Predicting Total Discharge into California's Central Valley from the Sierra Nevada Mountains

Jonathan Wong, Dean Kang, Randy Moran

ABSTRACT

We illustrate and predict the groundwater discharge, as shown through the Water Table Depth (catdef) from the Sierra Nevada Mountain Snowpack Reanalysis and other GRACE-DA variables. Using a ConvolutionalLSTM model we provide an 87% accuracy for a geospatial coordinate grid of 33 x 37, an approximate resolution of 36 Km^2. We investigated the variations of snowpack to assess the possible impact on Water Table Depth by varying snowpack input. Finally, we evaluated the benefit of offsetting the Snowpack input on improving our overall model.

---

1) Introduction

The Central Valley in California produces 25% of the nation's food supply yet comprises less than 1% of the farmland in the U.S[1]. The agricultural advantage of this region can be attributed to a unique combination of features, particularly its water infrastructure. Unfortunately, the Central Valley has been stricken with drought, with 2021 being the third driest year in more than 100 years of precipitation record[2]. Water availability has been going down due to changes in the climate via snowpack reduction. Farmers need to employ strategies to maximize crop yield and reduce risk or put at risk crops estimated at $17 billion a year.

We aim to provide an efficient means to predict future water runoff from the Sierra Nevada Mountains to the Central Valley. Our work utilizes existing data from previous research to build various demonstrative models. Using the derived historical snowpack estimates and assimilated data, including water table depth, runoff, root zone moisture content, and more, we built deep learning models that would predict and illustrate the historical runoff values for the Central Valley. The resulting models could, in the future, be used to take the current or forecasted snowpack and other feature data to predict the runoff totals. This would allow policymakers better to manage

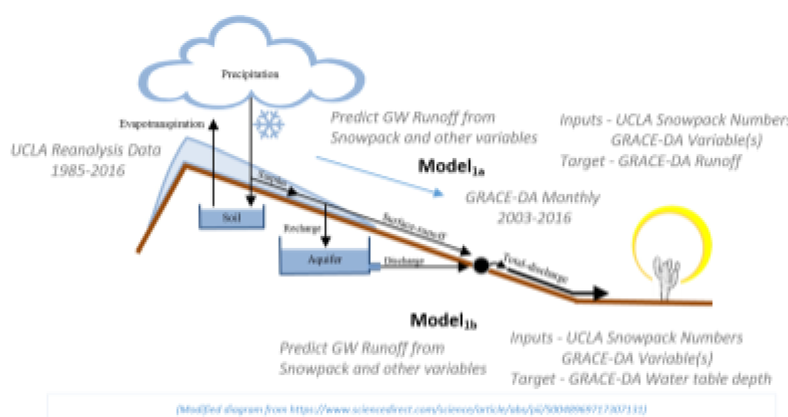


Figure 1 - Discharge Models

---

[1] https://ca.water.usgs.gov/projects/central-valley/about-central-valley.html
[2] https://californiawaterblog.com/2021/08/22/2021-drought-in-california-in-one-page/

the most important resource for agriculture, water, and allow farmers to optimize their crops based on the forecasted water availability.

We focused on building two models, the groundwater surface-runoff model, and the groundwater discharge model. For the latter, we utilized the feature catdef, the water table depth from the surface, to represent the discharge amounts.

2) Data and Methods

a) Data

Our two primary data sources for model development are the Landsat-Era Sierra Nevada Snow Reanalysis from Margulis et al.[3] for Snowcap input and Gravity Recovery and Climate Experiment data assimilation (GRACE-DA) from Getirana et al.[4] for the ground runoff and groundwater discharge. We used the well depth (catdef) to represent the groundwater discharge.

The Sierra Nevada Snow Reanalysis data contains the daily snowcap based on the assimilation of remotely sensed fractional snow-covered area data over the Landsat 5–8 record (1985–2016)[5]. The data was a 3D array containing latitude, longitude, and the Snow Water equivalent for the specific coordinate that was transformed initially into images 5701 x 6601. For use with the other data, we had to aggregate it to monthly values. To do so, we summarized the values and created a monthly total equivalent image.

