



The International Research Institute
for Climate and Society

Climate Variability and Change over South America (and other places)

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Outline

This presentation will describe research output from my time at IRI, where I am part of the Climate Program and, in particular, of the Near-Term Climate Change (NTCC) group.

Project:

Diagnosing Decadal-Scale Climate Variability in Current Generation Coupled Models for Informing Near-term Climate Change Impacts. NOAA CVP. Lead PI: L. Goddard.

1. Develop metrics and baselines for estimating the quality of decadal predictions
2. Determine the fidelity of the surface expression of oceanic decadal variability, and the associated climate teleconnections, in several state-of-the-art CGCMs



Develop metrics and baselines for estimating the quality of decadal predictions

Collaboration with US CLIVAR's Decadal Predictability Working Group

Clim Dyn
DOI 10.1007/s00382-012-1481-2

A verification framework for interannual-to-decadal predictions experiments

L. Goddard · A. Kumar · A. Solomon · D. Smith · G. Boer · P. Gonzalez · V. Kharin · W. Merryfield · C. Deser · S. J. Mason · B. P. Kirtman · R. Msadek · R. Sutton · E. Hawkins · T. Fricker · G. Hegerl · C. A. T. Ferro · D. B. Stephenson · G. A. Meehl · T. Stockdale · R. Burgman · A. M. Greene · Y. Kushnir · M. Newman · J. Carton · I. Fukumori · T. Delworth

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Abstract Decadal predictions have a high profile in the climate science community and beyond, yet very little is known about their skill. Nor is there any agreed protocol for estimating their skill. This paper proposes a sound and coordinated framework for verification of decadal hindcast experiments. The framework is illustrated for decadal hindcasts tailored to meet the requirements and specifications of CMIP5 (Coupled Model Intercomparison Project phase 5). The chosen metrics address key questions about

the information content in initialized decadal hindcasts. These questions are: (1) Do the initial conditions in the hindcasts lead to more accurate predictions of the climate, compared to un-initialized climate change projections? and (2) Is the prediction model's ensemble spread an appropriate representation of forecast uncertainty on average? The first question is addressed through deterministic metrics that compare the initialized and uninitialized hindcasts. The second question is addressed through a probabilistic



Develop metrics and baselines for estimating the quality of decadal predictions

My roles in the activity:

- to program, test and document a set of deterministic and probabilistic metrics to evaluate the skill of the CMIP5 decadal hindcasts
- to search for adequate scales for temporal and spatial averaging
- to develop a website to share the hindcasts evaluation and the Matlab code I developed

The International Research Institute for Climate and Society

Topics: Clouds, Precipitation, Temperature, Sea Level, Sea Surface Temperature, ENSO, El Niño, La Niña, Monsoon, Drought, Heatwaves, Floods, Wildfires, Sea Ice, Tropics, Regions: North America, Europe, Asia, Africa, South America, Resources: Data, Models, Tools, Publications, Sample Code.

U.S. CLIVAR DPWG

Hindcasts Skill Assessment

This website is a tool for the discussion within U.S. CLIVAR Working Group on Decadal Climate Predictability of verification metrics towards the development of a verification framework for decadal hindcasts. If you have any questions or comments, please contact Lisa Goddard.

The different sections present some preliminary results from the verification assessment of the DoPreSys perturbed physics hindcasts from the Hadley Centre, based on the model described in Smith et al. *Science* 317, 788 (2007).

Verification Metrics

Verification metrics should be chosen to answer specific questions regarding the quality of the forecast information. For example, they can identify where errors or biases exist in the forecasts to guide more effective use of them. The proposed questions address the accuracy in the forecast information and the representativeness of the forecast ensembles to indicate forecast uncertainty. Specifically, these questions are:

- Question 1: Do the initial conditions in the hindcasts lead to more accurate predictions of the climate?
- Question 2: Is the model's ensemble spread an appropriate representation of forecast uncertainty on average?
- Question 3: In the case that the forecast ensemble does offer information on overall forecast uncertainty, does the forecast-to-forecast variability of the ensemble spread carry meaningful information?

Final Version:
<http://clivar-dpwg.iri.columbia.edu/>

Prototype:
<http://iri.columbia.edu/~gonzalez/DPWG/>

Decadal Predictability Working Group

Overview | Deterministic Metrics | Probabilistic Metrics | Sample Code

Hindcasts Skill Assessment

This website is a tool for the discussion within U.S. CLIVAR Working Group on Decadal Climate Predictability of verification metrics towards the development of a verification framework for decadal hindcasts. If you have any questions or comments, please contact Lisa Goddard.

The different sections present results from the verification assessment of a few of the decadal hindcast experiments, mainly of CMIP5. For further details of the models and the forecast approach taken by each of the centers, please visit the CMIP5 data page: <http://cmip-pcmdi.llnl.gov/cmip5/>.

The verification metrics are chosen to answer specific questions regarding the quality of the forecast information. For example, they can identify where errors or biases exist in the forecasts to guide more effective use of them. The proposed questions address the accuracy in the forecast information and the representativeness of the forecast ensembles to indicate forecast uncertainty. Specifically, these questions are:

1. Do the initial conditions in the hindcasts lead to more accurate predictions of the climate?
2. Is the model's ensemble spread an appropriate representation of forecast uncertainty on average?

Version: dpwg-1.3.2 (2012-11-20 15:30:40 -0500)



Develop metrics and baselines for estimating the quality of decadal predictions

The deterministic verification metrics face **Question 1:**

Do the initial conditions in the hindcasts lead to more accurate predictions of the climate?

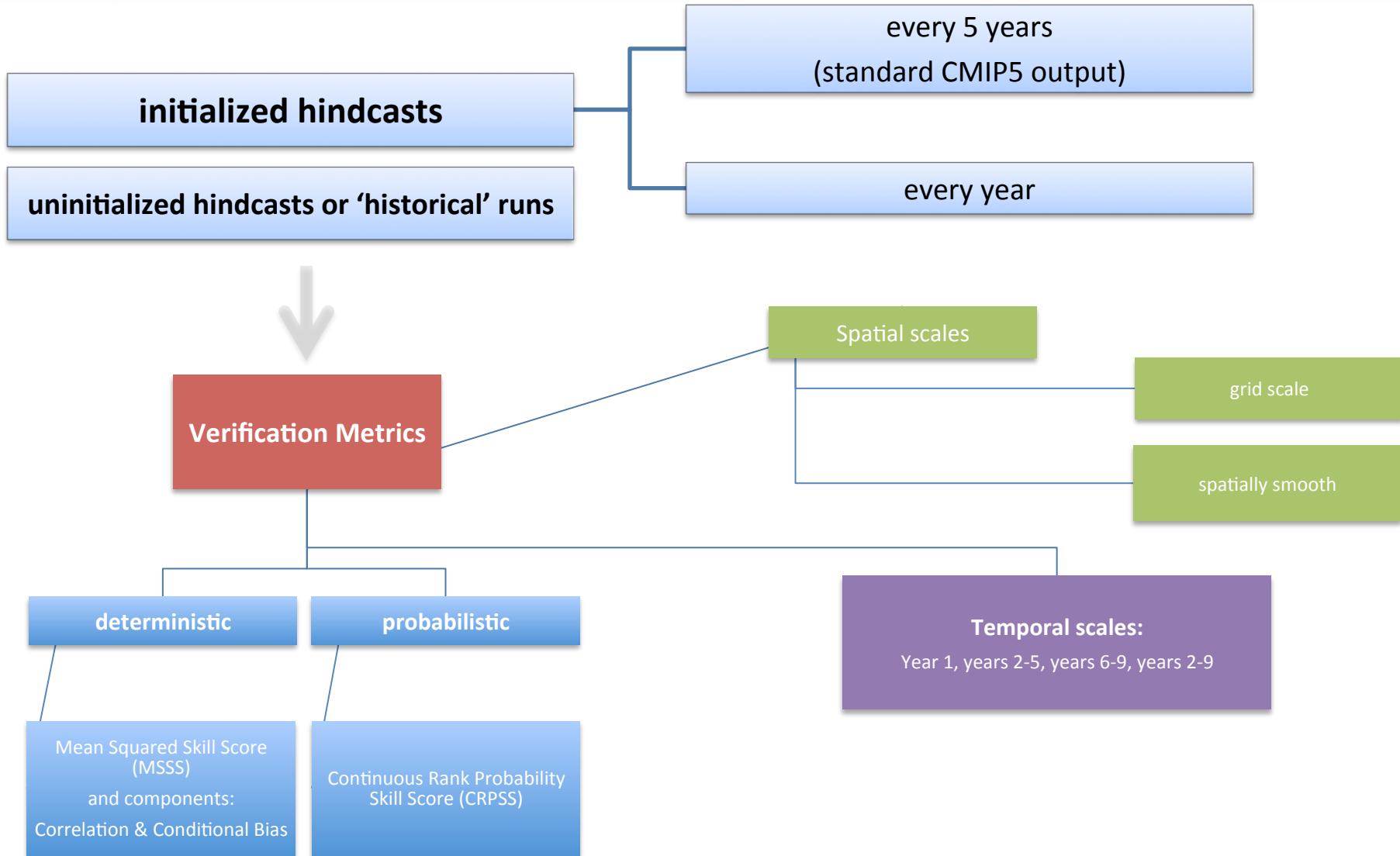
The probabilistic verification metrics face **Question 2:**

Is the model's ensemble spread an appropriate representation of forecast uncertainty on average?

and **Question 3:**

In the case that the forecast ensemble does offer information on overall forecast uncertainty, **Does the forecast-to-forecast variability of the ensemble spread carry meaningful information?**

Develop metrics and baselines for estimating the quality of decadal predictions

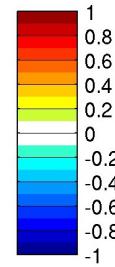
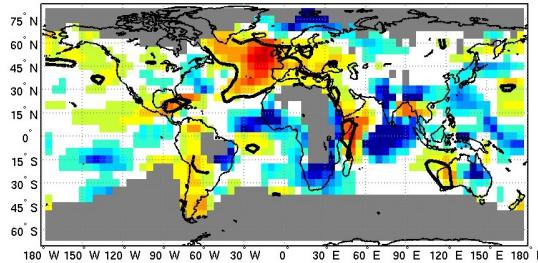


Develop metrics and baselines for estimating the quality of decadal predictions

Multi-model Ensemble Mean (12 models) – MSSS – years 2-5 – annual means

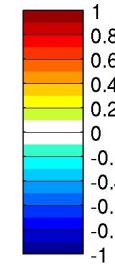
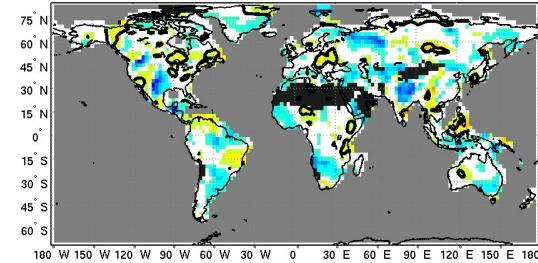
Temperature

MME temp MSSS: year 2-5 ann
Initialized - Uninitialized

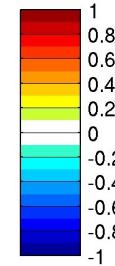
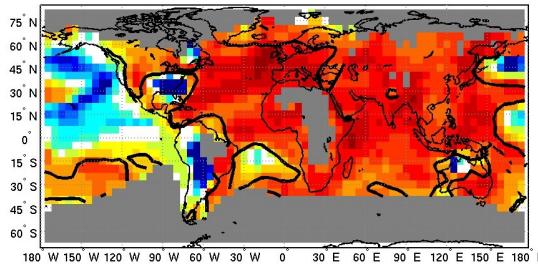


Precipitation

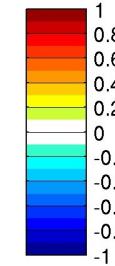
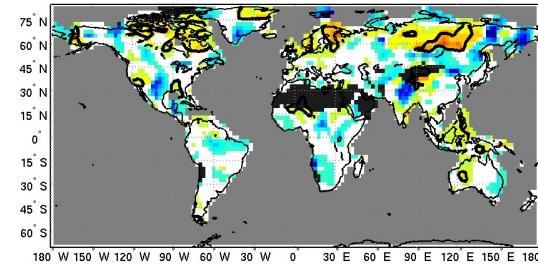
MME prcp MSSS: year 2-5 ann
Initialized - Uninitialized



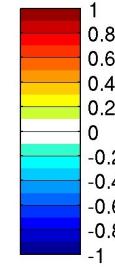
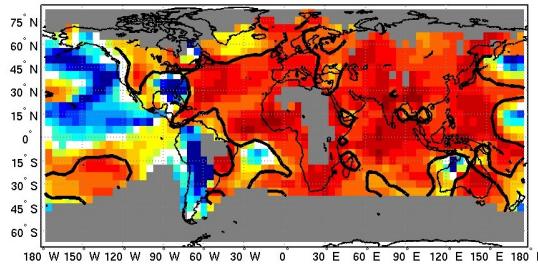
MSSS: Initialized Hindcast



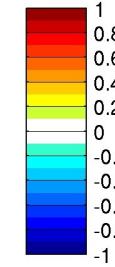
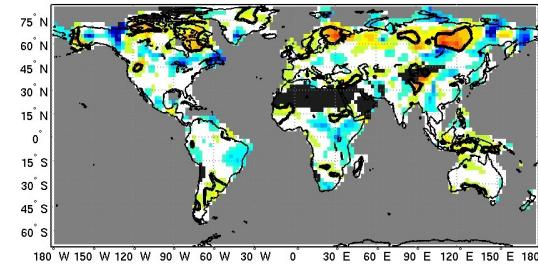
MSSS: Initialized Hindcast



MSSS: Uninitialized Hindcast



MSSS: Uninitialized Hindcast

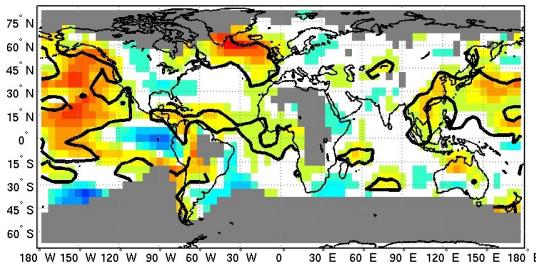


Develop metrics and baselines for estimating the quality of decadal predictions

Multi-model Ensemble Mean (12 models) – Correlation – years 2-5 – annual means

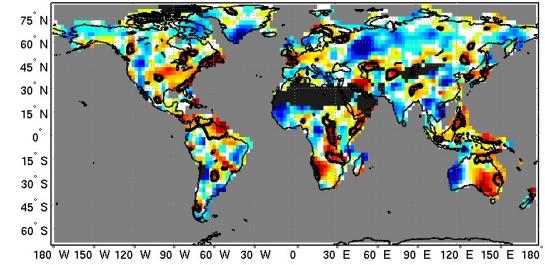
Temperature

MME temp Correlation: year 1 ann
Initialized - Uninitialized

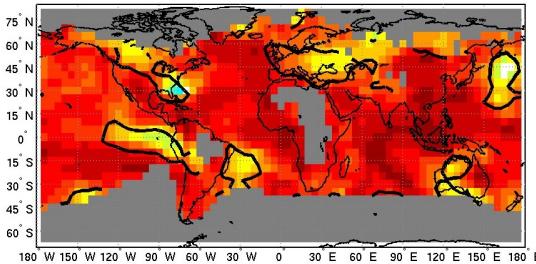


Precipitation

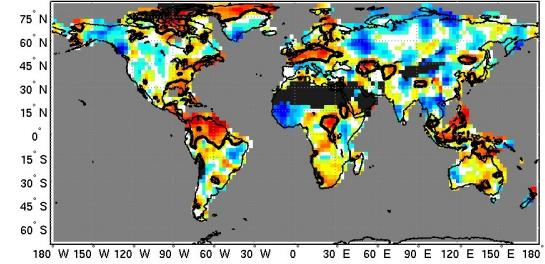
MME prop Correlation: year 1 ann
Initialized - Uninitialized



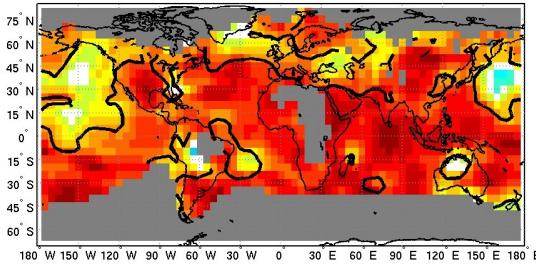
Correlation: Initialized Hindcast



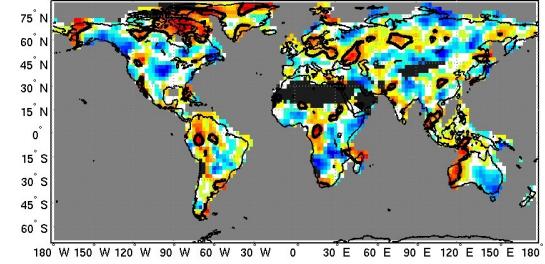
Correlation: Initialized Hindcast



Correlation: Uninitialized Hindcast



Correlation: Uninitialized Hindcast

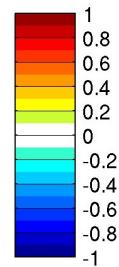
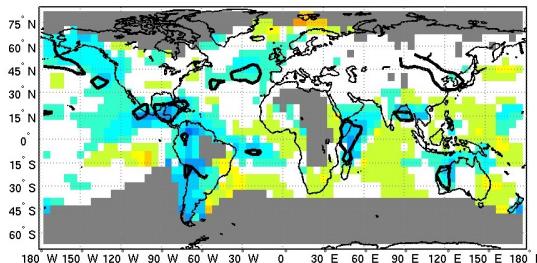


Develop metrics and baselines for estimating the quality of decadal predictions

MME (12 models) – Conditional Bias – years 2-5 – Spatially smooth - annual means

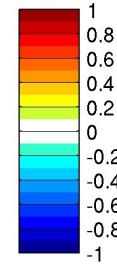
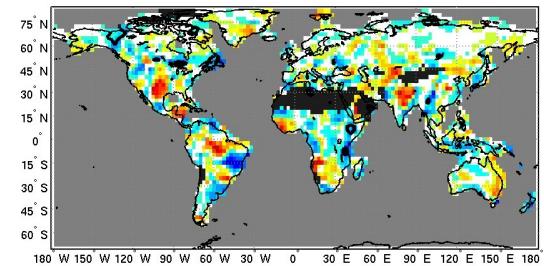
Temperature

MME temp Conditional Bias: year 2-5 ann
||Initialized| - |Uninitialized|

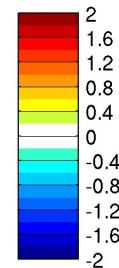
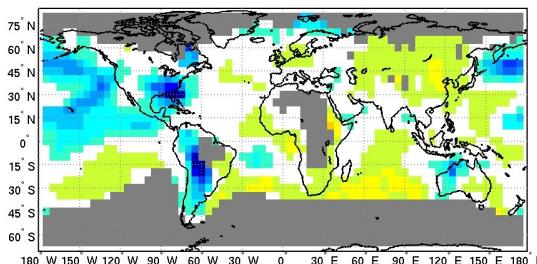


Precipitation

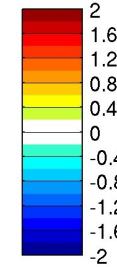
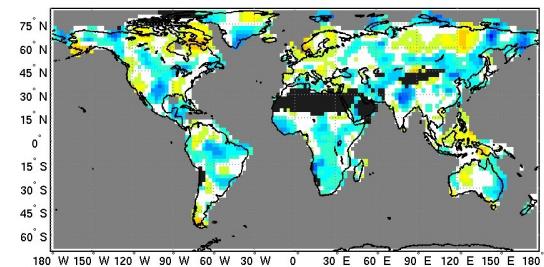
MME prcp Conditional Bias: year 2-5 ann
||Initialized| - |Uninitialized|



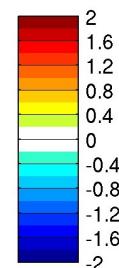
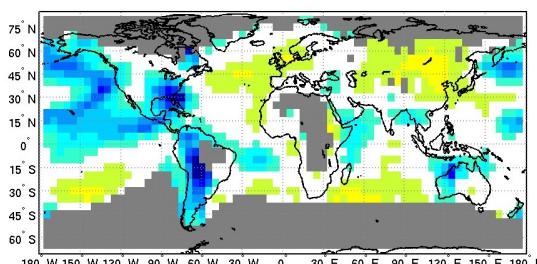
Conditional Bias: Initialized Hindcast



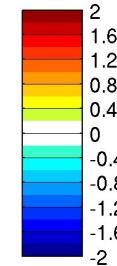
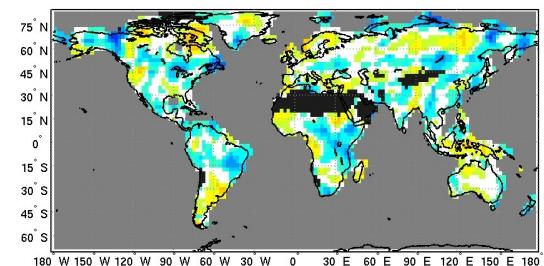
Conditional Bias: Initialized Hindcast



Conditional Bias: Uninitialized Hindcast



Conditional Bias: Uninitialized Hindcast

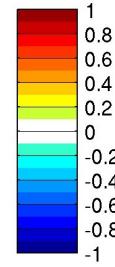
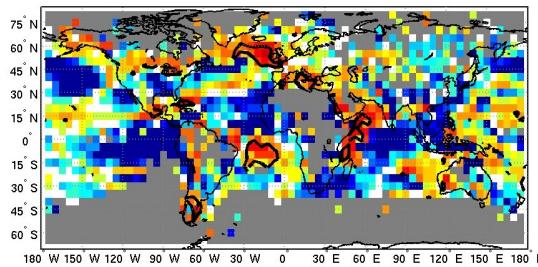


Develop metrics and baselines for estimating the quality of decadal predictions

CCSM4 – MSSS – years 2-5 – annual means

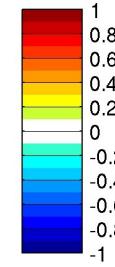
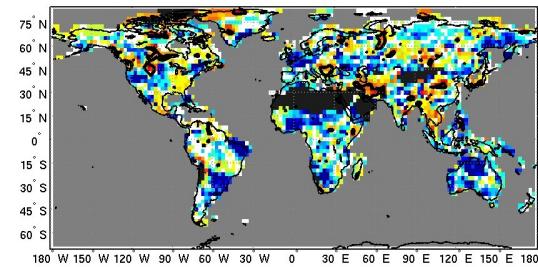
Temperature

CCSM4 temp MSSS: year 2-5 ann
Initialized - Uninitialized

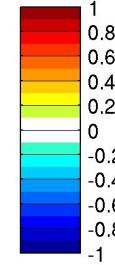
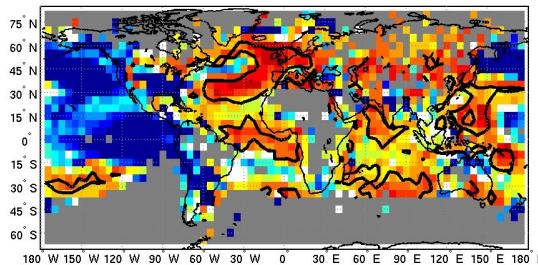


Precipitation

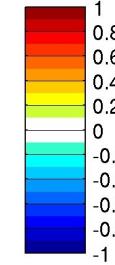
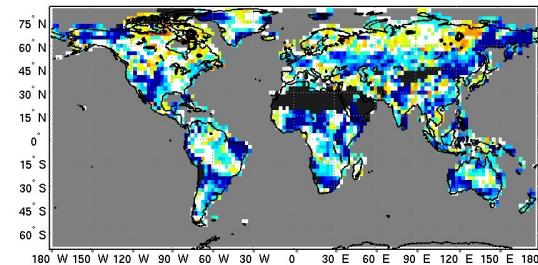
CCSM4 prcp MSSS: year 2-5 ann
Initialized - Uninitialized



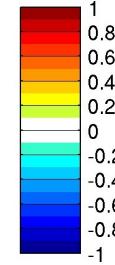
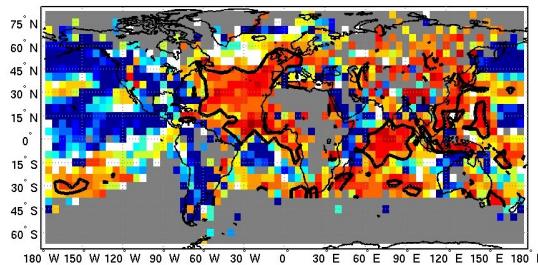
MSSS: Initialized Hindcast



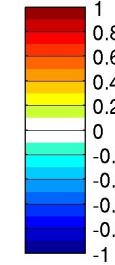
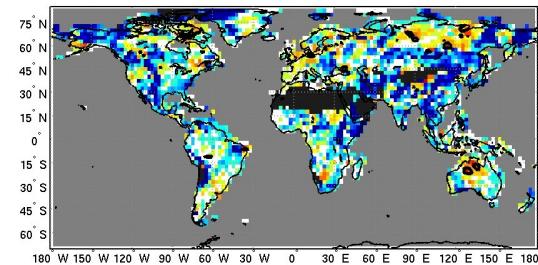
MSSS: Initialized Hindcast



MSSS: Uninitialized Hindcast



MSSS: Uninitialized Hindcast



Determine the fidelity of the surface expression of oceanic decadal variability, and the associated climate teleconnections

2 Main presentations

WCRP Open Science Conference (2011)

“Assessment of changes in regional precipitation and temperature regimes associated with decadal variability and the ability of climate models to reproduce them”

Assessment of changes in regional precipitation and temperature regimes associated with decadal variability and the ability of climate models to reproduce them

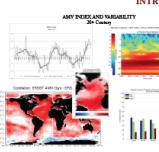
Paula L.M. Gonzalez (gonzaleml@iri.columbia.edu), Lisa Goddard (goddard@iri.columbia.edu), Arthur M. Greene (ampg@iri.columbia.edu)
The International Research Institute for Climate and Society, The Earth Institute at Columbia University, Palisades, NY, United States.



The need for climate information for the next few decades creates a requirement for adequate representations of both natural and anthropogenic factors. For that reason, it is essential to understand the significant surface expression of ocean-induced decadal variability and their predictability. The existence of precipitation and temperature decadal-scale regime shifts due to oceanic variability in regions like the US, Sahel and Northeast Brazil has been previously documented. The purpose of this work is to explore the dynamical features in these regions and on a global scale linked to temperature changes.

The ability of state-of-the-art GCMs, such as those used in the IPCC assessments, to represent such regional temperature and precipitation changes is explored. Additionally, we evaluate the contribution of ocean initialization in some of these GCMs to the prediction of the oceanic decadal variability and associated regional climate during the latter part of the 20th Century.

Atlantic multi-decadal variability (AMV), also known as Atlantic multi-decadal Oscillation (AMO) is characterized as the bimodal periodic oscillation between positive and negative phases of more than a decade. Many authors have shown that AMV has a significant impact on temperature and precipitation in several regions of the world.



INTRODUCTION AND MOTIVATIONS

The most relevant stochastic feature associated with the positive phase of the AMV (warmer than normal North Atlantic) is a migration of the ITCZ to the north over the North Atlantic, which is associated with a shift in the normal Sahel and a drier normal NE Brazil and parts of Western Africa.

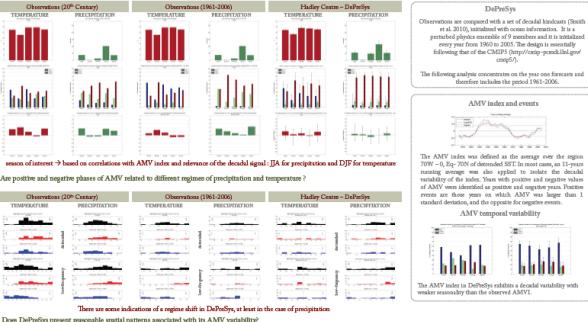
Other portions of the world like the United States, the Indian monsoon region, Australia also appear to have significant impacts of AMV. Recently, Ting et al. (2011) showed using 20th Century, 21st Century and pre-industrial runs from CMIP3 that the AMV is associated with a significant multi-decadal variability centered on the North Atlantic, though with different time variability features that the observed. They also showed that some of the AMV features are robust, such as an influence on Sahel rainfall trends to be robust within CMIP3.

This initial diagnostic part of the work focuses on assessing the ability of the CMIP3 ensemble to reproduce the observed decadal precipitation and temperature regimes in certain regions of interest.

Using simulations from the CMIP3 ensemble (IPCC, 2007), different authors have argued that there is an internal or external component of AMV (Ting et al. 2009 and references therein). It is argued that part of this multi-decadal internal source of variability is due to the internal variability of the observed global warming during the last decades (Delisio et al. 2011). However, the role of the ocean in this internal variability is still under debate. There is some degree of predictability associated with this variability and if state-of-the-art GCMs are able to reproduce it.

