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Rainfall estimation using a non-stationary geostatistical model and uncertain measurements

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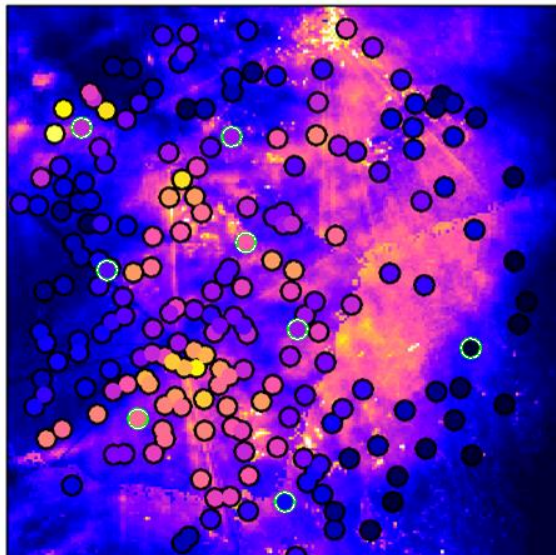
Merging radar - rain gauges: Kriging with External Drift (KED)



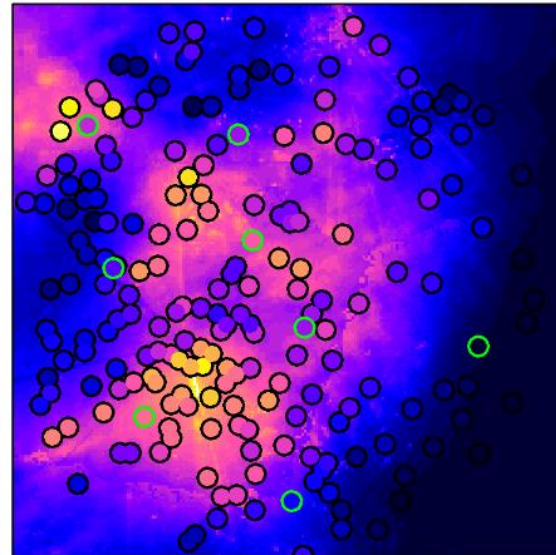
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1. KED: one of the best performing and most efficient methods
2. Estimate based on kriging interpolation of rain gauges
3. Mean as a linear function of the radar
4. Kriging Variance allows to calculate uncertainty

Radar and Rain Gauges



KED and Rain Gauges



Uncertainties in KED

1. Interpolation
2. Rain gauge measurement uncertainty
3. Radar uncertainty
4. ...more

We address 1, 2, and 3

Interpolation and trend estimation uncertainty

Measurements only in a limited number of points..

...but the estimation is areal

How uncertain is such estimation?