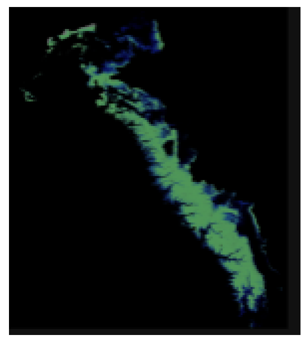


Figure 2 - Snowpack Reanalysis

[3] Margulis, S. A., Cortés, G., Girotto, M., & Durand, M. (2016). A Landsat-Era Sierra Nevada Snow Reanalysis (1985–2015), *Journal of Hydrometeorology*, *17*(4), 1203-1221. Retrieved Nov 13, 2021, from https://journals.ametsoc.org/view/journals/hydr/17/4/jhm-d-15-0177_1.xml

[4] Getirana, A., Rodell, M., Kumar, S., Beaudoing, H. K., Arsenault, K., Zaitchik, B., Save, H., & Bettadpur, S. (2020). GRACE Improves Seasonal Groundwater Forecast Initialization over the United States, *Journal of Hydrometeorology*, *21*(1), 59-71. Retrieved Nov 13, 2021, from https://journals.ametsoc.org/view/journals/hydr/21/1/jhm-d-19-0096.1.xml

[5] Margulis, S. A., Cortés, G., Girotto, M., & Durand, M. (2016). A Landsat-Era Sierra Nevada Snow Reanalysis (1985–2015), *Journal of Hydrometeorology*, *17*(4), 1203-1221. Retrieved Nov 13, 2021, from https://journals.ametsoc.org/view/journals/hydr/17/4/jhm-d-15-0177_1.xml

The GRACE-DA (2003 - 2016) provided a set of monthly data variables that represented the consolidated assimilation of data from various sources. The key data points for our analysis were the water table depth (catdef) measured in mm from the surface and runoff (overland runoff including throughflow) measured in kg m^2 s. Each of the variables contained values that represented a 36 square kilometer area giving us 33x37 km grid coordinate based on latitude and longitude. We were able to transform the data into 3D Arrays as shown in the heatmap in figure 3 for Water Table Depth (catdef).

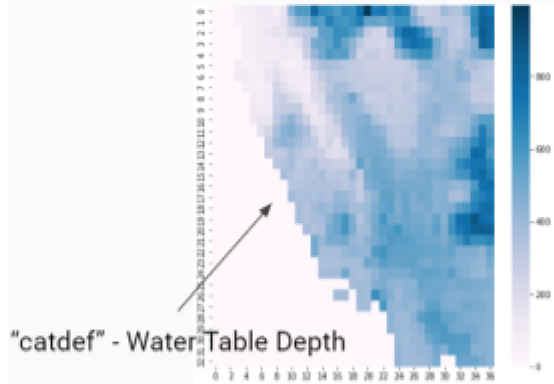


Figure 3: Water Table Depth - Heatmap

b) Preliminary Investigation

Our initial investigation was done by aggregating Snowpack and GRACE-DA data into monthly totals which allowed us to work more efficiently to determine relationships between the features and runoff. The work in the aggregate was meant to identify the best variables to use for further processing. We began by looking at two models, one to predict the Surface Runoff (Model 1a) and another to predict the Groundwater Discharge as represented by the Water Table Depth (Model 1b).

We first used Long Short-term Memory (LSTM) Models on the aggregated data to understand the key associations of snowpack and well depth (catdef), as well as the other variables available in the GRACE-DA dataset. We saw promising results using this approach in the paper Developing a Long Short-Term Memory (LSTM) based model for predicting water table depth in agricultural areas by Zhang et al[6]. It was our choice based on its ability to take into account previous timestep data for our seasonal sequence of data. Our first basic model run of aggregate Snowpack to Water Table Depth model had a R^2 accuracy of 72% for the test data. Though not stellar, it was an indication that this approach had

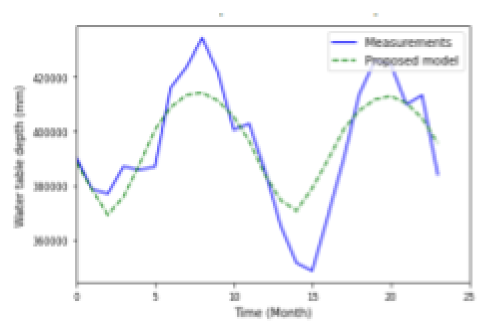


Figure 4 - Aggregate Snowcap Model

[6] Jianfeng Zhang, Yan Zhu, Xiaoping Zhang, Ming Ye, Jinzhong Yang ,Developing a Long Short-Term Memory (LSTM) based model for predicting water table depth in agricultural areas,*Journal of Hydrology, Volume 561, 2018, Pages 918-929*, ISSN 0022-1694, https://doi.org/10.1016/j.jhydrol.2018.04.065

promise. The R^2 accuracy describes the proportion of variation in the outcome that is explained by the predictor variables. In multiple regression models, R^2 corresponds to the squared correlation between the observed outcome values and the predicted values by the model. The Higher the R^2, the better the model[7].

