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Session HS7.4: Hydroclimatic change and unchange: exploring the
mysteries of variability, nature and human impact

Towards benefitting from diverse inferred features and foreseen behaviours of hydroclimatic variables in predictive modelling contexts (solicited)

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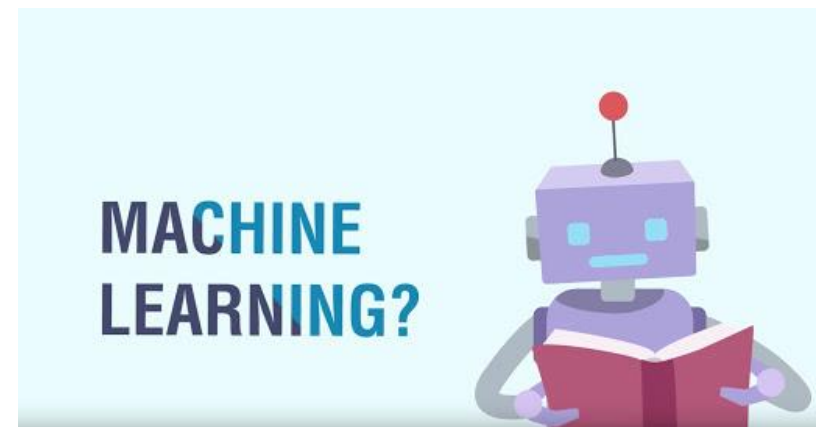
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Introduction

- The study of **hydroclimatic behaviours and features** is important (Montanari et al. 2013; Blöschl et al. 2019) and should be made both from the descriptive and from the predictive (or predictability) perspectives for:
 - ✓ creating new hydrological **knowledge (science)**; and
 - ✓ improving **modelling** frameworks in hydrology (**engineering**).
- Here, we focus on **predictive modelling** frameworks (mostly on hydrological time series forecasting frameworks) and on how to improve them.
- Much high-quality work has been conducted towards this important direction in several sub-fields of hydrology and geoscience.
- However, some **useful and realistic concepts** from the **time series forecasting** and the **machine learning** (or statistical learning) fields are underexploited in our field.
- We extensively discuss some of these concepts, together with related **key findings** and **implementation examples**.
- We believe that the exploration of the **mysteries of hydroclimatic variability and change** from this (mostly applied) perspective could reveal new aspects and complementary features.