- Based on the geo-statistical model
- Measured by the kriging variance

Rain gauge measurement uncertainty

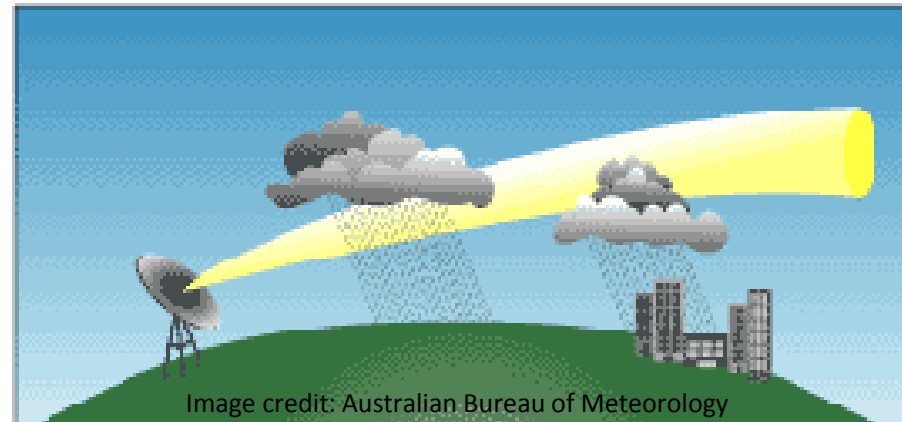
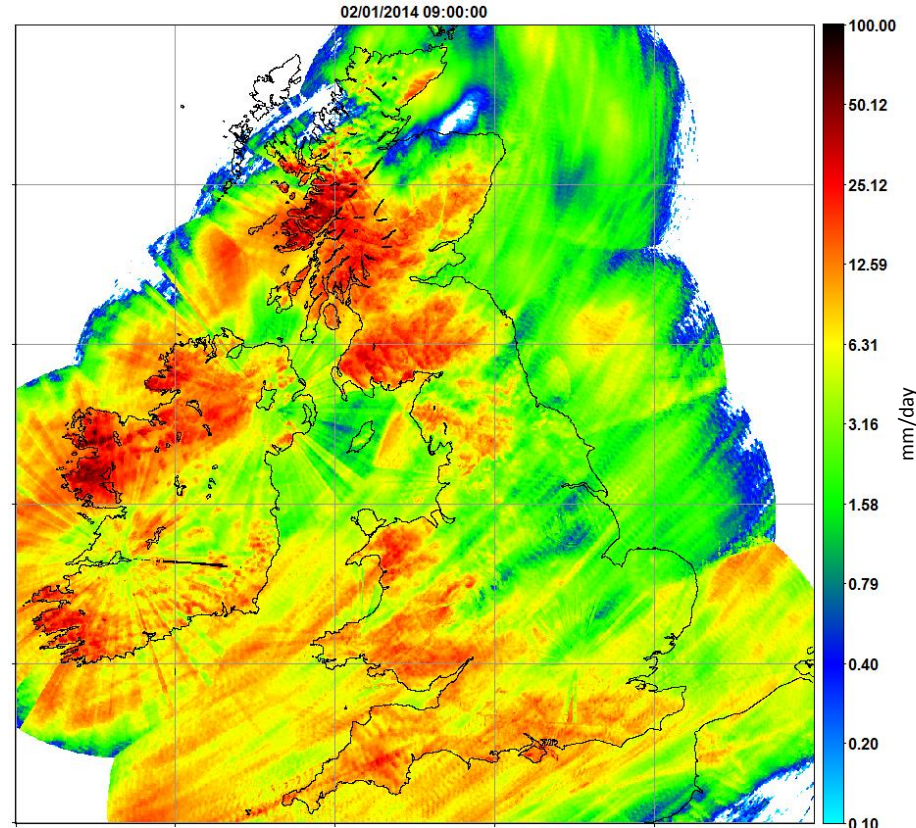
- ***Variogram nugget***: variance at short distance. Can represent measurement errors. It is spatially uniform.
- ***Kriging for uncertain data (KUD)***: assigns a specific nugget for each rain gauge, at each time step (space and time variant).

Radar Measurement uncertainty

- Radar is used differently in KED:
Mean = linear function of radar
- Spatially uniform radar errors are not influent
- In reality radar errors are spatially distributed



KED with non-stationary variance





Case Study



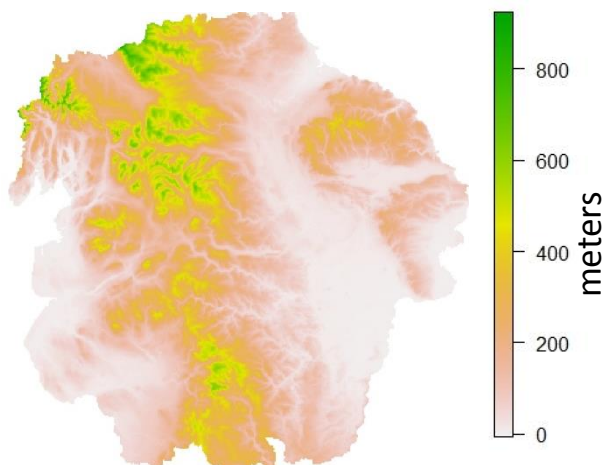
Event	Start	End	Duration (h)	Mean (mm/h)	Max (mm/h)	Max Acc. (mm)	Type
1	06/01/2016 23:00	07/01/2016 17:00	19	2.2	8	31	Frontal with orographic enhancement (Desmond storm)
2	27/03/2016 23:00	29/03/2016 11:00	13	2.0	16	65	Frontal
3	07/06/2016 10:00	08/06/2016 00:00	15	1.5	50	46	Highly convective (caused flash floods)
4	29/07/2016 02:00	29/07/2016 22:00	21	0.5	30	41	Frontal
5	13/09/2016 12:00	13/09/2016 22:00	11	3.0	3	37	Frontal with orographic enhancement



