National Centre for Atmospheric Science
NATURAL ENVIRONMENT RESEARCH COUNCIL

University of Reading

Evaluation of sub-seasonal precipitation forecasts for Africa

Felipe M. de Andrade

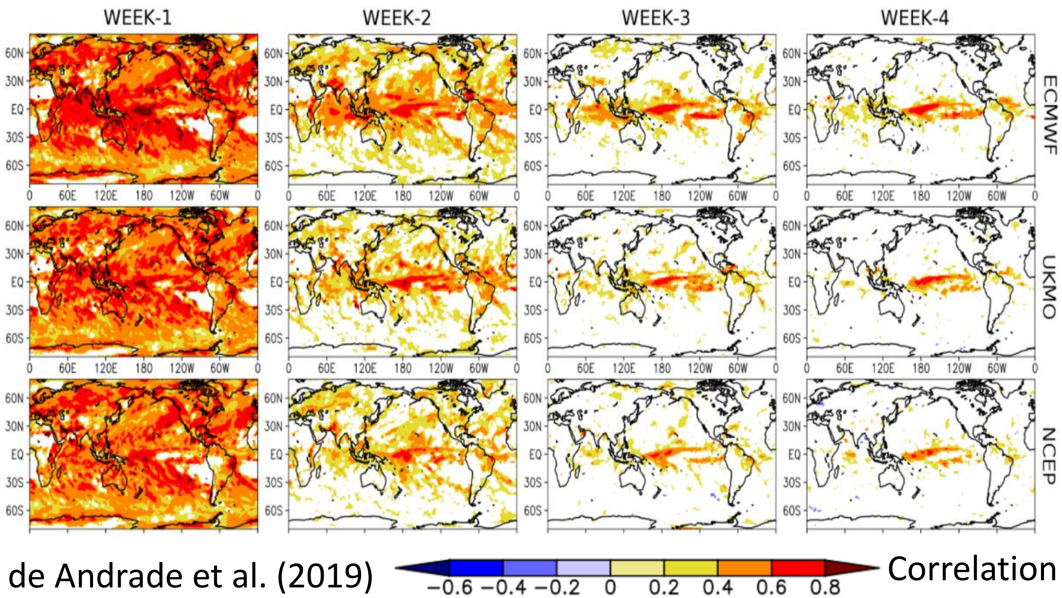
Acknowledgements: Matthew Young, Dave MacLeod, Linda Hirons, Steven Woolnough and Emily Black

2020 International Verification Methods Workshop Online (2020-IVMW-O)
S2S, S2D, Climate session
18-11-20

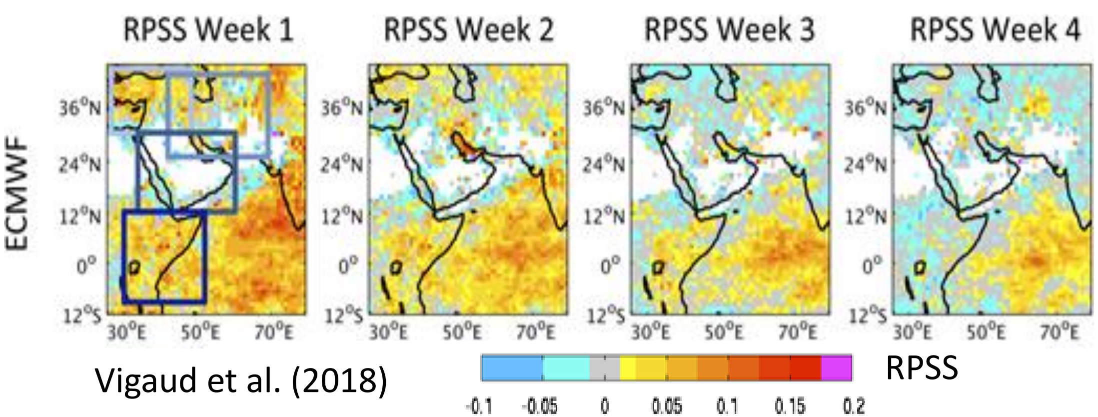
GCRF Global Challenges Research Fund
RESEARCH COUNCILS UK