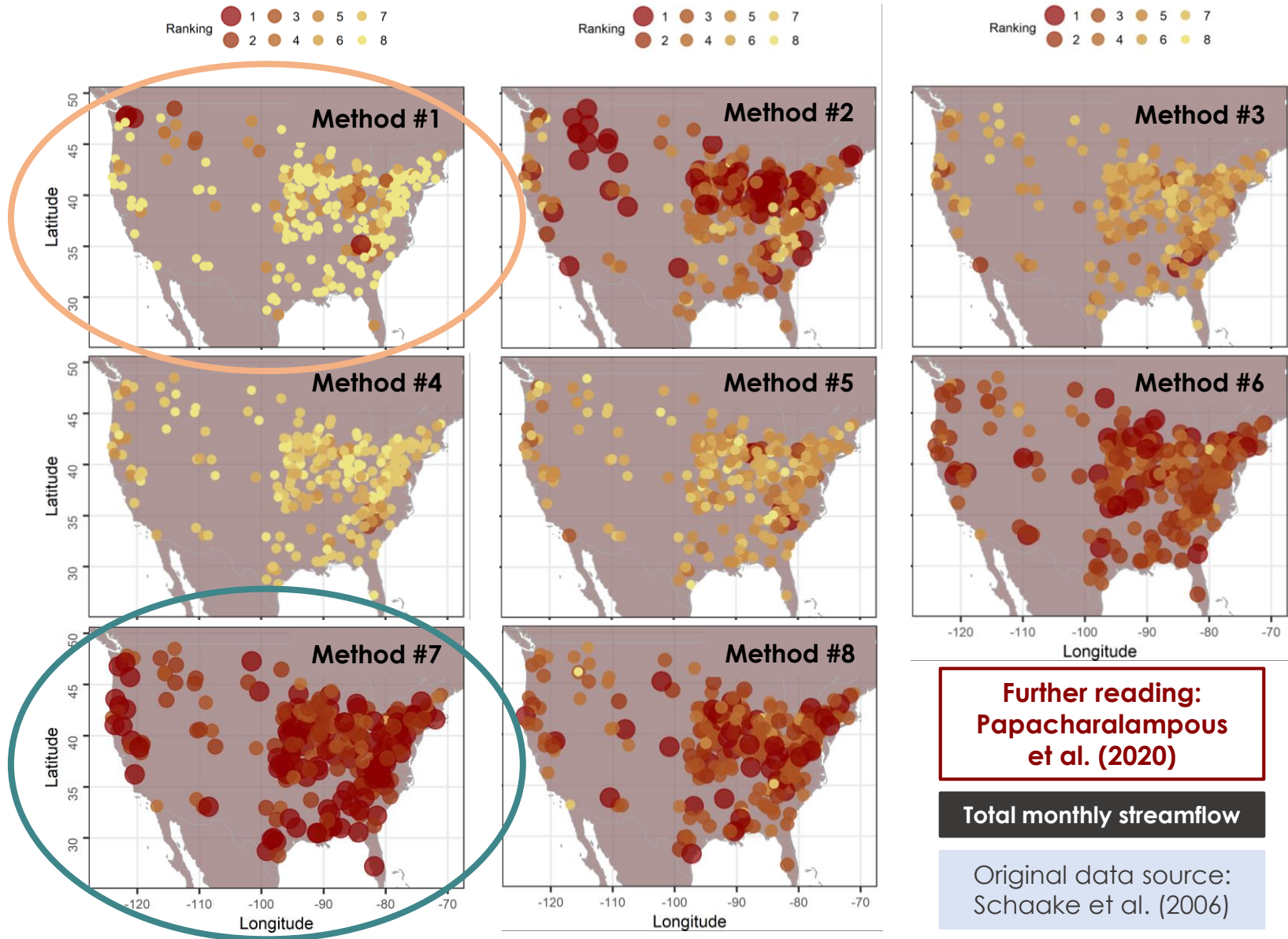


The “no free lunch” theorem and large-scale benchmarking

- The “**no free lunch**” theorem (Wolpert 1996) implies that single-case studies cannot stand as empirical proofs that a prediction method performs better than others.
- An optimal selection of prediction methods can be supported by **large-scale benchmarking**, which requires:
 - ✓ **large datasets** comprising many and diverse problem cases to be studied;
 - ✓ **multiple automatic, computationally convenient and fast predictive models**; and
 - ✓ **benchmarks** (i.e., simple models).

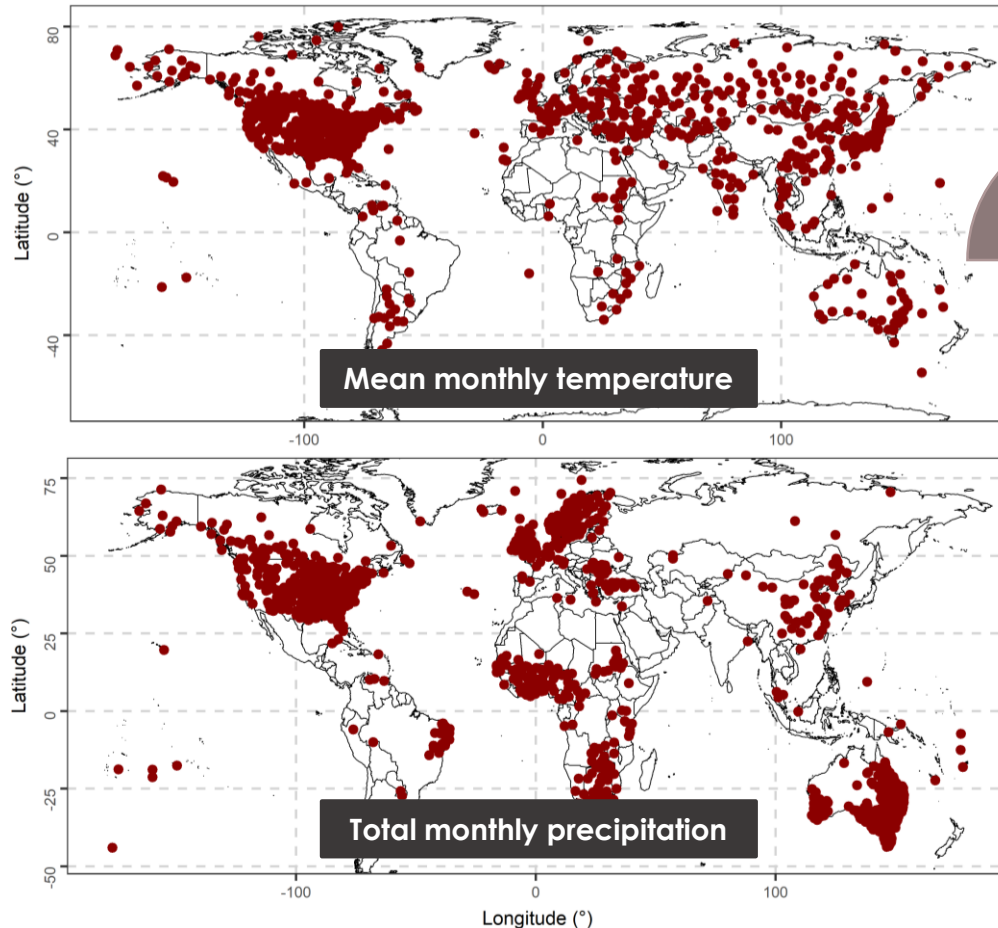


The “no free lunch” theorem and large-scale benchmarking



Which features are important for getting good predictions?

Further reading: Papacharalampous et al. (2018b)



Original data sources: Peterson and Vose (1997), Lawrimore et al. (2011)

Seasonality
Autocorrelation
Exogenous relationships
Long-range dependence
Shifts and trends

Examples

- Seasonal ARFIMA performs only slightly better than seasonal SES.
- Seasonal SES performs notably better than Prophet, and comparably to seasonal exponential smoothing with a trend term.

Analogous conclusions can be drawn for:



