Decadal Variability and Predictability of the West African Monsoon and Downstream Atlantic Hurricane Activity

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WAM, SST & Decadal Variability

Atlantic Multidecadal Oscillation

- (a) EOF 1 (31%) of observed LF JJAS rainfall anomalies.
- (b) EOF 1 (67%) of modeled LF JJAS rainfall anomalies.
- (c) Regression of observed LF JJAS rainfall anomalies on observed AMO Index. (d) Regression of modeled LF rainfall anomalies on modeled AMO Index. (e) Modeled Hurricane Shear Index (1958–2000), derived from ERA-40 database. (f) Modeled AMO Index (K), derived from HADISST. (g) Modeled JJAS Sahel rainfall anomalies. (h) Modeled JJAS west central India rainfall anomalies. (i) Modeled PC 1 of LF JJAS rainfall anomalies. (j) Modeled Hurricane Shear Index (1958–2000), derived from ERA-40 database. (k) Light blue lines mark the phase-switch of AMO.

- Figures 2a and 2c are normalized by the SD of observed rainfall. Figures 2b and 2d are normalized by the SD of modeled PC1 (261 mm/month). The modeled EOF1 explains much higher percentage of variance due to modeled PC1 (261 mm/month).

- The observed AMO Index is also in phase with the observed AMO Index. (d) Regression of modeled LF rainfall anomalies on modeled AMO Index. (e) Modeled Hurricane Shear Index (1958–2000), derived from ERA-40 database. (f) Modeled AMO Index (K), derived from HADISST. (g) Modeled JJAS Sahel rainfall anomalies. (h) Modeled JJAS west central India rainfall anomalies. (i) Modeled PC 1 of LF JJAS rainfall anomalies. (j) Modeled Hurricane Shear Index (1958–2000), derived from ERA-40 database. (k) Light blue lines mark the phase-switch of AMO.

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Question 1

How does the AMO impact Sahel rainfall in observations?
In Warm AMO Phases:
Do CMIP5 models capture the AMO – Sahel teleconnection and what processes are occurring/not occurring?
CMIP5 historical simulations fail to capture the amount of decadal variance (>10 years) in Sahel rainfall and the AMO

<table>
<thead>
<tr>
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<th>Observed</th>
<th>CMIP5 Hist. Mean</th>
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<tbody>
<tr>
<td>Sahel Rainfall</td>
<td>45 %</td>
<td>16 %</td>
</tr>
<tr>
<td>AMO</td>
<td>66 %</td>
<td>44 %</td>
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</table>
CMIP5 historical simulations simulate the correlation between decadal filtered Sahel rainfall and SST in the North Atlantic.

North Atlantic: $r=0.58$

- **Green**: > 90%
- **Yellow**: 70% – 90%
- **Orange**: 50% – 70%
- **Red**: < 50% (e.g. opposite sign to observed)

Color shows significance of correlation.
The performance is even worse when considering the relationship with the Indian Ocean.

Indian Ocean: $r=-0.60$

Color shows significance of correlation:
- GREEN > 90 %
- YELLOW 70 – 90 %
- ORANGE 50 – 70 %
- RED < 50 % (e.g. opposite sign to observed)
Why do some models with high decadal variance in the AMO have high Sahel rainfall decadal variance, but others do not?

- **High AMO decadal variance**
  - **High Sahel rain decadal variance** → 6 “GOOD”
  - **Low Sahel rain decadal variance** → 6 “POOR”
Rainfall Regressed onto AMO Index

CRU: OBS
GOOD MEAN
POOR MEAN

mm/day per SD

-0.5 -0.4 -0.3 -0.2 -0.1 0 0.1 0.2 0.3 0.4 0.5
The spatial pattern of the simulated AMO is highly important for the connection with Sahel rainfall.
Why is the tropical signal of the AMO weak in poor models?

- **Clouds:**
  - Larger (more realistic) total cloud amount and variability in eastern basin of good models
  - Is total mean cloud amount related to simulation of SST variability?