GCRF African SWIFT

Sub-seasonal precipitation forecast quality assessment: Background



de Andrade et al. (2019)



Vigaud et al. (2018)

Key points

- Skill reduction with increasing lead time
- After 2 weeks lead: more skilful forecasts over tropical oceanic regions

Motivation

Few studies have assessed sub-seasonal rainfall forecast quality over Africa (e.g., Olaniyan et al. 2018; Vigaud et al. 2018) → only regional evaluation

- Lack of a comprehensive assessment of sub-seasonal rainfall forecast quality for Pan-Africa:

Different attributes and a variety of metrics (Coelho et al. 2018)

- The contribution of potential climate drivers in modulating forecast quality also deserves an investigation.

Datasets: S2S hindcasts and GPCP precipitation

Model	Forecast length	Spatial resolution	Hindcast frequency	Hindcast period	Ensemble size	Ocean coupled	Sea-ice coupled
ECMWF	46 days	Tco639/319L91	Two per week	Past 20 years	11	Yes	No
UKMO	60 days	N216 L85	Four per month	1993-2016	7	Yes	Yes
NCEP	44 days	T126 L64	Daily	1999-2010	4+3*	Yes	Yes

*Three more perturbed members, extracted from 1-day lag after initializations, were added to the NCEP ensemble size.

-Four start dates per month: 1st, 9th, 17th, 25th

-Weekly accumulation:
days 5–11 (Week 1), 12–18 (Week 2), 19–25 (Week 3) and 26–32 (Week 4).

-Hindcasts verified against GPCP precipitation: Pan-Africa and selected regions

Forecast quality assessment: Metrics and drivers' contribution

Part 1

- Deterministic and probabilistic forecasts: variety of metrics and attributes

Metrics were computed for each model and weekly lead time using start dates falling within:

DJF, MAM, JJA, SON (common period: 1999-2010)

