Testing Machine Learning for Regional Climate Applications in the Pacific Northwest



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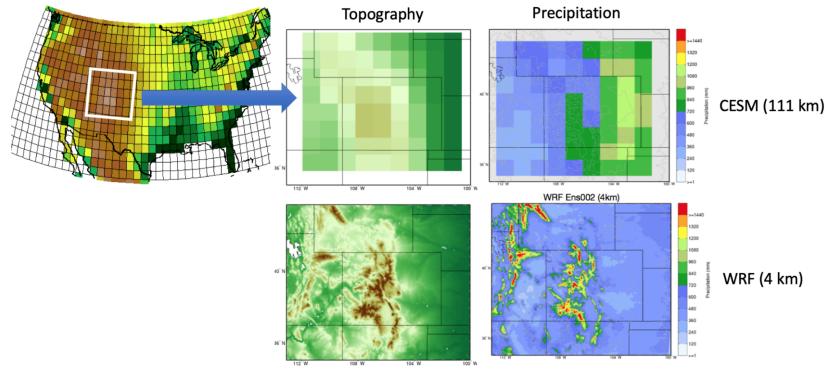




We need more detailed precipitation data than RCMs can directly provide



Climate Model Native Resolution and Application Resolution



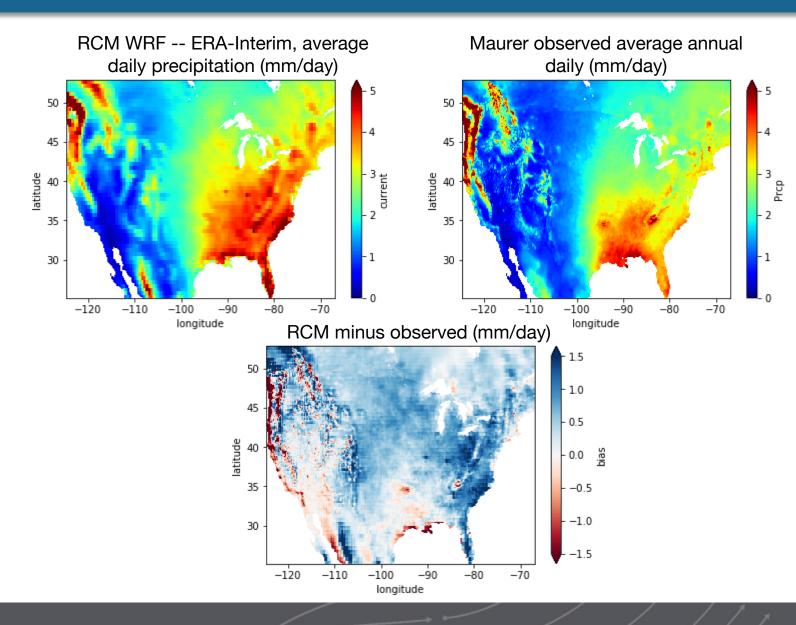
Data Details

Observations

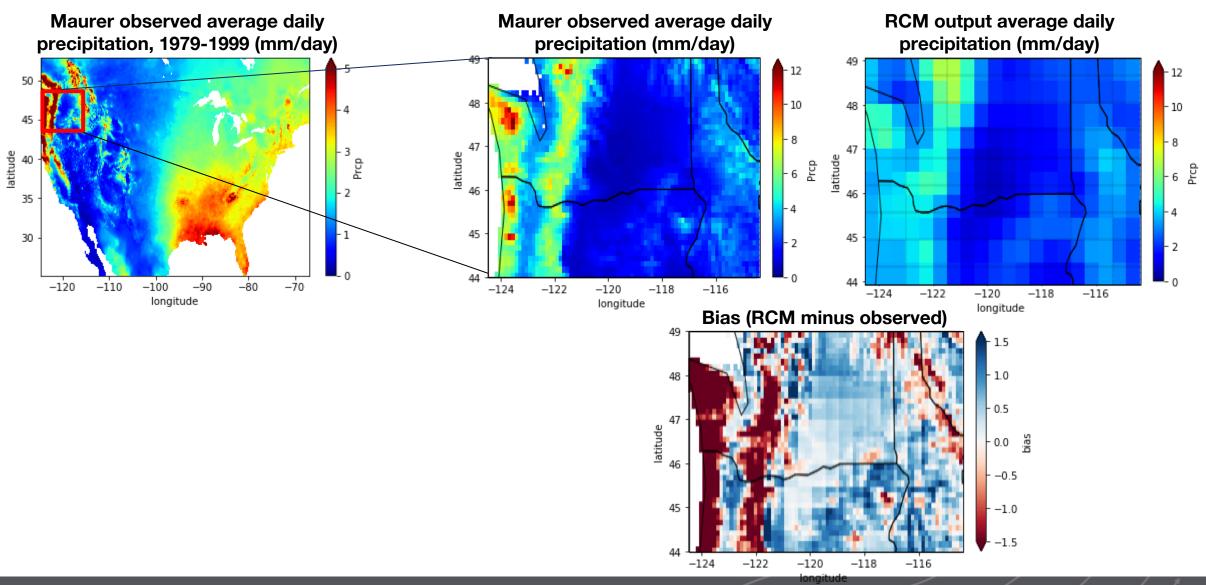
- Maurer gridded observed precipitation.
- ½ degree (~12km) US-wide data.
- Covers 1980-2010.

Regional Climate Model Output

- All simulations are part of NA-CORDEX.
- ERA-Interim driven WRF simulations at 50km. Simulations run over 1980-2010.
- MPI GCM driven WRF simulations at 50km.
- Historical period is 1976-2005.
- Future period is 2070-2099.
- RCP8.5 climate scenario from CMIP5.



