

How Much Can Model Output Statistics Improve Sub-Seasonal Prediction Skill?

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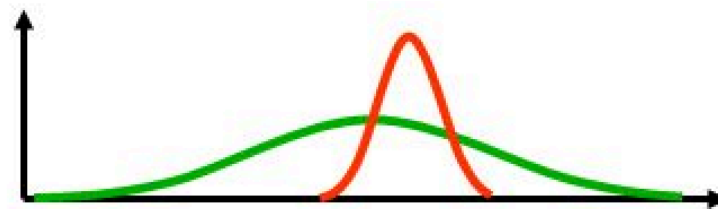
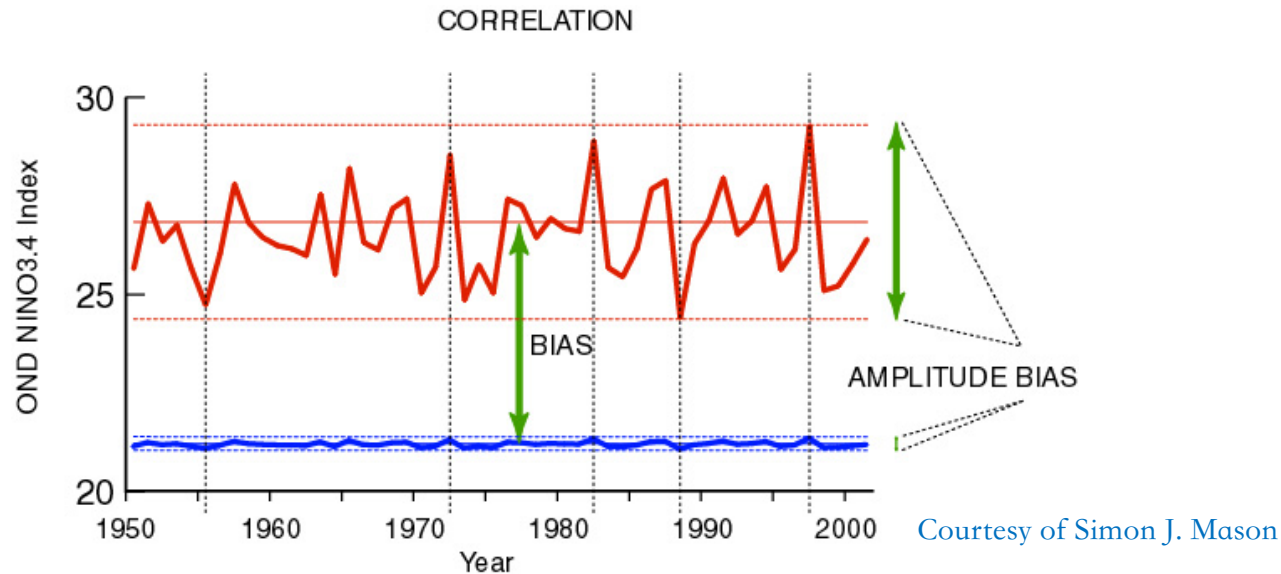
Model Output Statistics

- Because of uncertainties in initial/boundary conditions, unknown or unresolved physical processes and the chaotic nature of the climate system, *models are always subject to error*.
- Part of those errors are systematic, and can be corrected using **Model Output Statistics (MOS)**.
- Other errors are *not* correctible, and it is customary to provide an ensemble forecast to **quantify uncertainties**. This leads to probabilistic forecasts.



Model Output Statistics

- It is common to use Anomaly Correlation Coefficient to assess forecast skill, but it only measures *association*.
- There are a lot of other forecast attributes of interest!



Forecast PDF
Climatological PDF

Courtesy of Renate Hagedorn

Ignorance Score

The Ignorance Score (IGN), or negative log-likelihood score, of a probabilistic forecast of n categories can be written as (Good 1952; Roulston & Smith, 2002):

$$IGN = -\log_2(p_k) \quad k = 1..n$$

and it can be decomposed into reliability, resolution and uncertainty terms:

$$IGN = \underbrace{REL}_{\text{calibration}} - \underbrace{RES}_{\text{sharpness}} + \underbrace{UNC}_{\text{obs distribution}} \quad (\text{Weijs et al., 2010; Wilks, 2018})$$

- It measures the information deficit, or ignorance, of a person having a probabilistic forecast but not knowing the actual outcome.
- Units are *bits* of information. $IGN=0$ means perfect forecast (zero ignorance).
- Each bit of ignorance represents a factor-of-2 increase in uncertainty.
- Related to expected gambling return if used to place proportional bets on the future (cost-loss scenarios).

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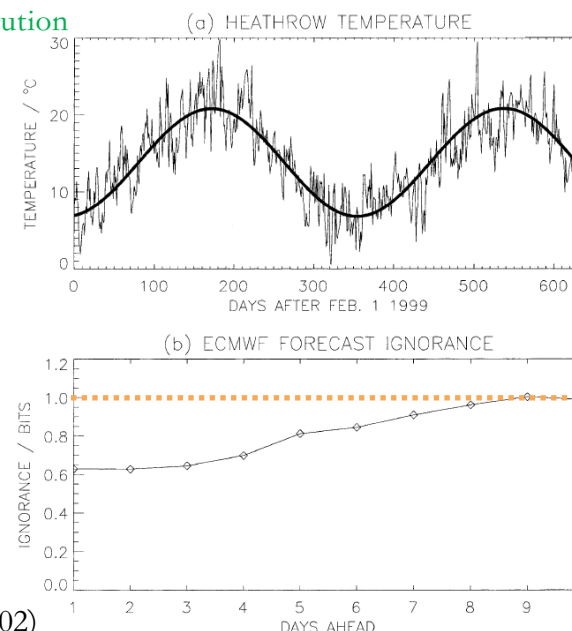
and it can be decomposed into reliability, resolution and uncertainty terms:

$$IGN = REL - RES + UNC \quad (\text{Weijs et al., 2010; Wilks, 2018})$$

calibration sharpness obs distribution

There are different ways to define a skill score for IGN. Here we use climatology as the reference. For equiprobable climatological categories,

$$ISS = -\frac{\log_2(p_k)}{\log_2(n)} \quad \left\{ \begin{array}{ll} > 1 & \text{Less info than climatology} \\ = 0 & \text{As good as climatology} \\ < 1 & \text{More info than climatology} \end{array} \right.$$