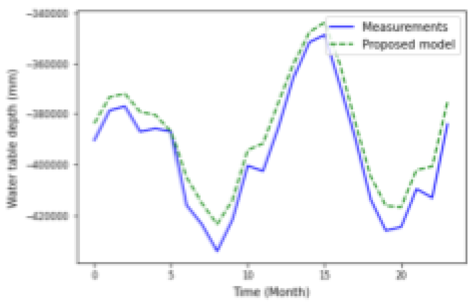


Figure 5 - Aggregate Snowcap and Rzmc Model

We then went through a trial and error approach, using the available GRACE-DA variables to see if we could add to the Snowpack and refine the accuracy of our model. Of all the variables we tried, the Root Zone Moisture Content (rzmc) had the most significant effect on accuracy. Adding just RZMC to Snowpack yielded a much better result, with an accuracy of 88.3% for the test data.

To do a more systematic evaluation of the variables, a bulk run was done with permutations of all the variable combinations. The brute force run was done across 550 combinations of features to find the most important features. Our result was the combination of Snowcap, Surface Excess (srfexc), Rain from Convection (RainfC) and Root Zone Moisture Content (rzmc) with a score of 93.8% accuracy for the 24 test months.

srfexc,RainfC,rzmc,month,snowcap	0.938387417980458
Tair,srfexc,RainfC,rzmc,month,snowcap	0.919341236164677
Tair,srfexc,rzmc,month,snowcap	0.917180793330258
Tair,srfexc,rzmc,evap,month,snowcap	0.902454228050345
Tair,rzexc,rzmc,month,snowcap	0.899156787266646
Tair,srfexc,Snowf,rzmc,month,snowcap	0.897602452559189
srfexc,RainfC,rzmc,evap,month,snowcap	0.895916763968457
Tair,srfexc,rzexc,rzmc,evap,month,snowcap	0.880141689997548
Tair,srfexc,rzexc,rzmc,month,snowcap	0.876798893403961
Tair,runoff,rzmc,month,snowcap	0.874338456219459

Table 1 - Top 10 Aggregate Combinations

[7] http://www.sthda.com/english/articles/38-regression-model-validation/158-regression-model-accuracy-metrics-r-square-aic-bic-cp-and-more/

Using the variables identified via the brute force approach for the Groundwater Discharge model, we evaluated the Surface Runoff. It also showed decent results in the aggregate model. Using the Snowpack, Rainfall (RainfC), Temp Air (Tair), RZ Moisture Content (rzmc) versus the runoff, resulted in an 82% R^2 accuracy value.

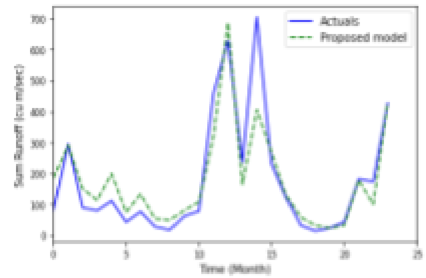


Figure 7 - Aggregate Surface Runoff model (1a)

c) Coordinate-based Investigation

The aggregate data investigation provided us the insights we needed to proceed with the primary goal of the project; the ability to predict and illustrate the historical runoff values for the Central Valley. In order to illustrate the runoff, we had to return to the coordinate based data and look to get coordinate based results. DOing so would allow us to see the impact by area based on the input. Having the coordinate predictions will allow policy makers and farmers to understand the expectations for specific locales. To that end, it was necessary to utilize deep learning and image based modeling techniques.

We opted to use a ConvLSTM which is essentially a Convolutional Neural Network (CNN) stacked on a Long Short Term Memory (LSTM) architecture. CNN and LSTM have been shown to work well with images and time series data, respectively. For sequential images, ConvLSTM's are known to provide great results.

In order to run the models on our machines the base snowcap model had to be reduced to either (256x256 or 128x128) and flattened to a 33 x 37 output node. This avoided out of memory issues we were getting on the model definitions. In future work, we can use higher resolution images in models along with greater computing resources to pave the way to better results.

