Decadal prediction of Sahel rainfall using dynamics-based indices

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LATMOS

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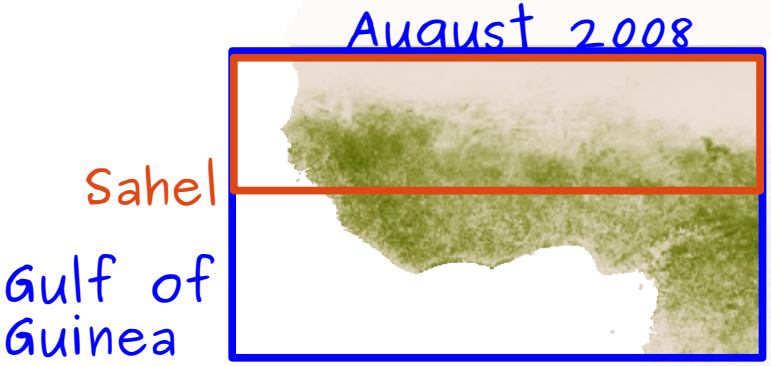
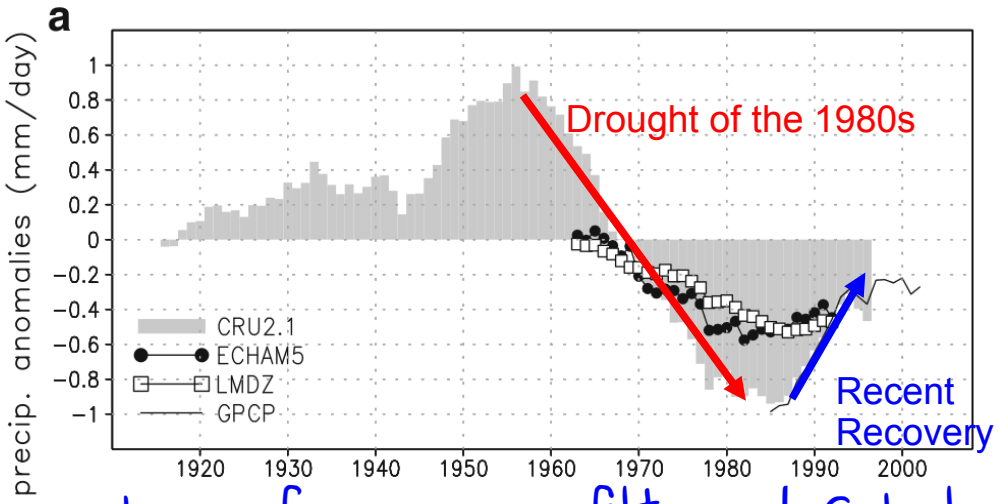
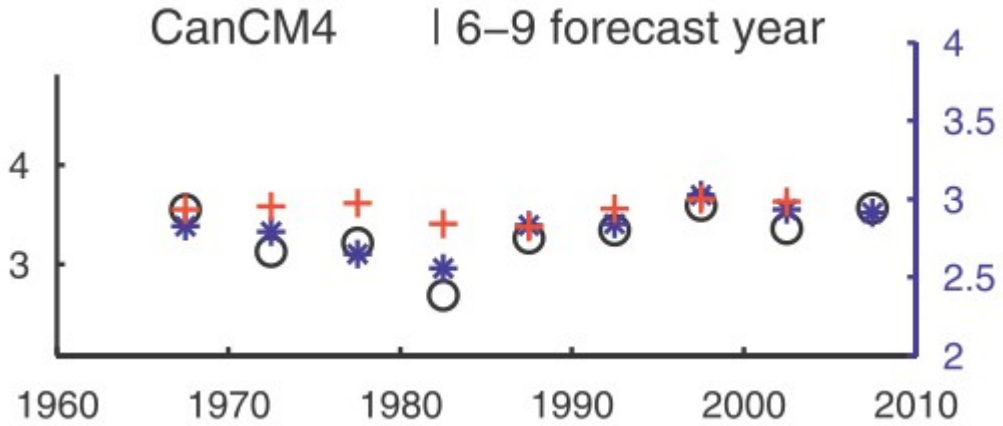
Sahel rainfall has shown marked decadal variability:



NDVI (Normalized Difference Vegetation Index)
Source: NOAA View Data Imagery Portal



Low-frequency filtered Sahel summer rainfall



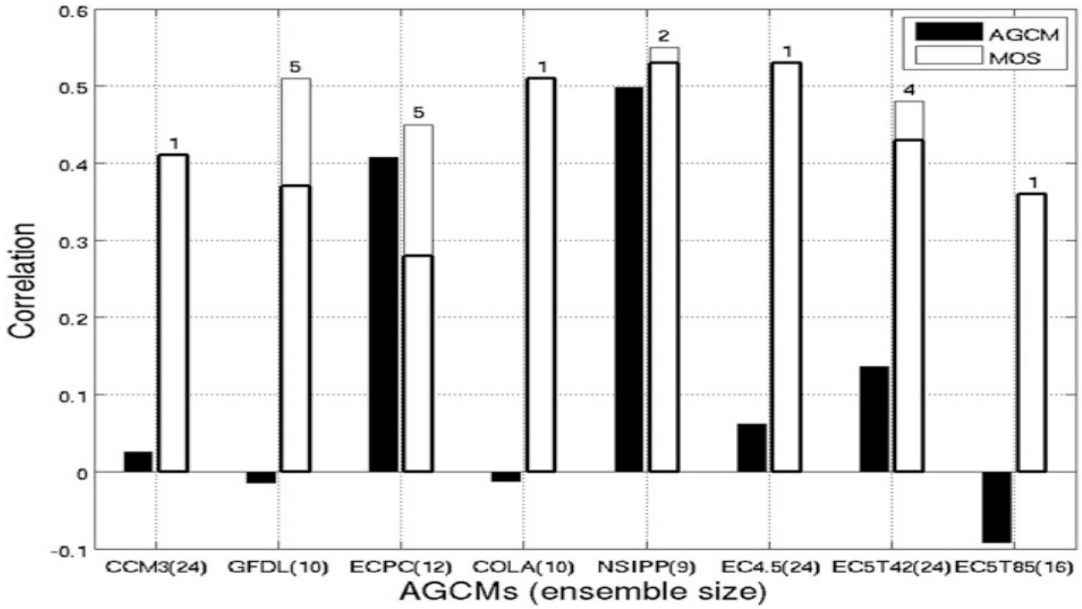
Some models are skilful in predicting Sahel rainfall variability (Gaetani and Mohino 2013; Martin and Thorncroft 2014)

Averaged 4-year rainfall summer anomalies for observations (circles), and initialized (stars) and non-initialized (crosses) CanCM4 simulations

Gaetani and Mohino (2013)

Up to now, all studies on decadal rainfall prediction in the Sahel have focused on GCM rainfall outputs.

However, GCMs are known to be typically more skilful in reproducing the variability of atmospheric dynamic variables rather than rainfall over West Africa.



Correlation between observed Sahel rainfall (1968–2001) and simulated AGCM Sahel rainfall (filled bars) and after applying a MOS to u at 925 hPa

Ndiaye et al. (2011)

Could we predict Sahel rainfall trends some years ahead using dynamics-based indices?