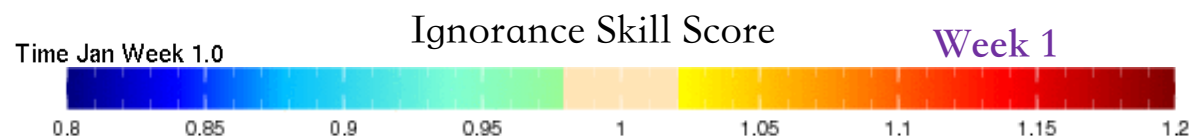
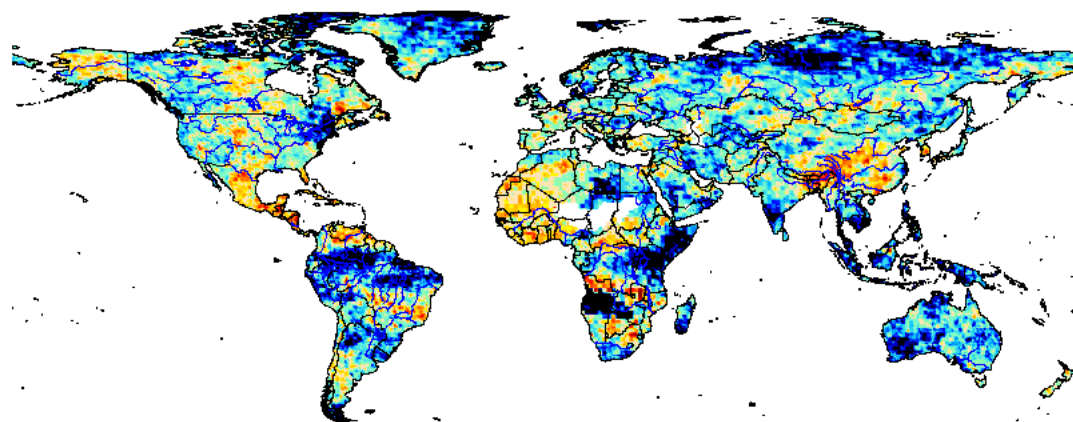
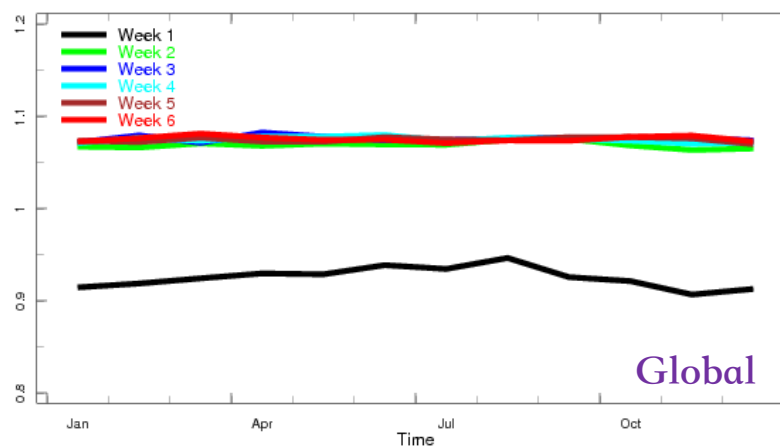


Roulston & Smith (2002)

Seasonality of Sub-seasonal Skill

Skill Assessment

- Model: ECMWF
- Rainfall
- Probabilistic
Hindcasts
- Obs: CPC Unified
- All initializations
available per month
(8-9)
- **Uncalibrated**
- IGN, RPSS, Brier
and decompositions,
for Week 1-6



Muñoz et al. (in prep)

