

snowyhydro



SHORT-TERM STREAMFLOW FORECASTING IN THE SNOWY MOUNTAINS

An experimental streamflow forecasting
system based on artificial neural networks

Thomas Chubb, Andrew Peace, and James Pirozzi
HEPEX 2018 workshop, February 8th, 2018

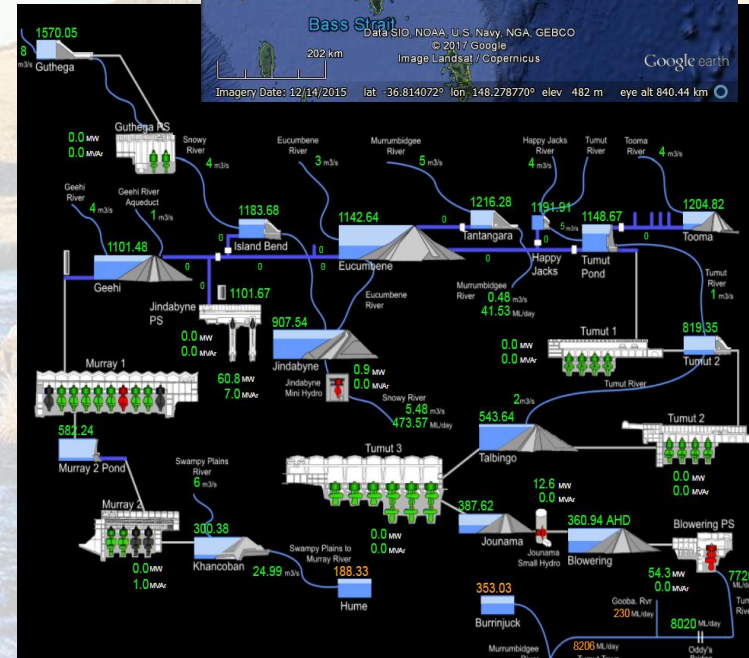
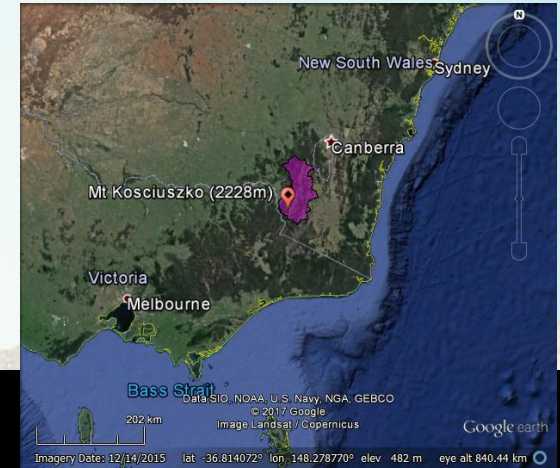


ANNIE:
A new inflow
forecasting
system



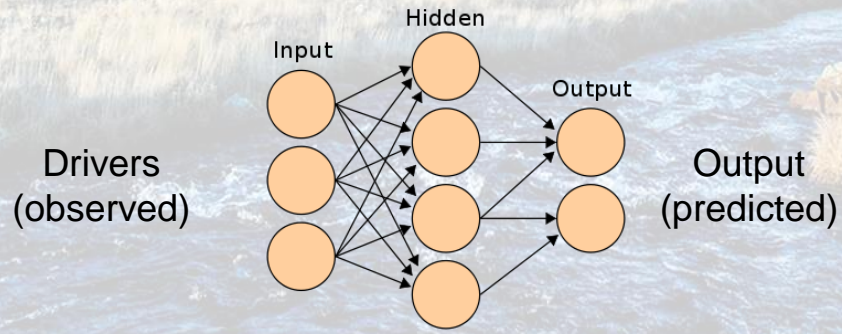
Background & motivation

- Inflow forecasts are essential in planning hydroelectric operations
 - Need water above plant to generate
 - Need airspace below plant to manage tailwater
 - Subject to constraints in Water Licence
- Legacy/operational inflow forecasts are prepared manually
 - Statistical: snowpack, daily rainfall, Tmax, etc...
 - Requires 2 staff, takes 2-3 hours
 - No information about timing or rate of peak flows
 - Unable to respond to changes in conditions