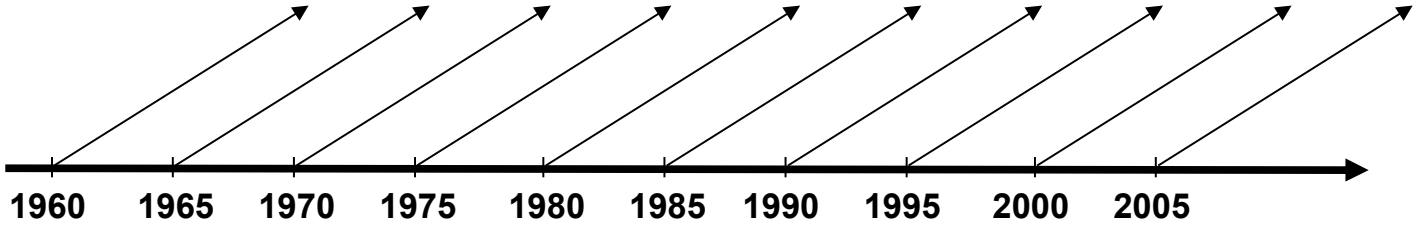
Aim of the work:

- Study the skill of CMIP5 decadal hindcasts in predicting Sahelian summer (JAS) rainfall USING dynamics-based indices
- Evaluate the additional skill coming from the initialization

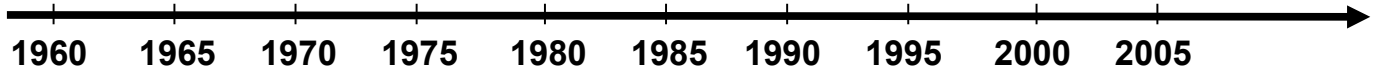
Data

CMIP5 simulations (14 models, range 3 to 10 ensemble memmbers)

- ***Decadal hindcasts*** (all forcings, including volcanoes, ***initialized***)



- ***Historical*** (all forcings, including volcanoes, ***no initialization***)



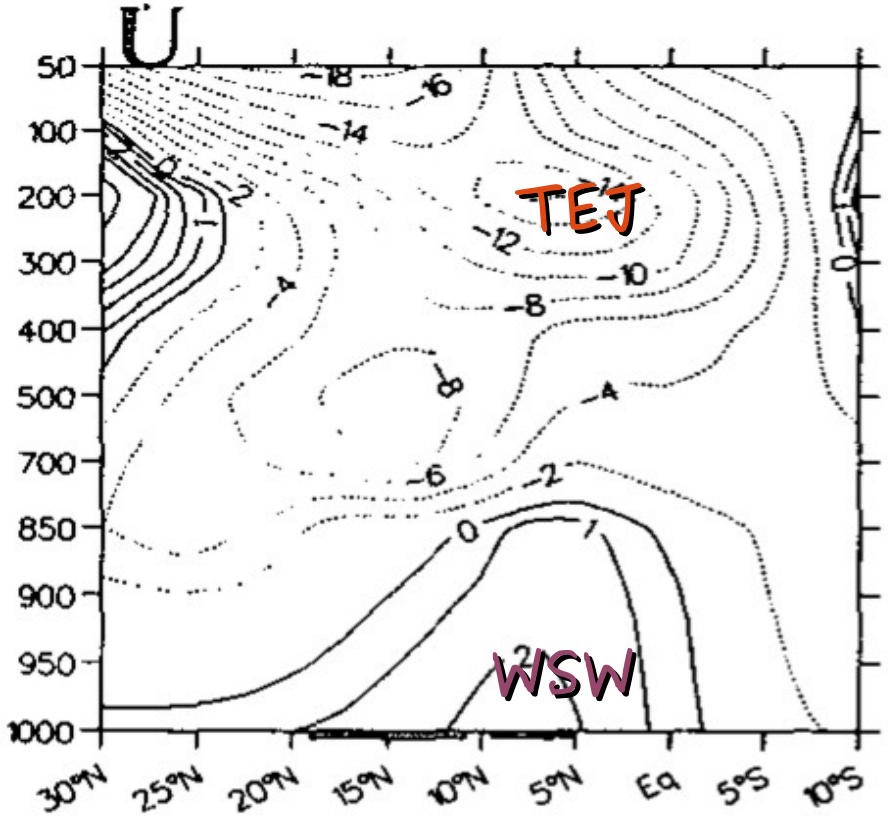
Observations

- CRU-TS3.1 dataset 1901-2009 (Harris et al. 2014)
- GPCP dataset 1979-present (Adler et al. 2003)
- ERA40 (Uppala et al. 2005)
- NCEP/NCAR Reanalysis (Kalnay et al. 1996)

Methods

We tested the potential of using wind fields for decadal prediction of Sahel rainfall

- Westerly surface winds (WSW)
- Tropical Easterly Jet (TEJ)



Fontaine et al. (1995): Latitude–Pressure profile of zonal winds (m/s) at 0º longitude in August

There is a strong link between winds at low and high levels

Definition of WAM index Fontaine et al. (1995):

WAMI=MOD925−U200
(standardized anomalies)

- WAMI definition independent from rainfall
- WAMI highly related to Sahel rainfall: +TEJ&+WSW → +Sahel rain

Methods

We tested the potential of using wind fields for decadal prediction of Sahel rainfall

There is a strong link between winds at low and high levels

To choose the appropriate region for the WAMI definition, we applied CEOF of MOD925 and U200 in reanalysis and historical sims.

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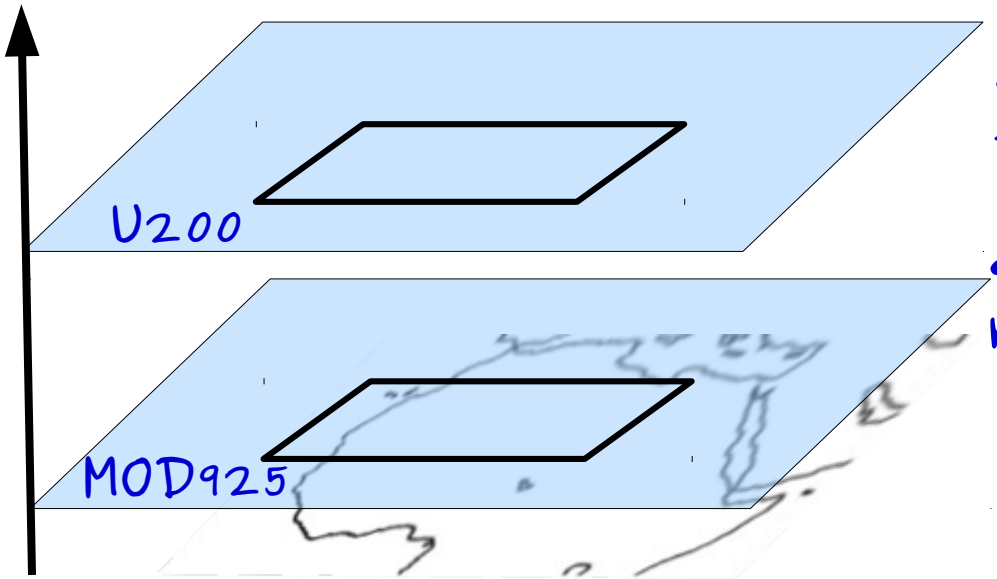