Better

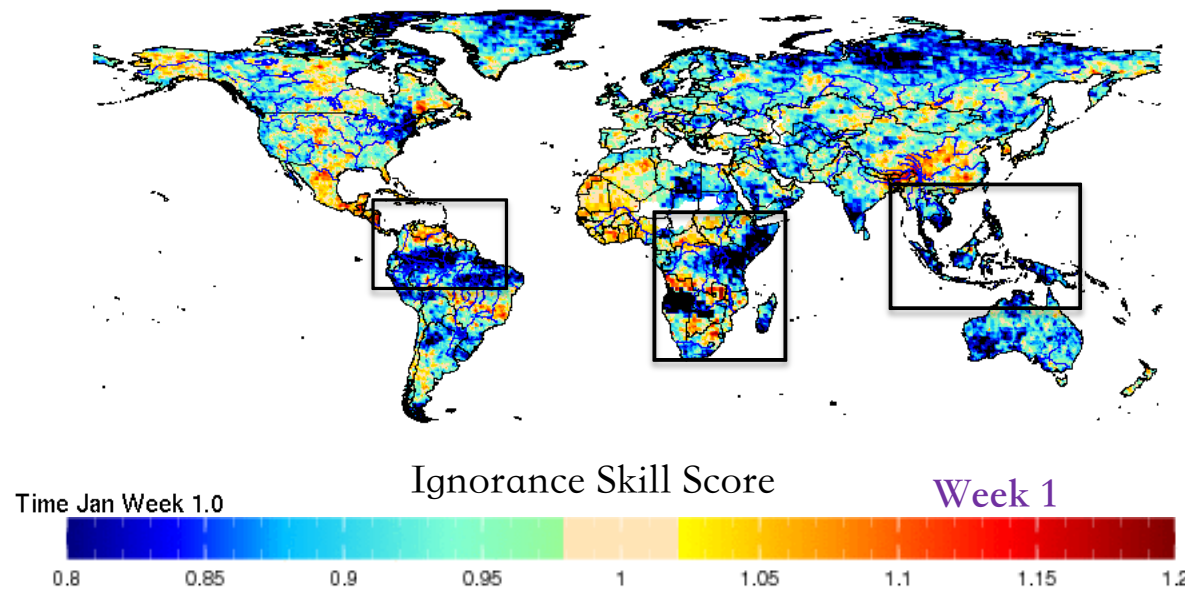
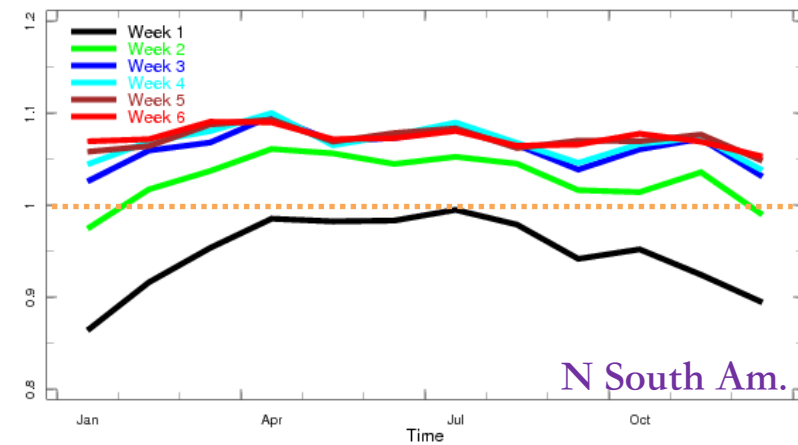
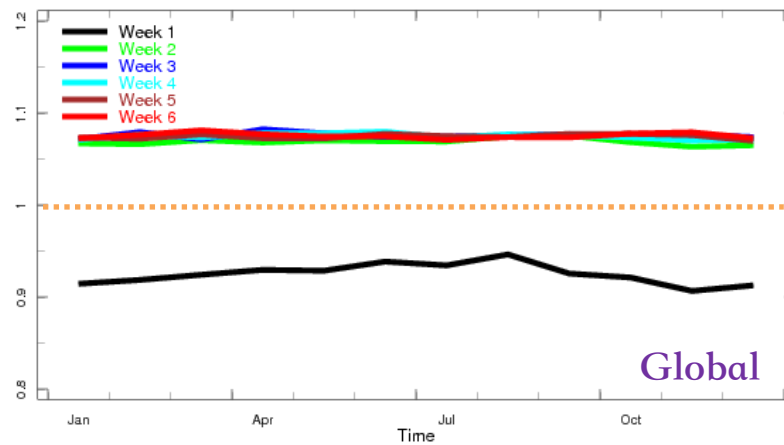
Climatology

Worse

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Seasonality of Sub-seasonal Skill



Muñoz et al. (in prep)