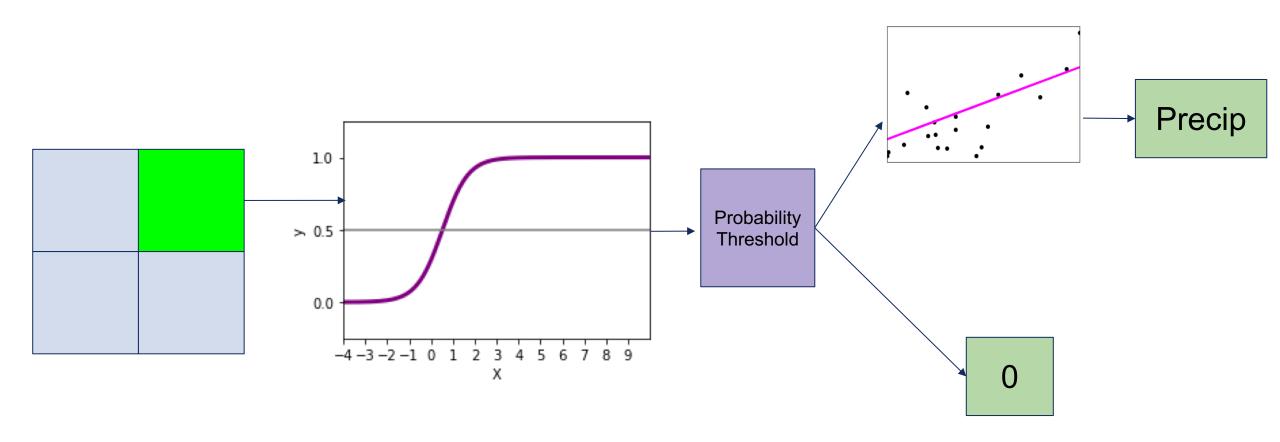
Focusing on the Pacific Northwest



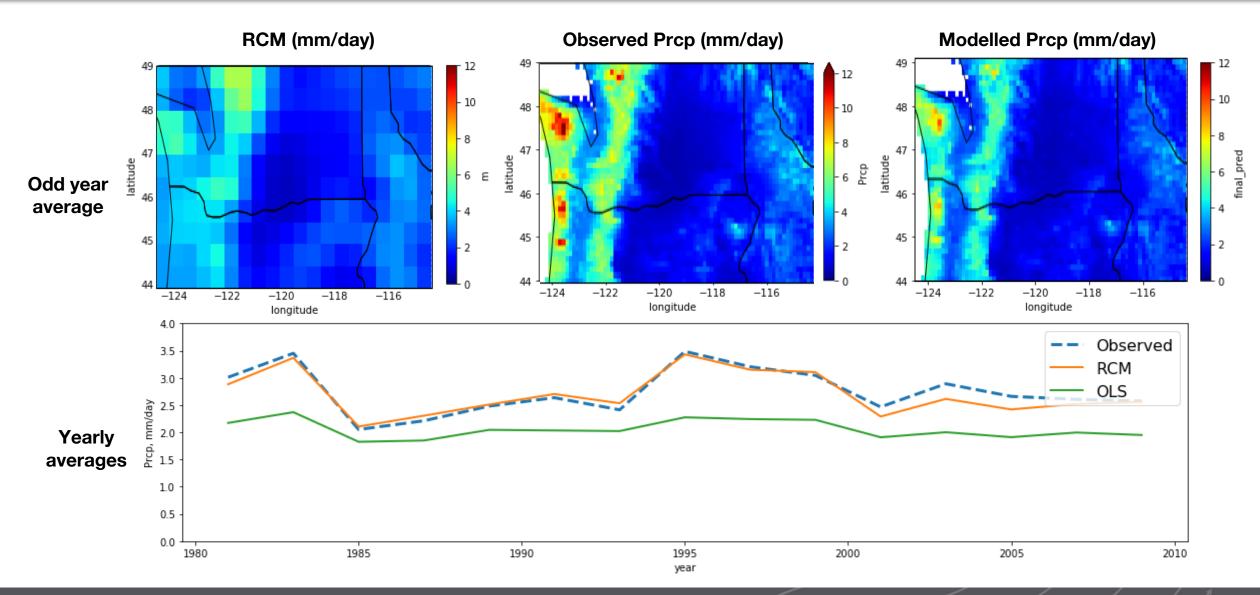
Three methods for statistical downscaling

- 1. Cellwise Linear Regression
- 2. Cellwise Random Forests
- 3. Convolutional Neural Network

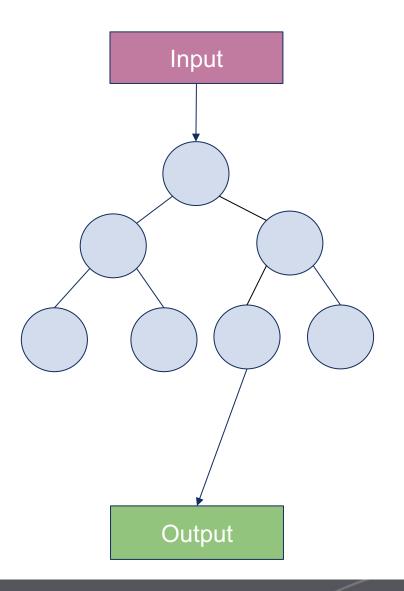
1. Cellwise Linear Regression - the details



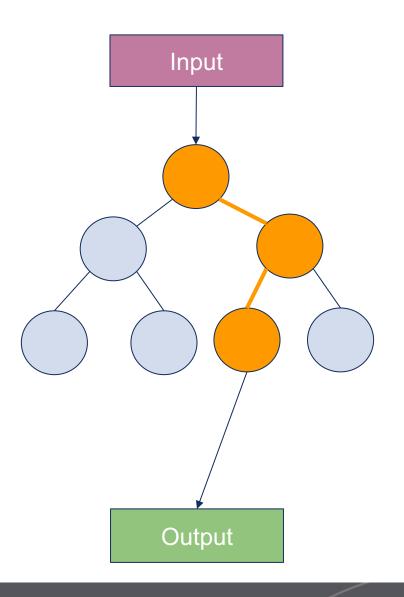
1. Cellwise Linear Regression - the results