Mean annual temperature

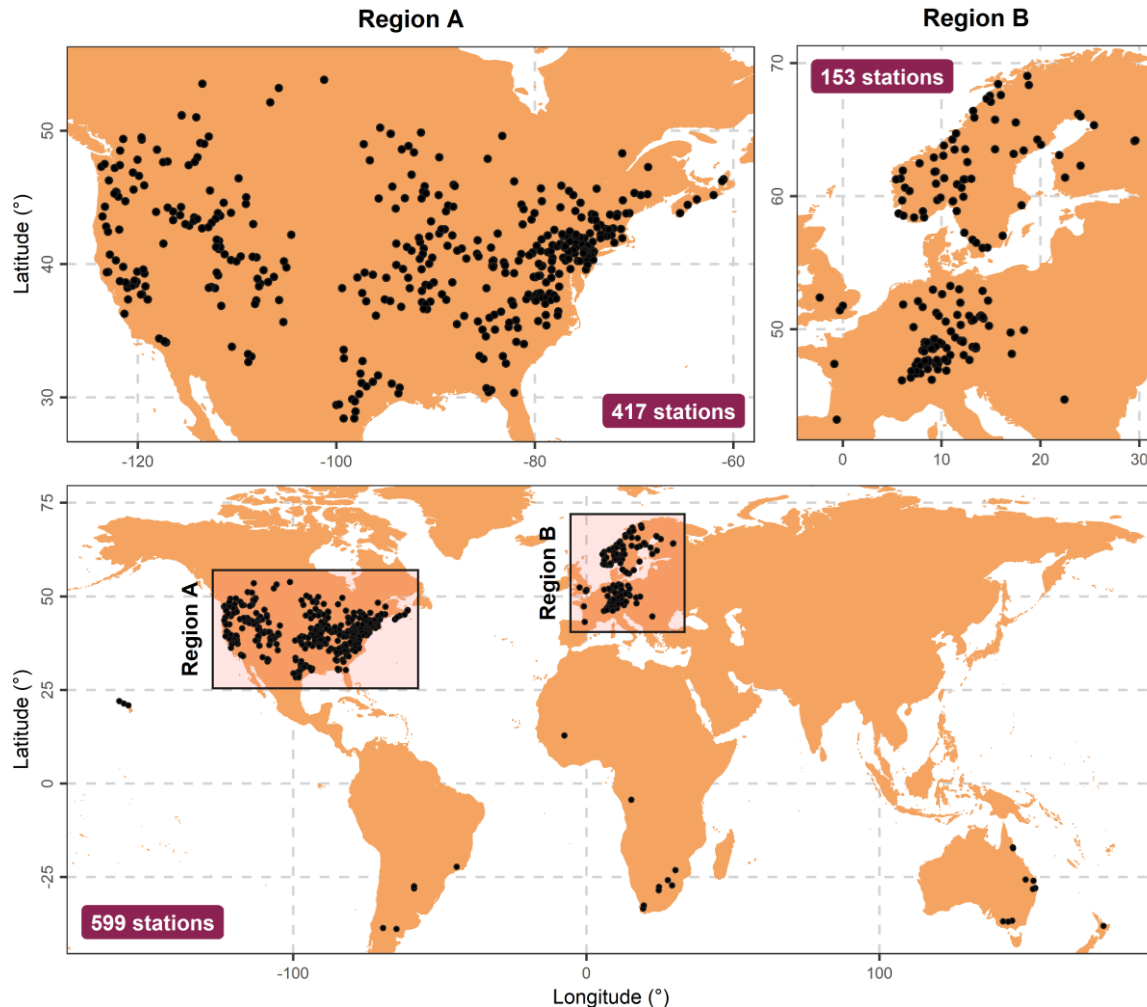
Mean annual precipitation

Mean annual streamflow

Daily streamflow

Further reading: Papacharalampous et al. (2018a), Papacharalampous et al. (2019), Tyrallis et al. (2021)

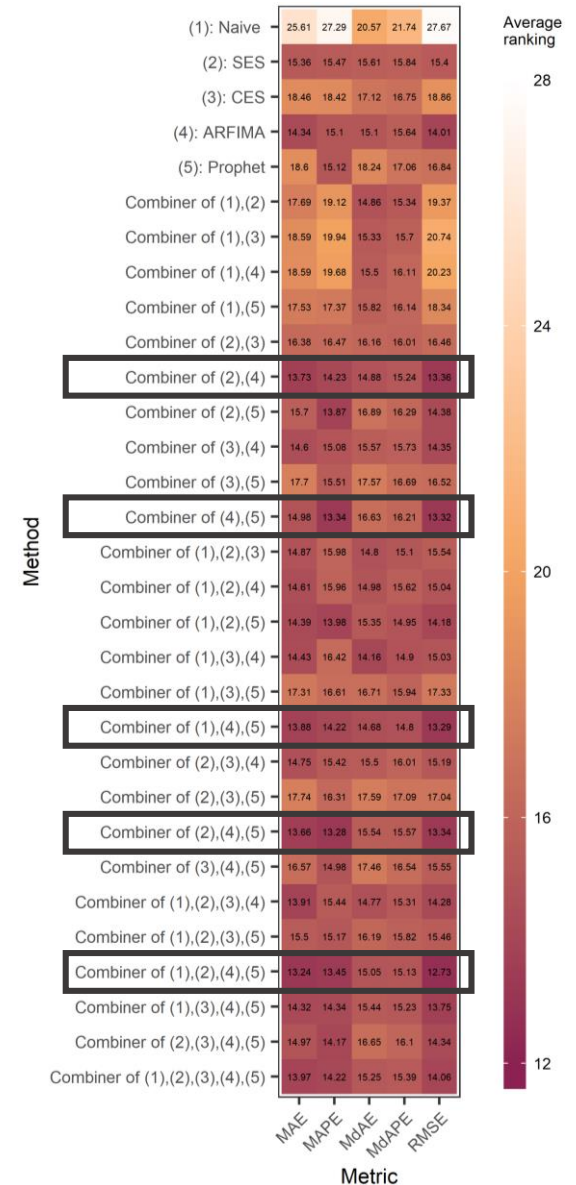
Forecast combination for benefitting from diverse foreseen behaviours



Further reading: Papacharalampous and Tyralis (2020)