- WAMI definition independent from rainfall
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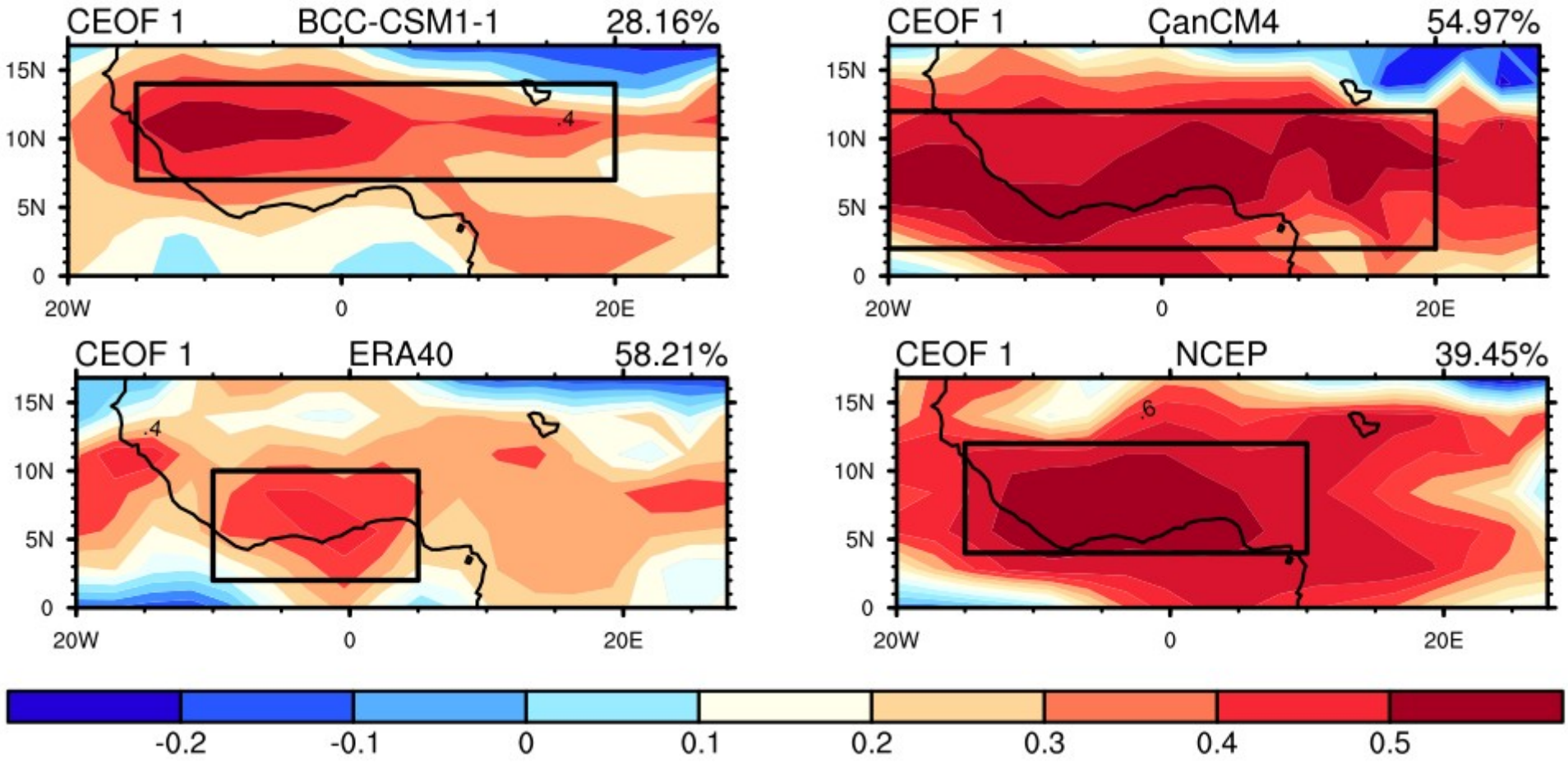
Results

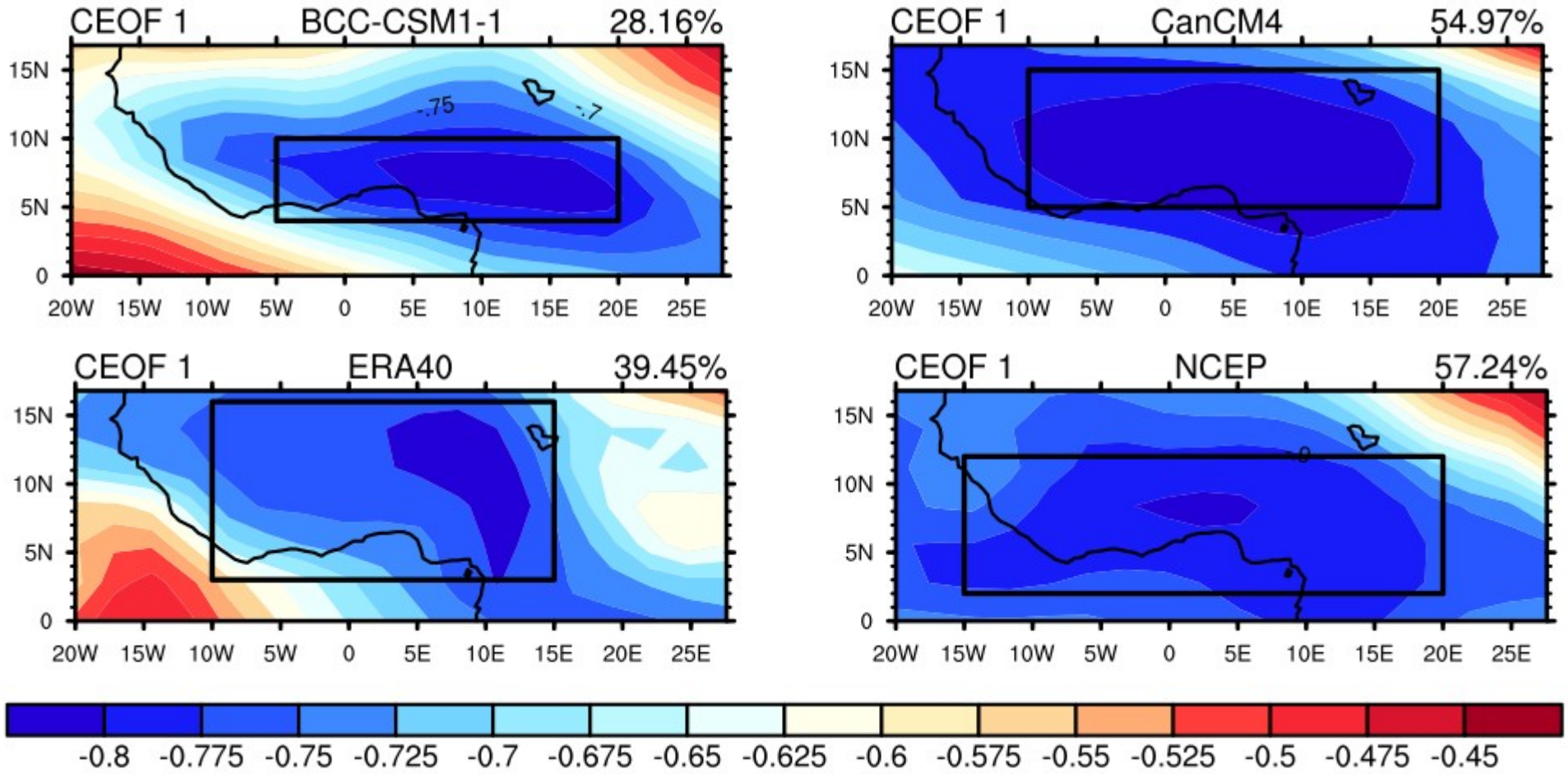
1st mode CEOF correlation patterns: MOD925 hPa