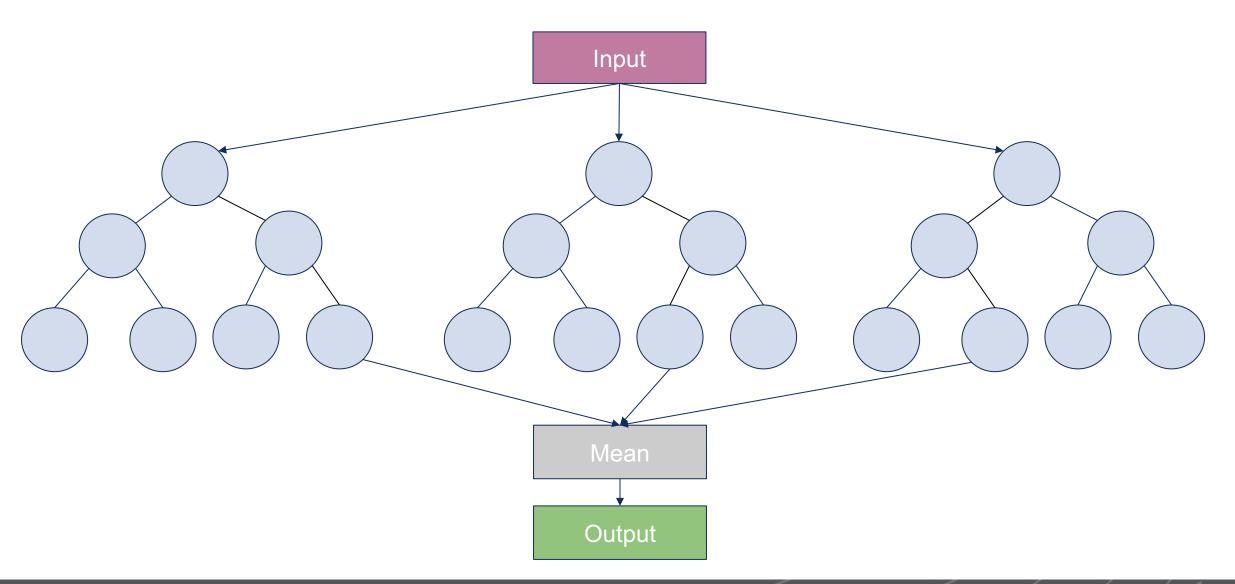
A decision tree



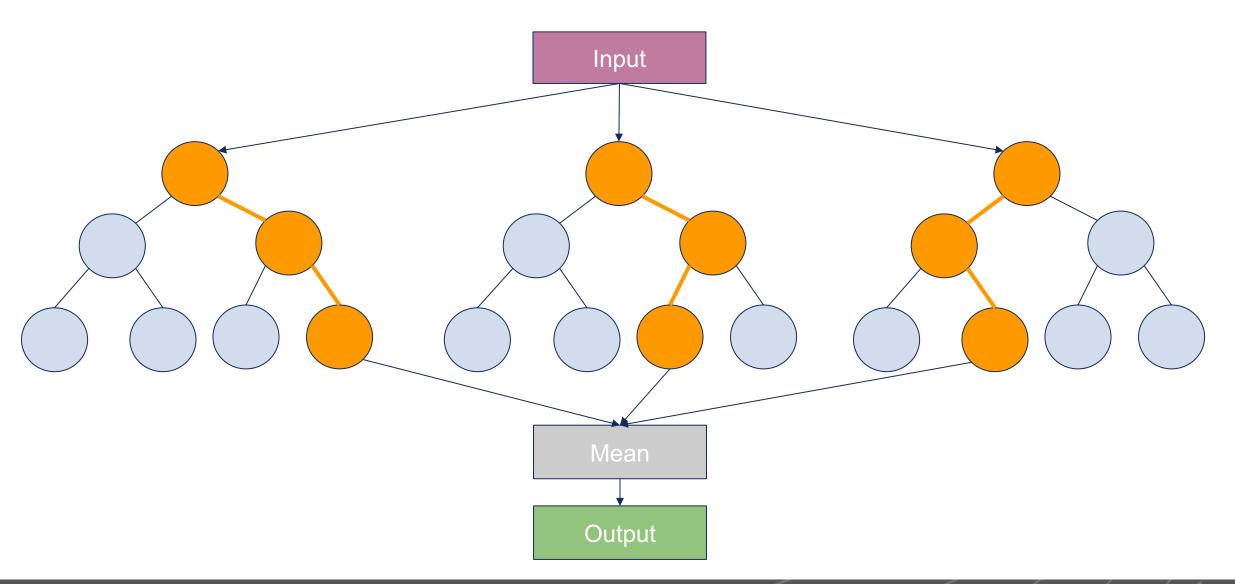
Traversing a decision tree



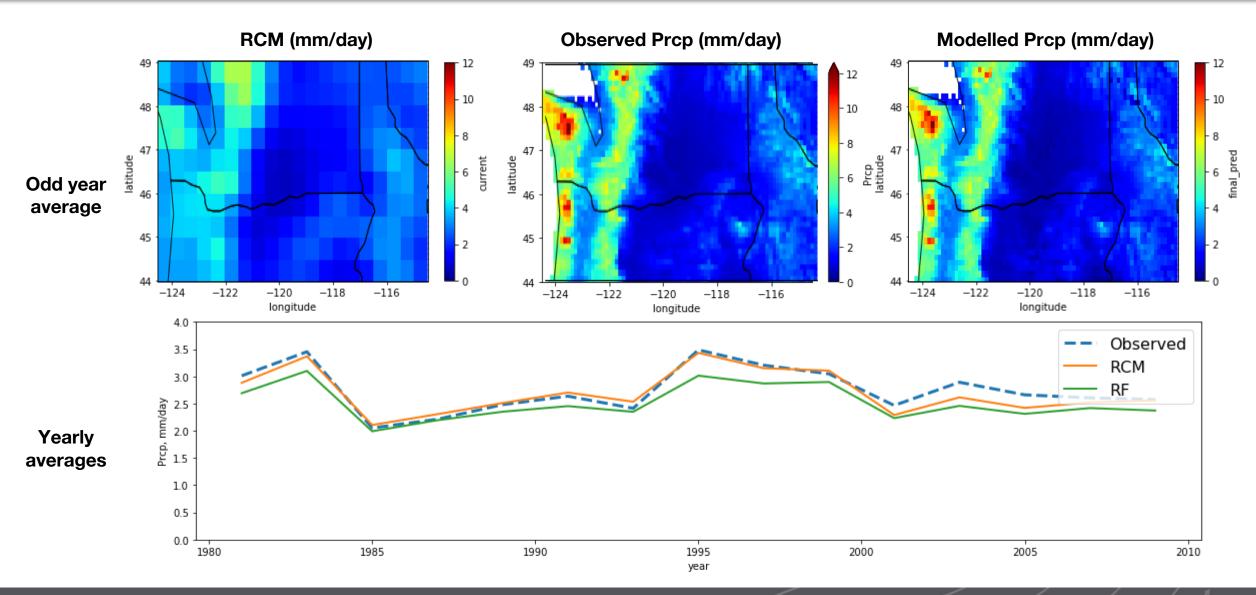
A random forest



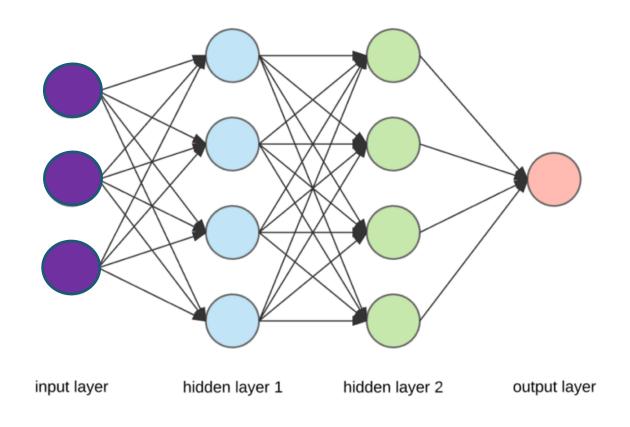
Traversing a random forest



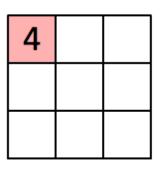
2. Cellwise Random Forest - the results



3. Convolutional Neural Network - the details



