Dynamical downscaling for societal applications

Water resources and agricultural management

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The International Research Institute
for Climate and Society
EARTH INSTITUTE | COLUMBIA UNIVERSITY

OUTLINE

1. DYNAMICAL DOWNSCALING & WATER RESOURCES IN AFRICA
    1.1. Motivation
    1.2. Regional scenarios
    1.3. Hydrological projections
2. FORECASTING WITH MULTI-CLIMATE/HYDROLOGICAL MODELS IN BRAZIL
    2.1. Motivation
    2.2. Methodology
    2.3. Results & Analysis
3. DYNAMICAL DOWNSCALING & AGRICULTURE IN BRAZIL
    3.1. Motivation
    3.2. Data & Methodology
    3.3. Climate variability and corn yields
    3.4. Corn yield potential predictability

PART 1: Dynamical Downscaling & water resources in Africa

Vigaud, N., B. Fontaine, P. Roucou, S. Kumar and S. Tyteca (2011) WRF/ARPEGE-CLIMAT simulated climate trends in West Africa, *Clim Dyn*, 36:925-944

Collet, L. (2010) Flow evolution in a large Sudano-Sahelian catchment under the constraint of climatic scenarios for the 21st century, HSM Report

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G-eau
Gestion de l'Eau, Acteurs, Usages

RESSAC

OUTLINE

1. DYNAMICAL DOWNSCALING & WATER RESOURCES IN AFRICA

1.1. MOTIVATION

What projections for West Africa at medium term?

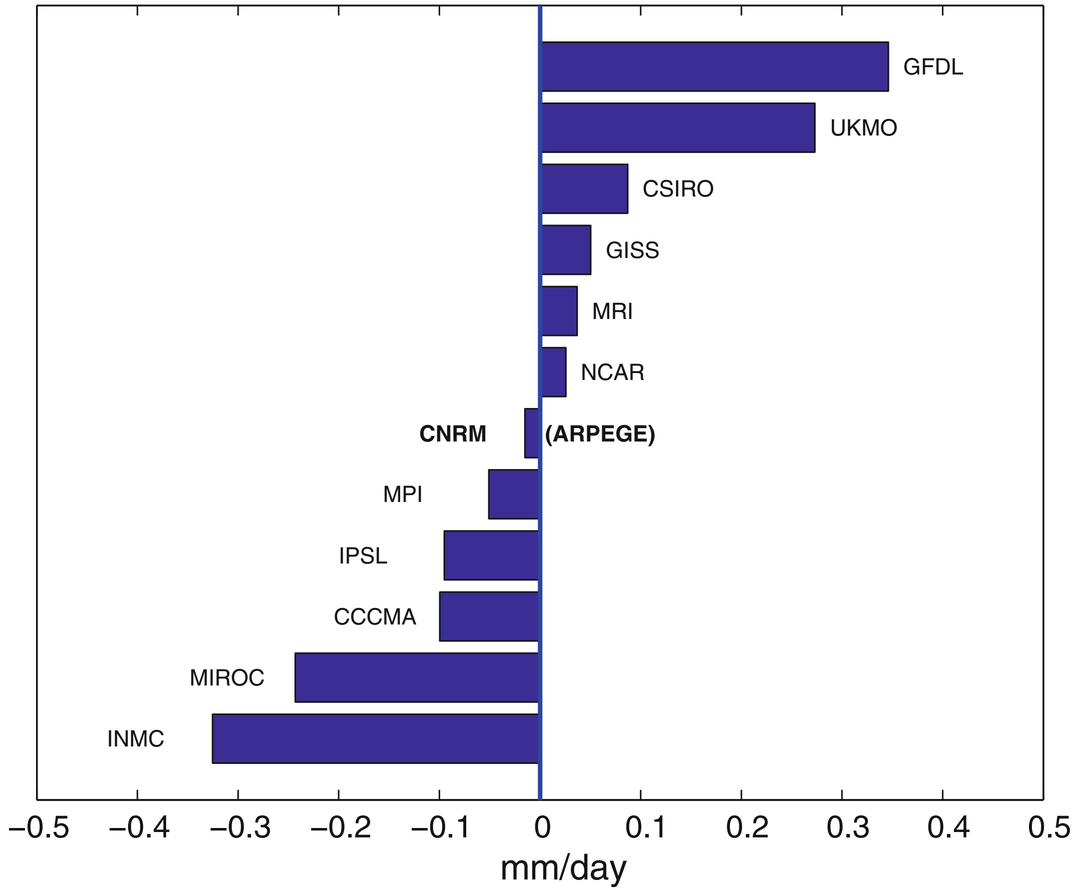
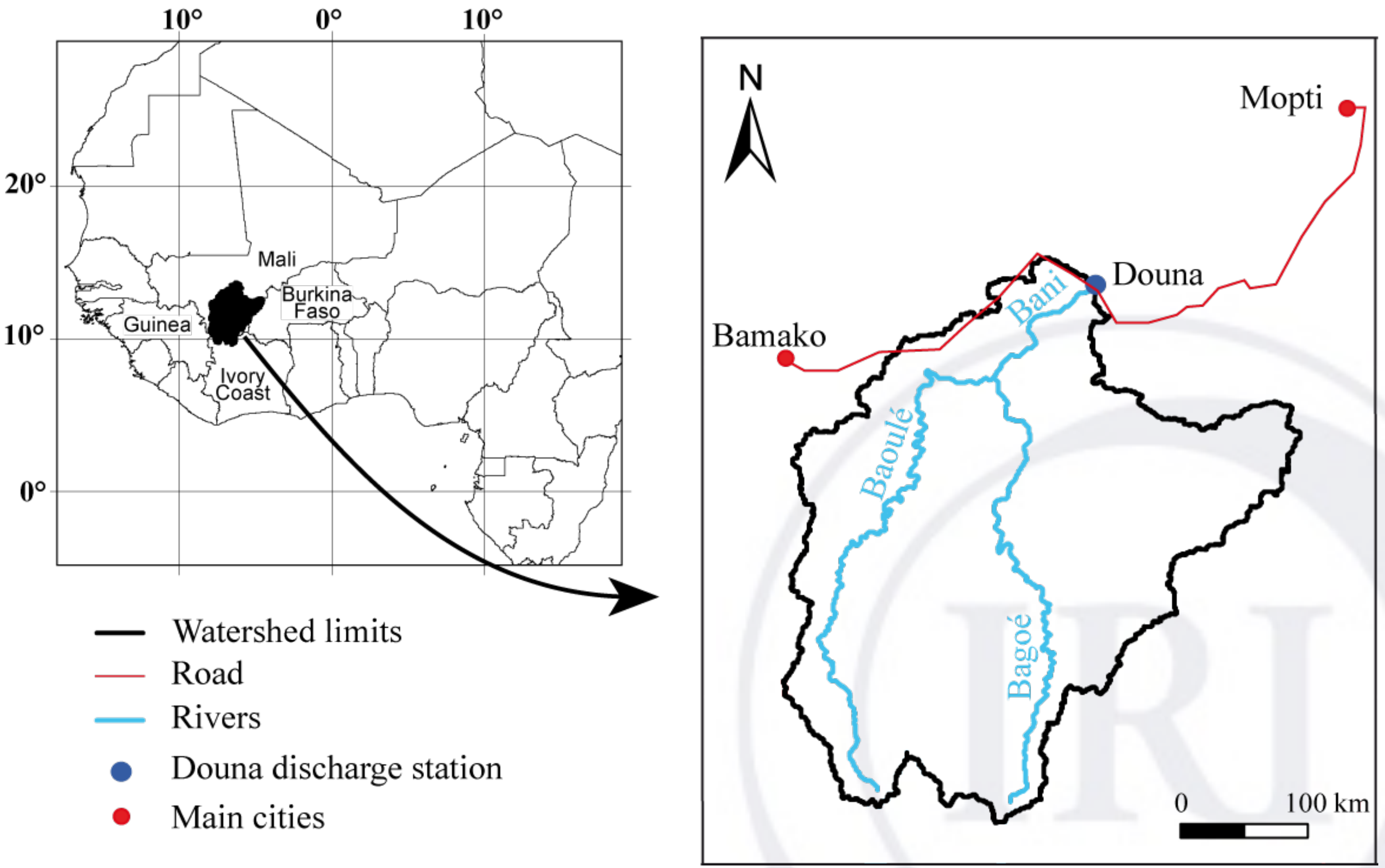


Fig. 1 Rainfall time evolution over a West African box (5°N–20°N; 20°W–30°E) for 12 GCMs available from the last IPCC AR4 exercise (http://www.mad.zmaw.de/IPCC_DDC/html/SRES_AR4/index.html) between the 2030's (A2 scenario) and the 1980s (20CM3 scenario)

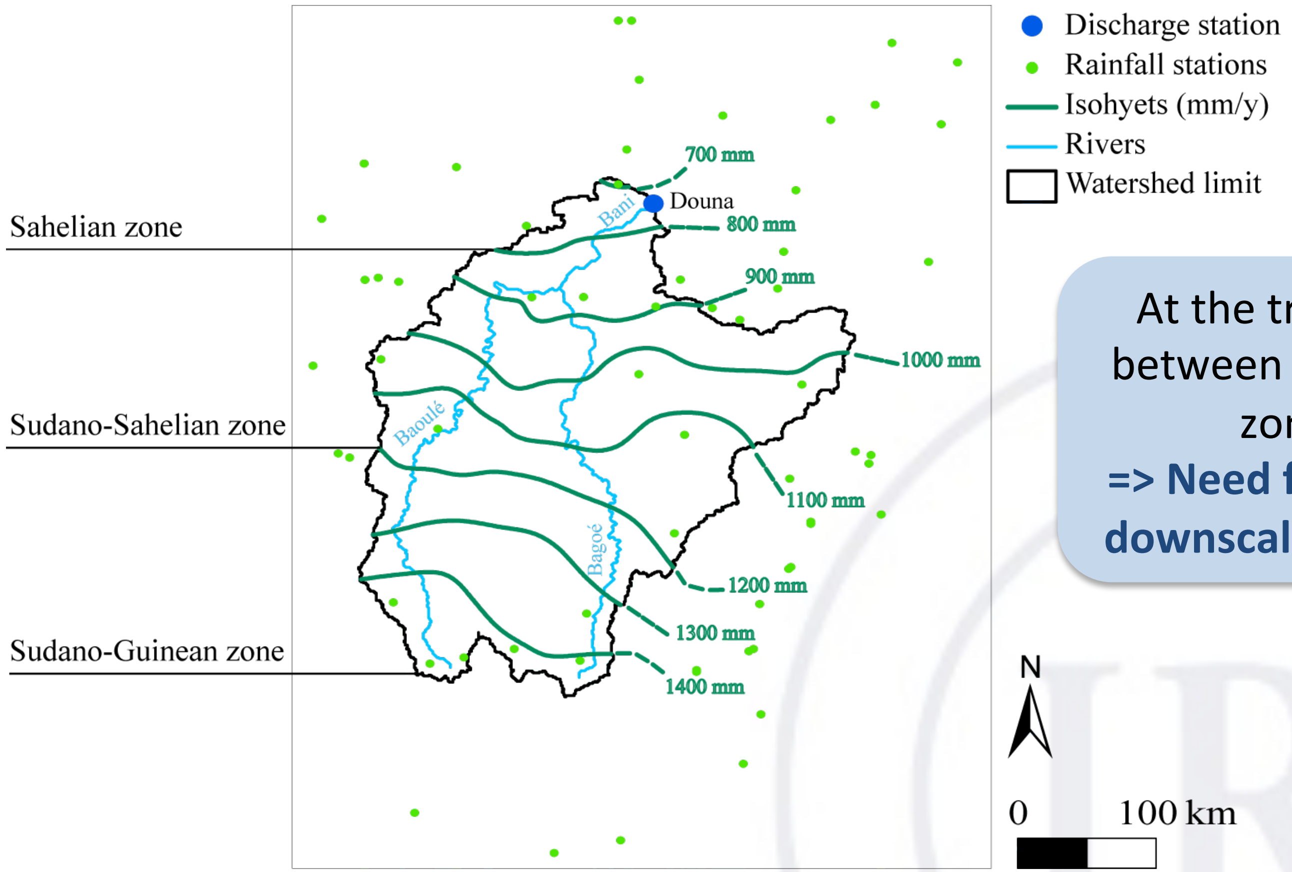
1.1. MOTIVATION

Study zone



1.1. MOTIVATION

Study zone



Isohyets, rainfall and discharge gauging stations over the Bani catchment

At the transition between 3 climatic zones
=> Need for spatial downscaling (RCM)

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1.2. Regional scenarios

1.2.1. Validation over an historical period

1.2.1.1. Climatology

1.2.1.2. Seasonal cycle

1.2.1.3. Rainfall statictics

1.2.2. A2 scenario projections & related dynamics

1.3. Hydrological projections

1.3.1. Hydrological modeling

1.3.2. Validation over an historical period

1.3.3. Multiple scenarios approach

1.3.3.1. Rainfall scenarios & projected PET

1.3.3.2. Projected discharge

1.2. REGIONAL SCENARIOS

Experimental setup

- **Regional Atmospheric Model:** Weather Regional Forecast model (WRF) version 3.0.1.1. developed by NCAR with the following physics,

  - Yosei University (YSU) Planetary Boundary Layer scheme,
  - NOAAH Land Surface Model,
  - Monin-Obukhov Surface Layer scheme,
  - Kain-Fritsch Cumulus parametrization scheme,
  - RRTM/Dudhia Long/Shortwave Radiation schemes.

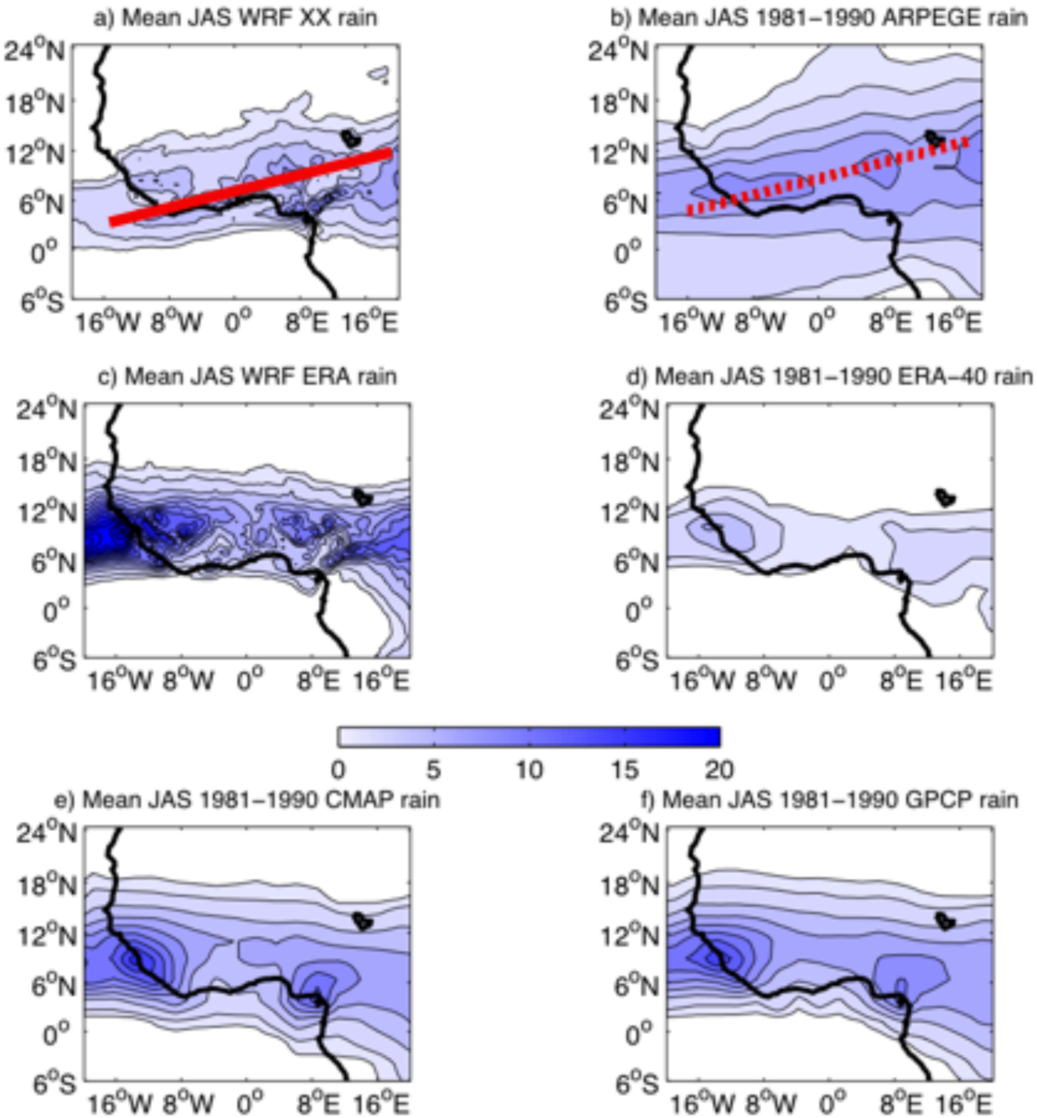
  Regional experiments were designed over a geographical domain between **10°S-45°N and 38°W-58°E** with,

  - Two types of large-scale forcings: **CNRM ARPEGE-CLIMAT output and ERA-40 re-analyses** (contemporary period) at 2.8°x2.8° and 2.5°x2.5° spatial resolution,
  - Boundary conditions imposed **every 12hrs**,
  - WRF output every 12hrs at a **50km x 50km** horizontal resolution (28 sigma levels on the vertical) after a **12 months spin-up**.

- **Rainfall data:** For validation purposes GPCP and CMAP rainfall estimates at a 2.5°x2.5° spatial resolution were used.