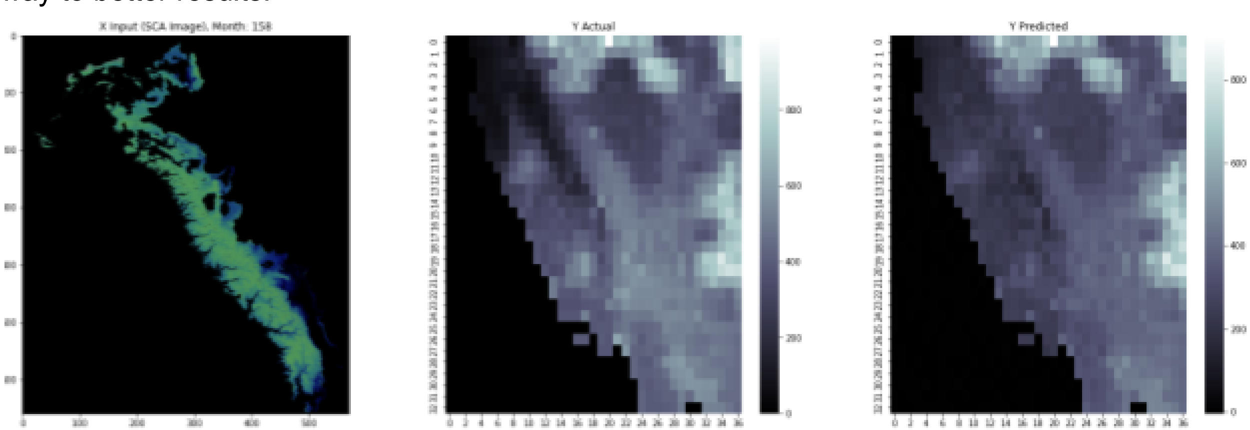


Figure 8 - Convolutional LSTM - Snowpack to Catdef

d) Nan ("Not A Number" or NULL) value elimination

As previously mentioned, the GRACE-DA is a high-dimensional dataset that covers a grid made up of 36 square kilometer location in Northern California. The southwest portion of the dataset that covers the ocean is populated with NULL values. We initially converted these NULL values to zeros in the predictor images and allowed the model to freely predict the ocean values. In theory, the predicted values for the ocean should have come out to all zeros but this was not so and can be attributed to the nature of machine learning. To eliminate this noise, we removed all variables with Nan values in the training set from consideration. Although this did not result in a significant increase in performance, this at least minimized computing resources.

3) Results

Once we had settled on the modeling approach we set out to investigate the coordinate based results on the aggregate investigation. The goal again was to predict and illustrate the discharge based on the snowpack and other variables. We reviewed 3 scenarios, a baseline model of the features from the bulk variable evaluation, the impact of global warming on the discharge by varying the Snowpack input and evaluating the models if the Snowpack image was offset one or more months from the resulting discharge. Given our time constraints for the project, we limited the final investigation to just the Groundwater discharge. We will leave the Surface Runoff investigation for a later study.

For all our models, we used a Convolutional LSTM model, running on an AWS NVIDIA Deep Learning AMI v21.06.0, with varying input dimensions based on whether it was a two or four variable model. We used Tensorflow 2.5.0 from within our Docker Container.
The variation in the input between the 2 and 4 is due to the combined input variables affecting the resulting image size after knitting together.

Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv_lst_m2d_2 (ConvLSTM2D)	(None, 1, 150, 322, 64)	156928
max_pooling3d_2 (MaxPooling3	(None, 1, 75, 161, 64)	0
conv_lst_m2d_3 (ConvLSTM2D)	(None, 1, 73, 159, 64)	295168
max_pooling3d_3 (MaxPooling3	(None, 1, 36, 79, 64)	0
flatten_1 (Flatten)	(None, 182016)	0
dense_3 (Dense)	(None, 1300)	236622100
dense_4 (Dense)	(None, 1300)	1691300
dropout_1 (Dropout)	(None, 1300)	0
dense_5 (Dense)	(None, 1221)	1588521

Total params: 240,354,017
Trainable params: 240,354,017
Non-trainable params: 0

Figure 9a - ConvLSTM Model Summary - 2 Variables

Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv_lst_m2d_2 (ConvLSTM2D)	(None, 1, 71, 327, 64)	156928
max_pooling3d_2 (MaxPooling3	(None, 1, 35, 163, 64)	0
conv_lst_m2d_3 (ConvLSTM2D)	(None, 1, 33, 161, 64)	295168
max_pooling3d_3 (MaxPooling3	(None, 1, 16, 80, 64)	0
flatten_1 (Flatten)	(None, 81920)	0
dense_3 (Dense)	(None, 1300)	106497300
dense_4 (Dense)	(None, 1300)	1691300
dropout_1 (Dropout)	(None, 1300)	0
dense_5 (Dense)	(None, 1221)	1588521

Total params: 110,229,217
Trainable params: 110,229,217
Non-trainable params: 0

Figure 9b - ConvLSTM Model Summary - 4 variables

We combined the coordinate based variables by combining the individual images into a single combination image. Figure 10 below is an example of a single tiled 4 image result of the RainfC, Srfexc, Rzmc, and Snowpack stitched together for input to the model. This concatenation approach allowed us to merge various image input sizes into a single image array for processing.