Mean annual streamflow

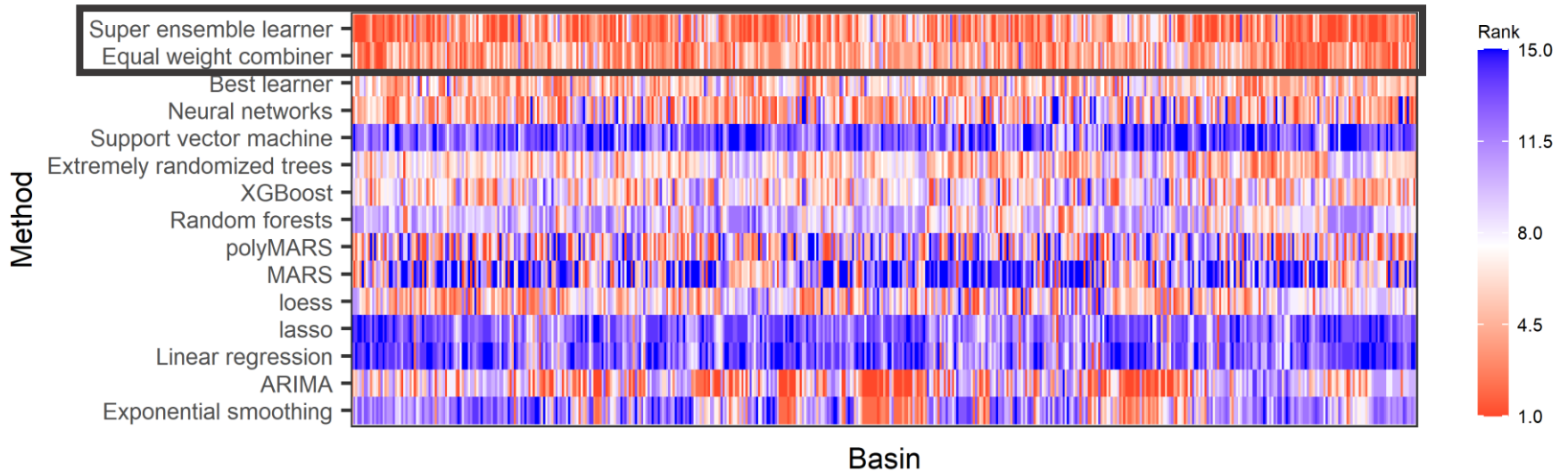
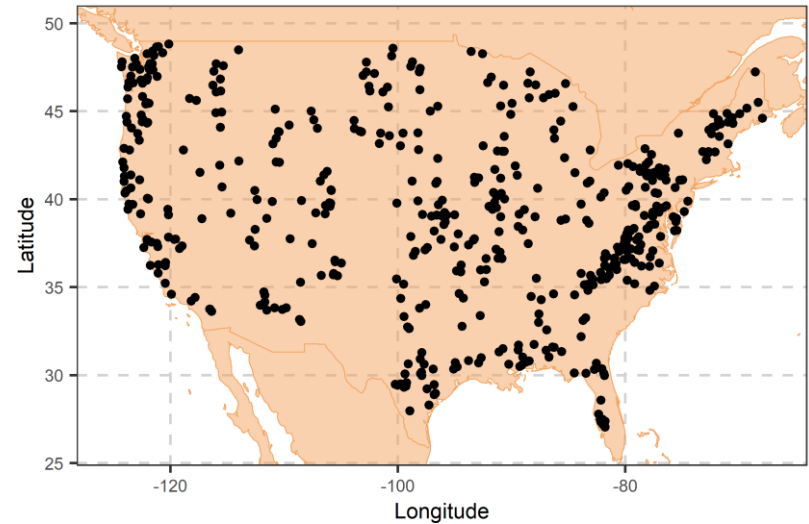
Original data source: Do et al. (2018)



Forecast combination for benefitting from diverse foreseen behaviours

Further reading: Tyrallis et al. (2021)

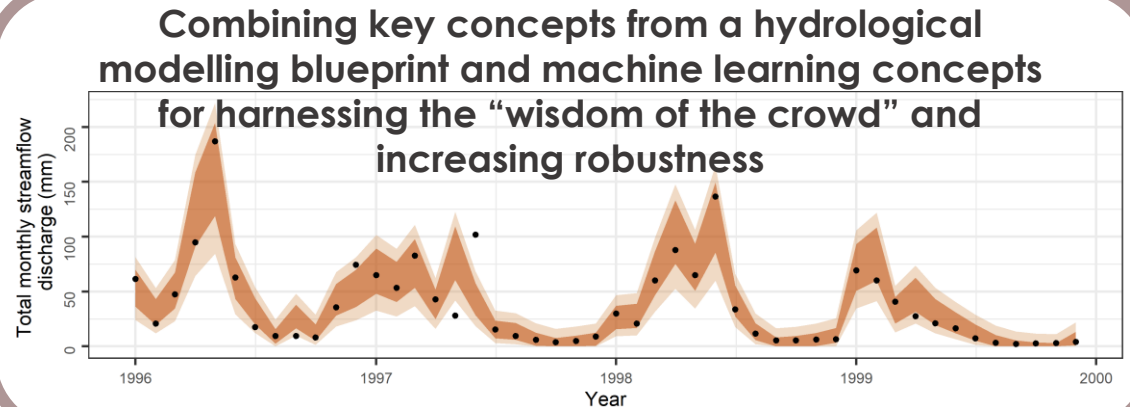
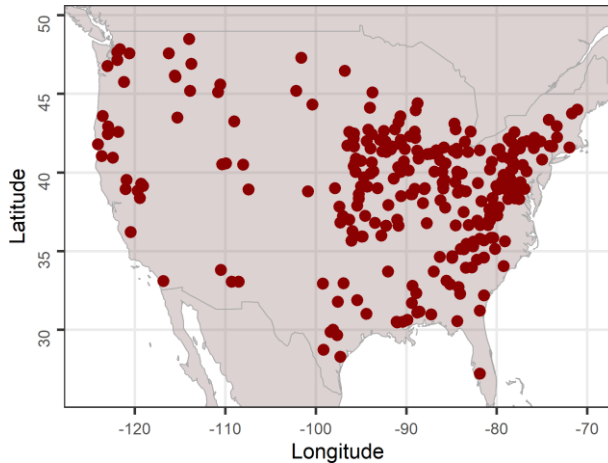
Method	Metric			
	RMSE	MAE	MEDAE	r^2
Super ensemble learner	3.69	2.7	4.82	3.77
Equal weight combiner	4.24	3.47	7.97	3.64
Best learner	5.73	5.36	6.6	5.74
Neural networks	5.94	7.33	8.41	6.39
Support vector machine	12.6	10.65	8.5	13.18
Extremely randomized trees	6.61	6.04	7.31	5.97
XGBoost	7.11	8.95	8.44	7.88
Random forests	8.92	8.67	9.31	8.72
polyMARS	7.82	7.71	7.44	8.05
MARS	10.18	8.37	4.64	10.18
loess	6.83	6.85	6.79	7.78
lasso	12.14	13.38	14.27	12.14
Linear regression	12.26	13.65	14.14	11.81
ARIMA	6.42	8.09	9.07	6.4
Exponential smoothing	9.51	8.78	2.29	8.36