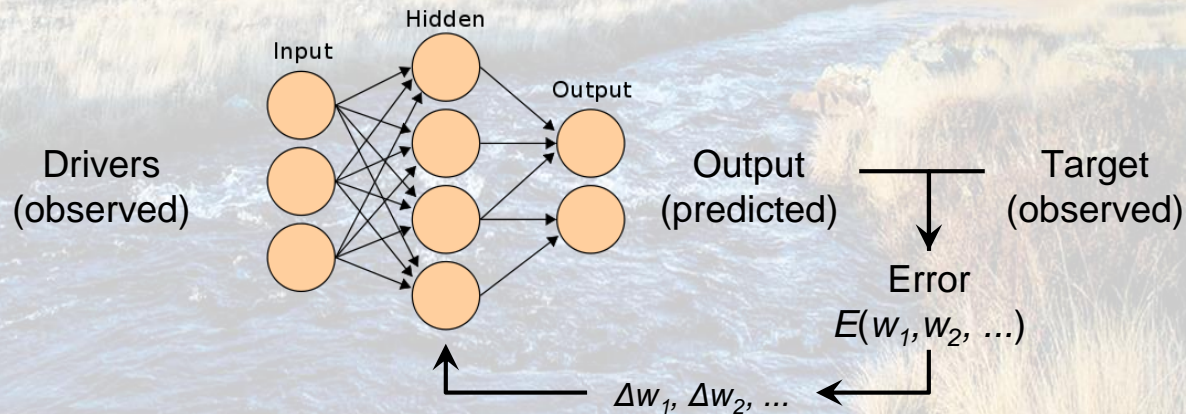
Why artificial neural networks (and what are they anyway)?

- ANNs are mathematical devices inspired by biological nervous systems.

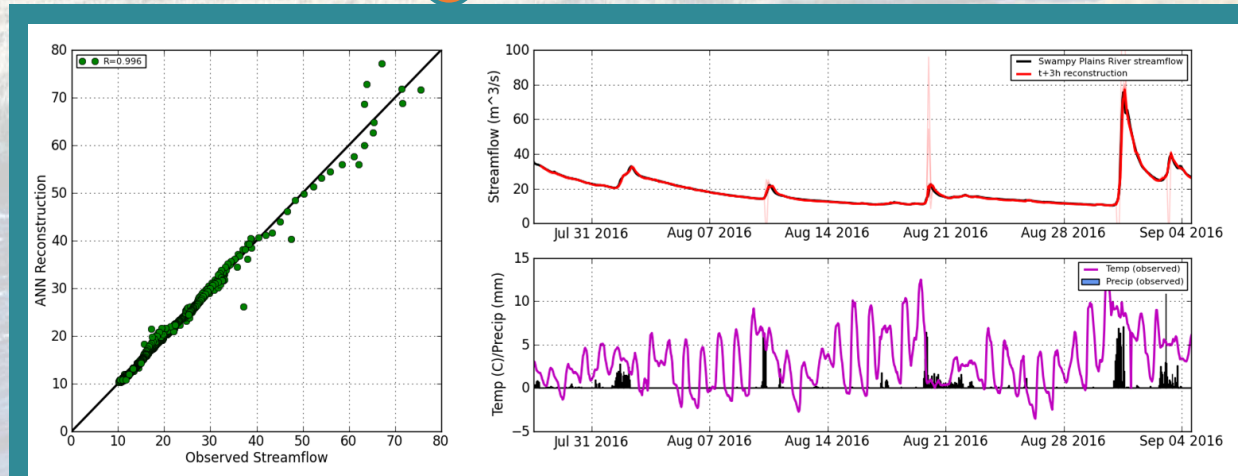
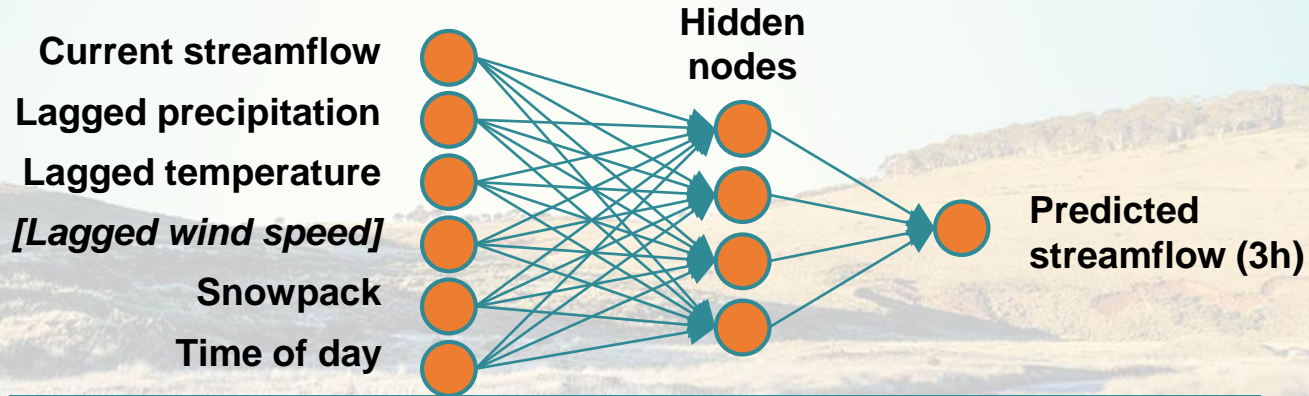


