Sierra Nevada Soil Moisture Response to Climate Change Studied through El Niño Seasons

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Abstract:

With increasing variability in the weather patterns due to Climate Change effects, monitoring the Sierra Nevada mountain range soil moisture content is critical as it can help mitigate natural disaster effects. Through non-constant snowpack patterns, it is valuable to understand how this factor along with other covariate effects will influence the level of water found in the ground soil. Over a four year period, daily data was collected over two depths at one site to monitor soil moisture content. We paired this data with another location's snowpack level and maximum air temperature in order to analyze how freezing, refreezing, and melting of snow will contribute to fluctuations in moisture content. Testing 4 different Multivariate Auto Regressive(MAR) models over an annual and seasonal period of time shed light on these interactions. An anticipated negative relationship (especially during El Niño year) between snowpack level and soil moisture was confirmed through statistical methods of estimation of parameters in a MARSS model. As previously mentioned, it is critical to understand how the weather patterns of El Niño years may result in varying soil moisture content as they may provide insight for the more intense weather conditions predicted to stem from our changing climate.

Key Words: Snowpack, soil moisture, El Niño , Preferential Flow Path, Sierra Nevada range, MARSS, Climate Evolution

Introduction:

An increase of methods allowing for interpretation of more openly accessible environmental and ecological data paired with the looming crisis of a rapidly changing climate call for this analysis. As precipitation levels become less predictable year to year, it would benefit communities and organizations to foresee how a spring, summer and fall will affect likelihoods of natural disasters such as fire, landslide, and flood(Kapnick, Yang, et al. 2018). In years with a larger quantity of precipitation(rain or snow), yield longer spring and summer cycles of snowpack melt and runoff. In collaboration to these effects, understanding how a maximum air temperature would affect the system by snowpack densification which occurs through snow freezing, melting and refreezing.

In order to conduct this study, UC Merced's Dr. Roger Bales and team, who have been working for 10 years collecting and publishing hourly and daily data, were consulted to gather soil moisture data at a site in the Sierra Nevadas with an elevation between 1660 and 2115 meters near Shaver Lake east of Fresno(Bales, R., M. Meadows, E. Stacy, X. Meng 2019). At this particular site, there exists data from 2008-2018 over several locations in the landscape: open area, drip edges, and two types of tree cover taken at several depths: 10, 30, 60, and 90 cm into the ground. With rich data to pull from, it was decided to pull the sensors at depths 10 and 60 cm in an open environment to maximize snowpack depth.

Our snowpack depth and airtemp site is located in Donner Pass at UC Berkeley's Central Sierra Snow Laboratories which is located at roughly 2100 meters. This location has been monitoring snow data including snowfall, snowpack depth, air temperature, and non-snow precipitation for 70+ years(Sanders, Robert 2022). Understanding how increased rain versus snow events will provide valuable information as to how the mountainous forest landscapes will retain water. As rain falls on snowpack, snow melts and when it refreezes, it is less porous which exhibits poor flow of water through this layer of snow(Yamaguchi, Hirashima, et al.). This warrants a study of interaction between melting snowpack and soil moisture content during El Niño years, as El Niño years tend to have larger quantities of rain on snow events.

Larger quantities of precipitation leads to a more than healthy forest. With the intention to understand how a difference in a given year's snow levels will penetrate through the ground, close attention was paid to our covariate interactions with soil moisture across the two depths. A deeper penetration of water would present more rich soil providing benefits for the surrounding ecosystem. While a healthy forest is positive, due to climate change’s trend towards increasingly variable seasons, the rich and dense forests are more prone to forest fires as this new growth begins to dry out over the course of summer and fall. In addition moist soil warrants a concern for landslides. Understanding and interpreting these drives may help create precautionary measures to reduce risk and damage of one of these events.