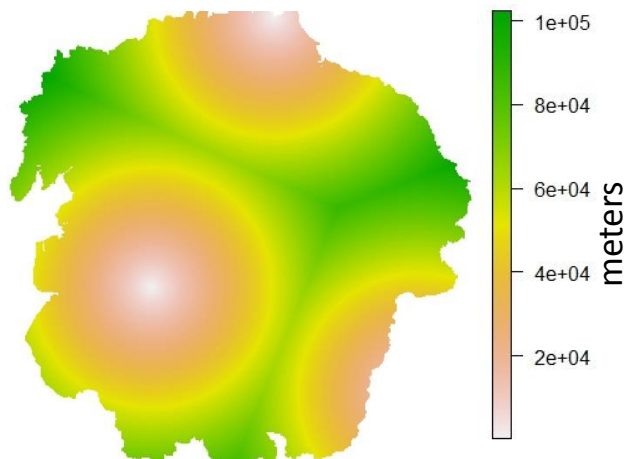
KED with non-stationary variance

Standard deviation = linear function of covariates

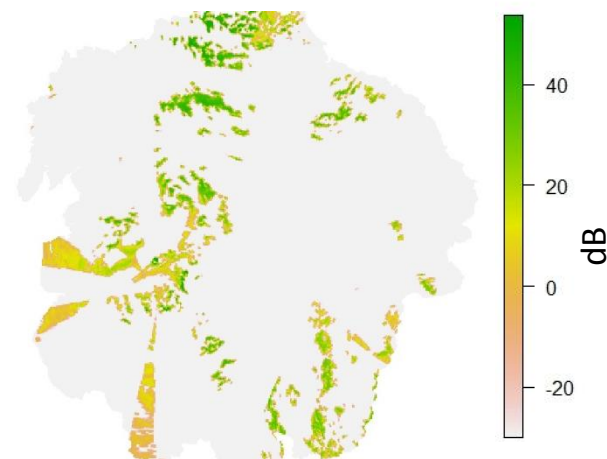
elevation



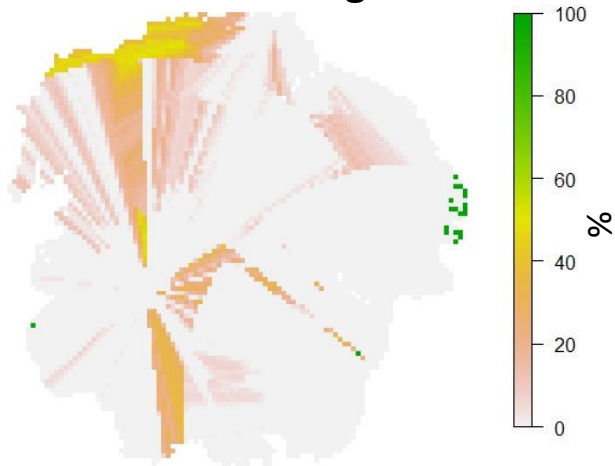
distance from the radar



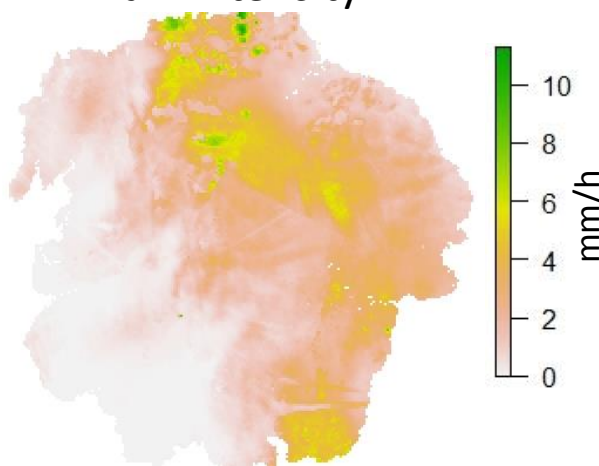
clutter