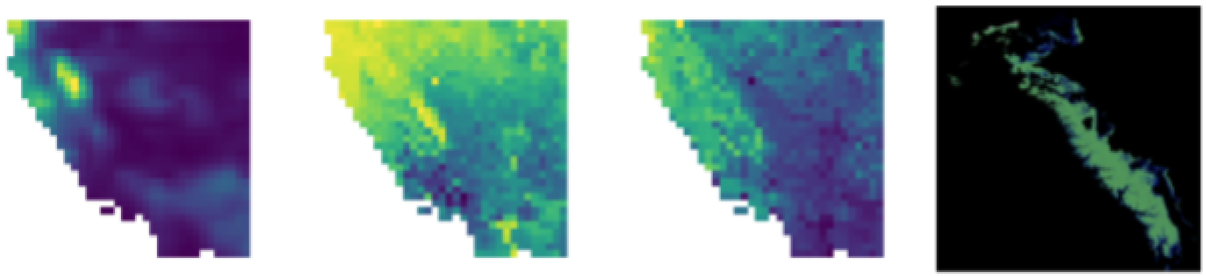


Figure 10 - Example Four variable image input for one specific month

a) Baseline Coordinate-based

We ran two and four variable baseline models using the ConvLSTM mentioned earlier. With these approaches we found that the two variable model (Snowcap, rzmc) had a higher overall R^2 accuracy score of 87.3% than the four variable (RainfC, Srfexc, Rzmc, and Snowpack) accuracy of 79.0% for the same month prediction. This conflicted with our earlier bulk run.

