Impact of satellite and in situ data assimilation on hydrological predictions

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Motivation
- Background
- The study area
- Data assimilation experiment
- Added value of data assimilation

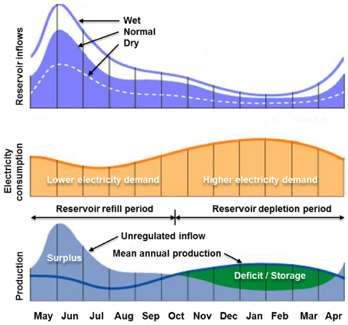
Results
- Benchmarking assimilation experiment
- Ensemble size selection, single variable assimilations
- Assimilation of product combinations

Conclusions

Hydropower plants in Sweden

1. More than 2100 hydro power plants
2. Total installed capacity: 16200 MW
3. 200 plants produce 94% of the power
4. Snow-melt fed reservoirs.

Annual reservoir management



Every day, compare forecasted remaining spring melt runoff to the remaining reservoir volume to fill-up: excess water can be used for production

1. Information requirements
   - Spring and summer snow-melt runoff and winter energy demand
   - Snow-melt runoff volume to store in reservoirs for winter production
2. Use of forecasts
   - Short-term and seasonal runoff forecasts during winter/spring to update production planning
   - Reservoirs must be filled by end of summer
   - Use as much excess water as possible for production during the current spring/summer
   - Avoid spilling (release of water from reservoirs that cannot be used for production)

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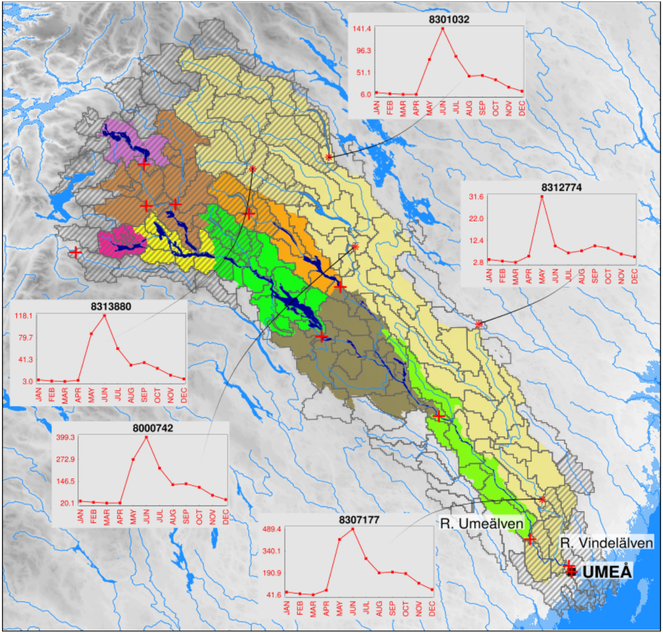
Objectives

1. Provide insights on which satellite products add value to discharge and reservoir inflow predictions
2. Assess economic value of assimilating satellite based snow data and runoff observations in a forecast system



•Northern Sweden •26000km^2 •Snow melt dominated

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The assimilation experiment

1. Two in-situ measurements: discharge and reservoir inflow.
2. Four satellite products: AET, PET (MODIS), FSC (500×500m), SWE (10×10km) (CRYOLAND).
3. 57 additional unique combinations of the six (63 in total).
4. Target variables: discharge and reservoir inflow.
5. European-scale Hydrological Prediction for the Environment (E-HYPE) model.
6. Assimilation done with the ensemble Kalman filter.
7. Model performance assessed with the KGE and its three components: $KGE = 1 - \sqrt{(\rho - 1)^2 + (\beta - 1)^2 + (\alpha - 1)^2}$.
8. Performance gain: $\Lambda = \dfrac{\theta^\star - \theta}{1 - \theta}$: $\theta, \theta^\star$ metric with and without assimilation