→ Increased low level wind jet

Results

1st mode CEOF correlation patterns: U200 hPa



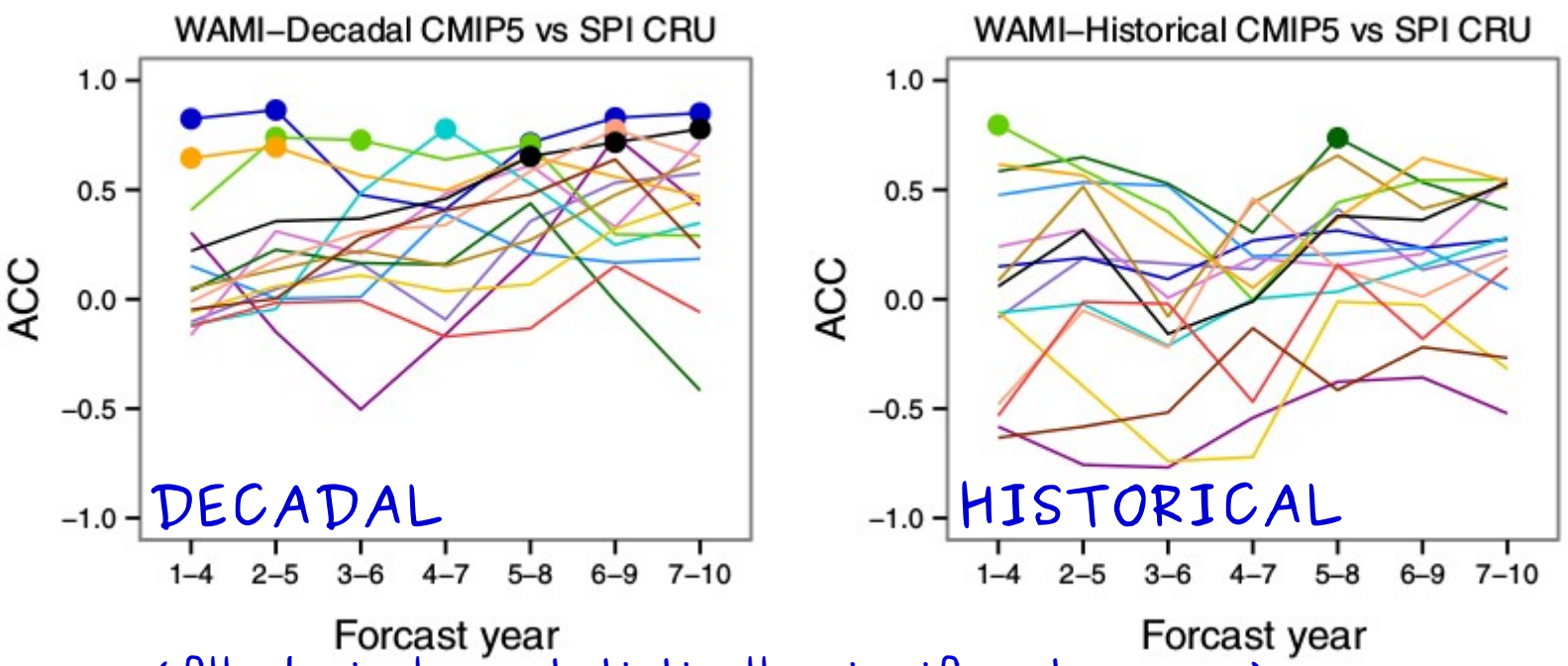
→ Increased tropical easterly Jet

→ Increased low level wind jet

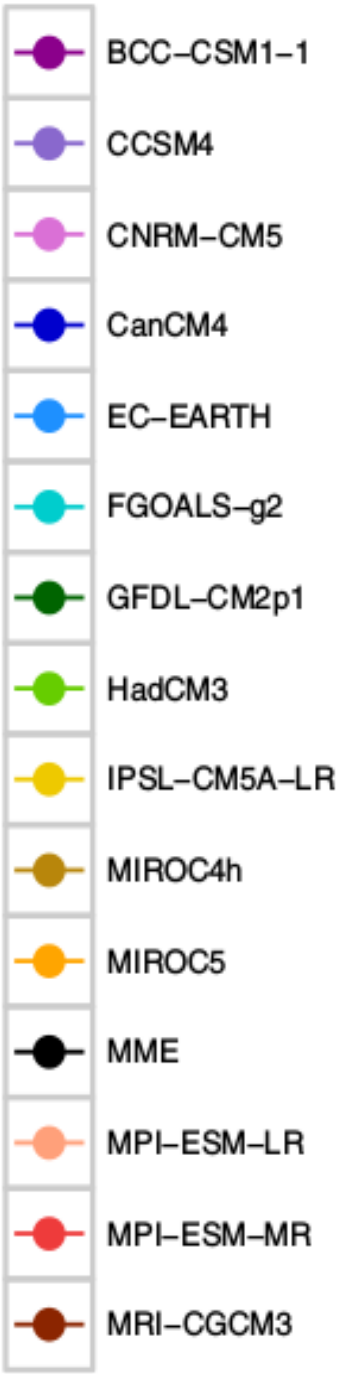
→ Increased Sahel rainfall (obs)

Results

ACC scores between WAMI from models and observed Sahel precipitation index (SPI: 10N20N–15W15E)



(filled circles: statistically significant $\alpha=0.05$)

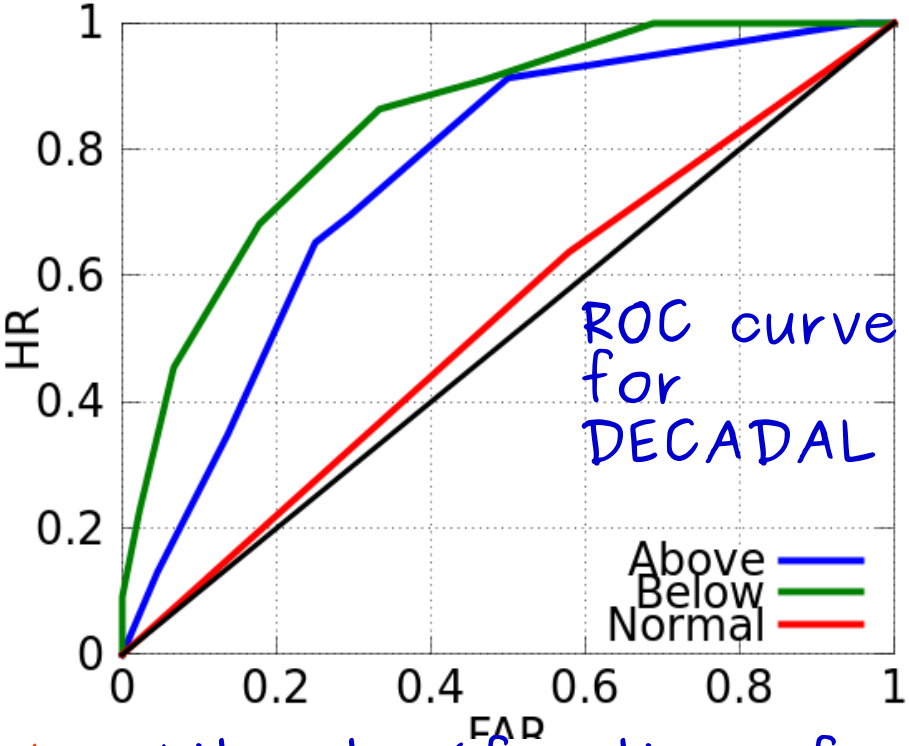


- better scores for decadal (initialized) simulations

- CanCAM4, HadCM3, MIROC5, FGOALS-g2, MPI-ESM-LR, BCC-CSM1-1, MME

Results

Average skill for probabilistic forecasts of three categories (above normal, below normal and normal) for WAMI models tested against SPI observations
(using all 14 models and all 7 lead times at once)