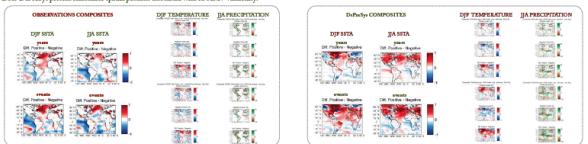
SAHEL

Does DePreSys reproduce accurately the seasonality of the region and the relative significance of the different components of the temporal variability (intrad, decadal, interannual) ?

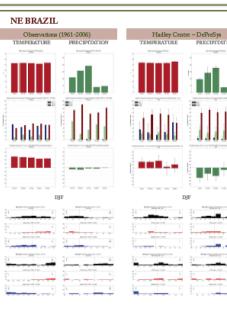
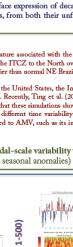
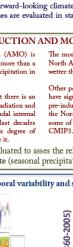
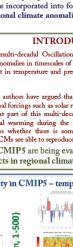
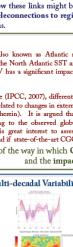
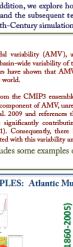
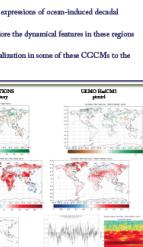


There were some indication of a regime shift in DePreSys, at least in the case of precipitation

Does DePreSys present reasonable spatial patterns associated with the AMV variability?



This work was supported by NOAA grant NA10OAR1329112. Authors would like to thank DePre team for allowing the use of the DePreSys results.



FINAL REMARKS

These preliminary results suggest that a ensemble of initialized breakdown from a state-of-the-art GCM is able to reproduce, to some extent, the behavior of Atlantic multi-decadal variability in the Sahel and Northeast Brazil, though with some differences.

Nevertheless, the experimental design used in this case (and in most recent decadal variability studies) is probably a period that is too short to account some important multi-decadal variability features, such as the long-term trend in the AMV index and the migration of the ITCZ.

The previous paper argues that the accuracy of the regime analysis is strongly region- and model-dependent and that more robust evidence could be drawn from a bigger set of models with more appropriate experiments.

This work was supported by NOAA grant NA10OAR1329112. Authors would like to thank DePre team for allowing the use of the DePreSys results.

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37th NOAA Climate Diagnostics and Predictability Workshop (2012)

“Diagnosing decadal-scale climate variability in current generation coupled models”



Diagnosing Decadal-Scale Climate Variability in Current Generation Coupled Models

Paula L.M. Gonzalez (gonzaleml@iri.columbia.edu), Lisa Goddard (goddard@iri.columbia.edu), Arthur M. Greene (ampg@iri.columbia.edu)



The International Research Institute for Climate and Society, The Earth Institute at Columbia University, Palisades, NY, United States.

ABSTRACT

Several studies have shown links between regional terrestrial climate and frequency variability (LFV) in both the Pacific and Atlantic Oceans, Atlantic Multi-decadal Variability (AMV) and Pacific Decadal Variability (PDV) being the best-described features. This week considers long observational records to identify whether these LFV mechanisms are associated with shifts in temperature and precipitation in a set of focus areas around the world.

In addition, we explore how these links might be incorporated into forward-looking climate information. The surface expression of decadal-scale variability in the ocean basin and its teleconnections to regional climate anomalies are evaluated in state-of-the-art GCMs, from both their unified pre-industrial control and 20th-Century simulations.

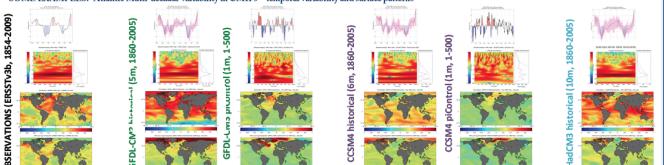
INTRODUCTION AND MOTIVATIONS

The most relevant stochastic feature associated with the positive phase of the AMV (warmer than normal North Atlantic) is a migration of the ITCZ to the north over the North Atlantic. This displacement results in a drier normal Sahel and a drier normal NE Brazil and parts of Western Africa.

Other portions of the world like the United States, the Indian monsoon region, Australia also appear to have significant impacts of AMV. Recent studies from the 20th Century, 21st Century and pre-industrial runs from CMIP3 that three simulations show a consistent multi-decadal variability centered on the North Atlantic, though with different time variability features than the observed. They also show that normal AMV has a significant impact related to AMV, with its influence on Sahel rainfall seems to be robust within CMIP3.

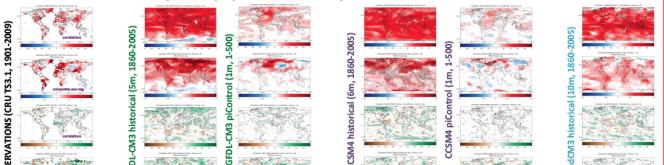
This poster includes some examples of the way in which CMIP3 models are being evaluated to assess the reliability of their decadal-scale variability with a strong focus on the teleconnections and the impacts in regional climate (seasonal precipitation and temperature seasonal anomalies).

SOME EXAMPLES: Atlantic Multi-decadal Variability in CMIP3 – temporal variability and surface patterns



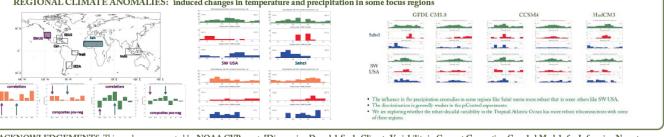
• Atlantic multi-decadal variability is present in all the models analyzed. The precise patterns and temporal features vary according to the model. Historical runs tend to overestimate the warming observed outside the Atlantic

AMV TELECONNECTIONS: JJA temperature and precipitation correlations and composites



• Teleconnections seem a little better in GFDL-CM3 and in HadCM3 through the overestimation of the warming is present.

• The pClouds runs show overall weak connections to precipitation and temperature over land.



• The influence on the precipitation anomalies in some regions like Sahel seems more robust than in others like SW USA.

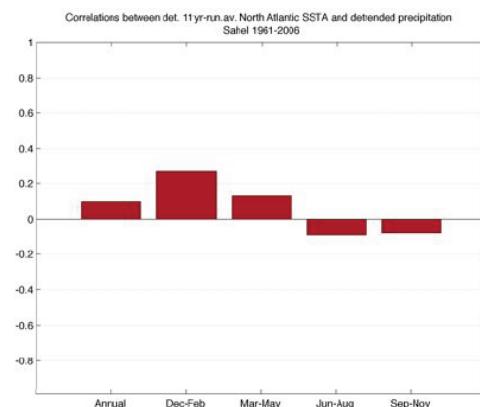
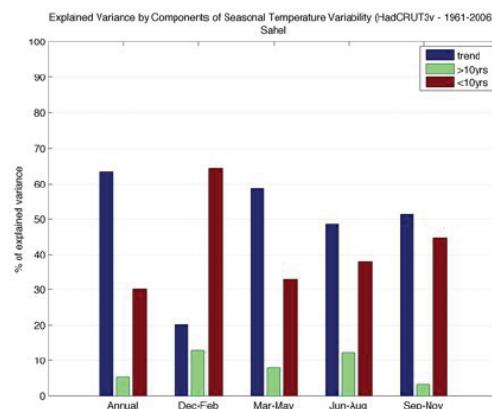
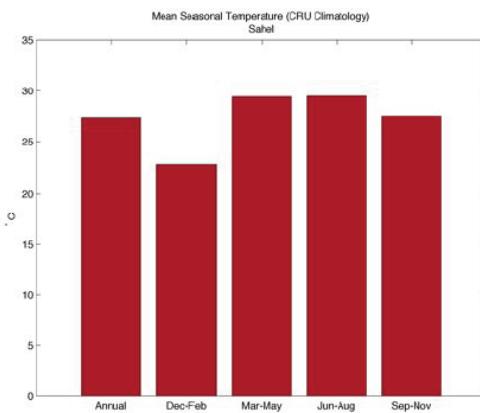
• An interesting feature is the observed decadal variability in the Tropical Atlantic Ocean has more robust relations with ENSO.

ACKNOWLEDGEMENTS This work was supported by NOAA CVP grant “Diagnosing Decadal-Scale Climate Variability in Current Generation Coupled Models for Informing Near-term Climate Change Impacts” (NA10OAR1329112 Amendment #24).

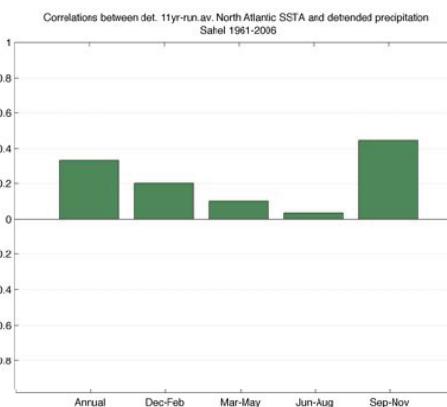
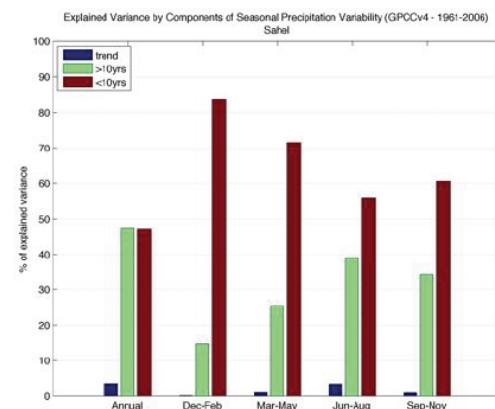
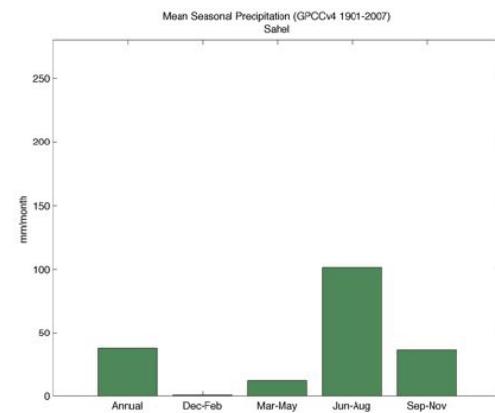
Observations (1961-2006)

SAHEL

TEMPERATURE



PRECIPITATION



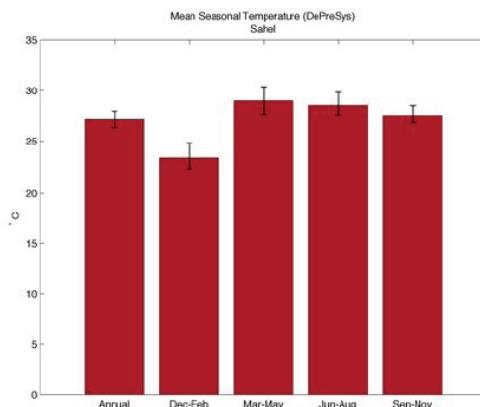
Seasonality

Time scales
decomposition

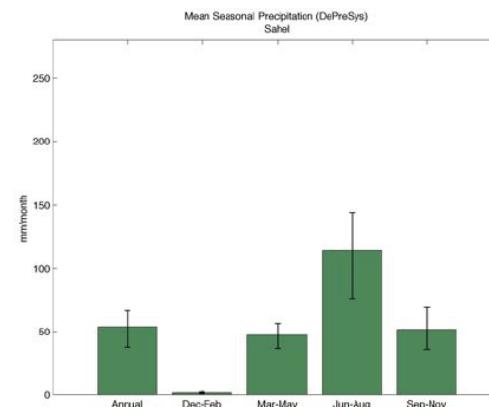
AMV
influence

SAHEL

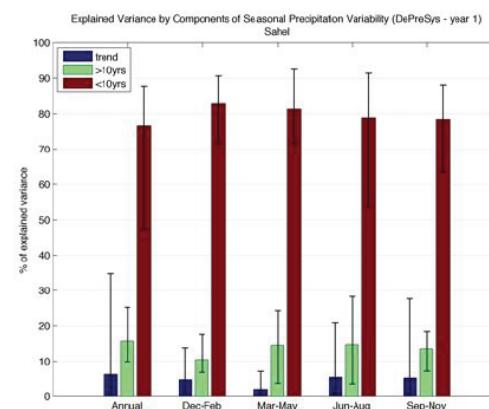
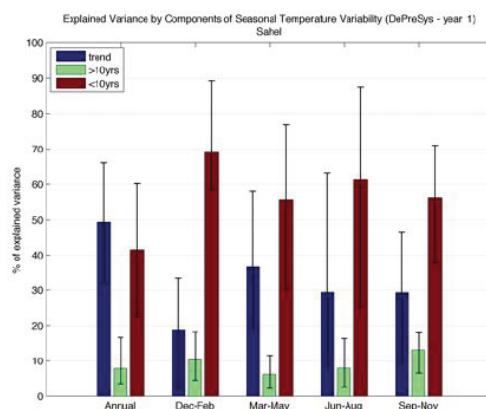
TEMPERATURE



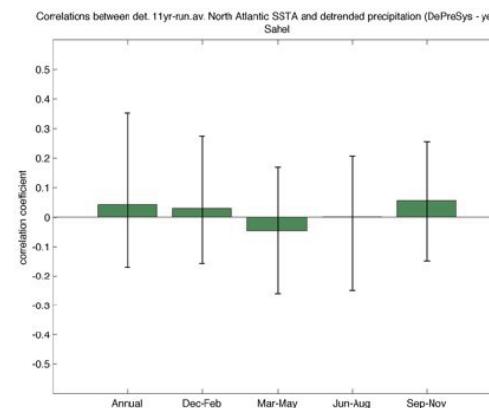
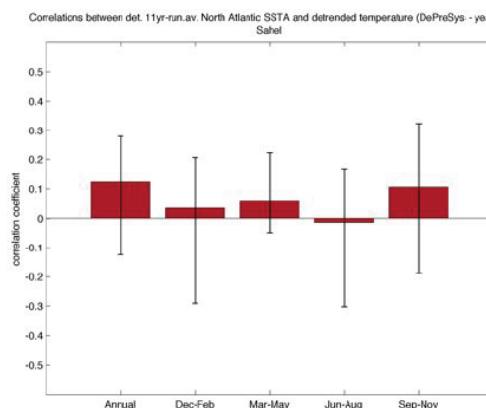
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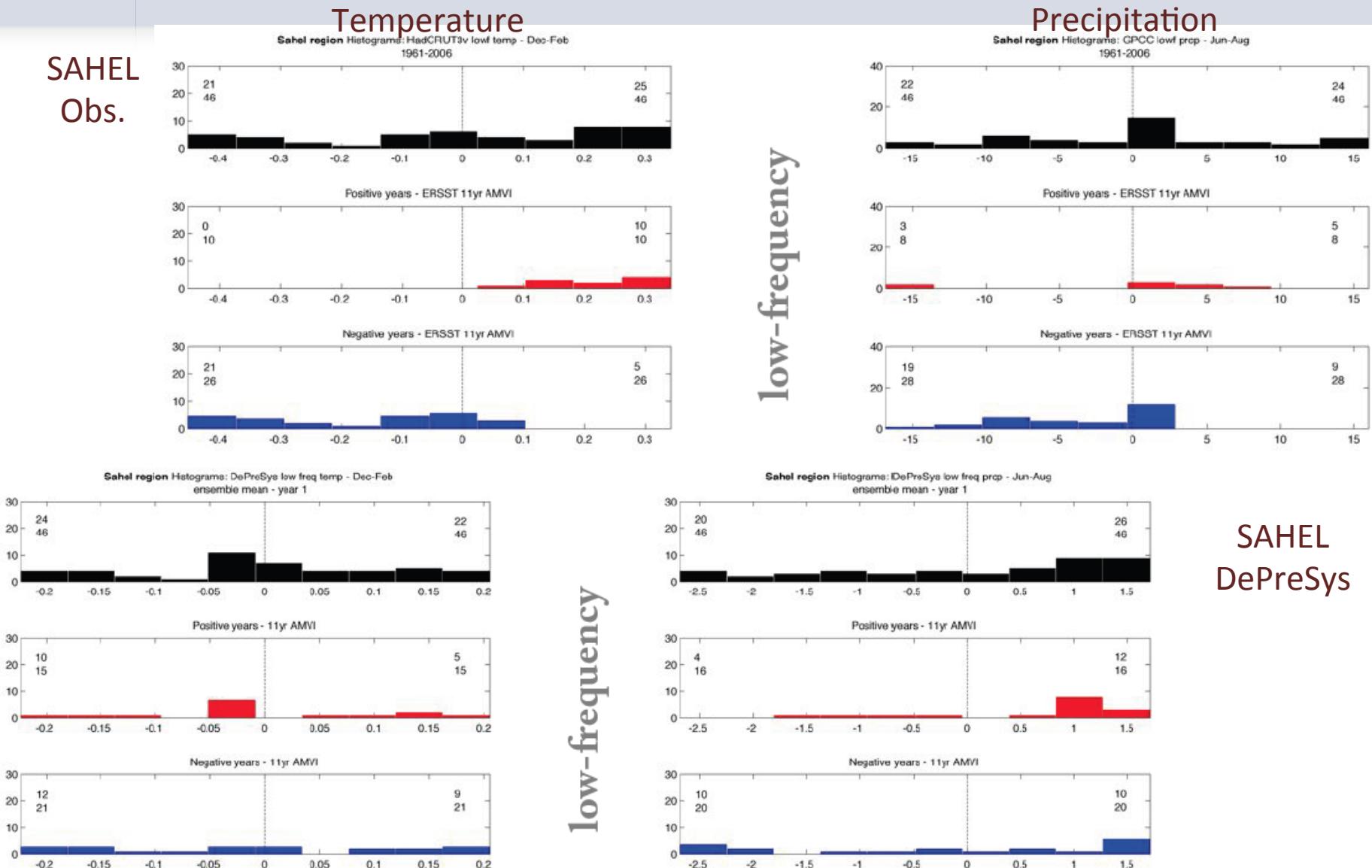
Time scales
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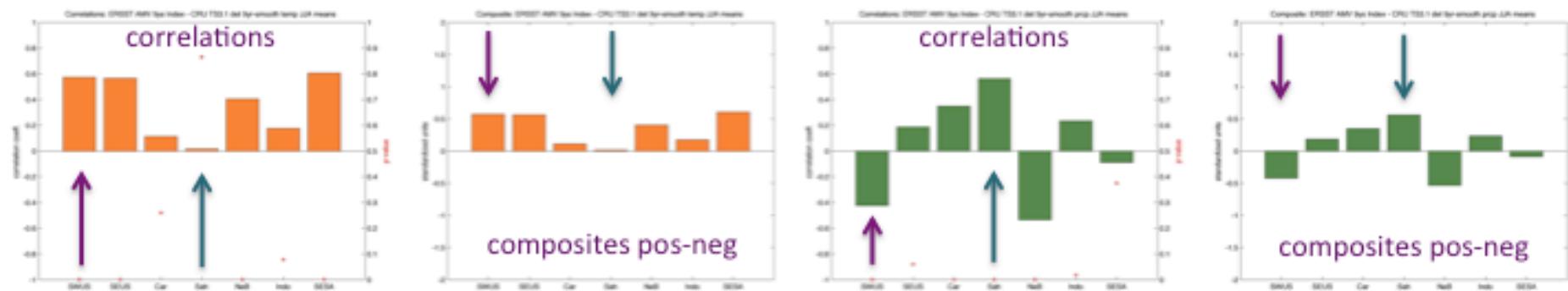
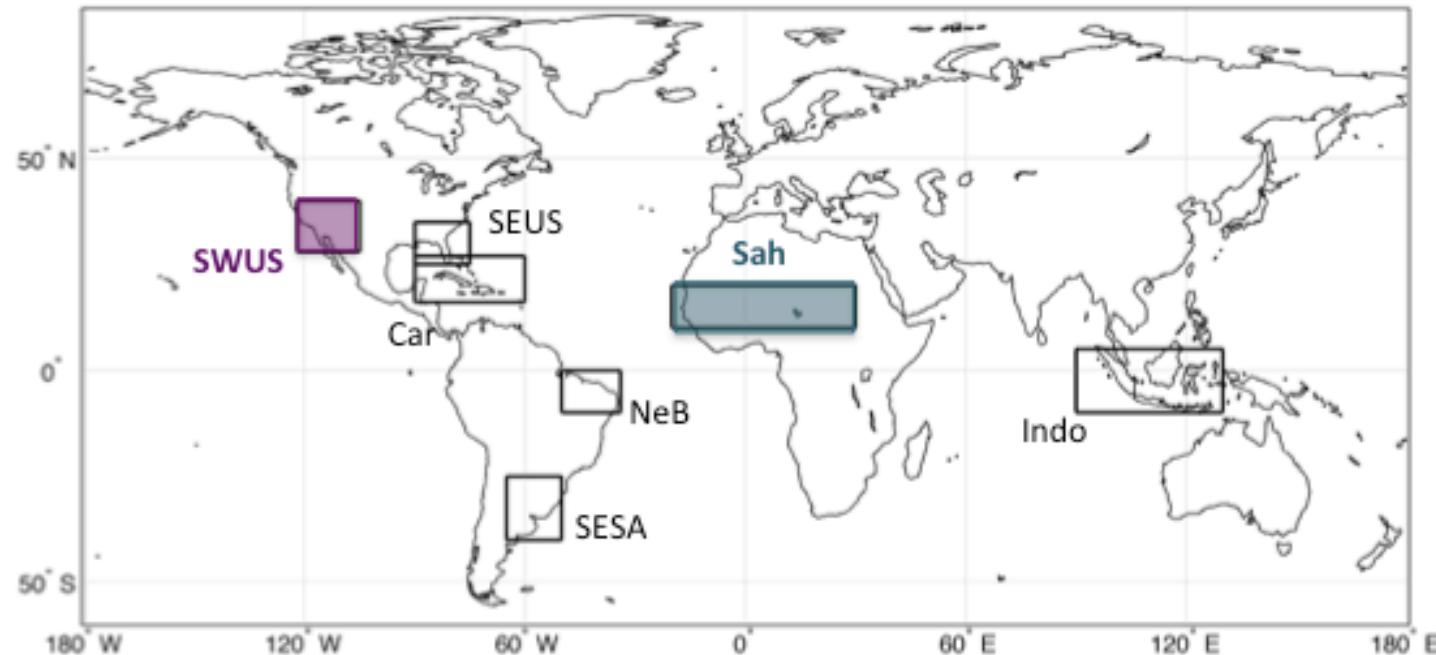
AMV
influence

Determine the fidelity of the surface expression of oceanic decadal variability, and the associated climate teleconnections

**SAHEL
Obs.**



Relationship between AMV and regional climate anomalies in CMIP5



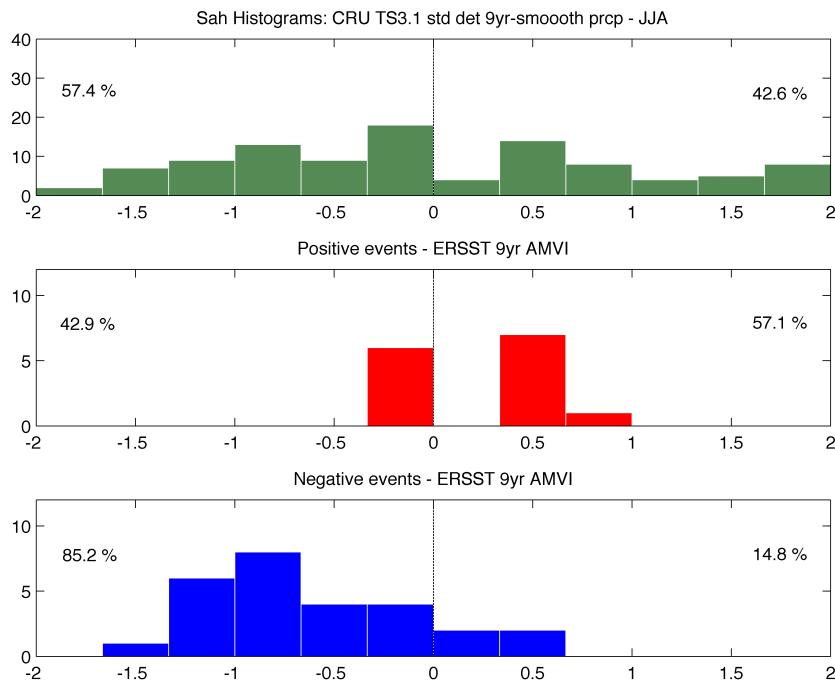
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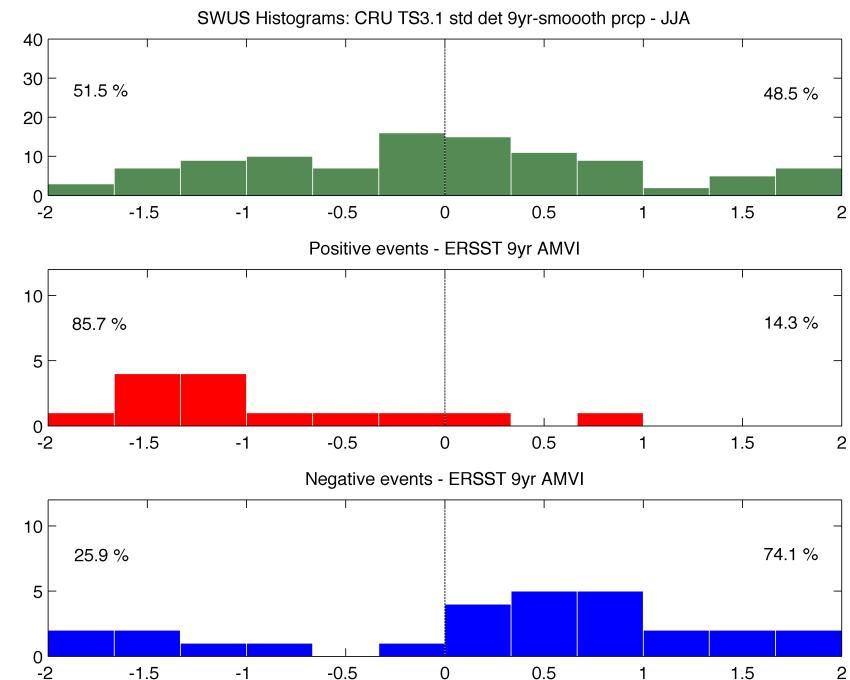
Relationship between AMV and regional climate anomalies in CMIP5

Example: Observations - precipitation – Sahel vs SW US

SAHEL



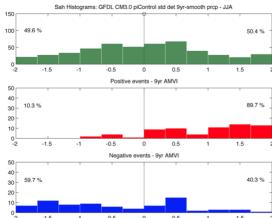
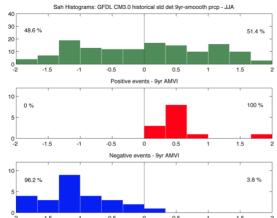
SW US



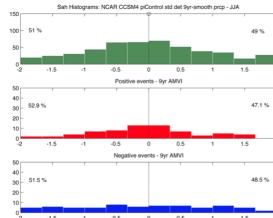
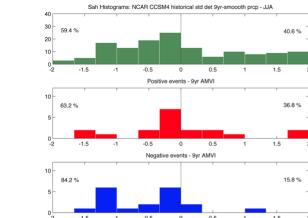
Relationship between AMV and regional climate anomalies in CMIP5

Example: historical/piControl - precipitation – Sahel vs SW US

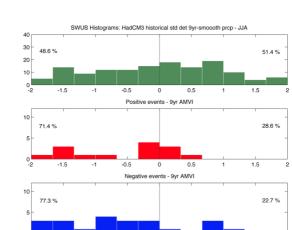
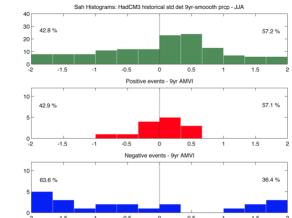
GFDL CM3.0



CCSM4



HadCM3



Sahel

SW USA

- The influence in the precipitation anomalies in some regions like Sahel seems more robust than in some others like SW USA.
- The discrimination is generally weaker in the piControl experiments.
- We are exploring whether the multi-decadal variability in the Tropical Atlantic Ocean has more robust teleconnections with some of these regions.



Exploring seasonal-to-decadal predictability and teleconnections in CMIP5 decadal hindcasts

AGU Fall Meeting (2011)

“Seasonal-to-interannual variability of precipitation over Southeastern South America en CMIP5 decadal hindcasts”



Seasonal-to-Interannual Variability of Precipitation over Southeastern South America in CMIP5 Decadal Hindcasts

Paula L.M. Gonzalez (gonzalez@iri.columbia.edu), Lisa Goddard (goddard@iri.columbia.edu)

The International Research Institute for Climate and Society, The Earth Institute at Columbia University, Palisades, NY, United States.



A set of decadal hindcasts has been designed for CMIP5 to explore the effect of initializing the models with information about the current state of the climate system. Some skill for the next year-to-decade may be gained if one can predict aspects of natural climate variability in addition to the anthropogenic trend. We explore the performance of the hindcasts over Southeastern South America (SESA), focusing mainly on precipitation. Over the 20th century this region experienced large trends, showed decadal-scale variability, and also exhibited strong seasonal-to-interannual variability, mainly due to an ENSO teleconnection. We show that some models are better able than others to predict ENSO-related teleconnections over this region, even at several years lead time. There is a suggestion that fidelity of the annual cycle, particularly the timing of the annual cycle, may be one factor in the better performance of these models. However, better performance at seasonal-to-interannual timescales does not necessarily lead to more accurate decadal predictions or representation of multi-decadal trends.