- **Dust:**
  - Good models decrease dust over N. Africa with increased SST, as expected
  - Poor models do not

- **Sulfate Aerosol Indirect Effect**
  - Require sulfates and clouds to be in same location for indirect effect to occur
  - This does not occur in poor models – primarily due to cloud distribution
Question 3

Can CMIP5 Decadal Hindcasts Predict Sahel Rainfall Variability?
Sahel Rainfall Simulation

Objectives

Sahel Rainfall Observations

Decadal Hindcasts

CMIP5 Historical/RCP45

Grey shading: +/- one standard deviation
A Relative SST index (RSI) is calculated following Giannini et al. (2013) as the annual mean subtropical North Atlantic SST minus the tropical mean (20°S-20°N) SST.

Models with a high RSI-Sahel rainfall correlation in historical simulations produce more skillful decadal hindcasts for both Sahel rainfall and the RSI.
Question 4

What about the impact on Hurricanes?
African Easterly Waves (AEWs)

Difference in Eddy Kinetic Energy (EKE) between warm and cold AMO phases

- AEWs vary decadally with the AMO
Tropical Cyclone Genesis

- No change in mean longitude but change in distribution

Increased tropical cyclone frequency in warm AMO years

→ Increased SST

→ Decreased vertical wind shear

→ Increased AEWs

a) Warm 13.1 storms per year

b) Cold 7.9 storms per year
AEWs in CMIP5?

**850 hPa**
- a) EKE 850 hPa: AMIP - Reanalysis Mean
- d) EKE 850 hPa: Historical - Reanalysis Mean

**700 hPa**
- b) EKE 700 hPa: AMIP - Reanalysis Mean
- e) EKE 700 hPa: Historical - Reanalysis Mean

**EKE (m²s⁻²): CMIP5 – multi-reanalysis mean**

- **AMIP**
- **Historical**
Summary

- SST plays a large role in decadal predictability of Sahel rainfall BUT need to improve SST and atmospheric teleconnection to have a real impact on Sahel rainfall and potentially hurricane prediction.

- CMIP5 models with well simulated AMO-Sahel teleconnections have a more realistic pattern of SSTs in the North Atlantic but SST errors could be due to errors with clouds, aerosol (sulfate and dust), ocean dynamics, vegetation?

- Decadal hindcasts of Sahel rainfall and the RSI have significant skill. Models that produce realistic correlations between the RSI and Sahel rainfall in historical simulations (not initialised with observations) have more skillful Sahel rainfall decadal hindcasts.

- Major errors in the simulation of AEWs in CMIP5 models → potentially large impacts on tropical cyclone simulation.


Vertical Wind Shear Regressed onto AMO Index

- Observed changes in wind shear with AMO phase
  - Reduced wind shear in warm AMO phases in MDR

- Good models similar pattern but weaker amplitude

- Poor models have little response to AMO variability
Precipitation Annual Cycle

Observations

Discontinuity from Southern hemisphere to Sahel

Rainfall peak too far South
Gulf of Guinea SST Annual Cycle

As in CMIP3 models: Warm anomaly in SE Atlantic and Gulf of Guinea in summer

Errors of up to 4°C

On interannual timescales:
warm Gulf of Guinea = dry Sahel
Sahel Precipitation Annual Cycle

- Summer monsoon peak is simulated but most models:
  - underestimate summer peak
  - overestimate spring rainfall
Larger (more realistic) total cloud amount and variability in eastern basin of good models

Is total mean cloud amount related to simulation of SST variability?
Role of Dust

- Dust load regressed onto AMO index

- Good Models:
  - As expected increase SST, increase rain, reduce dust

- Opposite seen in poor models
Role of Sulfate Aerosol Indirect Effects

Shading:
Mean sulfate aerosol load

Stippling: >50 % total cloud fraction

Need cloud and sulfate in same location for indirect effect to occur

✓ Good Models
✗ Poor Models