temperature and precipitation sensitivity of SRT were more equally dependent on both temperature and precipitation than they were in the A1SWE model.

<u>Transferability Assessment</u>

The A1SWE model constructed using only cold years was strong (Table 1). The model performed well when validated on warm years, with a slight tendency to over predict A1SWE (Figure 3a). For SRT, the calibration model was not quite as strong as for A1SWE (Table 1). The model performed acceptably in validation on warm years (Figure 3b), although it also tended to over predict slightly.

<u>Application</u>

Predicted historical A1SWE and SRT maps captured the general pattern of snow accumulation typical of the western United States (Figure 4a, c). The maximum predicted historical A1SWE was 3730mm and the maximum SRT was 168 days. Predicted future A1SWE showed substantial reductions in land area with SWE on April 1 (Figure 4b). For grid cells with at least 100mm predicted historical A1SWE, the mean decline in A1SWE was -78% and the maximum future A1SWE value was 2580mm. A few grid cells in the Middle and Southern Rockies had predicted future increases in A1SWE of up to 11%. Predictions of future SRT (Figure 4d) indicated no seasonal snow accumulation in large portions of the Southwest and substantial declines in the Cascades. The mean change in SRT was 19 days and maximum SRT in the future was predicted to be 150 days.

CONCLUSIONS

Spatial analog models of A1SWE and SRT provided very strong fits to the data and were able to capture the nonlinear relationship between these snow metrics and winter temperature and precipitation at SNOTEL sites. A conservative 2-fold non-random cross-validation test which calibrated the models on cold years and predicted for warm years revealed that the models transferred well to warmer conditions. Additional tests (not discussed here) with different sampling schemes revealed further strengths and weaknesses of the models. When applied to the MACAv2 data the spatial analog models provided predictions of future A1SWE and SRT.

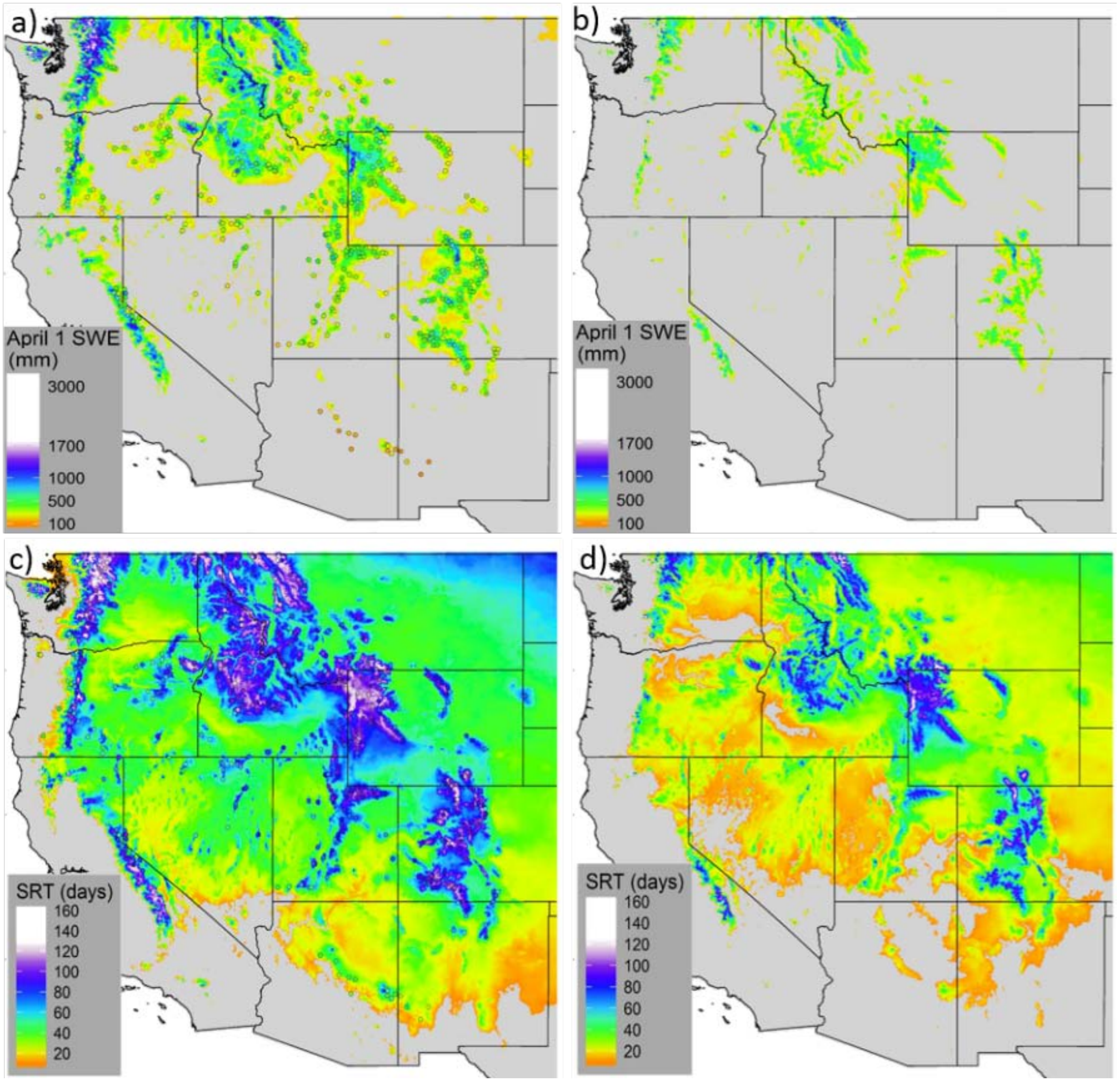

Figure 4. Predicted historical a) A1SWE and c) SRT and predicted future b) A1SWE and d) SRT.

Spatial analog models provide a straightforward and computationally efficient way to evaluate outputs from climate models and could be used to quickly evaluate differences in snowpack predictions from different GCMs in order to select models for further investigation. Future work includes evaluating how these predictions compare to outputs from more complex models of snow metrics. Finally, simple empirical models whose structure is guided by the data, not a priori assumptions, such as the model presented here, reveal insights about underlying physical processes that can inform theory and guide process representation in more complex models.

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