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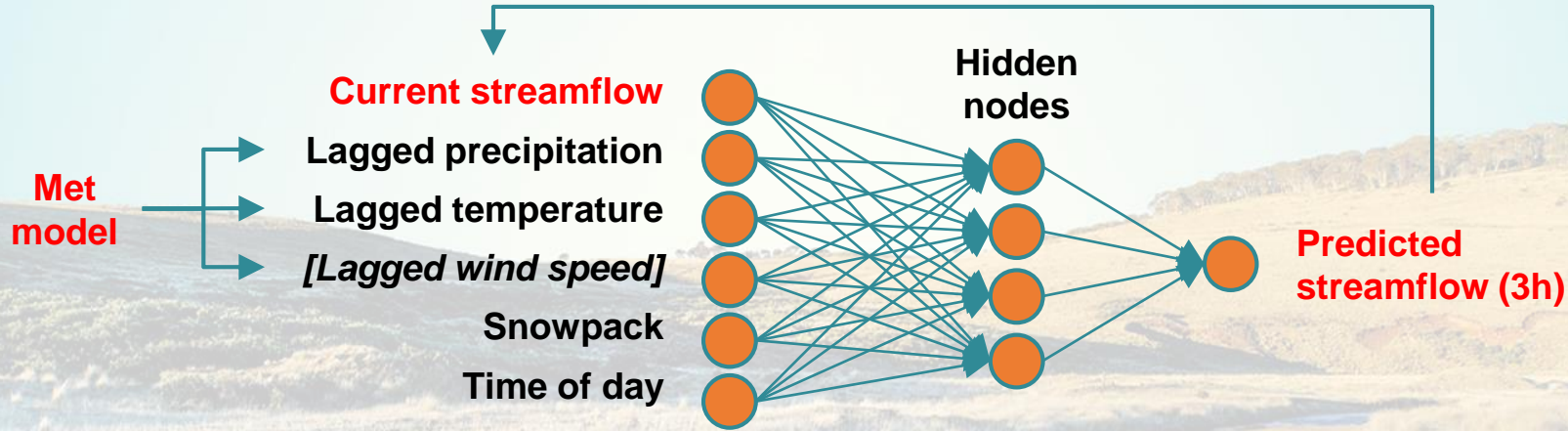
- ANNs are mathematical devices inspired by biological nervous systems.
- They can be “trained” to optimally fit arbitrary datasets.
 - Plenty of data available!