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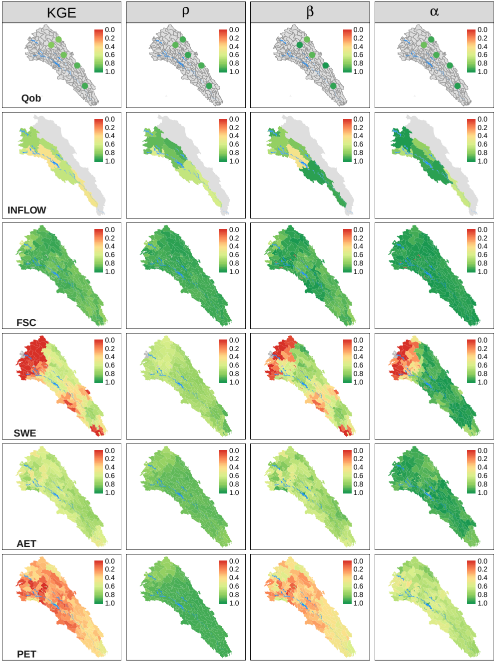
Assessing added value of data assimilation

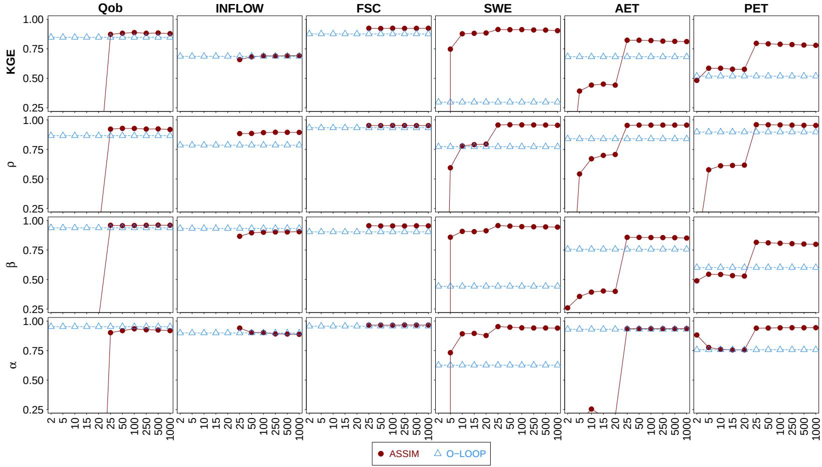
1. Seasonal forecasts of runoff as well as electricity demand (and price) may be rather uncertain.
2. Before onset of snow-melt, and in early phase of spring flood period, hydropower companies may still have high flexibility to adapt production planning as the conditions unfold.
3. Later in snow melt period, when the annual reservoir storages are closer to the maximum filing level, the flexibility is smaller, and forecasts becomes more important
4. Still, seasonal forecast before and early in the season are still used to make long-term production planning

Ongoing research to develop the economic model.

Benchmark



Sensitivity to the ensemble size



- Most assimilations stabilised with 25 members
- INFLOW KGE and β needed 100 members.

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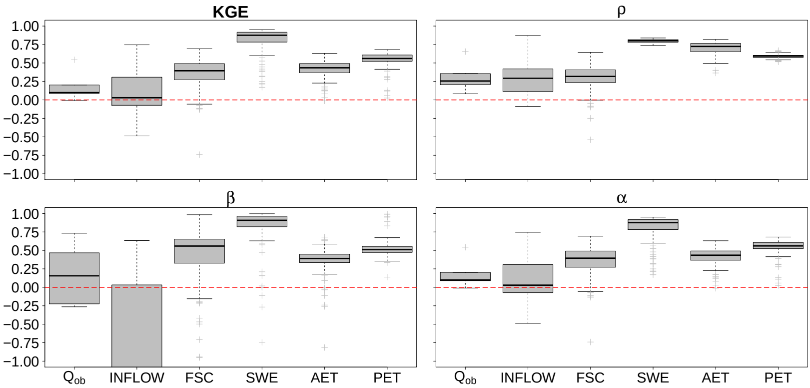
Gains in single variable assimilations



- High improvements in SWE, AET and PET
- Lower in Q_{ob} and INFLOW: high open-loop performance