Daily streamflow

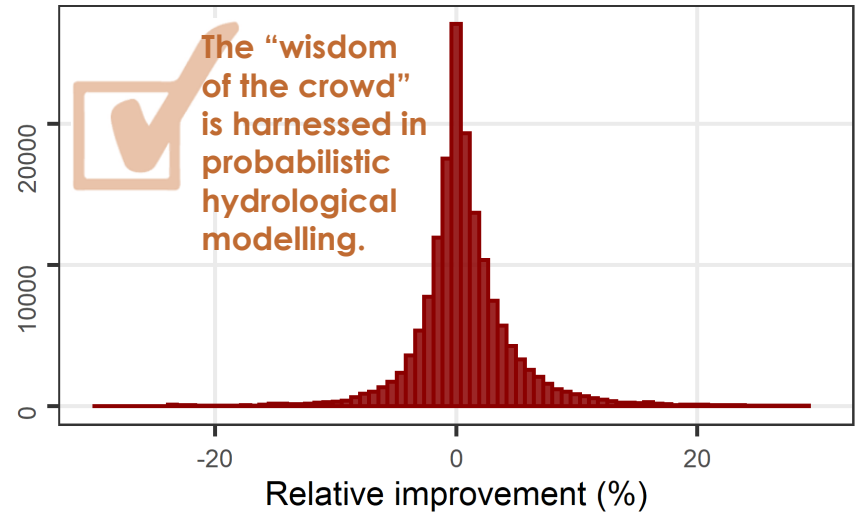
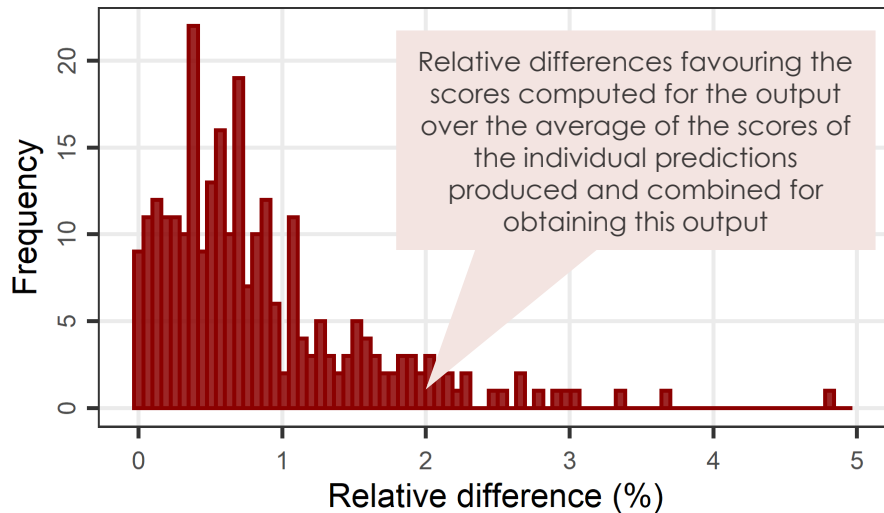
Original data sources: Newman et al. (2015), Addor et al. (2017)