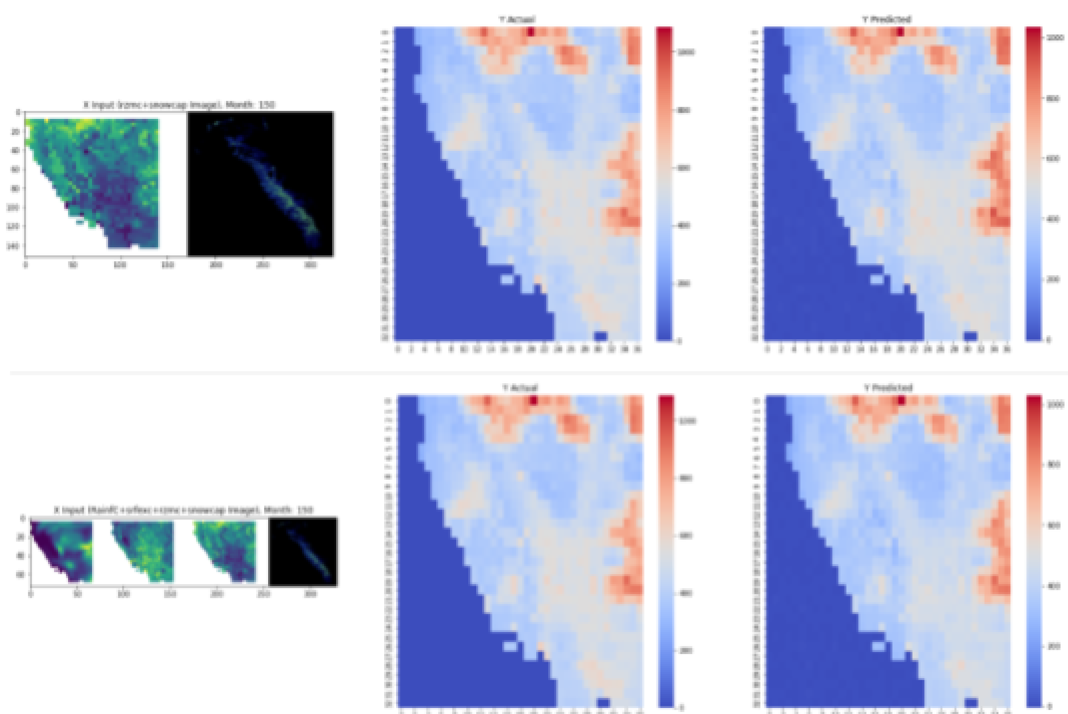


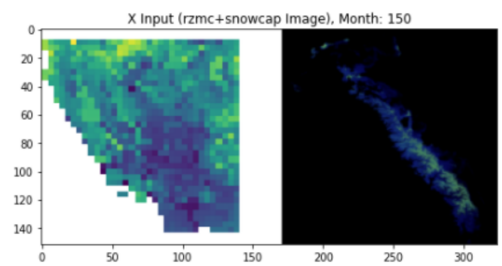
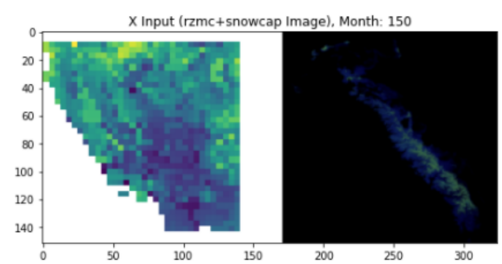
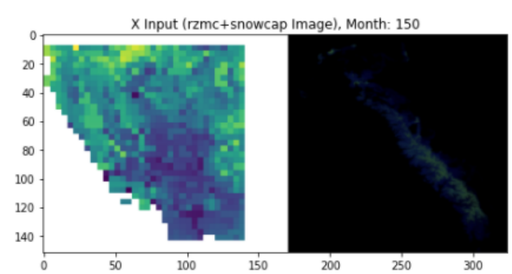
Figure 11 - Two and Four Variable Baseline Model for Water Table Depth (catdef)

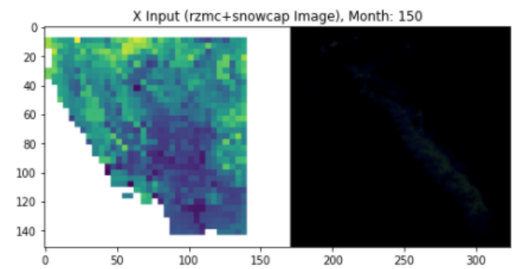
Though the four variable model was smaller, follow-on attempts to process a larger input four variable model only worsened the results. The best baseline coordinate based model was the two variable models.

b) Coordinate-based Snowpack Variation Model

In order to show the impact of the effects of climate change through the Snowpack, we ran subsequent model evaluations reducing the Snowpack numbers by 25, 50 and 75 percent of original. In order to assess the impact we compared the resulting aggregate Water Table Depth (catdef) of the outputs. Table 2 below shows the the numbers for the same specific month (150) and the percent reduction in catdef.

Table 2 - Snowpack Amount Variation Results

	Two Variable Model		
Snowpack Percent	Cumulative Catdef (mm)	Percent of Change from 100	Example Input Image(s)
100	399760.78		
75	400637.97	0.2%	
50	403564.72	1.0%	

25	404164.56	1.1%	

The increased Water Table Depth wasn't as impactful as expected. Having run this in the aggregate during our preliminary investigation we saw upwards of 4+% impact. In both cases, the lower percent impact results, relative to the size of change on the snowpack, may be due to the fact the rzmc was not altered equivalently. In practicality, the root zone moisture content would also be impacted by global warming and a reduction in snowpack. The alteration approach on other variables may not be as straightforward as altering the snowpack. For example, you would not see an equivalent reduction in temperature of the air (TAir). In fact, that variable would likely go up, but by how much? One tenth of a degree on average for every 25% in snowpack or one quarter? Each variable would need to be evaluated on its own and an assumption be made as to the adjustment.