1.2. REGIONAL SCENARIOS

Validation over an historical period: climatology

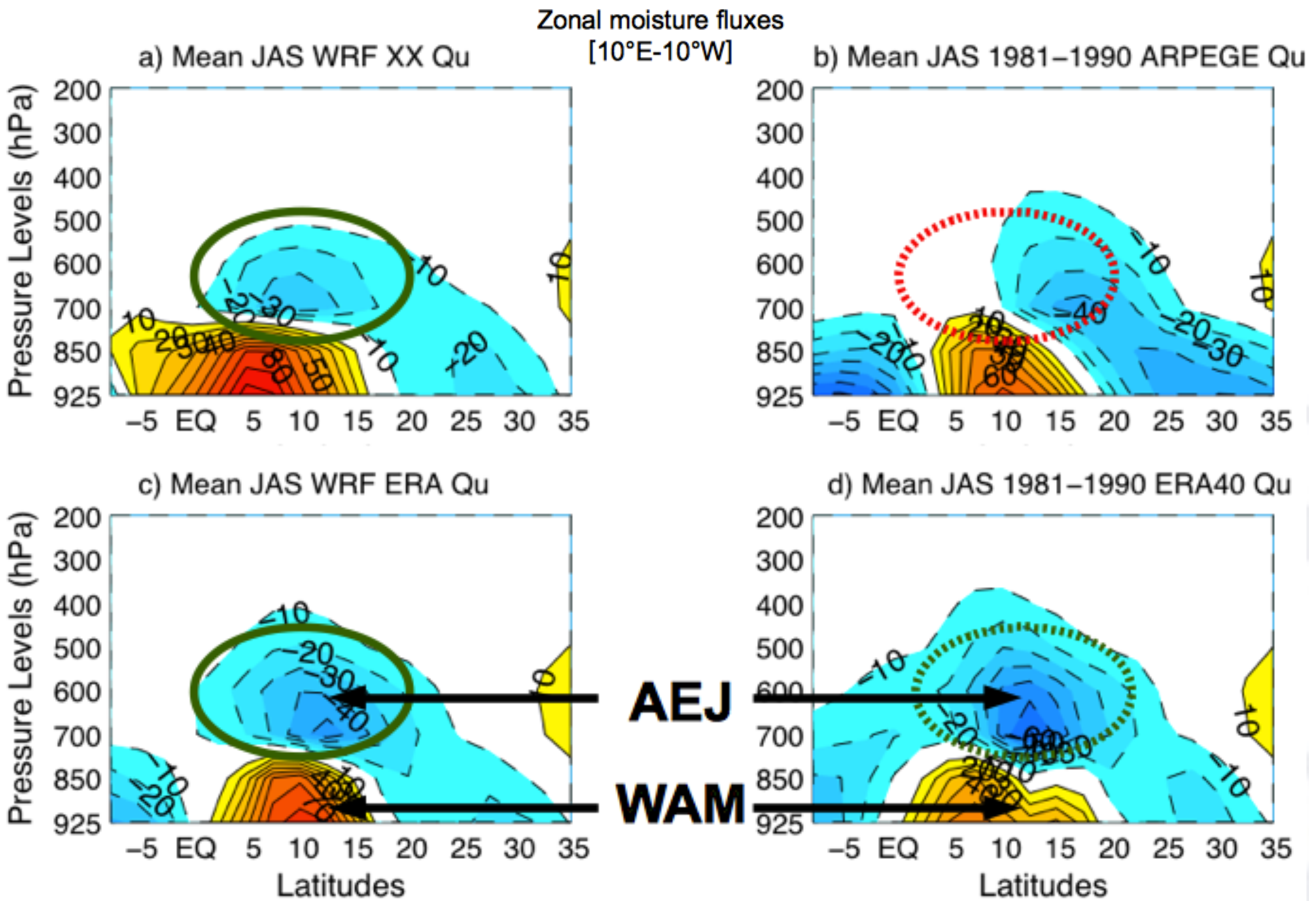


WRF simulated JAS rainfall

- ❖ Better representation of mean summer rainfall compared to ARPEGE
- ❖ BUT propagation of ARPEGE bias in the form of a NE/SW tilt

1.2. REGIONAL SCENARIOS

Validation over an historical period: climatology

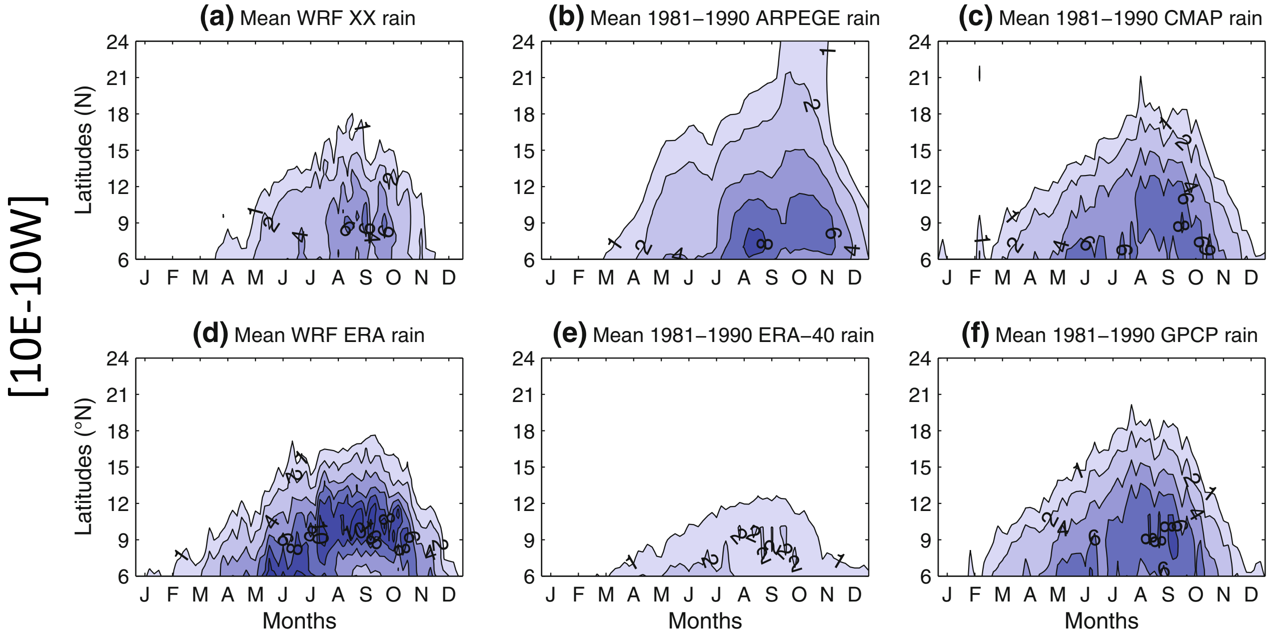


WRF simulated JAS rainfall

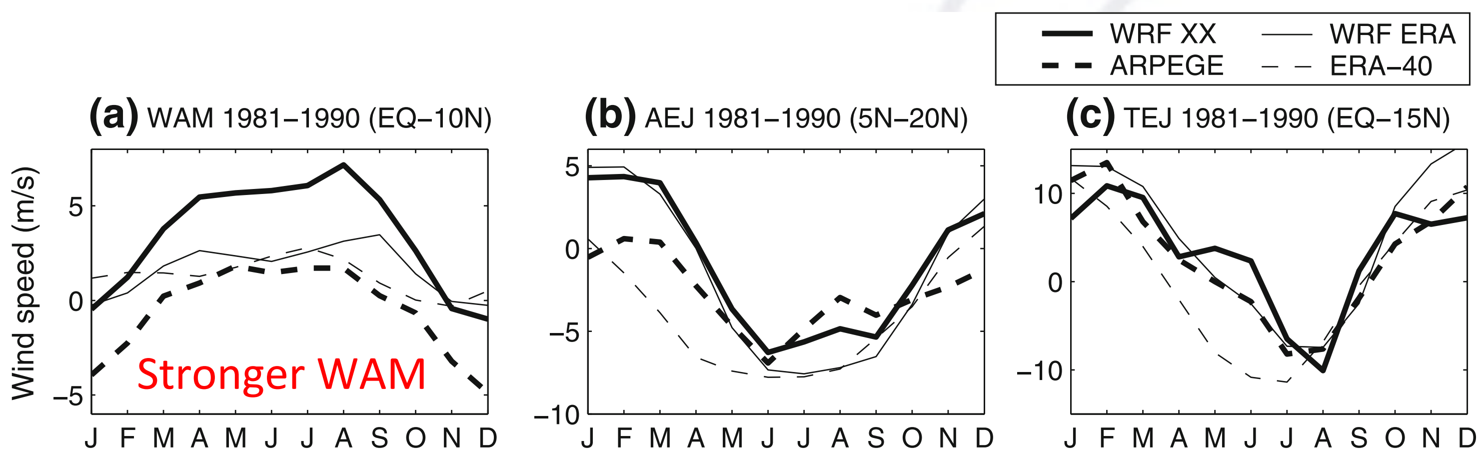
- ❖ Better representation of key features of the mean circulation compared to ARPEGE
- ❖ BUT propagation of ARPEGE bias in the form of stronger WAM

1.2. REGIONAL SCENARIOS

Validation over an historical period: seasonal cycle

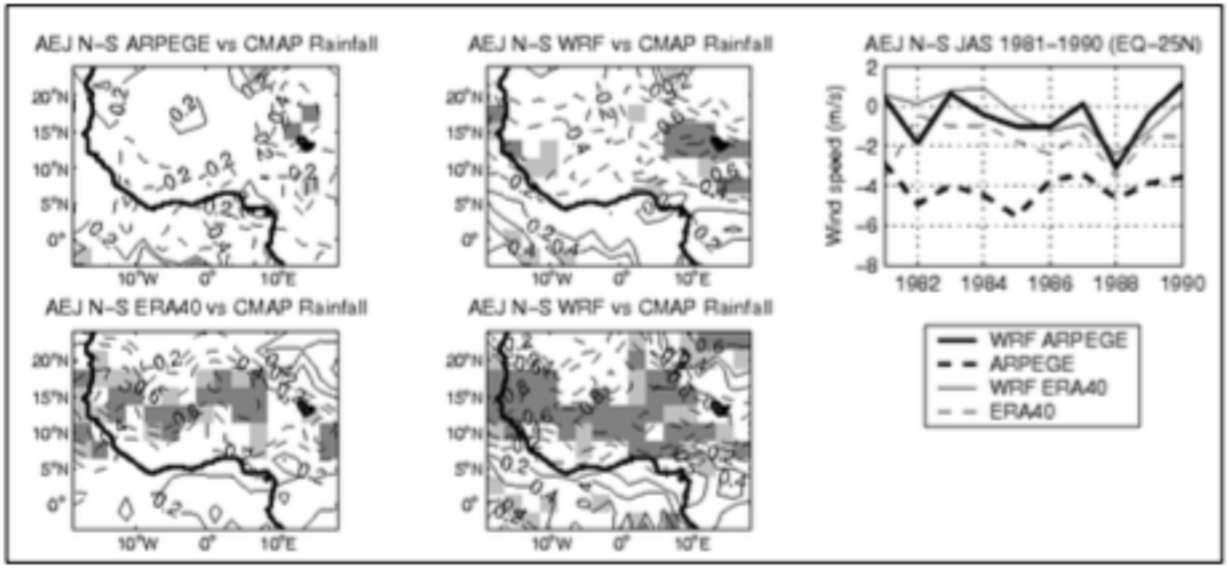


Seasonal cycle reasonably reproduced



1.2. REGIONAL SCENARIOS

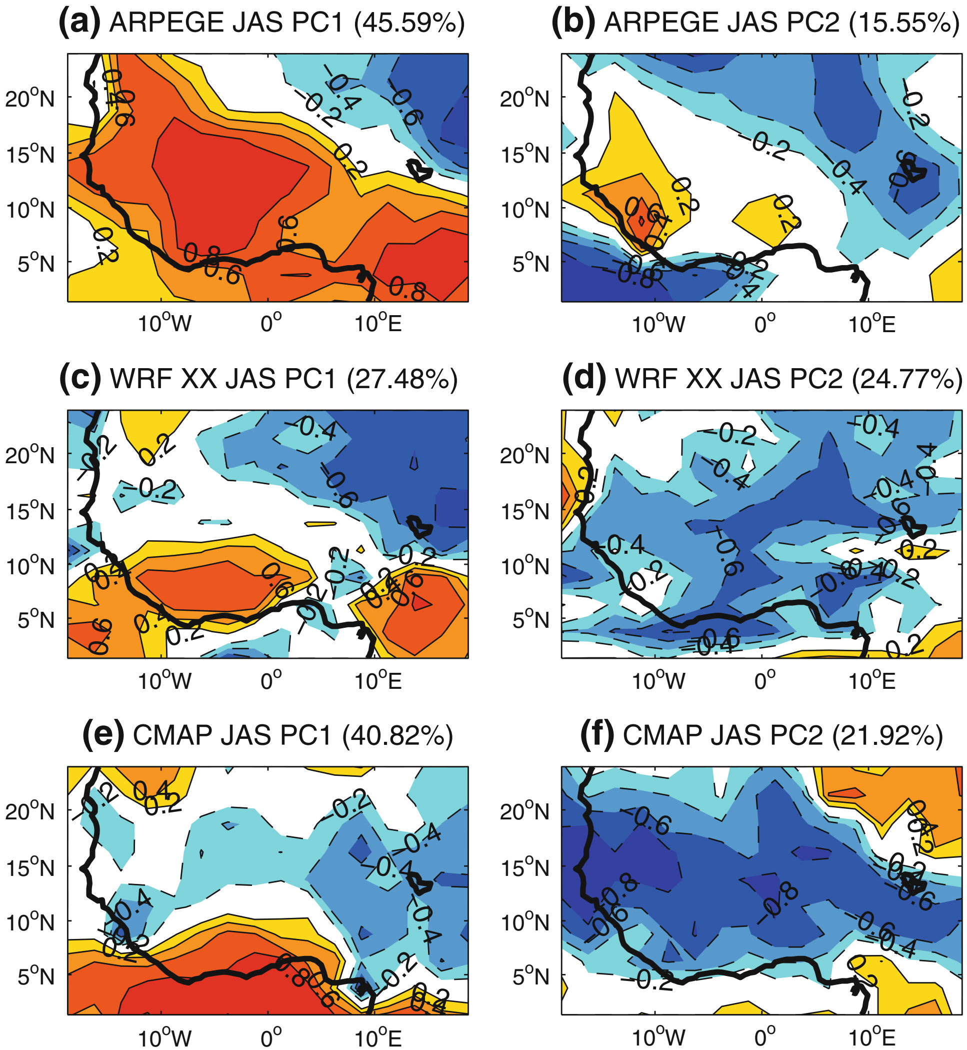
Validation over an historical period: seasonal cycle



Heterogeneous correlation maps of mean JAS difference between northern (10-25°N) and southern (EQ-10°N) part of the AEJ from WRF simulations (middle) forced by ARPEGE and ERA-40, and from their respective forcings (left), with CMAP JAS rainfall estimates over the 1981-1990 period. Shaded areas correspond to scores significant at 90% and 95% level (light and dark grey respectively) using Monte-Carlo simulations.

Better representation of the relationships between **AEJ dynamics** and **observed rainfall regimes** for regional simulations

Validation over an historical period: rainfall statistics



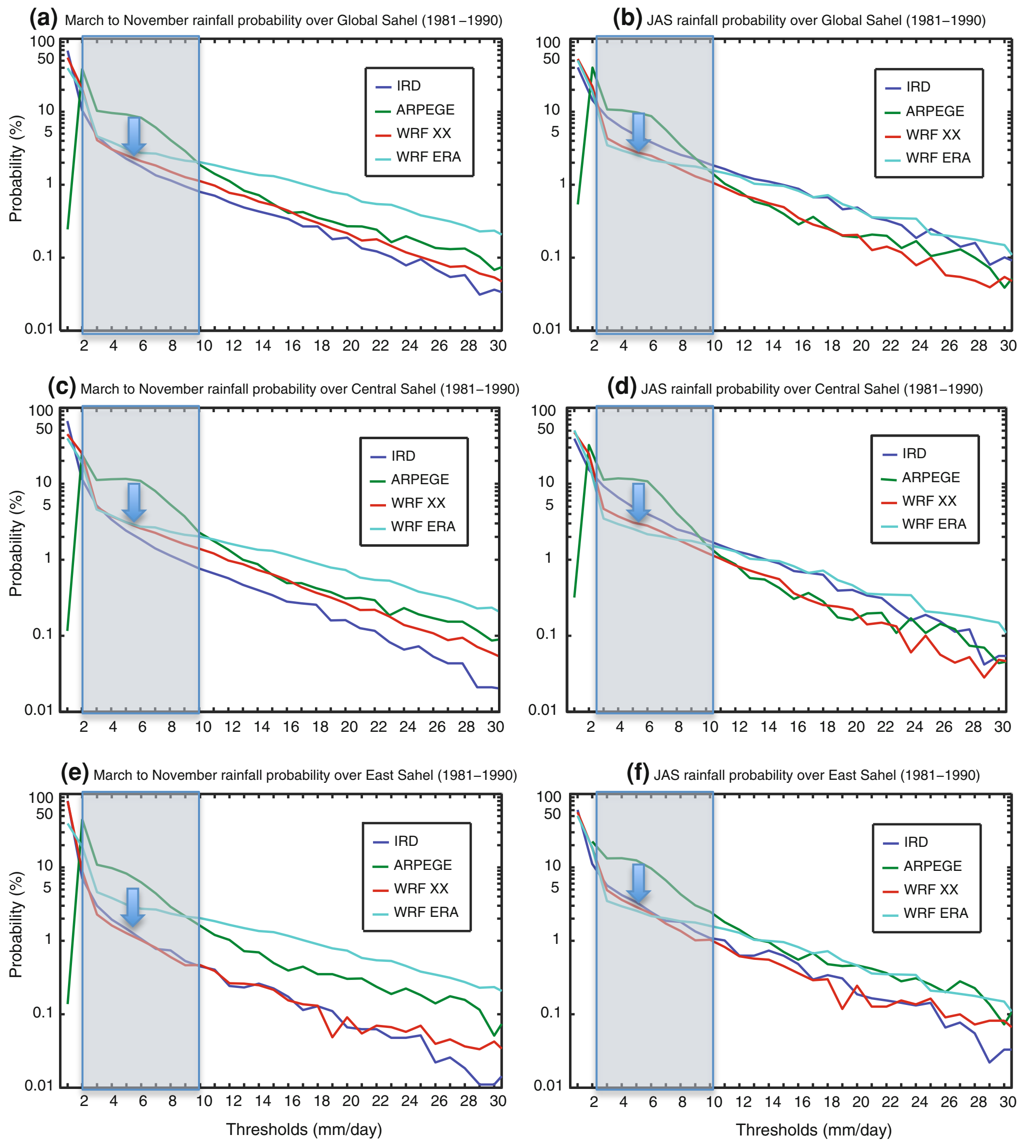
Guinean Mode Sahelian Mode

EOF JAS rainfall

- **CMAP:** 1 Guinean + 1 Sahelian modes
- **ARPEGE:** no discretization between Guinean & Sahelian region
- **WRF:** reproduce two distinct modes typical of Guinean & Sahelian rainfall

1.2. REGIONAL SCENARIOS

Validation over an historical period: rainfall statistics



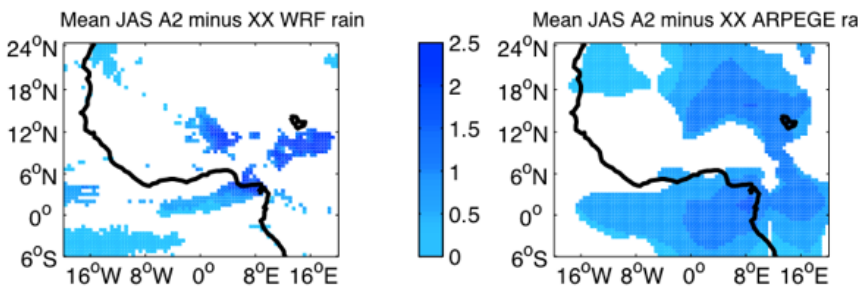
Sahel rainfall distributions

- ARPEGE and both WRF XX show **lower occurrences of less intense events** compared to observation, whereas **intense rainfall events are overrepresented**
- **WRF simulated** rainfall exhibit **distributions closer to observations** compared to ARPEGE showing strong bias for the occurrences of 2-10 mm/day rainy events

