

Coastal carbon sink dynamics under a low- or no-snow future

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Improving model projections of coastal water relations under a low- or no-snow future Historical

Motivation:

- Warming and compound extremes
- In tandem, higher ecosystem water use and biomass
- Resulting implications for fire and streamflow remain unknown

Figure 1 | Snowpack decline, elevated CO2 and increasing extremes such as wildfire and drought impacts on regional hydrology

Our understanding of photosynthesis and water use for coastal regions is very limited …

Scaling through ML applied to flux tower obs

Max Gaber

Evaluating Automated Machine Learning for the Upscaling of Gross Primary Production

Gaber M, Kang Y, Schurgers G, Keenan TF (2024) Using automated machine learning for the upscaling of gross primary productivity. Biogeosciences, 21, 2447–2472

Scaling through ML applied to flux tower obs Maoya Bassiouni

Machine learning framework within a big-leaf model to test hypotheses about stomatal sensitivity to environmental drivers

Scaling through ML applied to flux tower obs | **The Scaling through ML applied to flux tower obs**

- Dynamic long-term photosynthetic uptake
- Allows for tracking the impact of compound extremes and wildfire
- Directly accounts for the effect of CO2 on photosynthesis
- And changes in regional hydrology / snowpack

But groundwater plays an important role

- Access to groundwater greatly modifies ecosystem sensitivity to compound extremes
- Using two decades of observations, we show far lower impact of extremes when the water table is root accessible

WTD percentile (m)

Next steps …

- Using the machine learning models for inference of multi-factor extreme impacts
- Scale the impact of groundwater access on ecosystem responses
- Use ELM-MOSART to relate ecosystem water use to changes in streamflow

Figure 2 | Illustration of the methods for neural network (NN) training. Potential' water flux (WFpot) is predicted using NN models, trained on the empirical relationship between observed WF (WFobs) and its predictors, temperature (T), vapor pressure deficit (VPD) and photosynthetically active radiation (PAR), during days in which soil moisture is relatively high ('moist days'). The threshold between moist and dry days is optimized with respect to NN model performance. 'Actual' WF (WFact) is derived from NNs using all data and with soil moisture as an additional predictor. WFVPD is derived from NNs, trained at all data, but without soil moisture as a predictor. The target water flux can be evapotranspiration, or ET partitioned estimates of transpiration-evaporation.

Thank You