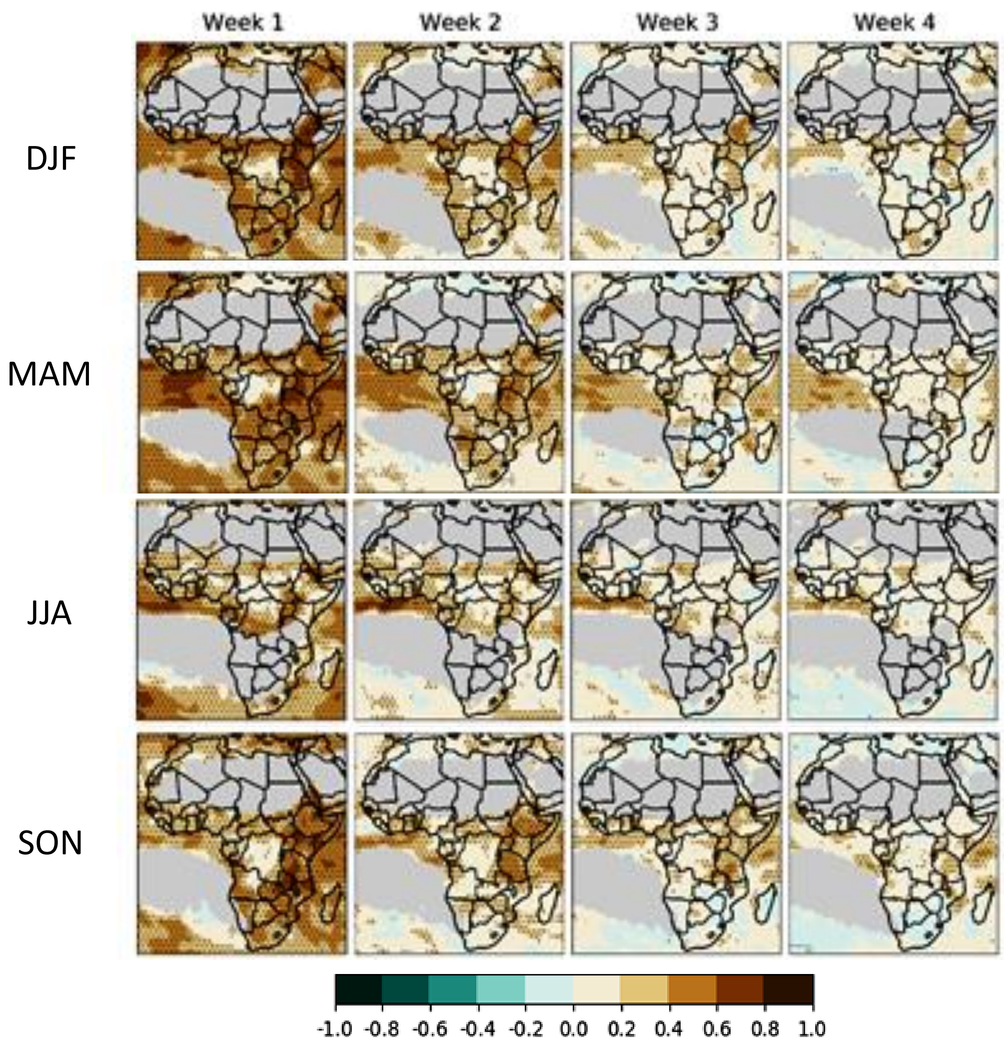
Part 2

- Drivers' modulation forecast quality (ENSO, IOD, and the MJO)

Association between OBS and hindcasts after