Simple ANN predicts near-term streamflow response accurately

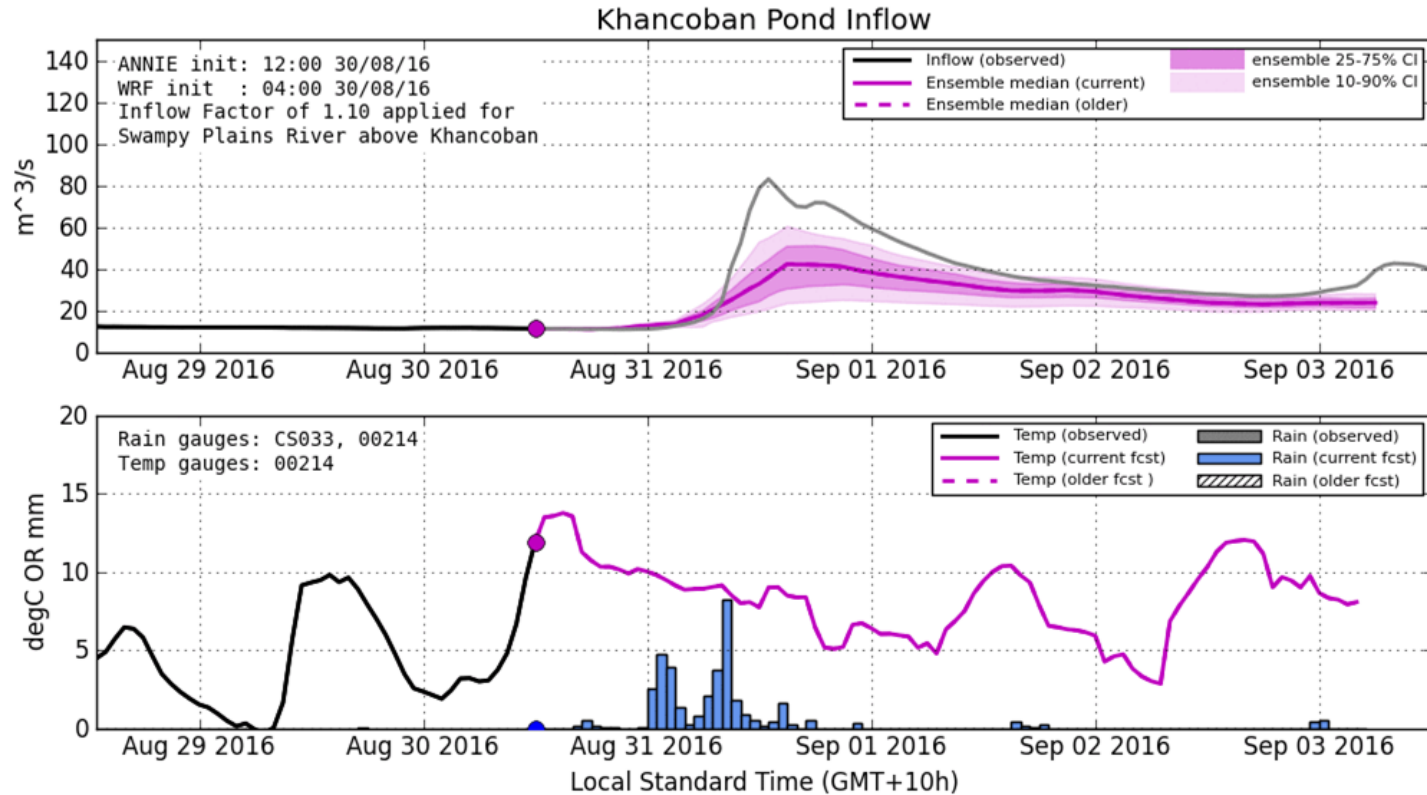


Recursion of neural network permits longer-term forecasts



- We use the Weather Research and Forecast model (WRF) to provide some meteorological drivers.
- Snow surveys are conducted once per week at three sites during winter.
- Seasonality of catchment behaviour is built in to the training; ANNs are trained using a 60 day-of-year window.
- Ensembles of neural nets and perturbed precipitation inputs to represent forecast uncertainty

ANNIE: the Artificial Neural Network Inflow Estimator





Evaluation of ANNIE forecasts



Guthega (Upper Snowy River) catchment



Mt Kosciuszko (2228m)