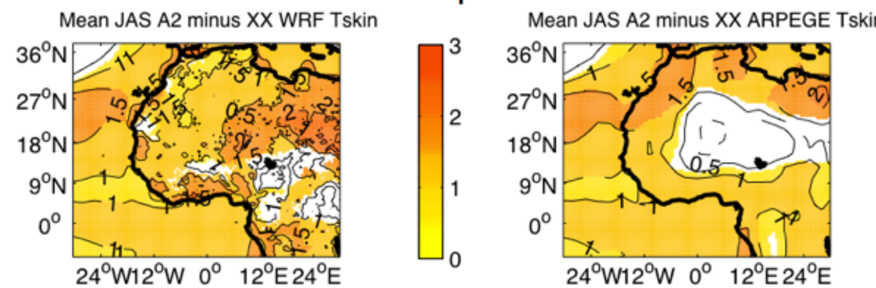
1.2. REGIONAL SCENARIOS

A2 scenario projections & related dynamics

Rainfall



Surface Temperatures

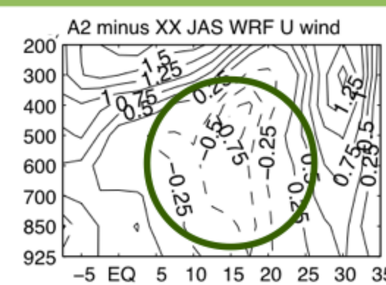


Summer rainfall **changes well reproduced** and **more relevant to the climatology**…

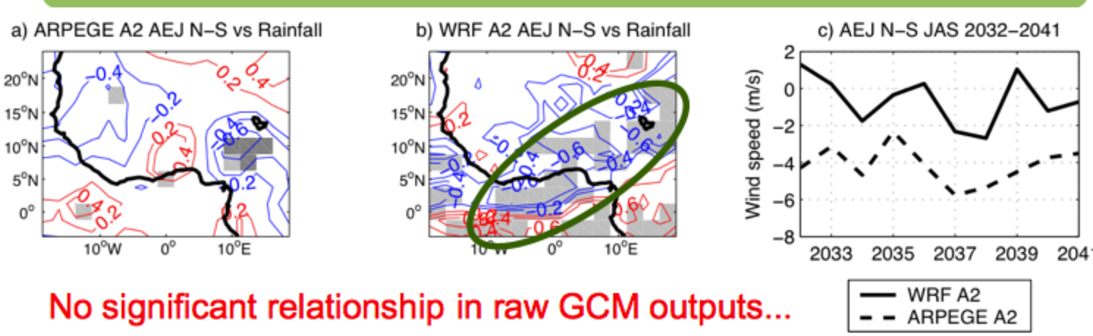
…associated **intensification** of the meridional **surface temperature gradient**

A2 Period:
2032-2041
XX Period:
1981-1990

Strengthening of the **AEJ** northwards



Main **rainfall changes** significantly **related to AEJ modulations**



No significant relationship in raw GCM outputs…

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1.3.3. Multiple scenarios approach

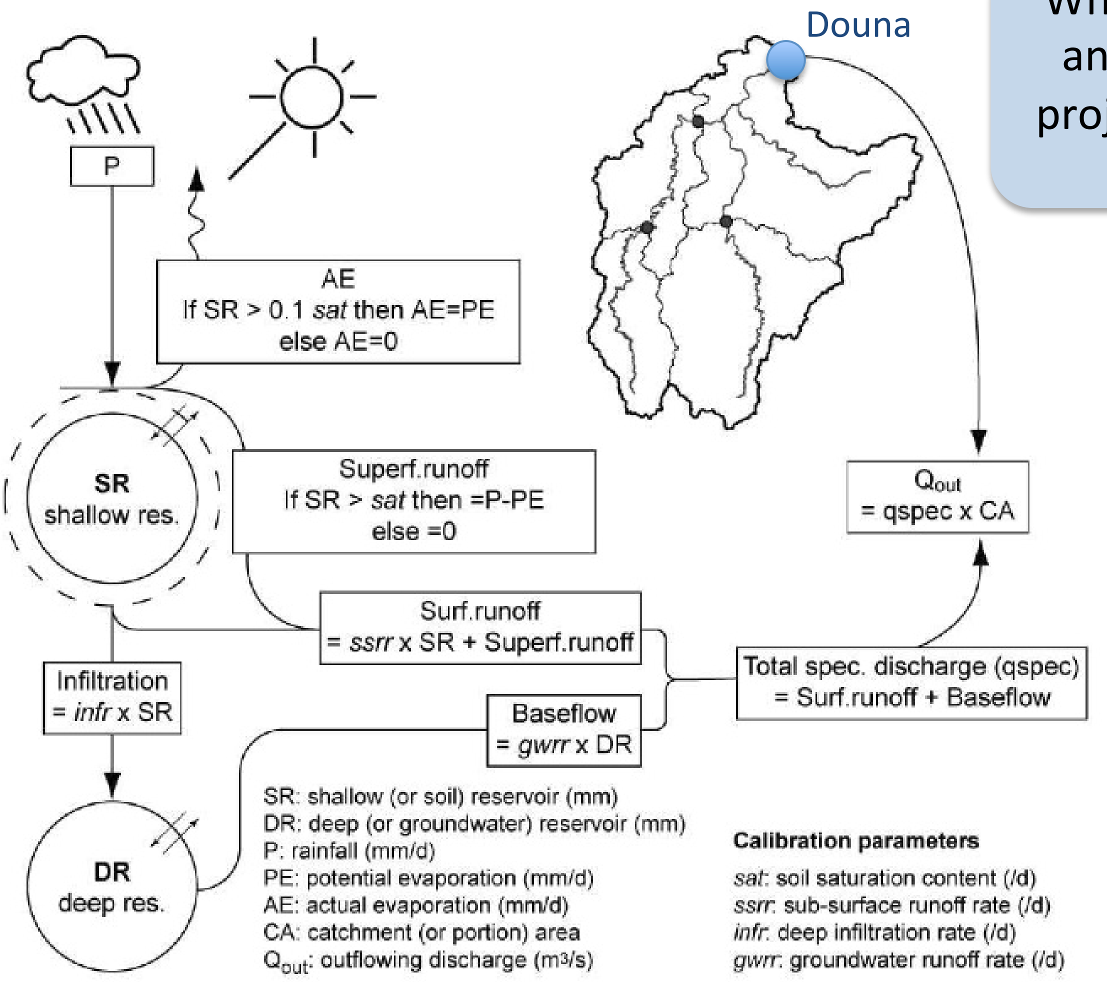
1.3.3.1. Rainfall scenarios & projected PET

1.3.3.2. Projected discharge

1.3. HYDROLOGICAL PROJECTIONS

Hydrological modeling

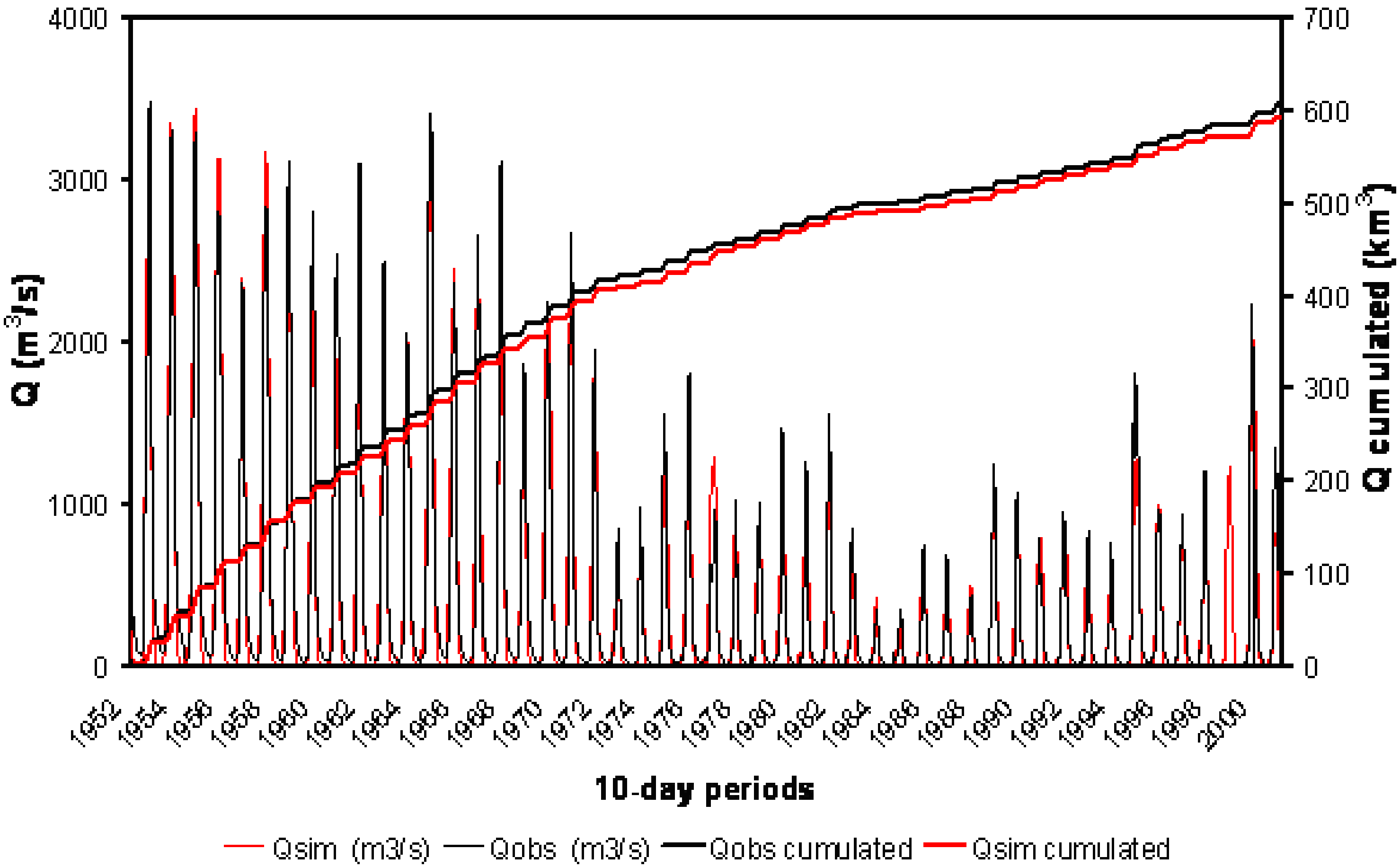
What are the short and longer terms projected discharge at **Douna**?



Principle of the HydroStrahler model (Ruelland et al., 2009)

1.3. HYDROLOGICAL PROJECTIONS

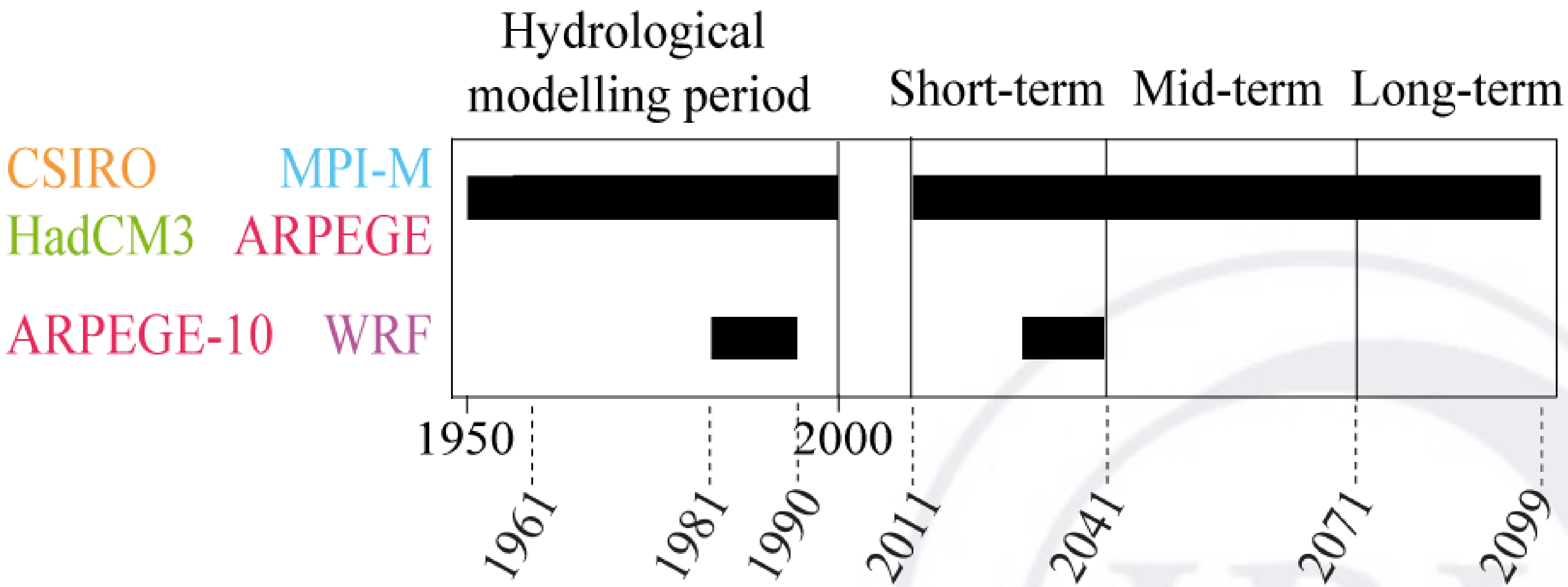
Validation over a historical period (1952-2000)



Observed hydrographs at Douna gauging station reasonably reproduced in hydrological model simulations

1.3. HYDROLOGICAL PROJECTIONS

Multiple scenarios approach



Different scenarios for different time-scales relevant to adaptation strategies

1.3. HYDROLOGICAL PROJECTIONS

Multiple scenarios approach

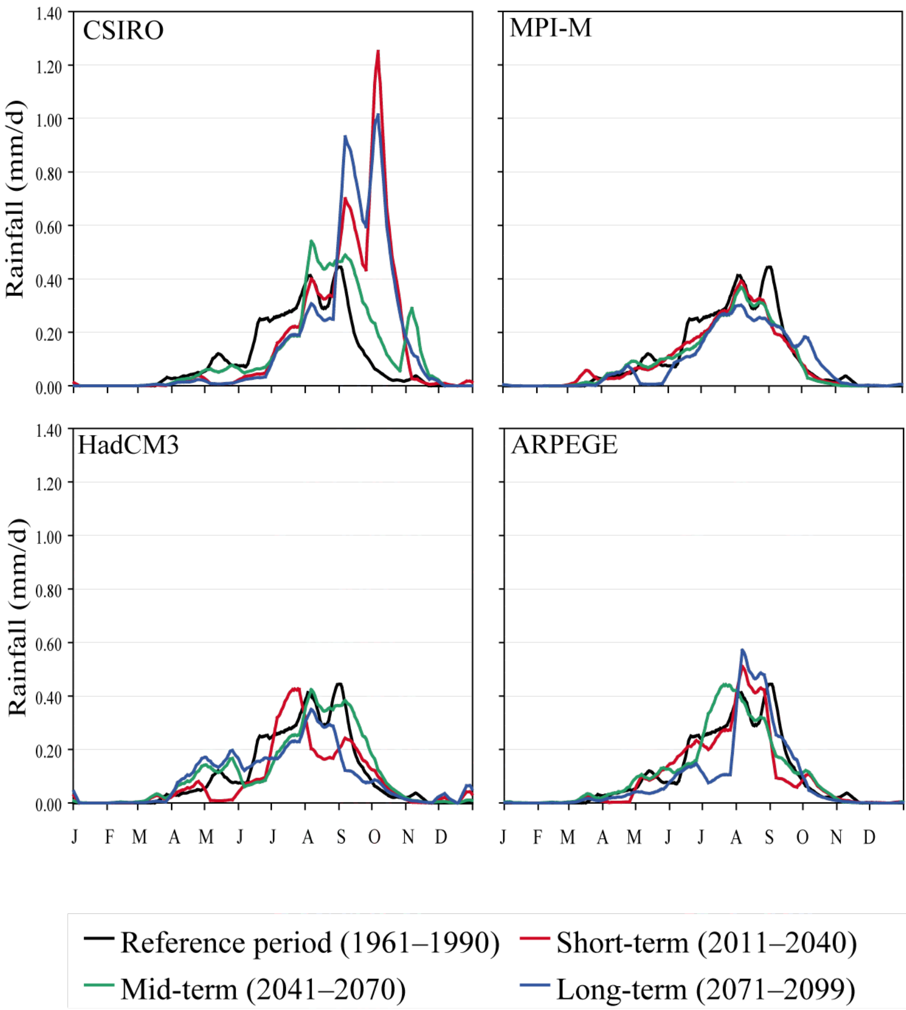
	Bias (%)			Delta (°C)		
	Short-term 2011-2040	Mid-term 2041-2070	Long-term 2071-2099	Short-term 2011-2040	Mid-term 2041-2070	Long-term 2071-2099
CSIRO	482	431	555	1.2	2.0	3.7
MPI-M	31	5	29	1.1	2.6	5.4
HadCM3	2	6	-4	1.2	2.7	4.8
ARPEGE	-5	-5	10	1.4	2.5	5.2
	2032-2041	–	–	2032-2041	–	–
ARPEGE-10	32	–	–	1.6	–	–
WRF	104	–	–	1.3	–	–

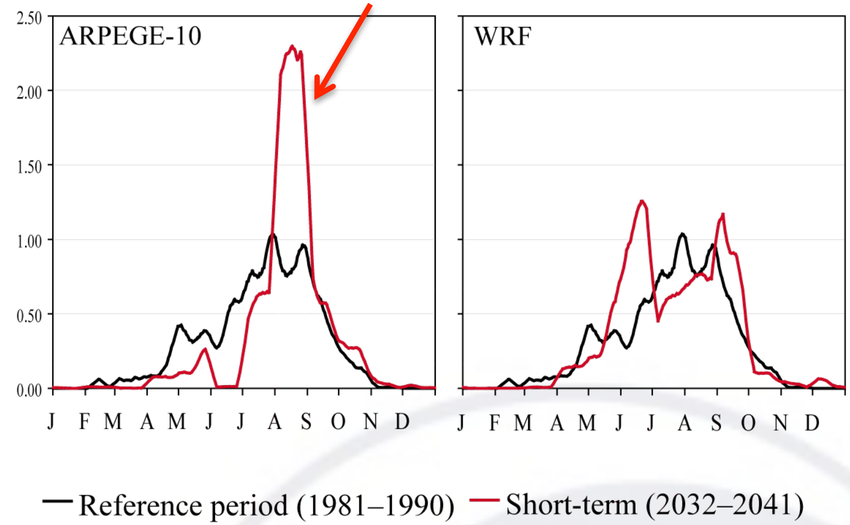
- ❖ **Different scenarios** lead to **different trends** in rainfall and surface temperatures
- ❖ **ARPEGE contrasting trends** for **short terms** projections depending on periods
- ❖ While **ARPEGE disagree with other GCMs** for short term, **WRF projections** are **within the range from GCMs ensemble**

