Leveraging experimental catchment data for model verification- Andes

James McPhee – Universidad de Chile INARCH Meeting October 15, 2024





Motivation: the need to provide answers to specific questions



Seasonal streamflow forecasting (Araya et al., 2023)



Glacier influence on streamflow (Ayala et al., 2020)



Reliable hydrological predictions in high-mountain areas remain an elusive objective

- Little to no observational meteorological networks
- Mountain precipitation unknown
- Limited remote-sensing capabilities
 - complex topography
 - cloudiness
 - high SWE accumulation
- Modeling parameterizations not yet fully tested in diverse geographic settings
- Feedback cycles: understanding and modeling
 - eg. glacier albedo

Gel

eg. marginal snowpacks



What can we learn from alpine experimental catchments and research stations?







CWARHM Approach (Knoben et al. 2022)

- Workflow preparation: domain discretization in 1) TIN; 2) Grid; 3) HRU
- 2. Model-agnostic preprocessing
 - a. NWP and reanalysis met forcings (ECMWF, ERA5-Land)
 - b. Scaled station-based local gridded met. reference product (Álvarez-Garretón et al., 2018; Boisier, 2023) -> daily precipitation, max/min air temperature
 - c. Downscaling of a. based on b.
- 3. Remapping of preprocessed forcings to model elements
- 4. Model-specific preprocessing
- 5. Visualization and analysis



SP-1. Regional Snow Modeling with CHM

Min theoretical area (m²)	Max RMSE (m)	Number of triangles	Area range (m²)	Median area (m²)	Mean area (m²)	Mean resolution (m)
2 500	15	215 000	400 – 1 780 000	18 000	27 600	166



Local wind speed observations

Wind speed: monthly correction factor applied to NWP output (ECMWF)



2-3 fold increase in w.s. during winter months.





High-resolution snow depth



100 km2 Few acquisitions per season+ m-scale





1 km2 Few acquisitions per season cm-scale

33.306°S

33 308%

33.312

33.314°S 33.316°S



LIDAR CHM1 CHM2 33.304°S - d 33.310°S TO 260°W 10255^W Snow depth (m) 0.2 0.4 0.6 0.8 0.0



Continuous snow depth



SP-3. Glaciohydrological impacts with CRHM



SP-3. Glaciohydrological impacts with CRHM



SP-3. Tinguiririca basin evaluation



Variable	RMSE	R2	KGE	r pearson	α	β
SWE (m.w.eq)	0.10	0.90	0.85	0.96	0.91	1.11
FSCA (%)	9.86	0.85	0.89	0.95	1.06	1.08



SP-3. Olivares basin evaluation (parameters from Tinguiririca)



Variable	RMSE	R2	KGE	r pearson	α	β
SWE (m.w.eq)	0.08	0.80	0.85	0.96	1.15	1.23
FSCA (%)	19	0.70	0.70	0.87	1.25	1.09





Dominant land cover classes:

-70.5

Setup: 5 x 5 km grid cells, GRUs defined by land cover and aspect, MMESH enabled.

SP-2. Drought impacts with MESH



From total precipitation to solid precipitation and then snow accumulation, the deficit amplifies for the megadrought but softens for La Niña years (in %).

This modulation is possibly related to the seasonal temperature anomalies (LN and MD capture well-defined meteorological signatures).

Average anomalies						
Variable	La Niña	Megadrought				
Precipitation (%)	-19.3	-26				
Storms temperature (°C)	-0.3	0.2				
Temperature JJA (°C)	-0.3	0.2				
Temperature OND (°C)	0.2	0				
Temperature JFM (°C)	-0.3	0.5				

SP-2. Drought impacts with MESH

С

b

а

Glacier GRU variables:

Megadrought	Long-term average	Annual contributi Q _{glacier} to	ion: Q (%)	Summer contribution: Q _{glacier} to Q (%)	
R	Aconcagu a	3.6 7.8			
M	Mapocho	2.8		5.9	
F F	Маіро	6		16	
my 3	Cachapoal	7.8 23.2			
3 5	Tinguiririca	5.8		20.3	
Overall: -3.3 %	Average anomaly	Annual Q _{glacier} , compared to long-term average (%)		Summer Q _{glacier} , compared to long-term average (%)	
0-30 0 30 60		LN	MD	LN	MD
_{al} /P _{annual} : 78.7 % puld be	Aconcagu a	-39	-80	-66	-84
	Mapocho	-36	-77	-64	-83
ng-term	Maipo	-22	-49	-37	-53
oducing	Cachapoal	-22	-34	-46	-43
	Tinguiririca	-22	-32	-50	-45



These three variables are already scaled by annual precipitation and could be interpreted as efficiencies.

The MD depicts less efficiency in producing snowmelt (compared to the long-term average) and producing runoff (compared to LN), and more efficiency in producing evaporation.

Summary and perspectives

- Physically based modeling tools offer the opportunity to assimilate data from diverse sources
- Experimental catchments are key to test hydrological hypotheses and identify avenues for improvement in hydrological predictions
- Combination of defensible models + assimilation of remote/in-situ data emerging as desirable strategy for timely hydrological predictions for social preparedness.





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