Forecast combination for benefitting from diverse foreseen behaviours



Total monthly streamflow

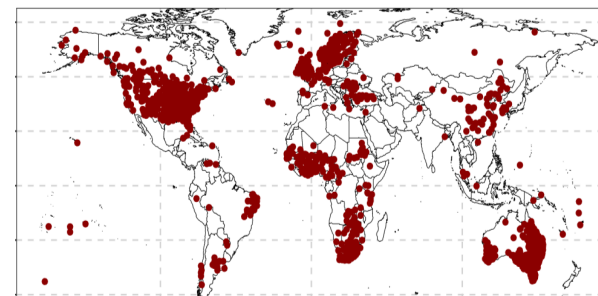
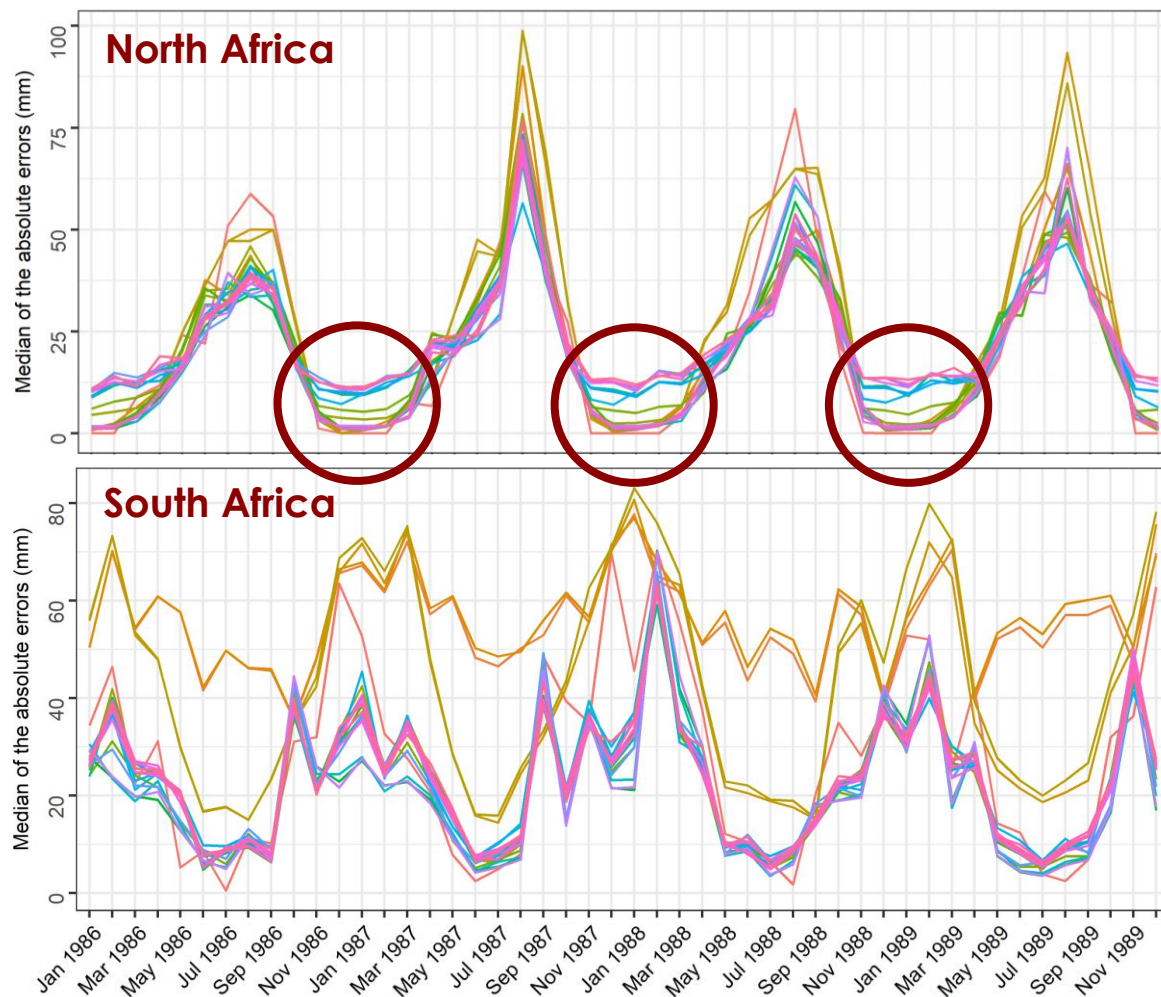
Hydrological modelling blueprint by Montanari and Koutsoyiannis (2012)



Original data source: Schaake et al. (2006)

Further reading: Papacharalampous et al. (2020)