1.3. HYDROLOGICAL PROJECTIONS

Rainfall scenarios

Due to Jan 2041 too wet in ARPEGE-10

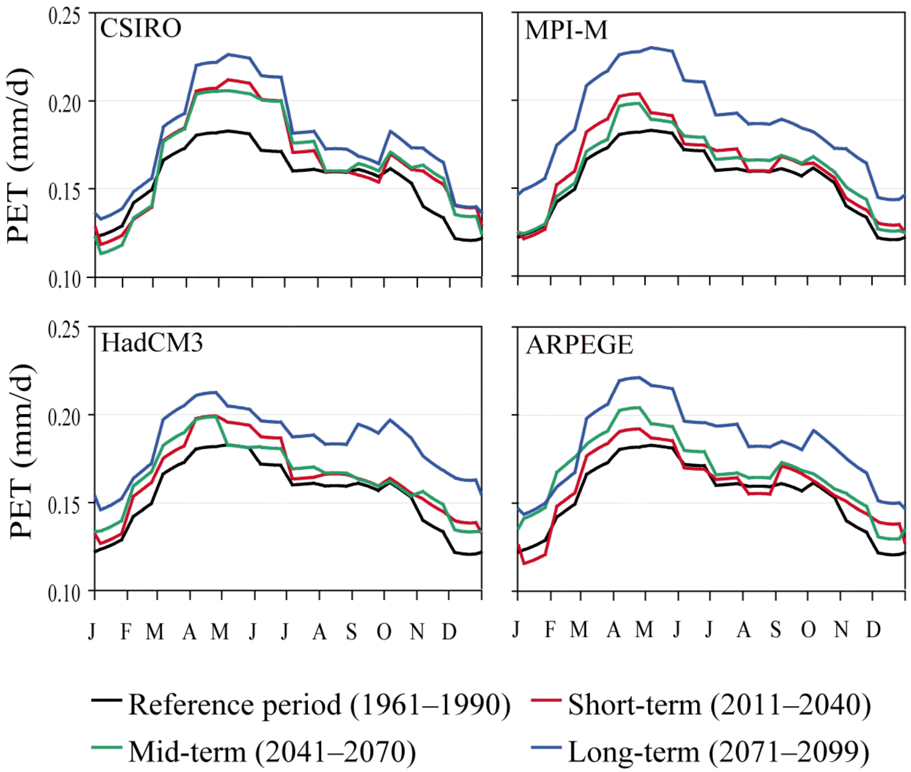


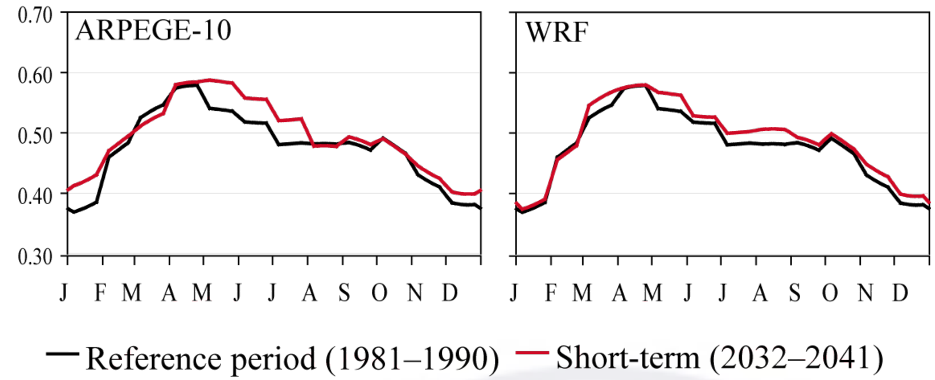


- ❖ Highest trends in CSIRO, other GCMs don't differ much from observation
- ❖ **ARPEGE-10 high level of changes** while **WRF** provides **projections closer to GCMs ensemble**

1.3. HYDROLOGICAL PROJECTIONS

Projected Potential EvapoTranspiration (PET)





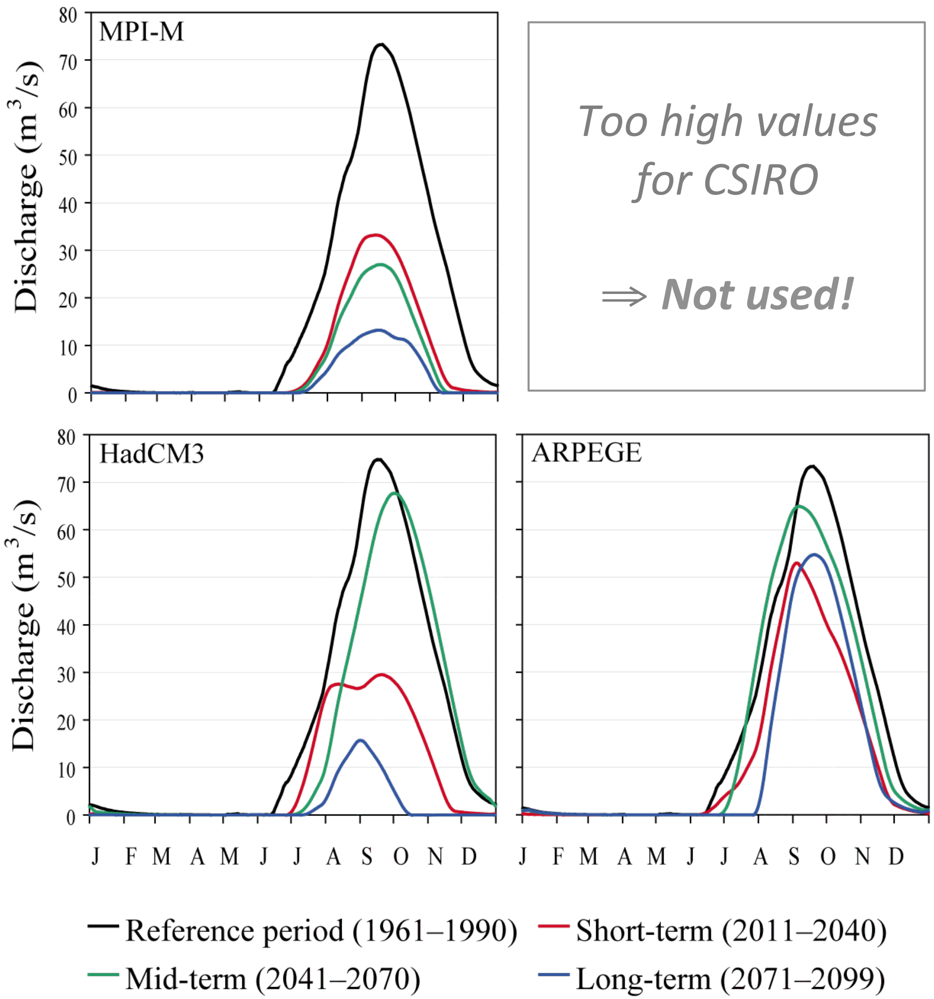
(PET based on simple calculations using surface temperature)

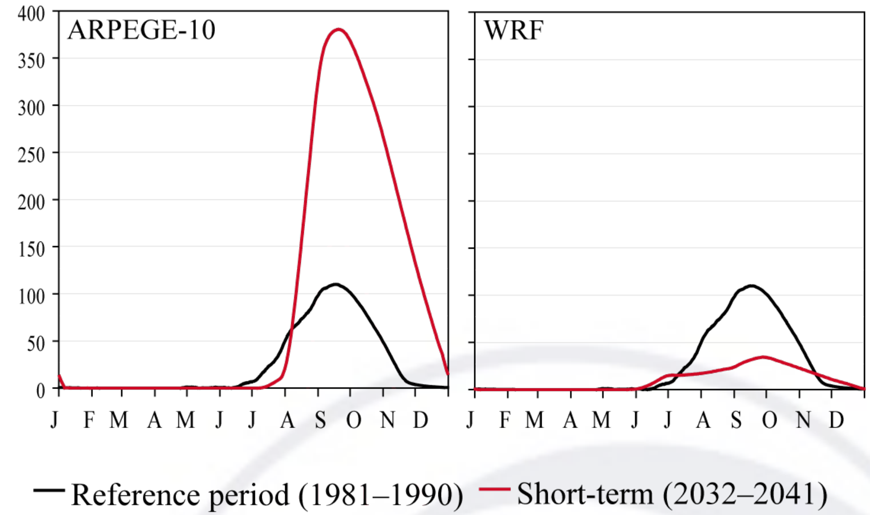
- All GCMs show **increasing PET**
- **ARPEGE-10 lower projections** at short term these are **reproduced** in the same fashion **by WRF**
- Hydrological model constrained by rainfall trends depending on GCMs with increasing PET but rainfall and PET work in opposition

=> Results from hydrological modeling cannot be predicted intuitively

1.3. HYDROLOGICAL PROJECTIONS

Projected discharge





- **All GCMs** produce **decreasing discharge** with time **except ARPEGE**
- **WRF** provides **discharge trend within the range** from **GCMs ensemble**
- **Simulated flood peaks** tend to occur at the **same time as observed**

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Rowell, D., C. Folland, K. Maskell, J. Owen and M. Ward (1992) Modelling the influence of global sea surface temperatures on the variability and predictability of seasonal Sahelian rainfall, *Geophys. Res. Lett.*, 19, 905908

Ruelland, D., V. Guinot, F. Levavasseur and B. Cappelaere (2009) Modelling the long-term impact of climate change on rainfall-runoff processes in a large Sudano-Sahelian catchment, *Proceedings of IAHS-IAH Convention "New Approaches to Hydrological Prediction in Data Sparse Regions"*, Hyderabad, India, 6-12 September 2009, IAHS Publ., 333: 59-68

PART 2: Forecasting with multi-climate/ hydrological models in Brazil

Block, P.J., F.A. Souza Filho, L. Sun and H.-H. Kwon (2009) A streamflow forecasting using multiple climate and hydrological models, *JAWRA*, 45:828-843

OUTLINE

2. FORECASTING WITH MULTI-CLIMATE/HYDROLOGICAL MODELS IN BRAZIL

2.1. MOTIVATION

- **Water resources planning/management** efficacy is **subject to** capturing inherent **uncertainties** stemming **from climatic and hydrological inputs and models**

- However, little consideration has been given to **methodologies that include coupling both multiple climate and multiple hydrological models**, increasing the pool of forecast ensemble members and accounting for cumulative sources of uncertainty

Aim: the framework presented here proposes the **integration of global climate models** (GCMs), **multiple regional climate models** (RCMs), and **numerous water balance models to improve streamflow forecasting** through generation of **ensemble forecasts**

2.1. MOTIVATION

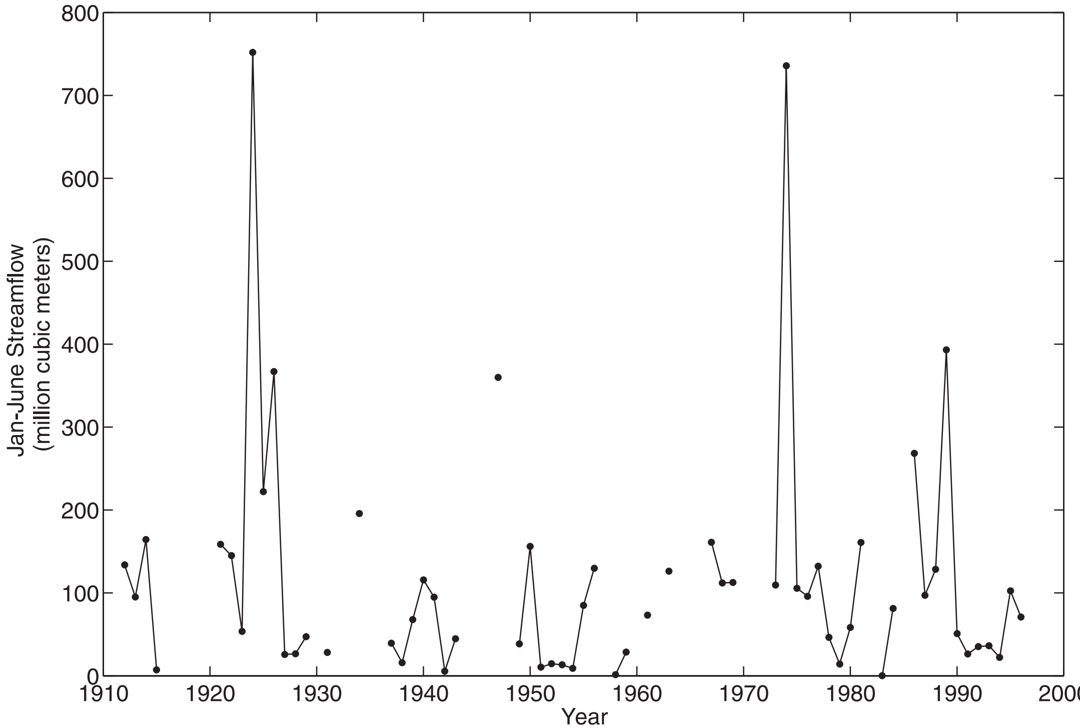
Application Site

❖ **The Iguatu basin**: lies within the larger Jaguaribe basin, a 72,000 km2 semi-arid area in northeast Brazil

2.1. MOTIVATION

Application Site

- **The Iguatu basin**: lies within the larger Jaguaribe basin, a 72,000 km2 semi-arid area in northeast Brazil and experiences one rainy season annually, from January to May



January to June Streamflow on the Jaguaribe River at Iguatu, Brazil, for 1912-1996.

OUTLINE

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2.2.1. Forecasting approach

2.2.2. Climate models & downscaling

2.2.3. Hydrological models

2.2.4. Multi-Model Hindcast Ensemble Combinations & skill scores

2.3. Results & analysis

2.3.1. Climate models downscaling & bias corrections

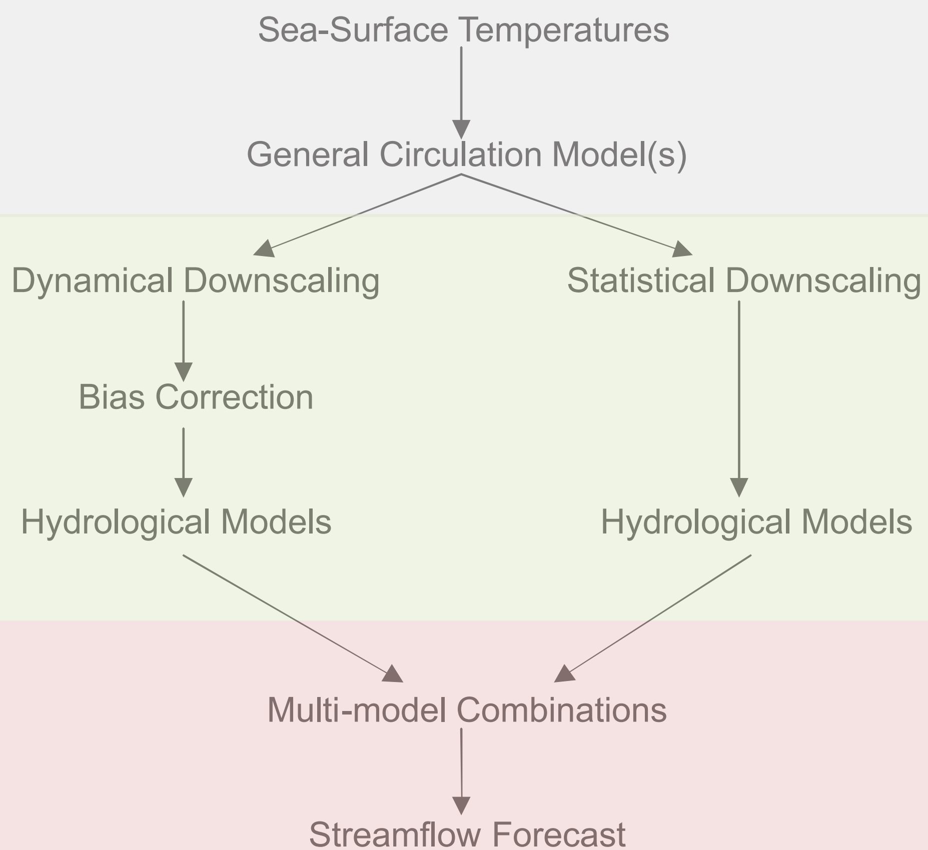
2.3.2. Validation of coupled climate/hydrological streamflow hindcasts

2.3.3. Validation of Multi-Model Ensemble combinations

2.3.4. January-June 1991 case study

2.2. DATA & METHODOLOGY

Forecasting Approach



① **GCMs precipitation forecasts** are **downscaled** with statistical and dynamical downscaling

② **RCM downscaled rainfall** are then **bias corrected** using hindcasts & past observations

③ **Downscaled precipitation** are fed **into hydrological models** to **forecast streamflow**

④ These are subsequently weighted/ combined to **create a multi-model ensemble** for probabilistic evaluation

To demonstrate the framework on the **Iguatu basin, a streamflow hindcast** is performed over the **1974-1996 period**

2.2. DATA & METHODOLOGY

Climate Models & Downscaling

❖ **GCMs:** Max Planck ECHAM4.5 *(Roeckner et al, 1996)*
NCEP MRF9 *(Kumar et al, 1996)*

Both are forced by observed SSTs to provide hincasts

❖ **RCMs:** NCEP Regional Spectral Model (RSM) *(Juang et al, 1997)*

An 10-run ensemble is produced with the nested RSM-ECHAM4.5 using observed SSTs (Jan-Jun, 1971-2000)

NB: similar RSM-MRF9 products were not available

❖ **Statistical Downscaling:** Principal Component Analysis (PCA)