1 _{×1}	1 _{×0}	1,	0	0
O _{×0}	1,	1 _{×0}	1	0
0 _{×1}	0,0	1,	1	1
0	0	1	1	0
0	1	1	0	0



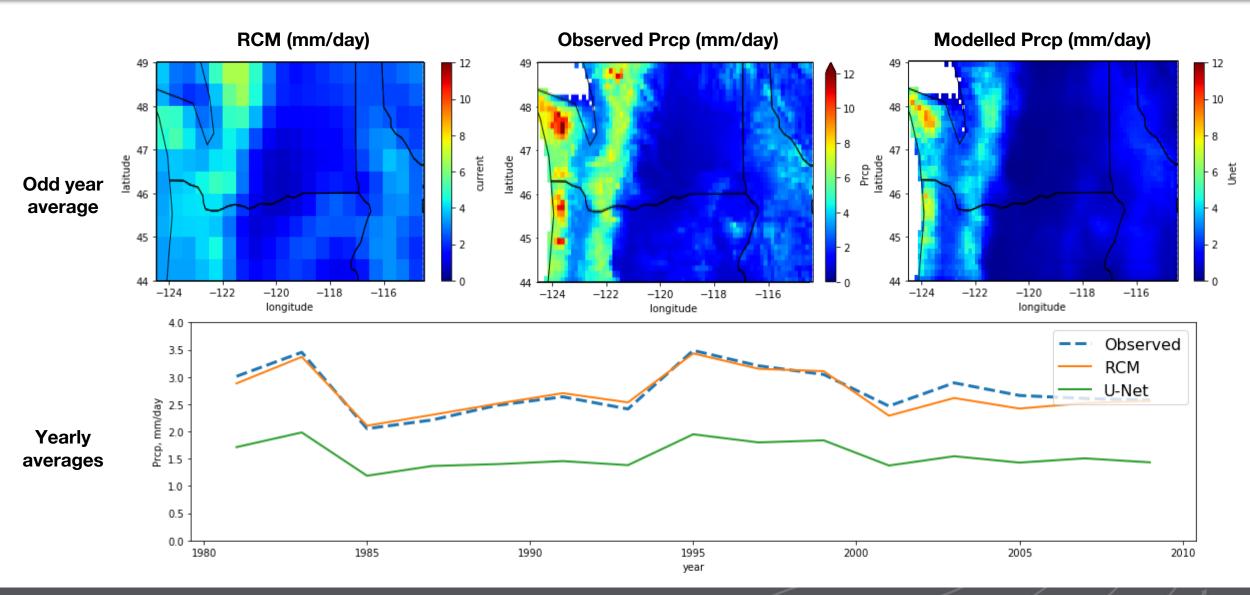
Image

Convolved Feature

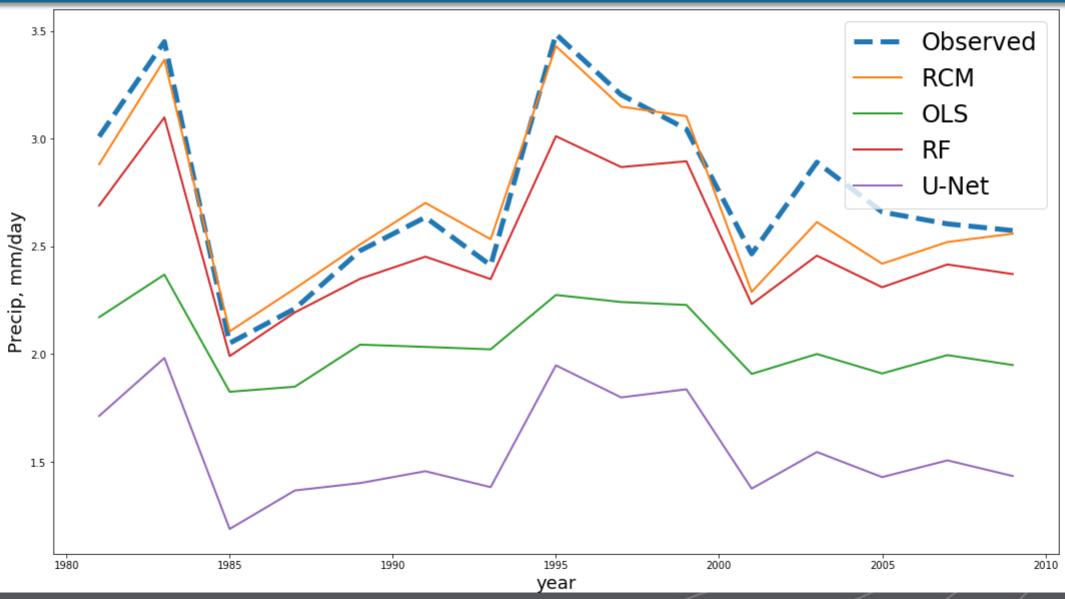
https://towardsdatascience.com/applied-deep-learning-part-1-artificial-neural-networks-d7834f67a4f6

https://hackernoon.com/visualizing-parts-of-convolutional-neural-networks-using-keras-and-cats-5cc01b214e59