Methods:

With this data, it was decided to perform research on a reduced set of parameters to minimize outside interactions which may produce unwanted noise. By enforcing collection in a clearing we are able to confirm that conditions at the two collections points will be similar up to some transformation due to weather patterns in our two different zones of the Sierra Nevadas. With this in mind, a Z-transform of the data was implemented in order to measure deviation from mean of our variables rather than actual values(Figure 1). This takes away the concern of encountering very small effects due to mismatched scaling of natural processes.

With the data in formatted correctly, an analysis of the time series presented a large deviation from mean trend in the data during the winter and spring of 2011 which was identified as seasonal variation from a standard year due to the El Niño weather events. After running several MARSS models with the entire dataset, a wish to be more intentional with the estimation of parameters prompted a more seasonal approach to the model creation. By choosing 200 day periods across winter and spring, we were able to track the soil moisture level as it diminishes alongside the warming of the air and the decrease of snowpack inherently causing an increase in water runoff. This allows for the comparison of models over 4 different years, one of which being an El Niño year.

Progressing with this idea, overlaying and creating composite plots of our data showed significant trends occuring in the year 2011 that did not present themselves elsewhere(Figure 2), reaffirming the belief that interactions of our models will vary in 2011 compared to 2008, 2009 and 2010. Starting out with a multivariate autoregressive state space(MARSS) model quickly progressed into a simpler multivariate autoregressive model (MAR). Removing the observational component of the model left us with the form $\mathbf{x}_t = \mathbf{B}*\mathbf{x}_{t-1} + \mathbf{U} + \mathbf{Cc} + \mathbf{W}_t$. X is the data that has been collected; a 2x200 matrix for each year. B is a 2x2 matrix defined to be which allows the model to estimate the interactions between the soil moisture at a depth of 60 cm and 10 cm from the timestep prior which is given as $\mathbf{X}_{t-1}$. The C matrix is also a 2x2 matrix which demonstrates how the two chosen covariates, snowpack depth and maximum air temperature interplay with the two states of soil moisture. The c represents our covariate data, also a 2x200 matrix for each year. The final component is the process error estimator which yields a 2x2 matrix for each state in our model.

Over the 4 model designs, a best overall model was selected that minimized AICc for the four seasonal models and keeps parameter freedom consistent across the years. Upon fitting the models, a plot of the estimations of parameters using bar graphs display interactions between objects in our model.

Results:

Prior to splitting up our data into yearly seasons, the non-converging structure chosen for the MARSS model led to the removal of the state space component and the reconstruction to a MAR model. Fitting the 4 different model structures across the 4 seasons resulted in minor variability in AICc which was enough to pull a best fit model. The chosen model's features include an unconstrained B matrix which allows for an estimation of the interaction between our data from the day prior to the day of estimation. This feature exhibits a relatively small cross correlation between the states or depths of the model and a very significant, near 1, autocorrelation. The convergent models call for a diagonal and equal Q-matrix which represents the variance across parameters that the model must account for. An unconstrained C matrix provides insight to the valuable questions of covariate data reactions for each component. An attempt at a model with drift provided little to no valuable information, so drift is 0. As before stated, removing the state space model yields an identity Z matrix and a zero R matrix for observational variance.

With optimized elements, analysis can begin. Figure 5 allows an easy view of the parameter estimation which has been bootstrapped in order to incorporate 95% confidence intervals. Important takeaways from this plot are that there is typically a positive relationship between the soil moisture content at depth 10 and the covariates, however in 2011, the year classified as an El Niño, displayed negative relationships for both covariates. In addition to this, the interstate interactions are both nearly positive in 2011.

Discussion:

With the aforementioned results a further analysis and interpretation needs to be considered. Upon finding a negative connection between the covariates and the 10 cm soil moisture content in 2011 bring forth an interesting comparison with the preceding years. This implies that as the temperature and snowpack decrease, the soil moisture content at 10 cm would seemingly increase. The snowpack decrease would be reasonable as the snow is melting and thus providing more seepage of moisture into the ground, however the decrease in temperature is something of interest that could and should be studied further. By taking into consideration more years, of which some being categorized as ENSO(El Niño), a richer trend could be viewed and extended hypotheses could be made and tested. As far as this research goes, there is a significant deviation from the non-ENSO years which aligns with the original hypothesis, however the deviation may not align with the anticipated results.