Better

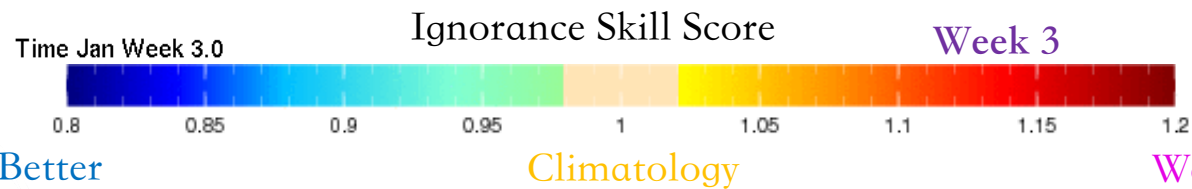
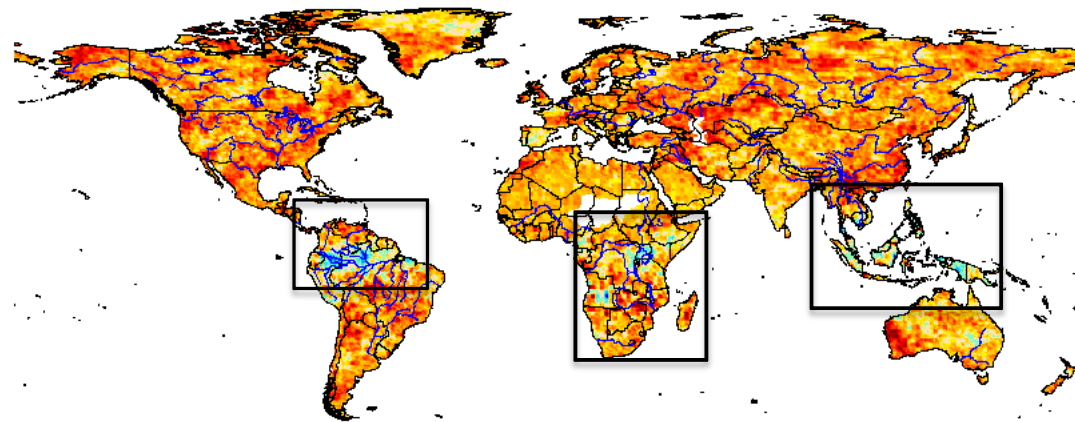
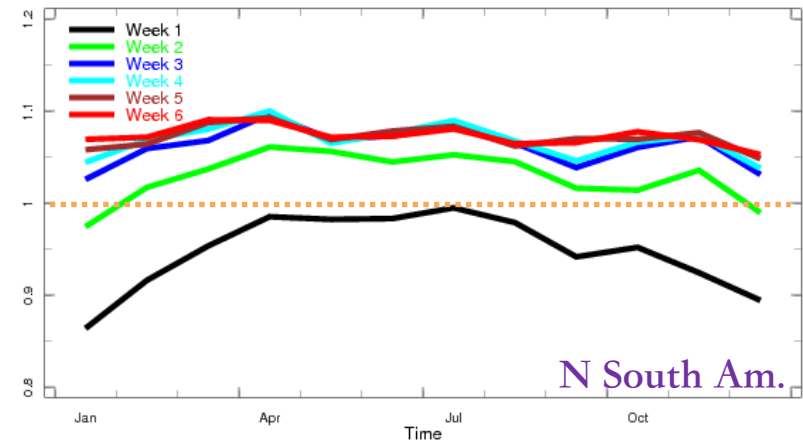
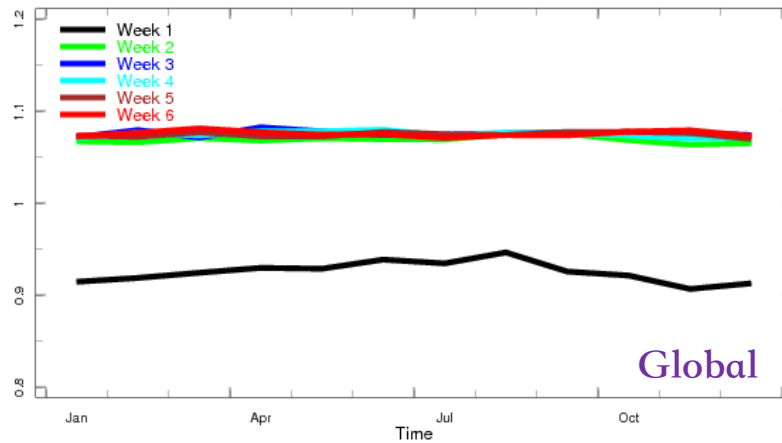
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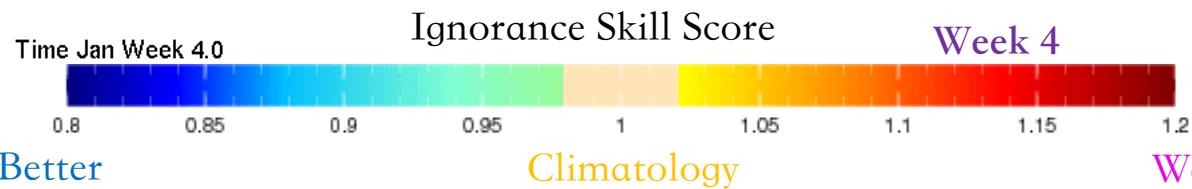
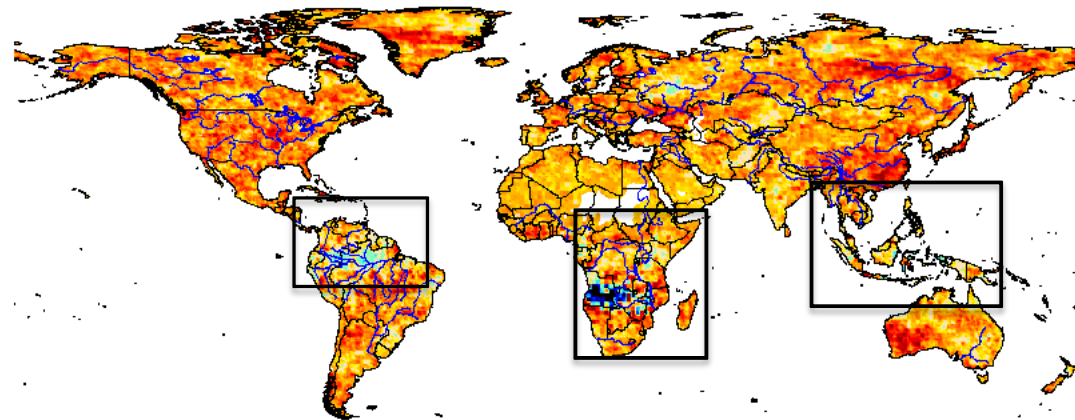
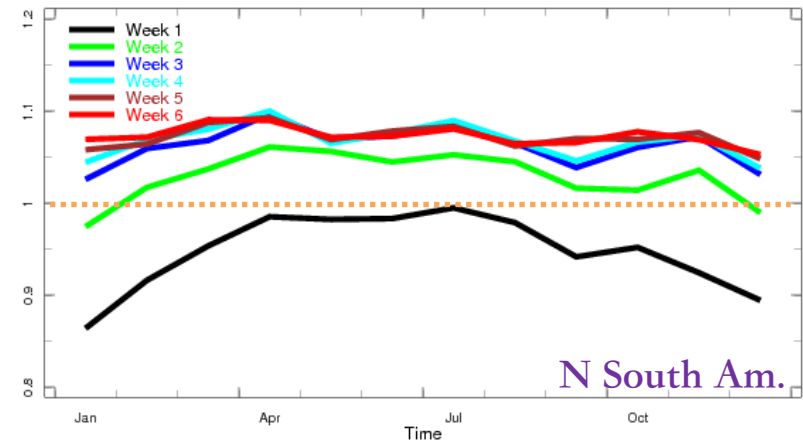
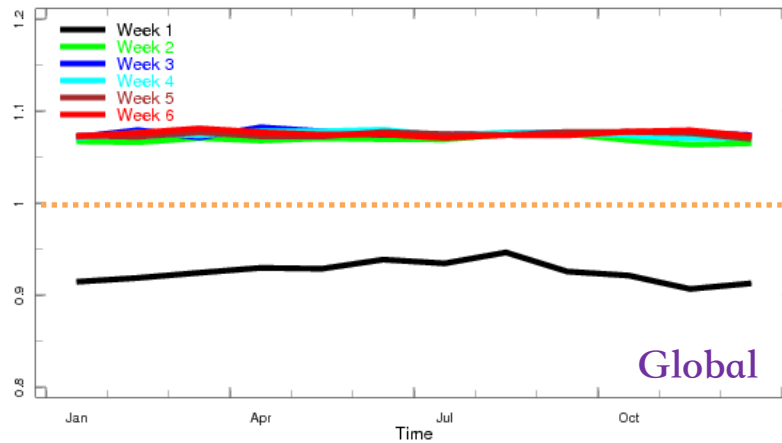
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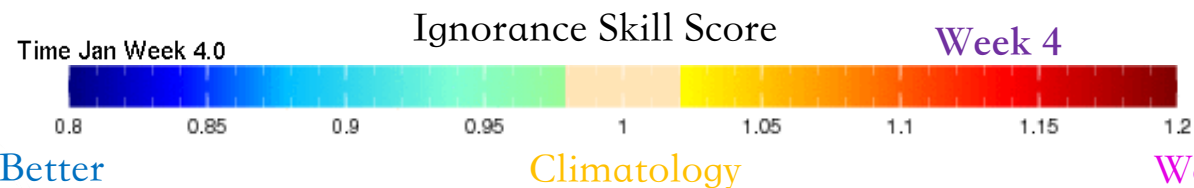
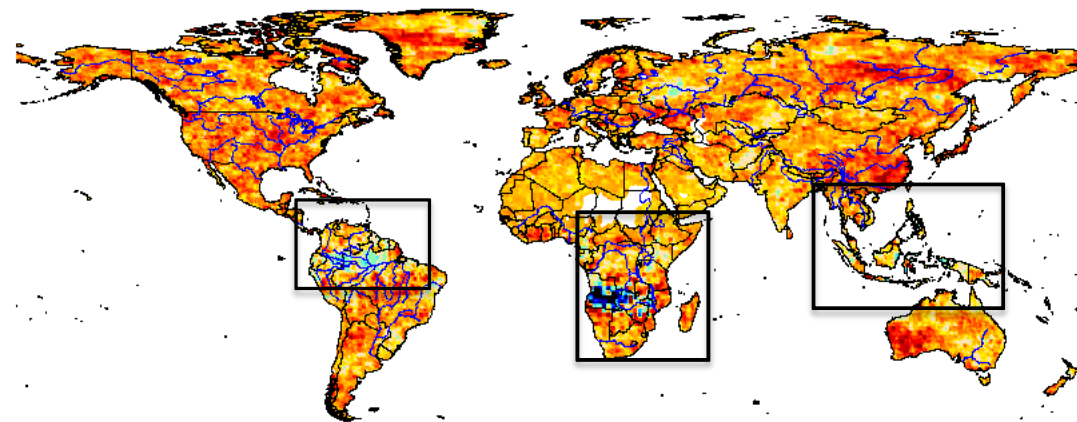
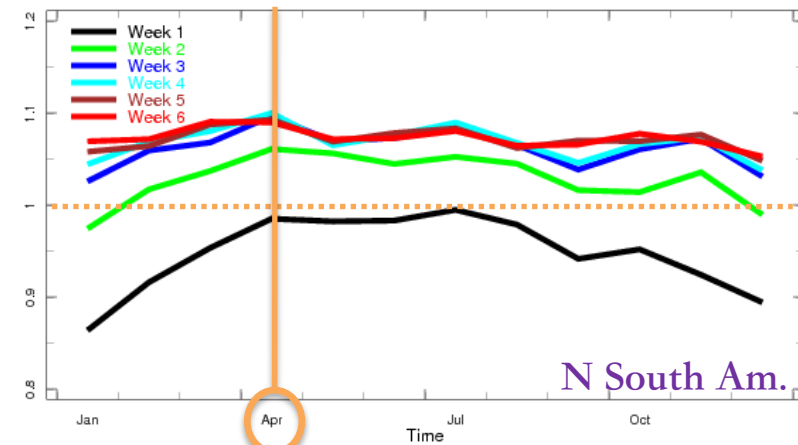
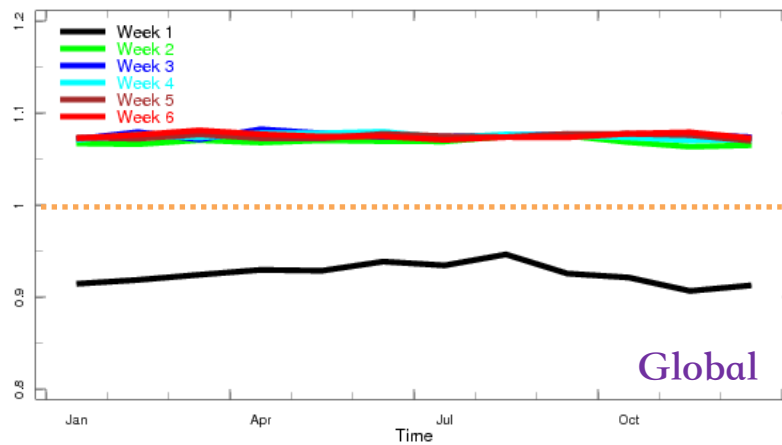
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Climatology