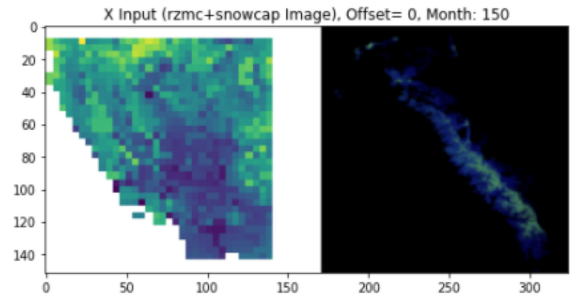
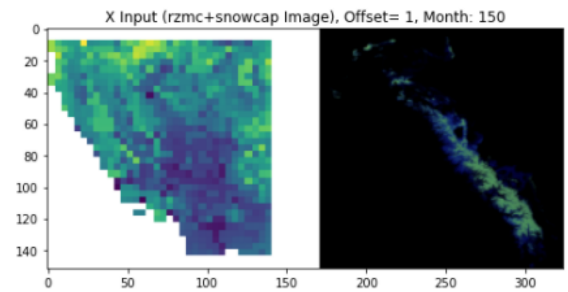
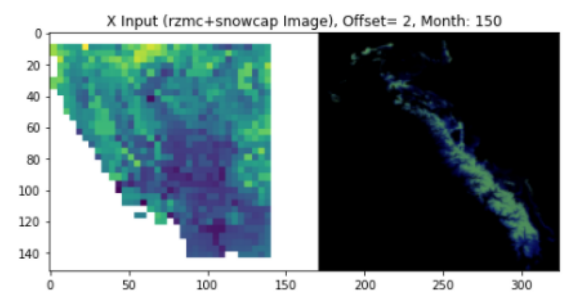
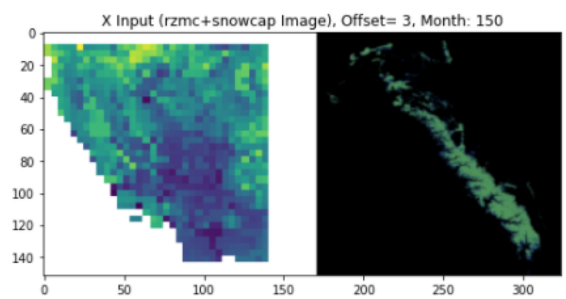
The result is that it shows an impact, just not as much as expected. Future iterations of this work can investigate an equivalent reduction/alteration in the other input variables, like rzmc.

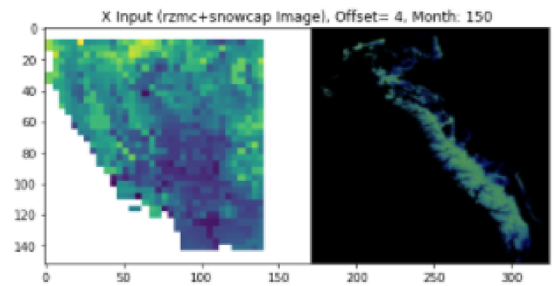
c) Snowpack Offset from Output Variables Model

One consideration that we wanted to explore was based on the logical assumption that it takes time for the Snowpack to affect the Water Table Depth, so offsetting the snowpack could result in higher accuracy. The model we used is supposed to account for that, by incorporating the sequencing in the memory. In order to test this we ran our baseline model again using a Snowpack image offset earlier by one, two and three months in order to assess the impact on the resulting prediction.

Table 3 - Snowpack Month Offset Results

	Two Variable Model	
Snowpack Offset in Months	R^2 Accuracy Score	Example Input Image(s)

<table>
<tr><td>0</td><td>87.3%</td><td></td></tr>
<tr><td>1</td><td>81.5%</td><td></td></tr>
<tr><td>2</td><td>71.7%</td><td></td></tr>
<tr><td>3</td><td>79.6%</td><td></td></tr>
</table>

4	38.9%	

The Table 3 above images above show the results for month 150, which in this case is June, 2015. As can be seen in the examples the snowpack increases as the offset gets higher. In the case of offset equal to 3, the snowpack image is from March.

4) Conclusions
   a) Final Opinions

During this project, we evaluated the use of deep learning models on predicting and illustrating the impact of the Sierra Nevada Snowpack on the discharge water in the Central Valley. Using both the Reanalysis Snowpack data and the GRACE-DA data, we worked through a number of aggregate models and coordinate-based models. Achieving an Water Table Depth R^2 score of 93% for the aggregate model and an 82.7 for the coordinate-based model, shows that the approach is valid and worth further investigation. The two variable model performed better than the four variable model on the coordinate based approach, even though the bulk assessment showed the four variable was optimal. This could be due to the image size we were working with or the limited month of data available (168 months). It also may be due to the fact that the additional input data variation in the coordinate model pushed us past the tipping point of model complexity[8]

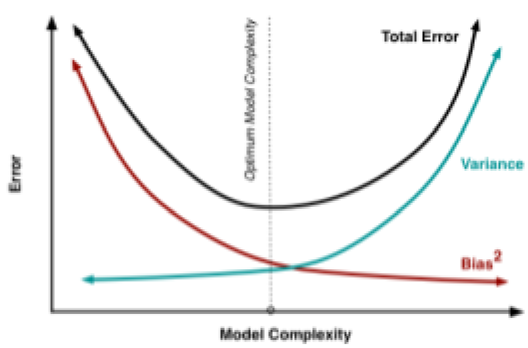


Figure 12 - Complexity Trade-off

[8] Fortmann-Roe, S, Understanding the Bias-Variance Tradeoff, http://scott.fortmann-roe.com/docs/BiasVariance.html#fnref:1

The Snowpack variations showed an impact by reducing the volumes, but not nearly as much as expected. The 1.1% aggregate Water Table Depth increase seemed far lower than the 75% reduction in snowpack. In the follow on section below we describe additional effort that could help identifying and explaining that result.