removing driver-related regression patterns

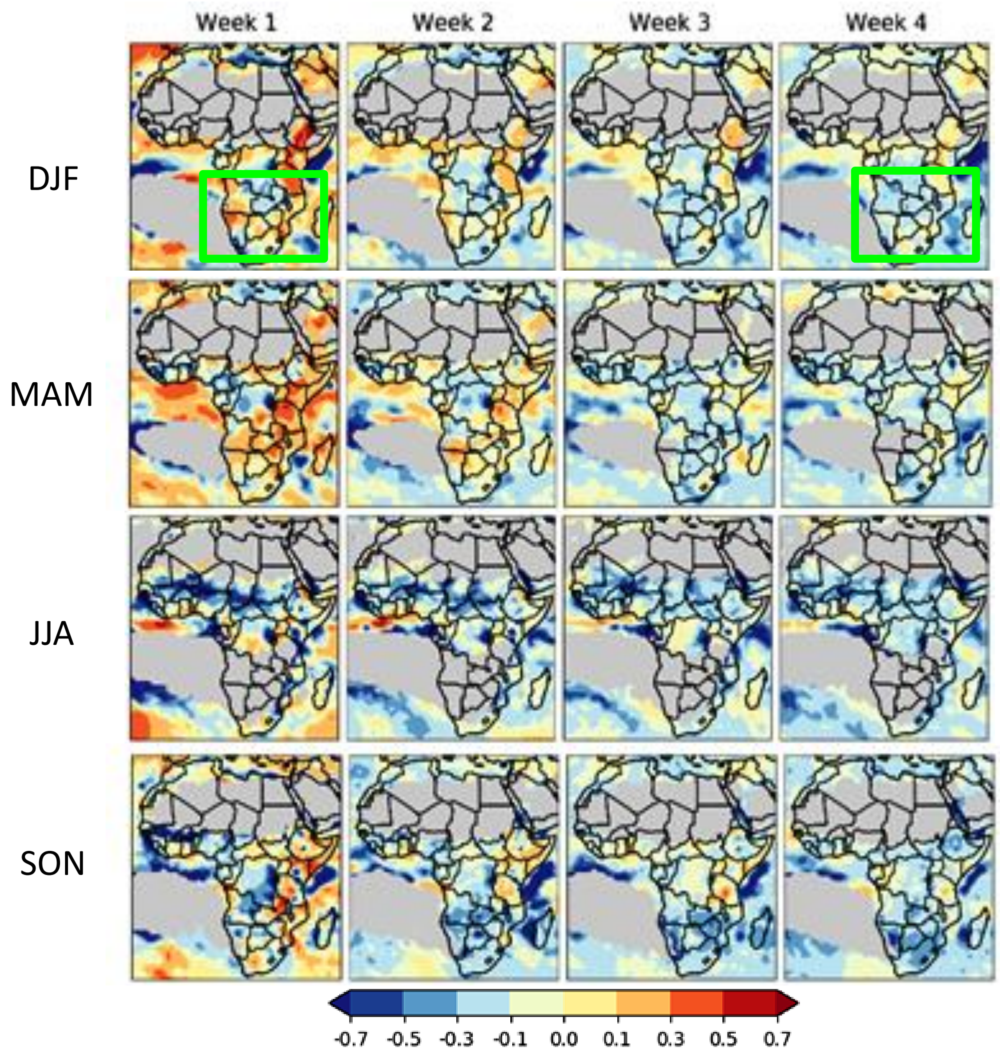
Calibrated forecasts: adding observed regression patterns to hindcasts