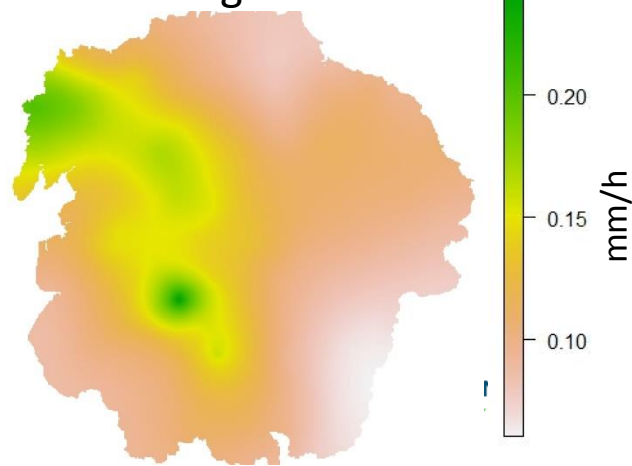
beam blockage



rain intensity



average error

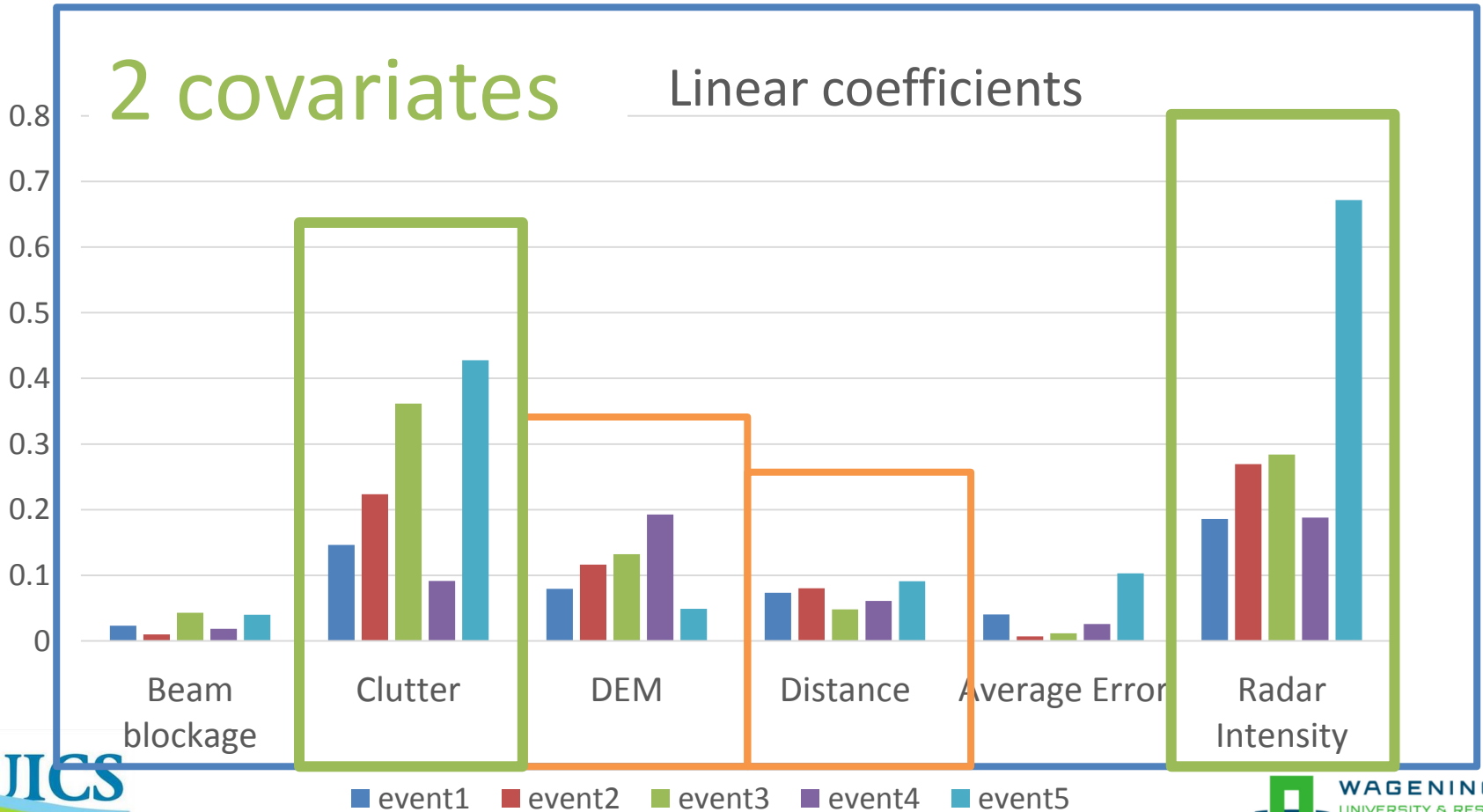


Maximum Likelihood

- Geo-statistical model (2 parameters)
- Mean = linear function of the radar (2 parameters)
- Standard deviation = linear function of the n covariates ($n+1$ parameters)