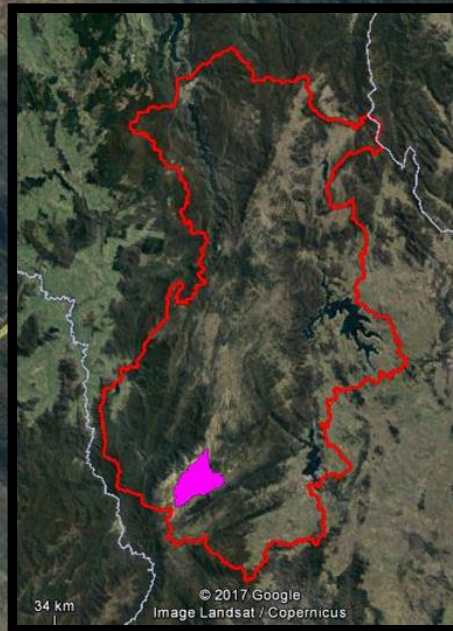
Guthega Weather Station

Snowy River Gauging Station (1598m)

Alpine Way

2620 m

Image © 2017 CNES / Airbus
© 2017 Google



34 km

© 2017 Google
Image Landsat / Copernicus

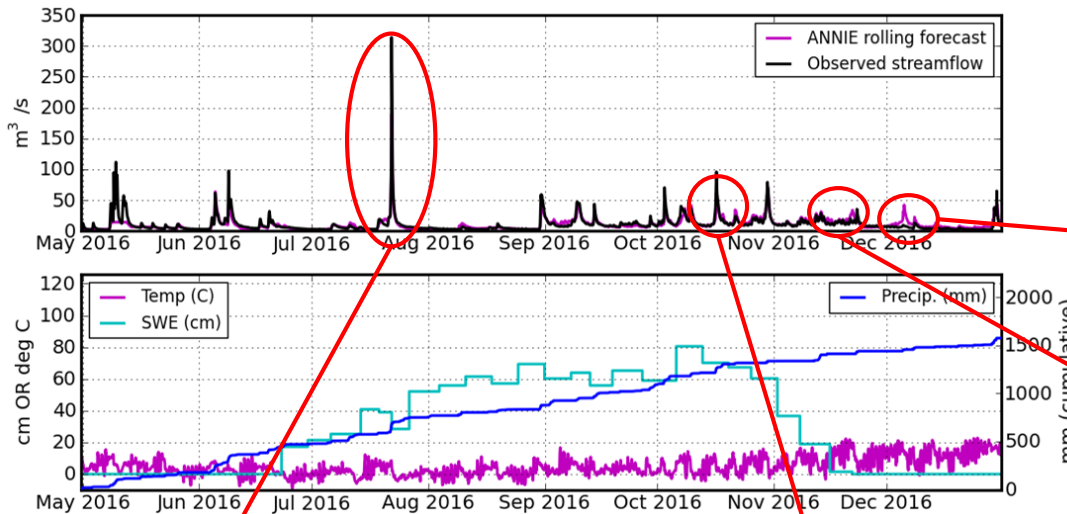
Cross validation approach

- Neural networks are trained for each week of 2011-2017:
 - Observations used (not model data).
 - Two week window dropped from training data.
 - Multiple configurations tested
- Evaluation of forecasts:
 - Created using OBSERVED drivers (“perfect prognosis”)



Config Name	Drivers
Control	streamflow, precipitation, temperature, SWE, snow density, time
Control+WS	streamflow, precipitation, temperature, SWE, snow density, wind speed , time
No Snow	streamflow, precipitation, temperature, SWE, snow density, time

“Perfect prognosis” results: case studies



Event 4

- Early summer moderate rainfall event (~20mm)
- No significant rainfall in 4 weeks previous

Event 1

- Extreme rain event (>100mm in 24h)
- Warm temps
- Unprecedented snowpack loss in July

Event 2

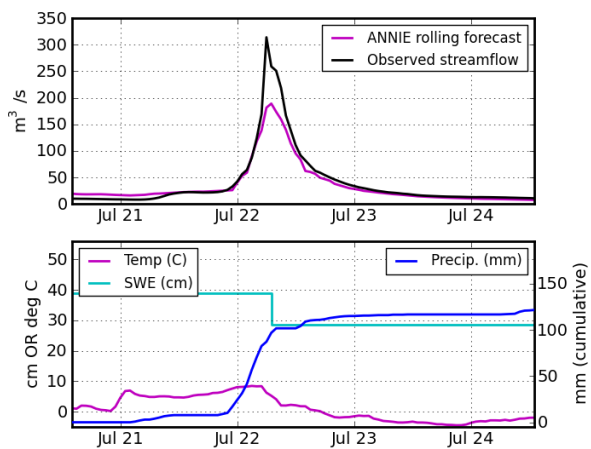
- Significant spring-time rain/snow event (50mm rain + 40mm snow).