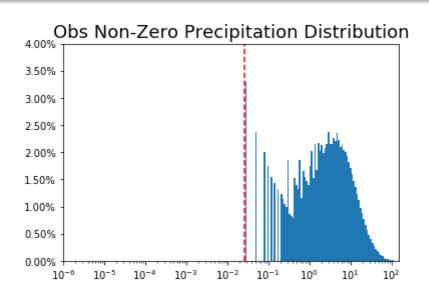
3. Convolutional Neural Network - the results

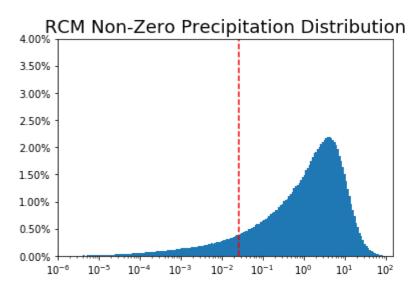


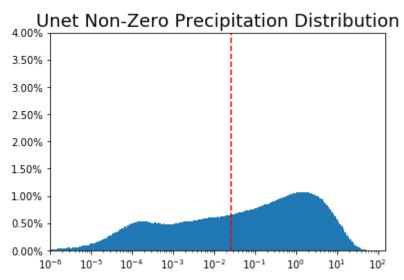
Models underpredict extreme precipitation events

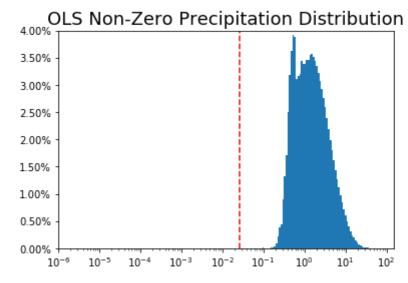


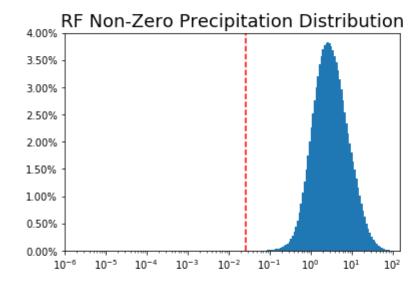
The underprediction comes from the distributions