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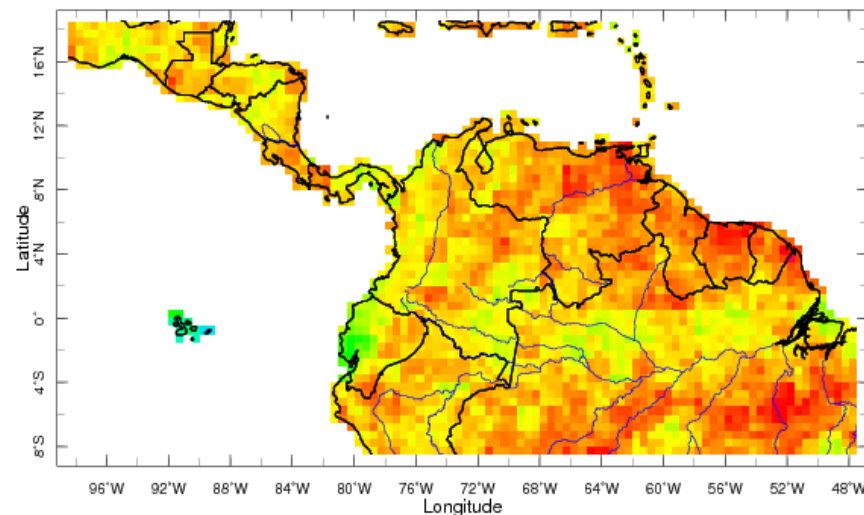
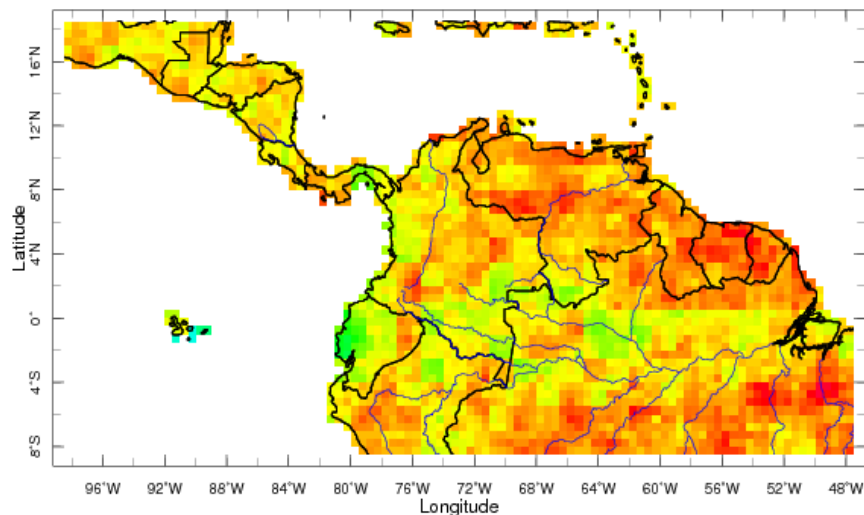
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Initializations: April