Selection of covariates

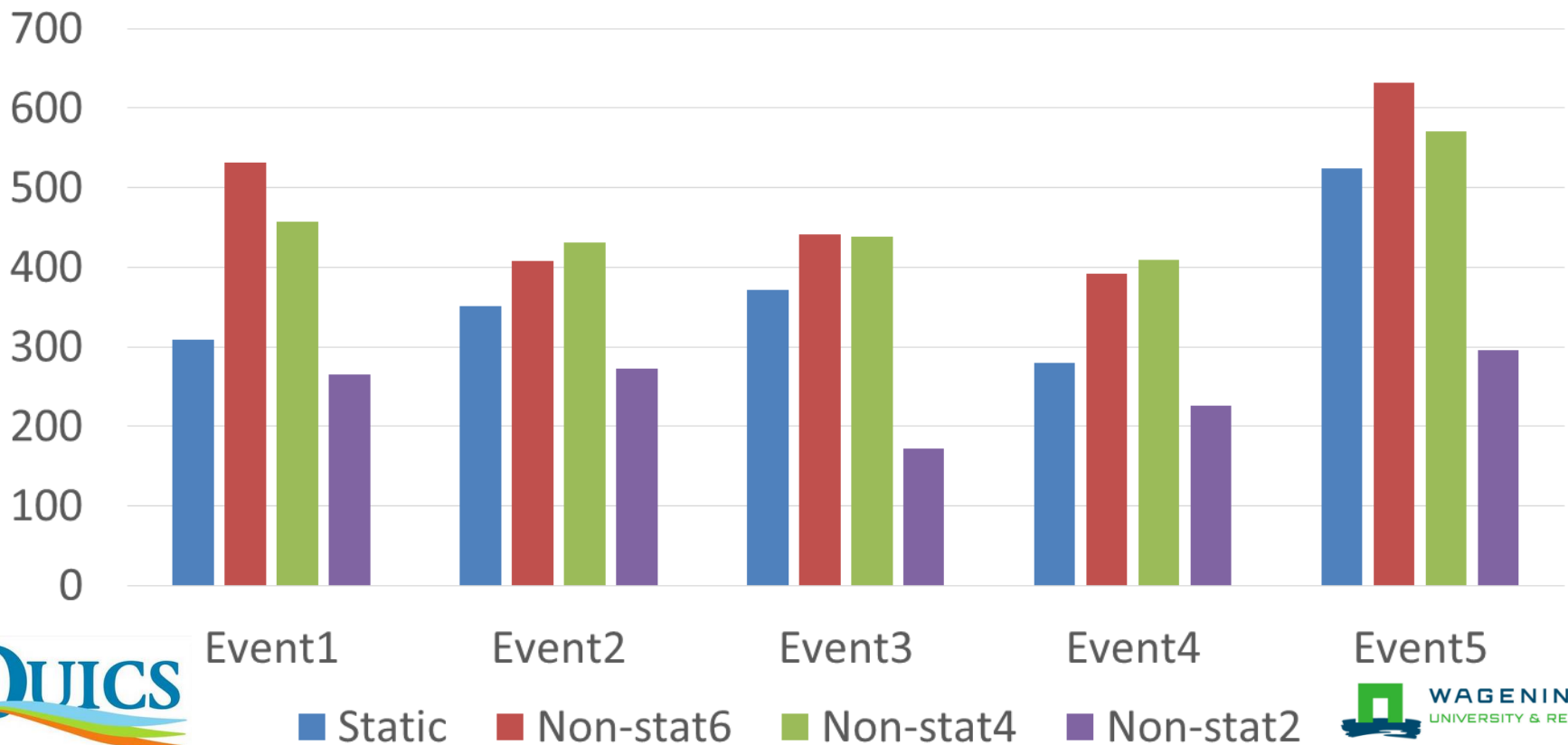
Improve estimation reducing parameters:
Which covariates are more important?