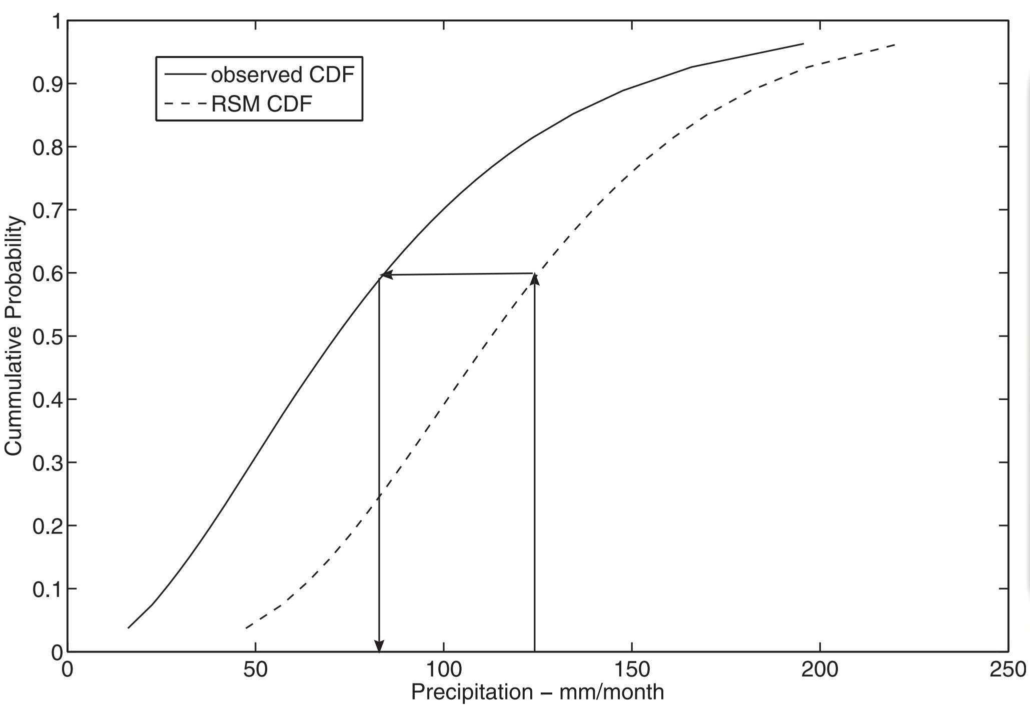
A cross-validated linear regression model with PCs of the GCM forecasted precipitation ensemble mean acting as predictors

NB: repeated for each month and each GCM

2.2. DATA & METHODOLOGY

Climate Models & Downscaling

- **Bias correction:** Probability mapping applied to monthly RSM precipitation data and is based on two cumulative distribution functions (CDFs): (1) the historical observed data, and (2) all RSM ensemble data pooled by months



1) Each CDF is **fit with a gamma distribution**

2) **A given monthly RSM precipitation** value from a hindcast ensemble member is **then bias corrected by mapping it from** the corresponding **month's pooled RSM CDF to** the **observed CDF**

2.2. DATA & METHODOLOGY

Hydrological Models

- **Conceptual model: Soil Moisture Accounting Procedure (SMAP)** model containing 2 reservoirs and 4 parameters. The rainfall-runoff component is founded on the Soil Conservation Service equation and utilizes basin average precipitation and evapotranspiration

(Souza Filho and Porto, 2003)

- **Non-linear watershed model: ABCD** model represents soil moisture storage, ground water storage, direct runoff, ground water outflow to the stream channel, and actual evapotranspiration. Inputs include precipitation and potential evapotranspiration

(Thomas, 1981; Thomas et al,1983)

2.2. DATA & METHODOLOGY

Multi-Model Hindcast Ensemble Combinations & Skill Scores

Three techniques are applied to seasonal streamflow hindcast totals aggregated from monthly values (Jan-Jun):

- **Simple pooling:** all ensemble members are given equal weight and joined into a single multimodel ensemble (MME) => superior to a single forecast due to its higher reliability *(Barnston et al, 2003; Robertson et al, 2004)*

- **Least Square Linear Regression:** assigns a weight to model ensembles based on the regression coefficient created by fitting individual ensemble means to observed conditions *(Van den Dool, 2008)*

- **Normal Density Kernel Estimator:** calculates the probability density at each hindcast observation from each model. Optimal weight for each model is obtained by maximizing the total likelihood over all time periods from all models *(Rajagopalan et al, 2002; Bishop, 2006)*

Skill scores: median and total root mean square error (RMSE), Pearson's correlation coefficient and Rank Probability Skill Score (RPSS)

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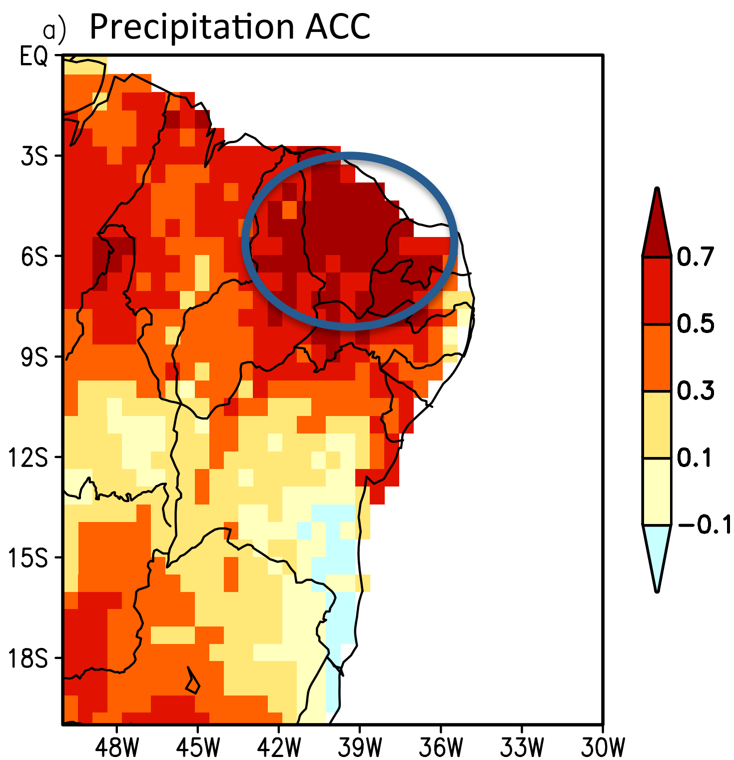
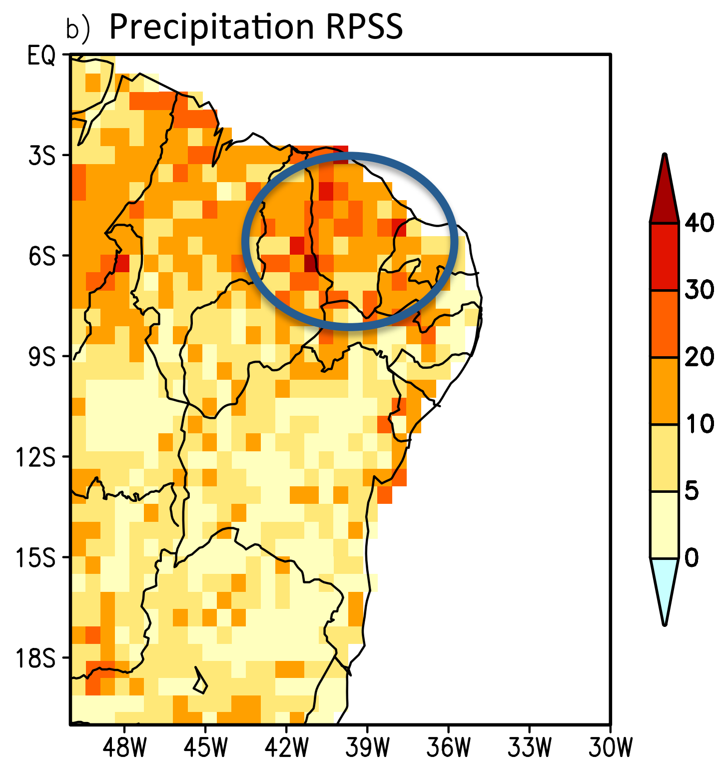
2.3. RESULTS & ANALYSIS

Climate Models Downscaling

Nested ECHAM4.5-RSM Jan-Jun Precipitation diagnostics





- **ACC:** strong performance suggests that much of the interannual variability of basin rainfall is associated with global SST variations
- **RPSS:** moderate skill (<10%) south of latitude 9S, but stronger skill (>10%) in northeast Brazil, particularly over the basin

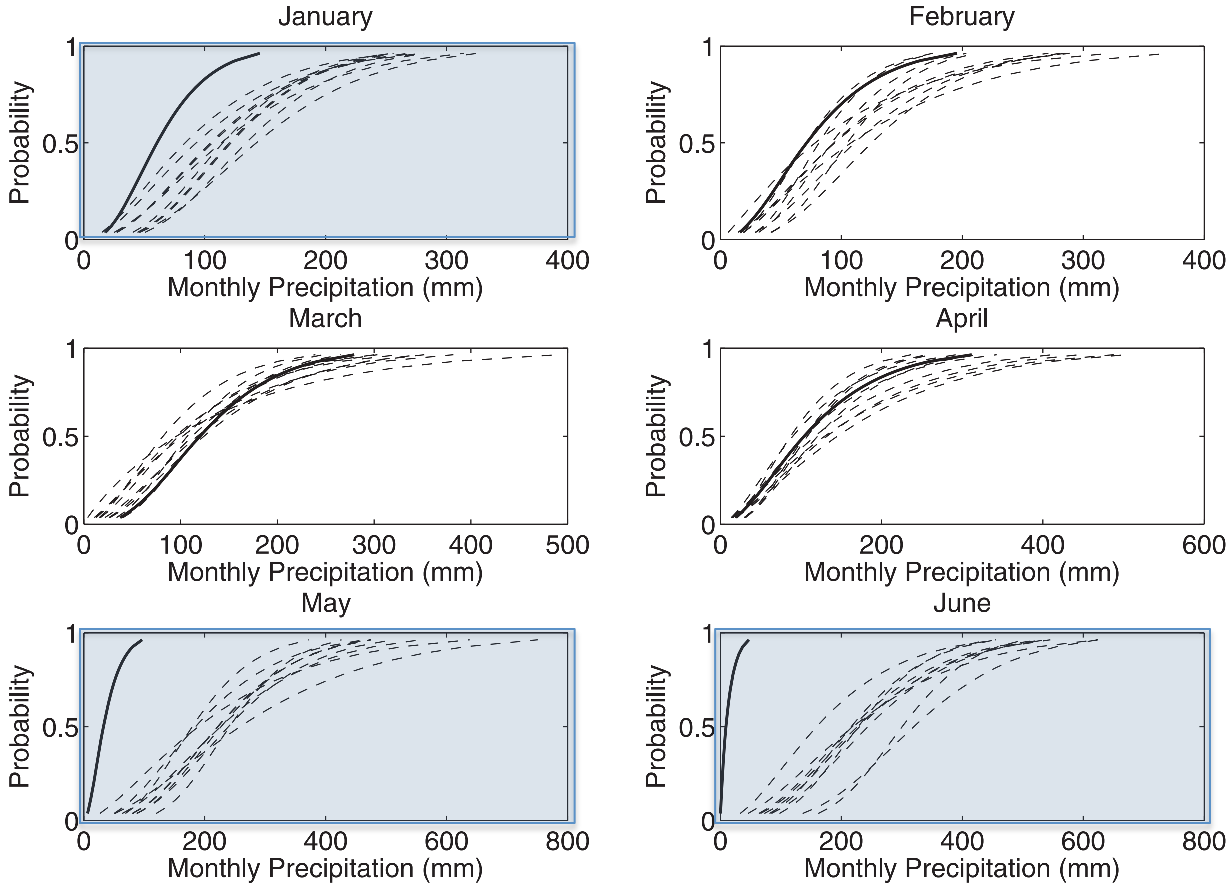
2.3. RESULTS & ANALYSIS

Monthly Model Bias Correction

Nested ECHAM4.5-RSM Jan to Jun precipitation model bias correction

Continuous line: observations

Dashed lines: 10 uncorrected RSM members

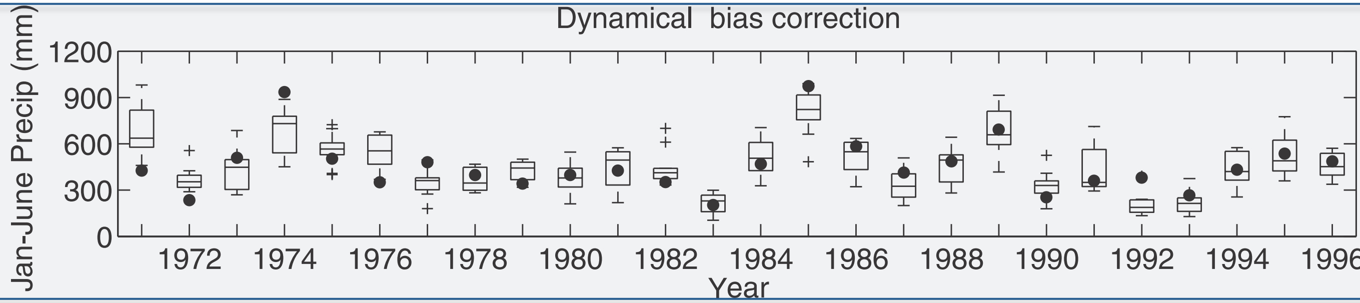


Raw RSM and observed CDFs required for **bias correction** of monthly precipitation

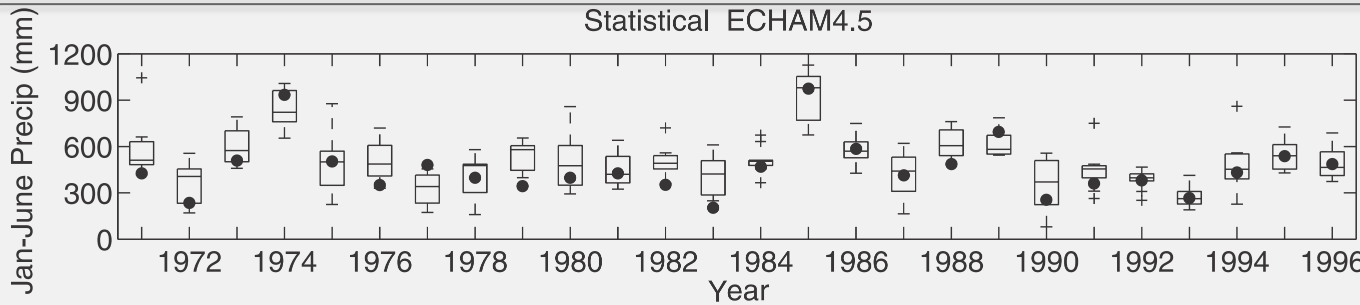
=> larger bias in the drier January, May, and June months

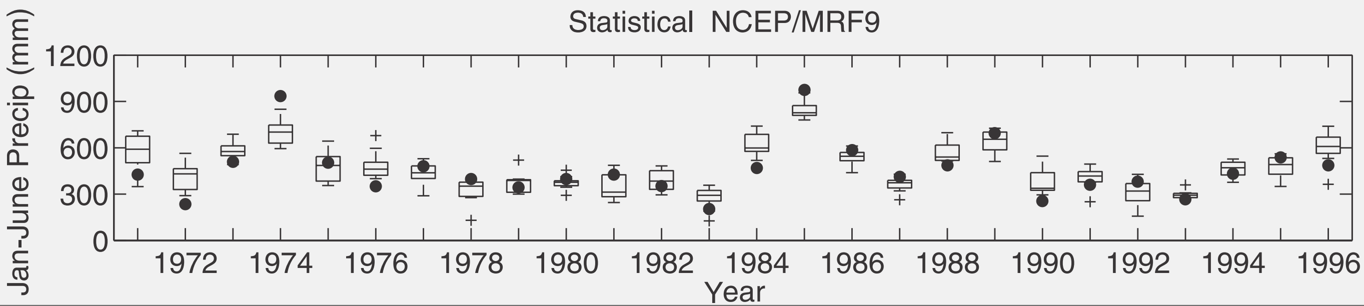
2.3. RESULTS & ANALYSIS

Models Downscaled Jan-Jun Precipitation



ECHAM4.5-RSM
bias corrected





Statistical Approach (ECHAM4.5/MRF9)

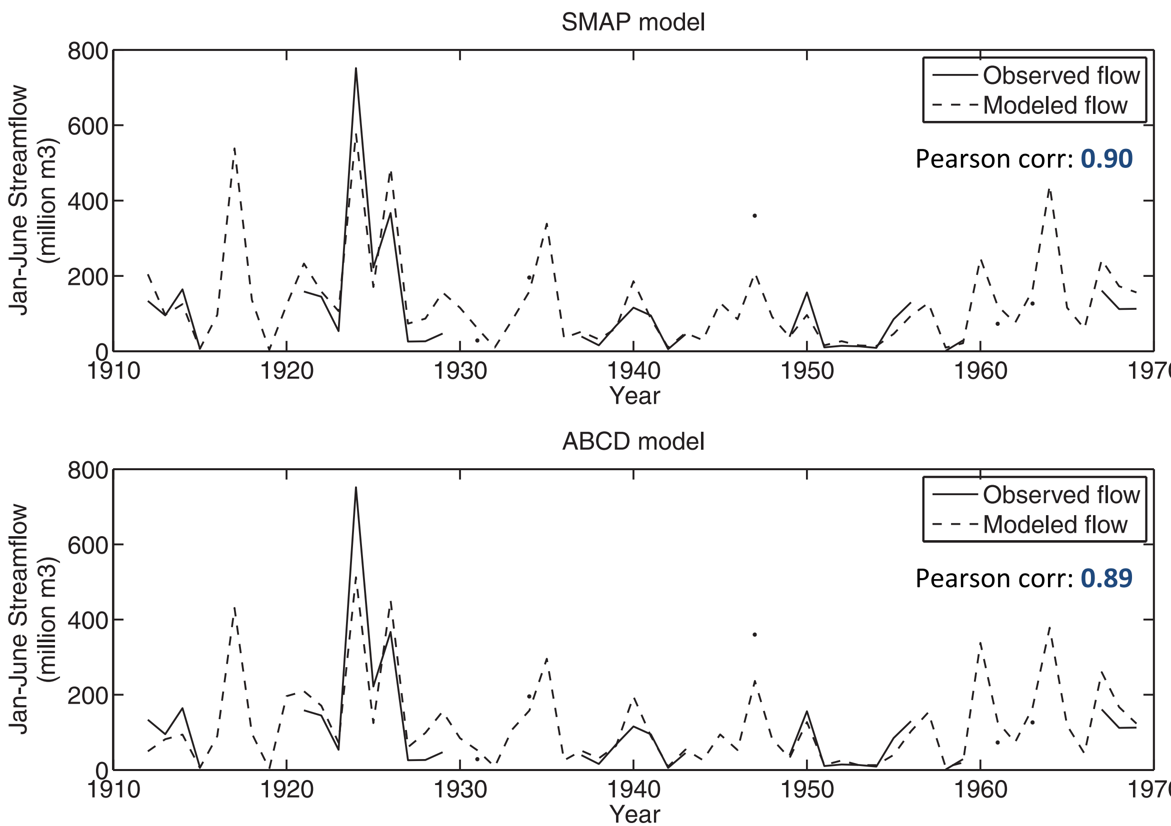
- Based on 10PCs explaining 79/65% of total variance
- High correlation coefficients (0.88/0.85) and robust median RPSS (0.27/0.55)

- For most years the **ensemble members envelop the observed value**
- **Comparable performance** of statistical and dynamical downscaling approaches

=> **Retaining both methods** remains prudent **for capturing structural uncertainty**

2.3. RESULTS & ANALYSIS

Jan-Jun Modeled Streamflow (1912-1969 Calibration)