	Decadal	Hitorical
Above (A)	0.51	0.14
Below (B)	0.69	0.33
Normal (N)	0.06	0.07

ROC scores for the three categories in the decadal and historical sims

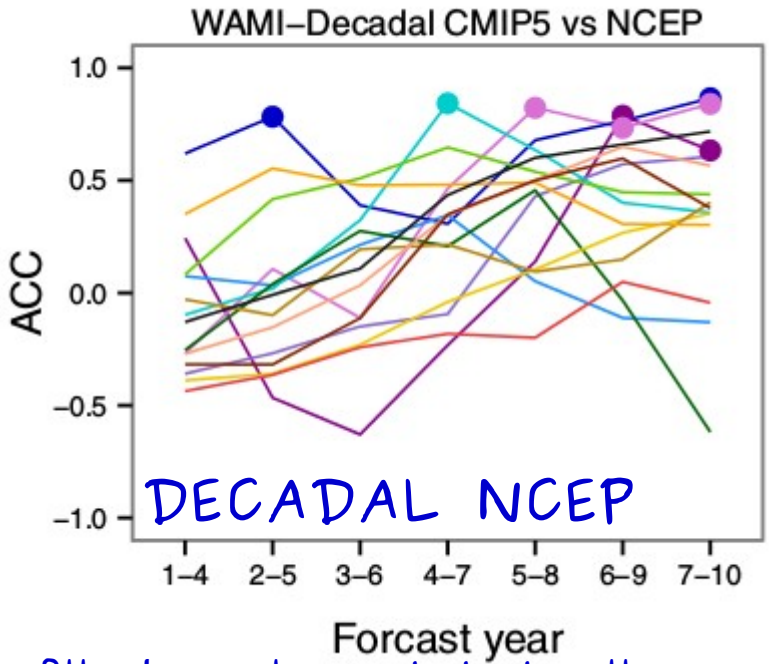
HR: hit rate (fraction of events for which an alarm was rightly issued)

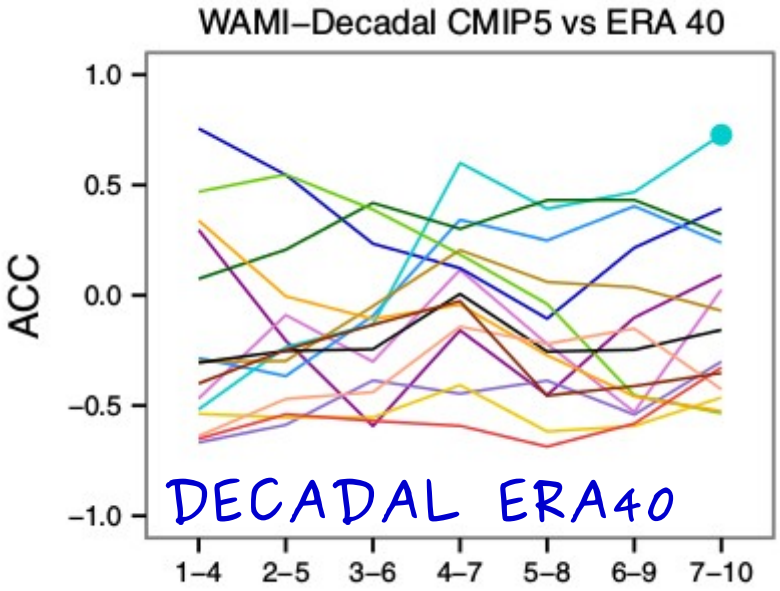
FAR: false alarm rate (fraction of non-events for which an alarm was wrongly issued)

→ better skill for Below than Above
→ better skill for decadal than historical

Results

ACC scores comparing WAMI sim against WAMI "obs"





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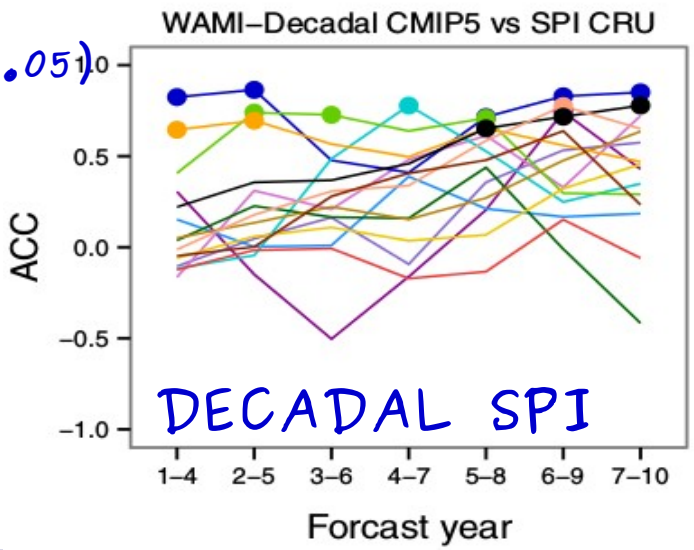
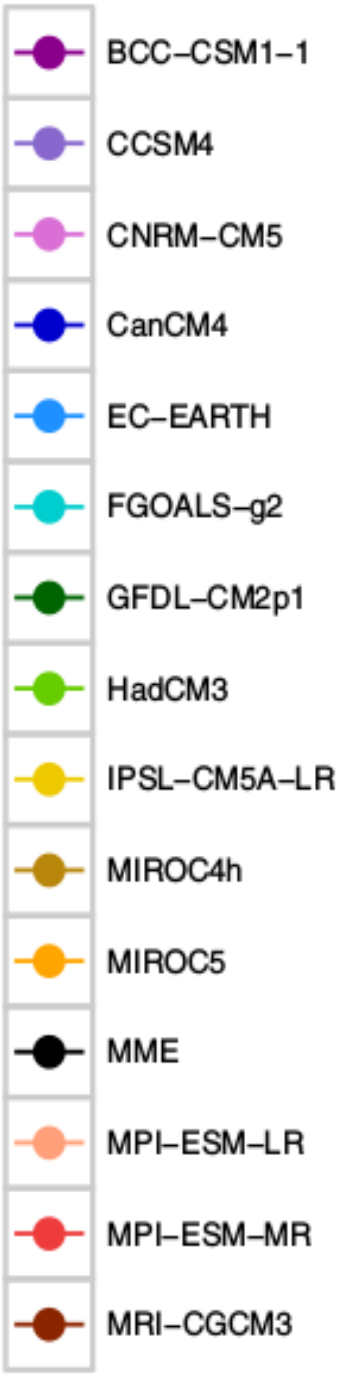