Furthermore, a near positive correlation between the two states of our model, may provide insights into the hypothesized increased interactions between the two depths during a year with higher precipitation as moisture a lower depth may be drawn to the surface given that a higher level of moisture deeper drives water to sit higher in the soil as opposed to finding its way deeper in the soil. Using differences in soil moisture content(Figure 3) instead of the raw measurement could also lead to a more focused analysis of an interaction of the two depths as increases and decreases tend to align in nearly the same process whereas sheer content may not be as related due to different pressures, drainage, and reuptake processes.

An unfortunate lack of evidence on freezing and refreezing effects of snow was exhibited in the analysis, however honing in on the parameters as well as incorporating another covariate such as rain and non-snow precipitation could yield results which would help test this hypothesis.

Finally, using these results and understanding these estimated parameters might in fact allow for prediction and further understanding of soil moisture content. This could promote studies on soil moisture content's role in fire spread, management, and prediction. In a similar manner, landslide severity can be studied in the lens of soil moisture, especially in years of high water content in soil. In addition, analyzing the duration of effects on environmental health would benefit as soil moisture tends to promote growth and longevity of forests in the event that natural disasters do not stunt this growth.

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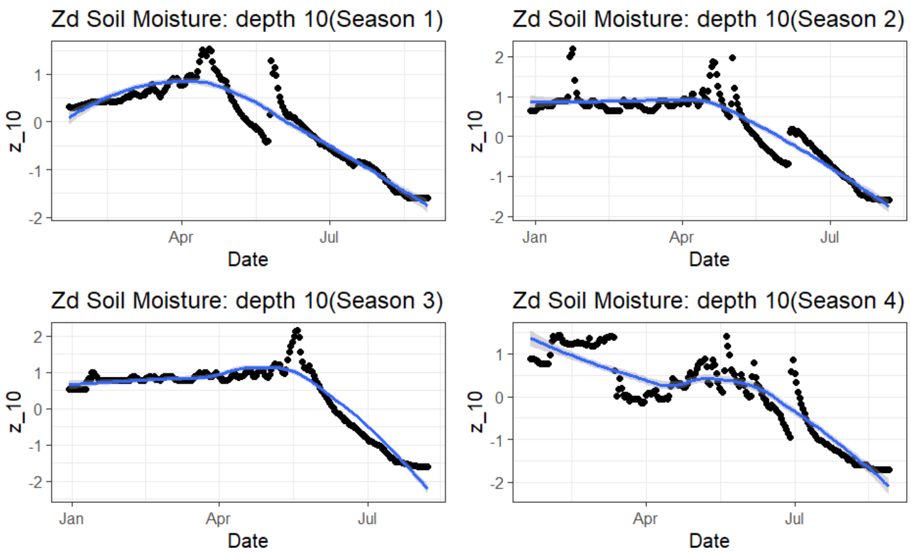
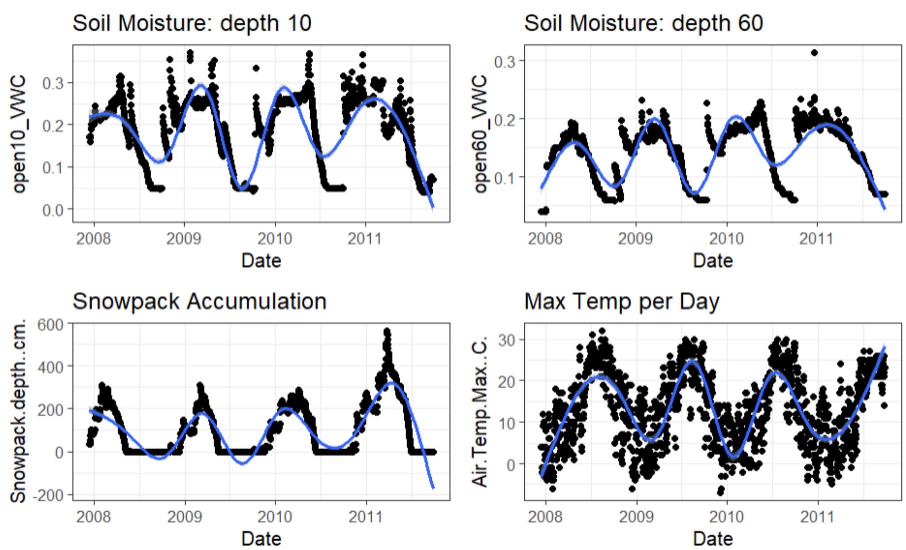
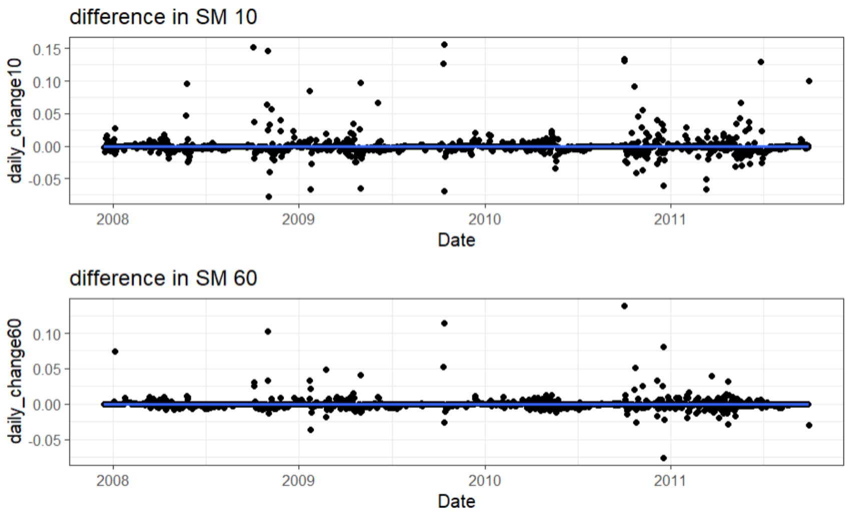
Tables and Figures:



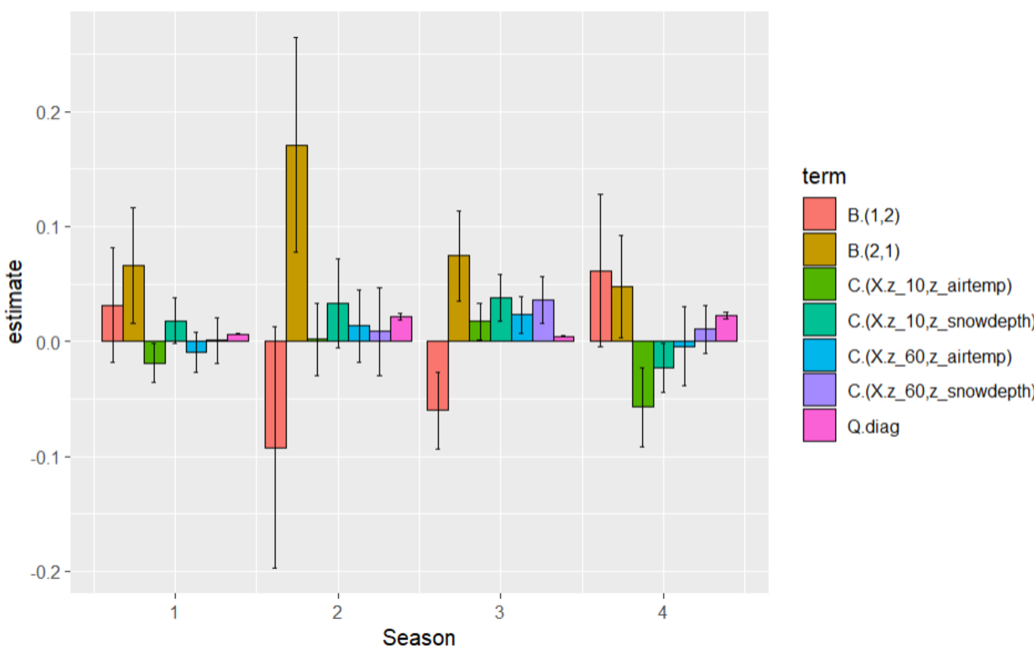
(Figure 1) Z-scored data has been trimmed into a 200 day time series for each year, allowing for a seasonal analysis. This data targets the timeframe as soil moisture decreases until a minimum is reached.