Event 3

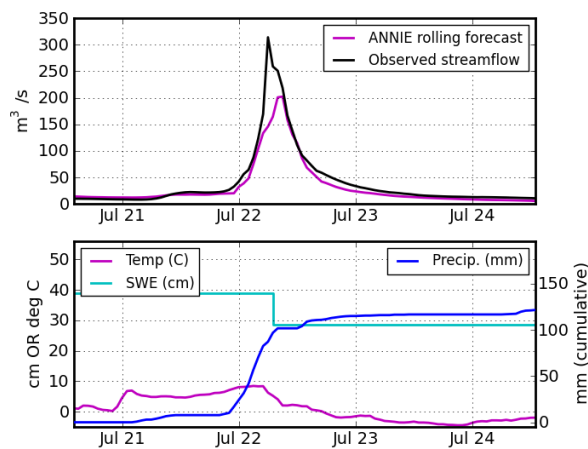
- Late spring, dry period
- Runoff due to pure snowmelt

Event 1: Extreme winter rainfall event

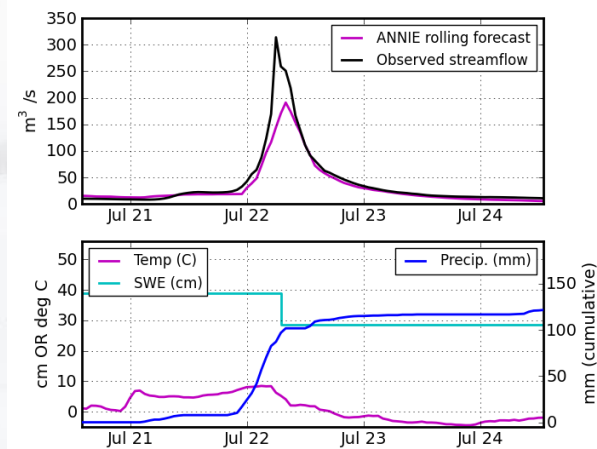
Control



Control+WS



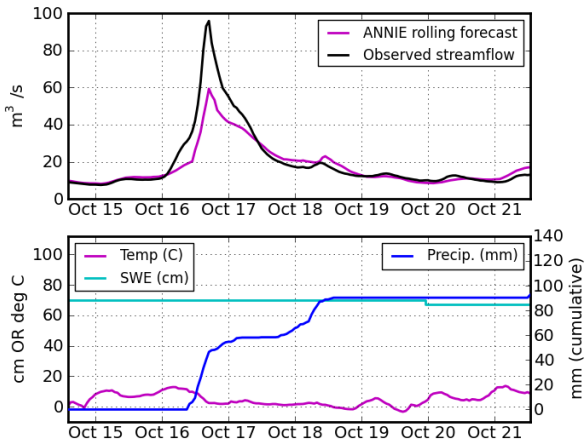
No Snow



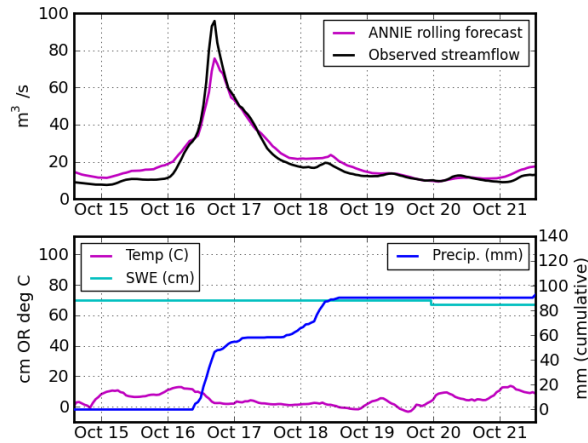
- Little difference between configurations for this event
- This extreme event is practically unprecedented in the training dataset