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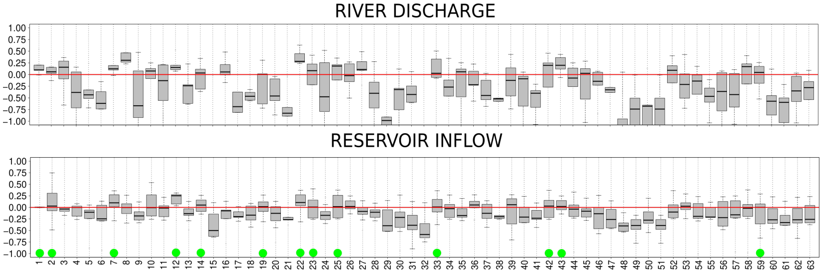
Performance of product combinations



- Informative: achieved gains in both Q_{ob} and INFLOW (13)
- Selection depends on target variable(s).

The informative assimilation gains

Assim	Q_{ob}	INFLOW	FSC	SWE	AET	PET	Λ^1	Λ^2
1	•						0.002	0.100
2		•					0.030	0.060
7		•	•				0.100	0.120
12	•	•					0.250	0.150
14		•			•		0.050	0.030
19		•				•	0.015	0.005
22	•	•	•				0.110	0.280
23		•	•	•			0.008	0.080
25	•	•		•			0.016	0.180
33	•	•			•		0.009	0.030
42	•	•	•	•			0.029	0.190
43	•	•	•		•		0.020	0.200
59	•	•	•		•	•	0.002	0.040

1 Q_{ob}

2 INFLOW

Number of times products produced gains

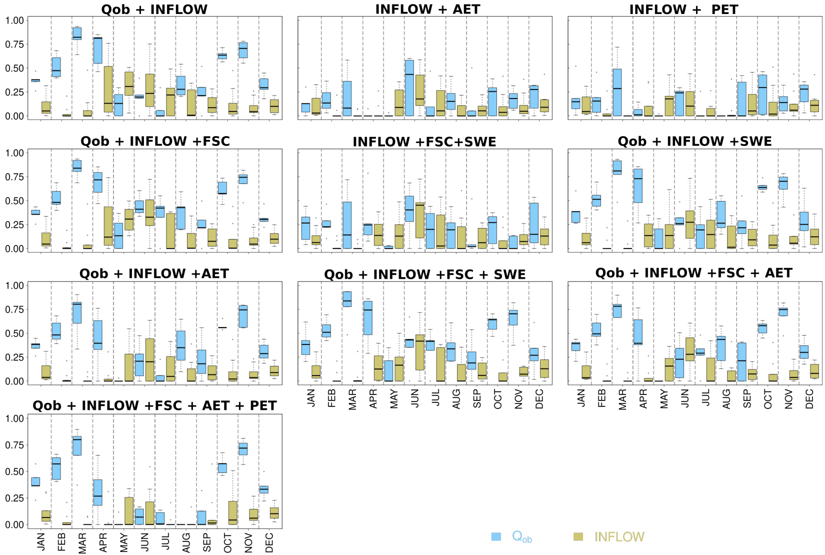
Product	KGE[1]	KGE[2]	ρ^1	ρ^2	β^1	β^2	α^1	α^2
Q_{ob}	15	10	18	13	17	5	9	0
Inflow	16	16	17	15	8	5	14	2
FSC	11	9	15	13	14	5	14	2
SWE	8	3	12	9	11	5	5	0
AET	10	5	10	7	13	9	11	0
PET	2	5	2	2	12	1	6	3

1 Q_{ob}

2 INFLOW

- Rank from the best: INFLOW, Q_{ob}, FSC, AET, SWE, PET.

Gains during different months for informative combinations



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1. Ensembles with 25 members were sufficient for all but Qob and INFLOW assimilations which required 100 members.
2. The assimilation exercise led to significant improvements in the model's prediction of both the PET and SWE.
3. The assimilation of the MODIS PET product did not improve the stream discharge and reservoir inflow predictions, which points to its limited value in data assimilation.
4. In situ data assimilations generally outperformed the satellite products.
5. From the 63 assimilation experiments, 13 informative combinations had KGE gains for both discharge and inflow.
6. Most of these also had gains during the spring melt months, hence potential for use in initialisation of reservoir inflow forecasts.

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