Results: estimation skills

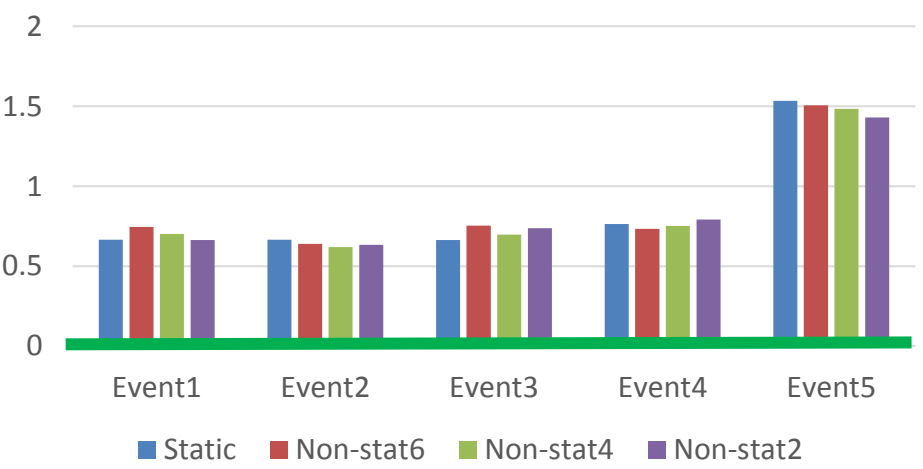
Akaike information criterion (AIC) = measure of relative quality of statistical models for a given set of data

AIC

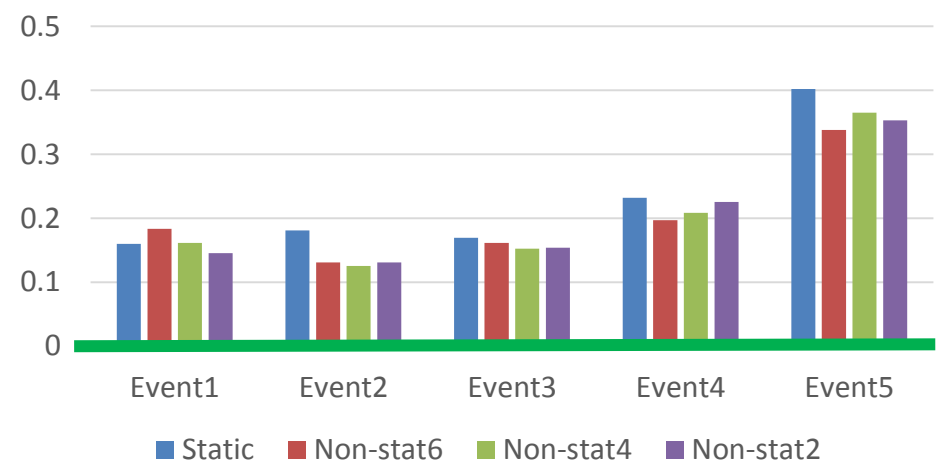


Results: deterministic validation

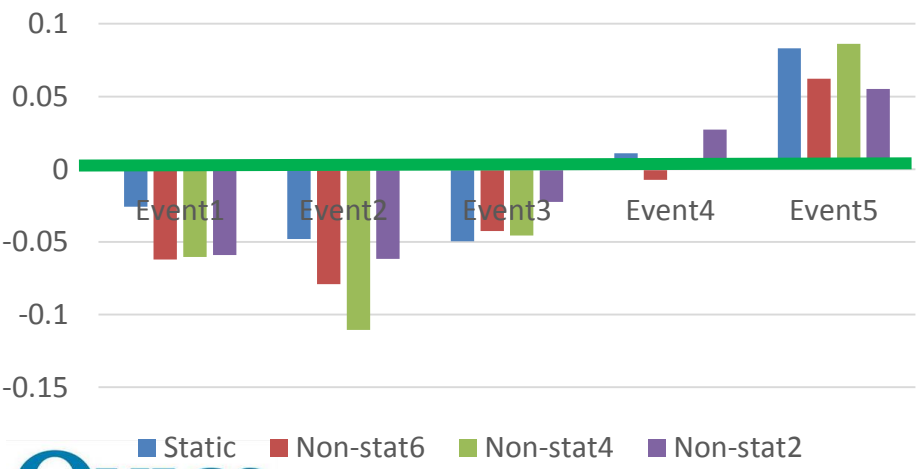
Root Mean Square Error [mm/h]