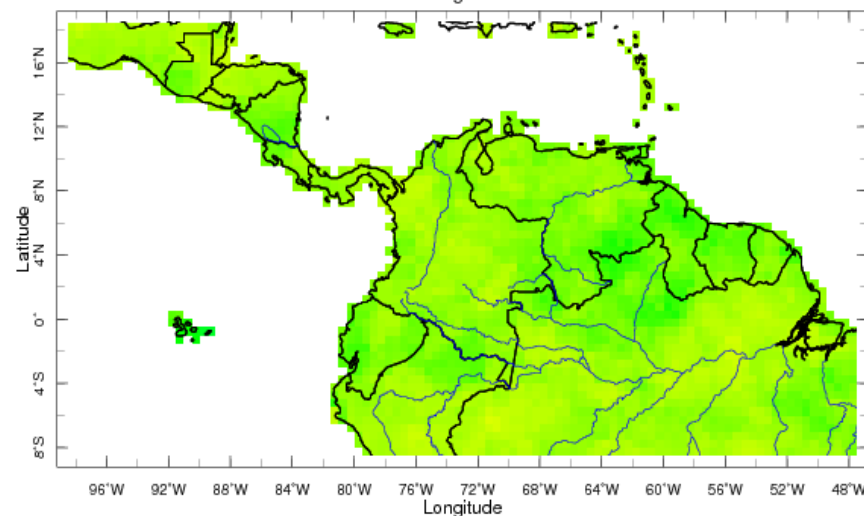
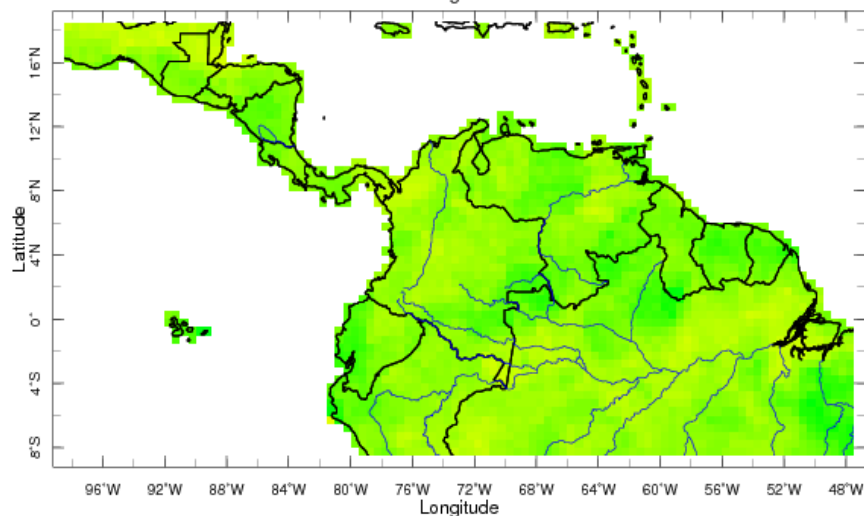
Week 3

Week 4

Uncalibrated



Calibrated (CCA)



Better

Ignorance Score
(bits)

Worse

Muñoz et al. (in prep)