Lastly, the Snowpack Month Offset from the resulting Water Table Depths did not show an increase in accuracy. In fact it got much worse going from 82.4% down to 68% offsetting the snowpack by 3 months.

b) Follow-on

There were a number of additional areas that we had planned to explore, but were abandoned due to the time constraints of the project.

The first area to continue the exploration is with the Surface Runoff model. We only scratched the surface on that model. The aggregate showed similar promising results as the Water Table Depth, with an R^2 score of 82%. When we migrated to the coordinate based models, we only did cursory exploration.

The second area for further exploration is with complementary models. In order to truly build a complete tool for predicting the Total Discharge, we had proposed a Model 2 for forecasting the snowpack from preceding snowpacks and a Model 3 that would predict the actual snowpack from LandSat images. Combined with our models, one could use satellite images to give snowpack numbers, then use those values to predict upcoming snowpack data, that could in turn be passed to our models for predicting the Total Discharge.

A third area of further research is with the input image sizes. We only scratched the surface on image scaling in order to create our predictions. Further computing capacity would be required to process the larger image sizes.

The final area to investigate is with the input variable variation. In our modeling, we only varied the Snowpack data. In reality, a reduction in Snowpack could have a corresponding impact in root zone moisture content. Determining the reduction of other variables is not as straightforward as a percentage reduction of the snowpack. For example, the temperature of the air is a variable (Tair) but if you reduced it by 75% that would not be reflective of reality, if the snowpack is reduced by 25%, it is likely due to warming, and thus the temperature could be assumed to go up; but by what amount. Though we discussed various modification options, we will pass that on to later groups to evaluate.

c) Acknowledgements

We would like to thank Dr. Alberto Todeschini and Dr. Puya H. Vahabi, our instructors at the UC Berkeley Ischool, for their assistance and guidance with our project. We would also like to thank Dr. Paolo D’Odorico and Dr. Manuela Girotto for the expertise, guidance and access to the GRACE-DA and the Sierra Nevada Snowpack Reanalysis datasets.

5) References

Fortmann-Roe, S, Understanding the Bias-Variance Tradeoff, June 2012, http://scott.fortmann-roe.com/docs/BiasVariance.html#fnref:1

Getirana, A., Rodell, M., Kumar, S., Beaudoing, H. K., Arsenault, K., Zaitchik, B., Save, H., & Bettadpur, S. (2020). GRACE Improves Seasonal Groundwater Forecast Initialization over the United States, *Journal of Hydrometeorology*, *21*(1), 59-71. Retrieved Nov 13, 2021, from https://journals.ametsoc.org/view/journals/hydr/21/1/jhm-d-19-0096.1.xml

Jianfeng Zhang, Yan Zhu, Xiaoping Zhang, Ming Ye, Jinzhong Yang ,Developing a Long Short-Term Memory (LSTM) based model for predicting water table depth in agricultural areas,*Journal of Hydrology, Volume 561, 2018, Pages 918-929*, ISSN 0022-1694, https://doi.org/10.1016/j.jhydrol.2018.04.065

Kassambara, A, Statistical tools for high-throughput data analysis, http://www.sthda.com/english/articles/38-regression-model-validation/158-regression-model-accuracy-metrics-r-square-aic-bic-cp-and-more/

Lund, J, California Weather Blog, 8/22/21, https://californiawaterblog.com/2021/08/22/2021-drought-in-california-in-one-page/

Margulis, S. A., Cortés, G., Girotto, M., & Durand, M. (2016). A Landsat-Era Sierra Nevada Snow Reanalysis (1985–2015), *Journal of Hydrometeorology*, *17*(4), 1203-1221. Retrieved Nov 13, 2021, from https://journals.ametsoc.org/view/journals/hydr/17/4/jhm-d-15-0177_1.xml

United States Geological Survey, https://ca.water.usgs.gov/projects/central-valley/about-central-valley.html