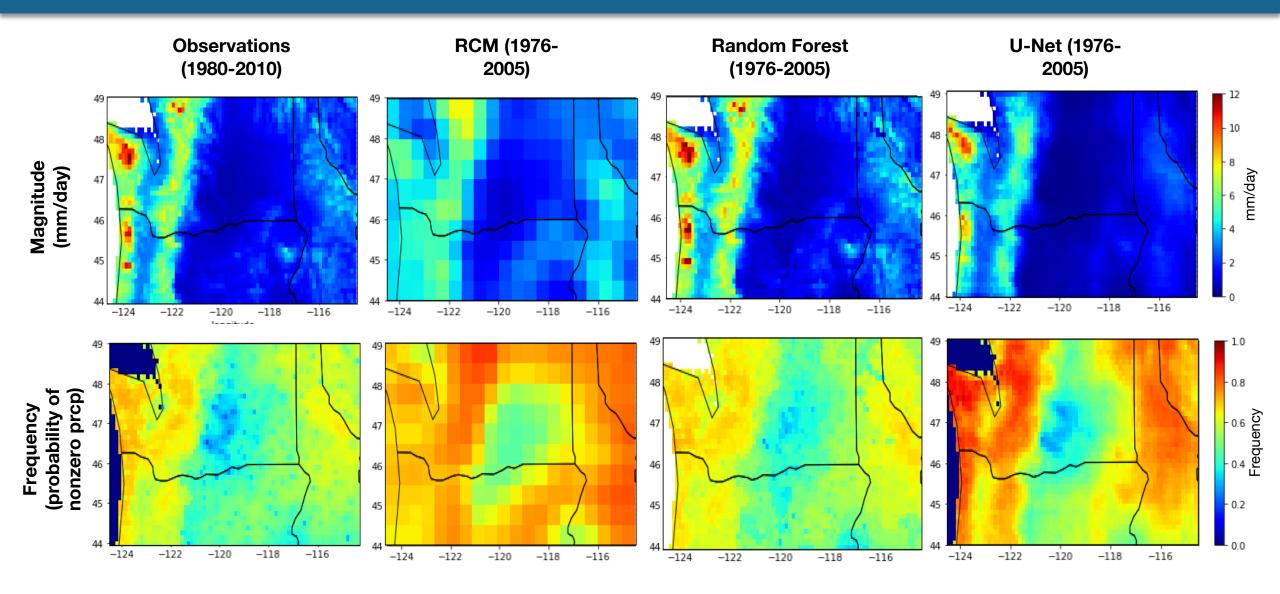






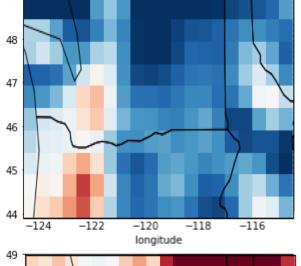


Historical Climate Evaluation

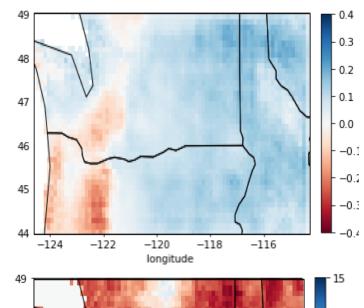


Difference Plots: More intense, less frequent precipitation

Future (2070-2099) precip intensity minus historical (1976-2005), mm/day

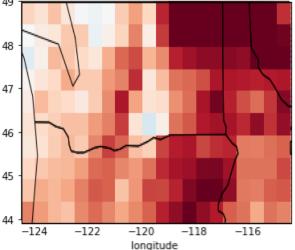


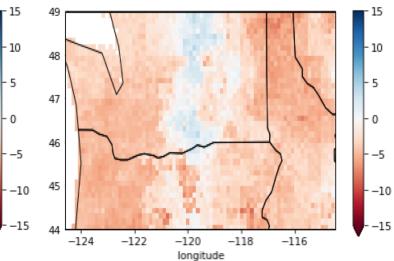
RCM

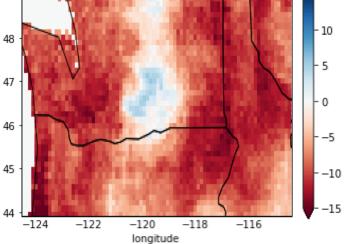


U-net

Future (2070-2099) frequency minus historical (1976-2005), change in days with non-zero precip







- 0.3

- 0.2

0.1

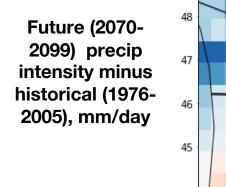
0.0

-0.1

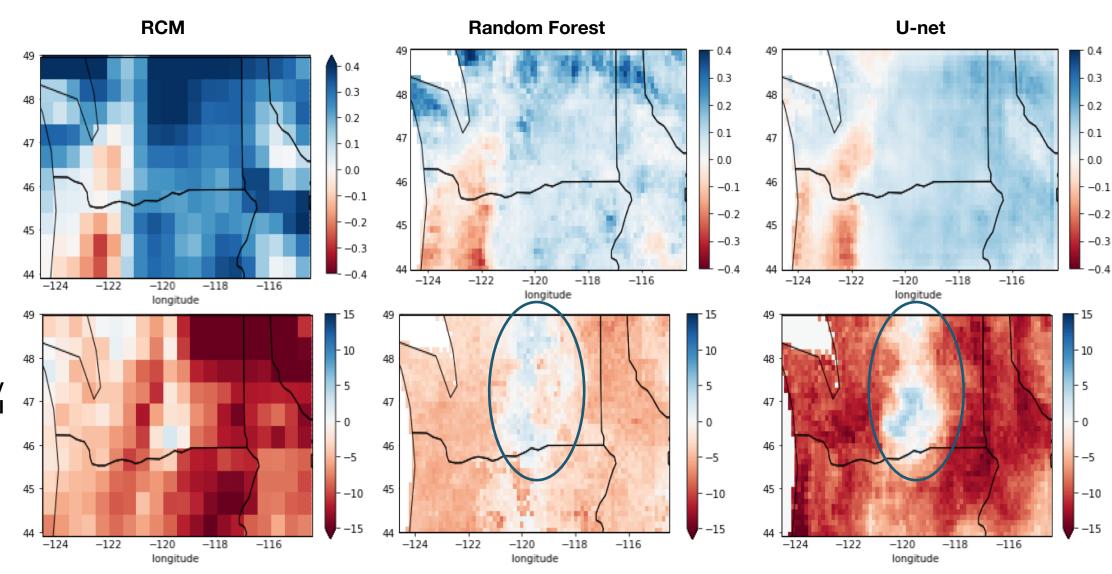
-0.2

-0.3

Difference Plots: More intense, less frequent precipitation



Future (2070-2099) frequency minus historical (1976-2005), change in days with non-zero precip



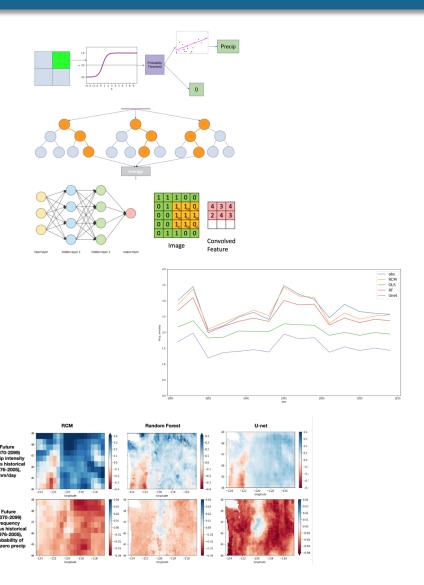
Conclusions and Future Work

Conclusions

- We implemented three methods for statistical downscaling
- Random forests best capture magnitude and variability of precipitation
- The U-Net and linear models underpredict variation and, as a result, magnitude
- Downscaling future WRF simulations suggests an increase in average and a decrease in frequency of precipitation