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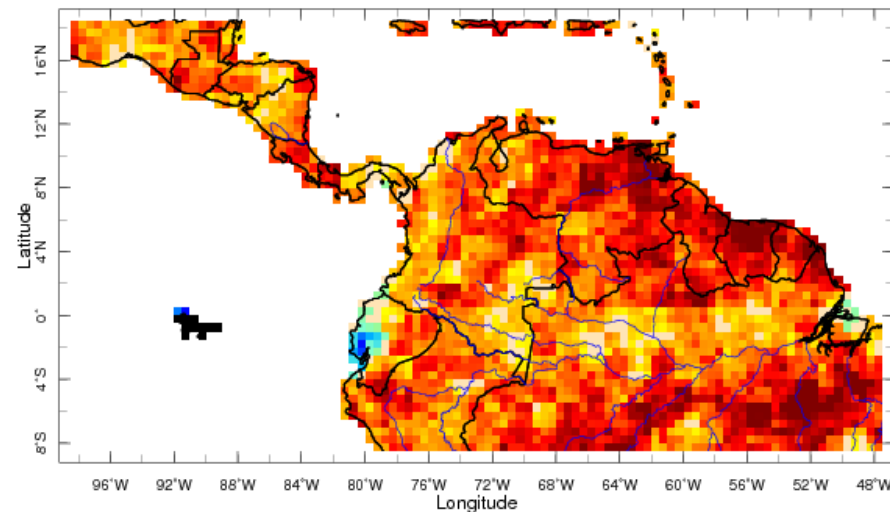
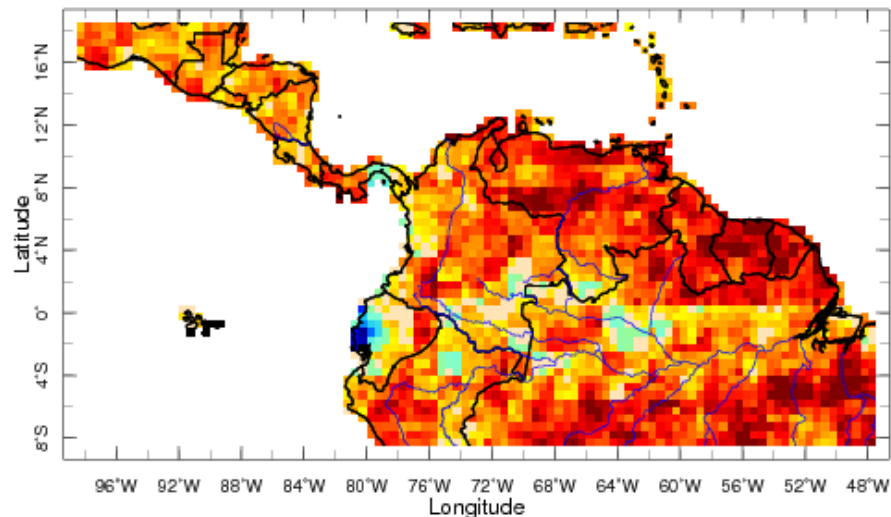
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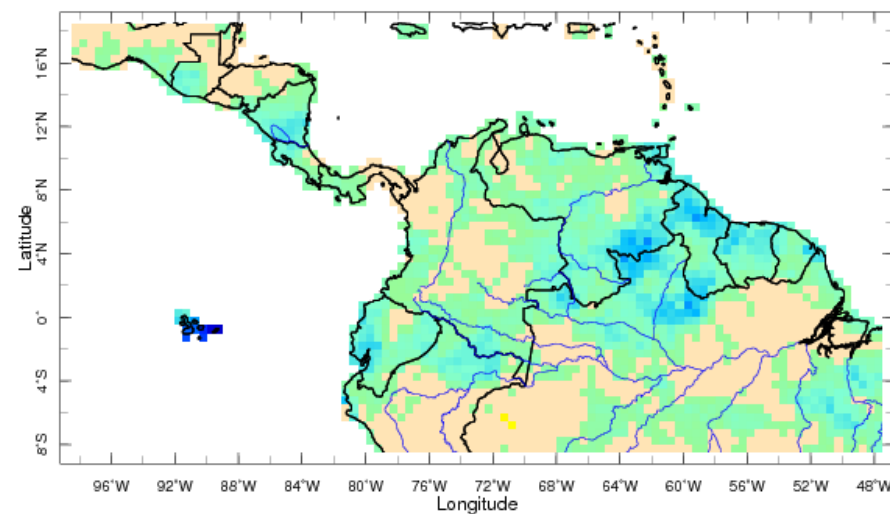
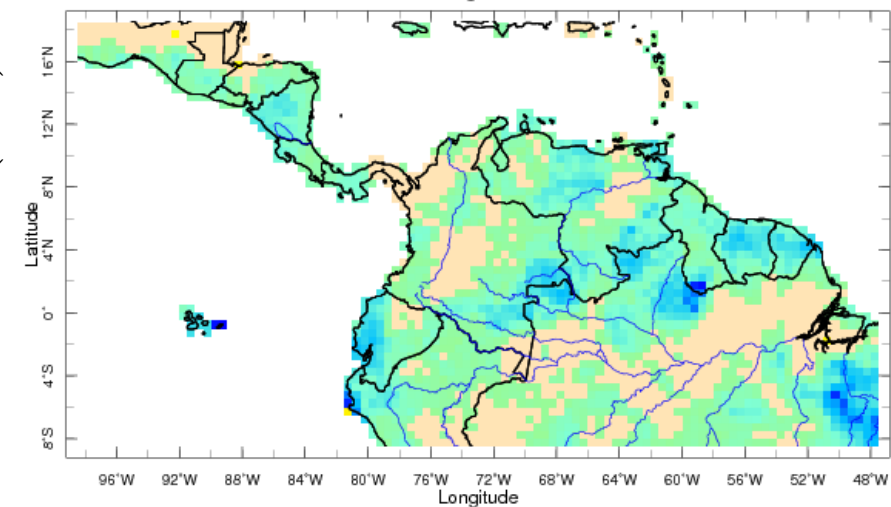
Week 3

Week 4

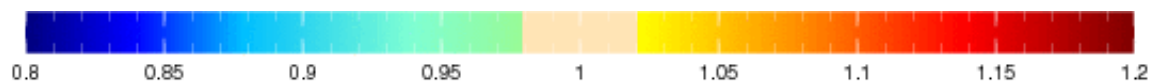
Uncalibrated



Calibrated (CCA)



Ignorance Skill Score



Muñoz et al. (in prep)

Better

Climatology

Worse

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PyCPT

Search or jump to...