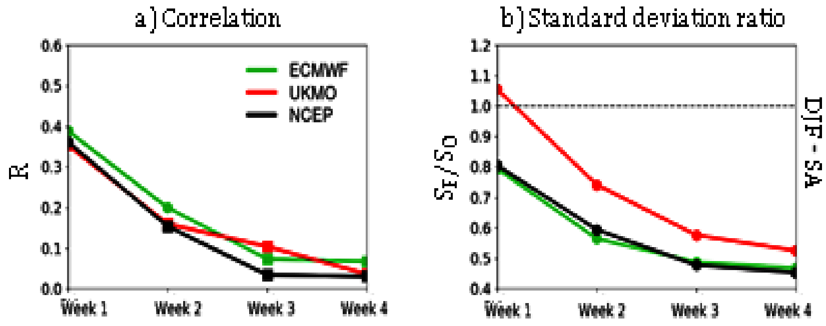
Deterministic forecast evaluation: Correlation (ECMWF x GPCP)



- Highest association for Week 1, reducing with increasing lead time
- Significant scores near the equator after Week 2

Deterministic forecast evaluation: MSSS (ECMWF x GPCP)

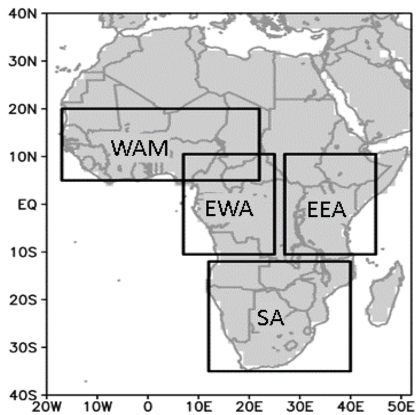




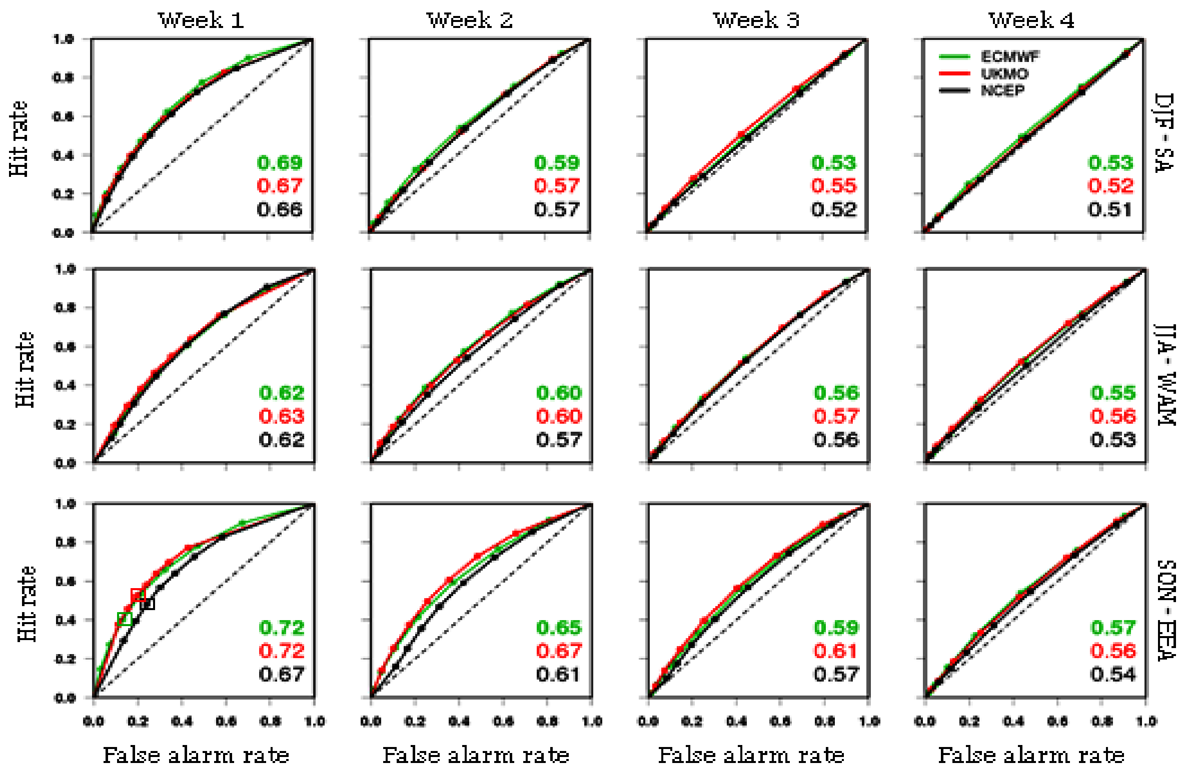
