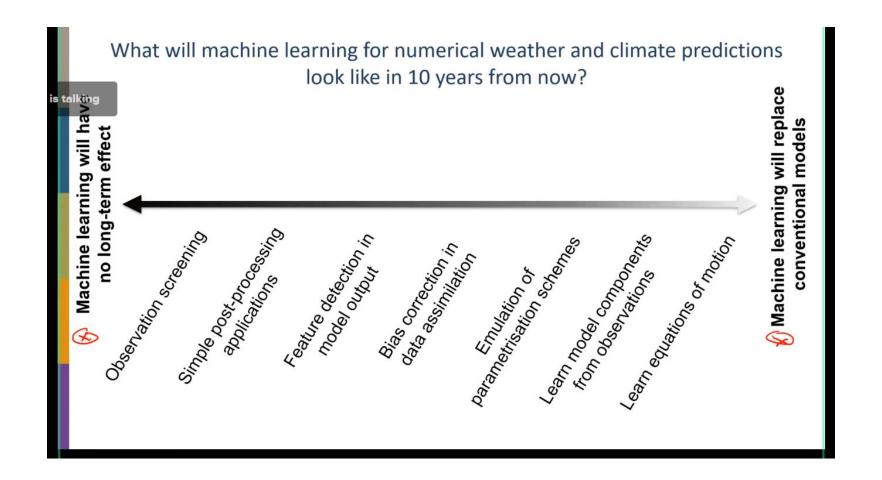
- Use of ensemble by the forecasters:
 - What do the forecasters use of the ensembles? (Probabilities? Percentiles? Pseudo-deterministic?)
 - Do not attribute "higher weight" to the control (or yes?) A. McCabe,
 MCH
 - Condense the information (H. Feddersen, C. Marsigli)
- Verification:
 - Neighbourhood (IMPROVER, N. Roberts)
 - testbed (high-impact weather)
- Applications in cascade:
 - Meteo-hydrological ensembles (like EFAS)
 - Sea-state ensembles (C.Wastl)
 - Combine the meteorological uncertainty with the uncertainty in the processes in cascade (hydro, marine, pollution ...)

- Stochastic physics:
 - identify the elements of the schemes which can benefit from a stochastic description
 - Include physical processes but even better the error of these physical processes! (M. Raschendorfer)
 - Estimate spatial and temporal scale of the uncertainties to determine the scales of the perturbations - > difficult (H. Christensen, I.-L. Frogner), use of ML (H. Christensen)
- Use the uncertainty in the estimated physiographic parameters to provide ensemble perturbations -> provide estimate of parameters with an estimate of uncertainty
- Use of Machine Learning:
 - Where? (H. Christensen, N. Roberts)
- SRNWP-EPS database:Value Chain
 - Proposal to populate the database of the Value Chain Project of WWRP with few European cases (plots, reports, any info)



What next? ML for **improved** stochastic parametrisation.

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- Many operational stochastic parametrisations are cheap, but ad hoc
- Can we improve on this by using Machine Learning to learn the stochastic parametrisation scheme?
- · MU-MIP dataset will ultimately provide ideal training data for this undertaking

Show proof of concept experiments comparing a stochastic NN to a bespoke stochastic parametrisation scheme

- Use Generative Adversarial Networks to learn a stochastic parametrisation for the toy atmospheric model, the Lorenz 96 system
- · Compare to bespoke stochastic parametrisations

Gagne, Christensen, et al, 2020, JAMES