DATA

This poster presents preliminary results from the following 5 sets of initialized decadal hindcasts:

1) IRI-COLA – initialized prior to 1960 by the start of the twentieth century. We explore the performance of the hindcasts over SESA, focusing mainly on precipitation. Over the 20th century this region experienced large trends, showed decadal-scale variability, and also exhibited strong seasonal-to-interannual variability, mainly due to an ENSO teleconnection. We show that some models are better able than others to predict ENSO-related teleconnections over this region, even at several years lead time. There is a suggestion that fidelity of the annual cycle, particularly the timing of the annual cycle, may be one factor in the better performance of these models. However, better performance at seasonal-to-interannual timescales does not necessarily lead to more accurate decadal predictions or representation of multi-decadal trends.

2) CCSm4-CM2.1a – perturbed initial conditions ensemble of 10 members with runs starting every 5 years from 1960 to 2005. The runs are 10 years long.

(Courtesy of George Boer and CCSm4)

3) COLA-CFSv2 – perturbed initial conditions ensemble of 4 members with runs starting every 5 years from 1960 to 2005. The runs are 10 years long. (Courtesy of Ed Schneider)

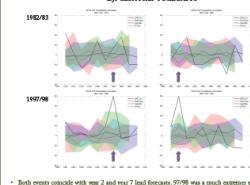
With the aim of comparing the performances of these models, only the runs available for CFSv2 were considered in the other two models. The simulated precipitation and surface temperatures were compared with the GPCPv2 and HadISST1 datasets, respectively.

THE REGION

Southeastern South America (SESA) (20°S-30°S, 50°W-70°W) includes unique parts of Argentina, Paraguay and Brazil (one map in SEASONAL CYCLE section). This region is characterized by the presence of the strong 20th Century wetting trend observed. Its rains are significantly influenced with the El Niño – Southern Oscillation (ENSO) phenomenon. This makes it an interesting case to evaluate the skill of the decadal hindcasts over a wide range of time scales.

- SESA precipitation → strong year-to-year variability, mainly due to ENSO
- 2 case studies: DJF 1982/83 and 1997/98

DJF SEAS PRECIP FORECASTS



- Both cases show with year 2 and 7 year lead forecasts. 97/98 was a much stronger event for the region and both exceed the bounds estimated by the hindcasts. CFSv2 forecast the closest values for that case, both for the 2nd and 7th lead times.
- CCSm4 and CFSv2 only see precipitation extremes for a 2-year lead forecast of 1997/98

INTERANNUAL VARIABILITY

DJF SST ANOMALIES

- CCSm4 shows reasonable teleconnections for both cases. The signal is stronger for the 2-year lead but still present for 7-year lead.
- CCSm4 shows deeper anomalies and small agreement between models and observations.
- CCSm4 has a strong cold bias throughout the Southern Ocean and little agreement for tropical Pacific SSTs, especially for 2yr lead.

REGRESSIONS BETWEEN SESA PRECIP AND SSTA

Obs DJF



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- CCSm4 has a strong cold bias throughout the Southern Ocean and little agreement for tropical Pacific SSTs, especially for 2yr lead.

LONGER TIMESCALES

DJF ROOT MEAN SQUARE ERRORS



- same skill for short leads, but bigger RMSE than 3-month lead initial forecast (ECHAM5)
- averages of lead times are much skillful than single lead times 2-5 and 6-9 are similar but less skillful than 10-12
- CCSm4 shows slightly smaller errors

DIFFERENT LEAD-TIME AVERAGES

TRENDS

MAGNITUDE OF TRENDS FOR DIFFERENT LEAD TIMES



- magnitudes of trends for individual lead times are in general captured by the ensemble
- no single model appears to be better at reproducing the magnitudes

LONGER LEAD-TIME RELIABILITY

REGRSSION OF THE OBSERVED TRENDS FOR LONGER LEAD-TIME PERIODS

- longer lead-time reliability expressed by the ensemble's growth, even when trends decrease for longer times
- the trends are very close to the observed ones for analysis lead-time ranges

REGRESSIONS OF THE OBSERVED TRENDS FOR LONGER LEAD-TIME PERIODS

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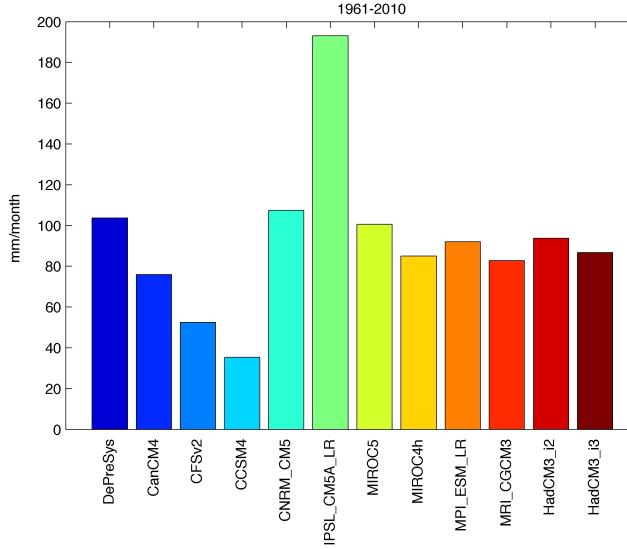
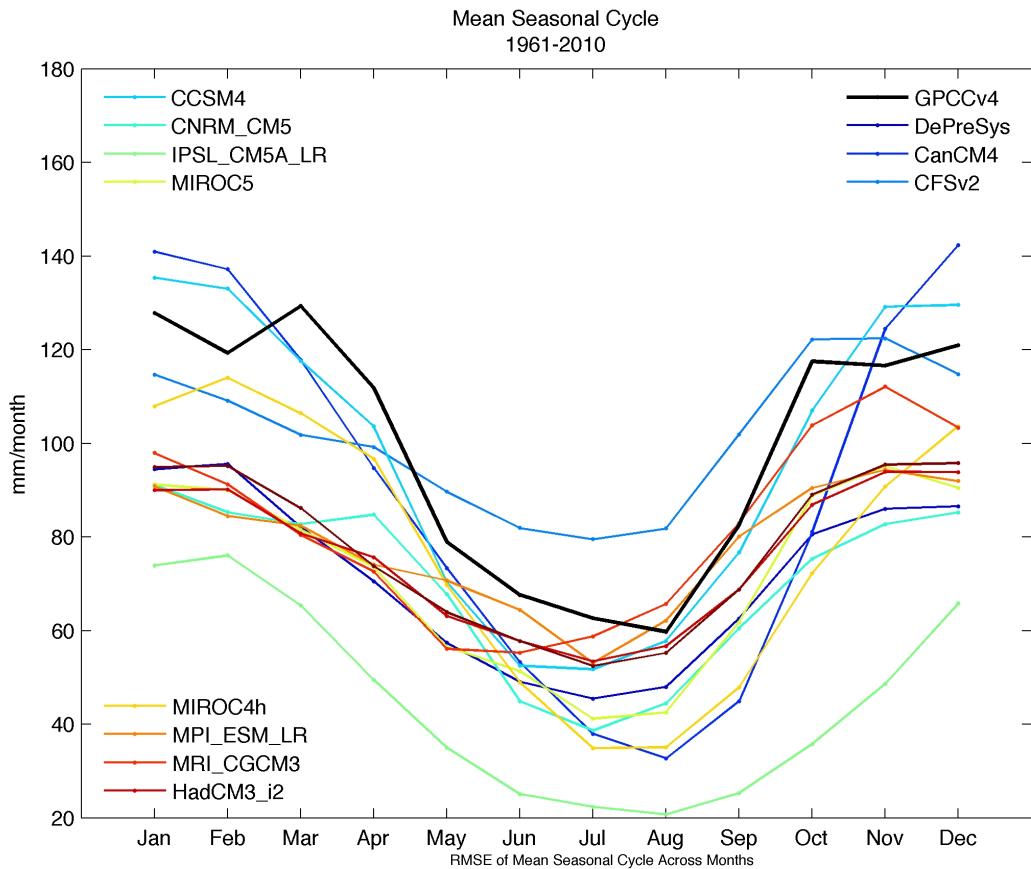
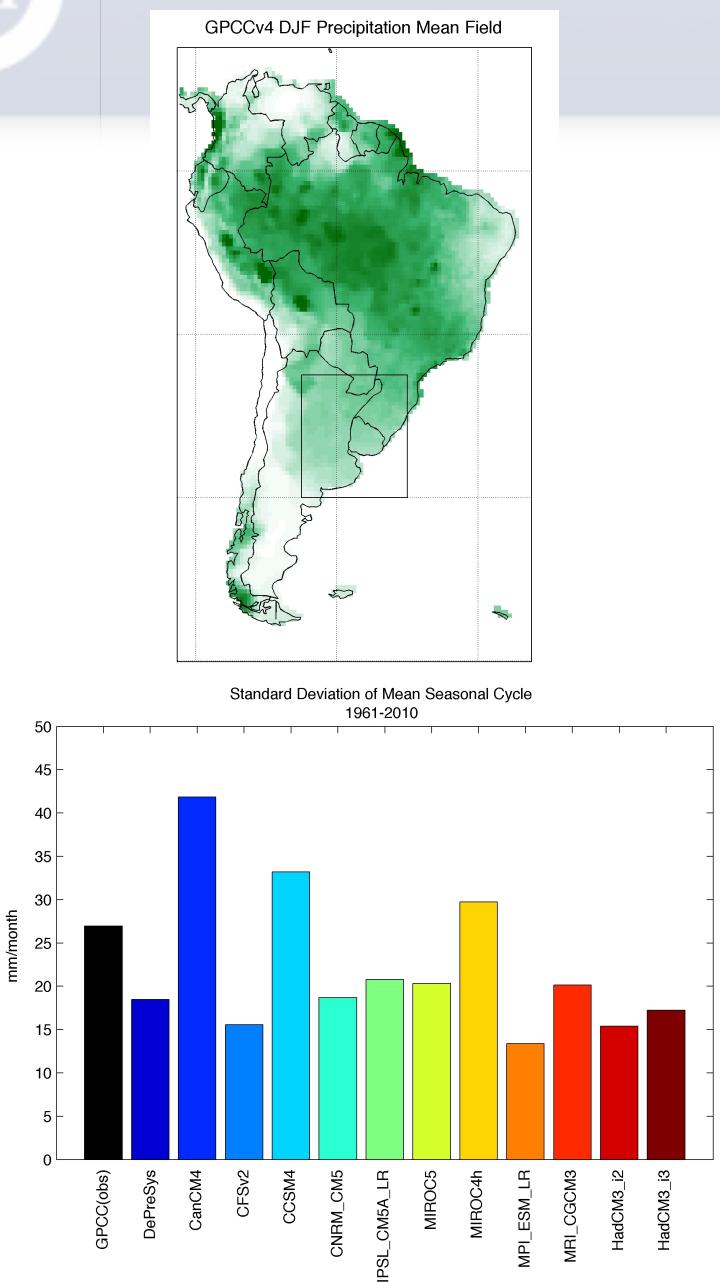
REGRESSIONS OF THE OBSERVED TRENDS FOR LONGER LEAD-TIME PERIODS

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REGRESSIONS

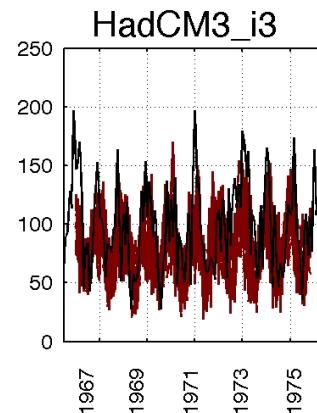
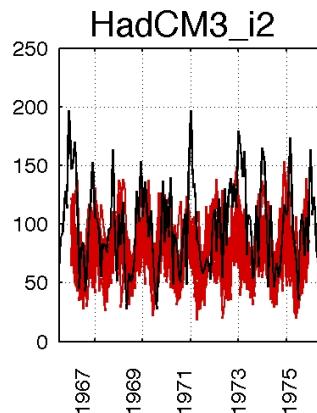
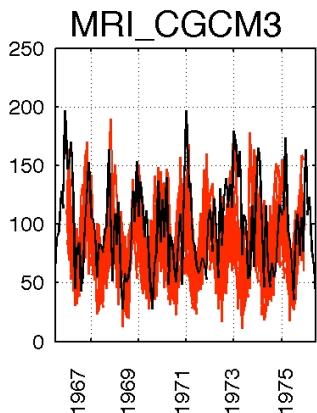
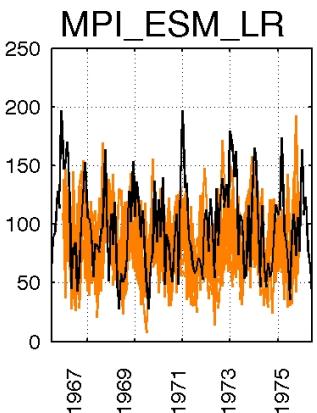
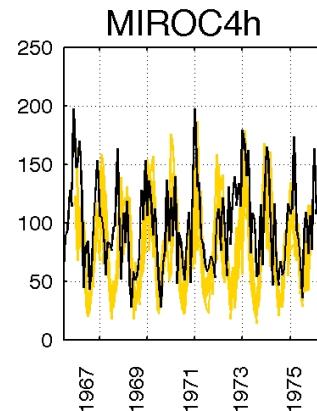
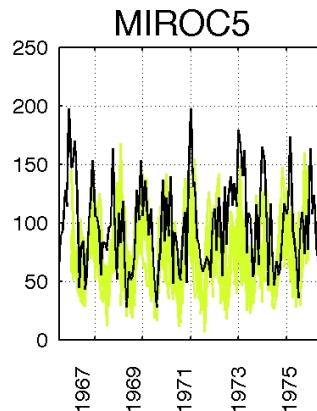
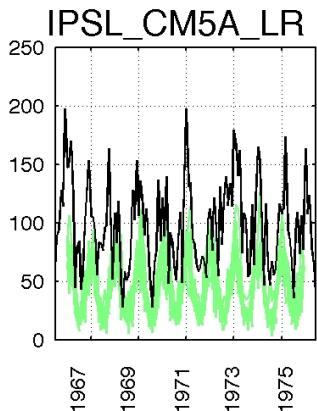
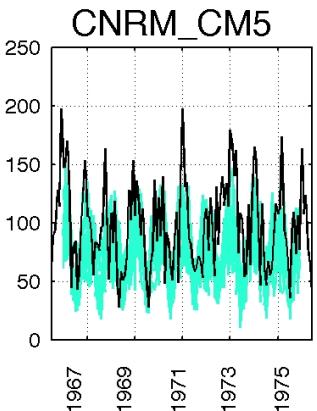
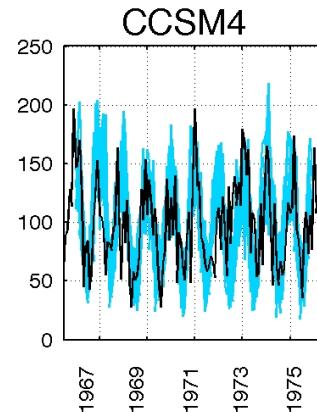
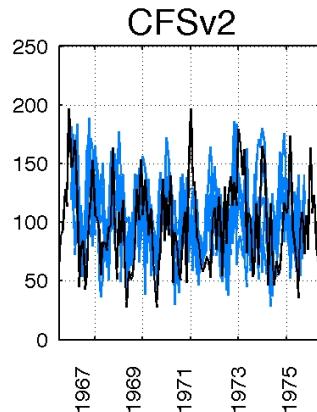
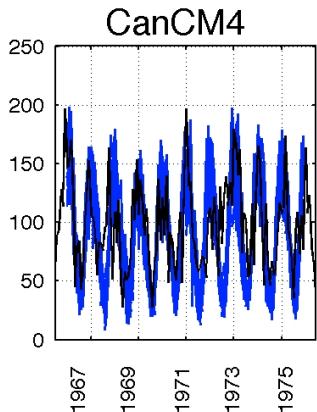
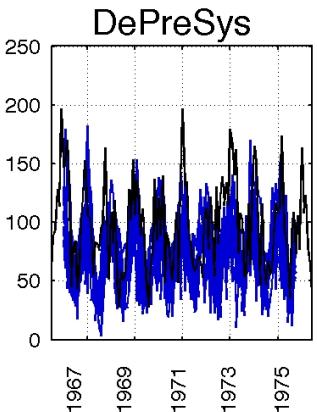


Seasonal cycle

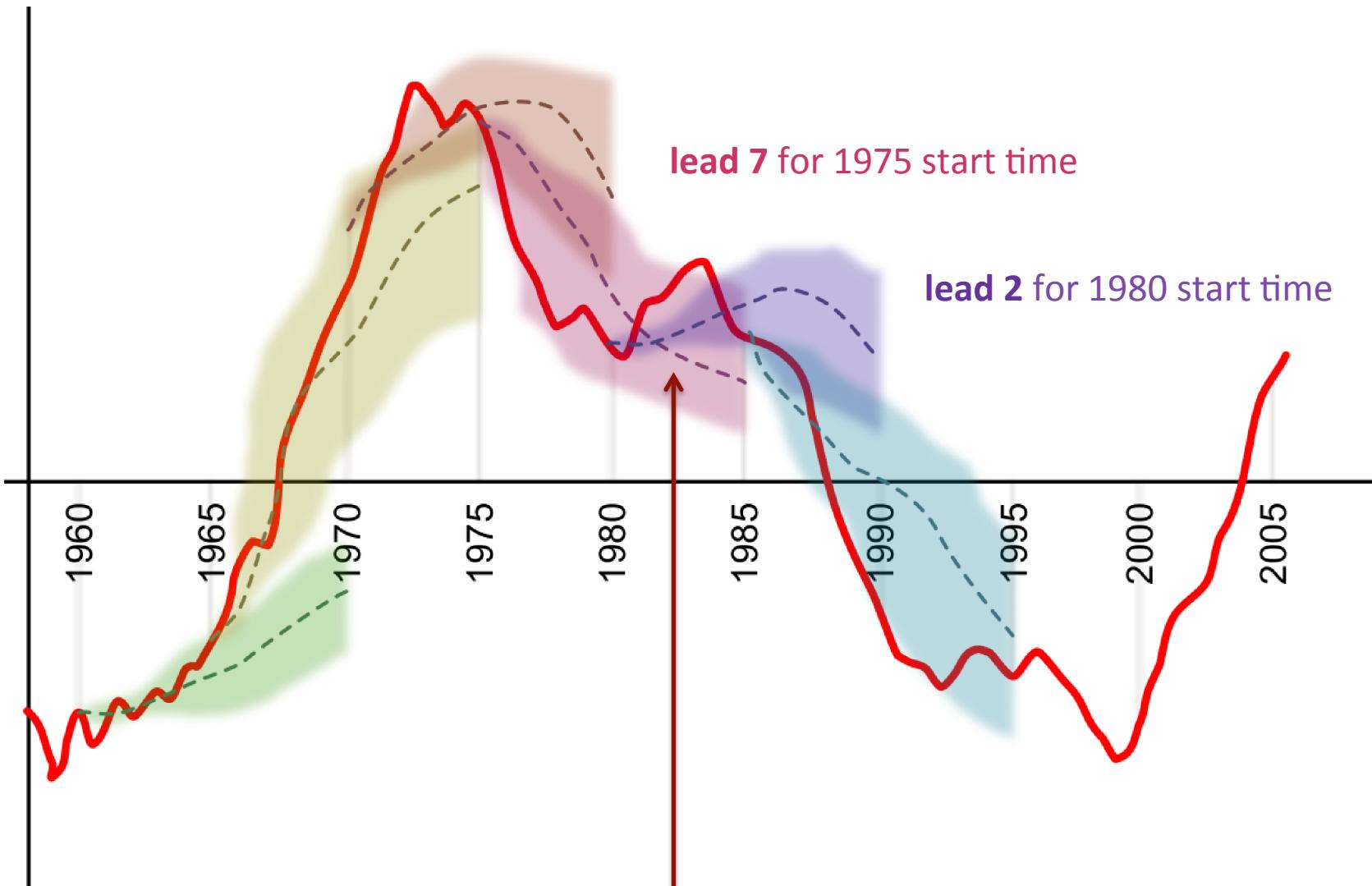




Raw Hindcasts - Monthly SESA Precipitation - Start time:1965



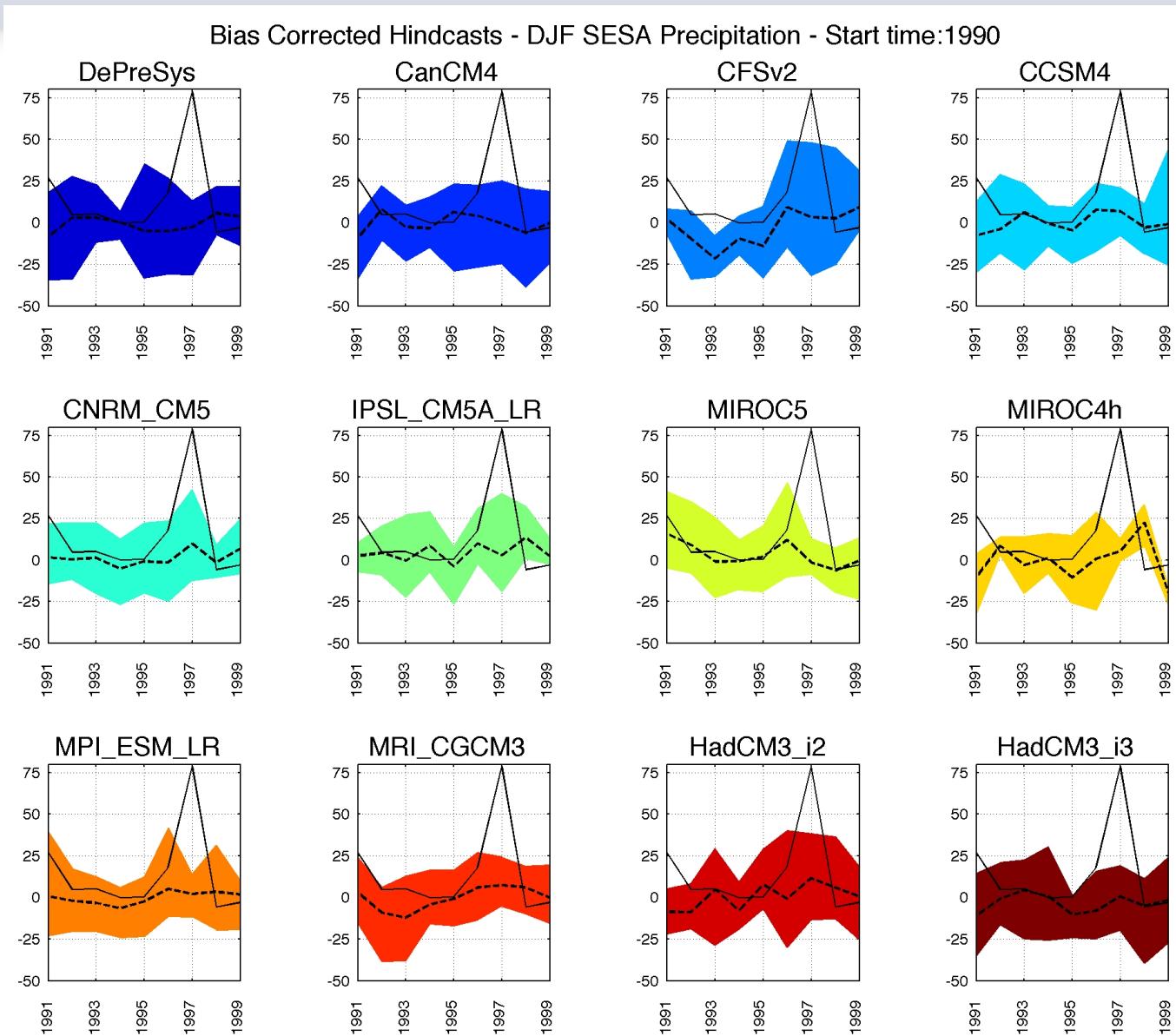
CMIP5 Decadal Hindcasts



The warm ENSO events of 82/83 and 97/98 are represented as both **lead 7** and **lead 2** in the decadal hindcasts ensemble

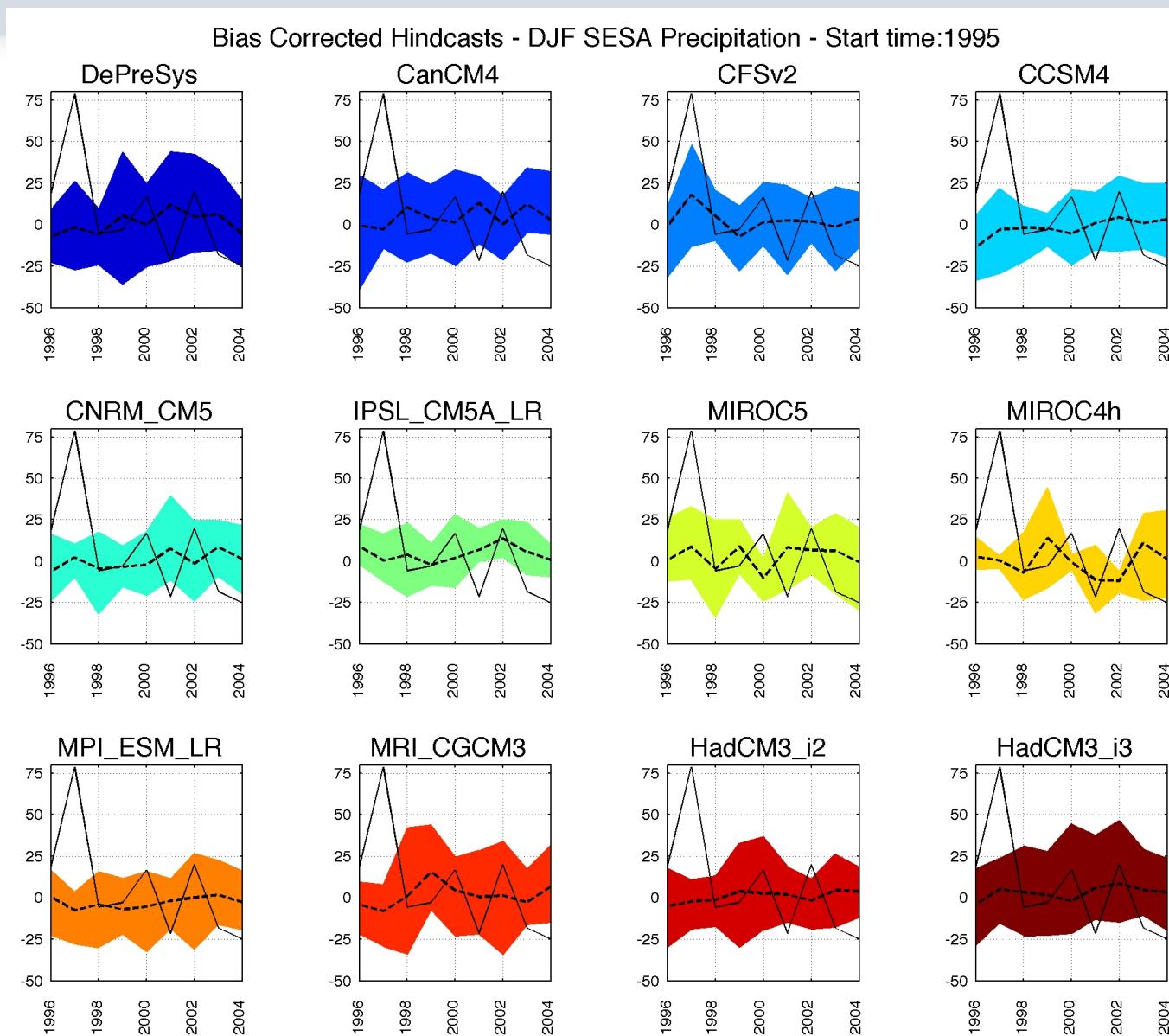
Exploring seasonal-to-decadal predictability and teleconnections in CMIP5 decadal hindcasts

El Nino 97/98
as 7-year lead



Exploring seasonal-to-decadal predictability and teleconnections in CMIP5 decadal hindcasts