agmunozs/PyCPT

Python interface for CPT

67 commits, 2 branches, 3 releases, 1 contributor

PyCPT - v1.1

Python interface for the CPT command line version

Authors

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Instructions:

```

In [9]: #####Model (choose between ECMWF, CFSv2, GEFS)
model="ECMWF"

#####Obs (choose between TRMM, CPC, IND1deg, INDp25deg)
obs="CPC"

#####MOS method (choose between None and CCA)
MOS="CCA"

#####Forecast date
#-- If ECMWF, it needs to be a Monday or a Thursday! CFSv2: any day; GEFS: Wednesdays.
mon="Jul" # Forecast month
fyr=2018 # Forecast year
fday=26 # Forecast day (Yesterday in CFSv2; real time)
training_season="Jun-Aug" # "Jun-Aug" #for CFSv2 and GEFS

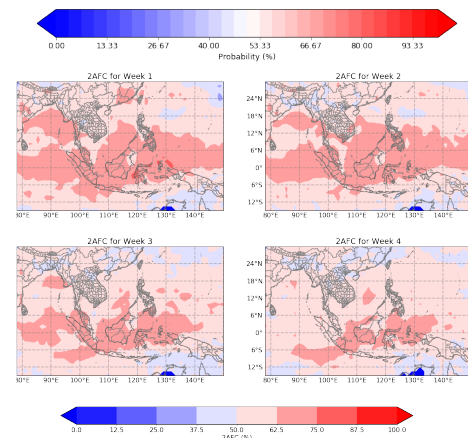
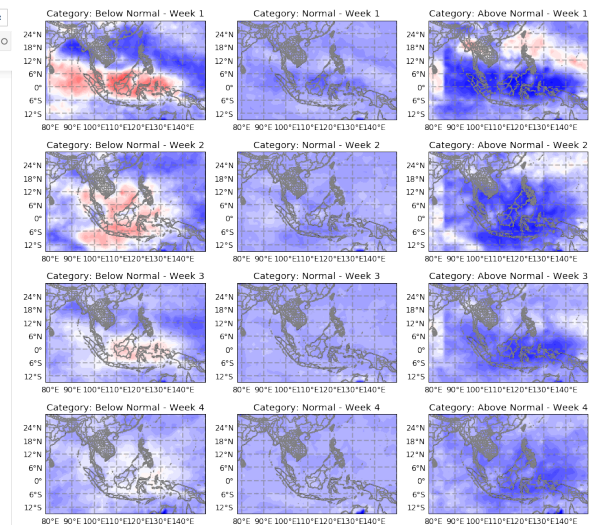
nwk=4 # Number of weeks to process (leads)

#####Witchos:
force_download = True #force download of data files, even if they already exist locally
# Rainfall frequency switch
rainfall_frequency = False #False gives total rainfall for forecast period

wetday_threshold = 3 #WET day threshold (mm) --only used if rainfall frequency is True!
threshold_potle = False #False for threshold in mm; Note that if True then it counts DRY days!!

#####Spatial domain for predictor
nlat=35 # Northernmost latitude
slat=-20 # Southernmost latitude
wlon=73 # Westernmost longitude
elol=155 # Easternmost longitude
# Spatial domain for predictand
nlat2=30 # Northernmost latitude
slat2=-15 # Southernmost latitude
wlon2=78 # Westernmost longitude
elol2=150 # Easternmost longitude

#####Forecast lead interval
# Lists for looping over lead times
wk = [1,2,3,4,14] # week-lead number label (week1, week2, week3-4)
# ECMWF - first day is day 0, 0000Z accumulated rainfall; specify day1=0 for week 1
# GEFS - first day is day 0.5 (daily average rainfall rate); specify day1=0 for week 1
# CFSv2 - first day is day 1, 0000Z accumulated rainfall order the first day; specify day1=1 for week 1
day1 = [0,7,14,21,14] # first lead day of target weeks
    
```



Funded by:

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 NOAA NA18OAR4310275 (Muñoz)
 Columbia World Project "ACToday" (Goddard)

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- **Python** interface for IRI's Climate Predictability Tool (CPT), a widely used research and application **Model Output Statistics/Prediction** toolbox.
- Publicly available: **GitHub**.
- Automatically downloads required **observations** (TRMM, CPC Unified) and **S2S model data** from the IRI Data Library (S2S Database and SubX – ECMWF, CFSv2, GEFS, others are being included).
- Computes climatologies, anomalies, a variety of **skill metrics** (uncalibrated and CCA-calibrated hindcasts) and **probabilistic sub-seasonal forecasts**.

Conclusions

- Sub-seasonal skill – as measured by the Ignorance Score – at *regional* scale tends to exhibit seasonality. *Global* sub-seasonal skill varies less along the year.
- Generally speaking, uncalibrated sub-seasonal forecast skill is worse than climatology after Week 2. There are some exceptions: Tropical South America, Eastern and Southern Africa, Maritime Continent.
- Model Output Statistics has the potential to improve forecast skill at sub-seasonal timescales. In particular, EOF-based MOS methods like Canonical Correlation Analysis (and Principal Component Regression) show clear skill improvement for different regions of the world, both in magnitudes and spatial patterns.
- Work in progress – stay tuned.

More details?

**Doss-Gollin,
James**

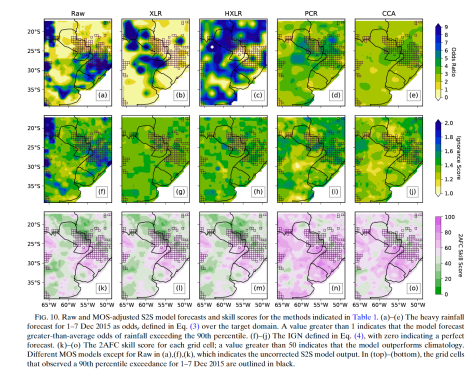
Heavy rainfall in Paraguay during the 2015-2016 austral summer: causes and sub-seasonal-to-seasonal predictive skill

P-C3-04

Thursday
20 Sept.

Center
Green

Doss-Gollin et al (JCLim 2018)



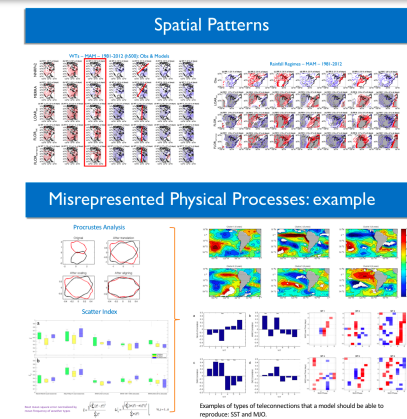
Munoz, Angel G
A Seamless Process-based Model Evaluation Framework for Subseasonal-to-Decadal Timescales

P-C3-09

Thursday
20 Sept.

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Muñoz et al (JCLim 2017; in prep.)



**Materia,
Stefano**

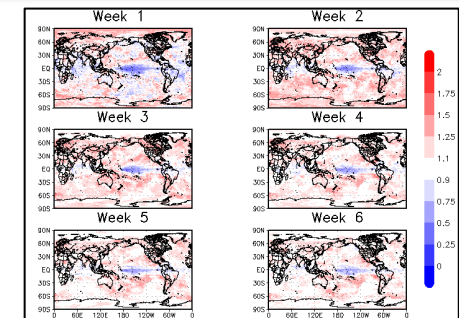
A multi-model approach for cold spell sub-seasonal prediction in Northern Turkey

P-A4-08

Wednesday
19 Sept.

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Materia et al (in prep.)



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