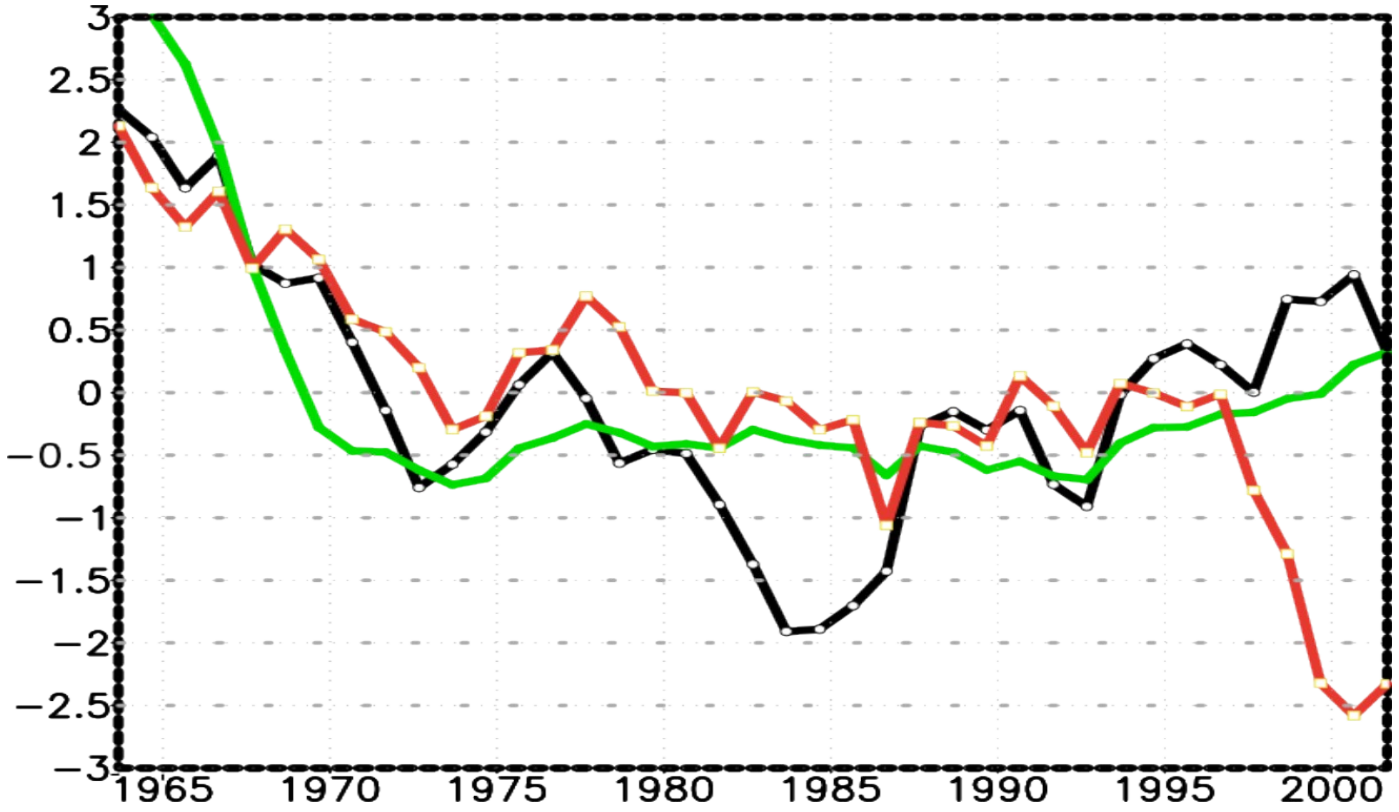


- general decrease in skill with NCEP

- complete loss of skill with ERA40 WHY?

Results

ACC scores comparing WAMI sim against WAMI "obs"



SPI (CRU, black)

MOD925 NCEP (green)

MOD925 ERA40 (red)

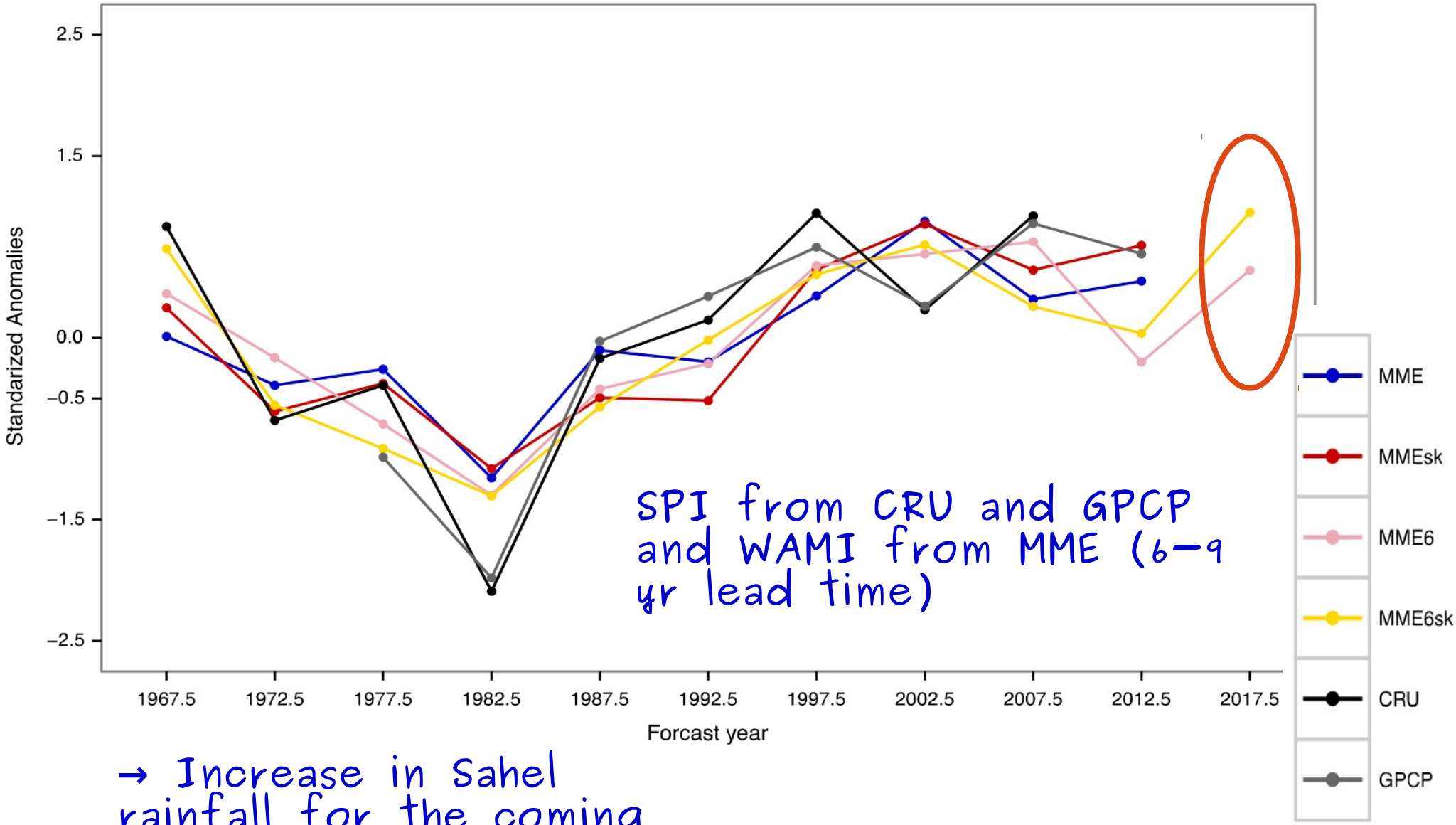
Standardized indices of low-frequency filtered SPI (CRU, black), and MOD 925hPa for NCEP (green) and ERA40 (red)

-complete loss of skill with ERA40 WHY?

Due to the ERA40 representation of low-level winds from 1997 onwards

Results

Sahel rainfall perspectives for 2016–2019



SPI from CRU and GPCP and WAMI from MME (6–9 yr lead time)

→ Increase in Sahel rainfall for the coming years

Conclusions

-Part of Sahel decadal variability could have been predicted using initialized GCM simulations (decadal simulations)

-The skill of the initialized (decadal) simulations is above the non-initialized (historical) ones both in deterministic and probabilistic forecasts

-The skill of decadal predictions is model dependent

-For some models, using a dynamics-based index instead of the direct output of rainfall can the skill of the decadal predictions → we recommend a two-fold approach

-Caution should be exercise when using ERA40 dataset for studies of decadal variability

-Perspective for the next coming 4 years (2016-2019) is increased Sahel rainfall w.r.t. the last 4 years (2011-2015)