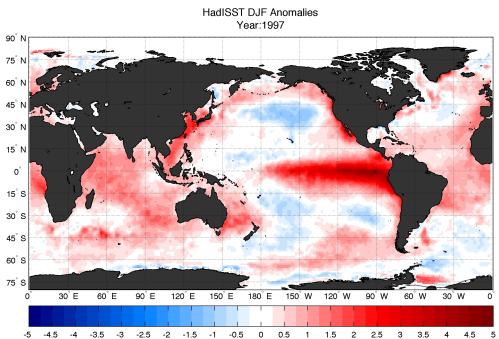
El Nino 97/98
as 2-year lead



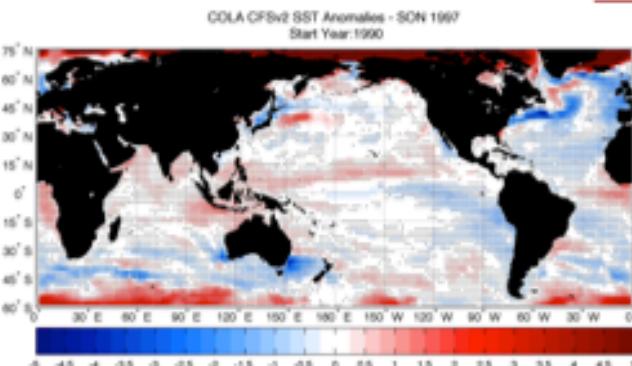


SST Anomalies

Obs: 97/98

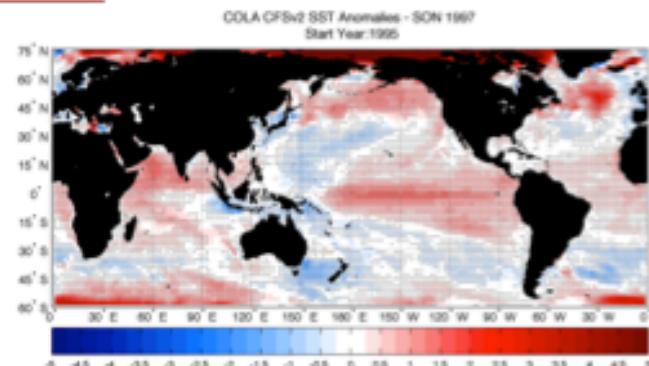


Fcst: 7-Year Lead

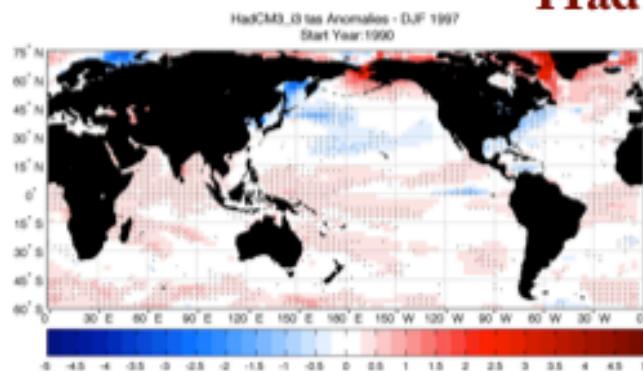


Fcst: 2-Year Lead

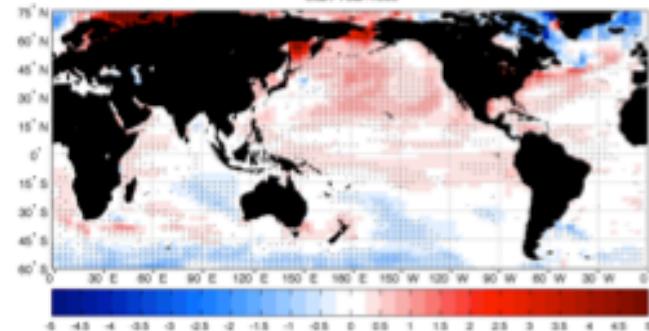
CFSv2



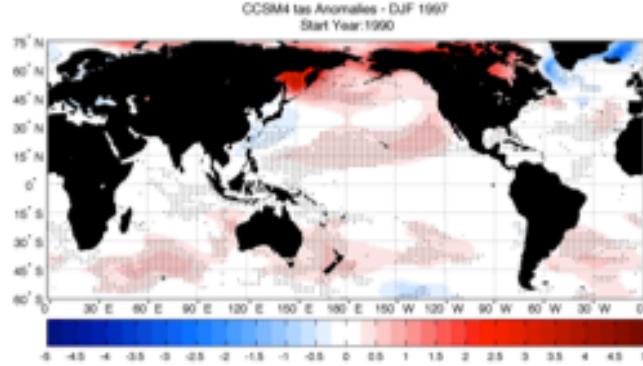
HadCM3_i3



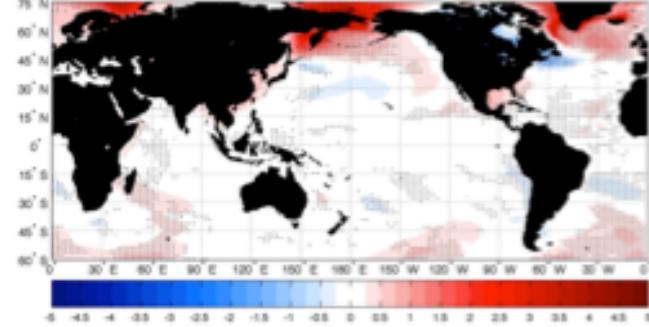
HadCM3_i3 tas Anomalies - DJF 1997
Start Year:1995



CCSM4

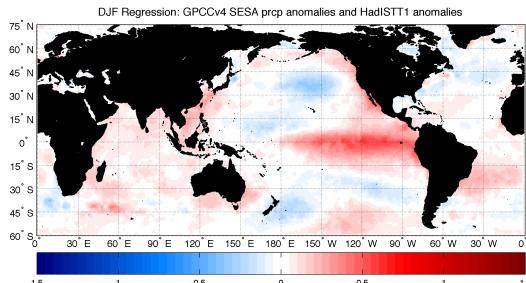


CCSM4 tas Anomalies - DJF 1997
Start Year:1995



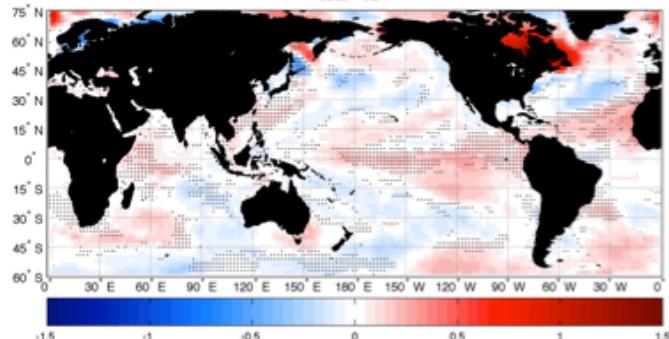
Regressions SESA precipitation vs SSTA

Obs



Fcst: 7-Year Lead

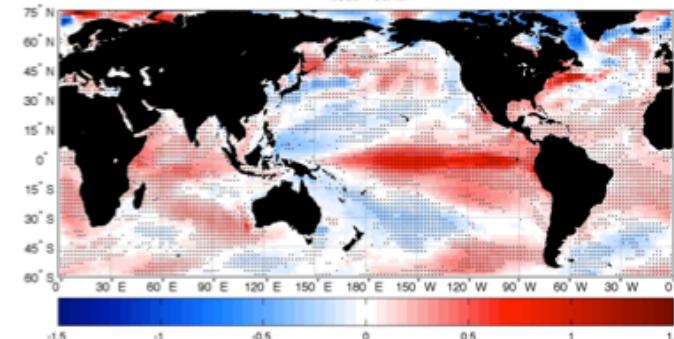
COLA CFSv2 - DJF ts regression with SESA DJF precipitation
Lead Year:7



Fcst: 2-Year Lead

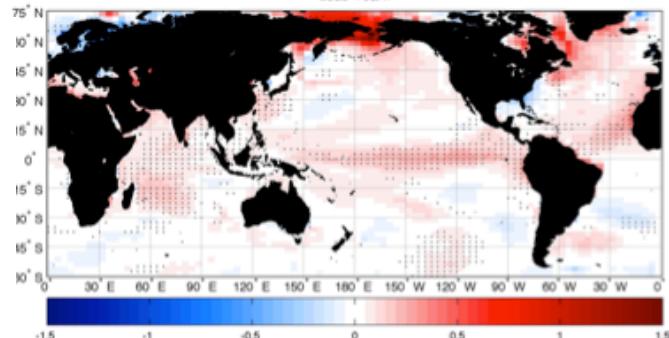
CFSv2

COLA CFSv2 - DJF ts regression with SESA DJF precipitation
Lead Year:2

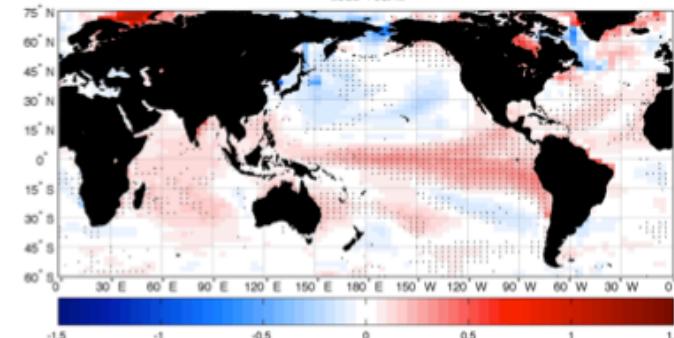


HadCM3_i3

HadCM3_i3 - DJF tas regression with SESA DJF precipitation
Lead Year:7

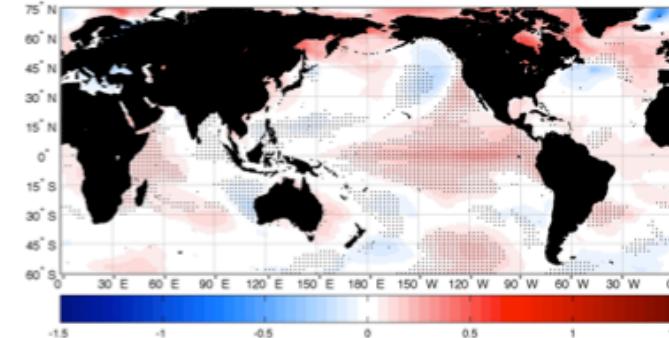


HadCM3_i3 - DJF tas regression with SESA DJF precipitation
Lead Year:2

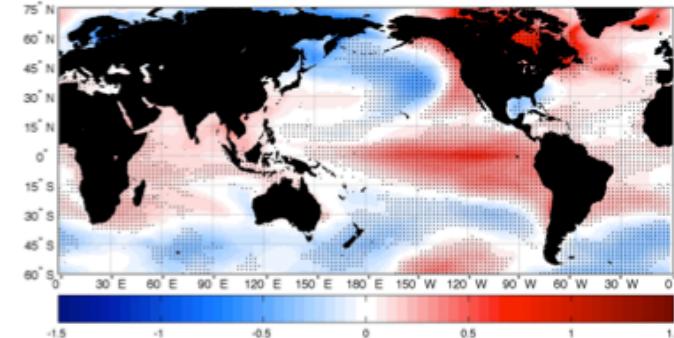


CCSM4

CCSM4 - DJF tas regression with SESA DJF precipitation
Lead Year:7

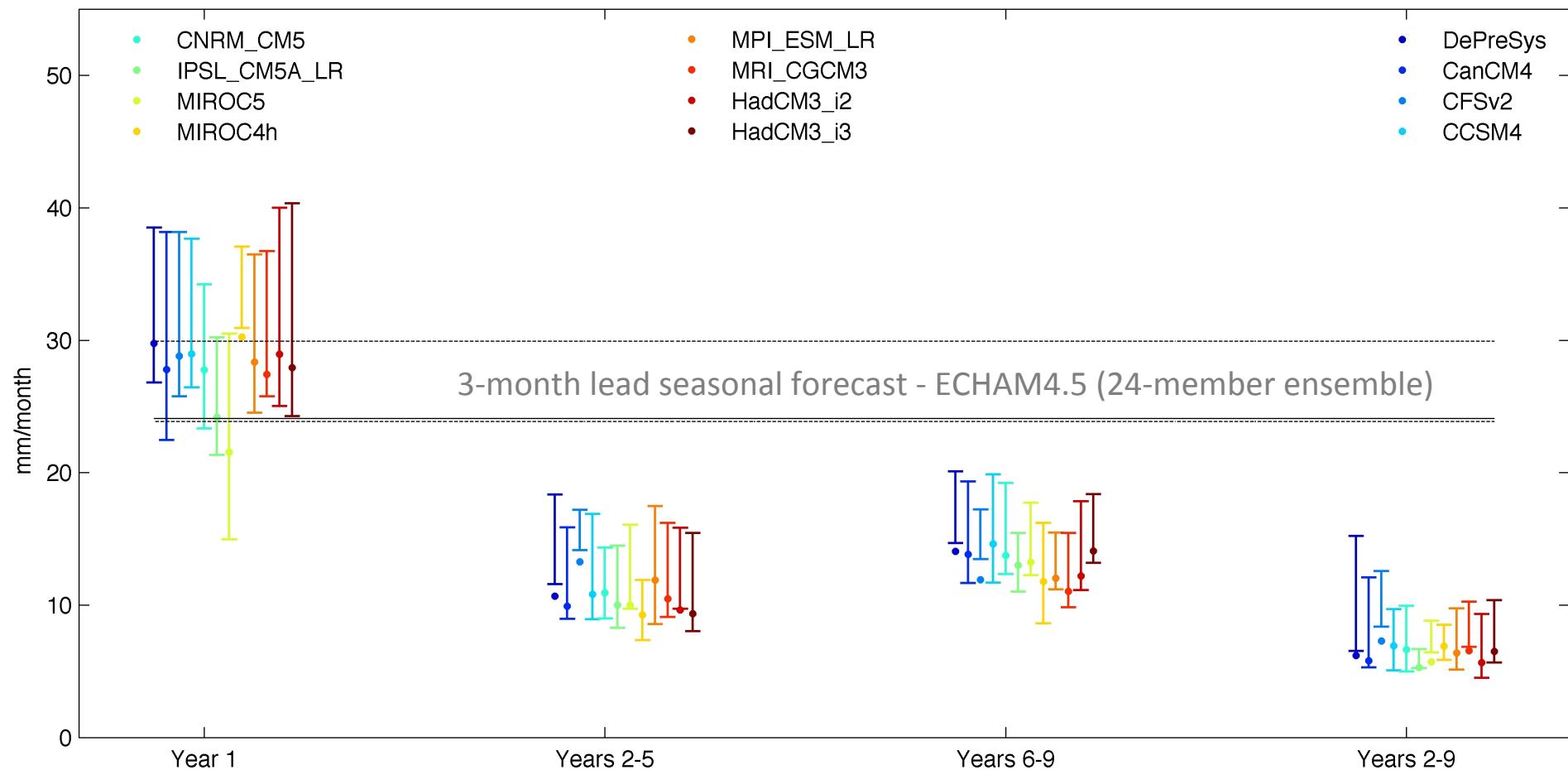


CCSM4 - DJF tas regression with SESA DJF precipitation
Lead Year:2



Exploring seasonal-to-decadal predictability and teleconnections in CMIP5 decadal hindcasts

SESA precipitation - Interannual-to-decadal skill (RMSE)





Development of multi-scale regional climate information

Projects:

Multi-scale Climate Information for Agricultural Planning in Southeastern South America for Coming Decades. NSF EaSM. PIs: Lisa Goddard, Walter Baethgen, Arthur Greene (IRI/Columbia University), Richard Seager (Lamont-Doherty Earth Observatory, Columbia University).

Integration of Decadal Climate Predictions, Ecological Models and Human Decision-making Models to Support Climate-resilient Agriculture in the Argentine Pampas. NSF EaSM. Lead PI: Guillermo Podesta (Univ. of Miami).

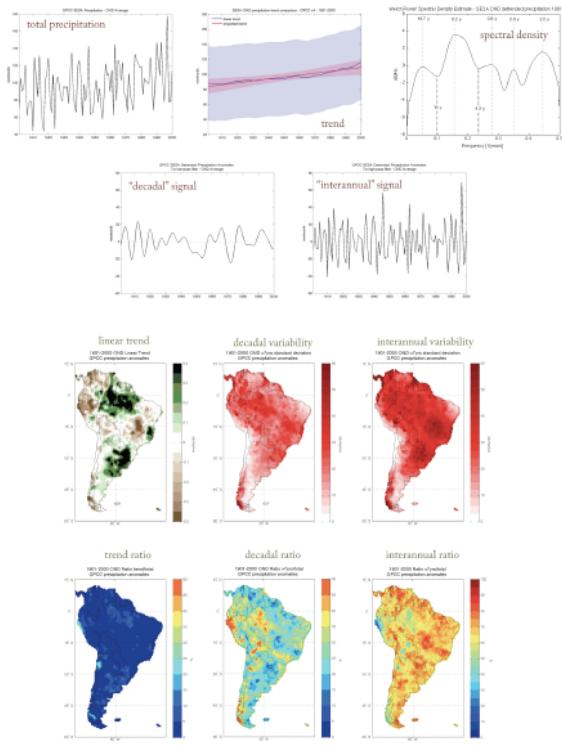
Climate information for the next few decades is required for both risk management and planning purposes. On this time horizon natural and anthropogenic factors can be equally important. We introduce here a strategy for the layering of information on different timescales – anthropogenically-forced climate change, natural low-frequency fluctuations and year-to-year variability – each with its associated uncertainty range. The approach involves the combination of dynamical and statistical projections, with specific methodologies being regionally tailored.

The example of South Eastern South America will be presented. Here, such information can play a crucial role in the development of land-use and water management policies. Approaches of varying complexity are considered in order to take advantage of observations, IPCC climate change projections and initialized decadal predictions, and to assess the uncertainties in these sources of information.

EXAMPLE: OND precipitation in South Eastern South America (SESA)

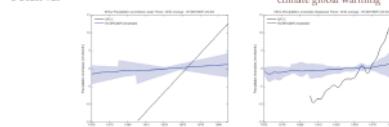
- OND was chosen for its strong coherent **variability and trend**, and for the importance of rainfall in that period to **regional agriculture**.
- The dataset chose was WMO's GPCC and some of the results might change slightly with different datasets.

1) Understanding the past: 20th Century Variability And Change



2) Looking towards the future

TREND



- The CMIP 3 coupled models used in the IPCC/AR4 highly **underestimate** the observed increase in SESA precipitation.

- To forecast short periods in the future, **linear trend extrapolation** may be a better estimate of the increase.

- If the time horizon is longer (i.e.: 50 years), the **regression** with the ensemble mean global temperature may be a better choice since it includes information from emission scenarios.

VARIABILITY

- i) **"Decadal climatology"**: characterization of variability that represents likely magnitude and persistence of anomalies, by generating numerous synthetic realizations based on historical observations.

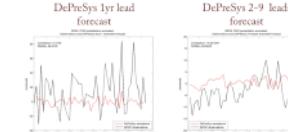
Observations outside range of possibilities according to WCRP/CMIP3

For periods in which deterministic forecasts have no skill, synthetic simulators provide useful information

Observations compared to synthetic "decadal climatology" (OND SESA at w/e 2.5, 25, 50, 97.5 percentiles for start)



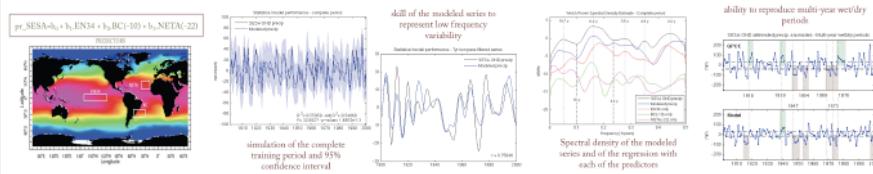
- ii) **Dynamical predictions**: seasonal-to-interannual forecasts have skill during ENSO extremes, but not for decadal timescales in this model.



iii) Statistical predictions:

- an alternative to dynamical predictions, possibly merged with dynamical forecasts if predictors can be represented by the models.
- observational predictors with large (decadal) lags are particularly useful.

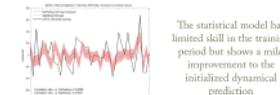
Example. Multiple linear regression model built with 3 : EN 3.4 Index (OND, yr 0); Brazil current SSTa Index (BC) [SON (t-10 yrs)] before and the NE Tropical Atlantic SSTa index (NETA) [SON (t-22 years)]. The model was trained using a moving 80-years window within 1901-2000.



3) Putting it together

Combining: dynamical predictions (One year lead EN34) + statistical simulations + trend estimations

Statistical model fed with 1yr lead forecasted EN3.4

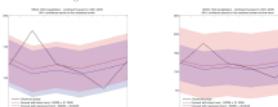


Validation of the statistical model forced by 1yr lead forecasted EN3.4

The statistical model has limited skill in the training period but shows a mild improvement to the initialized dynamical prediction

Independent forecasting period: 2001-2006

Uncertainty only for the statistical regression



Conclusions

This framework (work in progress) needs information on all timescales, which is not always available from a single tool (i.e.: a dynamical model).

- Observed trends are not correctly represented in dynamical models;
- Statistical models can complement information from dynamical models;
- "decadal climatology" based on past observations is needed when there is no signal or skill in deterministic prediction tools.



Multi-scale Climate Information for Agricultural Planning in Southeastern South America for Coming Decades

L. Goddard, W. Baethgen, A. Greene, R. Seager, P. Gonzalez, A.G. Munoz, A. Ines, C. Tebaldi, A. Ruane.



NSF EaSM
Pis Meeting
2012

1. International Research Institute for Climate & Society. Earth Institute, Columbia University. Palisades, NY, USA. 2. Lamont-Doherty Earth Observatory, Columbia University, Palisades, NY, USA. 3. Climate Central, Princeton, NJ, USA. 4. GISS, NASA/Columbia University, New York, NY, USA.

Motivation

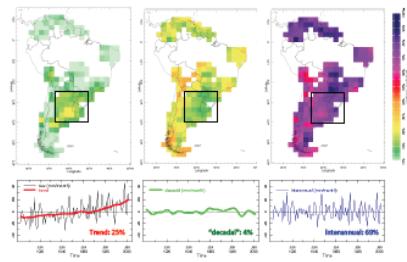
- The agricultural frontier of SE South America has expanded over the past several decades due to large increases in regional precipitation. Are these increases likely to persist in the future, or are they part of decadal variability, or both?

Objective

- To better understand the causes of climate variability and change in the region, and with that information, develop actionable climate information that can support agriculture planning for future decades.

Attribution: Decadal Variability versus Anthropogenic Change

Observations: Time Scale Decomposition

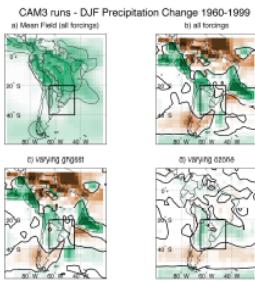


* Time-scales decomposition of South Eastern South America SONDJF precipitation

* Maproom: http://iri.ldeo.columbia.edu/maproom/Globe/Time_Scales/

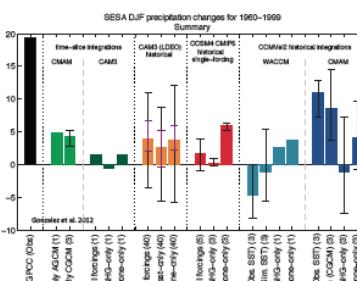
* For this region, the trend is more important than the decadal variability

- Ozone depletion is a significant driver of climate change in the Southern Hemisphere through its radiative and dynamical impacts^{1,2}. It has contributed significantly to an increase in subtropical precipitation in the SH³.
- The contribution of ozone to the wetting of SESEA in the 1960-1999 period is explored in 6 sets of numerical simulations⁴.



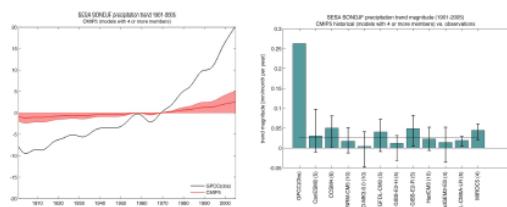
Gonzalez et al. 2012

Models: O₃ versus GHG



Experiments suggest that the contribution from ozone to increased precipitation in this region is comparable or larger than that from GHGs.

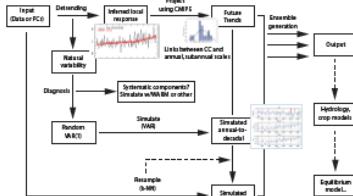
CMIP5 Models



- Coupled models are not able to capture the magnitude of the observed 20th Century trend, though they do better for the latter half of the century (i.e. GFDL CM3).
- The precipitation trend for this region should therefore be estimated through a different methodology. This will be informed by the attribution study.

Future Climate Information

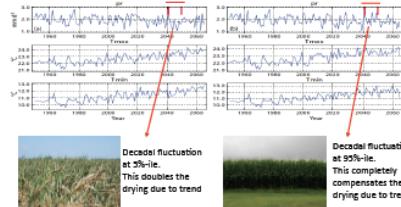
Layering Trend + Natural Variability



- A spatially-distributed observational record is decomposed into trend, annual-to-decadal and subannual components.
- Precipitation, Tmin, Tmax are modeled in a multivariate framework.
- Future regional trends may be informed by IPCC models; annual-to-decadal signal simulated with a first-order vector autoregressive (VAK) model.

Stochastic Simulations

Distributions for both trend and decadal fluctuations: Example drawn from South Africa⁵. Two simulations are shown for the same catchment in a large watershed in Western Cape ($\sim 19000 \text{ km}^2$, 171 catchments), at annual resolution



Summary

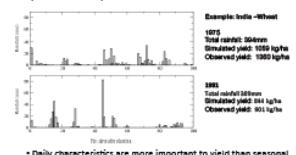
- Climate information for the coming decades must include realistic estimates, and associated uncertainties, for anthropogenic trends, interannual-to-decadal variability, and how those affect weather characteristics.
- Our approach includes dynamical model predictions, projections, and simulations, as well as assessment of past variability and change from observations, to create robust multi-scale climate information.
- The sensitivity of agricultural models to variability on different timescales will be tested.

References

- Goddard, L., M. J. Suarez, and J. S. Cole, "Web Tool Describes Variability in Twentieth-Century Climate," *Eos Trans. AGU* 93(25), 397-398, Nov. 2011.
- Poli, R., M. J. Polley, D.W. Magill, G.P. Correa, and S.M. Son, "Stratospheric ozone depletion: the main driver of 20th century precipitation changes in the Southern Hemisphere," *J. Clim.* Vol. 24, 205-212, 2011.
- Thompson, D.W., Solomon, S., Kushner, P.J., England, M.H., Orsi, K.M., Karoly, D.J., "Signatures of the Antarctic ozone hole in Southern Hemisphere surface climate change," *Nature Geoscience*, doi: 10.1038/Ngeo1296, 2011.
- Greene, A.M., L. Goddard, W. Baethgen, V. Cyle, and M. Segnon, "Impact of Polar Ozone Depletion on Subtropical Precipitation," *Science* 332(6023), 951-954, 2011.
- Gonzalez, P.M., Polley, L., Seager, R., Correa, G., "Impact of the 20th Century ozone depletion on increasing precipitation in South Eastern South America," *In preparation*, 2012.
- Greene, A.M., L. Goddard, W. Baethgen, V. Cyle, "Decadal climate simulations for the Berg and Breede Water Management Areas, Western Cape province, South Africa," *Water Resources Research*, Vol. 48, WIG0504, 2012.
- Challinor, A.J., Wheeler, T.R., Slingo, J.A., Craufurd, P.O., Grimes, D.F., "Design and optimisation of a large-area process-based model for crop yield projection," *Journal of Agricultural Science* 139(2), 133-144, 2005.
- Correa, G.S., Goddard, L., "The Multi-Scale Tropical Dynamics in Climate Change Projections," *J. Geophys. Res.* Vol. 22, 2009.

Weather Characteristics and Agriculture

Crop Yields depend on Weather Characteristics



- Daily characteristics are more important to yield than seasonal totals!

- Dowscaling will explore variations in transient weather characteristics related to variability (e.g. ENSO, AMO) and change.
- Perturbed physics ensemble (10 members).

Time Scale	Climate Change	Decadal Climate Variability (DV)	Spatial-to-Interannual (SI) Climate Characteristics	Weather Characteristics (Wx)
Baseline	Intergovernmental Panel on Climate Change (IPCC)	Decadal Climatology	Current Characteristics	Current Characteristics
Forecast	Reconstructed MME	Decadal Prediction + Unc.	Current Characteristics*	Hi-Resolution Downscaling

* Based on previous work (Coelho & Goddard, 2009). ENSO, which is the main contributor to SI variability over study region, is not projected to change in ENSO, so we assume Forecast SI = Current SI.