MSSS < 0 (low correlation and/or underestimation of variance)

Probabilistic forecast evaluation: ROC curve and AUC (coloured numbers)

African regions



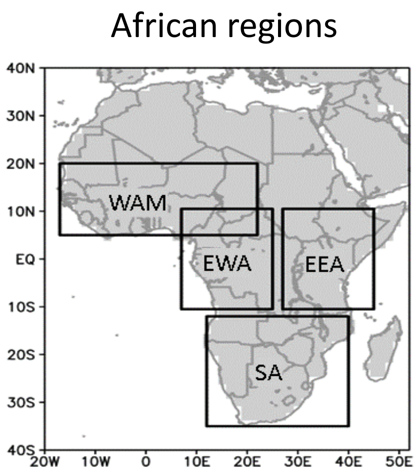
Upper tercile



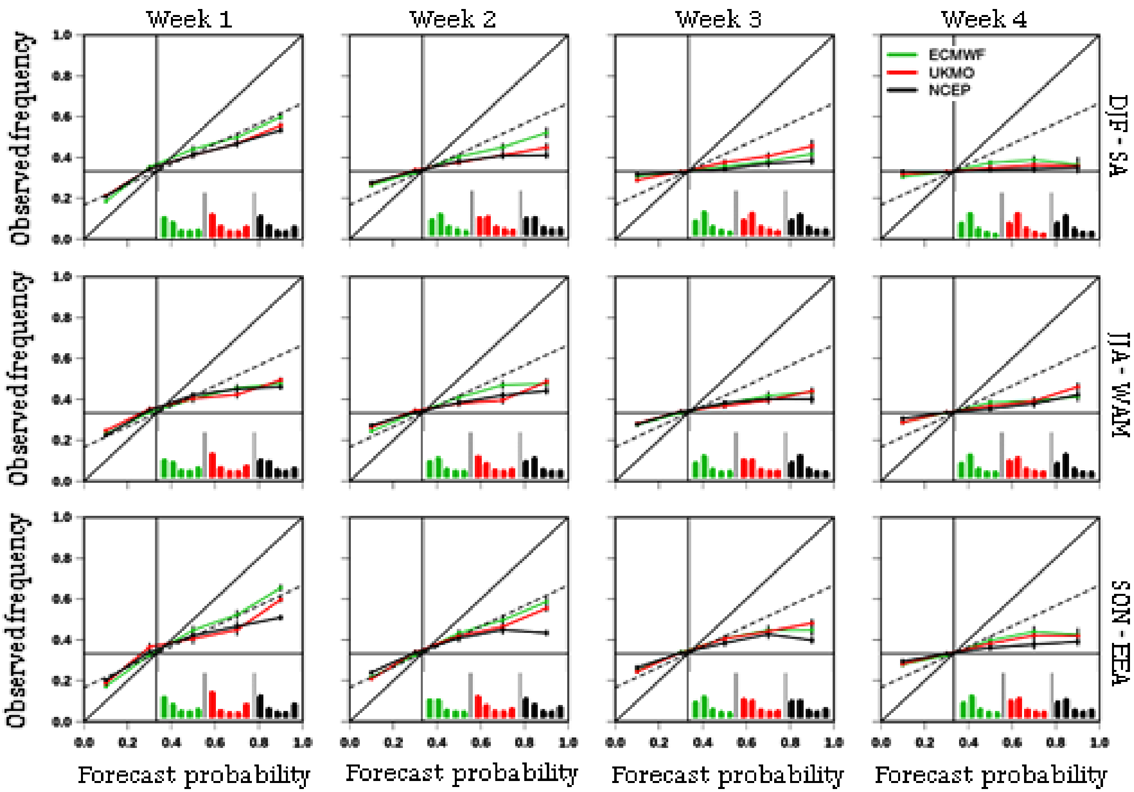
- Lower tercile: similar characteristics
- No discrimination in the near-normal category (all lead times)