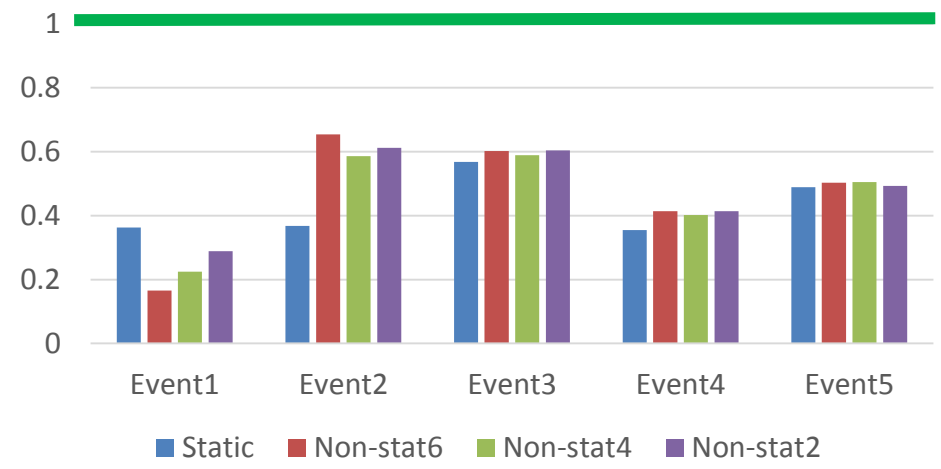
Mean Root Transformed Error [mm/h]



Bias [mm/h]



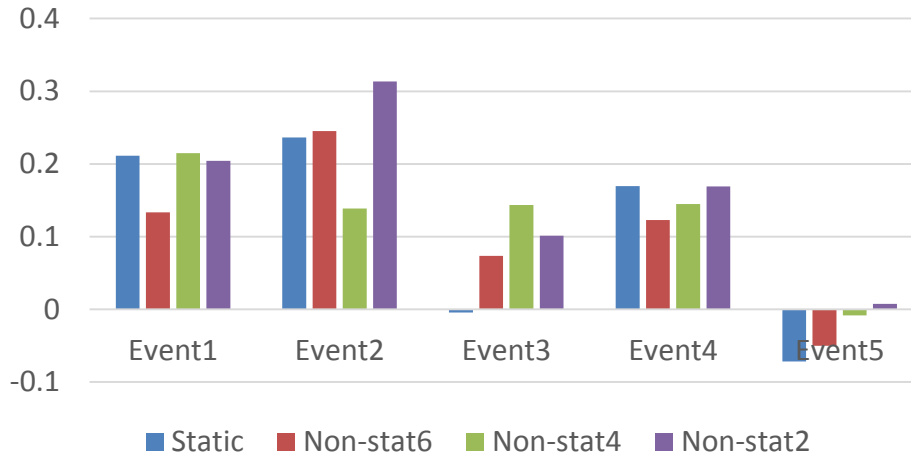
Hanssen-Kuiper Skill Score [-]



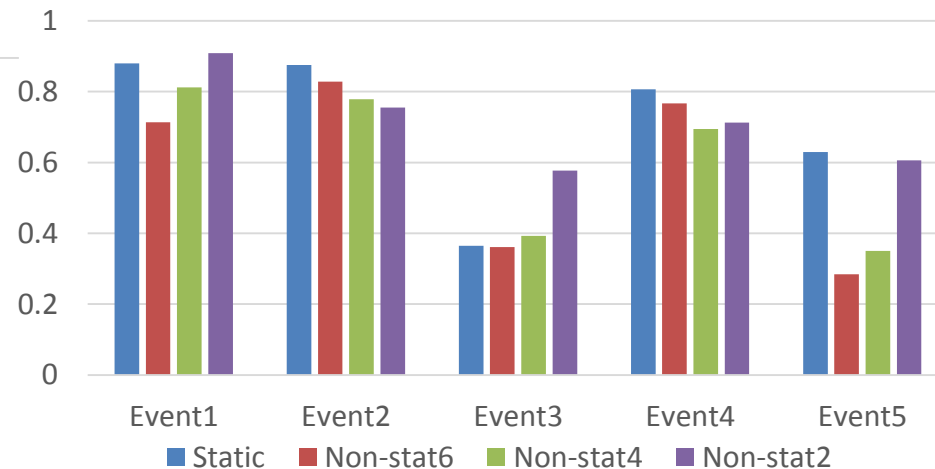
Results: probabilistic validation

The set of observation percentiles should be independent and uniformly distributed