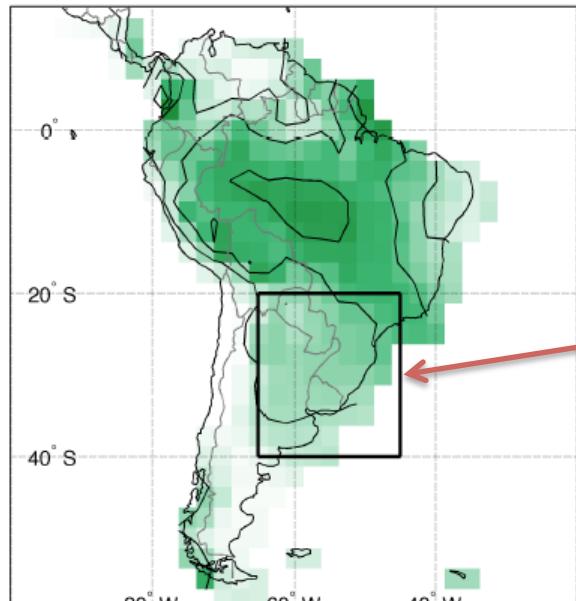


MOTIVATIONS

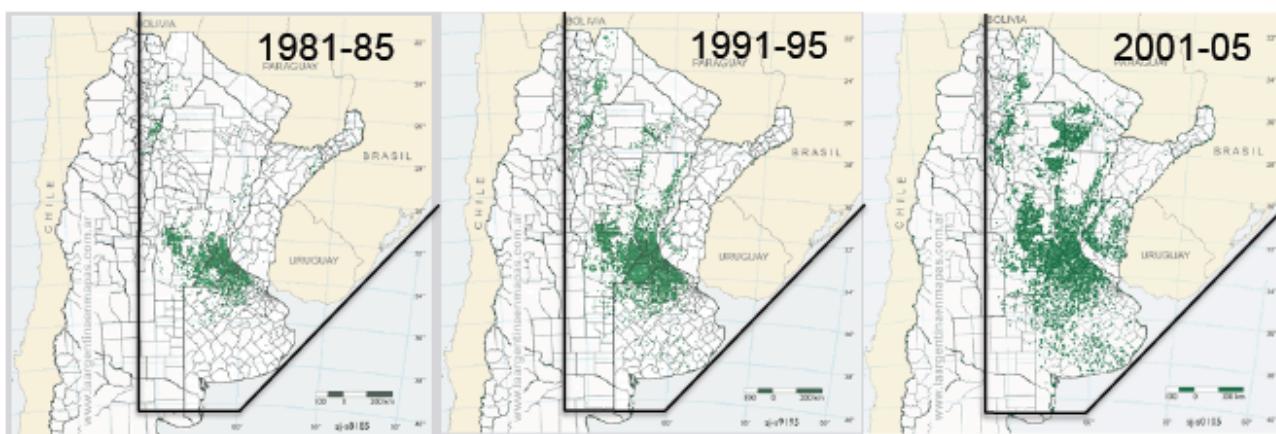
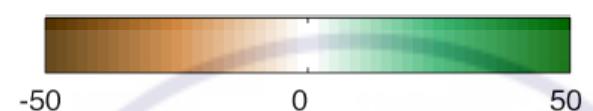
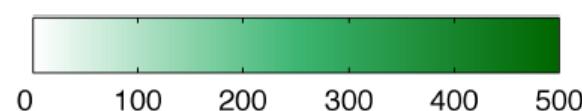
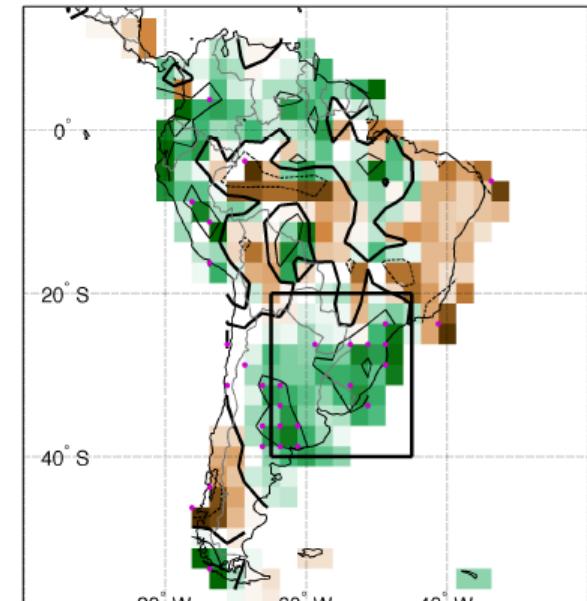
SESA has experienced a strong wetting trend over the complete 20th Century.

GPCCv4 DJF Precipitation 1960-1999

a) Mean



b) Change



Over the last decades, the wetting has been followed by the expansion of the agricultural frontiers.

FIGURE 1. Changes in soybean cropping area over time for Argentina. One dot = 1000 ha. Lines delimit Southeastern South America region shown in Figure 2.

MOTIVATIONS

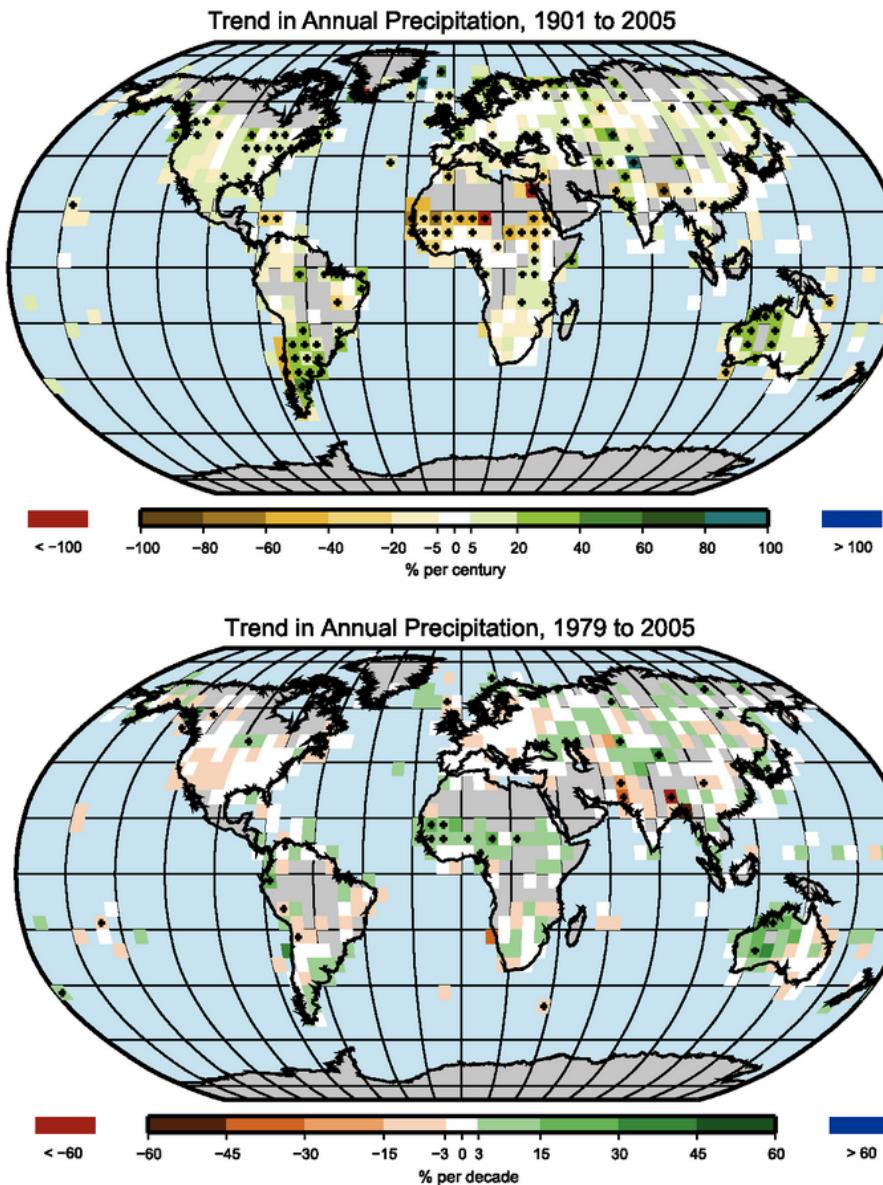
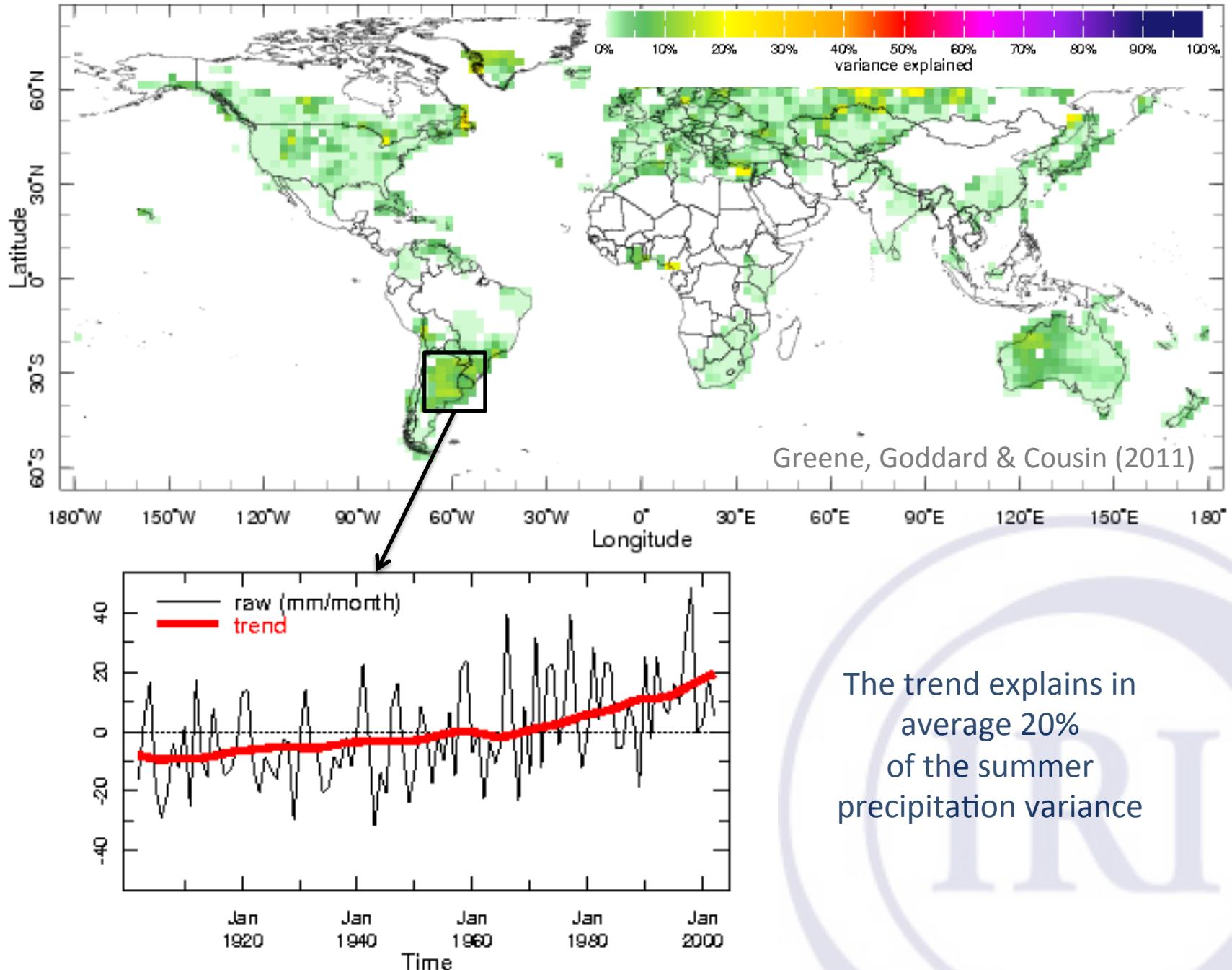


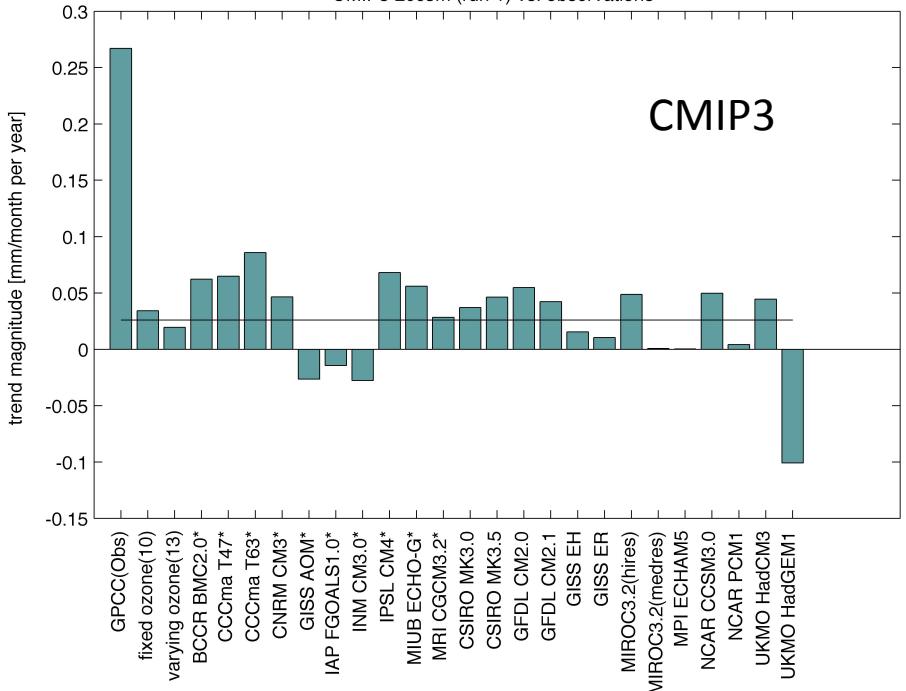
Figure 3.13. **Trend of annual land precipitation amounts for 1901 to 2005 (top, % per century) and 1979 to 2005 (bottom, % per decade)**, using the GHCN precipitation data set from NCDC. The percentage is based on the means for the 1961 to 1990 period. Areas in grey have insufficient data to produce reliable trends. The minimum number of years required to calculate a trend value is 66 for 1901 to 2005 and 18 for 1979 to 2005. An annual value is complete for a given year if all 12 monthly percentage anomaly values are present. Note the different colour bars and units in each plot. Trends significant at the 5% level are indicated by black + marks.

MOTIVATIONS

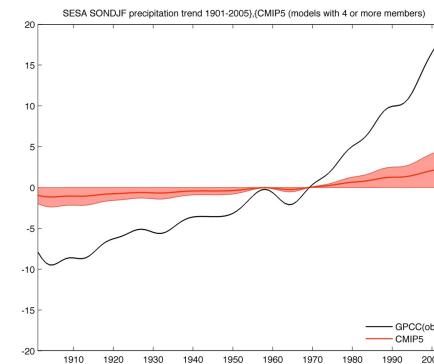


MOTIVATIONS: CMIP3/CMIP5 – 20th Century

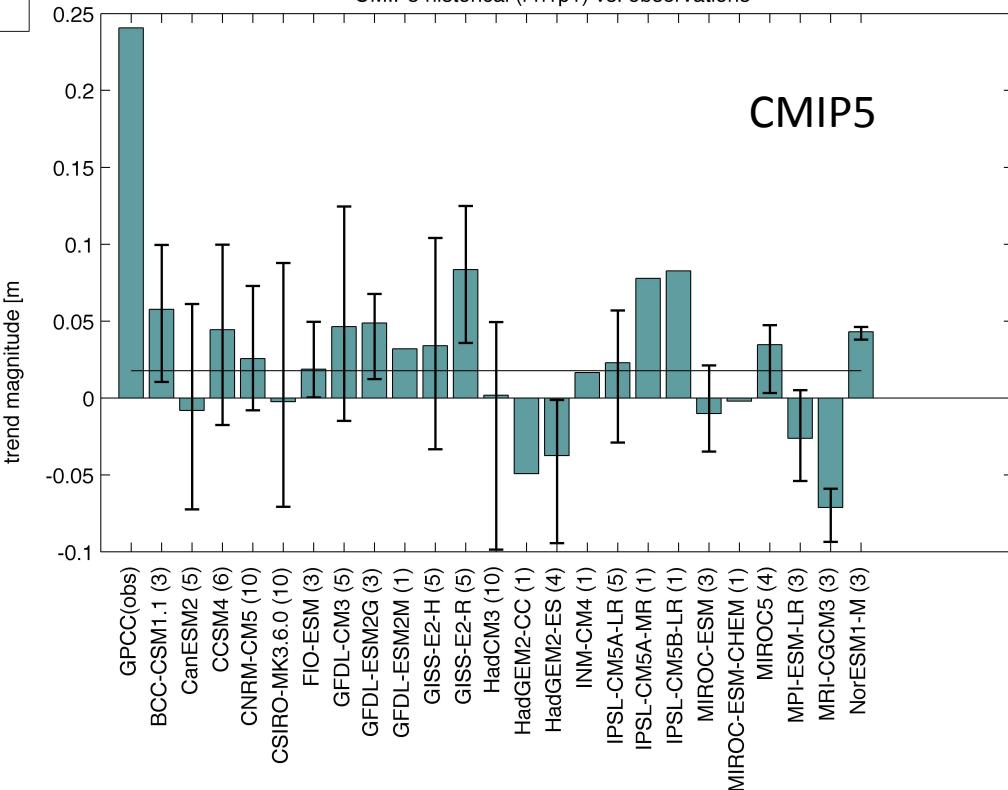
SESA DJF precipitation trend magnitude (1901-1999)
CMIP3 20c3m (run 1) vs. observations



CMIP3



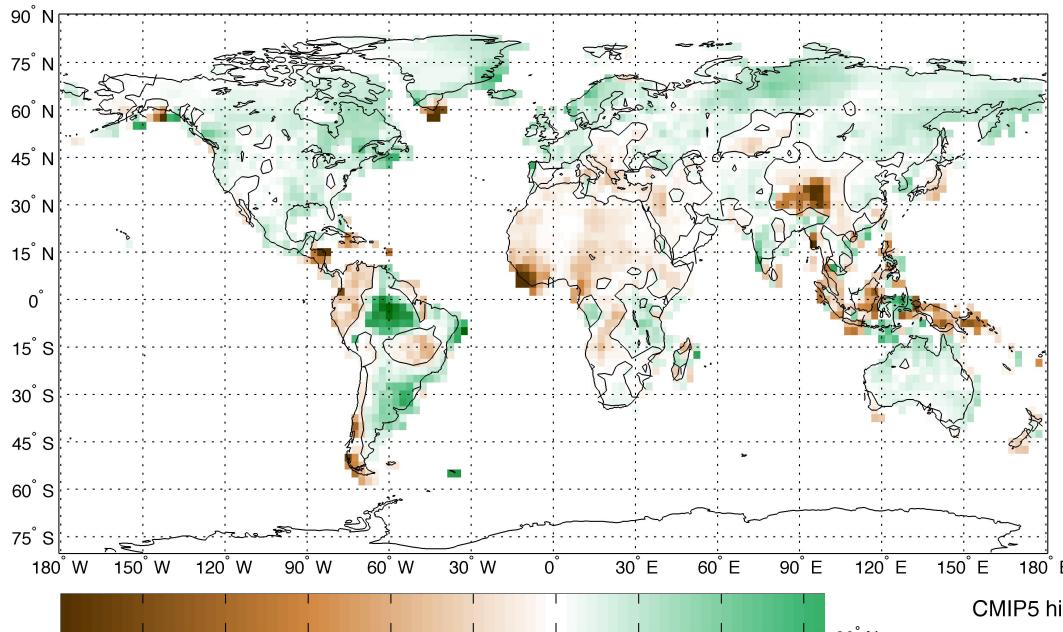
SESA DJF precipitation trend magnitude (1901-2005)
CMIP5 historical (r1i1p1) vs. observations



CMIP3 and CMIP5 models fail to reproduce the 20th Century wetting.

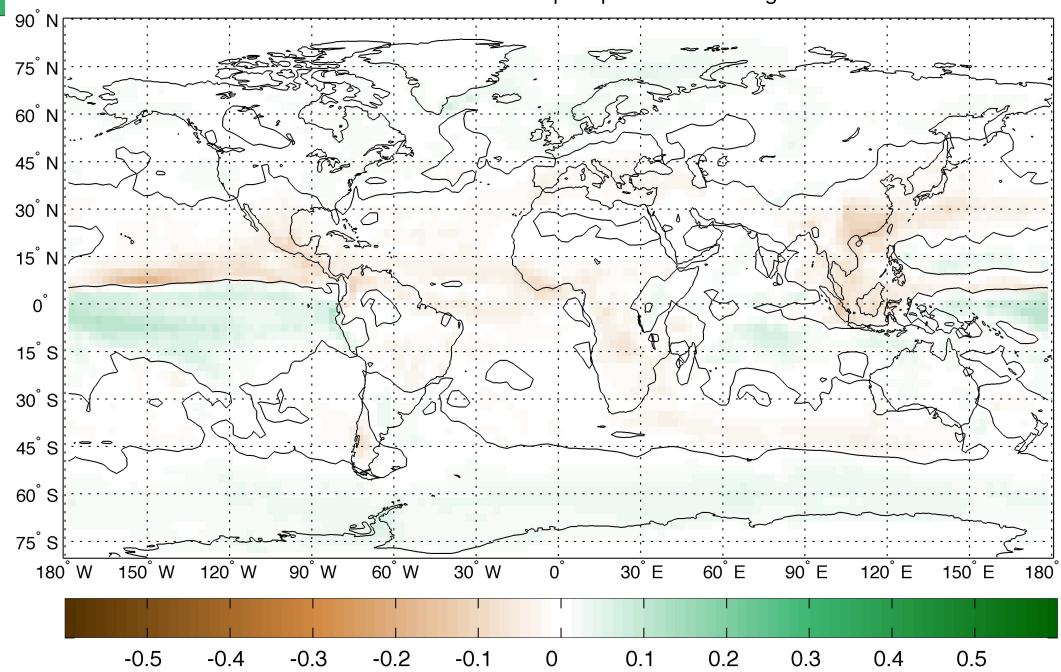
MOTIVATIONS: annual means – 20th Century

GPCC annual mean precipitation linear trend magnitude - 1901-2000



OBS

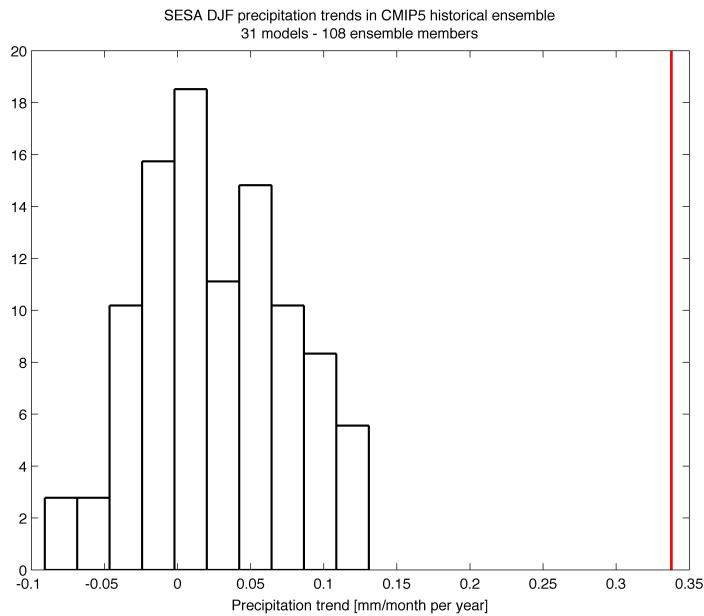
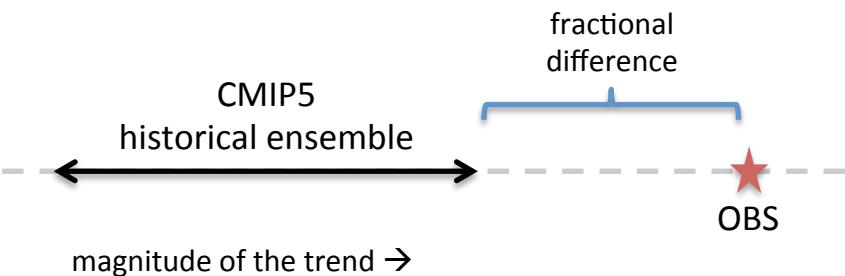
CMIP5 historical ensemble mean annual precipitation trend magnitude - 1901-2000



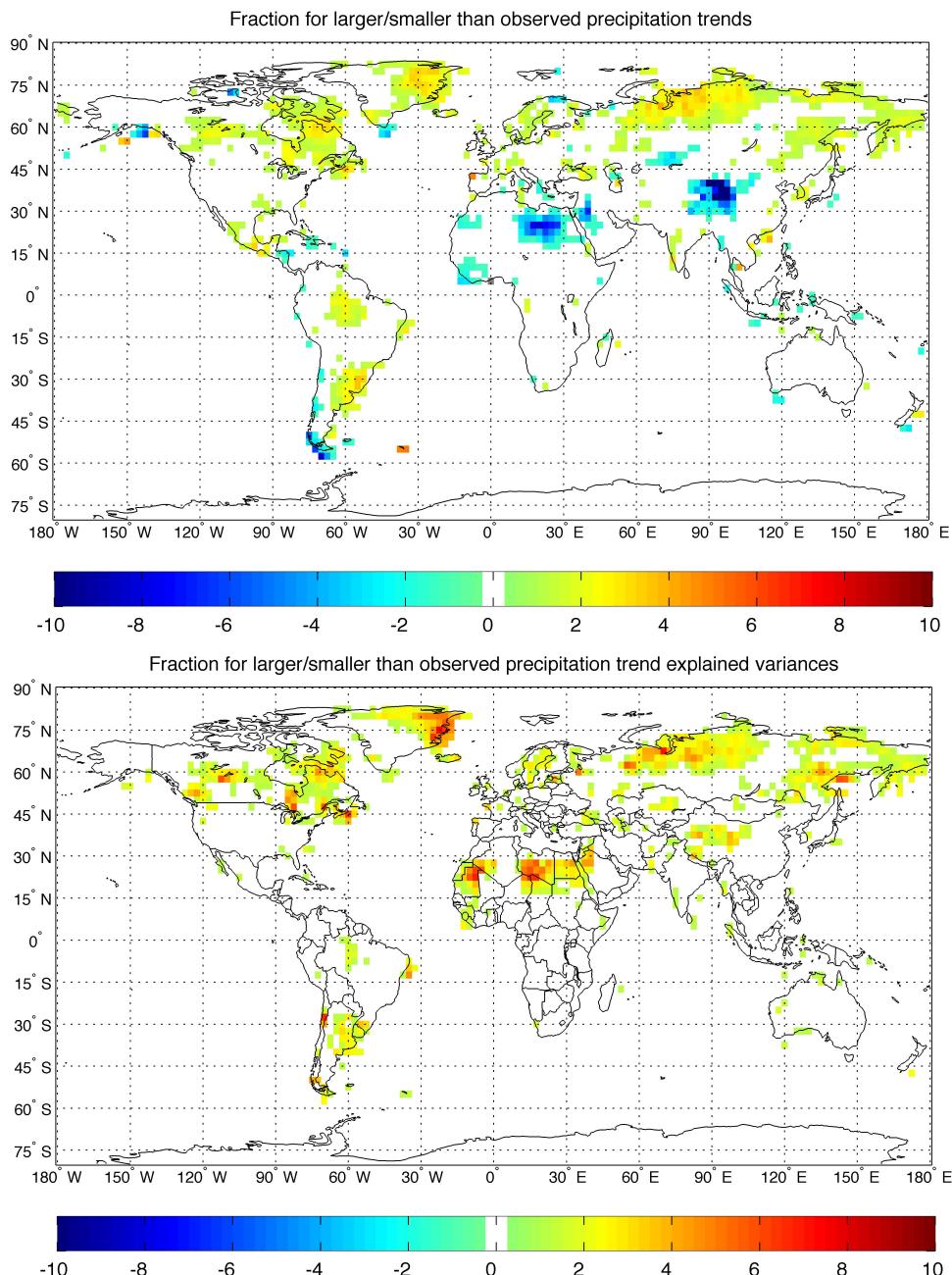
MME CMIP5

CMIP5 historical – annual mean precipitation – 20th Century

Comparing the magnitudes of the trend



Comparing the % of variance explained by the trend

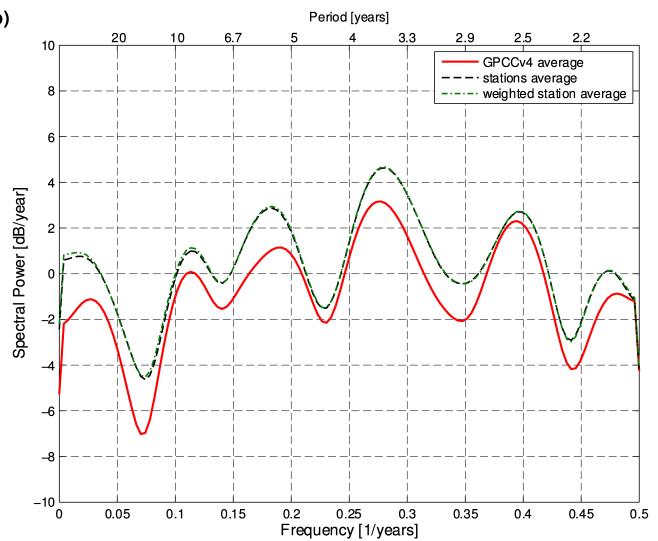
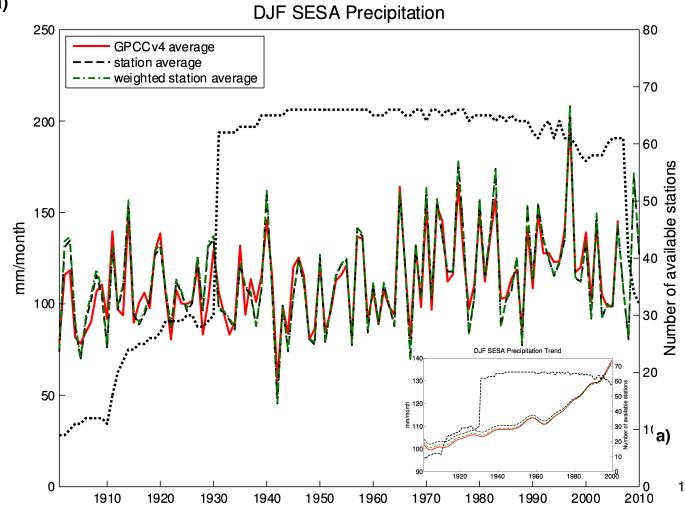


Short Communication

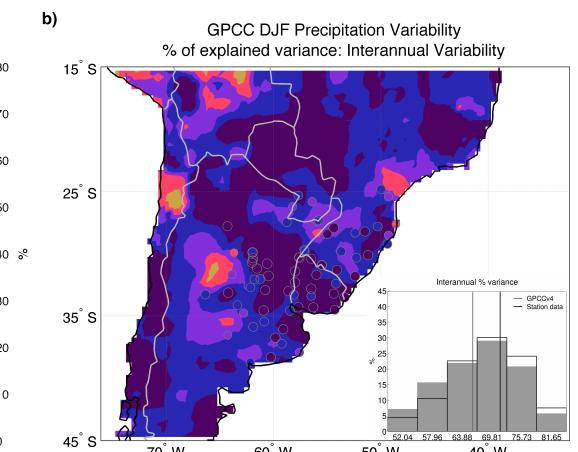
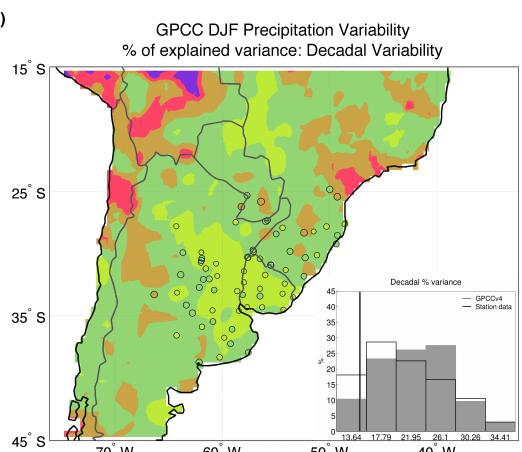
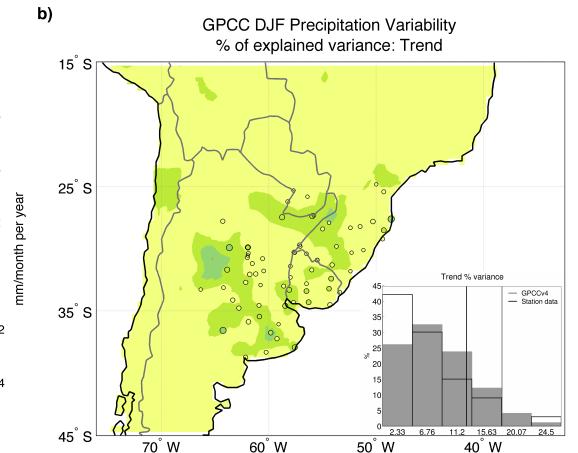
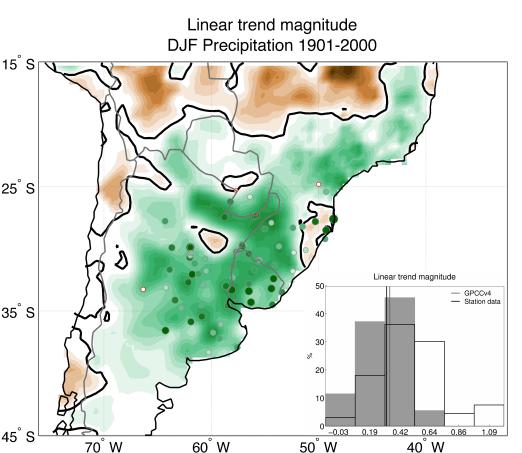
Twentieth-century summer precipitation in South Eastern South America: comparison of gridded and station data

P. L. M. Gonzalez,* Lisa Goddard and Arthur M. Greene

International Research Institute for Climate and Society, Earth Institute, Columbia University, Palisades, NY, USA



Can we trust century-long
gridded datasets over SESA?