- Clear reduction in discrimination from Weeks 1-2 to the following weeks
- Consistent with the reduction of forecast quality seen in other metrics

Probabilistic forecast evaluation: Attributes diagram



Upper tercile

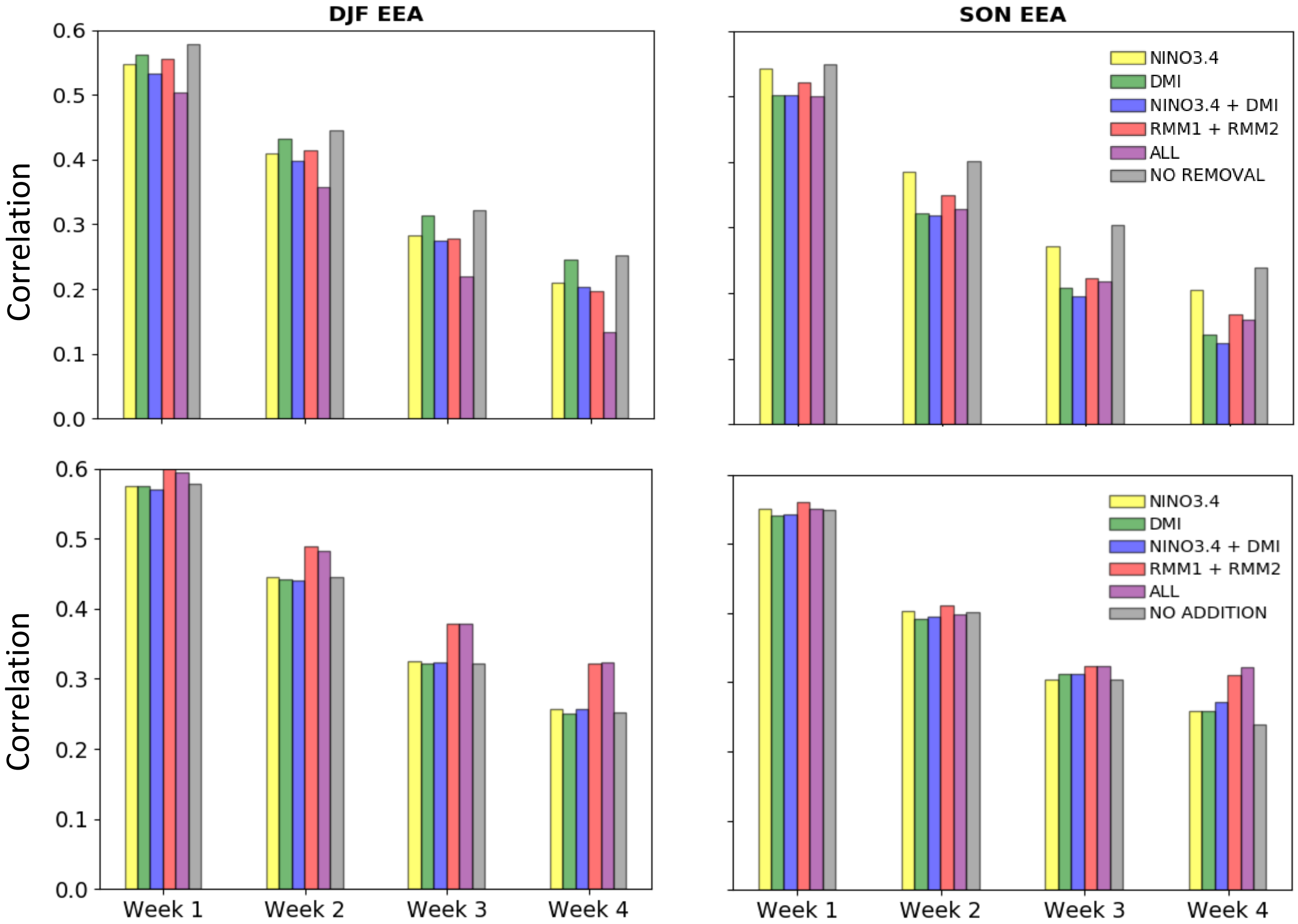


- After two weeks lead: maximum frequencies appearing around climatological frequency

- Better quality in Weeks 1-2, with slightly enhanced skill (above dashed line) for ECMWF over EEA and SA in Week 1

Overconfidence in all weeks

Drivers' modulation of forecast quality



Removing driver-related regression patterns

Adding observed driver-related regression patterns

Summary and conclusions

- Deterministic and probabilistic forecast assessments indicated reasonable agreement: Overall, better quality for ECMWF and East Africa

- Unskilful predictions were linked to low forecast association and/or large underestimation of predicted variance: Large amplitude and phase errors

- Overconfidence increased forecasting errors, inducing more unskilled forecasts, especially beyond two weeks lead: Need to apply calibration to obtain more reliable forecasts (e.g., using MOS)

- Despite identifying significant associations (particularly with the MJO), drivers could not account completely for the overall forecast quality: Need to assess other sources of predictability and improve drivers' representation within S2S models.

- Help forecasters identify regions, seasons and lead times with best forecast skill and support adequate use of sub-seasonal predictions: guide for forecast evaluation in Africa

National Centre for Atmospheric Science
NATURAL ENVIRONMENT RESEARCH COUNCIL

University of Reading

Thank you

Paper under review

de Andrade FM, Young MP, MacLeod D, Hirons LC, Woolnough SJ, and Black E (2020) Sub-seasonal precipitation prediction for Africa: Forecast evaluation and sources of predictability. Weather and Forecasting

National Centre for Atmospheric Science
NATURAL ENVIRONMENT RESEARCH COUNCIL

University of Reading

REFERENCES

Coelho, C. A. S., M. A. F. Firpo, and F. M. de Andrade, 2018: A verification framework for South American sub-seasonal precipitation predictions. *Meteorol. Z.*, **27**, 503-520.

de Andrade, F. M., C. A. S. Coelho, and I. F. A. Cavalcanti, 2019: Global precipitation hindcast quality assessment of the Subseasonal to Seasonal (S2S) prediction project models. *Cli Dyn.*, **52.,** 5451-5475

Olaniyan E, Adefisan EA, Oni F, Afiesimama E, Balogun AA, Lawal KA (2018) Evaluation of the ECMWF sub-seasonal to seasonal precipitation forecasts during the peak of West Africa monsoon in Nigeria. Front Environ Sci 6:4

Vigaud, N., M. K. Tippett, and A. W. Robertson, 2018: Probabilistic Skill of Subseasonal Precipitation Forecasts for the East Africa–West Asia Sector during September–May. *Wea. Forecasting*, **33**, 1513-1532