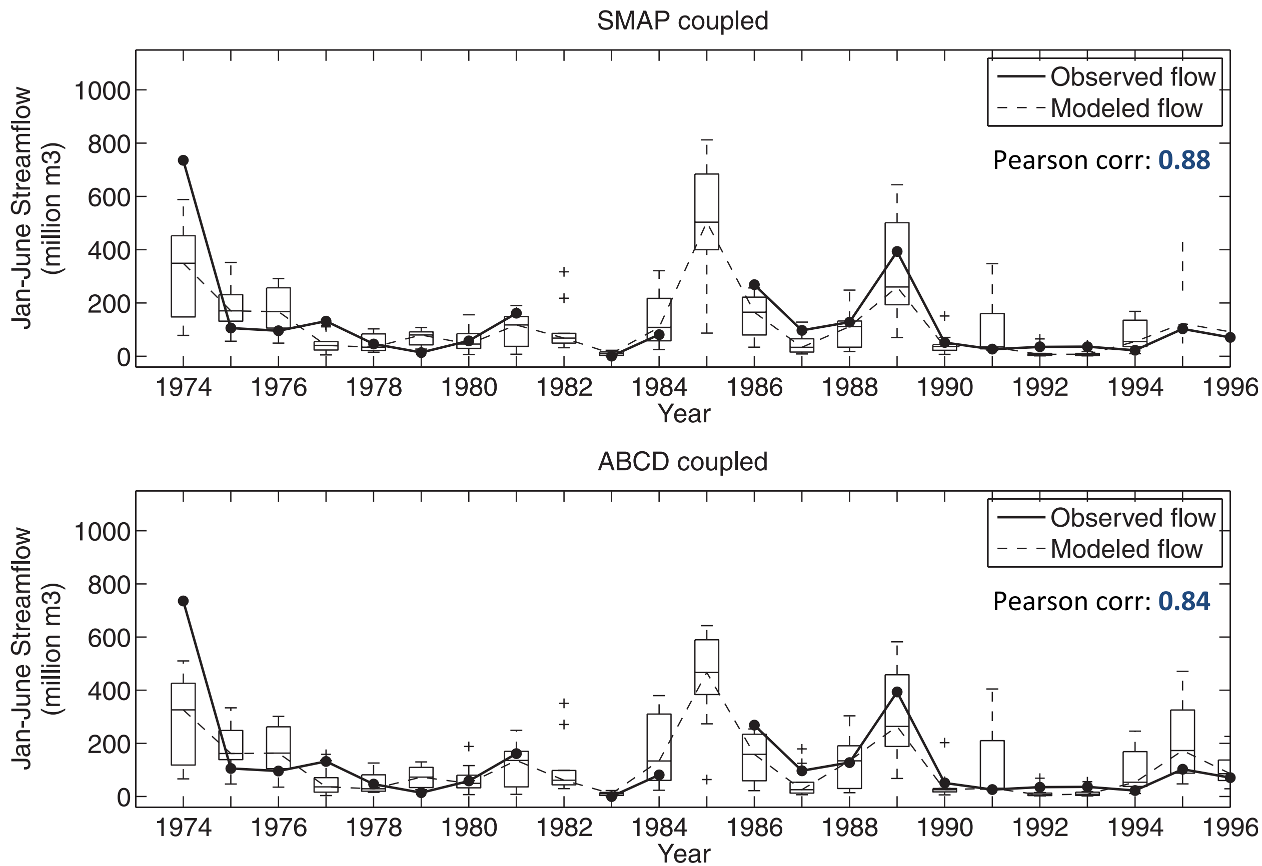


- The **models mimic observed streamflow** quite well (except for wettest 1924)
- **Monthly time-series** (not shown) **also indicate strong correlations (#0.90)**

2.3. RESULTS & ANALYSIS

Coupled Climate/Hydrological Model Hindcast (1974-1996 Validation)

Jan-Jun streamflow from ***ECHAM4.5 dynamically downscaled/bias corrected*** *precipitation*

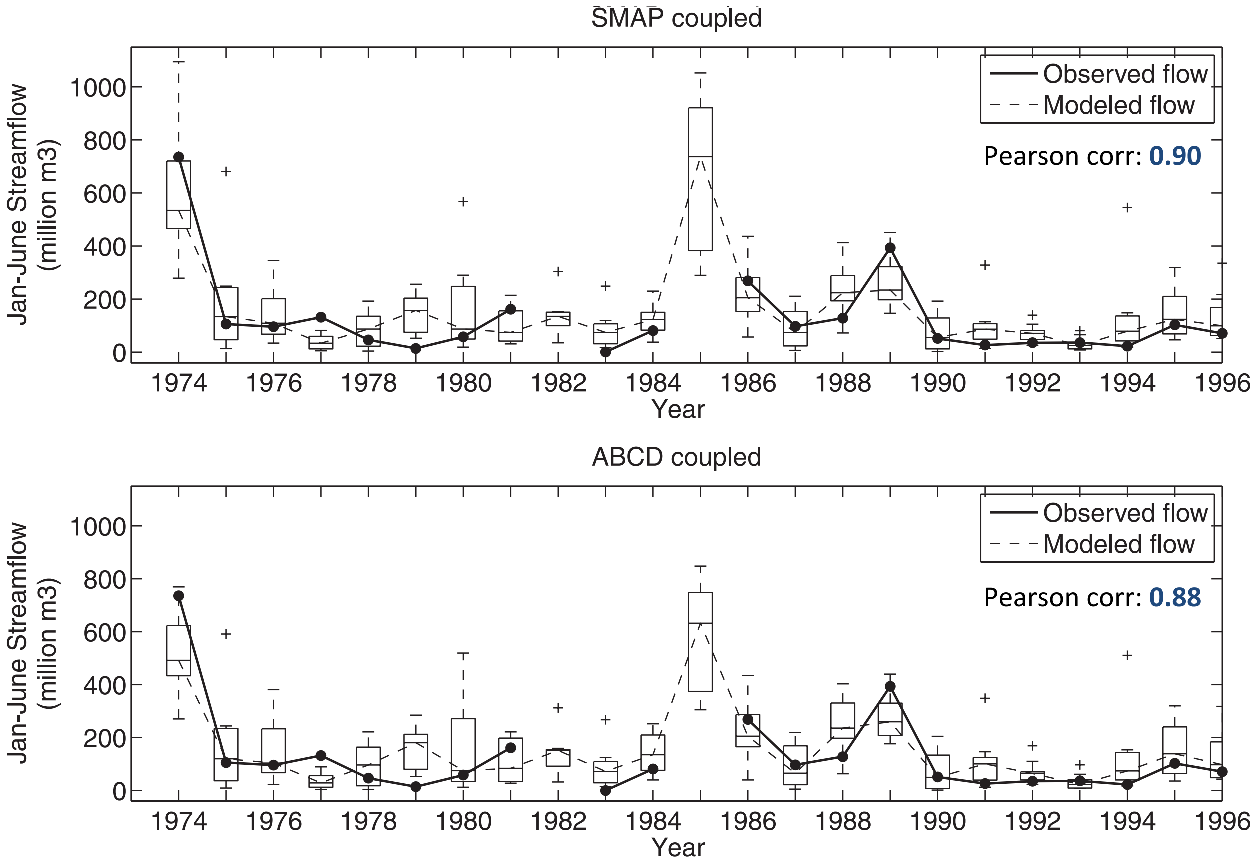


- **Strong model performance** according to seasonal correlation coefficients
- **Contrasting with calibration** period, both models **do well in estimating high flow** seasonal quantities, but are **less proficient for low flow** seasons

2.3. RESULTS & ANALYSIS

Coupled Climate/Hydrological Model Hindcast (1974-1996 Validation)

Jan-Jun streamflow from ***ECHAM4.5 statistically downscaled*** *precipitation*

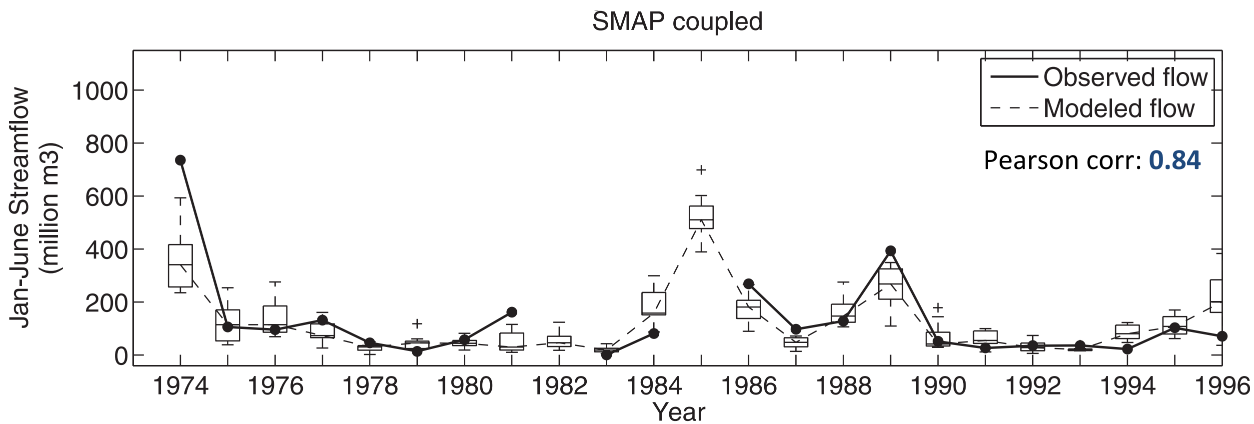


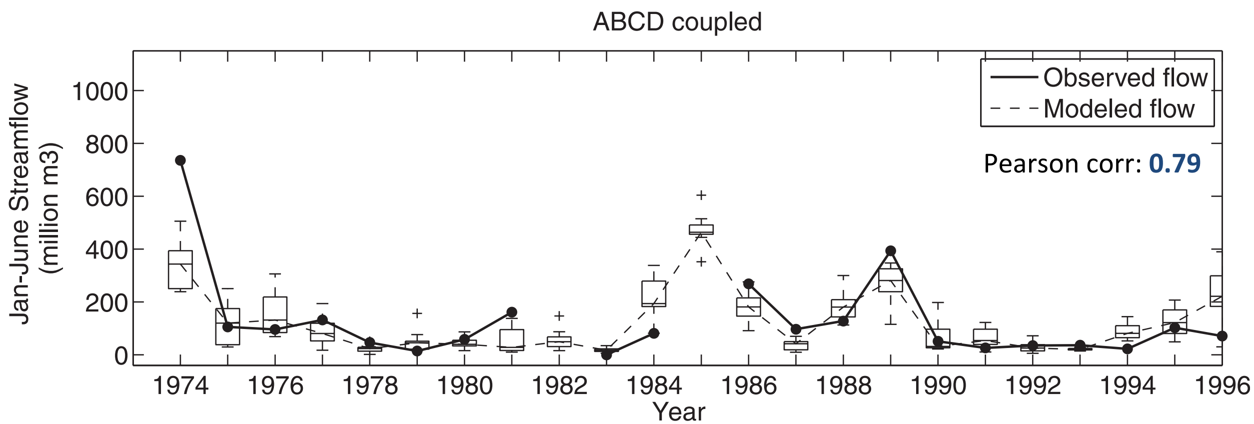
- **Strong model performance** according to seasonal correlation coefficients
- **Better approximation of 1974**, the wettest year in the hindcast period

2.3. RESULTS & ANALYSIS

Coupled Climate/Hydrological Model Hindcast (1974-1996 Validation)

Jan-Jun streamflow from ***NCEP/MRF9 statistically downscaled*** *precipitation*





- **Strong model performance** according to seasonal correlation coefficients
- **Less variance** under both hydrological models
- **Solid capture of the dry years** by all coupled methods.

2.3. RESULTS & ANALYSIS

Coupled Climate/Hydrological Model Hindcast (1974-1996 Validation)

Coupled Model	Correlation Coefficient	Root Mean Squared Error		RPSS
		Median	Total	
SMAP – Dynamical	0.88	100	1,707	0.42
ABCD – Dynamical	0.84	106	1,863	0.42
SMAP – Statistical ECHAM	0.90	81	962	–0.04
ABCD – Statistical ECHAM	0.88	88	1,069	–0.10
SMAP – Statistical NCEP	0.84	105	1,489	0.55
ABCD – Statistical NCEP	0.79	108	1,530	0.53

- Skill scores reasonably strong **=> features of the basin generally captured**
- **SMAP** coupled models appear **slightly superior** to the **ABCD** models
- **Larger differences** are evident **between downscaling techniques**
- **SMAP-Statistical-ECHAM** demonstrates **highest skill scores** (Corr and RMSE) but **performs inferiorly to climatology** (RPSS)

2.3. RESULTS & ANALYSIS

Multi-Models Ensemble Combinations (1974-1996 Validation)

Coupled Model	Correlation Coefficient	Root Mean Squared Error		RPSS
		Median	Total	
Pooled	0.90	90	-	0.21
Linear regression weighting	0.91	92	1,008	0.35
Kernel density estimator	0.92	90	962	0.55

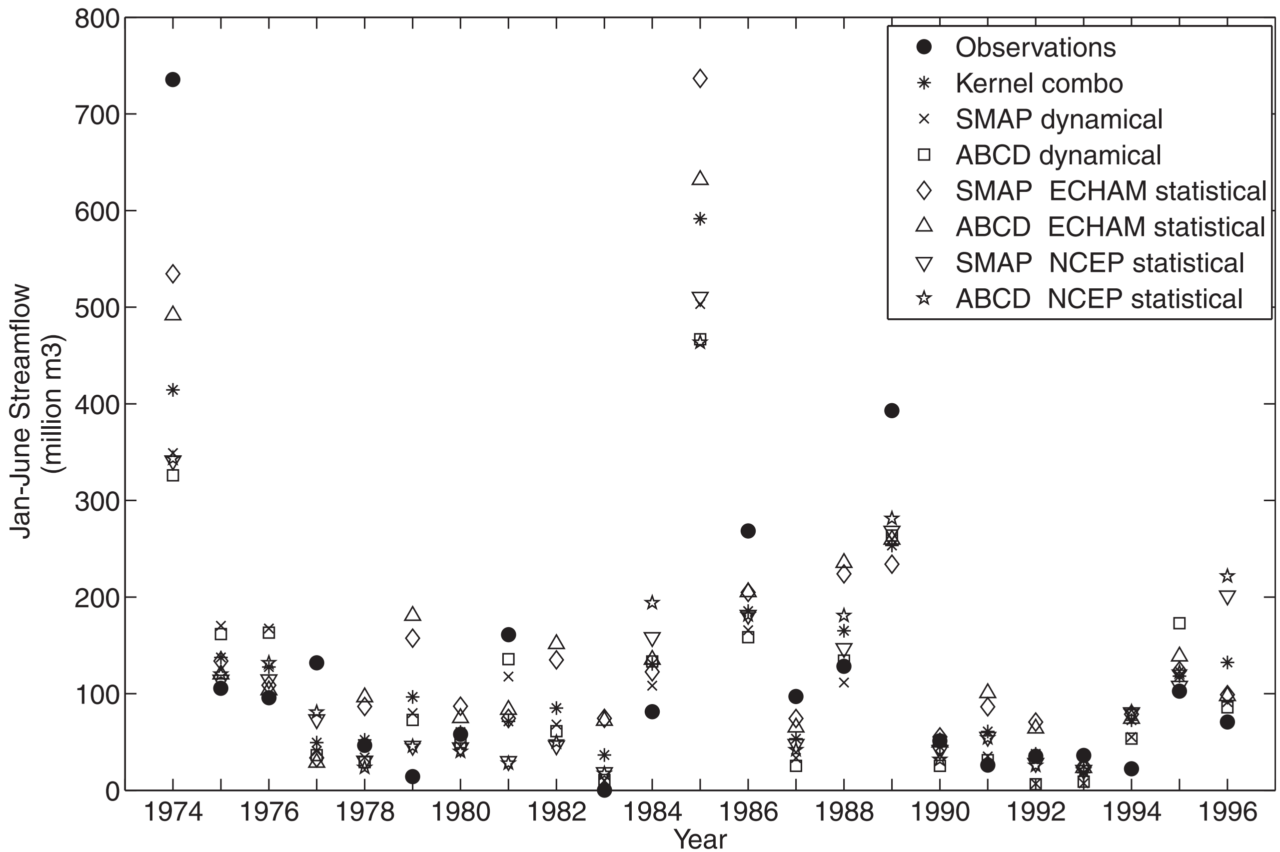
Notes: RPSS, rank probability skill score. Pearson correlation coefficients use ensemble medians.