Towards analysis-informed prediction frameworks



Total monthly precipitation

Forecasting method



North Africa

Medians of the Nash Sutcliffe efficiency values

Minimum: 0.49
Maximum: 0.71

South Africa

Medians of the Nash Sutcliffe efficiency values

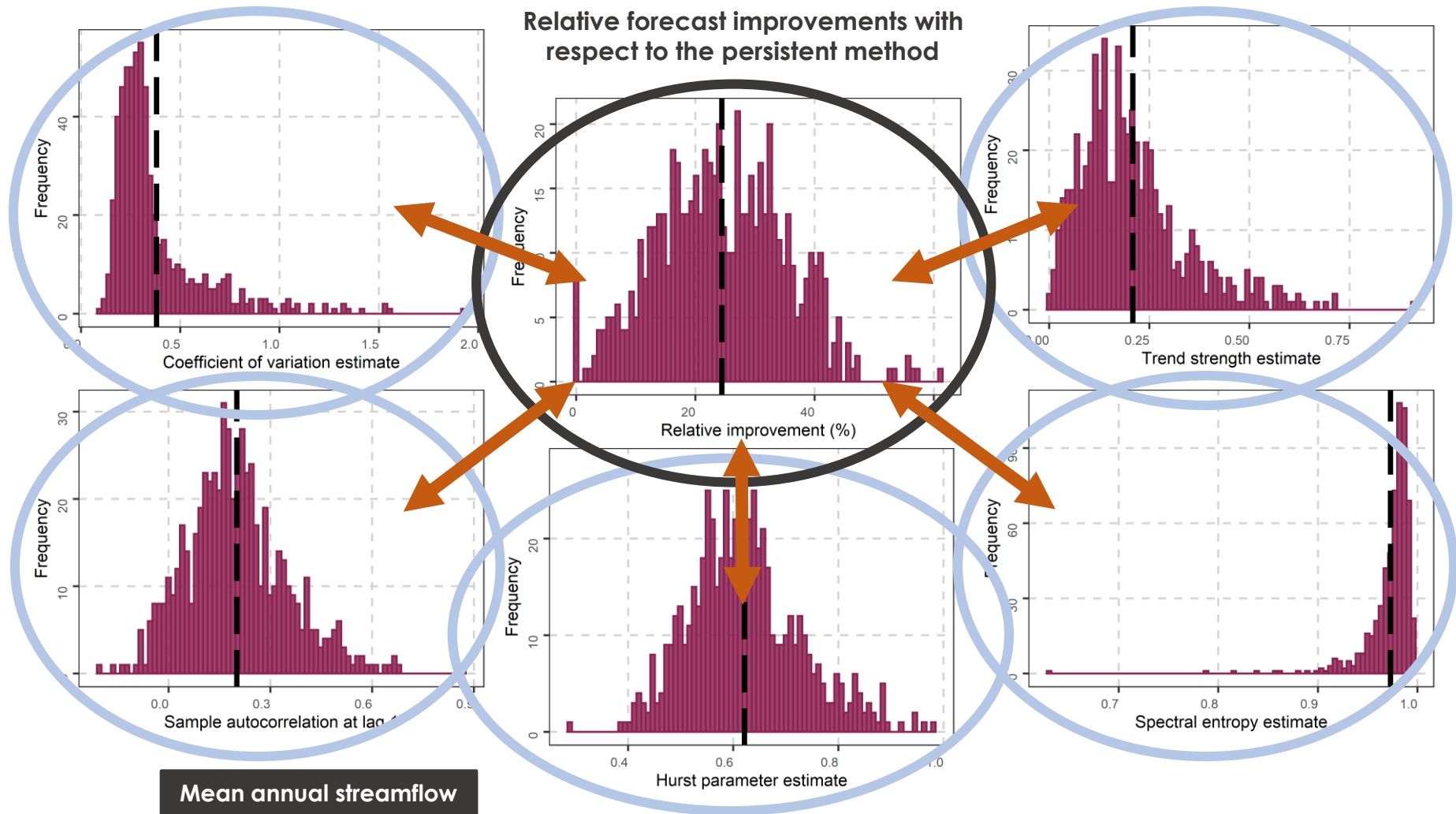
Minimum: -0.20
Maximum: 0.30

Further reading: Papacharalampous et al. (2018b)

Original data source: Peterson and Vose (1997)

Towards analysis-informed prediction frameworks

Benefitting from diverse inferred features



Original data source: Do et al. (2018)

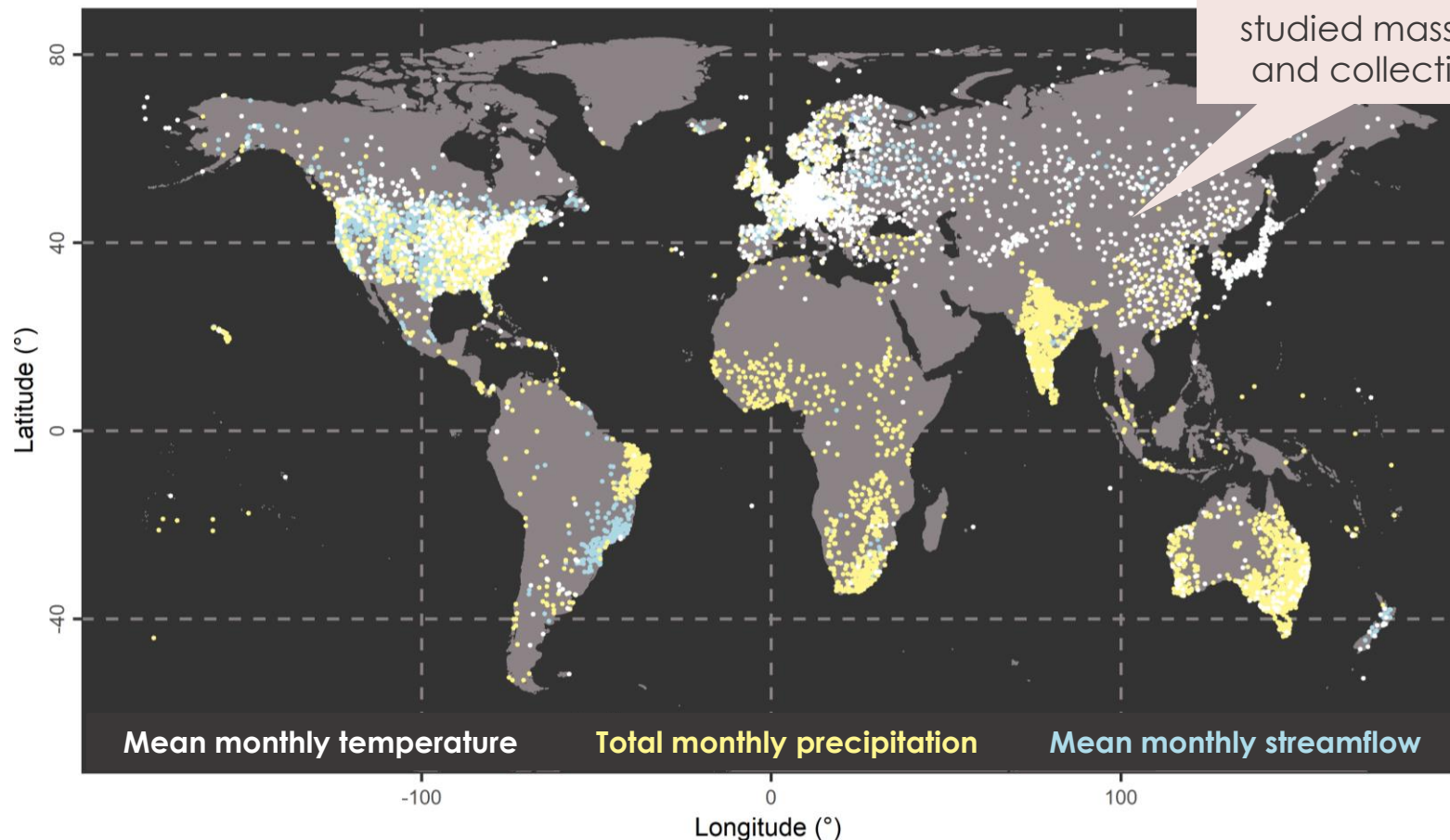
Further reading: Papacharalampous and Tyralis (2020)