MOTIVATIONS: why ozone?

Ozone depletion has been shown to be one of the main drivers of climate change in the Southern Hemisphere (e.g. Polvani et al. 2011)

In particular, it has been linked to the observed wetting of the SH subtropics (Kang et al 2011)

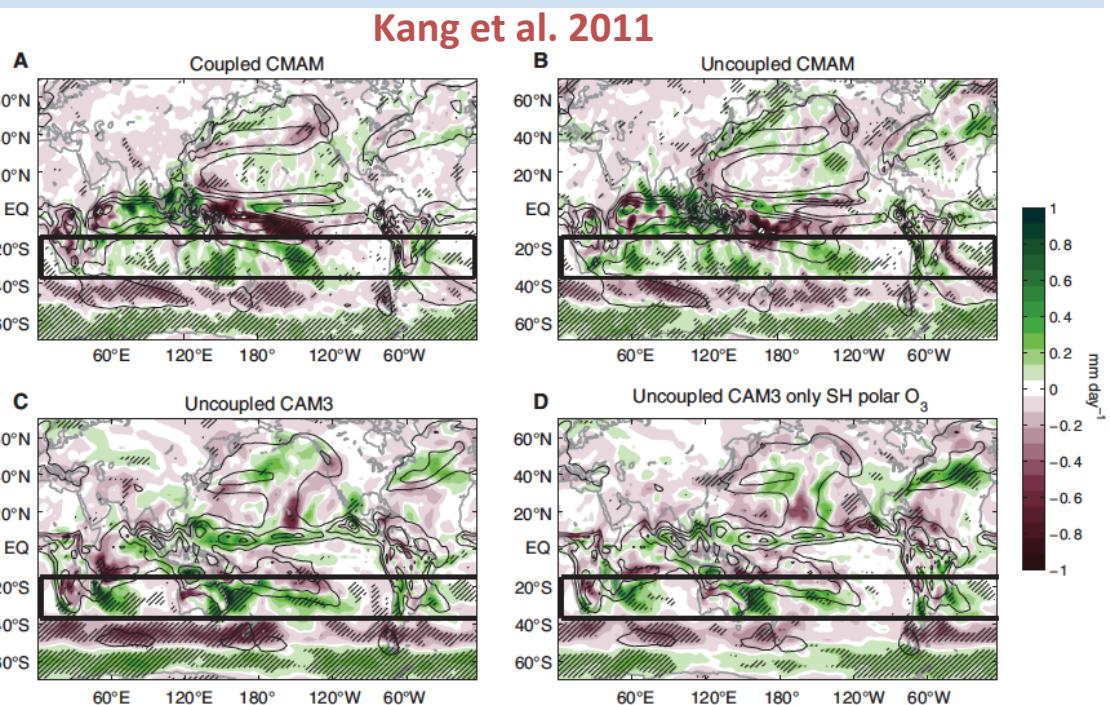
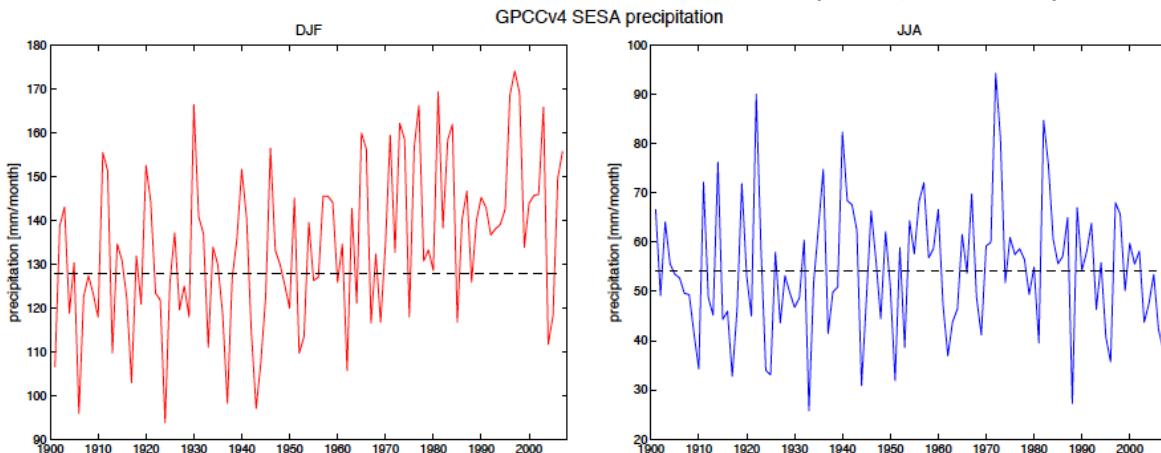


Fig. 2. Modeled precipitation change caused by the ozone hole. Shading shows austral summer precipitation difference (in mm day^{-1}) induced by ozone depletion in (A) the coupled CMAM, (B) the uncoupled CMAM, (C) the uncoupled CAM3, and (D) the uncoupled CAM3 with ozone depletion

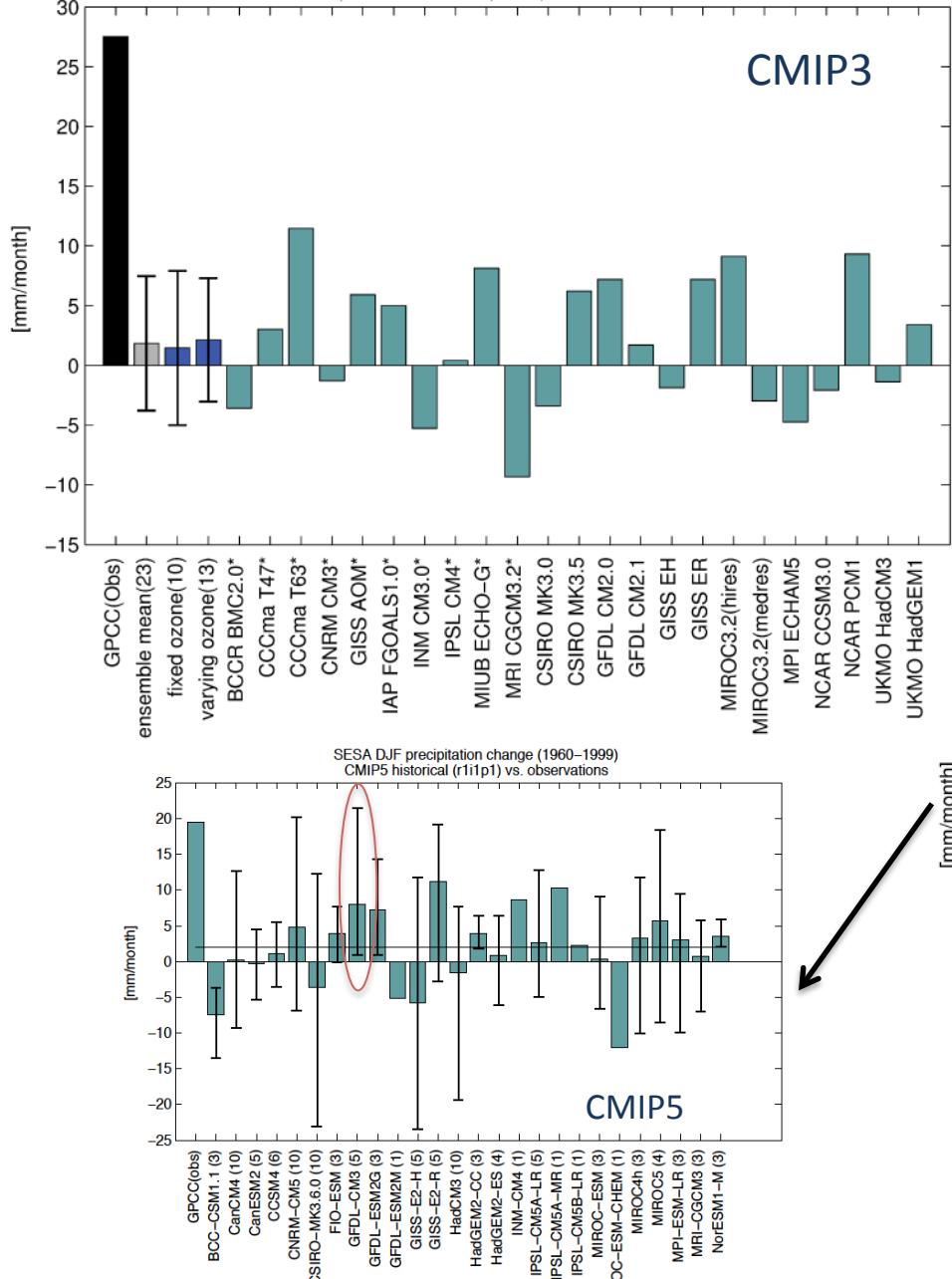
confined to 40°S to 90°S . Black contours show the mean precipitation in the respective reference integrations, with contour interval of 3 mm day^{-1} . Locations where the response is significant at the 95% confidence level are hatched.



The fact that the trend in SESA strengthens around 1960 and that this is only seen during summer could be evidences of the influence of ozone depletion.

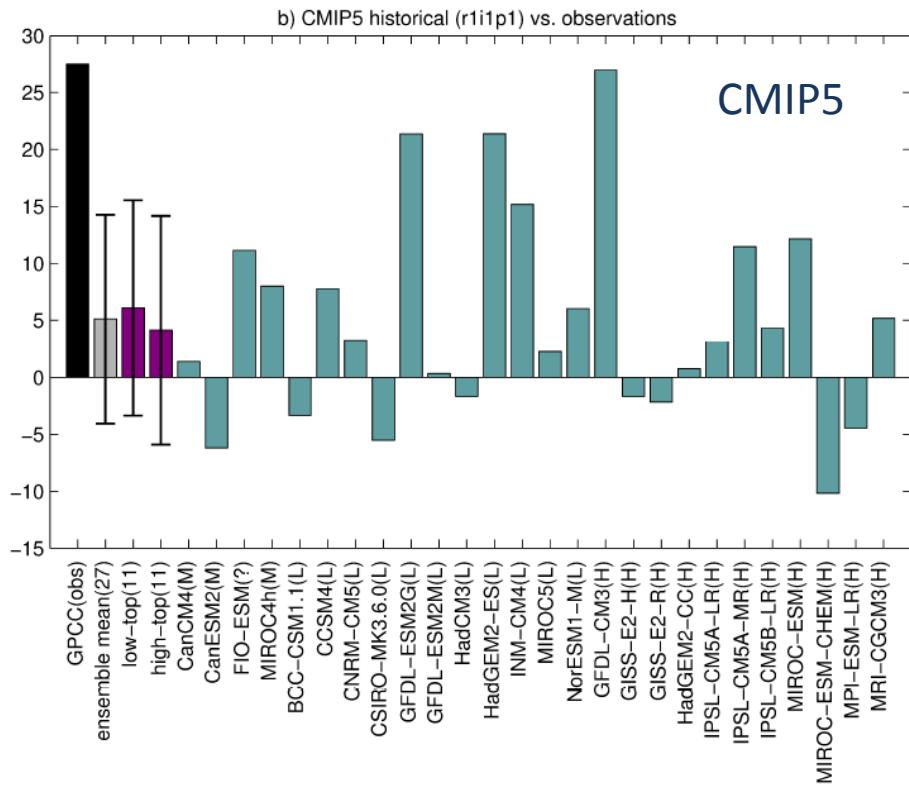
MOTIVATIONS: CMIP3/CMIP5 - 1960-1999

SESA DJF precipitation change (1960–1999)
a) CMIP3 20c3m (run 1) vs. observations



* Some CMIP5 models do better (e.g. GFDL CM3) but the spread is still very large.

* These ensembles provide inconsistent evidences of the influence of ozone depletion.





Impact of the 20th Century stratospheric ozone depletion on increasing precipitation in South Eastern South America

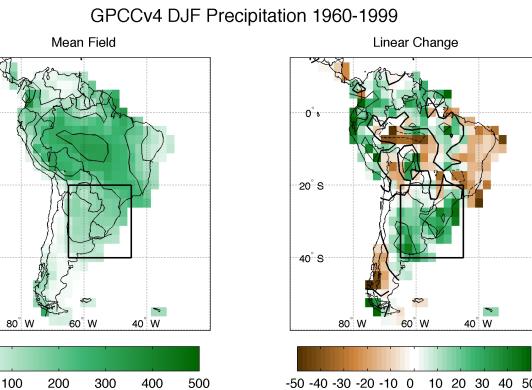
DESCRIPTION OF THE ENSEMBLE

type	model	resolution	reference paper	# integration name	brief description
time-slice	CAM3	T42 L26 (low top)	Polvani et al. (2011a)	1 reference 1 all-forcings 1 GHG-only 1 ozone-only	50 years, steady forcings @ 1960 levels, SSTs from obs as reference, but all forcings at @ 2000 levels as reference, but GHGs & SSTs @ 2000 levels as reference, but O ₃ @ 2000 levels
	CMAM	T63 L71 (high top)	Sigmond et al. (2010)	1 reference (CGCM) 3 ozone-only (CGCM) 1 reference (AGCM) 1 ozone-only (AGCM)	80 years, steady forcings @1979 levels, coupled model as CGCM reference, but O ₃ @ 2005 levels as CGCM reference, atmosphere only (SSTs from reference) as AGCM reference, but O ₃ @ 2005 levels
CAM3 transient	CAM3	T42 L26 (low top)	unpublished, but similar to Polvani et al. (2011a)	40 all-forcings 40 GHG-only 40 ozone-only	1950-2009, all forcings transient, SST from obs 1950-2009, only O ₃ transient 1950-2009, only GHGs and SSTs transient
CCSM4/CMIP5 transient	CCSM4	~ 1° L26 (low top)	Gent et al. (2011)	5 all-forcings 3 GHG-only 3 ozone-only	1850-2005, all forcings transient fixed 1850 forcings, but transient GHGs 1850-2005 fixed 1850 forcings, but transient O ₃ 1850-2005
CCMVal-2 transient	WACCM	~ 2° L66 (high top)	Garcia et al. (2007)	3 all-forcings 1 GHG-only 1 ozone-only	1960-2100, all forcings transient, modeled SSTs (REF-B2) as REF-B2, but halogens @ 1960 levels (SCN-B2b) as REF-B2, but GHGs and SSTs @ 1960 levels (SCN-B2b)
	CMAM	T31 L71 (high top)	McLandress et al. (2010)	3 all-forcings 3 GHG-only 3 ozone-only	1960-2100, all forcings transient, coupled GCM (REF-B2) as REF-B2, but halogens @ 1960 levels (SCN-B2b) as REF-B2, but GHGs and SSTs @ 1960 levels (SCN-B2c)

Table 1 Descriptions of the model output analyzed in this paper and the experimental design. In the fifth column, the name of each ensemble is preceded by the number of integrations with identical forcings (i.e. the ensemble size).

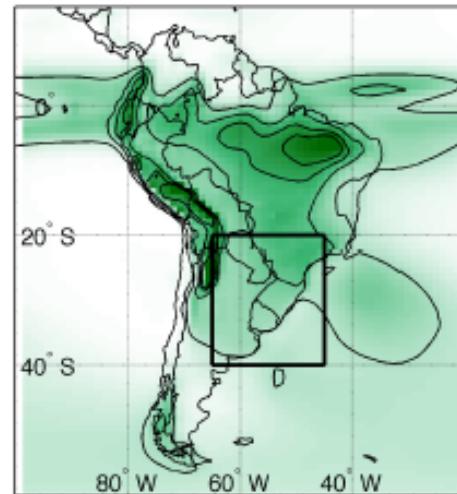
EXPERIMENTS: CCSM4/CMIP5 transient runs

CCSM4
(UCAR)
coupled (CAM4/POP2)
“1°” - L26
all-forcings (5m)
GHG-only (3m)
ozone-only (3m)
Gent et al. 2011

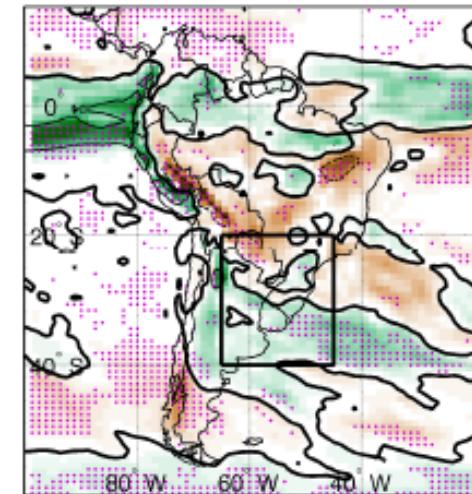


CCSM4/CMIP5 transient runs - DJF 1960-1999

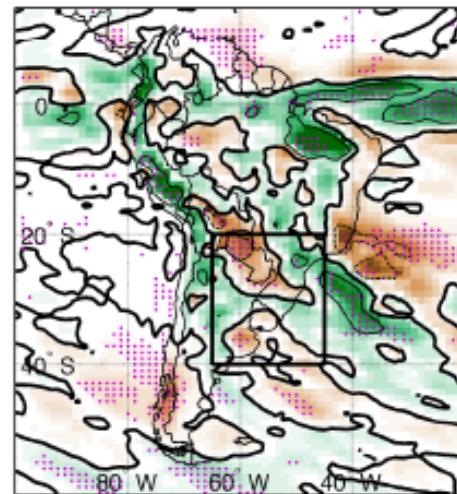
a) all-forcings (5) - Mean



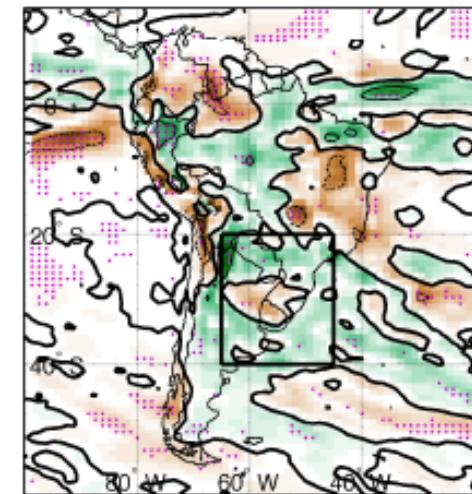
b) all-forcings (5) - Change



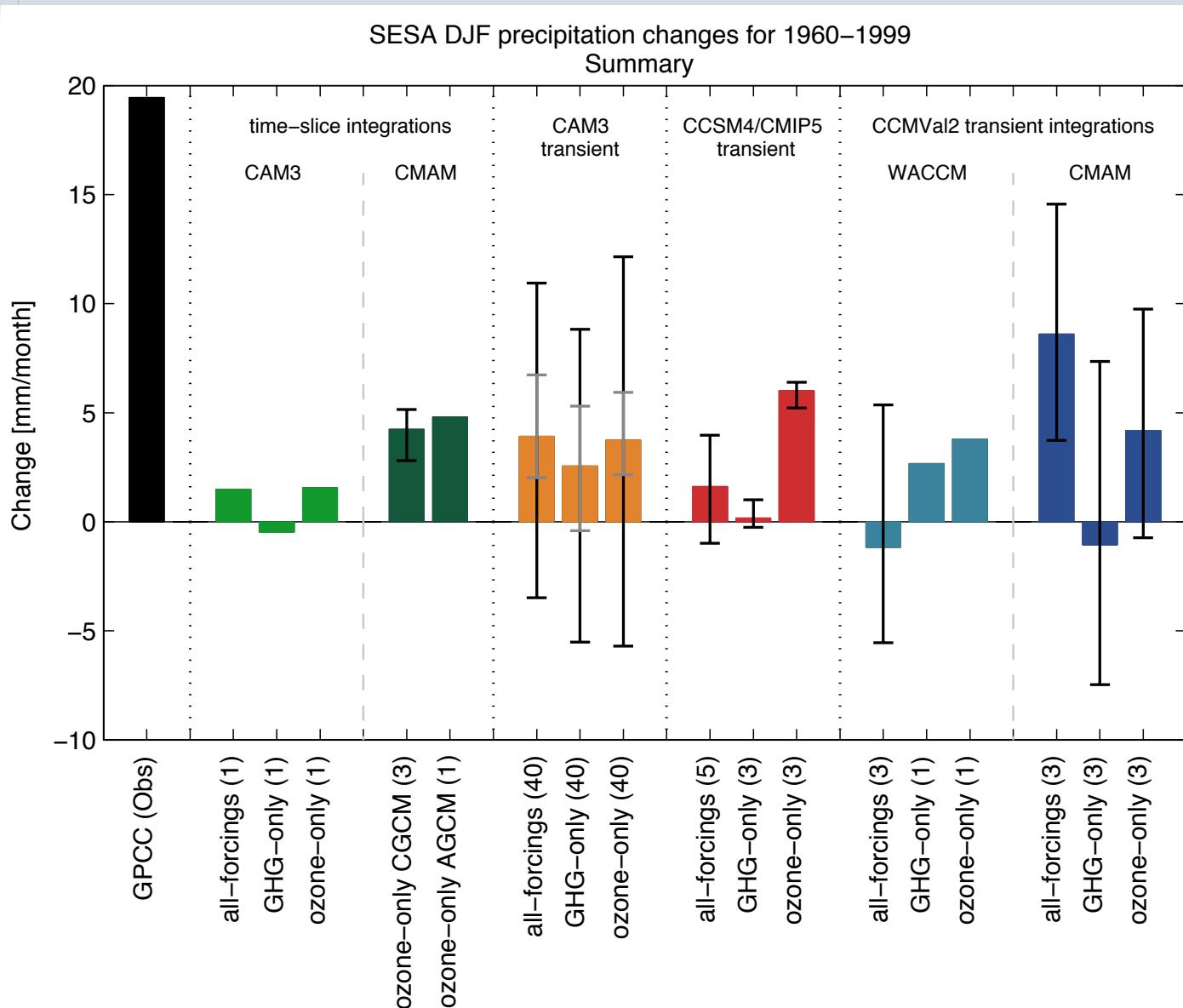
c) GHG-only (3) - Change



d) ozone-only (3) - Change

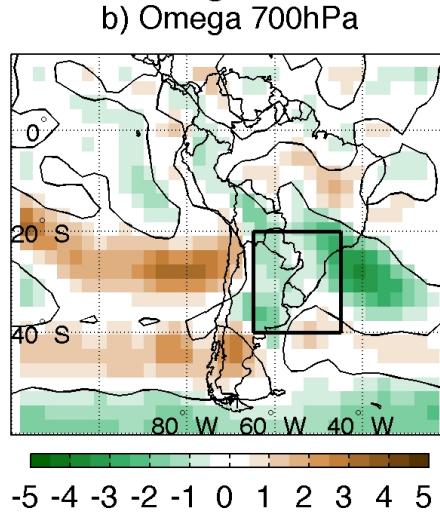
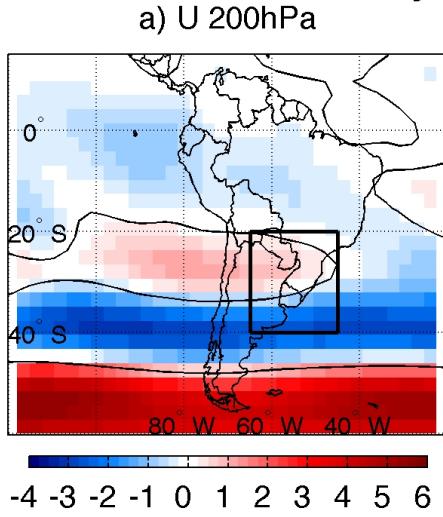


Impact of the 20th Century stratospheric ozone depletion on increasing precipitation in South Eastern South America

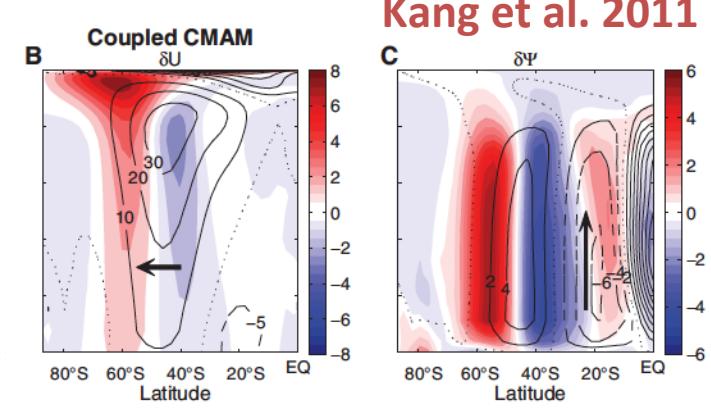
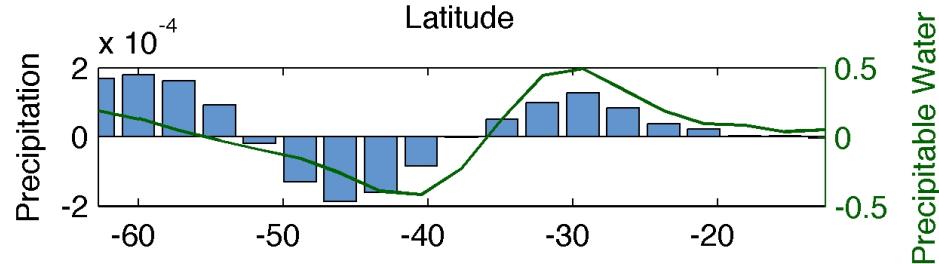
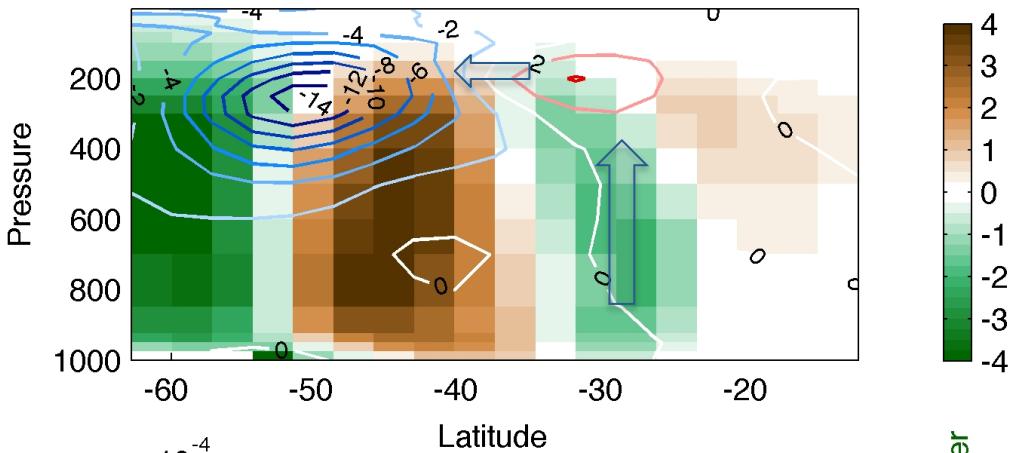