Future Works

- Adding stochasticity to zero/non-zero precipitation binary
- Further optimizing the U-Net



Acknowledgements

NCAR CISL





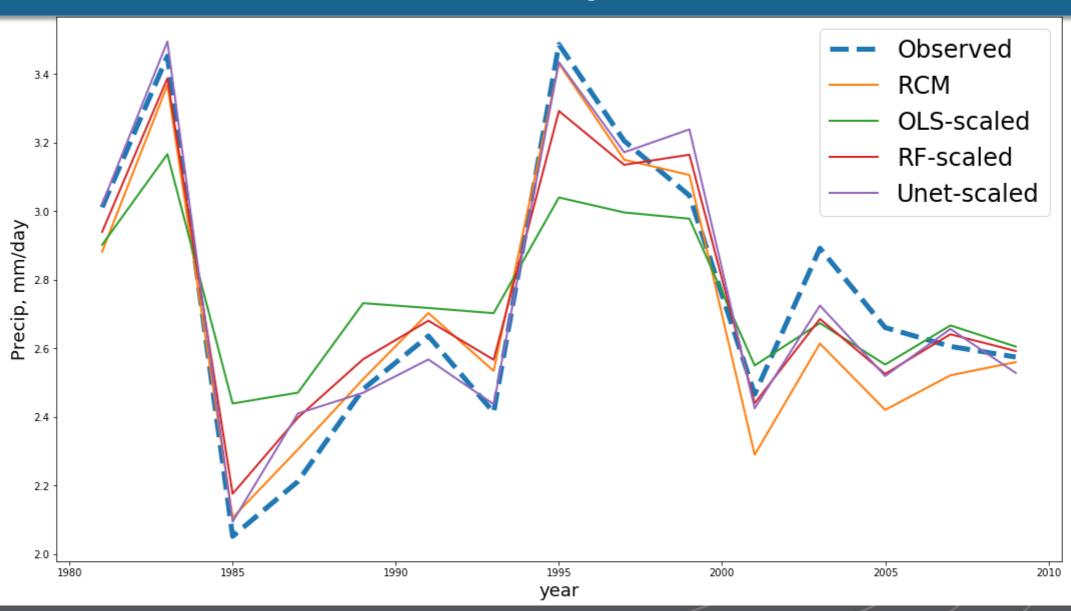
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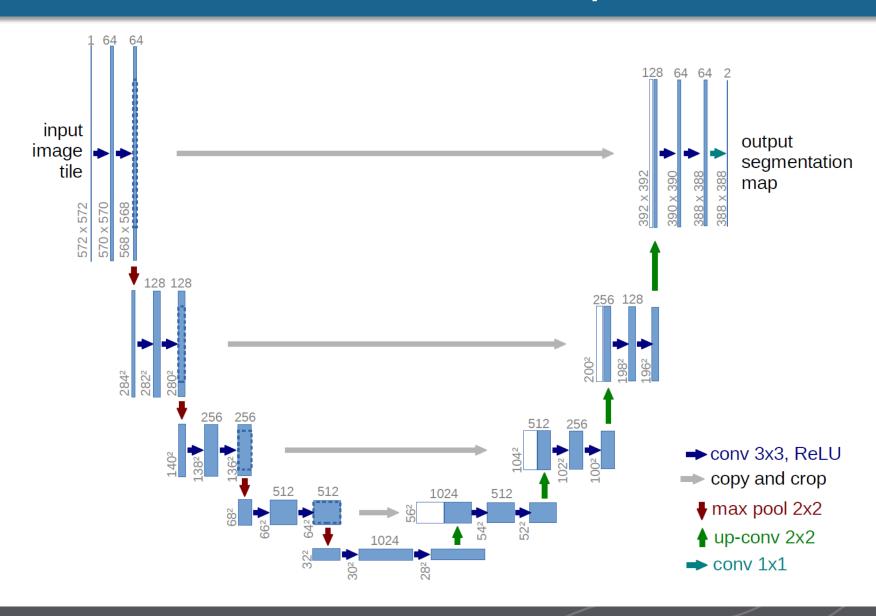