Towards analysis-informed prediction frameworks

Benefitting from approximately 60 diverse inferred features

Further reading: Papacharalampous et al. (2021)

Features should be studied massively and collectively

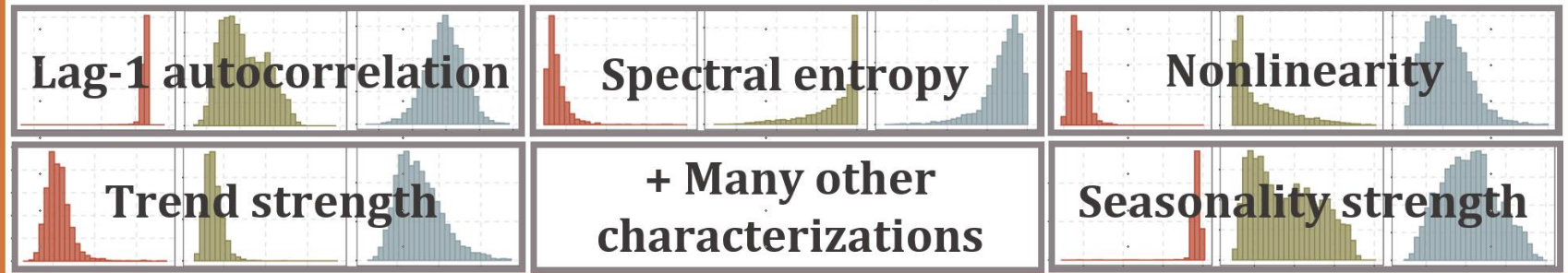


Original data sources: Peterson and Vose (1997), Menne et al. (2018), Do et al. (2018)

Towards analysis-informed prediction frameworks

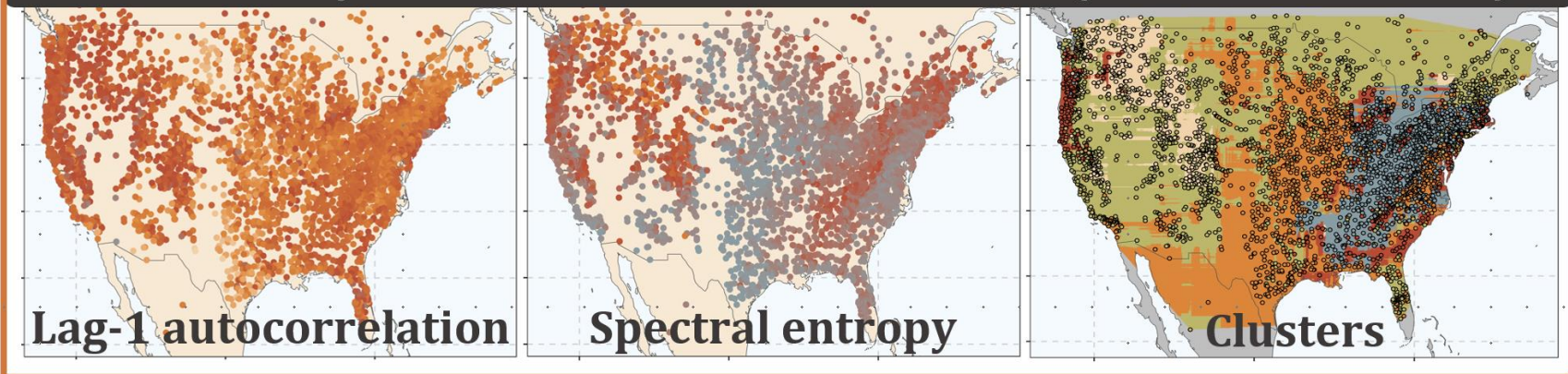
Further reading: Papacharalampous et al. (2021)

Global-scale characterization of monthly hydroclimatic time series



Spatial patterns and feature-based hydroclimatic time series clustering

Mean monthly streamflow across North America (+ other case studies)



Original data sources: Peterson and Vose (1997), Menne et al. (2018), Do et al. (2018)

Take-home messages

- Explorations of the **mysteries of hydroclimatic variability and change** from a predictive perspective can complement well explorations of the same mysteries from a descriptive perspective (and vice a versa).
- As long as their outputs are useful, prediction models do not have to be (but they can be) **interpretable**.
- There is no certainty and **“no free lunch”** in predictive modelling.
- **Large-scale benchmarking** and **ensemble learning** are ways to cope with this fact in a meaningful sense.
- By conducting large-scale benchmark tests, we can find:
 - ✓ **which methods perform well** (practically, better than others) in the long run; and
 - ✓ **which features are important** (practically, more important than others) for getting good predictions in the long run.
- An interesting example is **methods with trends**.
- Such methods are getting much attention in the hydrological literature; however, they do not offer improvements (as individual methods) in terms of predictive performance.

Take-home messages

- Selecting individual prediction methods is meaningful; however, preferably **multiple methods** should be integrated and combined for **maximizing the benefits** and **reducing the risks** from their use.
- Methods that would probably be discarded as individual ones based on their performance in the long run (e.g., methods with trends or naïve methods) might be proven important as parts of **ensemble methods**.
- The forecasts of **diverse methods** seem to complement themselves well in **forecast combination** contexts.
- Further improvements could be achieved through **analysis-informed combinations** and **analysis-informed integrations** of many and diverse prediction models.
- For achieving meaningful combinations and integrations in this regard, **many and diverse descriptive features** should be studied.
- A massive and collective examination of **hydroclimatic features** is also necessary for understanding **hydroclimatic variability and change**.
- Particular focus on a single feature (e.g., trends) could be misleading in **hydroclimatic time series analysis** contexts.

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