EXPERIMENTS: Dynamics of the simulated change

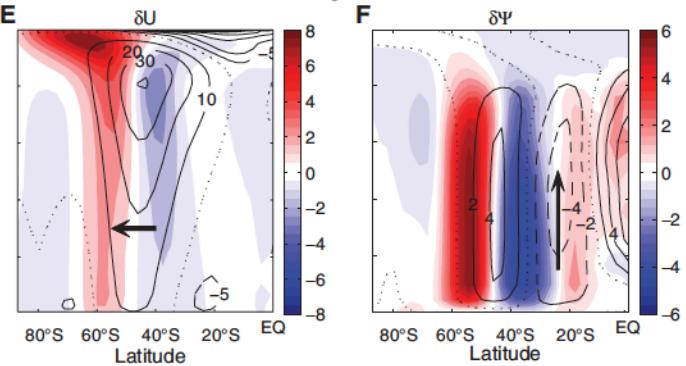
CAM3 LDEO ozone-only runs(40) - DJF Changes for 1960-1999



c) Zonal Mean change in Omega (shading) and U' V' (contours)



Incoupled CAM3 only SH polar O₃



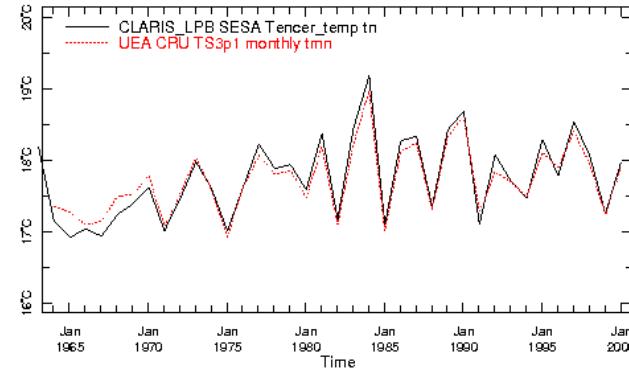
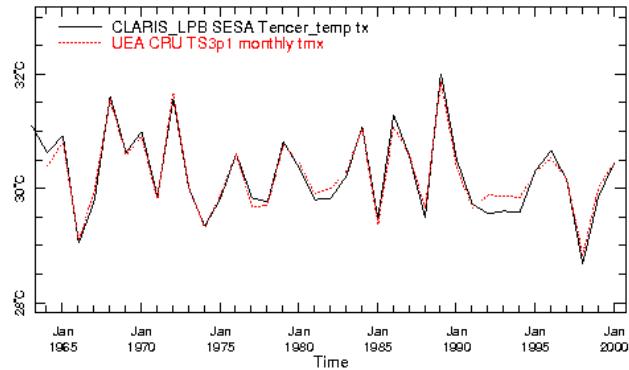
- poleward shift of extratropical jet
- upper level eddy momentum flux divergence (Eq flank)
- divergence balanced by southward upper tropospheric flow forcing upward motion
- increase in PW and precipitation

CONCLUDING REMARKS

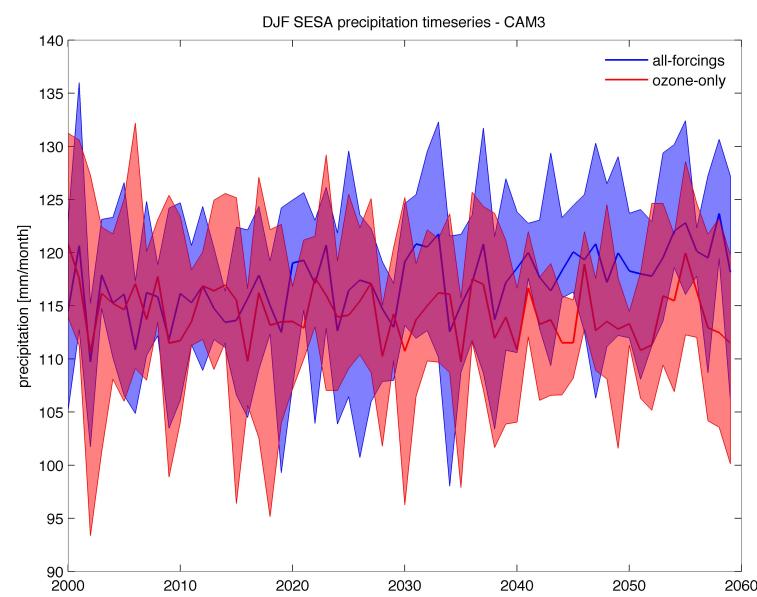
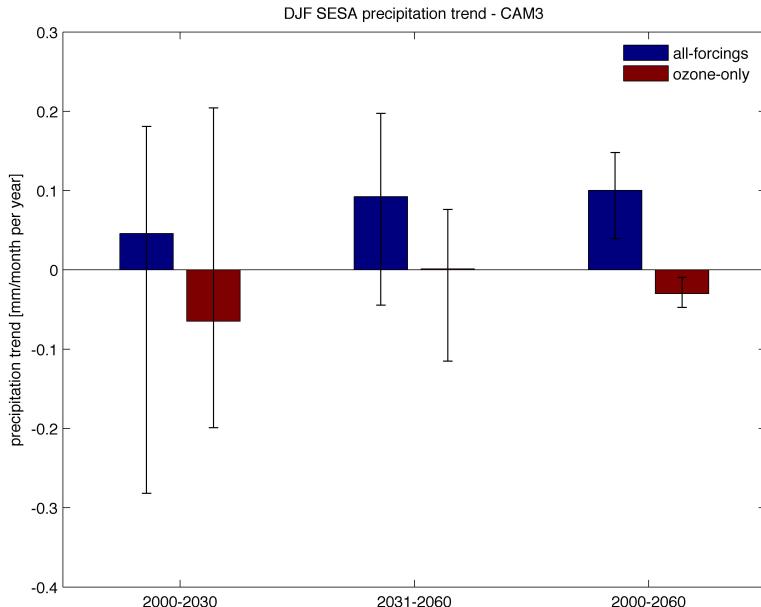
- Throughout the analyzed experiments stratospheric ozone depletion caused a precipitation increase in SESA
- In addition, the increase in GHGs cause smaller increases in precipitation or even a slight drying over SESA
- All the models considered underestimate the precipitation trend over SESA, but so do the CMIP3 and CMIP5 ensembles ...
- In the ozone-only experiment using **CAM3** (40 members), as shown by Kang et al. (2011), the radiative-driven changes in the stratosphere force the **extratropical jet to shift poleward**. The associated changes in the **eddy momentum fluxes** in the vicinity of South America generate an **upper level mass divergence** that is compensated with **upward motion and moisture convergence**, forcing **increased precipitation in SESA**.

NEXT STEPS

- Through the associated changes in cloudiness, this mechanism might also be important to explain changes in local temperature, especially DJF Tmin (not a lot of available model output ...)



- Explore projections for future SESA change in “single-forcing” experiments





Other research for the SESA region

MOTIVATIONS

15 OCTOBER 2010

SEAGER ET AL.

5517

Tropical Oceanic Causes of Interannual to Multidecadal Precipitation Variability in Southeast South America over the Past Century*

RICHARD SEAGER AND NAOMI NAIK

Lamont-Doherty Earth Observatory of Columbia University, Palisades, New York

WALTER BAETHGEN AND ANDREW ROBERTSON

International Research Institute for Climate and Society, Palisades, New York

YOCHANAN KUSHNIR AND JENNIFER NAKAMURA

Lamont-Doherty Earth Observatory of Columbia University, Palisades, New York

STEPHANIE JURBURG

Columbia College, Columbia University, New York, New York

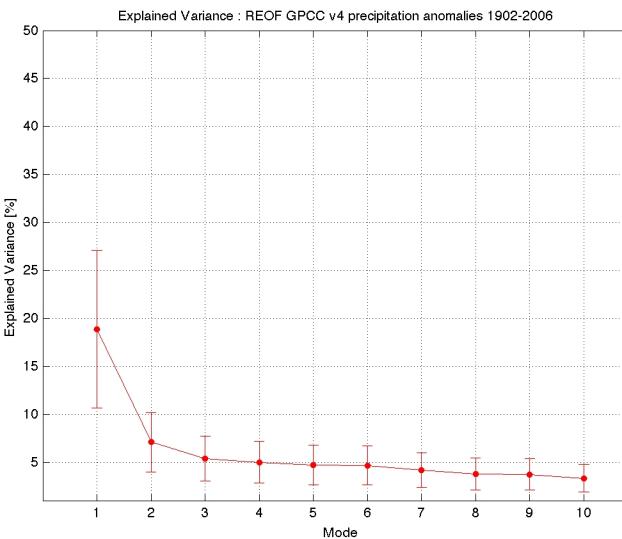
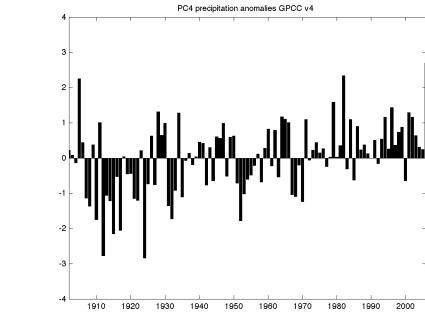
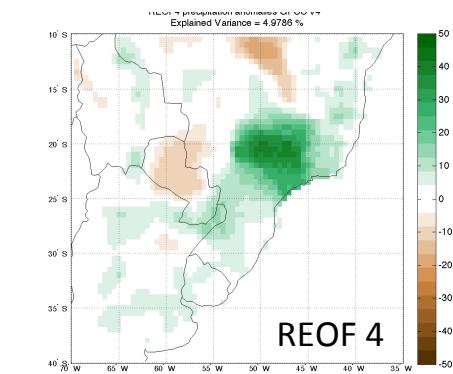
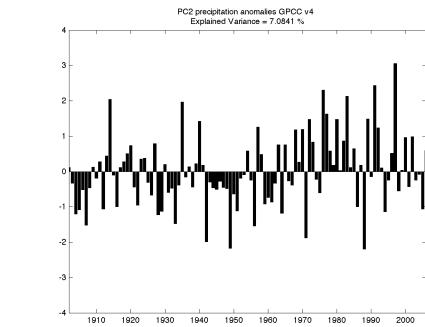
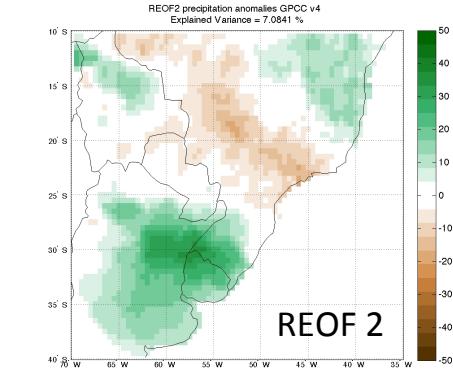
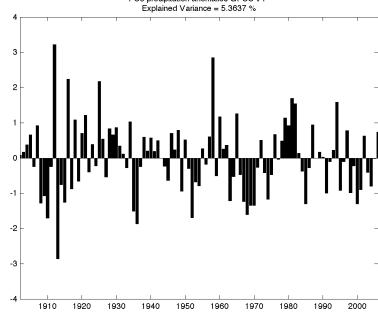
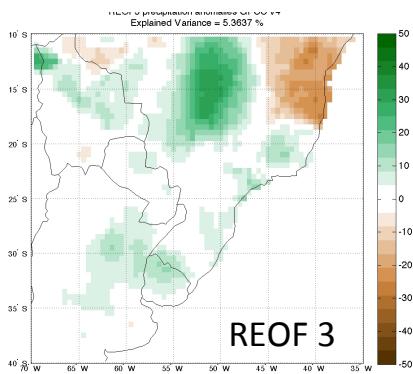
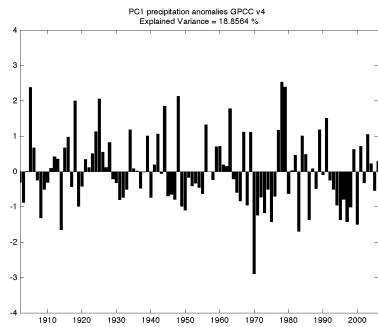
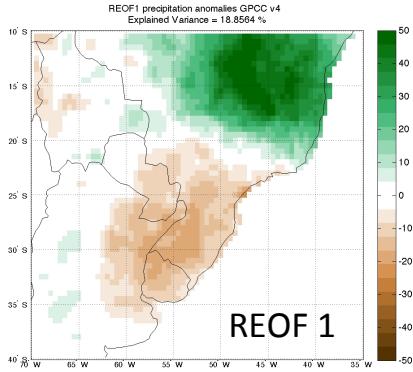
Clim Dyn
DOI 10.1007/s00382-011-1141-y

We are still exploring the mechanisms that might be responsible for SESA precipitation increases

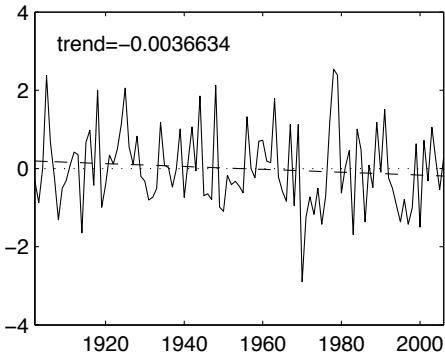
Summer precipitation variability over Southeastern South America in a global warming scenario

C. Junquas • C. Vera • L. Li • H. Le Treut

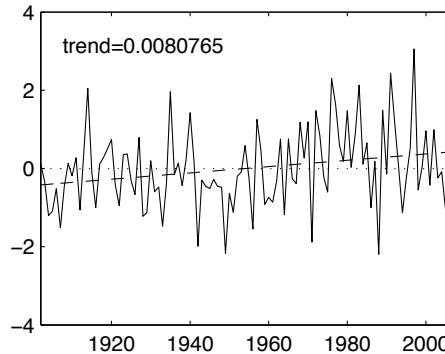
Rotated EOF DJF precipitation anomalies



REOF Analysis GPCC precipitation anomalies – 1902–2006
PC1

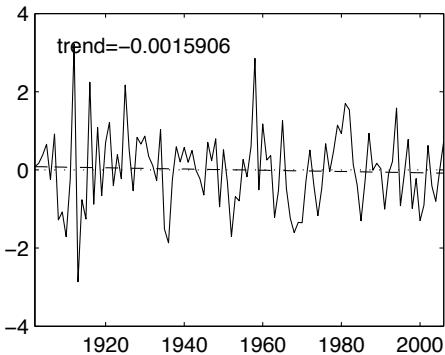


PC2

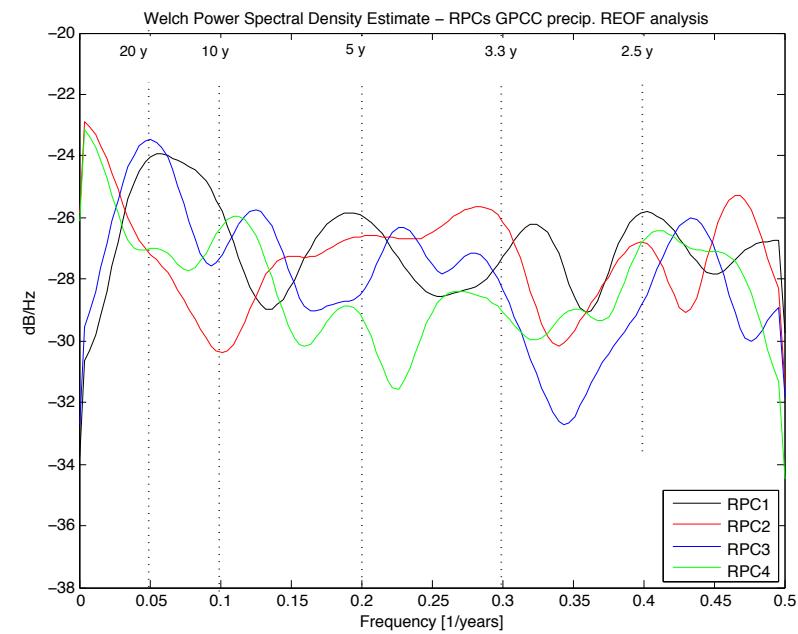
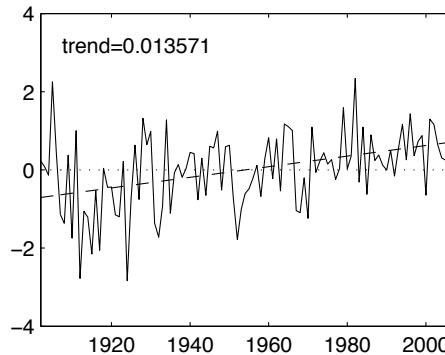


Temporal properties of PCs

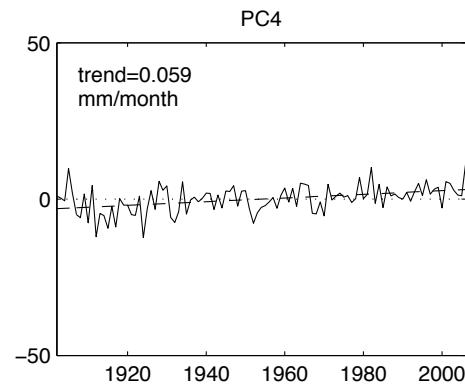
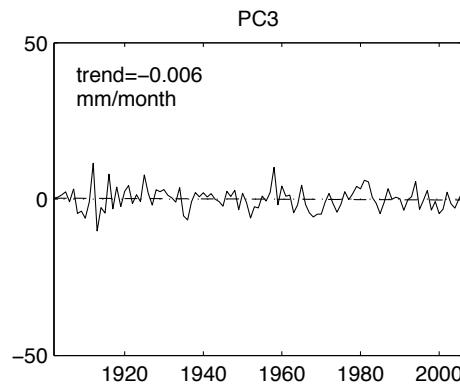
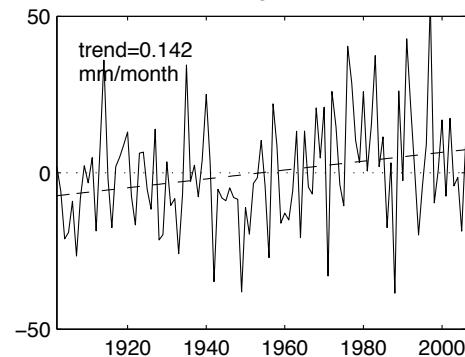
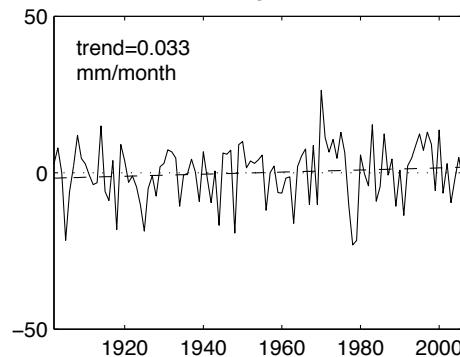
PC3



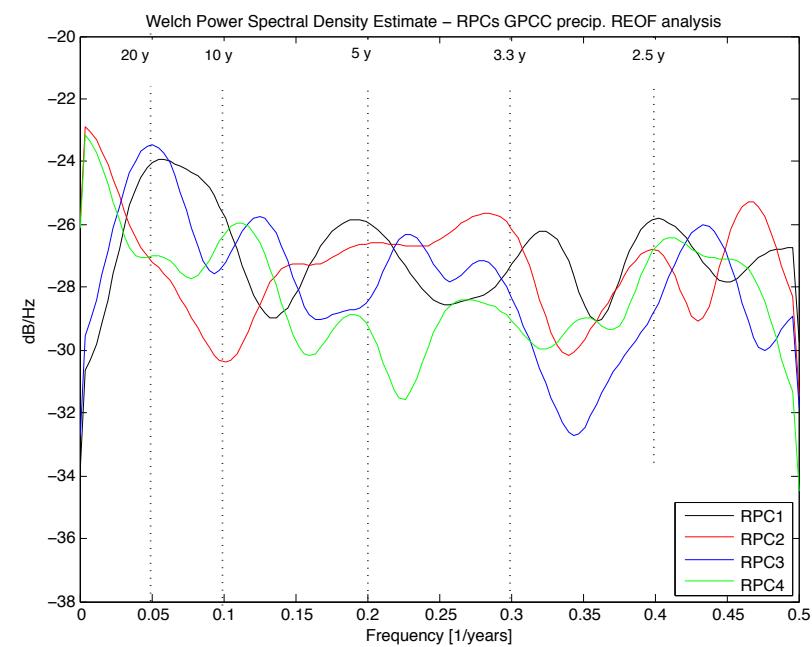
PC4



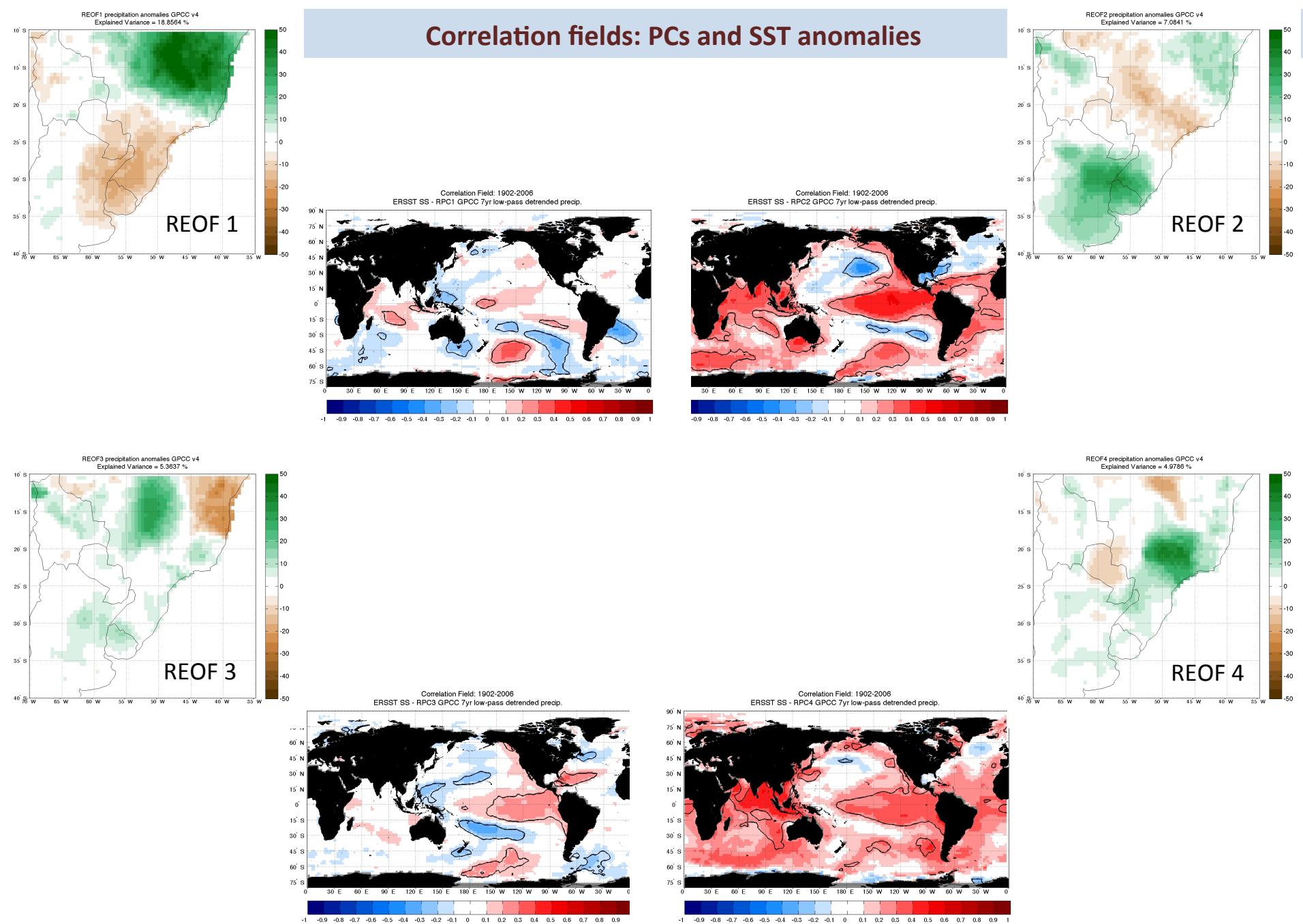
SESA reconstructed precipitation – Rotated EOF Analysis – 1902–2006



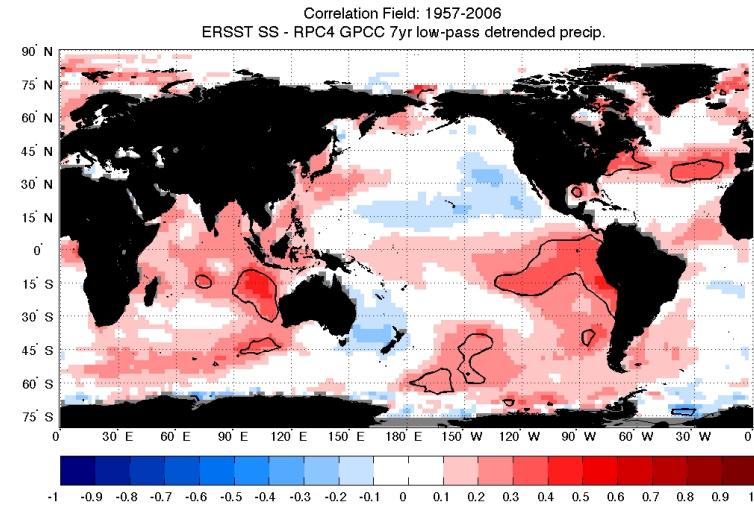
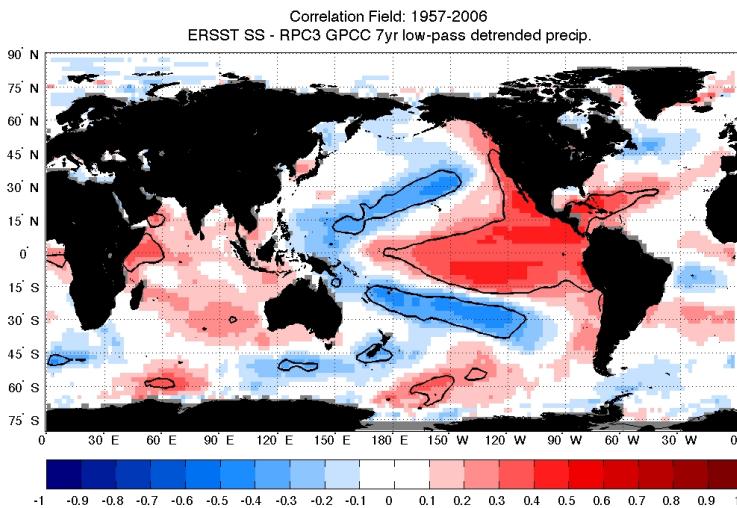
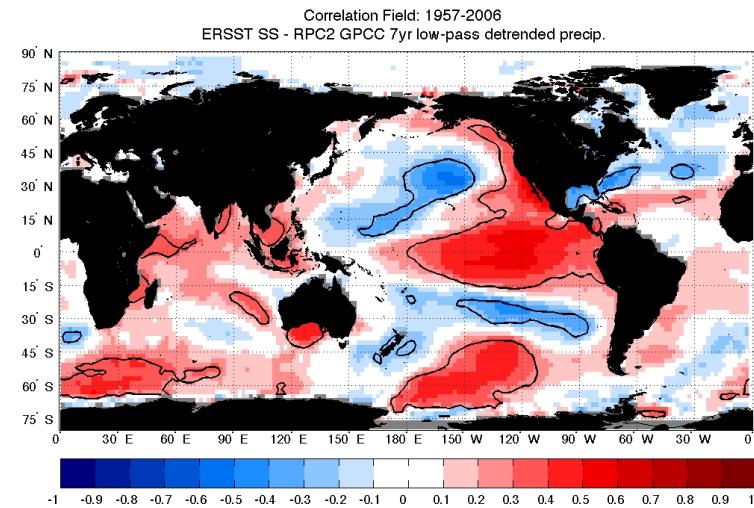
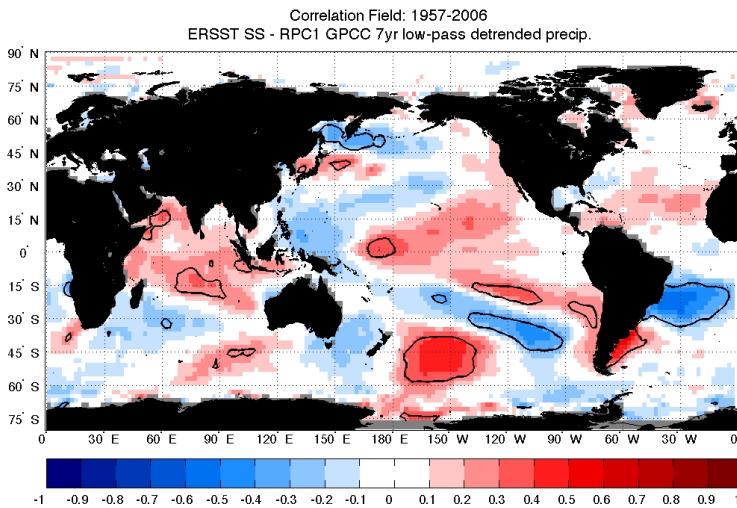
Temporal properties of SESA reconstructed precipitation