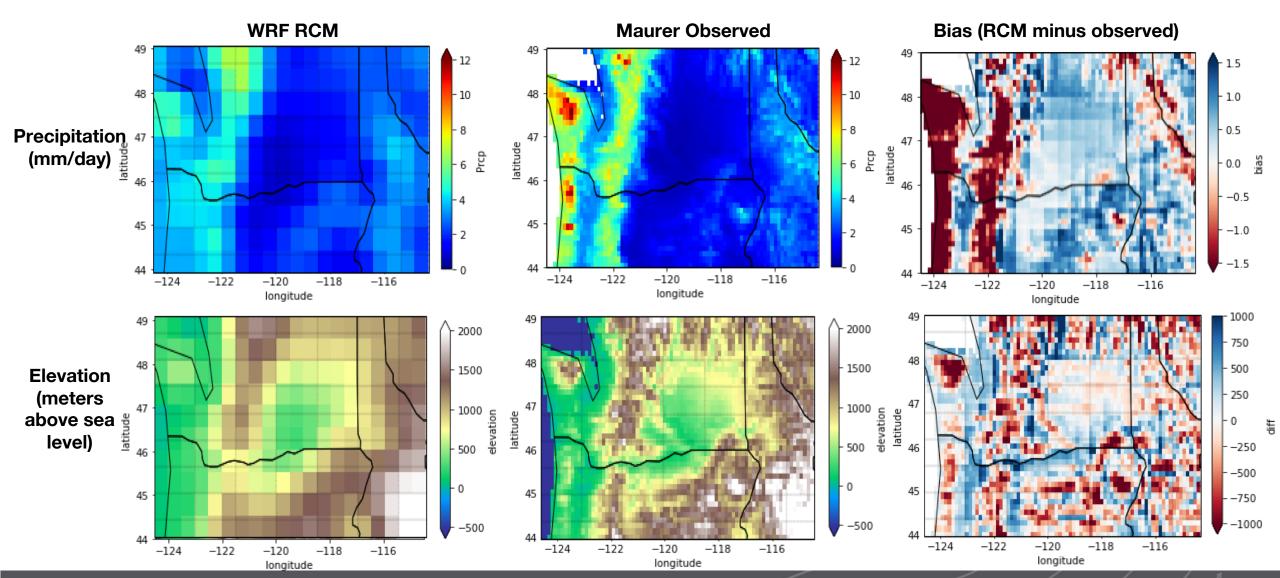
Extra Slides: Scaling the Models



Extra slides: a U-Net example



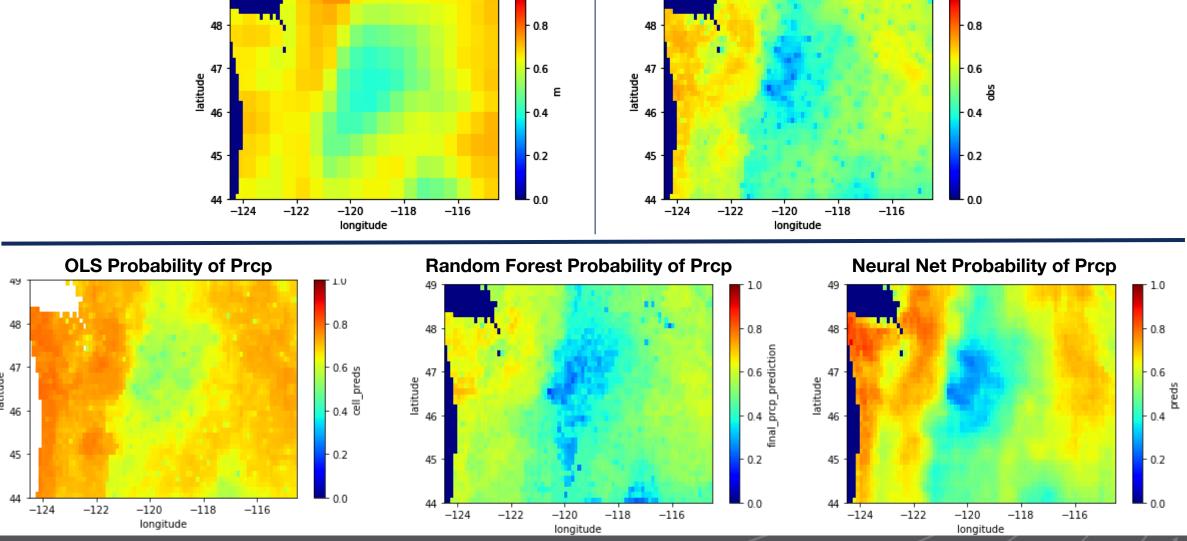
Extra Slides: Topography



Extra Slides: Frequency of Precipitation

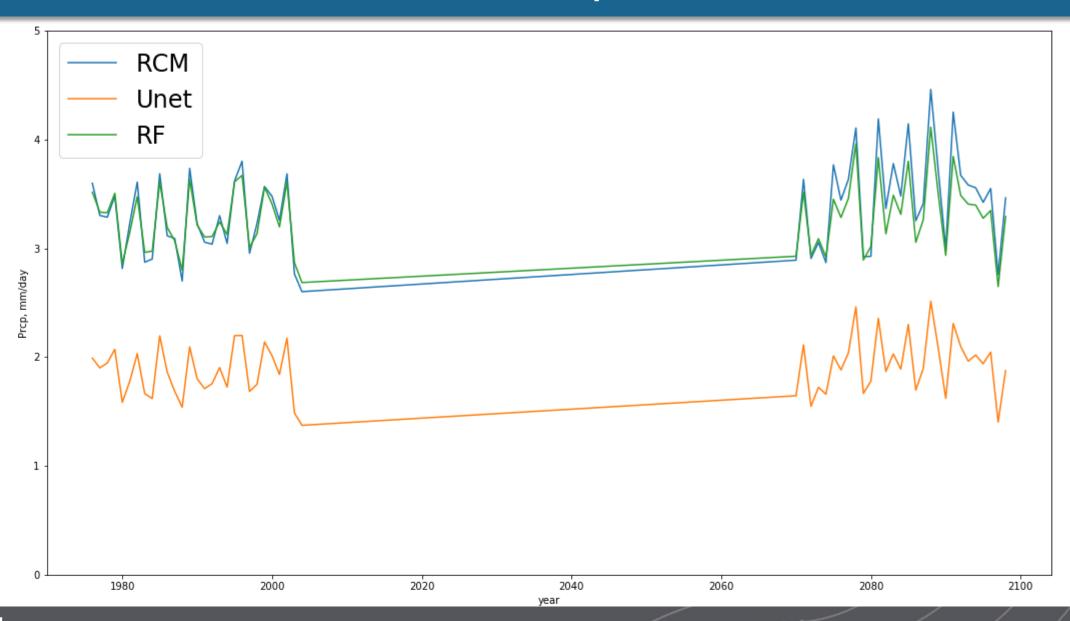
1.0

Observed Probability of Prcp



RCM Probability of Prcp

Extra Slides: Future Precipitation Trends



Extra Slides: Distribution Stats

Model	Mean	50th percentile	95th percentile	Variance
Observations	2.75	0.12	10.42	39.61
RCM	2.70	0.74	10.29	32.24
Linear Regression	2.06	1.51	9.18	7.59
Random Forest	2.51	0.26	11.33	24.81
U-Net	1.56	0.09	8.40	13.80