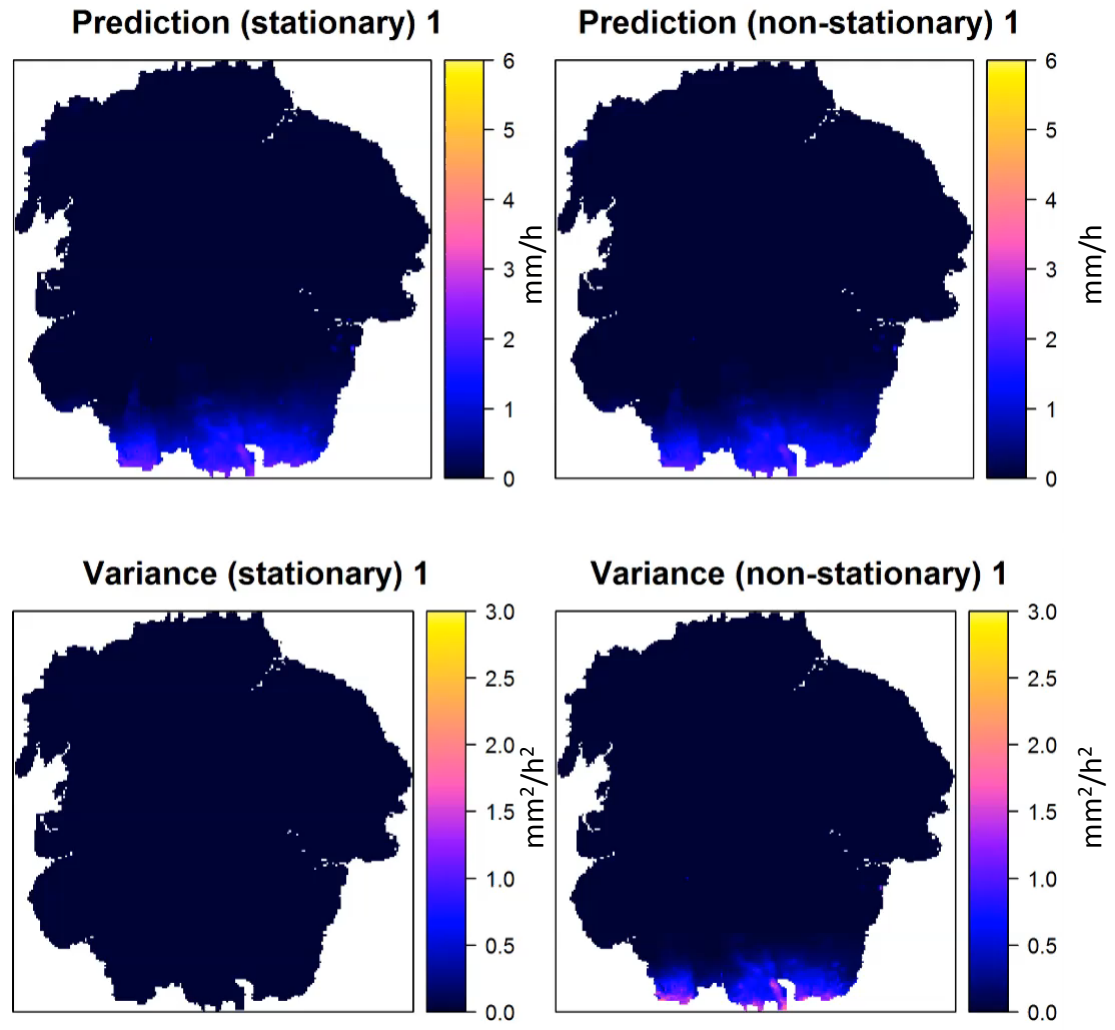
Kendall Tau Test of independence



R² Uniformity Test



Results



Conclusions

- The method shows potential, but needs some improvements
- Balance between more information and parameter identifiability
- More effective for convective events (event3)

Space for improvement

- Time variant covariates
- Time variant selection of relevant covariates
- Transformation of covariates to better suit a linear function
- Test other optimisation methods

Thank you!!!

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