Climate change-resilient snowpack estimation with machine learning

17 October, 2024 ELLIIT Focus Period, Linköping University

Marianne Cowherd + many others Including Utkarsh Mital, Stefan Rahimi, Andrew Schwartz, Lucas

Including Utkarsh Mital, Stefan Rahimi, Andrew Schwartz, Lucas Vargas Zeppettello, Ruby Leung, Manuela Girotto, and Dan Feldman





The domain science perspective:



Immerzeel et al., 2019



We only manage snow as well as we measure it.



MRIGHT

- NEWS

Unusually Early Cold Storm Dusts Sierra Nevada Peaks With Rare August Snow

By The Associated Press Aug 24 Save Article





We only manage snow as well as we measure it.

How is snow measurement impacted by climate change?





Snow pillow network in the western US (excluding Alaska)





50 acific Northwe Snow pillow network in the western US 48 Missouri (excluding Alaska) 46 300 44 Latitude [°] 65 75 250 -Jpper Colorado All other 200 -Count states 38 -150 -Alaska Lower Colorado 36 100 -34 -32 -125.0 -122.5 -120.0 -117.5 -115.0 -112.5 -110.0 -107.5 -105.0 50 Longitude [°] 0 1940 1960 1980 2000 2020 Year of 1st measurement DEPARTMENT of ENVIRONMENTAL SCIENCE, POLICY, AND MANAGEMENT 7 ESPM



In what decade will half of measurements be below 10% of the historical mean peak snow water equivalent?

Cowherd et al. "Climate change-resilient snowpack estimation in the Western United States." *Communications Earth & Environment* 5.1 (2024): 337.











What we do in the catchments:





 $Q = \sum_{i=1}^{n} a_i SWE_i + e \qquad \begin{array}{c} Current \\ management \\ practices \end{array}$

"These predictions depend on the presence of measurable snowpack, as well as a consistent relationship between observed peak snow conditions and streamflow." -Livneh and Badger 2020





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Article | Published: 20 April 2020

Drought less predictable under declining future snowpack

Ben Livneh 🖂 & Andrew M. Badger





POLICYFORUM

CLIMATE CHANGE

Stationarity Is Dead: Whither Water Management?

P. C. D. Milly,^{1*} Julio Betancourt,² Malin Falkenmark,³ Robert M. Hirsch,⁴ Zbignie w W. Kundzewicz,⁵ Dennis P. Lettenmaier,⁶ Ronald J. Stouffer⁷

2008

Climate change undermines a basic assumption that historically has facilitated management of water supplies, demands, and risks.



POLICYFORUM

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2008





How similar are spatial patterns of snowpack to the previous 30 years?





When snowpack patterns change, can we use those measurements to make accurate predictions about the rest of the basin?







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How is snow measurement impacted by climate change? A: Climate change makes it harder to use snow observations in traditional frameworks



We only manage snow as well as we measure it.

How is snow measurement impacted by climate change? A: Climate change makes it harder to use snow observations in traditional frameworks

... because those frameworks do not reflect the underlying processes that control snow distribution



A U-Net can be a set of convolutions that represents why snow is distributed across a region





Try again, this time with the U-Net:





A U-Net can be a set of convolutions that represents why snow is distributed across a region



ESPM

A U-Net can be a set of convolutions that represents why snow is distributed across a region



ESPM







U-Net Pros:

- 1. Works well with only snow pillow input
- 2. <u>Multi-scale model for a multi-scale process</u>
- 3. Robust to climate change
- 4. Robust to loss of observation
- 5. As high-resolution as your elevation map
- 6. Technically data-driven, theoretically physicsinformed

U-Net Cons:

- 1. Computationally expensive*
- 2. Extra work to make it explainable
- 3. Not inherently physical



Interpreting models: Connecting regional processes to local observations



In real life: Regional snow amounts are distributed locally by elevation, latitude, topographic position, vegetation, albedo variations, local clouds, subsequent rain, etc.



Interpreting models: Connecting regional processes to local observations



In the training data: *Numerically connecting 1-degree scale atmospheric states to sub-10-km-scale snowpack.*

- Some direct representation of processes
- Some parameterization
- Some missing



Interpreting models: Connecting regional processes to local observations



In the neural network: We try to learn a set of convolutions that represent snow processes.





Machine learning for climate-**resilient*** measurement interpretation



Rahimi, Stefan, et al. "An overview of the western United States dynamically downscaled dataset (WUS-D3)." *Geoscientific Model Development* 17.6 (2024): 2265-2286.



Climate change-driven nonstationarity introduces unique challenges in interpreting measurements, especially for management



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Snowpack is a sentinel for climate-hydrology feedbacks



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Snowpack is a sentinel for climate-hydrology feedbacks

Machine learning techniques – when appropriately matched to the environmental system – can make measurements *more* useful. Sometimes it is <u>mandatory</u>.



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Machine learning techniques – when appropriately matched to the environmental system – can make measurements *more* useful. Sometimes it is <u>mandatory</u>.

Machine learning is a useful tool for bridging observations and simulations



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Thank you!







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Photo: Jeremy Snyder/LBL EESA

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