(Figure 2) A look at the data in use for our models. Notice the abnormal activity during the 2011 years, including where the minimum is achieved, where are the peaks, and the more variable maximum plateau.



(Figure 3) A look at the data if differencing was taken into account. 2011 variability is interesting and unique to this scale of time series. 2009 has larger fluctuations but 2011 is more dynamic.



(Figure 5) Parameter estimation from MAR model with confidence intervals plotted as a bar graph. Note the removal of B's diagonal which is close to 1 in order to see more clearly the small variation in B's off diagonal and the C matrix values. Season 1,2,3,4 correspond to the seasons starting in 2008, 2009, 2010, 2011 respectively.

Season	Z Matrix (2x2)	B Matrix (2x2)	Drift(U)	Q:Error Var (2x2)	C Matrix (2x2)	(R:Obs Var, A)	AICc
1	Identity	Unconstrained	0	Diagonal/Unequal	Unconstrained	(0,0)	-1022.36
1	Identity	Unconstrained	0	Diagonal/Equal	Unconstrained	(0,0)	-948.75
1	Identity	Unconstrained	unequal	Diagonal/Equal	Unconstrained	(0,0)	-1029.59
1	Identity	Unconstrained	0	Diagonal/Equal	Diagonal/Equal	(0,0)	-1029.55
2	Identity	Unconstrained	0	Diagonal/Unequal	Unconstrained	(0,0)	-425.11
2	Identity	Unconstrained	0	Diagonal/Equal	Unconstrained	(0,0)	-422.65
2	Identity	Unconstrained	unequal	Diagonal/Equal	Unconstrained	(0,0)	-418.81
2	Identity	Unconstrained	0	Diagonal/Equal	Diagonal/Equal	(0,0)	-427.85
3	Identity	Unconstrained	0	Diagonal/Unequal	Unconstrained	(0,0)	-1116.00
3	Identity	Unconstrained	0	Diagonal/Equal	Unconstrained	(0,0)	-1127.25
3	Identity	Unconstrained	unequal	Diagonal/Equal	Unconstrained	(0,0)	-1114.85
3	Identity	Unconstrained	0	Diagonal/Equal	Diagonal/Equal	(0,0)	-1098.55
4	Identity	Unconstrained	0	Diagonal/Unequal	Unconstrained	(0,0)	-415.17
4	Identity	Unconstrained	0	Diagonal/Equal	Unconstrained	(0,0)	-400.98
4	Identity	Unconstrained	unequal	Diagonal/Equal	Unconstrained	(0,0)	-398.99
4	Identity	Unconstrained	0	Diagonal/Equal	Diagonal/Equal	(0,0)	-394.31

(Figure 6) A table showing the 4 tested model structures with their associated AICc scores. For each season, the model order is identical and parameter requirements are the same. The selected model is that which is highlighted in green(the second proposed structure for each season).