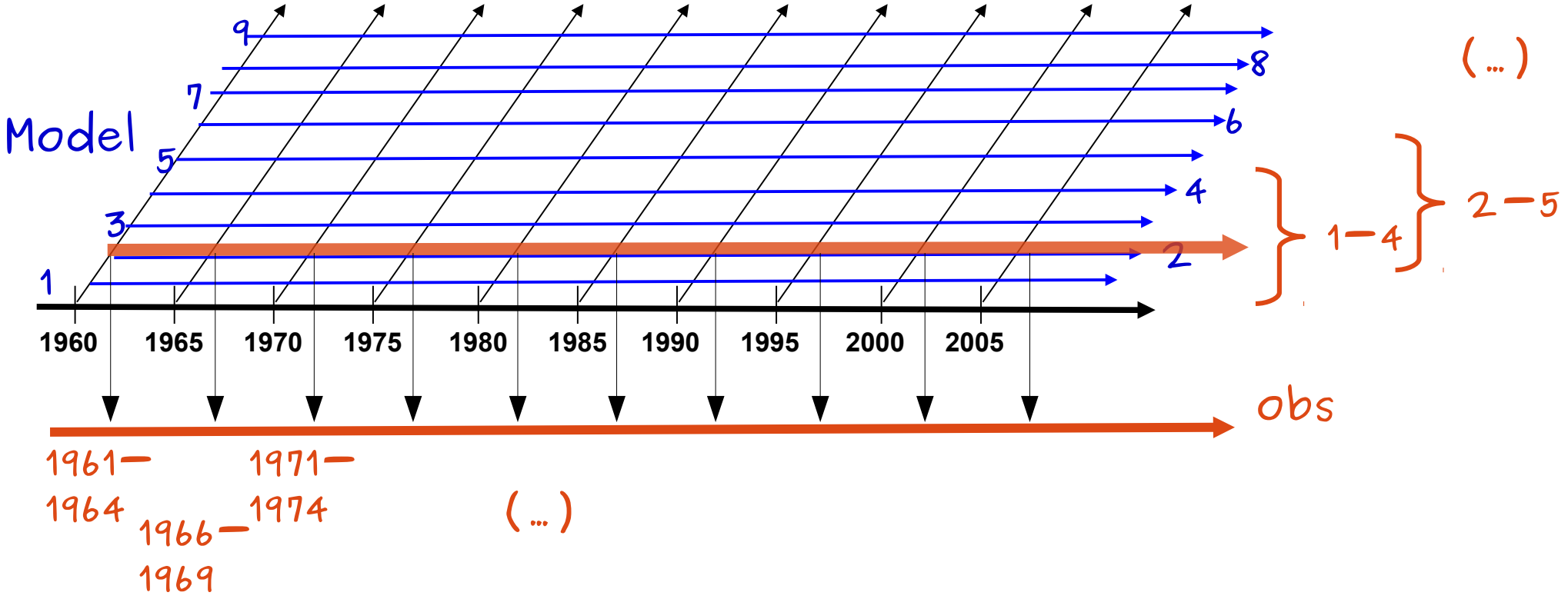
Data

14 Models

Model name	Res.	Decadal	Historical	Initialization
BCC-CSM-1	T42 (~2.8º)	4	3	Full field
CanCM4	T42 (~2.8º)	10	10	Full field
CCSM4	1.25º x 0.9º	10	6	Full field
CNRM-CM5	T127 (~1.4º)	10	10	Full field
EC-EARTH	T159 (~1.125º)	5	4	Full field
FGOALS-g2	2.8º x 3.0º	3	5	Full field
GFDL-CM2.1	2.5º x 2.0º	10	10	Full field
HadCM3	3.75º x 2.5º	10	10	Full field
IPSL-CM5A-LR	3.75º x 1.875º	6	6	Anomaly
MIROC4h	T213 (~0.6º)	3	3	Anomaly
MIROC5	T127 (~1.4º)	6	5	Anomaly
MPI-ESM-LR	T63 (~1.9º)	10	3	Anomaly
MPI-ESM-MR	T63 (~1.9º)	3	3	Anomaly
MRI-CGCM3	T159 (~1.125º)	9	3	Anomaly

Methods

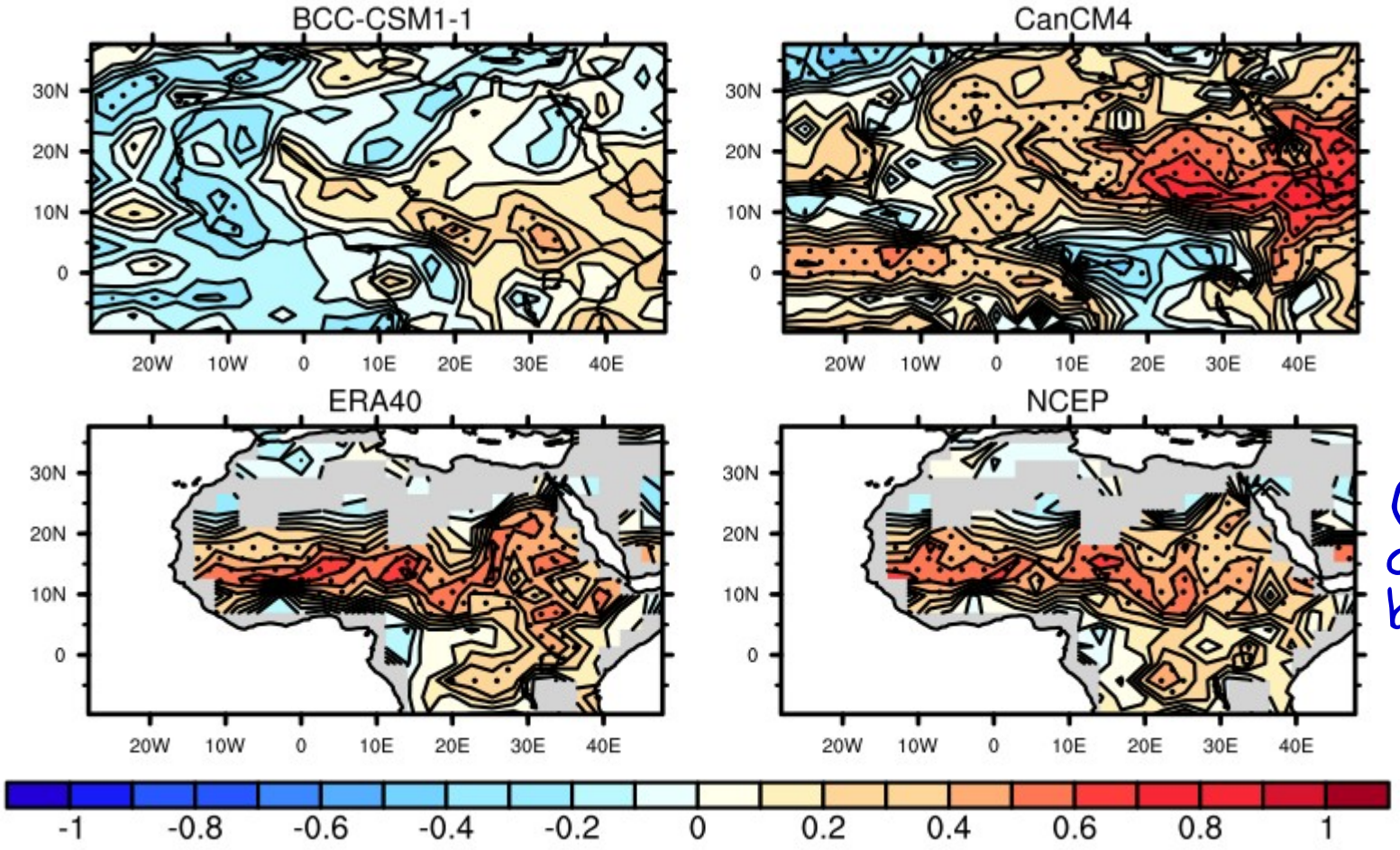
To focus on decadal time scales we average outputs using a 4-year running mean



We apply predictive skill metrics to anomalies defined in the forecast dimension (removing stationary drifts) ACC (Anomaly Correlation Coefficient) and RMSE (Root Mean Square Error). We also test probabilistic forecasts.