Event 2: Springtime rainfall/snowfall

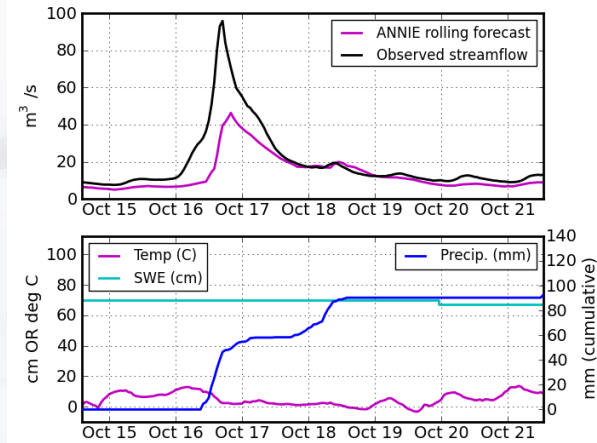
Control



Control+WS



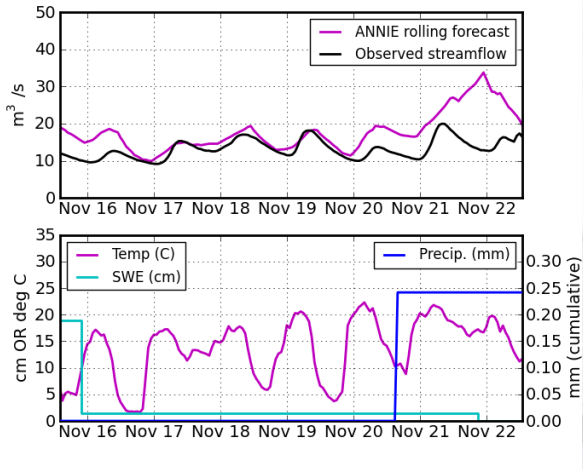
No Snow



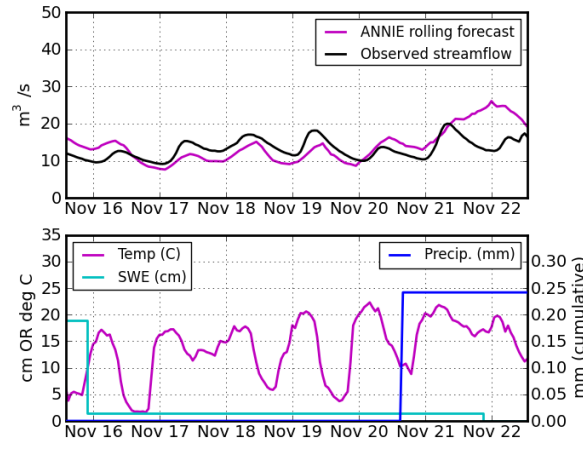
- Control+WS seems to slightly outperform Control
- No Snow configuration has muted response to rainfall