- **Kernel density estimator** approach emerges as **most skillful**
- **Correlation** coefficients are **superior to single model** ensemble results
- **Errors** and **categorical skill scores** (RPSS) **as good or better than single models**

2.3. RESULTS & ANALYSIS

Multi-Models Ensemble Combinations (1974-1996 Validation)

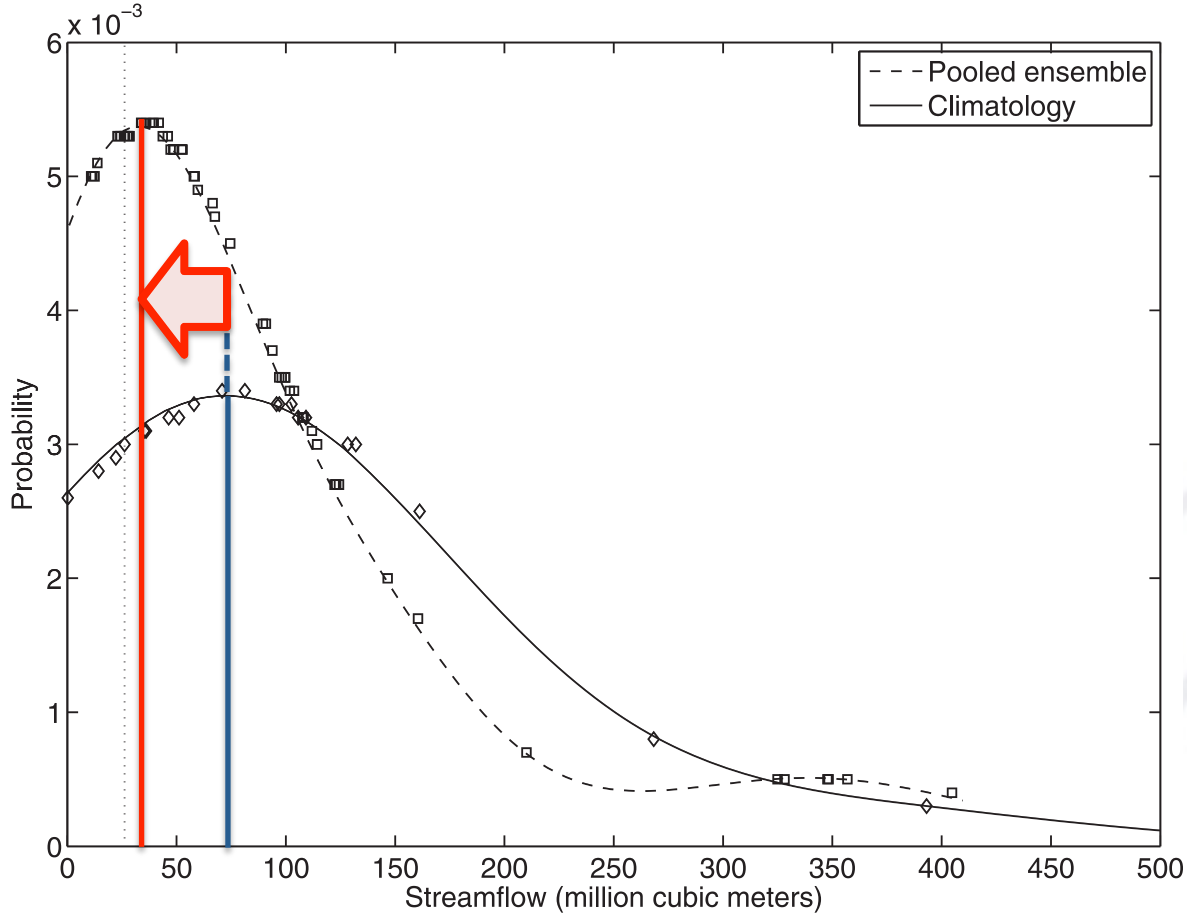
Median seasonal streamflow from models ensemble combined with the kernel density estimator



Kernel combination does not produce the best estimate for any given year, but **out- performs any single hydrological model** approach over the hindcast period

2.3. RESULTS & ANALYSIS

January-June 1991 Case Study: Total Streamflow PDFs (dry year)



Streamflow forecast ensembles may be used to construct **probability density functions (PDFs) beneficial for risk-based decision making**

Pooled ensemble hindcast **PDF shifted left of the climatological PDF**

=> Relatively less streamflow

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PART 3: Dynamical downscaling & agriculture in Brazil

Sun, L., H. Li and M.N. Ward (2007) Climate variability and corn yields in semi-arid Ceará, Brazil, *J. Appl. Meteor. Climatol.*, 46:226-240

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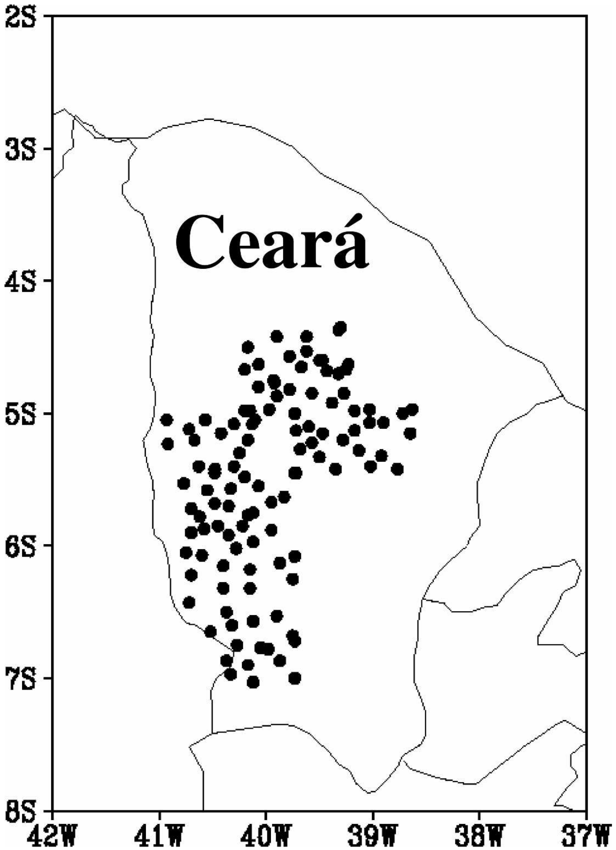
OUTLINE

3. DYNAMICAL DOWNSCALING & AGRICULTURE IN BRAZIL

3.1. MOTIVATION



Network of rainfall stations in the Sertão Central region of Ceara

- The state of Ceará, situated in **semi-arid northeast Brazil**, occupies an area of **146 348 km2** where crop production is highly vulnerable to climate variability
  (Chimeli et al, 2002)

- Previous studies indicated that the **corn yields in Ceará are highly correlated with ENSO** and suggested that ENSO can be used to predict corn yields
  (Rao et al, 1997)

- However, **yield predictions showed large biases** when compared with observations

=> Need to find a better index to represent climate influence on corn yields

- **Corn** is the pre-dominant rain-fed crop, it is **planted in January or early February**, and it takes **90-120 days to reach maturity**

=> same **FMAM growing season** used every year

3.2. DATA & METHODOLOGY

Corn Yields Data

- Corn data **aggregated at state level** for the **1952-2001** period obtained from **IPLANCE** (a)

- The **trends** in corn yields that are believed to be **unrelated to climate** effects are **removed**

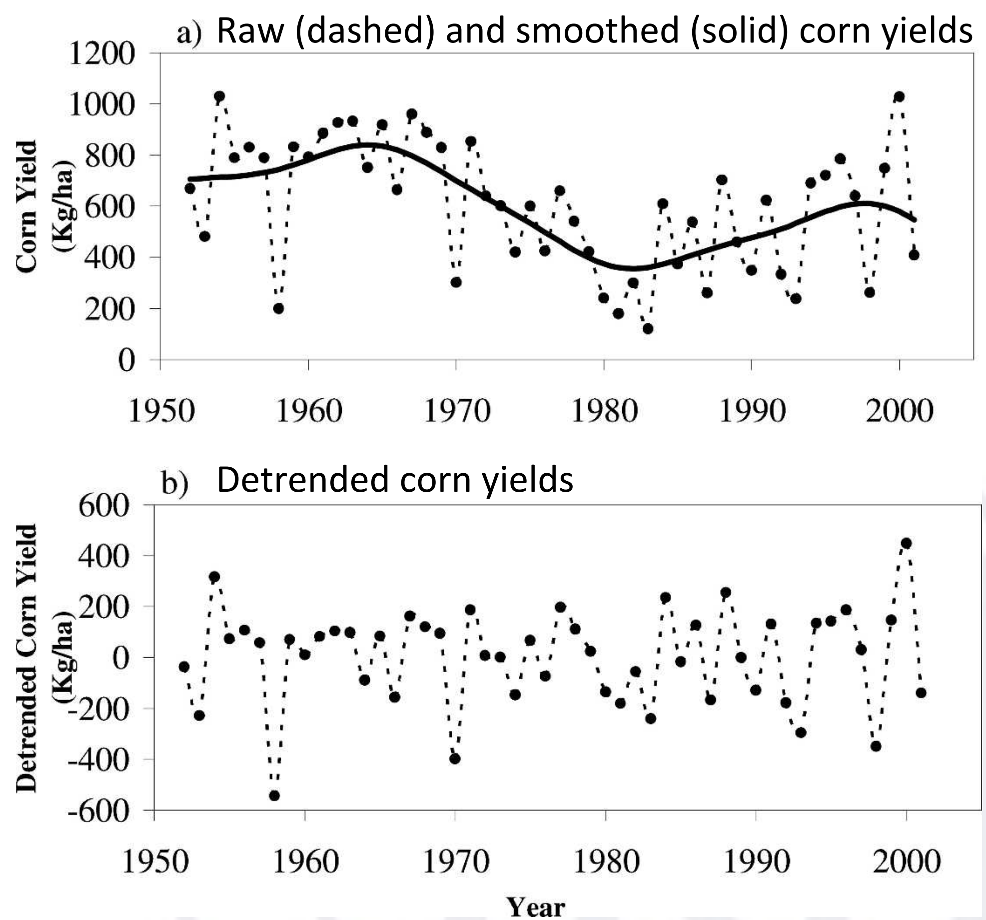
⇒ **Low-pass spectral smoothing filter** applied to the raw yield data to separate higher- and lower-frequency trends *(Press et al, 1989)*

N.B.: the 10-yr smoothing chosen is subjective

- **Detrended yields** display **large interannual variability** (b)

- Subsequent analyses are done on the **normalized detrended yield data**

IPLANCE: Fundação Instituto de Pesquisa e Informação do Ceará



Time-series of corn yields (kg/ha) for the Sertao Central region of Ceara

3.2. DATA & METHODOLOGY

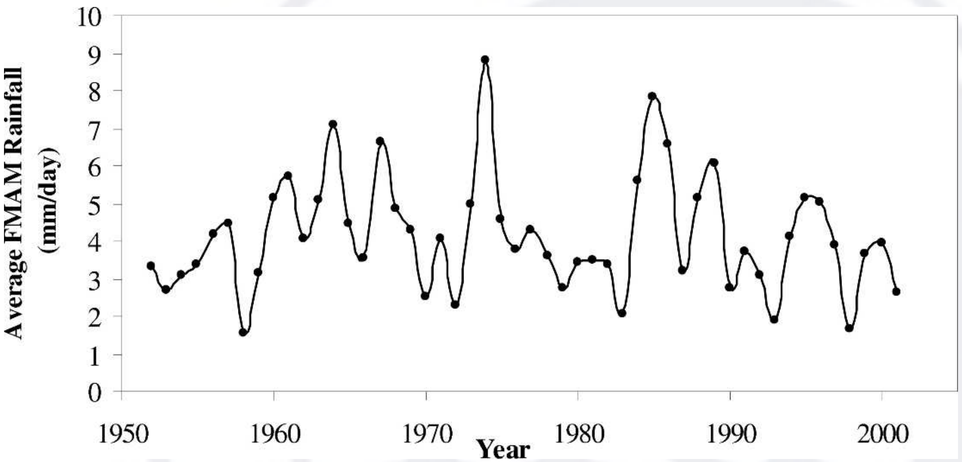
SSTs & Rainfall

- **SSTs: -** observed seasonal SSTs from NOAA/CPC
  - Niño-3.4 SST anomaly ([5°S–5°N;170°–120°W])
  - Tropical Atlantic SST anomaly dipole ([5°–20°N;60°–30°W]/[0°–20°S;30°W–10°E])

- **Observed rainfall:** -observed seasonally from **dense network** over Sertão Central region
  - -correlation analysis shows that the **Sertão Central region** can be treated as a **homogeneous region for daily rainfall**

The **number of stations with complete daily records** used to calculate seasonal mean rainfall and daily rainfall statistics varies from **50 stations in the 1950s, 80 from the 1960s to 1980s**, and **30 in the 1990s**

Mean seasonal rainfall display **large interannual variations** over the Sertão Central region



Observed Feb-May (FMAM) rainfall over the Sertão Central region of Ceara

3.2. DATA & METHODOLOGY

Rainfall Hindcasts

A **global with a nested regional model** are used to generate rainfall hindcasts

- **Global model:** ECHAM4.5 at T42 spatial resolution (#2.8deg x 2.8deg)
  (Roeckner et al, 1996)

- **Regional model:** NCEP Regional Spectral Model (RSM) at 60km spatial resolution
  (Juang and Kanamitsu, 1994; Juang et al, 1997)

The RSM domain encompasses Brazil and the entire tropical Atlantic

- **Experimental design:** -10 ECHAM4.5 members forced by observed SSTs over 1971-2000
  -Related RSM members generated from 6hourly ECHAM4.5 output for the January-May period (1971-2000)

N.B.: January is used as spin-up for RSM runs and is discarded in the following analyses

3.2. DATA & METHODOLOGY

Statistical Metrics

- **Linear correlations:** to examine relationships between climate & corn yields

- **Linear regressions:** to simulate corn wields from climate variables

- **Goodness-of-fit:** 3 measures used to evaluate corn yields simulations,
  - *Coefficient of determination r^2 (square of correlation coefficient)*: describes the proportion of the **total variance of the observed corn yields explained by the climate variables**. One limitation is that its values are highly sensitive to outliers

    (Legates and McCabe, 1999)

  - *Index of agreement d:* measures the **degree to which the observed data are approached by the predicted data**, and overcomes the insensitivity of r^2 to differences in the observed and predicted means and variances

  - *Mean Absolute Error (MAE):* represents the **overall error** and is less sensitive than RMSE to errors in large predicted departures from the mean

    => considered a more robust measure of accuracy *(Hansen et al, 2004)*

- **Variance ratio:** to estimate **potential predictability** of rainfall generated by the nested RSM. It represents the **proportion of the total variance that can be explained by SST forcing**

OUTLINE

3. DYNAMICAL DOWNSCALING & AGRICULTURE IN BRAZIL

3.1. Motivation

3.2. Data & Methodology

3.2.1. Corn yields data

3.2.2. SST & rainfall

3.2.3. Rainfall hindcasts

3.2.4. Statistical metrics

3.3. Climate variability & corn yields

3.3.1. Relationships between climate variables & corn yields

3.3.2. Corn yields simulations using observed climate data

3.4. Corn yields potential predictability

3.4.1. Dynamical model validation: simulated climate indexes

3.4.2. Dynamical model validation: simulated corn yields anomalies

3.3. CLIMATE VARIABILITY & CORN YIELDS

Relationships between climate variables & corn yields

❖ **Hypotheses:**

① Climate variables averaged over the whole growing period are used due to limited climate predictability

② Rainfall is the main limiting resource for crop growth in semiarid tropical regions

(Barron et al, 2003; Hansen and Indeje, 2004)

❖ **Corn yields** significantly **correlated to Nino3.4** (a) and **tropical Atlantic dipole** (b)

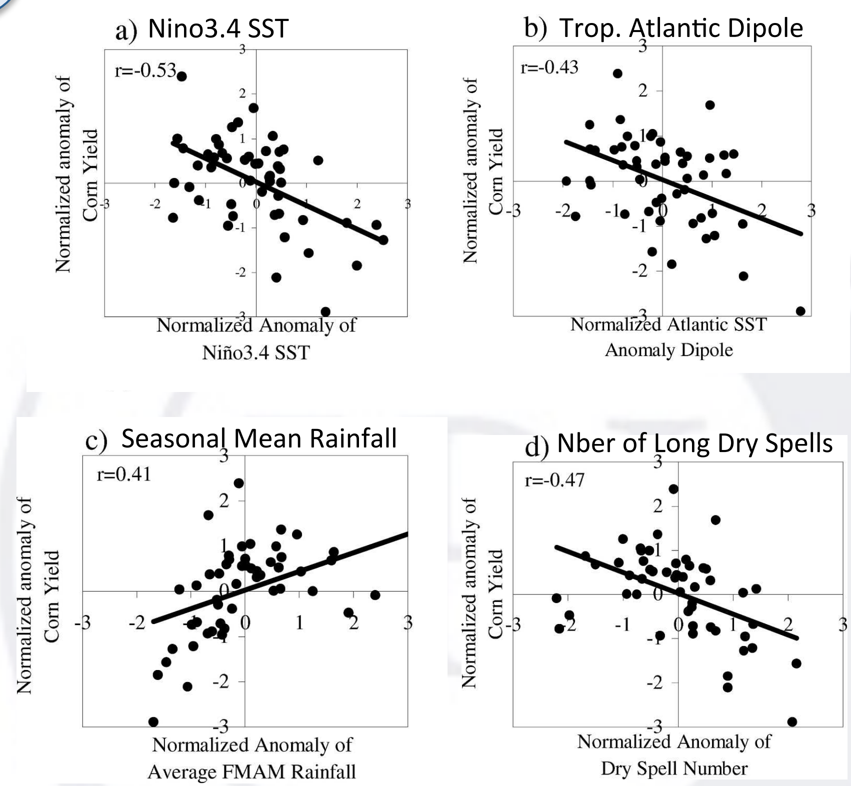
❖ **Corn yields** generally **associated with the seasonal mean rainfall anomalies** (c)

❖ **Corn water stress** due to a soil water deficit is often **associated with dry spells longer than 10 days**

⇒ **Long dry spell definition:** 10 or more consecutive days with rainfall < 2mm/day)

Corn yields anti-correlated with normalized anomalies of the **number of long dry spells** (d)

Linear regression with corn yields



3.3. CLIMATE VARIABILITY & CORN YIELDS

Relationships between climate variables & corn yields

- ❖ Both frequency and duration of dry spells can affect corn yields

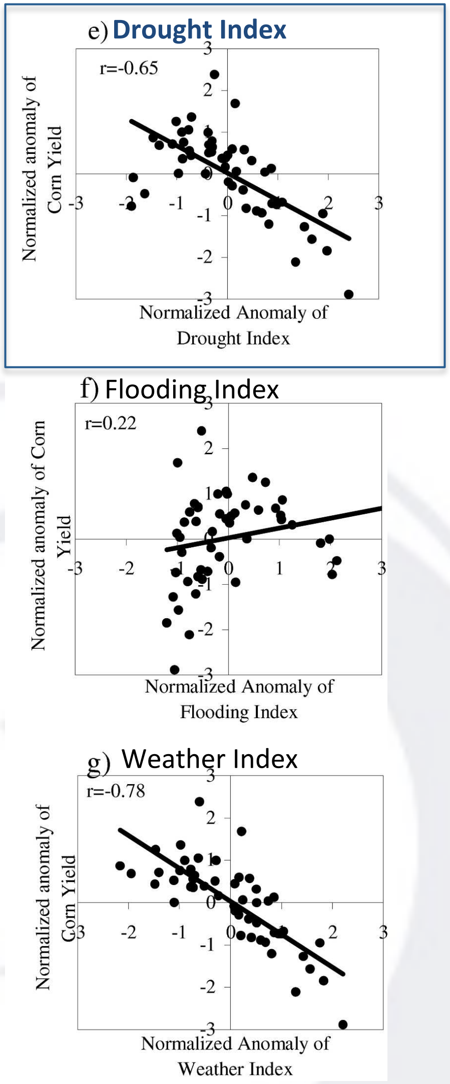
⇒ use of a **drought index** to measure the severity of drought conditions:

$$D_{\text{index}} = \sum_{i=1}^{n} L_i W,$$

$$\text{where } L_i \text{ is the length of the } i\text{th dry spell and } W = \begin{cases} 1 & \text{if } L_i < 10 \\ 5 & \text{if } L_i \geq 10 \end{cases}.$$

- ❖ **Dry spell definition:** 3 or more consecutive days with rainfall < 2mm/day

- ❖ **Corn yields** are **correlated with normalized anomalies of drought index (e)** which appears as a better parameter than the number of long dry spells (d)



3.3. CLIMATE VARIABILITY & CORN YIELDS

Relationships between climate variables & corn yields

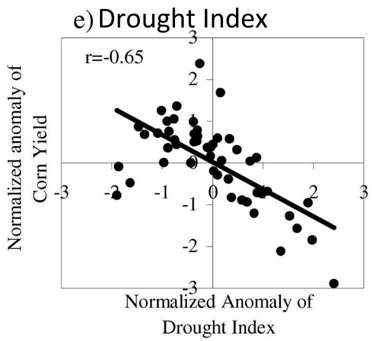
- Because of the shallow soil layer, flooding conditions associated with wet spells in the region wash away corn plants, resulting in low plant density.
  => use of **flooding index** to measure the severity of flooding conditions:

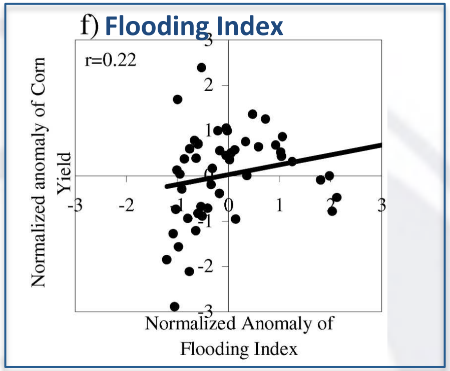
$$F_{\text{index}} = \sum_{i=1}^{n} L_i W,$$

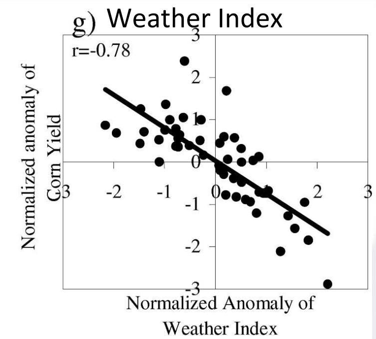
where L_i is the length of the ith wet spell and $W = \begin{cases} 1 & \text{if } L_i < 10 \\ 5 & \text{if } L_i \geq 10 \end{cases}.$

- **Wet spell definition:** 3 or more consecutive days with rainfall>2mm/day

- Corn yields **not significantly correlated with the flooding index (f)** which may be due to recurrent drought episodes and low frequency of wet spell occurrences over the region







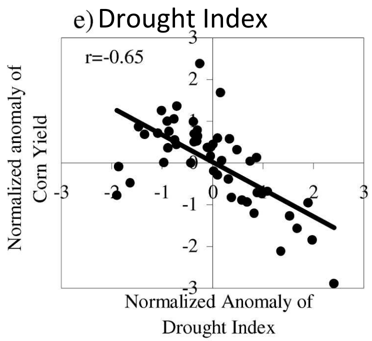
3.3. CLIMATE VARIABILITY & CORN YIELDS

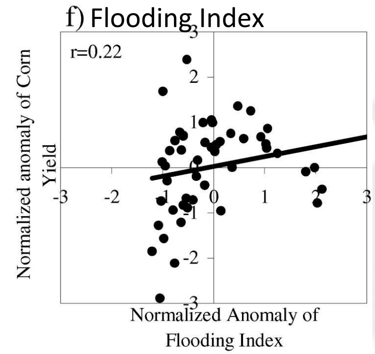
Relationships between climate variables & corn yields

❖ To combine the impact of drought and flooding conditions
⇒ use of **weather index** to measure the severity of flooding conditions:

$$W_{\text{index}} = \begin{cases} D'_{\text{index}} & \text{if } D'_{\text{index}} > 0 \\ D'_{\text{index}} + F'_{\text{index}} & \text{if } D'_{\text{index}} \leq 0 \quad \text{and} \quad F'_{\text{index}} > 1.5 \\ D'_{\text{index}} - F'_{\text{index}} & \text{if } D'_{\text{index}} \leq 0 \quad \text{and} \quad 0 \leq F'_{\text{index}} \leq 1.5 \end{cases},$$

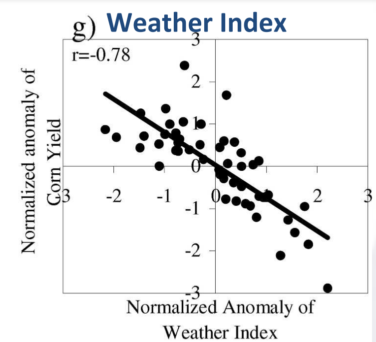
where $D'_{\text{index}}/F'_{\text{index}}$ are normalized anomalies of drought/flooding index





❖ Corn yields **significantly correlated with the weather index (g)** through a quasi-linear relationship

⇒ The **weather index** appears as the **best climate index** to represent the climate impacts on corn yields



<u>N.B.:</u> 1) the weather index is closely associated with seasonal mean rainfall only when the weather index is extremely high or low
2) the weather index isn't correlated with seasonal mean rainfall when its variations are less than one standard deviation

=> The **weather index** can be treated as an **independent variable except for years with extreme anomalies**

3.3. CLIMATE VARIABILITY & CORN YIELDS

Corn yields simulations using observed climate data

❖ Each of the **four climate variables** (Nino3.4, Atlantic dipole, seasonal mean rainfall and weather index) are used **to estimate corn yields by linear regression**

*<u>N.B.:</u> the **distribution of these variables** can be **approximated as normal** as shown by observation except for **seasonal mean rainfall** to which a **Box and Cox (1964) transformation** is **applied***

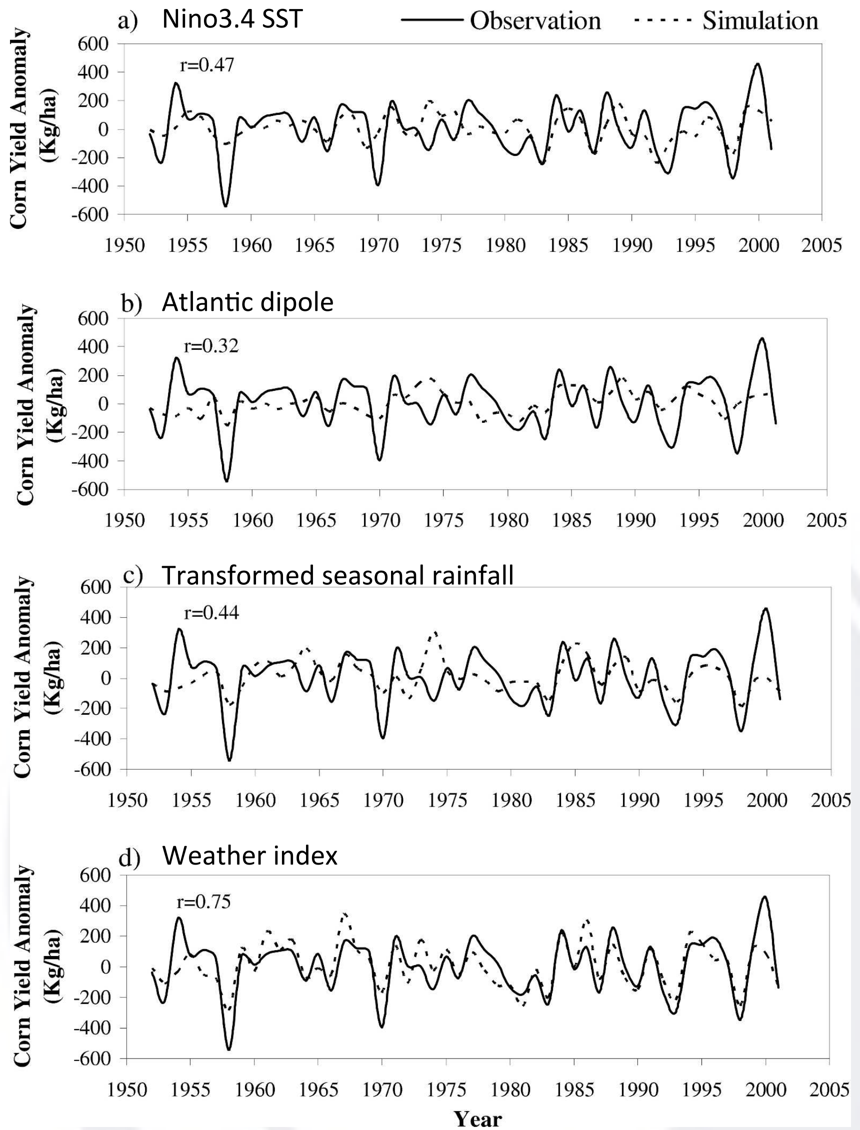
❖ **Leave-one-out cross validation:**

① **For each year i**, the model is solved by **linear regression using the observed corn yields and the climatic variable** from **all** of the **years except** for the **year i**

② **The simulated yield is calculated from the fitted slope**, **intercept** and the **observed climatic variable for the year i**

(Hansen and Indeje, 2004)

Simulated corn yields anomalies



3.3. CLIMATE VARIABILITY & CORN YIELDS

Corn yields simulations using observed climate data

- The corn yields simulations using the **weather index** tend to **agree most closely** with the **observations**, and ranks first in all three goodness-of-fit measures:

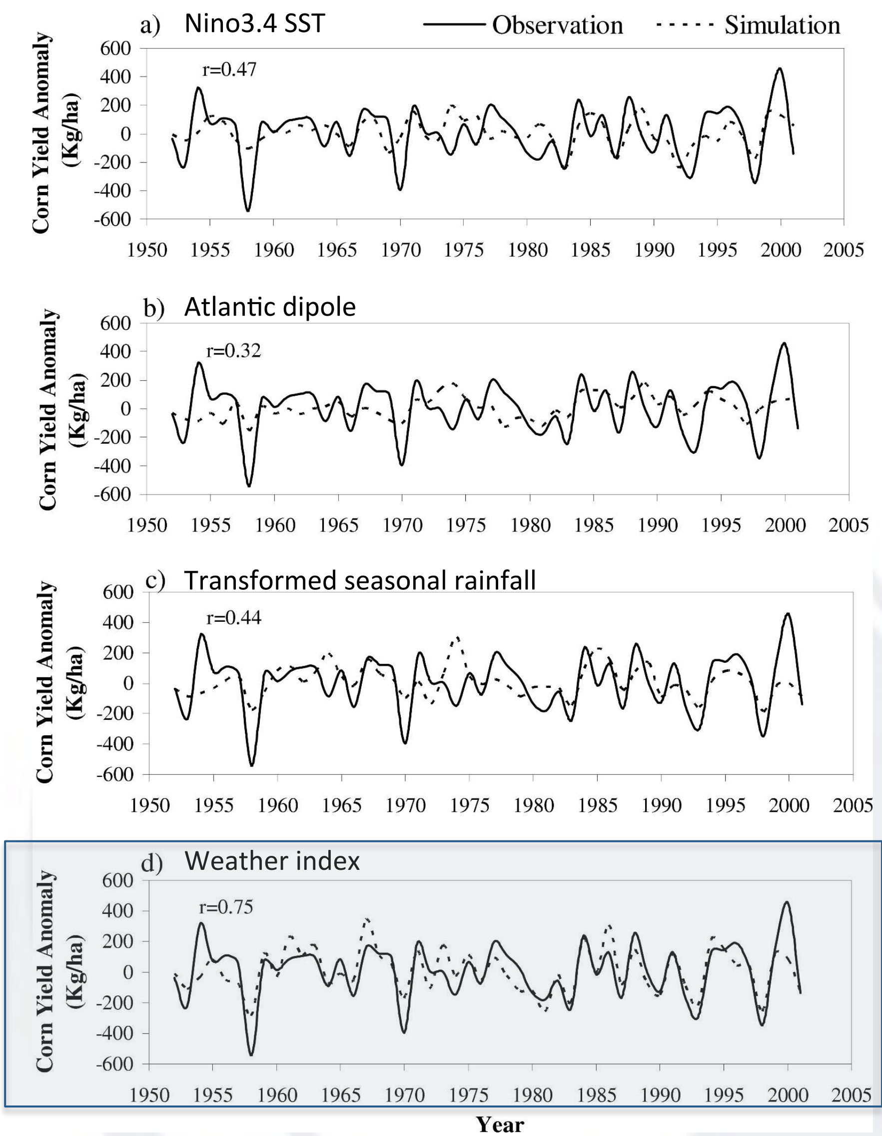
Predictor	Niño-3.4 SST	Atlantic dipole	Seasonal rainfall	Weather index
r^2	21.7	10.4	19.2	56.8
MAE (kg ha^{-1})	128.4	144.0	130.5	91.0
d	0.61	0.49	0.59	0.85

  - It accounts for 56.8% of yield variance
  - It agrees most with observations (d=0.85)
  - It has the least amount of errors (MAE=91.0)

- The **Niño-3.4 SST ranked second**, followed by the seasonal mean rainfall, while the **Atlantic dipole is the least effective predictor** for the corn yield

- **No improvement with the "seasonal mean rainfall"** predictor relative to the SST indices

Simulated corn yields anomalies



OUTLINE

3.4. CORN YIELD POTENTIAL PREDICTABILITY

Dynamical model validation: simulated climate indexes

- **All four indexes are calculated for each of the 10 integrations on every model grid box**, then the mean of each index is computed over the 10 integrations and the 13 grid boxes over the region

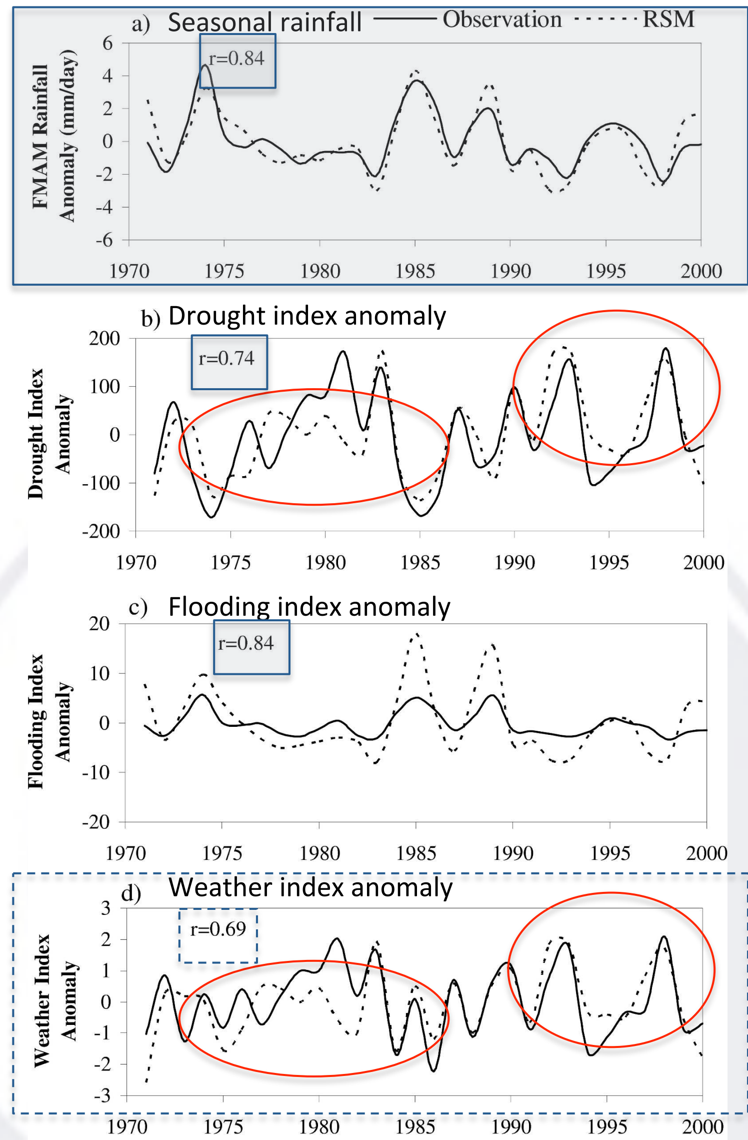
- **Seasonal mean rainfall:** the model simulated the observed anomalies well, but produced **relatively large biases**: 3/2 years with positive/negative biases
  => Model biases seem to be **random**

- **Drought index:** agrees well with observation, however drought index anomalies are well reproduced/**show large biases** in 1971 and 1999/**1973, 1976, 1977, 1981, 1988, and 1994**

- **Flood index:** hindcasts **highly correlated** with observation **but inter-annual variability stronger**

- **Weather index: reproduces better inter-annual variability**, **main biases** are associated with **biases of the drought index**

Simulated climate indexes



3.4. CORN YIELD POTENTIAL PREDICTABILITY

Dynamical model validation: simulated climate indexes

	Seasonal rainfall	Drought index	Flooding index	Weather index
r^2	70.2	54.2	71.0	47.4
MAE	0.83	78.0	5.6	0.64
d	0.89	0.76	0.53	0.84
Variance ratio	0.71	0.68	0.59	0.54

- The large values of the **variance ratio** for all four variables suggest that **SST forcing has a statistically significant** and, therefore, **predictable influence on the interannual variability** of local **seasonal mean rainfall** and **weather statistics**

- Hindcasts show **significant agreement with the observations and account for a large portion of the observed variance** for all four variables during the FMAM season

- **Seasonal mean rainfall** hindcasts **agreed most closely** with the observations **and accounted for most of the observed variance** during the 30-yr period **=> highest potential for predictability**

  +

  Seasonal rainfall model is able to capture the interannual variability of weather index which may significantly contribute to corn-yield predictions

3.4. CORN YIELD POTENTIAL PREDICTABILITY

Dynamical model validation: simulated corn yields anomalies

- **Box and Cox (1964) transformation** is applied to **seasonal mean rainfall** hindcasts

- **Linear regression** is applied to produce **corn yields** simulations using transformed **seasonal mean rainfall** and **weather index** from **RSM model output**

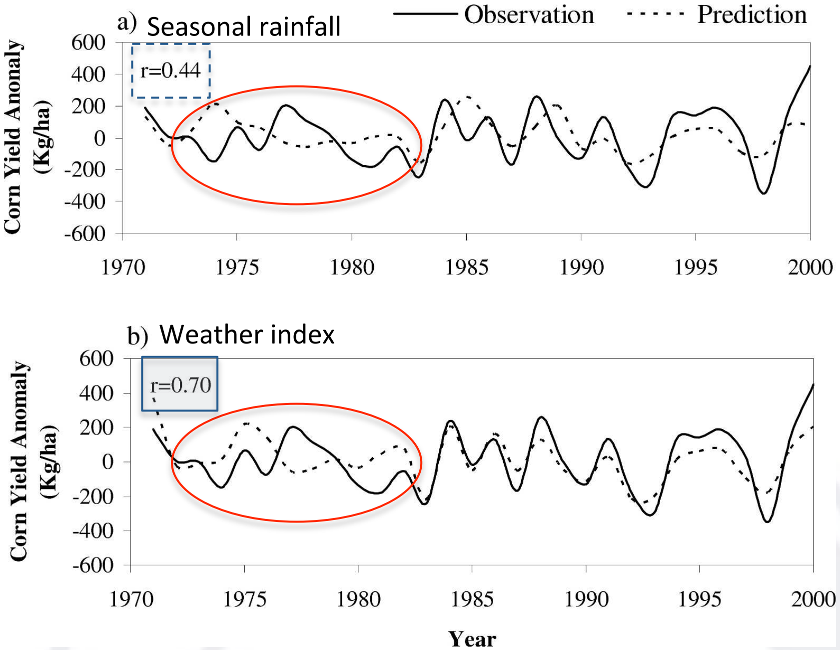
- **Simulated corn yields** using the seasonal mean rainfall or the weather index **are significantly correlated with the observations**

- **Although the RSM has better skill for the seasonal mean rainfall than the weather index, yield simulations with the weather index** are **better than** those with the **seasonal mean rainfall**

- **Corn simulation skill using the RSM weather index** shows only a **small shortfall** from that using observed weather index

  => Potentials for predictability!!!

Simulated corn yields anomalies



Poor corn yields simulations from 1975-82

Observed weather index exhibits **large inter-annual variability**, and **the model failed to reproduce** the observed anomalies

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