Correlation fields: PCs and SST anomalies

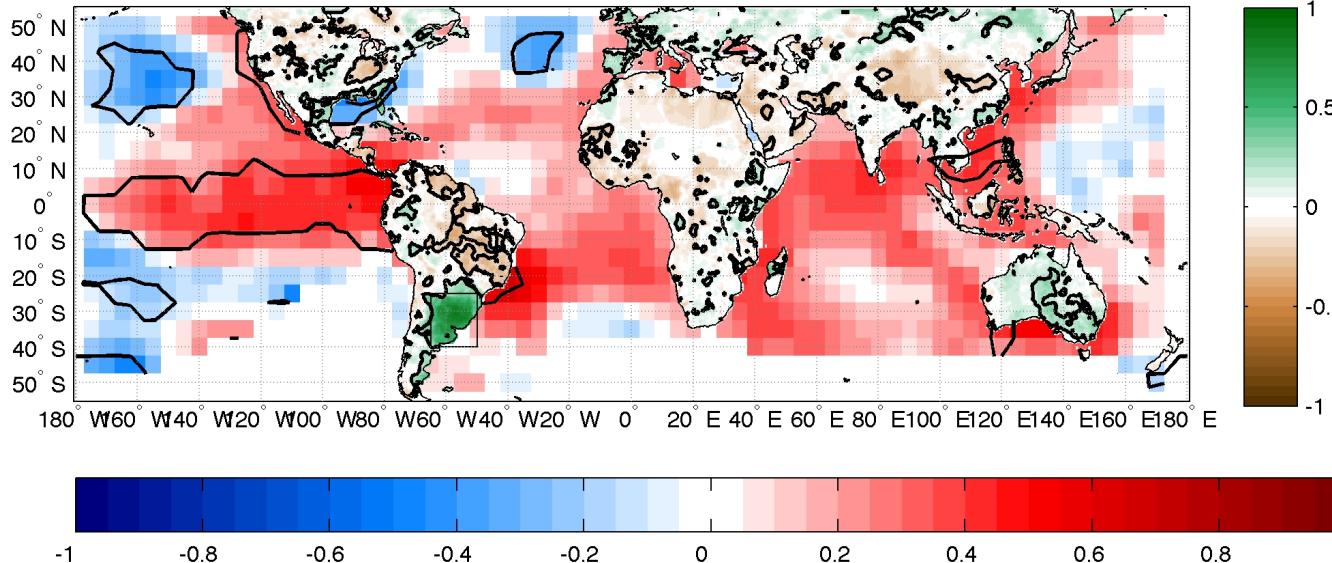


Correlation fields: PCs and SST anomalies Seem more stable then EOFs for shorter period 1957-2006

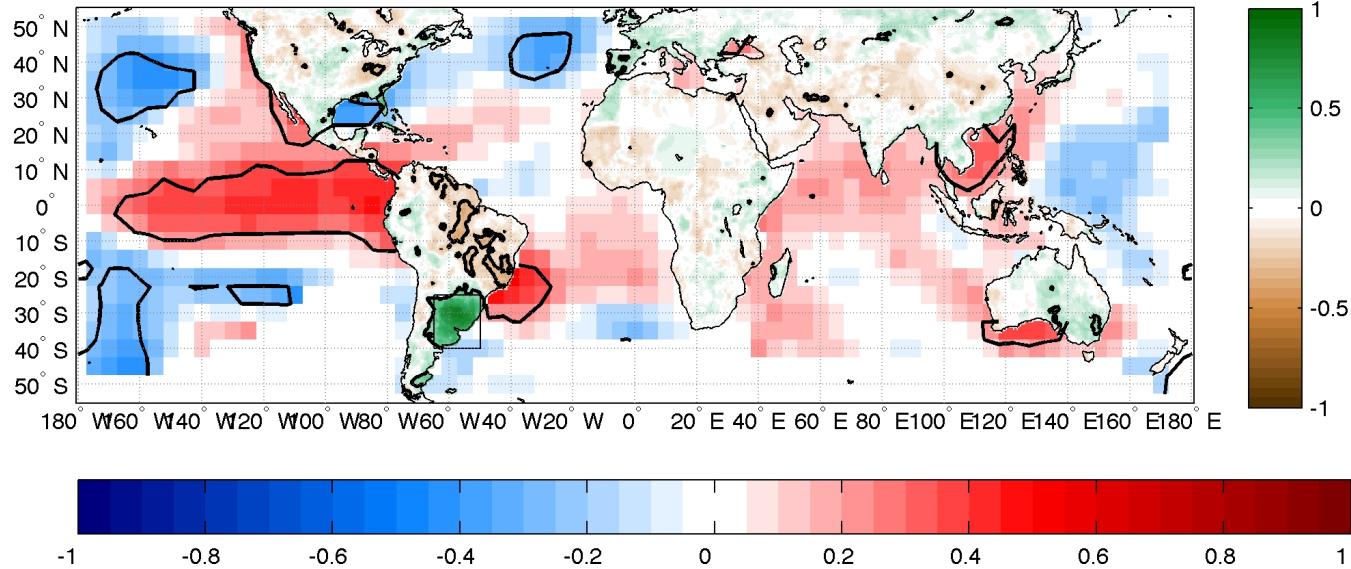


CORRELATIONS SESA PRECIPITATION

Correlations with GPCC SESA DJF precipitation
GPCC precipitation anomalies & Kaplan SST anomalies



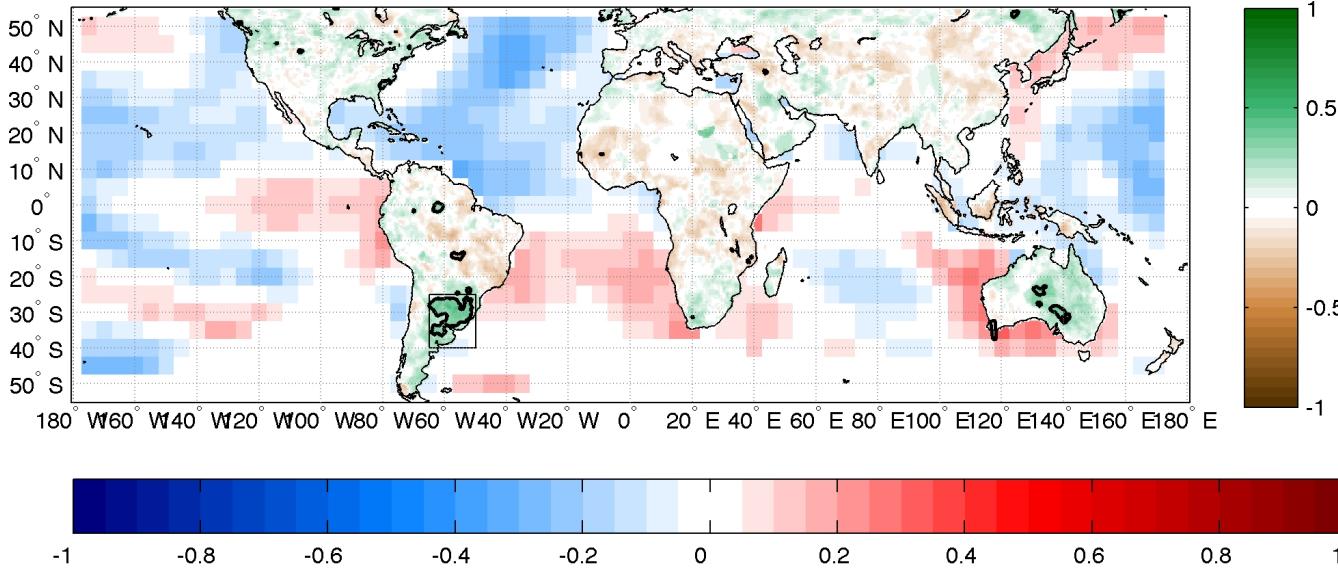
Correlations with GPCC SESA DJF detrended precipitation
GPCC precipitation anomalies & Kaplan SST anomalies



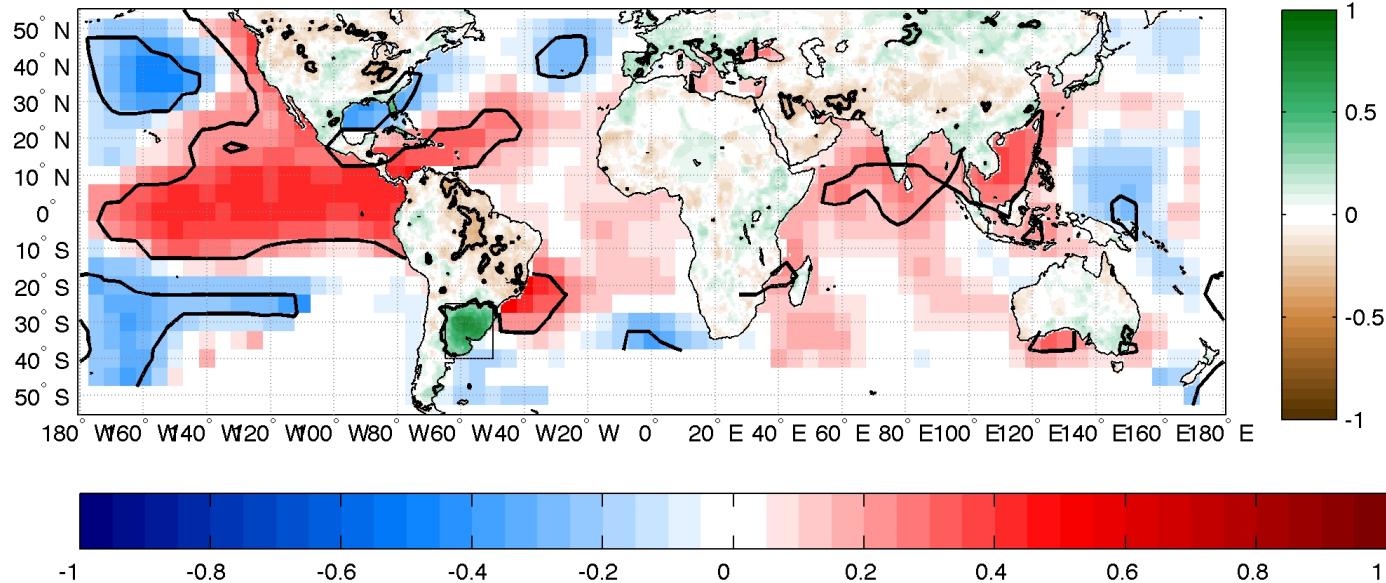
CORRELATIONS SESA DETRENDED PRECIPITATION

CORRELATIONS SESA "DECADAL" PRECIPITATION

Correlations with GPCC SESA DJF low-freq precipitation
GPCC precipitation anomalies & Kaplan SST anomalies



Correlations with GPCC SESA DJF high-freq precipitation
GPCC precipitation anomalies & Kaplan SST anomalies

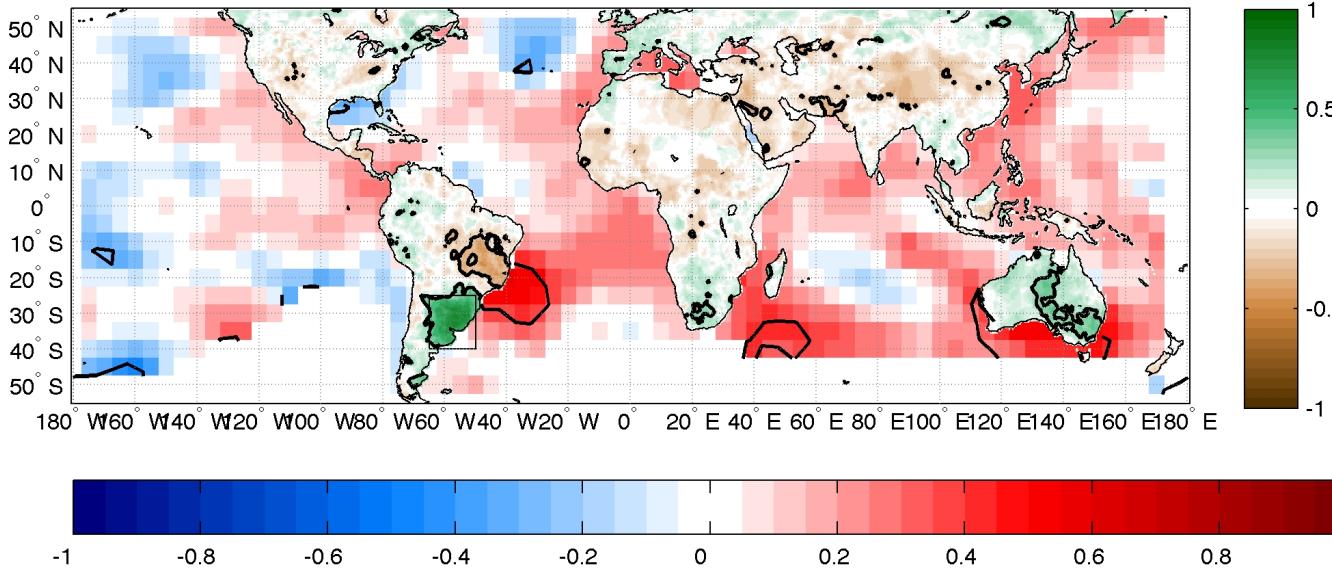


CORRELATIONS SESA "INTERANNUAL" PRECIPITATION

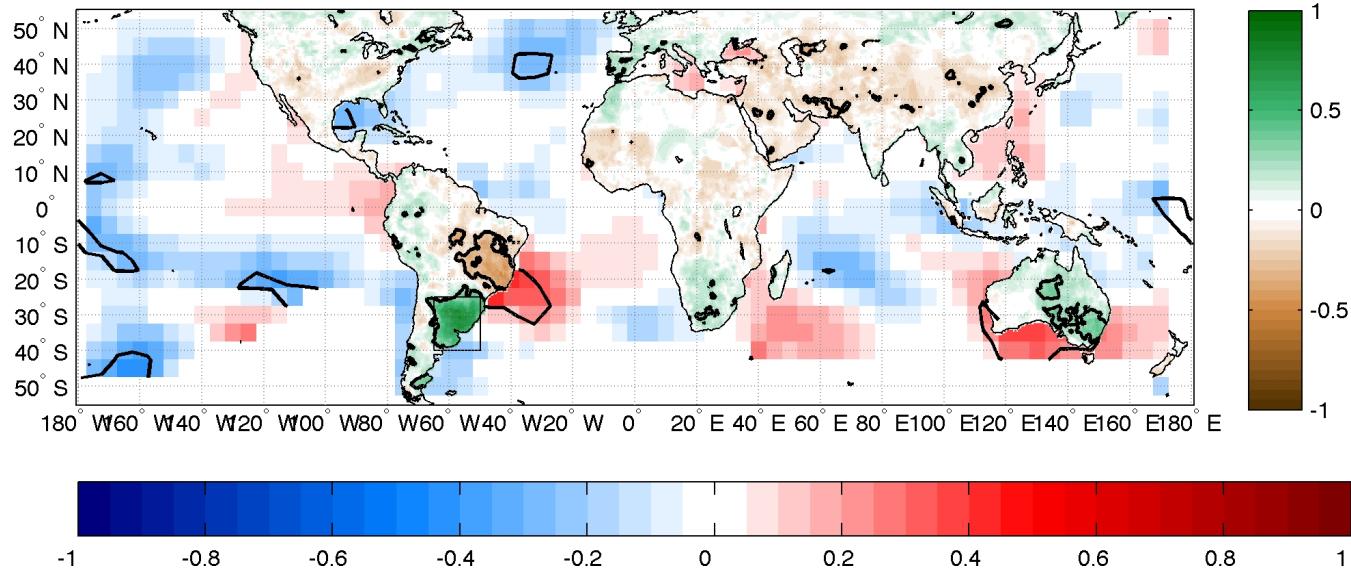
Correlations with GPCC SESA DJF noEN34 precipitation
GPCC precipitation anomalies & Kaplan SST anomalies

CORRELATIONS

SESA PRECIPITATION after ENSO removal

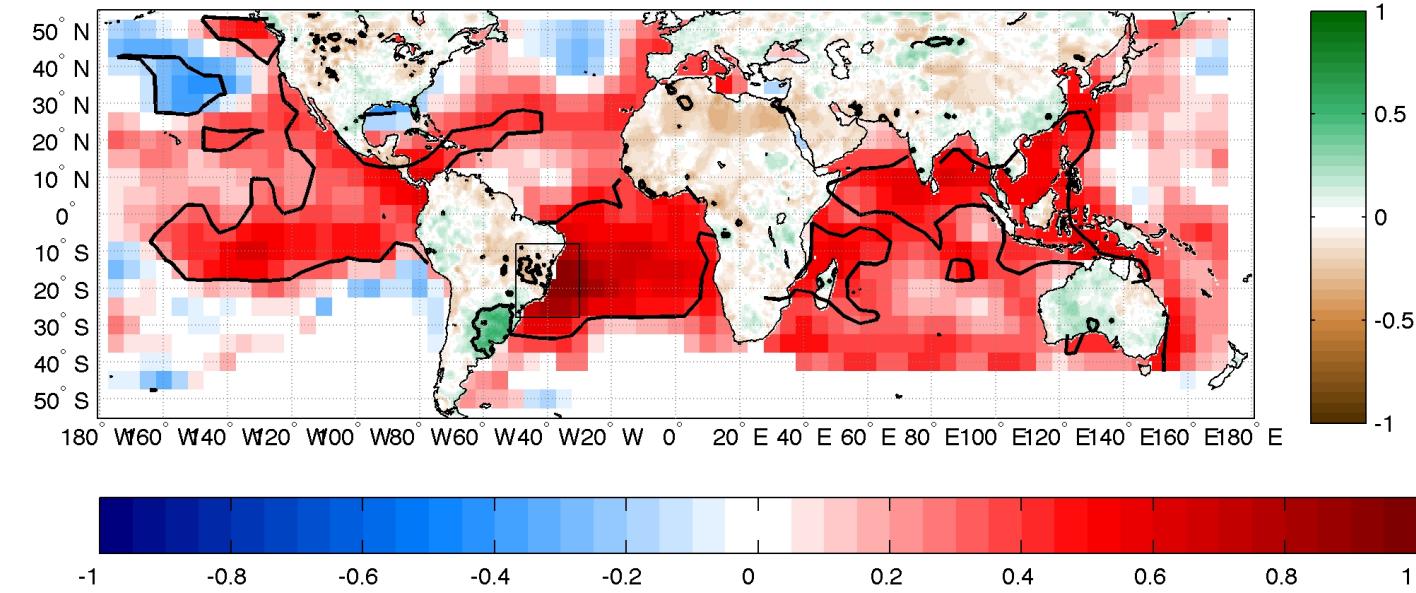


Correlations with GPCC SESA DJF noEN34 detrended precipitation
GPCC precipitation anomalies & Kaplan SST anomalies



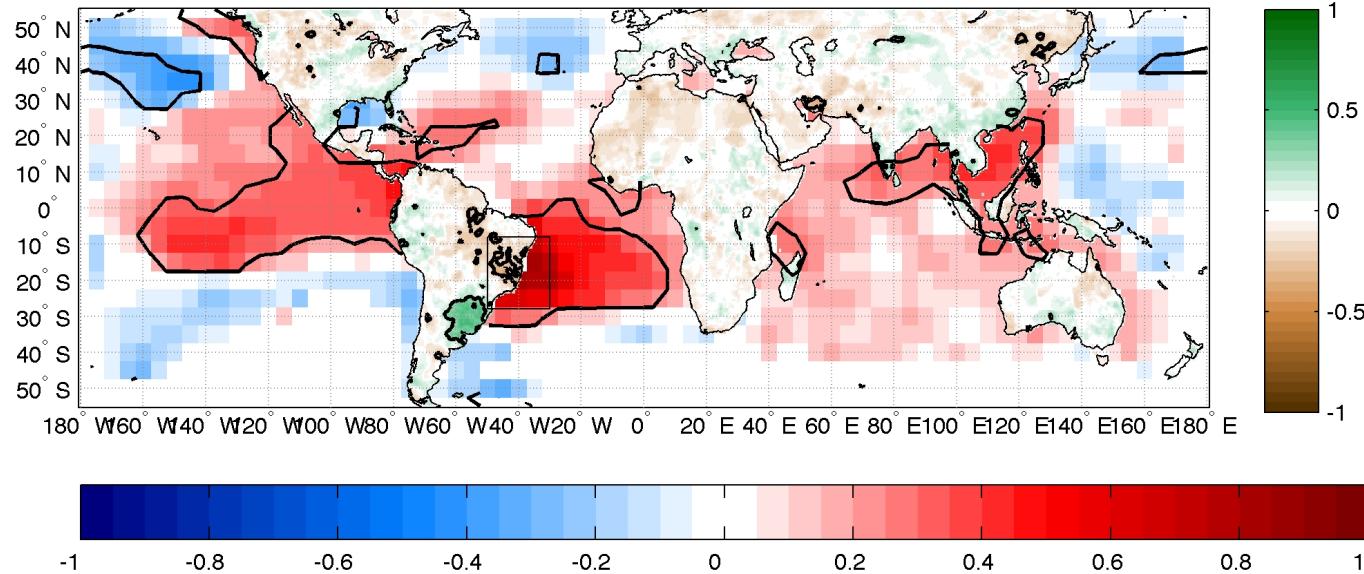
CORRELATIONS
SESA DETRENDED
PRECIPITATION
after ENSO removal

Correlations with BC Kaplan sstA
GPCC precipitation anomalies & Kaplan sst anomalies



CORRELATIONS
BC SSTA

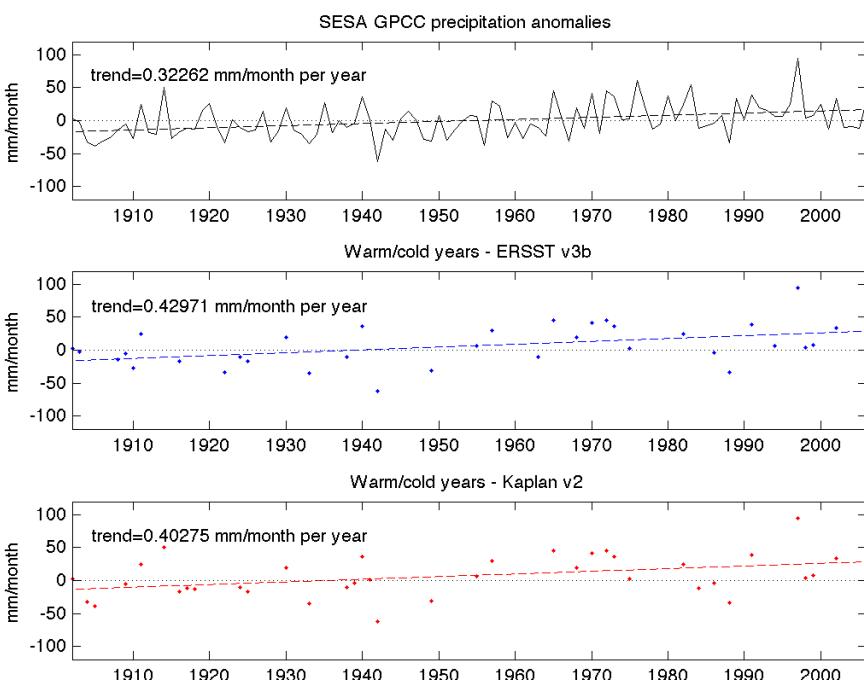
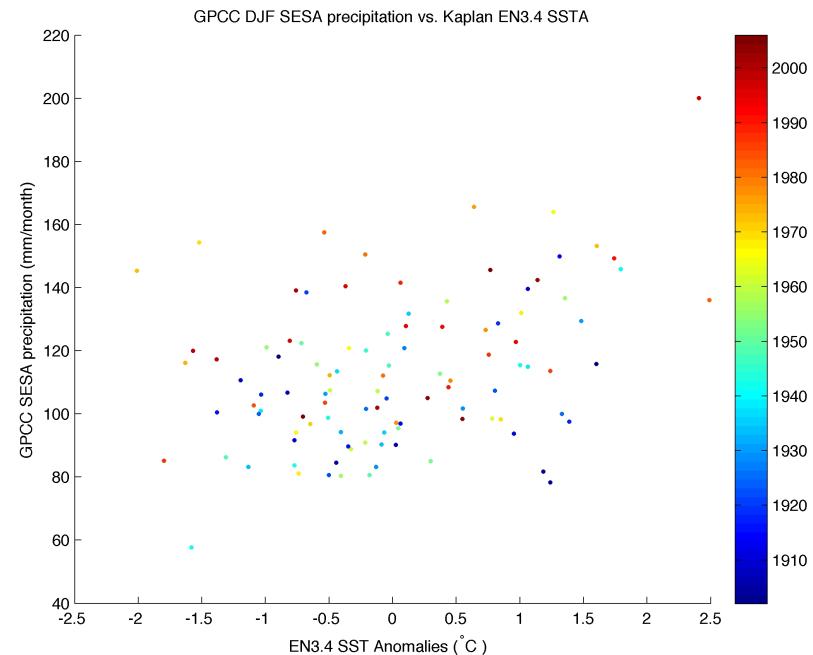
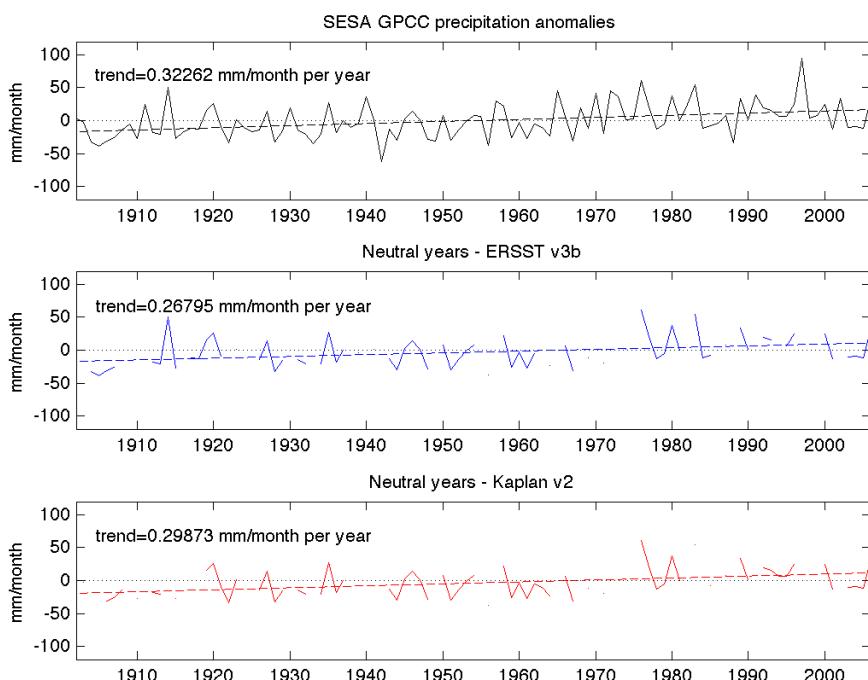
Correlations with Correlations with BC Kaplan detrended sstA
GPCC precipitation anomalies & Kaplan sst anomalies



CORRELATIONS
BC detrended SSTA

DJF PRECIPITATION LINEAR TREND ENSO DISCRIMINATION ?

COLD/WARM ENSO years show twice the trend than NEUTRAL years





The International Research Institute
for Climate and Society

**Thanks!
¡Muchas Gracias!**

gonzalez@iri.columbia.edu