Event 3: Late spring pure snowmelt

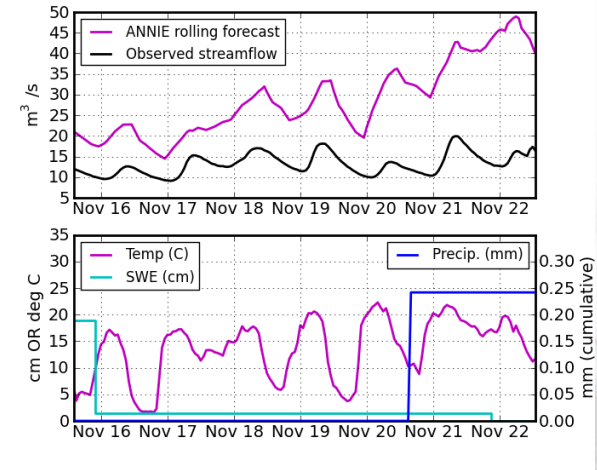
Control



Control+WS



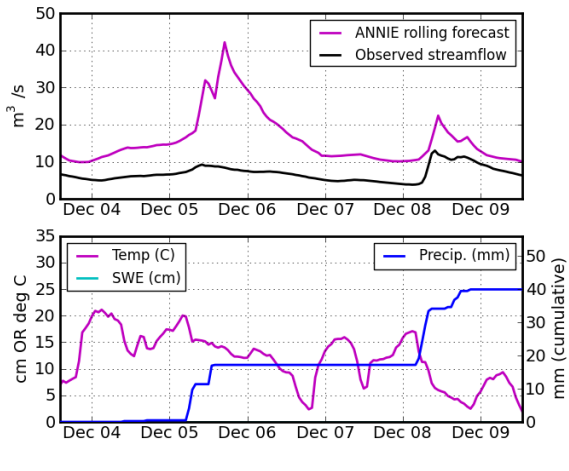
No Snow



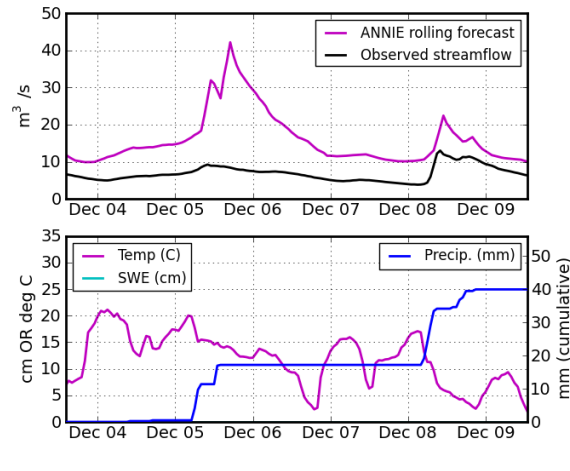
- All configurations show a diurnal cycle (fits to time of day and temperature)
- Diurnal cycle on both Control and Control+WS matches observations much more closely
- No Snow configuration drifts away from observations

Event 4: Early summer rainfall after dry spell

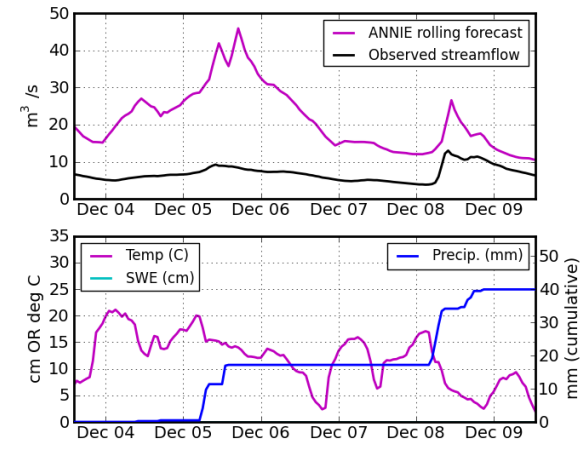
Control



Control+WS



No Snow



- This example shows the potential benefit of incorporating a soil moisture parameter
- No particular advantage to any of the configurations

Objective intercomparison of configurations

- Compared “hindcasts” for 2011-2017 for these three configurations using RMSE and Bias
- VERY SIMILAR performance overall
- NO SNOW shows decrease of skill in winter/spring (particularly Nov)
- CTRL+WS is (probably insignificantly) better than CTRL.

	RMSE			Bias		
Jan	1.97	1.90	1.93	0.10	0.14	0.11
Feb	9.01	9.09	9.04	-0.63	-0.72	-0.60
Mar	7.44	7.30	7.32	-0.31	-0.36	-0.36
Apr	1.70	1.52	1.60	-0.17	-0.14	-0.12
May	4.85	4.76	4.50	-0.25	-0.24	-0.22
Jun	3.57	3.45	3.69	-0.20	-0.23	-0.18
Jul	3.73	3.52	4.12	-0.19	-0.14	-0.21
Aug	1.55	1.45	1.69	0.18	0.24	0.17
Sep	5.02	5.04	5.04	0.26	0.21	0.12
Oct	4.76	4.56	5.42	0.95	0.90	0.79
Nov	2.99	3.01	3.93	0.22	0.24	0.95
Dec	2.26	2.37	2.46	0.26	0.21	0.26
Ann	4.64	4.58	4.76	0.02	0.01	0.06
	CTRL	CTRL+WS	NO SNOW	CTRL	CTRL+WS	NO SNOW

Summary

- ANNIE is an experimental inflow forecasting tool currently in use at Snowy Hydro.
- Short-term streamflow response to meteorological drivers is characterised by an ensemble of artificial neural networks.
- Recursion over these provides a multi-day streamflow forecast.
- Formal validation of the model is under way with some interesting early results.
- Use of snow improves winter/spring forecasts
- Use of a soil moisture variable has the potential to improve summer forecasts

Thanks for your attention!
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