Results

1st mode CEOF correlation with rainfall (not used in CEOF analysis)

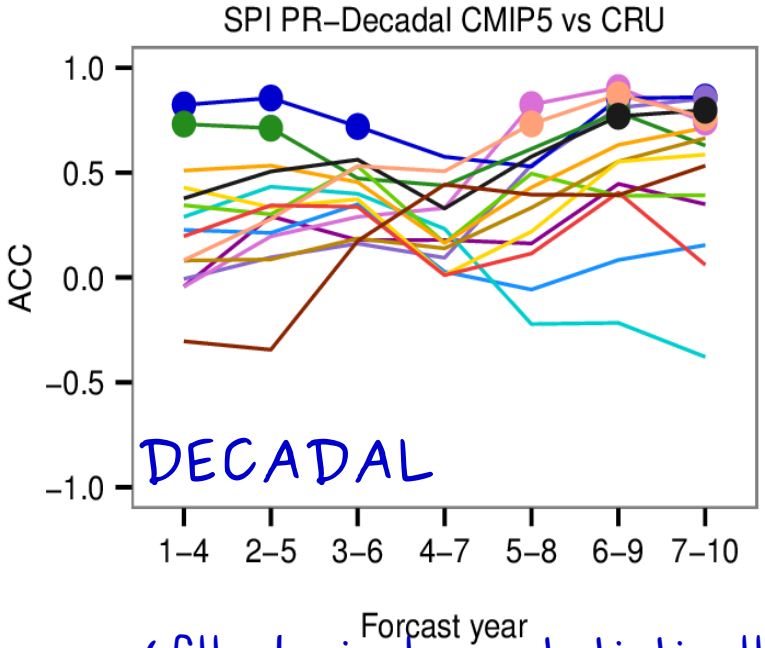


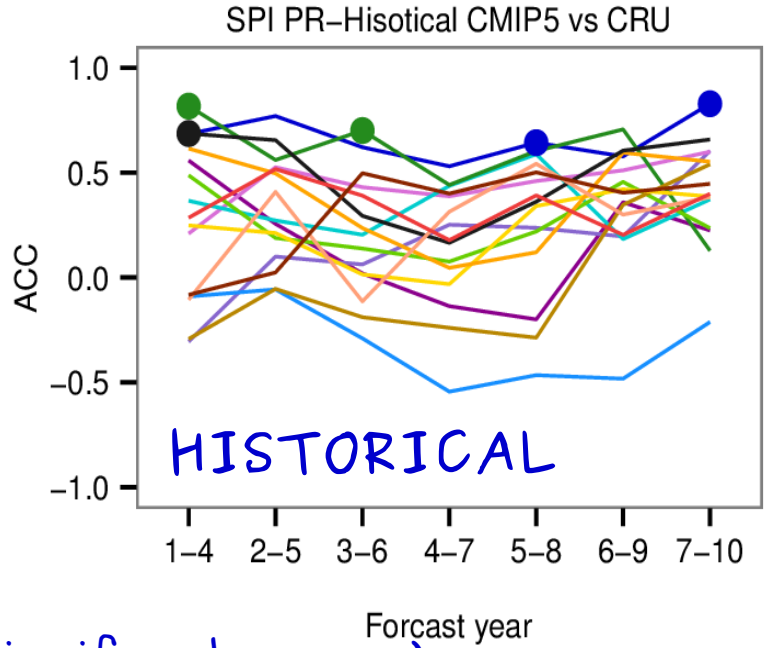
(Using CRU dataset for both)

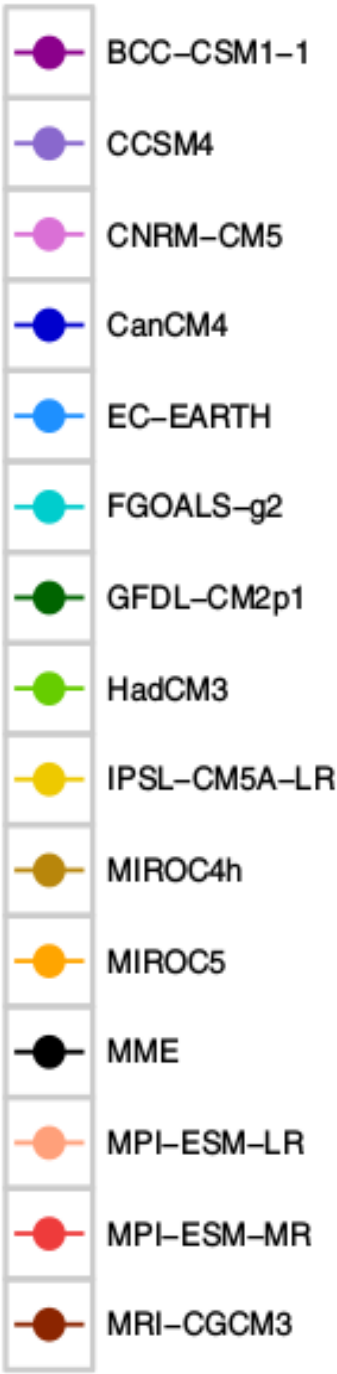
→ PC of first CEOF mode is related to positive Sahel rainfall anomalies

Results

ACC scores for Sahel precipitation index (SPI: 10N20N–15W15E) between model and observations







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Gaetani and Mohino (2013)

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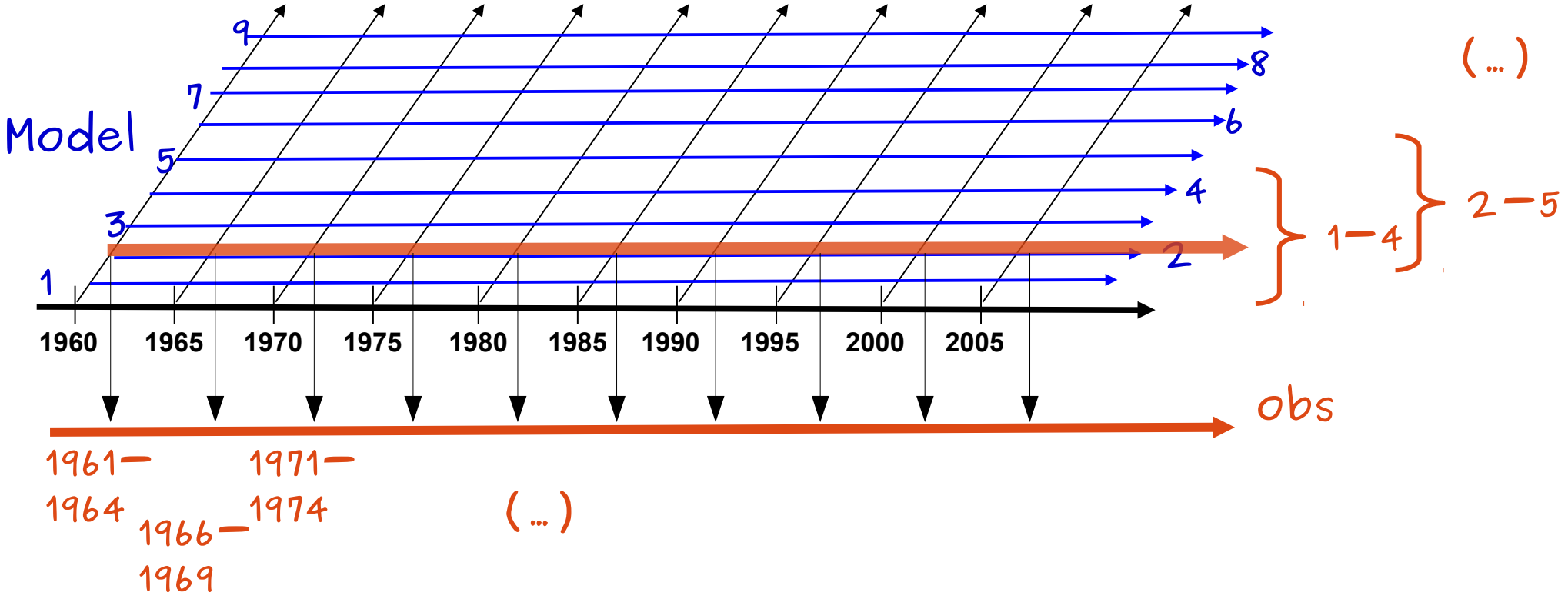

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